NEW DIRECTIONS OF DIGITAL ECONOMY, ENERGY TRANSITION, AND CLIMATE CHANGE IN THE POST-COVID-19 ERA: APPLICATION OF MACHINE LEARNING AND OTHER ADVANCED ANALYTICAL TECHNIQUES

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frontiers Research Topics

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New directions of digital economy, energy transition, and climate change in the post-COVID-19 era: application of machine learning and other advanced analytical techniques

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Editorial: New directions of digital economy, energy transition, and climate change in the post-COVID-19 era: application of machine learning and other advanced analytical techniques

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Editorial on the Research Topic
New directions of digital economy, energy transition, and climate change in the post-COVID-19 era: application of machine learning and other advanced analytical techniques

1 Introduction

Since the outbreak of COVID-19, international energy prices have fluctuated dramatically, leading to historic shifts in energy supply and demand and causing significant disruption to the global energy system (Yu et al., 2021). In response, countries worldwide have embraced green, low-carbon, efficient, and renewable energy as key components of energy transition (Yu et al., 2023). As the world moves into the post-COVID-19 era, accelerating the clean use of fossil fuels and upgrading energy structures has become a critical challenge for all nations (Shen et al., 2024). The pandemic has catalyzed transformative changes in lifestyles, production methods, economic systems, and governance models, pushing humanity toward the digital economy (Wang et al., 2023). The digital economy, empowered by data and technology, has spurred industrial refinement, automation, and intelligent development, reducing energy and resource consumption while providing favorable conditions for global industrial upgrades, energy transition, and climate action. The digital economy's wide application across industries, from energy to manufacturing and transportation, has proven to reduce CO_2 emissions, offering technical support for energy transition and climate improvement (Lu et al., 2023). This editorial synthesizes findings from 16 papers that explore the intersections of the digital economy, energy transition, and climate change, focusing on the application of machine learning and advanced analytical techniques in the post-pandemic era. These

studies illuminate new pathways for reducing carbon emissions, enhancing green innovation, and navigating the global energy transition.

2 Digital economy and carbon emission reduction

The development of the digital economy has emerged as a critical factor in reducing carbon emissions, particularly in the context of industrial and regional transformations (Lu et al., 2023). Several studies provide empirical evidence that digital technologies can reduce carbon emissions by optimizing industrial structures, improving resource allocation, and fostering green innovation. Lyu et al. examined how digital economy development in China has reduced carbon emission intensity, with regional disparities showing more significant effects in the eastern provinces. Similarly, Liu et al. demonstrated how the integration of digital technologies in Chinese cities improves carbon efficiency, particularly in large-scale and resource-based cities.

The relationship between digitalization and carbon emissions extends beyond individual industries. Lyu et al. explored how digital value chain embeddedness impacts trade-related carbon emissions across 41 countries, revealing an inverted U-shaped relationship. The environmental benefits of digitalization only become apparent once a country reaches a certain threshold of digital integration, with developing countries lagging behind in realizing these benefits. Jiang et al. used the panel data of 275 cities in China to analysis the non-linear effect of digital economy on industrial structure upgrading and urban carbon emissions. In addition, Li et al. used the CFPS data in China and investigated the influence of digital economy on private donation behavior.

3 Industrial transformation and green innovation

Industrial sectors are at the forefront of the global push for carbon neutrality, and digital technologies are playing an increasingly important role in driving green innovation. Liu et al. focused on China's industrial green transformation, which is being driven by digitalization and technological advances. The study identified regional disparities, with more developed areas making faster progress in green industrial practices. This echoes the findings of Zhong et al., which examined the coupling between the digital economy and green development in Guangdong Province. The research showed that cities with stronger digital economies tend to have better green development outcomes, but significant regional imbalances persist.

The construction industry, traditionally a high-emission sector, is also undergoing a digital transformation. Yang et al. explored how digital construction technologies are reducing carbon emission intensity in Chinese enterprises by enhancing innovation capacity and improving productivity. This paper highlights the potential for digital technologies to accelerate green transitions in traditionally resource-intensive industries, particularly through the adoption of new tools and processes. The role of digital technologies in supporting green innovation is further explored in Gao et al., which used machine learning to assess the impact of industrial land-use policies on firms' green technology innovation. The study found that reforms in land-use policies significantly promote green innovation, especially in regions with advanced digital infrastructure.

4 Energy transition and the role of digital infrastructure

The global energy transition is a key component of efforts to combat climate change, and digital technologies are playing a crucial role in facilitating this shift. Yan et al. examined the impact of the Broadband China Policy on rural households' adoption of clean renewable energy. The study found that digital infrastructure significantly influences clean energy adoption, though the effects vary by region. The role of financial systems in supporting energy transitions is also highlighted in Jia et al., which investigated how financial openness influences energy structure transformation. The study found that financial reforms are critical to enabling investments in clean energy, particularly in regions with underdeveloped financial markets.

Machine learning and artificial intelligence (AI) are also being applied to optimize energy use and reduce emissions. Xie and Wang explored the nonlinear carbon reduction effects of AI across Chinese provinces, finding that AI technologies can significantly reduce carbon emissions, particularly in regions with high levels of digital infrastructure and economic development. In addition, Li and He used the text analysis method to directly construct the national, provincial, and prefecture-level environmental policy uncertainty index (EPUI) in China and investigated the impact of EPUI on China's energy transition.

5 Corporate sustainability, ESG, and the post-pandemic green shift

In the post-pandemic era, corporate sustainability efforts are becoming increasingly focused on environmental, social, and governance (ESG) performance. Several papers explore how digital technologies and machine learning are enhancing corporate efforts to reduce carbon emissions and align with ESG goals. Ye and Xu provided empirical evidence that strong ESG performance is associated with significant reductions in corporate carbon emissions. The study highlights that digital transformation amplifies the effectiveness of ESG strategies, suggesting that companies with advanced digital tools are better positioned to meet their sustainability goals. The impact of resource dependence on corporate ESG performance is further examined in Fei et al., which found that companies in regions with high resource dependence tend to have lower ESG scores, particularly in environmental and social dimensions. This study argued that digital tools can help mitigate the negative effects of resource dependence by enabling more efficient resource use and improving corporate governance practices.

The COVID-19 pandemic has also reshaped corporate investment strategies, with implications for green development. He et al. documented the negative impact of the pandemic on

green investment in China, as firms faced financial constraints that limited their ability to invest in sustainable projects. However, the study also found that while overall investment levels were maintained, the structure of investments shifted away from green initiatives. This finding underscores the importance of targeted financial policies to support green investment in the post-pandemic recovery.

6 Conclusion

All the 16 papers reviewed in this editorial collectively highlight the transformative potential of the digital economy, machine learning, and advanced analytical techniques in driving energy transitions and addressing climate change. This unique edition encompasses four distinct yet interconnected thematic areas that hold significant relevance in the context of the digital economy, energy transition, and climate change in the post-COVID-19 era. These areas include Digital Economy and Carbon Emission Reduction, Industrial Transformation and Green Innovation, Energy Transition and the Role of Digital Infrastructure, and Corporate Sustainability, ESG, and the Post-Pandemic Green Shift. Collectively, these areas offer numerous practical pathways and enrich the existing body of literature by seamlessly integrating the digital economy into energy transition strategies aimed at mitigating the impact of climate change.

Digital technologies are already contributing to carbon emission reductions, enhancing industrial green innovation, and supporting the global shift toward renewable energy. However, significant challenges remain, particularly in ensuring equitable access to digital infrastructure and financial resources, which are critical to realizing the full potential of these technologies. As we move into the post-COVID-19 era, it is essential for policymakers, businesses, and researchers to collaborate on leveraging digital tools to accelerate the transition to a sustainable, low-carbon economy. By integrating digitalization with green policies and supporting innovation across industries, the global community can make meaningful progress toward achieving climate goals and ensuring a resilient, sustainable future.

In order to realize these objectives, it is essential to expand future research endeavours into diverse domains. Noteworthy areas for prospective investigation, as highlighted by the authors, include extending the research scope across various industries and geographies to afford a comprehensive insight into the impact of ESG performance on carbon reduction within distinct business environments (Ye and Xu). Furthermore, it is necessary to delve into the dynamics of the interplay between the digital economy and sustainable development pre- and post-epidemic, elucidating the coupling and coordination mechanisms, as well as to holistically assess the repercussions of the COVID-19 outbreak on the interrelationship between digital economy and sustainable practices (Zhong et al.). Lastly, a pertinent suggestion posits the necessity of investigating the influence of AI on carbon emissions through an analysis of spatial spillover effects (Xie and Wang). These delineated avenues for future research not only promise valuable insights for forthcoming studies but also present opportunities for the inception of specialized editions to delve deeper into these pertinent themes.

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Does digital economy development reduce carbon emission intensity?

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Carbon emissions from human activities are the main cause of climate warming. Under the background of economic and social digital transformation, accurately assessing the carbon emission reduction effect of the development of the digital economy is of great significance for countries to deal with climate warming in the post-COVID-19 era. This paper constructs a dynamic evaluation model of orthogonal projection to measure the level of digital economy development at the provincial level in China from 2007 to 2019. On this basis, the panel fixed effects model and mediation model are used to empirically test the impact of digital economy development on carbon emission intensity and its mechanism. The results indicate that: (1) The development of China's digital economy is unbalanced among regions, showing a geospatial pattern of decreasing from east to west. (2) China's carbon emission intensity has a trend of decreasing year by year, and there are geospatial differences of "high in the west and low in the east" and "high in the north and low in the south." (3) The digital economy development can effectively reduce regional carbon emission intensity through industrial structure optimization effect and resource allocation effect, and the industrial structure optimization effect can suppress carbon emission intensity more obviously. (4) The development of digital economy in different regions has different degrees of reducing carbon emission intensity. The development of digital economy in the eastern region has a stronger inhibitory effect on carbon emission intensity than that in the middle and western regions, and the development of digital economy in economically developed regions can suppress carbon emission intensity more. This paper provides enlightenment for policy makers to deal with climate warming.

KEYWORDS

carbon emission intensity, digital economy, dynamic orthogonal projection, geospatial differences, mediation model

1. Introduction

Global warming has seriously affected the living environment of human beings, and coping with climate warming has become a common issue faced by all countries in the world (Liu et al., 2021). Existing studies have shown that carbon dioxide emitted by human economic activities is the main cause of climate warming (An et al., 2021).

Therefore, controlling carbon dioxide emissions is the main way for countries around the world to cope with climate warming. As the world's second largest economy, China is a major emitter of global carbon dioxide (Yu et al., 2021). According to statistics from the British Petroleum database, China's carbon emissions reached 6.926 billion tons in 2006, surpassing the United States to become the world's largest carbon emitter; and in 2021, China's carbon emissions rose to 10.523 billion tons, accounting for about 33% of global carbon emissions. As a responsible major country, China has taken the initiative to take responsibility for carbon emission reduction. At the seventy-fifth session of the United Nations General Assembly, the Chinese government made it clear: "China strives to achieve carbon peak by 2030 and achieve carbon neutrality by 2060." The proposal of the "dual carbon goal" shows China's determination to cope with climate warming, which is also in line with the green development concept advocated by China (Wang et al., 2023). However, according to the enlightenment brought by the environmental Kuznets curve and the practical experience of the carbon emission reduction process of developed countries, there are multiple challenges in achieving the "dual carbon goal" in China (Shi et al., 2021). Compared with developed countries, China not only faces the pressure of carbon emission growth brought by incremental energy demand, but also needs to improve the low-carbon substitution of stock energy. At the same time, the huge development differences between regions in China also constitute the constraints of achieving the "dual carbon goal" (Guo et al., 2023).

It is worth noting that the systematic promotion stage of the "dual carbon goal" is also the stage of rapid development of the digital economy. At present, digital technology represented by information and communication technology, cloud computing, the Internet and artificial intelligence has made innovative breakthroughs and achieved deep integration with the real economy. According to the White Paper on the Development of China's Digital Economy (2022), the scale of China's digital economy accounted for more than 1/3 of the gross domestic product (GDP) in 2021, and the average annual growth rate was higher than the growth rate of GDP. With the rapid development of the digital economy, the environmental effects of the digital economy have received extensive attention from the academic community. Some scholars believe that the information and communication technology industry and e-commerce industry in the digital economy, as environmentally friendly industries, can optimize the industrial structure by squeezing out industries with high energy consumption and high emissions, thus promoting economic and social low-carbon development (Zhang W. et al., 2022; Lyu et al., 2023). Other scholars believe that the wide application of digital technology increases electricity consumption and thus has a negative impact on the environment (Salahuddin and Alam, 2015; Lin and Huang, 2023). So, what is the impact of digital economy development on carbon emission intensity? What is its impact mechanism? Clarifying this issue not only helps to accurately assess the carbon emission reduction effect of the digital economy, but also provides useful suggestions for China to achieve the "dual carbon goal."

Based on this, this paper measures the carbon emission intensity of Chinese provinces in 2007–2019 under the IPCC sectoral accounting algorithm. In addition, a framework for measuring the development level of digital economy development at the provincial level in China was constructed, and a dynamic evaluation method based on orthogonal projection was used to measure the development level of digital economy in 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in China. On the basis of examining the evolution trend of China's regional carbon emission intensity and digital economy development level, the panel fixed effects model and mediation model were used to empirically test the impact and mechanism of digital economy development on carbon emission intensity.

The possible contributions of this paper are as follows: First, this paper incorporates the digital economy and carbon emission intensity into the same analytical framework, and divides the development of the digital economy into the digital industrialization dimension and the industrial digitization dimension, and respectively examines their impact on carbon emission intensity. Second, this paper constructs the index system of digital economy development level at the provincial level, and uses the dynamic evaluation method based on orthogonal projection to measure the digital economy development level of each province in China, which enriches the research content of existing digital economy measurement. Third, this paper further examines the impact mechanism of digital economy development on carbon emission intensity, and finds that digital economy reduces carbon emission intensity through industrial structure optimization effect and resource allocation effect.

2. Literature review and theoretical hypothesis

2.1. Digital economy development and carbon emission intensity

With the increasing prominence of global warming, carbon emission reduction has received continuous attention from the academic community (Liu et al., 2021; Yi et al., 2022). Among them, the influencing factors of carbon emissions are the focus of scholars' research (Liu et al., 2022). Domestic and foreign scholars have discussed the influencing factors of carbon emissions with different methods and from different angles (Cai et al., 2021; He et al., 2022). Scholars mainly use Kaya identity (Ma and Cai, 2018; Eskander and Nitschke, 2021), Divisia index method (Ma and Cai, 2018; Eskander and Nitschke, 2021), and Laspeyres index decomposition method (González and Martínez, 2012; Chen et al., 2021) decompose the influencing factors of carbon emissions. Although the conclusions of different methods are different, it is generally believed that technological innovation (Zhang G. et al., 2022), energy structure (Pui and Othman, 2019), industrial structure (Han and Jiang, 2022), and economic growth (Xiao and Peng, 2023) are the main factors affecting carbon emissions.

With the development of the digital economy, scholars have begun to pay attention to the relationship between the digital economy and carbon emissions (Yang et al., 2022). The relationship between digital economy development and carbon emissions is complex. The development of digital economy has both positive and negative effects on the environment (Moyer and Hughes, 2012; Dong et al., 2022). Although the application of digital technology improves the efficiency of energy conservation and

emission reduction and reduces the loss in the production process, the expansion of production scale increases energy demand and may lead to an increase in total carbon emissions (Zhou et al., 2019; Wang et al., 2022b). Andrae and Edler (2015) found that the rapid development of information and communication technology (ICT) has been accompanied by an exponential increase in total carbon emissions. Salahuddin and Alam (2015) argued that the wide application of digital technology has increased data generation, transmission and processing, resulting in an increase in demand for electricity, which in turn increases carbon emissions.

Other scholars believe that the industrial linkage emission reduction effect produced by the development of the digital economy plays a greater role than the incremental effect of energy consumption (Koomey et al., 2013; Yi et al., 2022). Yi et al. (2022) used provincial panel data to evaluate the relationship between digital economy and carbon emissions, and found that the development of digital economy has significant carbon emission reduction effects. The research of Niu et al. (2022) shows that digital investment improves energy efficiency, which in turn reduces carbon emissions in the production process. Zhang W. et al. (2022) believes that the development of the digital economy has produced more new clean industries, which has a crowding-out effect on industries with high energy consumption and high emissions, thereby reducing carbon emissions. Han and Jiang (2022) further examined the relationship between digital economy and carbon production efficiency, and found that the digital economy development reduced energy consumption per unit of GDP and improved carbon productivity. Based on the differences in the existing research conclusions, this paper further examines the environmental effects of the development of digital economy. Different from the existing research, this paper examines the impact and mechanism of digital economy development on carbon emission intensity from the regional level, and further considers the heterogeneity of geospatial differences and economic development differences. Based on the above literature conclusions, this paper proposes hypothesis 1.

> **H1:** The digital economy development has positive and negative effects on carbon emissions, but an inhibitory effect on regional carbon emission intensity.

2.2. Impact mechanism of digital economy development on carbon emission intensity

As a new economic form, digital economy has become a new driving force for the upgrading of industrial structure (Chen et al., 2022). Existing research shows that the digital economy promotes the upgrading of industrial structure through industrial integration effect and technology diffusion effect (Hao et al., 2023). The internal logic of industrial upgrading shows that the emergence of new industries and new models will gradually replace traditional industries and traditional economic models, and drive the upgrading of traditional industries through input-output linkages, thus realizing the comprehensive optimization of industrial structure. In the digital age, the speed of technology diffusion and change is faster than ever before, which provides favorable conditions for industrial organization innovation, but also enhances the competition mechanism and promotes the continuous optimization of industrial organization (Tang and Li, 2022). Industrial digitalization will also accelerate the elimination of inefficient enterprises, thereby improving the overall production efficiency of the industry and realizing the optimization of the industrial structure. The optimization of industrial structure improves the efficiency of energy utilization, which has a positive impact on reducing carbon emission intensity (Hao et al., 2023). Based on this, hypothesis 2 is proposed.

> **H2:** The digital economy development reduces carbon emission intensity by optimizing industrial structure.

The internal structure of economic form determines the efficiency of resource allocation, and the allocation and combination mode of various production factors is the main factor affecting carbon emission intensity (Wang et al., 2021). Under the digital economic form, economic entities can obtain more adequate market information, and the matching between supply and demand is more accurate, which can improve the resource search efficiency of market entities (Wu et al., 2022). At the same time, the application of digital technology can improve the utilization efficiency of production factors by optimizing the production process (Zhang Z. et al., 2022). Intelligent production process reduces energy waste, and improves energy utilization. Digital economy improves resource allocation by improving resource search and resource utilization efficiency, which helps to reduce undesired output in the production process and reduce carbon emission intensity (Chen, 2022). Based on this, hypothesis 3 is proposed.

> **H3:** The digital economy development reduces carbon emission intensity by improving resource allocation.

Digital industrialization and industrial digitization provide a collaborative environment for innovation activities and accelerate the progress of carbon emission reduction technology (Yin and Yu, 2022). The improvement of innovation efficiency depends on the efficient interconnection of information (Niu et al., 2023). The digital economy based on information and communication technology provides an efficient way for innovation subjects to obtain information and enriches the information resource elements needed for innovation (Kohli and Melville, 2019). In addition, the improvement of innovation efficiency requires efficient collaboration between innovation subjects (Zhuo and Chen, 2023). Compared with the traditional economic form, the digital economy makes the innovation subjects more closely linked and more likely to produce collaborative innovation effects (Li et al., 2023). The application of digital innovation achievements in traditional production methods has an indirect impact on improving efficiency and reducing pollution (Gao et al., 2022). Based on this, hypothesis 4 is proposed.

> **H4:** The digital economy development reduces carbon emission intensity by improving innovation efficiency.

3. Materials and methods

3.1. Measurement of level of digital economy development

3.1.1. Method

In order to ensure the objectivity and accuracy of the measurement results, and consider the degree of difference of the evaluation index values, this paper uses a dynamic evaluation method based on orthogonal projection to measure the digital economy development level of 30 provinces in China.

It is assumed that the digital economy development level of $v_1, v_2, \ldots, v_n$ in a period of time should be measured. Therefore, it is necessary to collect the original data of all the evaluated objects, which includes m indicators during $t_1, t_2, \ldots, t_N$. Based on this, the panel data matrix $x_{ij}(t_k)$ $(i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m;\ k = 1, 2, \ldots, N)$ can be obtained. Since the dimensions are different between the data, the original data needs to be adjusted to dimensionless. This paper uses a globally improved normalization method to process the data, which results in a standardized matrix $Y(t_k) = y_{ij}(t_k)$. In the process of calculating the weighted normalization matrix, this paper first uses the entropy value method to determine the index weight, and then determines the ideal solution and the negative ideal solution. In all periods and all evaluated objects, the maximum value of the j -item indicator is called the ideal solution of the indicator, while the minimum value is called the negative ideal solution of the indicator. Finally, the "vertical" distance $P_i(t_k)$ of the ideal solution of each region is calculated. For each evaluated object, the distance between the negative ideal solution and the ideal solution is constant, so there are:

$$P_i(t_k) = \left|(a - b) \cdot (a - V_i(t_k))\right| \tag{1}$$

where a represents the ideal solution F^+ after translation, that is, $\overrightarrow{0}$ vector, and b represents the negative ideal solution F^- after translation. Further simplifying Equation 1, we can get:

$$P_i(t_k) = \left|F^- \cdot V_i(t_k)\right| = \sum_{j=1}^{m} f_j^- v_{ij}(t_k) \tag{2}$$

where $P_i(t_k)$ values are smaller, the better. The $P_i(t_k)$ is standardized to obtain the final evaluation value. After standardization $P_i(t_k)$ becomes $P_i^*(t_k)$, as follows:

$$P_i^*(t_k) = \frac{max_{1 \le i \le n} P_i(t_k) - P_i(t_k)}{max_{1 \le i \le n} P_i(t_k)} \tag{3}$$

where $P_i^*(t_k)$ is the dynamic evaluation score of the evaluated object i in period t_k. Further, $P_i^*(t_k)$ pairs are weighted twice to calculate the comprehensive evaluation score P_i^* of the evaluated object i in the period from t_1 to t_N. Based on the research of Zhu and Lei (2012), the time weight (w_k) is calculated by using the idea of "thick today and thin ancient". That is, within the time period $[t_1, t_N]$, the weight of the t_k period is as follows:

$$w_k = k / \sum_{k=1}^{N} k \ (k = 1, 2, \cdots, N) \tag{4}$$

where, $\sum_{k=1}^{N} w_k = 1$ and $w_k > 0$. According to the Equation 4, the weight values at different times can be calculated, and then the secondary weighted weight value can be obtained. Therefore, the total evaluation value s_i of i in the time period $[t_1, t_N]$ is:

$$P_i^* = \sum_{k=1}^{N} w_k P_i^*(t_k) \tag{5}$$

where, w_k represents the time weight value at time t_k; $P_i^*(t_k)$ represents the evaluation value of evaluation object i at the t_k moment, and its size and ranking can be calculated by Equation 3. The evaluation value P_i^* and total ranking of the ith evaluation object in the time period $[t_1, t_N]$ can be calculated by Equation 5.

3.1.2. Indicators

Based on the consideration of the comprehensiveness, representativeness and availability of evaluation indicators, and combined with relevant literature (Chen et al., 2022; Wang et al., 2022a; Zhang L. et al., 2022), this paper constructs the measurement system of digital economy development in various provinces in China around digital industrialization

TABLE 1 Evaluation index system of digital economy development.

First-level index	Second-level index	Third-level index	Weight
Digital industrialization	Industry scale	Number of employees in information service industry	0.0543
		Total amount of the telecommunication service	0.0555
	Communications capability and service level	Internet penetration rate	0.0662
		Long-distance optical cable line length	0.0638
		Number of Internet broadband access ports	0.0566
		Mobile telephone switch capacity	0.0622
		Mobile subscription	0.0664
Industrial digitalization	Agriculture	Agricultural added value	0.0610
		Rural electricity consumption	0.0487
	Industry	Industrial added value	0.0582
		Proportion of patents granted	0.0609
		Proportion of revenue from new product sales	0.0650
	Service industry	The added value of the tertiary industry	0.0582
		Per capita insurance premium income	0.0611
		Number of mobile Internet users	0.0612
		Total retail sales of consumer goods per capita	0.0634
		Per capita express delivery volume	0.0371

and industrial digitalization, and the specific indicators are shown in Table 1. The data comes from the "China Statistical Yearbook," "China Information Yearbook," and CSMAR digital economy database.

3.1.3. Results

Table 2 shows the score of digital economy development level of 30 provinces in China from 2007 to 2019. The results show that the score of digital economy development level in each province has an obvious growth trend in 2007–2019. From the perspective of time nodes, 2007–2015 is the initial period of digital economy development. This period is the stage of rapid integration of digital technology and real economy, and the growth rate of digital economy is slow. 2016–2019 is the stage of rapid development of the digital economy, which is mainly due to the government's strong investment in digital construction.

In order to show the differences in the development level of digital economy among different regions, ArcGis software was used to draw the spatial pattern distribution map of digital economy development in each province of China in 2007, 2013, and 2019. It can be seen from Figure 1 that the development of China's digital economy is uneven among regions, showing a geographical spatial pattern of decreasing in the east, middle and west, and obvious differences between the east and the west. From the time dimension, the development level of digital economy in the east, middle and west regions have a trend of increasing year by year. This reflects the phenomenon of "digital divide" caused by the imbalance of development between regions in the era of digital economy, and advanced regions have more advantages in the development of digital economy than backward regions.

3.2. Measurement of carbon emission intensity

3.2.1. Method

To study the impact of the digital economy on carbon emissions under the "dual carbon goal", we must first measure the carbon emissions. In this paper, the carbon emission coefficient method is used to measure China's interprovincial carbon emissions. The required data are the amount of energy consumption in each province and city and the corresponding carbon emission factor. Among them, the main types of energy consumption that cause carbon emissions are coal, gasoline, kerosene, crude oil, coke, diesel, fuel oil and natural gas. Among them, the carbon emission factors of various energy sources need to be estimated. In this paper, the carbon emissions of each province are measured under the IPCC sectoral accounting algorithm. The calculation formula is as follows:

$$C_{it} = \sum (E_{ijt} \times \delta_j \times \eta_j) \tag{6}$$

among them, C_{it} represents the estimated carbon emissions of province i in t year; E_{ijt} represents j energy consumption of province i in t year; δ_j is the average low calorific value of j energy; η_j is the carbon emission coefficient of j energy, and the relevant values are shown in Table 3.

Carbon emission intensity is the CO_2 emission per unit of real GDP, and its calculation formula is as follows:

$$CI_{it} = \frac{C_{it}}{GDP_{it}} \tag{7}$$

among them, CI_{it} is the carbon emission intensity of i province in t year; C_{it} represents the carbon emissions of province i in t year; GDP_{it} represents the real GDP of province i in t year.

3.2.2. Results

According to the calculated carbon emission intensity data of each province, the spatial distribution map of carbon emission intensity of each province in China in 2007, 2013, and 2019 is drawn. As shown in Figure 2, China's carbon emission intensity shows the geographical spatial differences of "high in the west and low in the east" and "high in the north and low in the south." Resource-based provinces bear more carbon emissions, and the carbon emission intensity in economically developed regions is lower, indicating that there is a "profit and loss deviation" phenomenon in China's carbon emissions. From the time dimension, the carbon emission intensity in various regions of China has a trend of decreasing year by year. This shows that since the 18th CPC National Congress, the concept of low-carbon development advocated by China has been well implemented.

3.3. Research design

3.3.1. Model design

This paper constructs the following panel fixed effects model to study the impact of digital economy development on carbon emission intensity:

$$CI_{it} = \beta_0 + \beta_1 digital_{it} + \rho X_{it} + \delta_t + \zeta_i + \varepsilon_{it} \tag{8}$$

In Equation 8, i, t represent province and year, respectively; CI_{it} is the dependent variable, namely carbon emission intensity. The independent variable $digital_{it}$ is the level of digital economic development. X_{it} is the control variable; β_0 is the intercept term; δ_t is the year-fixed effects; ζ_i is the individual (province)-fixed effects; ε_{it} is the random disturbance term. The research goal of this paper is to test the impact of digital economy development on carbon emission intensity at the provincial level in China, so it focuses on the significance, direction and size of the coefficient β_1.

3.3.2. Variables and data sources

The dependent variable is carbon emission intensity (*CI*). The independent variable is the level of digital economic development (*digital*). Mechanism variables include: Industrial structure optimization (*indust*). Industrial structure optimization is represented by the ratio of the tertiary industry to the secondary industry (Zhao and Xi, 2022). Resource allocation (*tfp*). Resource allocation is measured by total factor productivity of each province (Xi and Mei, 2022). Innovation efficiency (*innov*). Innovation efficiency is measured by DEA method (Li et al., 2018). According to the existing research conclusions, this paper selects the following control variables: Energy structure (*es*). Energy structure is an important factor affecting the carbon emission intensity of region.

TABLE 2 Score of digital economy development level.

Year	2007	2009	2011	2013	2015	2017	2019
Beijing	0.1707	0.1997	0.2400	0.3009	0.3869	0.4833	0.5709
Tianjin	0.0793	0.0825	0.0856	0.1056	0.1267	0.1749	0.2111
Hebei	0.0715	0.1103	0.1242	0.1636	0.1911	0.2405	0.3645
Shanxi	0.0372	0.0572	0.0637	0.0867	0.0953	0.1231	0.1823
Inner Mongolia	0.0298	0.0495	0.0616	0.0817	0.0960	0.1287	0.1817
Liaoning	0.0727	0.1003	0.1135	0.1478	0.1820	0.2092	0.2560
Jilin	0.0565	0.0977	0.0739	0.0643	0.0837	0.1208	0.1844
Heilongjiang	0.0414	0.0633	0.0673	0.0870	0.1041	0.1415	0.1821
Shanghai	0.1293	0.1622	0.1759	0.2662	0.3371	0.4602	0.5371
Jiangsu	0.1674	0.2148	0.2650	0.3520	0.4301	0.5145	0.7241
Zhejiang	0.1553	0.1883	0.2186	0.2923	0.4012	0.5405	0.7868
Anhui	0.0531	0.0759	0.0987	0.1258	0.1685	0.2212	0.3261
Fujian	0.0758	0.0993	0.1185	0.1568	0.1993	0.2503	0.3538
Jiangxi	0.0320	0.0410	0.0493	0.0743	0.1052	0.1494	0.2339
Shandong	0.1205	0.1648	0.1866	0.2369	0.2755	0.3363	0.4628
Henan	0.0754	0.1101	0.1181	0.1574	0.2015	0.2558	0.4093
Hubei	0.0753	0.0915	0.1068	0.1412	0.1850	0.2352	0.3479
Hunan	0.0764	0.4410	0.1017	0.1444	0.1758	0.2132	0.3152
Guangdong	0.2461	0.3083	0.3219	0.4132	0.5148	0.6731	1.0000
Guangxi	0.0515	0.0672	0.0679	0.0892	0.1063	0.1452	0.2268
Hainan	0.0095	0.0074	0.0359	0.0420	0.0437	0.0609	0.0866
Chongqing	0.0956	0.0936	0.1014	0.1029	0.1424	0.1736	0.2307
Sichuan	0.0898	0.1238	0.1224	0.1733	0.2213	0.2738	0.4157
Guizhou	0.0228	0.0330	0.0488	0.0568	0.0764	0.1090	0.1974
Yunnan	0.0329	0.0501	0.0582	0.0827	0.1041	0.1362	0.2258
Shaanxi	0.0427	0.0658	0.0785	0.0979	0.1216	0.1602	0.2523
Gansu	0.0164	0.0272	0.0357	0.0517	0.0614	0.0791	0.1303
Qinghai	0.0001	0.0069	0.0048	0.0169	0.0293	0.0534	0.0723
Ningxia	0.0000	0.0112	0.0175	0.0339	0.0464	0.0657	0.0913
Xinjiang	0.0236	0.0376	0.0514	0.0751	0.0928	0.1094	0.1753

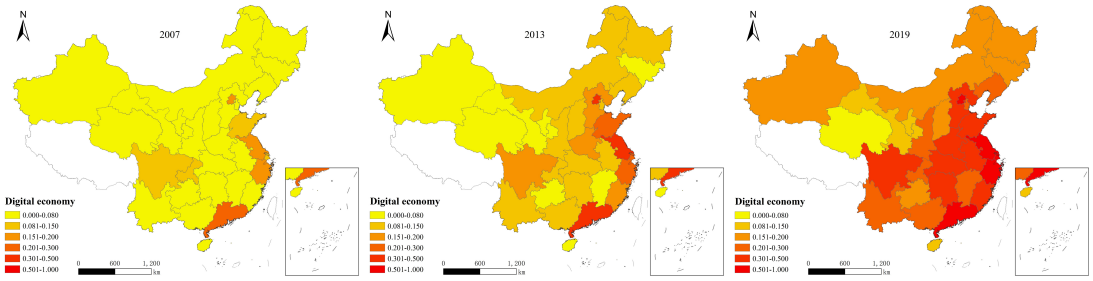


FIGURE 1
Spatial distribution of China's digital economy development level in 2007, 2013, and 2019.

The energy structure with too high proportion of coal often has higher carbon emission intensity. Therefore, it is expressed by the ratio of coal consumption to total energy consumption (Guan et al., 2023). Population density (*popu*). Regions with higher population density have greater demand for energy consumption and more frequent socio-economic activities (He et al., 2023), which are more

TABLE 3 Average low calorific value and carbon emission coefficient of various energy sources.

Type	Raw coal	Coke	Gasoline	Diesel oil	Kerosene	Crude oil	Fuel oil	Natural gas
δ_j (kj/kg)	20,908	28,435	43,070	42,652	43,070	41,800	41,816	38,931
ς_j (kg/TJ)	95,333	107,000	70,000	74,100	71,500	73,000	77,400	56,100

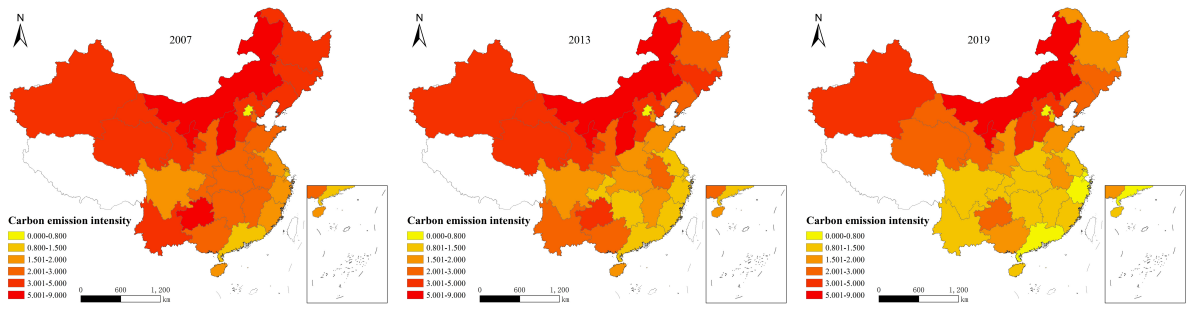


FIGURE 2
Spatial distribution of China's carbon emission intensity in 2007, 2013, and 2019.

likely to affect carbon emission intensity. Foreign direct investment (*fdi*). Foreign direct investment is expressed by the ratio of foreign direct investment to real GDP. Openness to the outside (*open*). Openness to the outside is expressed by the ratio of total import and export to real GDP (Tiba and Belaid, 2020). Environmental regulation (*er*). Environmental regulation is expressed by the proportion of environmental pollution control investment in real GDP.

The data sources of this paper are "China Statistical Yearbook", "China Social Statistical Yearbook" and statistical yearbooks of various provinces and cities, the website of the National Bureau of Statistics, CNRDS database, CEADs database, and Wind database. Considering the availability of data, the panel data of 30 provinces in China (except Tibet and Hong Kong, Macao, and Taiwan) from 2007 to 2019 are finally selected. Descriptive statistics of variables are shown in Table 4.

4. Results and discussion

4.1. Benchmark regression results

Considering that regional differences and time factors may affect the estimation results, this paper uses the fixed effect model to estimate the parameters, and the results are shown in Table 5. It can be seen from columns (1) and (2) of Table 5 that the regression coefficient of digital economy development (*digital*) is negative at the 1% significance level, indicating that the improvement of digital economy development level in each region can promote the reduction of carbon emission intensity. The core explanatory variables in columns (3) and (4) were digital industrialization, and the core explanatory variables in columns (5) and (6) were industrial digitalization, and the results showed that the regression coefficients of digital industrialization and industrial digitalization were significantly negative, indicating that both inhibited the increase of carbon emission intensity. However, there are differences in the inhibitory effect of the two on carbon emission intensity. The absolute value of the regression coefficient of digital industrialization is greater than that of industrial digitization, indicating that digital industrialization has a greater inhibitory effect on carbon emission intensity. In the integration stage of digital economy and real economy, the process of industrial digitization often lags behind digital industrialization, which is the main reason for the difference in impact.

4.2. Endogenous treatment

Although carbon emission intensity is a relative quantity index, which can alleviate endogenous problems to a certain extent, it cannot rule out endogenous problems caused by missing variables. If the factors that affect both the digital economy and the carbon emission intensity are not controlled, it will lead to endogenous problems, such as relevant policies and technological changes. First, using fixed effects model can alleviate endogenous problems to a certain extent. Second, construct the instrumental variables of digital economy development to reduce endogenous bias. The previous benchmark regression uses fixed effects, which alleviates endogeneity to some extent.

Construct instrumental variables to alleviate endogenous problems. Refer to the practice of Bartik (2006) to construct instrumental variables, that is, the first-order difference ($\Delta digital_{it}$) of the development of the digital economy and the intersection ($digital_{it-1}$) of the lag phase ($\Delta digital_{it} = digital_{it-1}$) of the development of the digital economy are used as instrumental variables. The considerations for constructing the instrumental variable are as follows: Firstly, carbon emission intensity will not affect the development of the digital economy in the previous period. Choosing a lag period can effectively avoid the endogeneity that may be caused by reciprocal causation, which also shows that the instrumental variable satisfies the exogenous hypothesis. Secondly, the level of development of the digital economy in the previous period will affect the current period. Choosing the intersection of the lag phase of the digital economy and the

TABLE 4 Descriptive statistics of variables.

Definition	Variables	Mean	SD	Min	Med	Max
CI	Carbon emission intensity	2.527	1.661	0.343	2.085	10.210
digtial	Digital economy development	0.163	0.142	0.000	0.121	1.000
digtial_1	Digital industrialization	0.140	0.118	0.000	0.102	1.000
digtial_2	Industrial digitalization	0.198	0.172	0.000	0.150	1.000
indust	Industrial structure	1.081	0.622	0.500	0.894	5.169
tfp	Resource allocation	1.518	0.747	0.070	1.443	2.900
innov	Innovation efficiency	0.462	0.231	0.068	0.422	1.000
es	Energy structure	0.574	0.186	0.019	0.601	0.903
popu	Population density	0.282	0.120	0.062	0.263	0.597
fdi	Foreign direct investment	0.401	0.526	0.048	0.206	5.849
lnopen	Openness to the outside	−1.740	0.970	−4.368	−1.964	0.587
er	Environmental regulation	1.403	0.688	0.300	1.245	4.240

TABLE 5 Benchmark regression results[a].

Variables	*CI*					
	(1)	(2)	(3)	(4)	(5)	(6)
digtial	−2.9206***	−1.3632***				
	(−11.5679)	(−4.4021)				
digtial_1			−3.4913***	−1.9186***		
			(−12.5392)	(−5.7179)		
digtial_2					−2.1916***	−0.7683***
					(−9.7948)	(−2.9878)
es		−1.6462***		−1.5772***		−1.7955***
		(−3.2092)		(−3.1376)		(−3.4590)
popu		3.2365***		2.9662***		3.6226***
		(8.0981)		(7.5432)		(9.2847)
fdi		0.0965		0.1143*		0.0736
		(1.4448)		(1.7404)		(1.0925)
lnopen		0.1609*		0.1800**		0.1848**
		(1.8714)		(2.1786)		(2.1016)
er		−0.0066		0.0002		−0.0122
		(−0.1267)		(0.0030)		(−0.2318)
constant	3.0036***	1.6013***	3.0165***	1.7985***	2.9608***	1.4122***
	(63.8766)	(5.0063)	(67.2096)	(5.6432)	(59.0132)	(4.4216)
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390	390	390
R^2	0.2715	0.3994	0.3046	0.4201	0.2109	0.3821

[a]The t statistics are in parentheses, *$p < 0.010$, **$p < 0.05$, ***$p < 0.01$. FE denotes fixed effects. The fixed effects include individual (province)-fixed effects and year-fixed effects. The notes for the following tables are the same.

first-order difference as the instrumental variable can meet the correlation assumption (Lyu et al., 2023). This paper uses the two-stage least squares method of instrumental variables to estimate.

In order to ensure the reliability of the endogenous test results, this paper also takes the carbon emission intensity measured by the apparent method as the dependent variable for regression. The estimation results are shown in **Table 6**. Columns (1) and (2) are based on the carbon emission intensity calculated by the IPCC sector accounting method as the dependent variable; columns (3) and (4) are based on the carbon emission intensity calculated by

the apparent method as the dependent variable. The results show that the instrumental variable has a significant strong correlation with the independent variable. The F statistic in the weak *IV* test is much larger than the judgment value at the 10% level. The instrumental variable satisfies the correlation hypothesis and there is no weak correlation problem. In addition, the digital economy development (*digtial*) is significantly negative at the significance level of 10%, indicating that the results are still robust after controlling endogenous problems.

4.3. Robustness test

Referring to the existing research, the model robustness test was carried out by substituting variables and removing outliers. One is to replace the dependent variable. The carbon emission intensity of each province calculated by the apparent method calculated by the apparent method in the CEADs database was selected as the replacement variable. The second is to eliminate outliers. That is, the values in the carbon intensity data are replaced by values that are 5% below the average and 95% above the average. In Table 7, columns (1), (3), and (5) are listed as the regression results of the dependent variable after tail shrinking. Columns (2), (4), and (6) are the regression results after replacing the dependent variable. After tail shrinking and replacing the dependent variable, the independent variable were still significant, and the direction and magnitude of the coefficients were consistent with the benchmark estimates, indicating that the model estimation had high confidence and proved the robustness of the research conclusions.

4.4. Heterogeneity analysis

4.4.1. Analysis of geospatial differences

In order to examine the regional differences in the impact of digital economy development on carbon emission intensity, this paper divides the sample into eastern, middle and western regions, and still uses the panel fixed effects model for regression. As shown in Table 8, there are significant spatial differences in the impact of digital economy development on carbon emission intensity. Compared with the east, the impact of the development of digital economy in the middle and western regions on reducing carbon emission intensity is more obvious. The reason may be that the eastern regions is economically developed, the carbon emission intensity is much lower than that of the middle and western regions, and the space for reduction is limited, so the role of the digital economy in reducing carbon emissions is not as good as that of the middle and western regions.

4.4.2. Analysis of differences in economic development

Is there a difference in the impact of digital economy on carbon emission intensity under different economic development levels? This paper divides the samples into economically developed regions and economically underdeveloped regions based on the average per capita GDP of each province. The grouping regression results are shown in Table 8. The regression results of developed and underdeveloped regions are significantly negative at the level of 1%, but the absolute value of the regression coefficient in underdeveloped regions is greater than that in developed regions. It shows that the digital economy has a more obvious effect on reducing the carbon emission intensity in underdeveloped regions. The results of heterogeneity analysis provide guidance for policymakers to achieve the "dual carbon goals".

4.5. Mechanism test

According to mechanism analysis, the development of digital economy reduces carbon emissions per unit output through industrial structure optimization effect, resource allocation effect and innovation effect. This section tests the above influence mechanism. The test process is divided into three steps: Firstly, the independent variable are regressed with the mechanism variables, and the regression coefficients represent the impact of the digital economy on the intermediary variables. Secondly, the digital economy and carbon emission intensity are regressed to verify the impact of the digital economy on carbon emission intensity. Finally, the digital economy, intermediary variables and carbon emission intensity are regressed to verify whether the digital economy has an impact on carbon emission intensity through intermediary variables. The mechanism test model is constructed as follows:

$$mechanism_{it} = \alpha_0 + \alpha_1\, digital_{it} + \rho X + \delta_t + \zeta_i + \varepsilon_{it} \quad (9)$$

$$CI_{it} = \beta_0 + \beta_1\, digital_{it} + \rho X + \delta_t + \zeta_i + \varepsilon_{it} \quad (10)$$

$$CI_{it} = \sigma_0 + \sigma_1 digital_{it} + \sigma_2 mechanism_{it} + \rho X + \delta_t + \zeta_i + \varepsilon_{it} \quad (11)$$

among them, $mechanism_{it}$ contains three mechanism variables: $indust_{it}$, tfp_{it} and $innov_{it}$, which verify the industrial structure optimization effect, resource allocation effect and innovation effect, respectively, and the other variables are the same as the Equation 8. Equation 9 is used to verify the impact of the digital economy on the intermediary variables; Equation 10 is used to verify the impact of the digital economy on carbon emission intensity, that is, the benchmark regression; Equation 11 is used to verify the mechanism effect of the digital economy on carbon emission intensity.

Table 9 shows the results of the mechanism test. The results of columns 1, 3, and 5 demonstrate that the development of digital economy can promote the upgrading of industrial structure, improve total factor productivity and improve innovation efficiency. Among them, the impact of digital economy development on promoting industrial structure upgrading and improving total factor productivity has passed the 1% significance level, but the innovation efficiency has not passed the significance test. The results of columns 2 and 4 demonstrate that the industrial structure optimization effect and resource allocation effect have passed the 5% significance level, which proves the existence of intermediary effect. The coefficient of structural optimization effect and resource allocation effect is significantly negative, which verifies the previous theoretical mechanism analysis. This shows that the digital economy suppresses carbon emission intensity through the industrial structure optimization effect and resource allocation effect, which verifies H2 and H3. However, the innovation efficiency does not play an inhibitory role in reducing carbon emission intensity. The possible reason is that China's

TABLE 6 Endogenous test results[a].

Variables	*digtial*	*CI*	*digtial*	*CI_1*
	First stage (1)	Second stage (2)	First stage (3)	Second stage (4)
digtial		−1.1029*		−1.1252***
		(−1.8747)		(−4.2471)
digtial_iv	6.5101***		6.5101***	
	(20.9361)		(20.9361)	
constant	0.2834***	−1.2641***	0.2834***	−0.9470***
	(11.0026)	(−3.3390)	(11.0026)	(−5.5542)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390
R^2	0.6893	0.6435	0.6893	0.6622
Over-identification test	*NO*	/	*NO*	/
Weak IV test	438.14 [16.38]	/	438.14 [16.38]	/

[a]Over-identification test shows that there is no over-identification; the *Cragg − Donald Wald F* statistic is reported in the weak *IV* test, and the judgment value at the 10% level is in the brackets.

TABLE 7 Robustness test results.

Variables	*CI*	*CI_1*	*CI*	*CI_1*	*CI*	*CI_1*
	(1)	(2)	(3)	(4)	(5)	(6)
digtial	−1.2036***	−1.8646***				
	(−4.3338)	(−3.1358)				
digtial_1			−1.7888***	−2.3570***		
			(−5.9724)	(−3.6105)		
digtial_2					−0.6320***	−1.1814**
					(−2.7373)	(−2.4133)
constant	1.4091***	1.6106***	1.6146***	1.7918***	1.2272***	1.3942**
	(4.9126)	(2.6224)	(5.6758)	(2.8899)	(4.2796)	(2.2931)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390	390	390
R^2	0.4334	0.1178	0.4580	0.1255	0.4157	0.1080

FE denotes fixed effects. The fixed effects include individual (province)-fixed effects and year-fixed effects.
[a]The t statistics are in parentheses.
**$p < 0.05$, ***$p < 0.01$.

current innovation efficiency mechanism has not yet played a role, even at the expense of the environment.

5. Conclusion

Under the background of global climate change and digital transformation, it is of great practical significance to study the impact of digital economy development on carbon emission intensity. This paper constructs a measurement model of digital economy development level and carbon emission intensity at the provincial level in China, and on this basis, examines the impact and mechanism of digital economy development on carbon emission intensity. The results show that: (1) The development of China's digital economy is unbalanced among regions, showing a geographical spatial pattern of decreasing from east to west. (2) China's carbon emission intensity has a decreasing trend year by year, but there is a spatial difference of "high in the west and low in the east." (3) The development of digital economy can effectively reduce regional carbon emission intensity, but the impact of digital industrialization and industrial digitalization on regional carbon emission intensity is different, and digital industrialization has a more significant effect on reducing regional carbon emission

TABLE 8 Heterogeneity analysis results.

Variables	*CI*				
	East	Middle	West	Developed regions	Underdeveloped regions
digtial	−0.4211**	−2.2333***	−2.1632***	−0.5325***	−3.7053***
	(−2.0299)	(−3.4151)	(−6.0209)	(−3.1814)	(−5.1913)
constant	1.6754***	4.2736***	−0.2583	0.9756***	1.8866***
	(5.8533)	(7.8686)	(−1.3102)	(3.4909)	(4.0849)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	143	117	130	239	151
R^2	0.7021	0.6378	0.7578	0.6802	0.4134

TABLE 9 Mechanism test results.

Variables	Industrial structure optimization effect		Resource allocation effect		Innovation effect	
	indust	*CI*	*tfp*	*CI*	*innov*	*CI*
digtial	1.4446***	−0.5829*	2.0492***	−1.3777***	0.0757	−1.3837***
	(9.1056)	(−1.7605)	(3.6838)	(−4.3599)	(0.5510)	(−4.4923)
indust		−0.5402***				
		(−5.4109)				
tfp				−0.0826**		
				(−2.3874)		
innov						0.2701**
						(2.2691)
constant	0.7760***	2.0205***	0.9867*	1.5943***	0.1462	1.5618***
	(4.7355)	(6.3657)	(1.7174)	(4.9573)	(1.0296)	(4.9040)
Control variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Province FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Obs	390	390	390	390	390	390
R^2	0.5048	0.4454	0.1018	0.3995	0.0865	0.4080

FE denotes fixed effects. The fixed effects include individual (province)-fixed effects and year-fixed effects.
[a]The t statistics are in parentheses.
*$p < 0.010$, **$p < 0.05$, ***$p < 0.01$.

intensity. (4) The digital economy has different effects on reducing carbon emission intensity in different regions. The inhibitory effect of developing digital economy on carbon emission intensity in the middle and western regions is stronger than in the eastern region. Compared with developed regions, the development of digital economy in underdeveloped regions has a greater inhibitory effect on carbon emission intensity. (5) The development of digital economy reduces carbon emission intensity through industrial structure optimization effect and resource allocation effect, and the industrial structure optimization effect suppresses regional carbon emission intensity more obviously, and carbon emission intensity is not reduced through innovation effect at this stage.

Clarifying the relationship between the development of digital economy and carbon emission intensity has important policy implications for the global response to climate change and China's realization of the "dual carbon goal." The development of digital economy is based on digital technology. Promoting digital technology innovation is to lay a solid foundation for the development of digital economy from the "root," and is a long-term and effective strategic measure to promote the role of digital economy in reducing carbon emissions. First, implement relevant policies to support the development of the digital economy, provide differentiated financial and tax support for the development of digital technology innovation enterprises, and focus on supporting the growth of "specialized and new" digital enterprises. Second, promote digital industrialization and industrial digitization, relying on the existing information and communication infrastructure, focusing on the construction of AI industry center, big data center, 5G base station service, industrial Internet service and other digital industry projects to meet the needs of the digital transformation of the real economy. Third, narrow the differences in the development of regional digital economy, formulate

digital economy development strategies in accordance with local conditions, and give full play to their own resource advantages, increase the introduction of technology and talents, and create regional characteristic digital economy industries.

Data availability statement

The original contributions presented in this study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YL: conceptualization, methodology, resources, and validation. LZ: data curation, software, writing—original draft preparation, and visualization. DW: writing—reviewing and editing and supervision. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Impacts of environmental policy uncertainty on urban environmental pollutant emissions in China: a study based on textual analysis

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Studies mainly focuses on measuring the economic policy uncertainty in different countries. However, few studies have focused on the construction of the environmental policy uncertainty index (EPUI). This paper selects 460 newspapers from the China National Knowledge Infrastructure (CNKI) newspaper database from 2001 to 2016, and uses the text analysis method to directly construct the national, provincial, and prefecture-level EPUI of China. We have analyzed the distribution and fluctuation trend of the EPUI, and use two-way fixed effect model with panel data to investigate the impact of environmental policy uncertainty on environmental pollutant emissions at the city level. An important discovery has been made through our research, indicating that the rise in environmental policy uncertainty is likely to result in a reduction of pollutant emissions such as urban industrial sulfur dioxide and carbon dioxide. However, this reduction comes at a cost to the promotion of the development of urban secondary industry. The Chinese EPUI constructed for the first time in this article provides significant basic data for research in the environment and energy fields, and also provides important empirical evidence for achieving China's carbon peak and carbon neutrality goals.

KEYWORDS

post-COVID-19 era, energy transition, energy structures, pollutant emissions, environmental policy uncertainty, advanced analytical techniques

Highlights

- EPUI is constructed on national, provincial, and prefecture-level in China.
- An increase in EPUI can reduce sulfur dioxide and carbon dioxide emissions.
- EPUI can reduce pollutant emissions through the channel of the scale of the secondary industry.
- The EPUI in China's northern provinces is higher than that in southern provinces.

1 Introduction

For a long time, China's rapid economic growth has always been inseparable from the huge consumption of resources and energy, which has caused serious environmental pollutions (e.g., water pollution, air pollution, and land pollution). Environmental

policies (such as pollution emission policies, carbon trading policies (Wang et al., 2023), carbon tax policies, etc.) are an important way to solve environmental pollution problems. Since China considered environmental protection as a basic state policy in its Party Congress work report in 1992, the party and state leaders have always attached great importance to the promulgation and implementation of environmental policies. In 2003, the "Scientific Outlook on Development" clearly stated that we should adhere to sustainable development and build a resource-saving and ecological protection-oriented society (Liu et al., 2021b). In 2012, the Chinese government incorporated the construction of ecological civilization into the "five in one" overall layout of the cause of socialism with Chinese characteristics. In 2018, the Chinese government wrote ecological civilization into the Constitution. This series of measures show that China's environmental protection work is constantly being strengthened, and environmental policies have moved from a single policy to comprehensive regulation. As of 4 August 2021, a total of 6,122[1]environmental protection laws, regulations, and departmental rules have been promulgated and implemented by departments at all levels. Numerous environmental policies cover a wide range of fields, and there are obvious differences in the time, frequency, and intensity of their promulgation, as well as the impact of the policies, which has a non-negligible impact on China's environmental governance and high-quality economic development (Huang and Luk, 2020).

Since the outbreak of the global financial crisis in 2008, the world economy has moved from an era of "great easing" to an era full of high uncertainty (Handley and Limão, 2017). How to construct various uncertainty indexes has become a hot topic in academic circles at home and abroad, among which the most influential is the economic policy uncertainty index. The index can be traced back to Baker et al. (2016), who use the text analysis method to construct the economic policy uncertainty index of global and major economies based on the evaluation of mainstream news media. The index provides a new analytical tool for understanding how information is delivered to the market and arouses public reaction. Since its publication, the economic policy uncertainty index has been widely concerned and cited by scholars from all over the world (Pirgaip and Dinçergök, 2020; Xia et al., 2020).

As the world's second-largest economy, China has been more and more studied on its policy uncertainty. During the past 40 years of reform and opening-up, China has implemented many policy trials and reforms in the process of economic development, which has inevitably caused the negative impact of various policy uncertainties on the Chinese economy. In this case, how to accurately characterize policy uncertainty and examine its negative impact on China's economic growth is of great practical significance for achieving high-quality growth of China's economy. Therefore, many scholars have carried out systematic and in-depth research. For example, Huang and Luk (2020) construct a monthly index of China's economic policy uncertainty based on the text data of newspapers from 2000 to 2018. At the same time, they use the same method to construct the uncertainty index of China's fiscal policy, monetary policy, trade policy, and exchange rate policy. Yu et al. (2021) construct an annual index of economic policy uncertainty for 30 provinces in China based on the China National Knowledge Infrastructure (CNKI) newspaper database from 2008 to 2011. It is a bit regrettable that most of the existing research focuses on policy uncertainty at the economic level while ignoring policy uncertainty at other levels, especially the environmental level, which provides a new exploration space for this study.

In 2020, General Secretary Xi Jinping proposed at the 75th session of the United Nations General Assembly the green development goal of "striving to reach carbon peak by 2030 and carbon neutrality by 2060". The proposal of this goal means that China's economy and society will usher in unprecedented low-carbon reform. Carbon neutrality is both an opportunity and a challenge. At present, China's energy consumption level is much higher than the world average, and the task of reducing overcapacity and adjusting the economic structure remains arduous. Under the carbon neutrality goal, Policy uncertainty has a great impact on investment decisions of enterprises and individuals. Relevant studies mainly focus on the impact of economic policy uncertainty. From the perspective of enterprise and individual investment, some scholars believe that the uncertainty of economic policy will inhibit enterprise and individual investment. Baker et al. (2016) believe that the existence of economic policy uncertainty enables enterprises and individuals to delay spending and investment due to the risk of market uncertainty. Based on the data from 2006 to 2011, it finds that the increase of policy uncertainty will lead to a sharp and sustained decline in the economy, and GDP, private investment and total employment will all decline. Gulen and Ion (2015) finds that since investment is irreversible, policy uncertainty will cause enterprises to take strategic prevention, thus inhibiting enterprise investment. For companies with a high degree of investment irreversibility and companies that are more dependent on government expenditure, this relationship is more prominent. At the same time, from a broader perspective, some scholars also find the negative impact between uncertainty and enterprise investment. According to the real option theory, uncertainty increases the waiting value and leads firms to make investment decisions cautiously. For firms facing a high degree of uncertainty, it may be best to limit investments and increase cash holdings in preparation for postponing investments to the next period (Bernanke, 1983; McDonald and Siegel, 1984; Abel and Eberly, 1996). In addition, some scholars also study the impact of environmental policies on investment. Greenstone (2002) uses a natural experiment to study investment differences between plants in counties with no binding environmental regulations and plants in the same industry in counties with environmental regulations. The study finds that employment, investment and output fell in counties with binding rules compared with those without; Garofalo and Malhotra (1995) provide evidence that stricter environmental regulations increase the capital used to deal with pollution, but reduce the manufacturing capacity of an industry, which also shows that environmental policies moderately crowd out productive investment of firms by increasing investment in pollution reduction. Based on the above analysis, we can know that the uncertainty of environmental policy caused by multiple

1 The data comes from the Pkulaw Law Database and its official website is http://www.pkulaw.cn/.

politics will not only directly change the consumption and investment decisions of residents and enterprises, but also affect their confidence and expectations to a large extent, thus indirectly affecting the production scale of enterprises and the adjustment of industry structure. Therefore, selecting an appropriate method to truly reflect China's overall and regional environmental policy uncertainty is crucial for the early realization of the dual carbon goals (i.e., carbon peak and carbon neutrality).

Because of the above considerations, this article attempts to construct China's national, provincial, and prefecture-level environmental policy uncertainty index (EPUI) by adopting the text analysis method and combining the construction method of the economic policy uncertainty index proposed by Baker et al. (2016). In terms of data processing, this paper selects 460 newspapers in the CNKI newspaper database from 2001 to 2016 as the data source for text analysis. These 460 newspapers are widely distributed in 31 provinces, municipalities, and autonomous regions in China, with broad representativeness.

Compared with the existing literature, the marginal contribution of this article mainly covers the following two points: first, the existing literature usually adopts indexes such as the environmental officials' turnover in the local government and the intensity of environmental regulations to indirectly measure the environmental policy uncertainty. This way of depiction has certain limitations and cannot well reflect the true level of environmental policy uncertainty. Given this, this paper selects 460 newspapers distributed in 31 provinces, municipalities, and autonomous regions in China as the data source, and adopts the construction method of Baker et al. (2016) on economic policy uncertainty index to construct China's national, provincial, and prefecture-level EPUI from 2001 to 2016 for the first time, which provides very important basic data for the empirical research of environment. At the same time, the EPUI constructed in this paper also has great application value in the fields of economy, energy, and corporate decision-making. Second, under the dual carbon goals, the first-constructed EPUI is applied to the pollutant emission reduction at the city level in China, and an important discovery is obtained: environmental policy uncertainty will achieve the goal of pollutant emission reduction at the cost of reducing the output value of urban secondary industry. The research conclusions of this paper provide an important experience for policymaking to achieve the dual carbon goals.

The structure of the paper is organized as follows: Section 2 is the literature review; Section 3 is the construction and distribution of China's EPUI at different levels; Section 4 is the application of China's EPUI; Section 5 is the main conclusions and policy recommendations.

2 Literature review

Judging from the existing literature, at present, the measurement methods of policy uncertainty index are roughly divided into two categories. The first type is to measure policy uncertainty by constructing a synthetic index, such as Baker et al. (2016), Huang and Luk (2020), and Yu et al. (2021). Baker et al. (2016) pioneer the construction of an index based on newspaper text to measure economic policy uncertainty, and apply this construction method to different countries and regions. After calculating the preliminary economic policy uncertainty index, Baker et al. (2016) use manual reading and review to select articles containing keywords, and combine the manually calculated index with the index obtained by the text analysis method. The obtained indexes are compared to test the effectiveness of the computer-constructed economic policy uncertainty index. The results show that the economic policy uncertainty indexes calculated by the two methods are highly positively correlated. Huang and Luk (2020) improve the index construction method proposed by Baker et al. (2016) from the aspects of standardized processing and keyword selection. They divide the target article by all articles containing the keyword "economy" in the current month for standardized processing, which effectively avoids the systematic estimation bias caused by the different layouts and content of comprehensive newspapers. Yu et al. (2021) improve the Chinese economic policy uncertainty index constructed by Baker et al. (2016) based on the contextual difference between Chinese and English expressions, and expand the Chinese economic policy uncertainty index from national level to provincial level for the first time. Similarly, Li et al. (2021b) adopt the index construction method of Baker et al. (2016), replacing "economy" with "trade" to construct the uncertainty index of China's trade policy. Meanwhile, the construction method of the composite index can be widely used to measure other economic indicators besides the uncertainty of policy. For example, Guo et al. (2023) develop a city-level power shortage index in China using the text analysis method and analyze the relationship between power shortage and firm productivity.

The second category is to measure policy uncertainty based on relevant economic variables or policy variables, such as Fernández-Villaverde et al. (2011), Julio and Yook (2012), Shah et al. (2021), and Tran and Houston (2021). This type of literature mainly uses the time series model to measure policy uncertainty. For example, Fernández-Villaverde et al. (2011) use particle filter and Bayesian method to extract the time-varying volatility of government expenditure and taxation, and use such time-varying volatility to characterize fiscal policy uncertainty. Using the simultaneous equation state-space model and Kalman filtering method, Anzuini et al. (2020) calculate the time-varying volatility of taxation and use it to express the uncertainty of fiscal policy. Fu and Luo (2021) adopt the method proposed by Fernández-Villaverde et al. (2011) to construct China's monetary policy uncertainty. Mumtaz and Surico (2018) point out that the central bank mainly achieves the ultimate goal by anchoring the intermediary target through policy tools, which are difficult to directly observe and quantify, and the monetary policy uncertainty can be measured by calculating the random volatility of the intermediary target of monetary policy. In addition, some researchers use the turnover of government officials to measure policy uncertainty (Julio and Yook, 2012; Li et al., 2021a). For example, Julio and Yook (2012) use election time in countries around the world as a proxy variable for policy uncertainty, because existing policies may be changed due to the change of leaders with different policy preferences. Cheng et al. (2021) use the turnover of municipal party secretary or mayor as the proxy variable for political uncertainty. Liu et al. (2021a) use the political connection of corporate leaders to measure political uncertainty. Francis et al. (2021) select Google political election news, tax

TABLE 1 Provincial distribution statistics of 460 newspapers.

Province	Number of newspapers	The proportion of newspapers in the total number of newspapers (%)	Number of articles reported	The proportion of articles reported in total articles reported (%)
Shanghai	11	2.39	521,492	4.78
Yunnan	9	1.96	204,691	1.88
Inner Mongolia	10	2.17	193,498	1.77
Beijing	83	18.04	3,451,415	31.66
Jilin	10	2.17	181,175	1.66
Sichuan	21	4.57	397,989	3.65
Tianjin	4	0.87	49,288	0.45
Ningxia	8	1.74	63,684	0.58
Anhui	13	2.83	168,934	1.55
Shandong	14	3.04	261,381	2.40
Shanxi	18	3.91	318,848	2.92
Guangdong	23	5	767,260	7.04
Guangxi	8	1.74	160,373	1.47
Xinjiang	17	3.7	161,546	1.48
Jiangsu	19	4.13	432,949	3.97
Jiangxi	9	1.96	158,424	1.45
Hebei	17	3.7	377,578	3.46
Henan	20	4.35	436,180	4.00
Zhejiang	13	2.83	298,238	2.74
Hainan	5	1.09	64,024	0.59
Hubei	12	2.61	248,554	2.28
Hunan	14	3.04	235,658	2.16
Gansu	16	3.48	307,677	2.82
Fujian	13	2.83	204,005	1.87
Tibet	7	1.52	51,339	0.47
Guizhou	10	2.17	207,715	1.91
Liaoning	14	3.04	262,140	2.40
Chongqing	3	0.65	61,655	0.57
Shaanxi	12	2.61	300,103	2.75
Qinghai	9	1.96	121,144	1.11
Heilongjiang	18	3.91	233,895	2.15
Total	460	100	10,902,852	100

Source: Compiled by the author.

expiration index, CPI forecast difference, federal procurement forecast difference, and other factors to construct a political uncertainty index by the weighted method.

Based on the above literature, it can be found that the current research on policy uncertainty mainly focuses on economic policy, fiscal policy, monetary policy, trade policy, and political elections, while few literature investigates environmental policy uncertainty. In particular, no literature has investigated the uncertainty of China's environmental policy, and a few existing literature only uses changes in the intensity of environmental regulation or climate to describe the uncertainty of environmental policies (Liu et al., 2018; DeLuque and Shittu, 2019; Schubert and Smulders, 2019). In

TABLE 2 Keyword criteria used to identify the EPUI.

Environment (in English)	Environment, environmental protection, pro-environment, pollution, energy consumption, emission reduction, pollution discharge, ecology, green, low carbon, air, chemical oxygen demand, sulfur dioxide, carbon dioxide, PM10, PM2.5
Environment (in Chinese)	环境, 环境保护, 环保, 污染, 能耗, 减排, 排污, 生态, 绿色, 低碳, 空气, 化学需氧量, 二氧化硫, 二氧化碳, PM10, PM2.5
Policy (in English)	Environmental protection department, environmental protection bureau, supervision, oversight, inspection, remediation, rectification, governance, protection, policy, measure, method, suggestion, public, government, department, reform, tax, rule, regulation, ordinance
Policy (in Chinese)	环保部门, 环保局, 监管, 监督, 督察, 整治, 整改, 治理, 保护, 政策, 措施, 办法, 建议, 公共, 政府, 部门, 改革, 税, 规章, 规则, 条例
Uncertainty (in English)	Uncertain, probabilistic, unspecified, fluctuating, shocking, unstable, undetermined, ambiguous, unclear, not clear, doubtful, unpredictable, inestimable, unforeseeable, incalculable, unexpected, non-predicative, imponderable
Uncertainty (in Chinese)	不确定, 不确定性的, 不明确, 波动, 震荡, 不稳, 未明, 不明朗, 不清晰, 未清晰, 难料, 难以预料, 难以估计, 无法预料, 无法估计, 不可预料, 不可预计, 不可估计

view of this, the article adopts the uncertainty index construction method proposed by Baker et al. (2016), and selects 460 newspapers in the CNKI newspaper database from 2001 to 2016 as the data source for text analysis, and constructs China's EPUI at the national, provincial and prefecture level for the first time. This would provide very important basic data for empirical research of the environment, and provide significant empirical support for guiding how to achieve China's dual carbon goals.

3 Construction and distribution of China's EPUI

3.1 Index construction

The method of constructing China's EPUI in this paper is consistent with Baker et al. (2016). We have selected 460 newspapers from the CNKI newspaper database from 2001 to 2016 as the source of this article. These 460 newspapers are widely representative, covering China's 31 provinces, municipalities, and autonomous regions. Table 1 reports the basic statistics on the sources and distribution of 460 newspapers.

Table 2 reports the identification criteria for keywords related to environmental policy uncertainty. If a news report contains at least one keyword of "environment", "policy" and "uncertainty" at the same time, then it is considered as the target article. In the process of keyword screening, this paper firstly conducts text processing and word frequency analysis on texts used in the study, and selects words that appear more frequently as alternative word sets. Then, through manual reading and borrowing the words used in existing research as keywords to be considered in index construction (Baker et al., 2016). The specific construction method of EPUI is shown as follows:

(1) According to the definition of the target article, the number of target articles in each month of each newspaper is sorted out and recorded as A_{it}. Among them, i is the i-th newspaper, and t is the t-th month. In order to avoid the impact of differences in the total number of articles in different newspapers and different months, we conduct scale processing on the target number of articles per month for each newspaper, that is, $X_{it} = A_{it}/B_{it}$. B_{it} is the total number of articles in the i-th newspaper in the t-th month.

(2) Normalize X, namely, $Y_{it} = X_{it}/\delta_i$. δ_i is the standard deviation of $\{X_{it}\}$ to get the average normalized frequency of all sample newspapers, namely, $Z_{it} = \sum Y_{it}/i$,

(3) The EPUI of different monthly frequencies in China is obtained, $ENPU = Z_t{}^*100/M$, and M represents the serial average value of $\{Z_t\}$. The annual EPUI of different levels in China can be calculated employing the arithmetic average method. The larger the index is, the stronger the uncertainty of environmental policy is.

(4) The EPUI of China from 2001 to 2016 constructed in this paper includes national, provincial, and prefecture levels. In the specific construction process, this paper selects national, provincial, and prefecture-level newspapers as the data source. Among them, at the national level, 460 newspapers are used as the data source; at the provincial level, 460 newspapers are classified into 31 provinces, cities, and autonomous regions according to the place of publication; at the prefecture level, 460 newspapers are classified into prefecture-level cities according to the publication location. Then, calculate according to the above steps in turn, and finally get China's EPUI at the national, provincial, and prefecture levels.

3.2 Fluctuation characteristics of China's EPUI

Figure 1 shows the fluctuation trend of China's EPUI at the national level. As can be seen from Figure 1, China's EPUI from 2001 to 2011basically fluctuates within the range of 50–110. During this period, the Chinese government's environmental protection policy was relatively stable. In addition to revising and promulgating environmental protection laws and regulations, environmental economic policies have entered a stage of centralized design and promotion. For example, in 2005, the fifth plenary session of the 16th Party Central Committee put forward the policy of building a resource-saving and environment-friendly society. In October 2007, the "Energy Conservation Law of the People's Republic of China" was revised. In February 2008, the "Water Pollution Prevention and Control Law of the People's Republic of China" was revised.

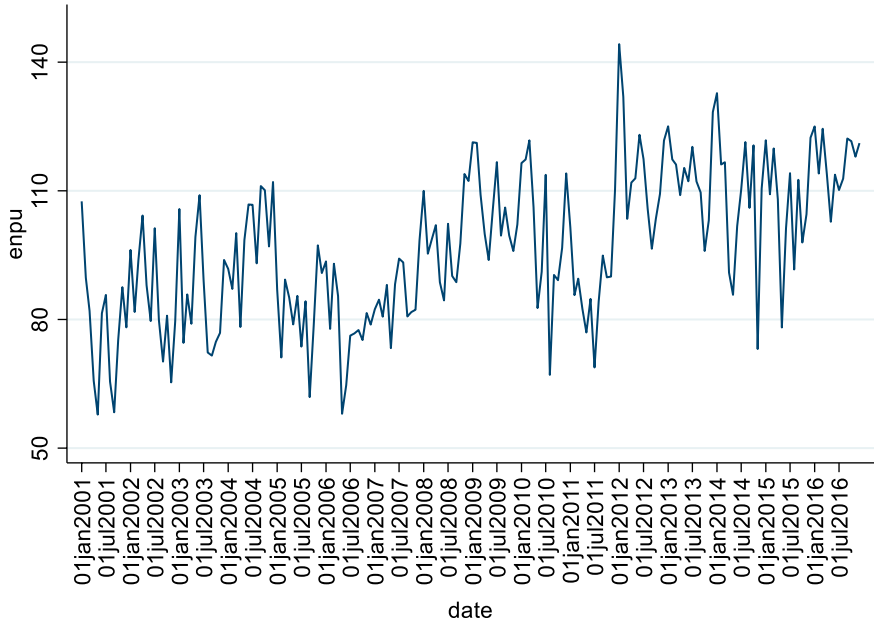


FIGURE 1
The fluctuation trend of China's EPUI from 2001 to 2016.

Compared with the period from 2001 to 2011, China's EPUI showed a volatile increase from 2012 to 2016. In 2012, the 18th National Congress of the Communist Party of China (CPC) was held, and the new central leadership was elected. At the same time, the work focus of "vigorously promoting the construction of ecological civilization and reversing the deterioration of the ecological environment" was put forward. The report of the 18th National Congress of the CPC incorporated "ecological civilization" into the "five-in-one" overall layout of socialism with Chinese characteristics, and for the first time proposed "promoting green, circular, and low-carbon development" and "building a beautiful China". Improving environmental quality has gradually become the core goal and the main task of environmental protection, and environmental policy reform has entered a stage of deepening and sublimation, which have opened the prelude to the volatile rise of China's EPUI. At the third plenary session of the 18th CPC Central Committee in 2013, the Party Central Committee pointed out that "protecting the ecological environment with systems". From September to October 2013, the "National Ten Articles" on air pollution prevention and control played an important role in promoting the control of air pollution and environmental protection, greatly increasing the uncertainty in the implementation and formulation of environmental policies. During this period, China's EPUI showed a rapid rise.

Figure 2 is the distribution map of EPUI at provincial level in China in 2001. China's provincial EPUI is only available in 26 provinces in 2001, missing 5 provinces[2], cities, and autonomous regions, with an average value of 89. And the maximum value is in Qinghai Province, with an index of 170. The minimum value is Tibet, which has a value of 0. Overall, the EPUI in western China is higher than that in central China, and that in central China is higher than that in eastern China.

Figure 3 shows the distribution of EPUI at provincial level in China in 2016. In 2016, China's provincial EPUI is available in 31 provinces and cities. Among them, the average value of EPUI is 111, the maximum value is 161 in Shanghai. The minimum value is in Jilin, with a value of only 79. Overall, China's central inland provinces and eastern coastal provinces have significantly higher EPUI than other regions.

Figure 4 reports the mean distribution of EPUI at provincial level in China from 2001 to 2016. During this period, the average value of EPUI is 99, the maximum value is 114 in Jilin. The minimum value is in Chongqing, which is only 88. As can be seen from Figure 2 to Figure 4, the EPUI of northern provinces of China is significantly higher than that of southern provinces, which reflects that compared with northern provinces of China, southern provinces have better continuity and consistency in the formulation of environmental policies, thus showing relatively lower environmental policy uncertainty.

Figure 5 shows the distribution of EPUI at prefecture level in China in 2001. There are only 28 prefecture-level cities available with EPUI data in 2001. The average value of EPUI is 77, the maximum value is 215 in Xining; the minimum value is 0 in Lhasa. As can be seen that the distribution of EPUI at prefecture level in China is roughly consistent with that in corresponding provinces. Meanwhile, the EPUI of prefecture-level cities in western China is higher than that of central China, and the EPUI of prefecture-level cities in central China is higher than that of eastern China. Compared with EPUI at provincial level, EPUI

2 In 2001, data were missing for five provinces and cities: Tianjin, Heilongjiang, Shandong, Hainan and Ningxia Hui Autonomous Region.

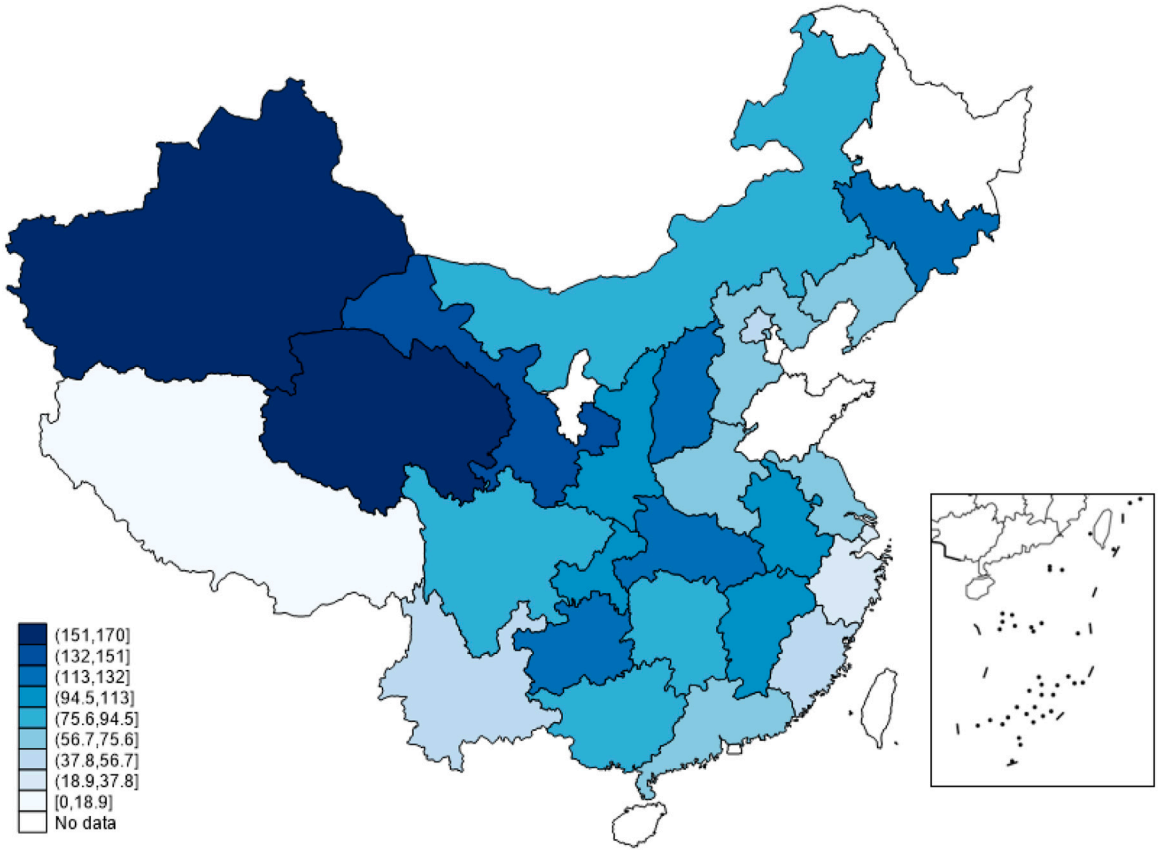


FIGURE 2
The distribution of EPUI at provincial level in China in 2001.

at prefecture level can reflect the fluctuation trend of China's EPUI from a more microscopic perspective.

As shown in Figure 6, the EPUI at prefecture level in China in 2016 is distributed in 240 prefecture-level cities with an average value of 103.9, and the maximum value is Xigaze City with an index of 214.5. This is closely related to China's continuous increase in the formulation and implementation of policies on ecological and environmental protection in Tibet. The minimum value is Jinzhou City, Shiyan City, Hami City, Hetian City, Honghe Hani, and Yi Autonomous Prefecture, Kizilsu Kirgiz Autonomous Prefecture, Nyingchi City, Shannan City, Chaozhou City, Kashgar City, Cangzhou City. The EPUI of all these prefecture-level cities is 0. As can be seen that the EPUI of central and eastern coastal cities in China is significantly higher than that of other cities.

Figure 7 shows the mean distribution of the EPUI at prefecture level in China from 2001 to 2016. We find that the environmental policy uncertainty in eastern and northeastern China is relatively high. Among them, Hulunbuir in Inner Mongolia and Chengde in Hebei Province have the highest EPUI, which is related to the geographical location of the two cities. Hulunbuir locates in the Songhua River basin and Chengde is in the Haihe River and Huaihe River basins. Their geographic location determines that water resource protection and regulatory policies are issued and adjusted more frequently, thus showing a high degree of uncertainty. In contrast, the EPUI of Nagqu City in Tibet is the lowest, with a value of only 75. By comparing Figures 5–7, it can be found that the EPUI of northern cities in China is significantly higher than that of southern cities, which is consistent with the distribution of Figures 2–4. Further analysis shows that over time, the EPUI distribution at provincial and prefecture level in China shows obvious regional transfer characteristics, that is, high EPUI gradually shifts from western China to central, eastern, and northeastern China. One possible explanation is that the economic development in western China is relatively lagging behind other regions, which made relevant departments in western China pay more attention to economic development than environmental protection, making local governments lag behind other regions in the introduction and revision of environmental protection policies. As a result, the EPUI in western China is lower than that in other regions.

3.3 The robustness test and accuracy test of China's EPUI

In this part, we will test the robustness and accuracy of China's EPUI, focusing on two aspects: one is the construction of large-scale X_{it}; the other is the instability that may be caused by the selection of newspaper samples.

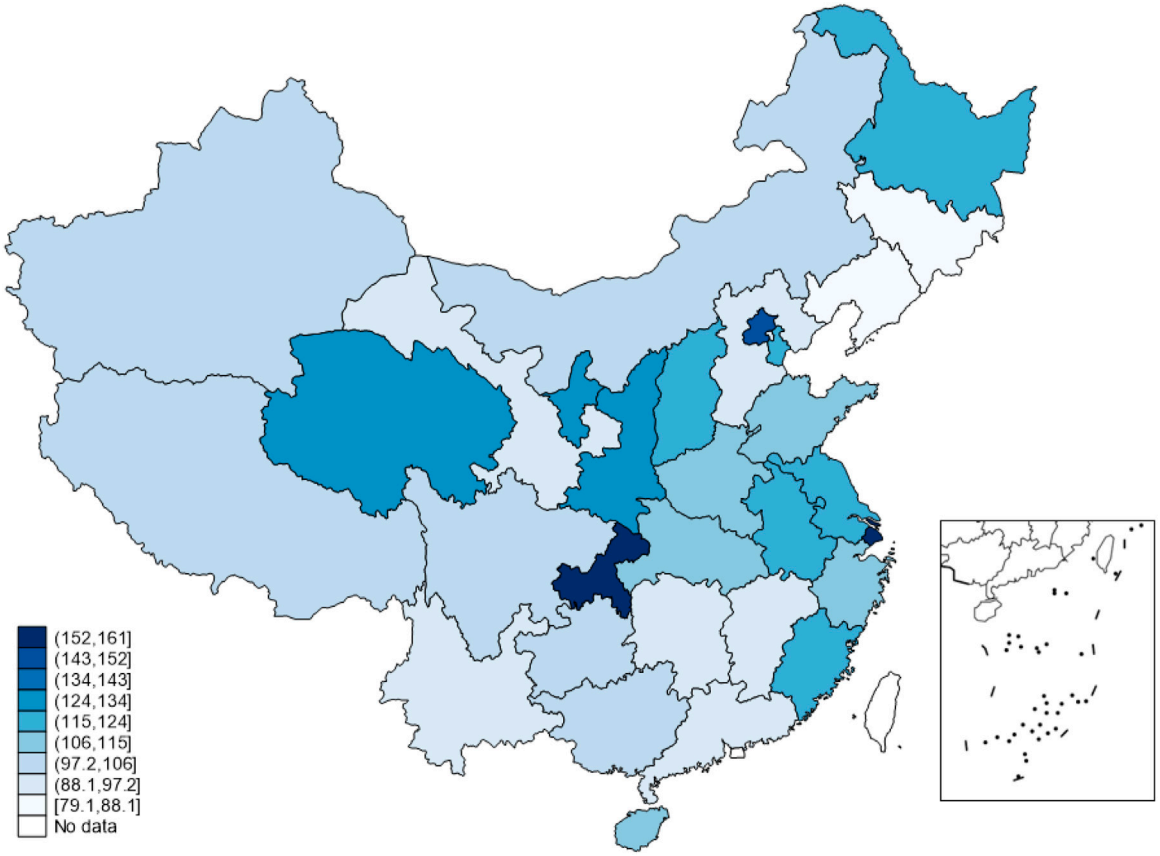


FIGURE 3
The distribution of EPUI at provincial level in China in 2016.

First, the construction of large-scale X_{it}. In the process of constructing Chinese EPUI, $X_{it} = A_{it}/B_{it}$. Where, A_{it} is the target number of articles in each newspaper in each month, and B_{it} is the total number of articles in the i-th newspaper in the t-th month. However, there is a certain difference between the number of daily target articles and the total number of articles in each newspaper. If the number of monthly target articles and the total number of articles are directly used to construct large-scale X_{it}, certain deviation may occur. In view of this, we construct the daily $X_{it,}$ namely, $DX_{it} = DA_{it}/DB_{it}$, where DA_{it} is the daily target number of articles in the i-th newspaper in the t-th month, and DB_{it} is the total number of daily articles in the i-th newspaper in the t-th month. Then, perform calculations according to Step 2 to step 4, and finally, get the daily data of China's EPUI from 2001 to 2016. We use the arithmetic average method to calculate the monthly data of China's EPUI (denoted as EPUI_day). Combining Table 3; Figure 8, we can see that EPUI_day is highly positively correlated with EPUI, with a correlation coefficient of 0.8154. In addition, the fluctuation trend of EPUI constructed in two different ways is almost the same, indicating that the EPUI constructed in the benchmark scenario in this paper is robust.

Second, the selection of newspaper samples. In the process of constructing China's EPUI, we select the data of 460 newspapers distributed in 31 provinces, municipalities, and autonomous regions in China as the newspaper data source, covering the period from 2001 to 2016. In order to test whether the constructed EPUI depends on the selection of newspaper samples, we replace the newspaper samples used in constructing the index, so as to test the correlation between the indexes constructed by different newspaper samples to conduct the robustness test. If the correlation is high, it demonstrates that the EPUI does not depend on the selection of newspaper samples and has high robustness. Otherwise, it means that the EPUI depends on the selection of newspaper samples, and the robustness is low.

The specific processing method is as follows: classify the newspapers in the CNKI newspaper database, and extract the party newspapers of prefecture-level city organs as the article source for constructing EPUI (denoted as EPUI_dang). Because the influence of Party newspapers is different from that of ordinary newspapers. Qin, Strömberg, and Wu (2018) provide some evidence that Party papers focus on political goals, whereas commercial papers focus on economic goals. It shows that the party newspaper has more expression and greater influence in terms of policy uncertainty. Compared with other types of newspapers, Party newspapers in different regions have a wider and more important influence on corporate decision-making.

As can be seen from Table 3; Figure 9, EPUI constructed from 303 prefecture-level party newspapers is highly positively correlated with the EPUI constructed from 460 newspapers, with a correlation coefficient of 0.7930. Obviously, the fluctuation trends of the two

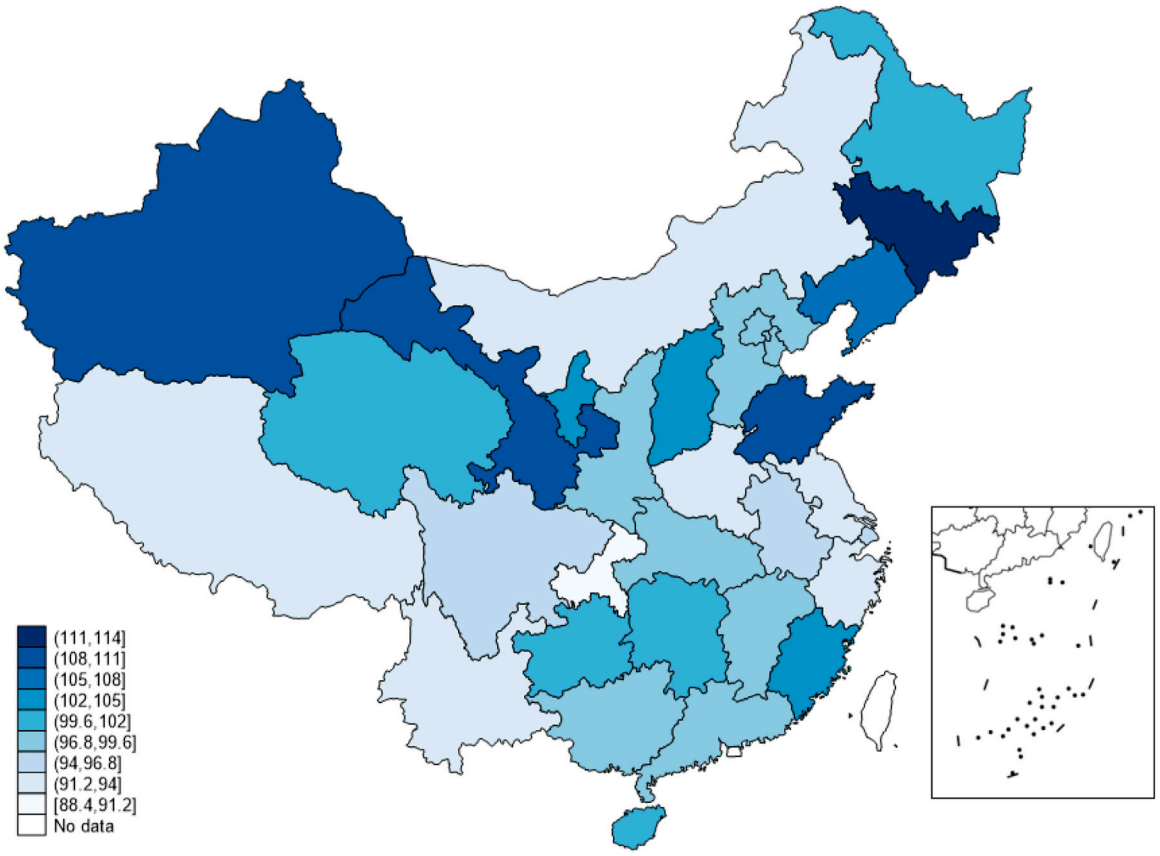


FIGURE 4
The mean distribution of EPUI at provincial level in China from 2001 to 2016.

indexes are the same, manifesting that the Chinese EPUI constructed in this article is robust.

4 The application of China's EPUI

4.1 Data description and variable selection

In this paper, the application scenario of China's EPUI is set at the city level. Data in this article is from the "China City Statistical Yearbook" from 2001 to 2016. The explained variable is the emission of environmental pollutants at the prefecture-level cities, which is recorded as Pollution. Regarding the research settings in existing literature (Huang et al., 2020), this paper selects urban industrial sulfur dioxide emission (denoted as SO_2) and carbon dioxide emission (denoted as CO_2) as proxy indicators of environmental pollutant emissions. The larger the value, the more pollutants are emitted. In the econometric regression analysis, all pollutant emissions are taken as natural logarithms, which are recorded as ln SO_2 and ln CO_2, respectively.

The core explanatory variable is China's prefecture-level EPUI constructed for the first time in this paper. Take the natural logarithm and record it as lnEPUI. In view of the possible endogenous problems between the EPUI and urban pollution emissions, we adopt the logarithm of the EPUI lagging one period as the core explanatory variable. At the same time, a series of city-level control variables are also controlled. First, urban population density, that is, the number of people per unit of land. In this article, it is obtained by dividing the total population of a city by the city's land area in that year, denoted as DP, and the unit is person per square kilometer. Second, the city's gross domestic product *per capita*, that is, the urban GDP *per capita*, is calculated in this paper by dividing the annual GDP of a city by the total population, denoted as PGDP, and the unit is yuan per person. In the econometric regression analysis, the urban GDP *per capita* is logarithmized and recorded as ln PGDP. Third, the scale of urban industrial enterprises is mainly represented by the number of industrial enterprises above the designated size in the municipal area, which is recorded as ES. Forth, urban public finance expenditure is expressed by the logarithm of the city's total public finance expenditure in the current year and recorded as ln PFE. Fifth, the development status of urban tertiary industry is measured by the proportion of urban tertiary industry's GDP and denoted as TI. Sixth, the level of urban greening is measured by the completed green coverage rate in the city, denoted as GL. Seventh, the logarithm of the output value of urban

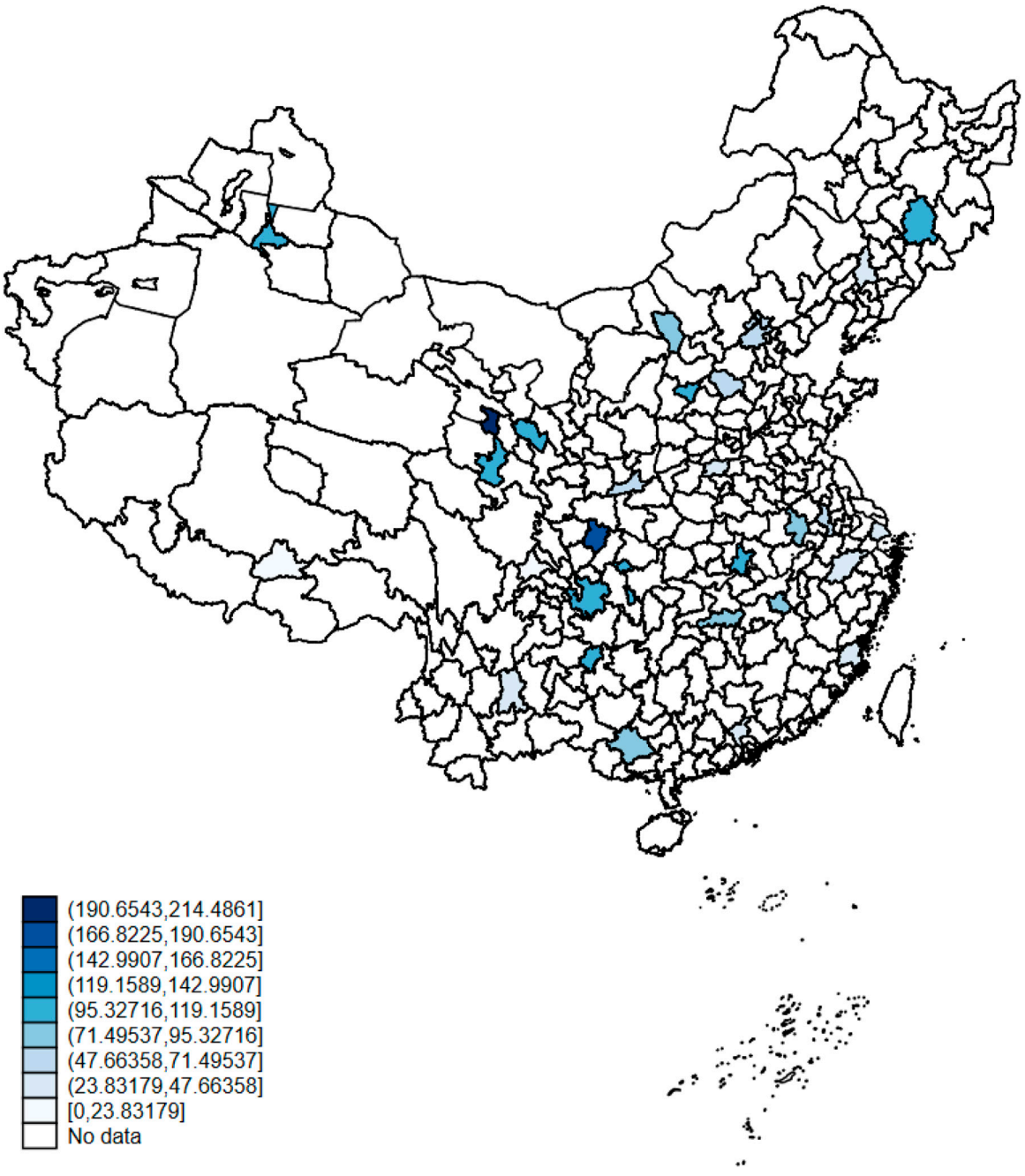


FIGURE 5
The distribution of EPUI at prefecture level in China in 2001.

secondary industry is recorded as ln SGDP. In addition, we also control the city fixed effect and year fixed effect in the econometric regression analysis, which are recorded as City FE and Year FE, respectively.

Table 4 reports the descriptive statistics of relevant variables. As can be seen from Table 4 that the average value and standard deviation of urban industrial sulfur dioxide emission are significantly higher than those of carbon dioxide, indicating that city managers should pay more attention to sulfur dioxide emission reduction in the environmental pollution control. At the same time, it should be noted that industrial sulfur dioxide emissions vary greatly among different cities. The minimum value of China's city-level EPUI is 0 and the maximum value is 6.913, manifesting that different cities have great differences in issuing and revising local environmental protection laws and regulations. Through the descriptive statistics of the average value, standard deviation, minimum and maximum of each variable, it can be found that there are big differences in the level of economic development, population distribution, and economic structure of different cities in China.

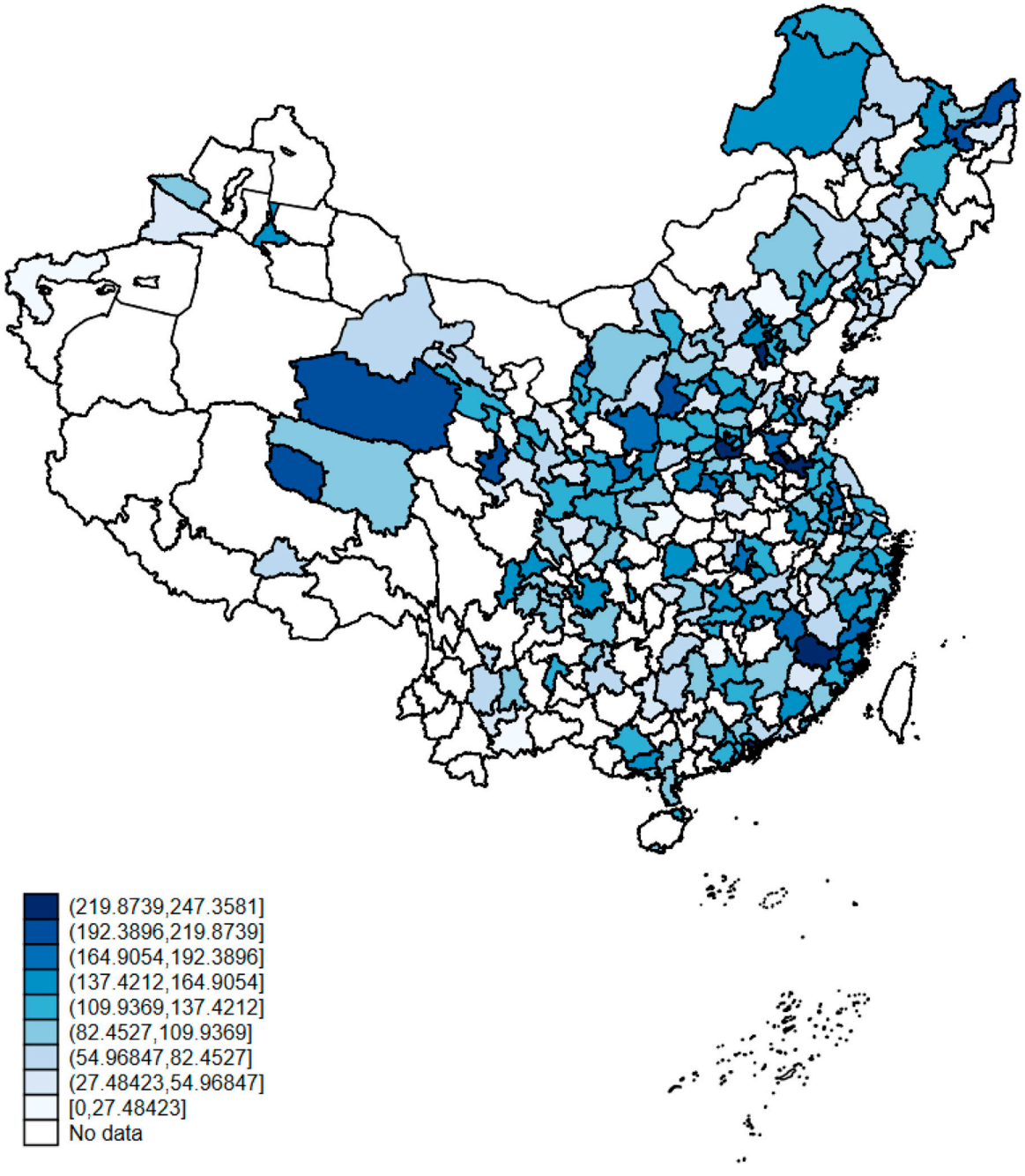


FIGURE 6
The distribution of EPUI at prefecture level in China in 2016.

4.2 Econometric regression model setting

This article uses a two-way fixed effect model with panel data to study the impact of city-level environmental policy uncertainty on urban environmental pollutant emissions. The measurement model is set as follows:

$$Pollution_{i,t} = \beta_0 + \beta_1 \cdot \ln ENPU_{i,t-1} + \beta_2 \cdot X_{i,t} + \lambda_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

Wherein, $Pollution_{i,t}$ refers to the pollutant emissions of the city i in year t, including industrial sulfur dioxide emission and carbon dioxide emission. ln $LNENPU_{i,t-1}$ is the logarithm of the EPUI of the city i in year t-1, $X_{i,t}$ is the set of control variables of the city i in year t. λ_i is the city fixed effect, γ_t is the year fixed effect, and $\varepsilon_{i,t}$ is the error term. β_1 is the most concerned variable in this article. Positive value of β_1 suggests that the increase of urban environmental policy uncertainty will promote urban pollutant

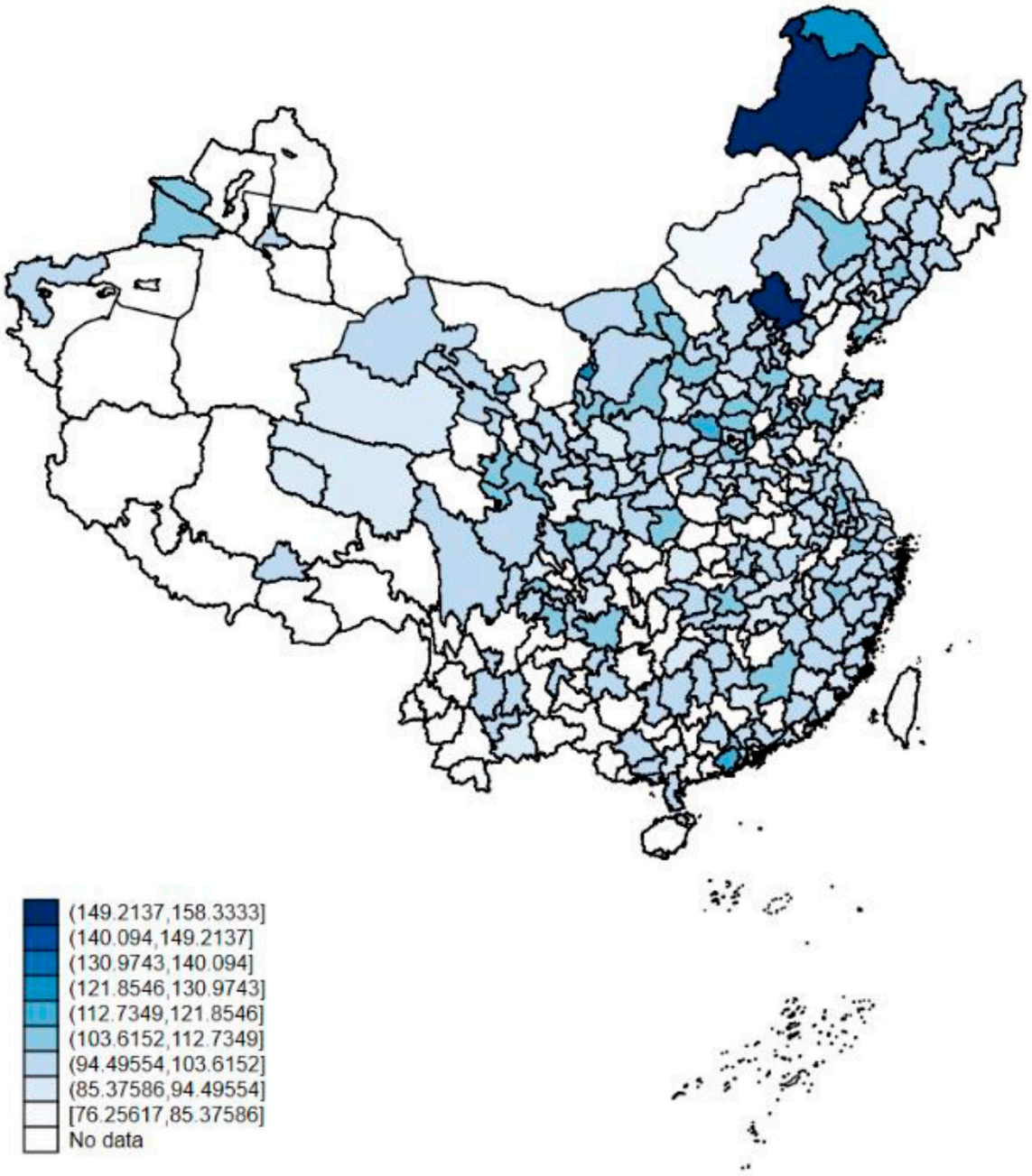


FIGURE 7
The mean distribution of EPUI at prefecture level in China from 2001 to 2016.

TABLE 3 Construction of the correlation coefficient matrix of EPUI with different characteristics.

	EPUI	EPUI_day	EPUI_dang
EPUI	1		
EPUI_day	0.8154	1	
EPUI_dang	0.7930	0.8073	1

emissions, while the negative value indicates to inhibit urban pollutant emissions.

4.3 Econometric regression results and analysis

Table 5 reports the benchmark regression results. Columns 1 and 3 report the direct impact of environmental policy

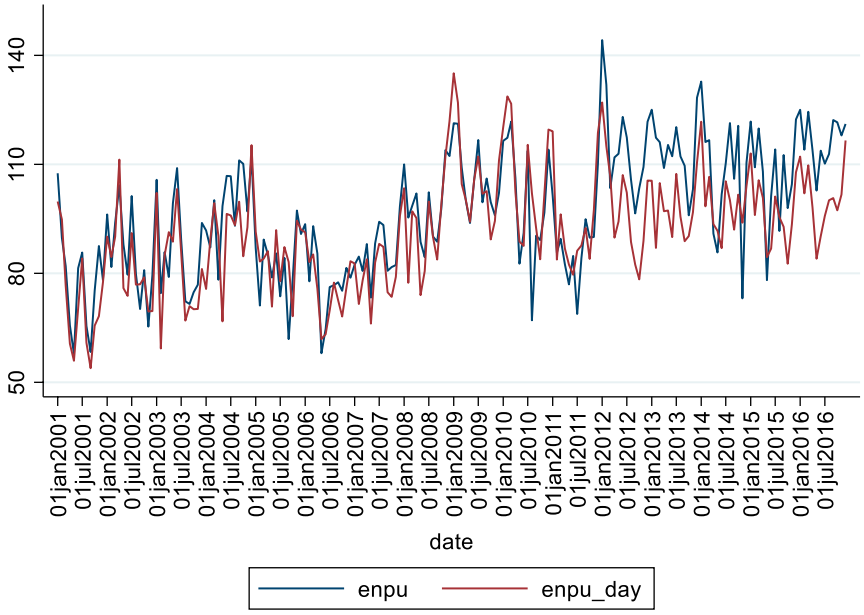


FIGURE 8
The fluctuation trends of EPUI and EPUI_day from 2001 to 2016.

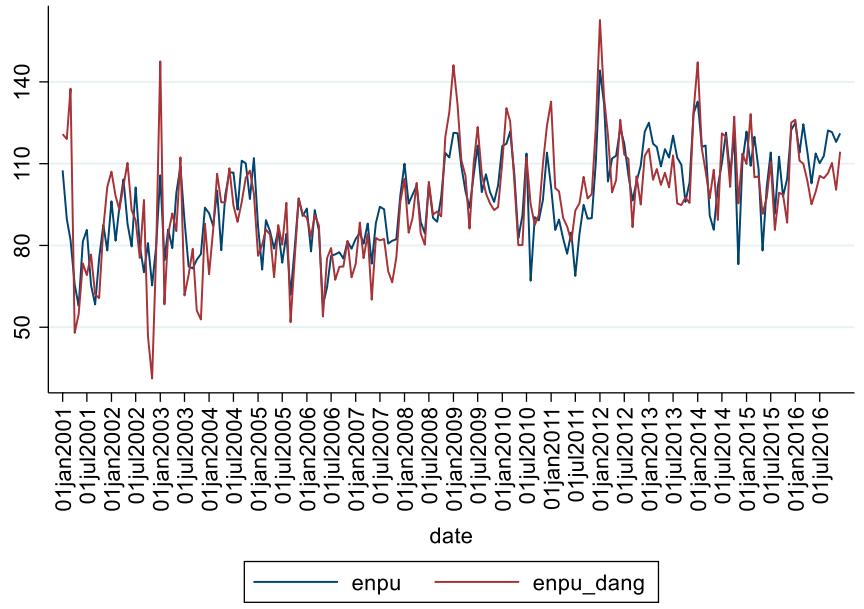


FIGURE 9
The fluctuation trends of EPUI and EPUI_dang from 2001 to 2016.

uncertainty on urban industrial sulfur dioxide and carbon dioxide emissions without adding any control variables. The results show that the coefficient of β_1 is significantly negative, indicating that the increase of environmental policy uncertainty will inhibit urban pollutant emissions. Columns 2 and 4 report the regression results after controlling for factors such as urban population density, economic development level, economic structure, and urban green rate. The regression results show that the coefficient of β_1 is still significantly negative. When urban environmental policy uncertainty increases by 1%, urban industrial sulfur dioxide emission decreases by about 0.145%, and carbon dioxide emission decreases by about 0.053%. This result is quite different from that of Yu et al. (2021), who find that when local economic policy uncertainty increases, enterprises will use more cheap and dirty energy (such as oil and coal) to avoid the risk impact of policy change, thus greatly increasing their carbon

TABLE 4 The descriptive statistics of relevant variables at city level in China.

Variables	Definition	Obs.	Mean	S.D.	Min	Max
ln SO_2	Logarithm of industrial sulfur dioxide emissions	2,314	9.282	2.372	4.533	13.43
ln CO_2	Logarithm of carbon dioxide emissions	2,642	3.025	0.681	0.613	5.445
ln SGDP	Logarithm of actual output value of the secondary industry	2,020	15.05	1.225	10.96	17.95
ln EPUI	City-level EPUI logarithm	2,647	4.260	1.210	0	6.913
DP	Urban population density	2,097	1,089	955.1	13.11	11,449
ln PGDP	Logarithm of urban GDP *per capita*	2,293	10.62	0.712	7.972	13.06
ES	Number of industrial enterprises above designated size_Municipal area	2,318	783.5	1,546	5	18,474
ln PFE	Logarithm of public finance expenditure_Municipal area	2,313	13.46	1.253	9.571	18.05
TI	The proportion of tertiary industry in GDP_Municipal area	2,309	0.392	0.095	0.111	0.853
GL	Completed green coverage rate_Municipal area	2,285	0.375	0.084	0.004	0.929

TABLE 5 Benchmark regression results at city level.

Variables	(1)	(2)	(3)	(4)
	ln SO_2	ln SO_2	ln CO_2	ln CO_2
ln $ENPU_{i,t-1}$	**−0.0604****	**−0.140*****	**−0.0342*****	**−0.0534*****
	(0.0234)	(0.0386)	(0.00701)	(0.0131)
DP		−0.00278**		−0.00149**
		(0.00108)		(0.000628)
ES		−5.76e-05		−4.82e-05**
		(4.95e-05)		(2.02e-05)
ln PFE		0.571*		0.202**
		(0.297)		(0.0933)
ln PGDP		0.00307		0.149**
		(0.182)		(0.0633)
TI		−0.291		−1.813***
		(1.428)		(0.534)
GL		−1.489***		0.266*
		(0.516)		(0.151)
Constant	10.00***	4.927	3.205***	0.264
	(0.100)	(5.028)	(0.030)	(1.576)
Observations	2,032	1,502	2,360	1,803
R-squared	0.811	0.624	0.756	0.796
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjusted R-squared	0.782	0.554	0.725	0.765

Notes: robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
The dependent variables in Table 5 are logarithm of urban industrial sulfur dioxide emission and carbon dioxide emission respectively.
Columns 1 and 3 report the direct impact of environmental policy uncertainty on urban industrial sulfur dioxide and carbon dioxide emissions without adding any control variables. Columns 2 and 4 report the regression results after controlling for factors such as urban population density, economic development level, economic structure, and urban green rate. The regression results show that the coefficient of β_1 is still significantly negative. When urban environmental policy uncertainty increases by 1%, urban industrial sulfur dioxide emission decreases by about 0.14%, and carbon dioxide emission decreases by about 0.053%.

TABLE 6 The regression results of the impact of environmental policy uncertainty on the output value of secondary industry.

	(1)	(2)
ln $ENPU_{i,t-1}$	**−0.163*** **	**−0.143** **
	(0.0575)	(0.0627)
DP		0.00503
		(0.00342)
ES		0.000411
		(0.000252)
ln PFE		0.190
		(0.719)
ln PGDP		0.0325
		(0.398)
TI		−6.320*
		(3.262)
GL		−2.625**
		(1.095)
Constant	27.64***	24.54**
	(0.252)	(11.13)
Observations	2,061	1,814
R-squared	0.941	0.948
City FE	YES	YES
Year FE	YES	YES
Adjusted R-squared	0.933	0.940

Notes: robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Dependent variable in Table 6 is the logarithm of the output value of urban secondary industry. Control variables are not added in Column 1 of Table 6 and they are added in Column 2. The results of Column 2 mean with every 1% increase in environmental policy uncertainty, the output value of urban secondary industry will decrease by 0.143%.

dioxide emission. We believe that the scale of urban secondary industry is an important factor to explain the inhibitory effect of environmental policy uncertainty on urban pollutant emissions. Theoretically speaking, the secondary industry is the main body of industrial sulfur dioxide and carbon dioxide emissions, and is the key target of urban pollutant control. The people's yearning for a better life has forced the central government and local governments at all levels to continuously increase the intensity of environmental regulation, and to successively promulgate various environmental protection policies, which in turn makes the environment policy uncertainty increase steadily. This phenomenon is particularly evident in China's eastern coastal cities, where the economic development is relatively high (as shown in Figures 6, 7;). The risk impact caused by environmental policy changes will restrain the growth rate and scale of urban secondary industries to varying degrees. In this case, urban pollutant emissions will also decrease. However, it should be noted that the reduction of urban pollutant emissions is achieved at the expense of economic development. Of course, the channel of urban secondary production scale still needs to be more rigorously verified.

In this paper, two methods are used to verify the secondary production scale channel through which environmental policy uncertainty affects urban pollutant emissions. The first is to directly analyze the impact of urban environmental policy uncertainty on the output value of secondary industry, that is, to replace the explained variable in the benchmark regression with the logarithm of the output value of urban secondary industry. The measurement model is set as:

$$\ln SGDP_{i,t} = \beta_0 + \beta_1 \cdot \ln ENPU_{i,t-1} + \beta_2 \cdot X_{i,t} + \lambda_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

$\ln SGDP_{i,t}$ represents the logarithm of the output value of secondary industry in the i-th city in the t-th year, and the definitions of other variables are the same as Eq. 1. Table 6 reports the relevant regression results. Control variables are not added in Column 1 of Table 6, while control variables such as urban population density, economic development level, economic structure, and urban green rate are added in Column 2. The results show that the coefficients β_1 in Columns 1 and 2 in Table 6 are both significantly negative, indicating that the increase of environmental policy uncertainty will inhibit the development of secondary industry and reduce its scale. With

TABLE 7 The regression results of adding the interaction term of environmental policy uncertainty and the output value of secondary industry.

Variables	(1)	(2)	(3)	(4)
	ln SO_2	ln SO_2	ln CO_2	ln CO_2
ln $ENPU_{i,t-1}$ × ln $SGDP_{i,t}$	−0.0232***	−0.0203***	−0.00689***	−0.00699***
	(0.00631)	(0.00696)	(0.00200)	(0.00221)
ln $ENPU_{i,t-1}$	−0.433***	−0.347**	−0.113**	−0.110**
	(0.151)	(0.155)	(0.0479)	(0.0483)
ln $SGDP_{i,t}$	0.0428	0.0403	0.00430	0.00174
	(0.0394)	(0.0424)	(0.0158)	(0.0152)
DP		−0.00253**		−0.00133**
		(0.00104)		(0.000585)
ES		−3.73e-05		−3.57e-05
		(5.79e-05)		(2.28e-05)
ln PFE		0.600**		0.210**
		(0.295)		(0.0890)
ln PGDP		0.0368		0.157**
		(0.175)		(0.0613)
TI		−0.421		−1.937***
		(1.482)		(0.527)
GL		−1.716***		0.182
		(0.533)		(0.164)
Constant	10.22***	3.369	3.319***	0.101
	(1.056)	(4.753)	(0.434)	(1.487)
Observations	1,716	1,500	2,045	1,801
R-squared	0.621	0.627	0.764	0.801
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Adjusted R-squared	0.561	0.558	0.734	0.772

Notes: robust standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

every 1% increase in environmental policy uncertainty, the output value of urban secondary industry will decrease by 0.143%.

The second is to add the interaction term between the output value of urban secondary industry and environmental policy uncertainty in the benchmark regression equation. The measurement model is set as follows:

$$Pollution_{i,t} = \beta_0 + \beta_1 \cdot \ln ENPU_{i,t-1} \cdot \ln SGDP_{i,t} + \beta_2 \cdot \ln ENPU_{i,t-1} + \beta_3 \cdot \ln SGDP_{i,t} + \beta_4 \cdot X_{i,t} + \lambda_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

The regression results are shown in Table 7. The estimated results in Table 7 show that the estimated coefficient of $\ln ENPU_{i,t-1}$ is significantly negative, which is completely consistent with the benchmark regression results in Table 5. The estimated coefficient $\ln SGDP_{i,t}$ is positive, demonstrating that the larger the scale of urban secondary industry is, the larger the emissions of industrial sulfur dioxide and carbon dioxide will be, which is completely consistent with the research results of existing literature (Huang et al., 2020). The estimated coefficient of the interaction term is significantly negative, indicating that environmental policy uncertainty can reduce urban pollutant emissions by downsizing the output value of secondary industry. In other words, such a way of reducing emissions is achieved at the expense of economic development.

In summary, combined with the regression results in Tables 5–7, it can be concluded that the increase of environmental policy uncertainty will reduce pollutant emissions such as urban industrial sulfur dioxide and carbon dioxide, at the expense of downsizing the output value scale of urban secondary industry. It should be noted that the channel through which environmental policy uncertainty affects urban pollutant emissions is not limited to the scale of secondary industry. There are other transmission channels, such as green investment and technology upgrading. In the future, we would conduct more in-depth and detailed research if we obtain data on green investment and technological upgrading at city level in China.

4.4 Robustness check

We conducted a battery of robustness checks for our baseline analysis to solve the missing variables and endogenous problems that could exist in the estimation.First, we used the GMM regression by using ENPU with one lag as instrumental variable.On the one hand, we used the difference between the ENPU at the prefecture-level city level and the average ENPU at the provincial level as instrumental variable (IV) of the current year's EPU. The regression results are shown in Table 8. The estimated results in Table 8 show that the estimated coefficient of $\ln ENPU_{i,t-1}$ is significantly negative, which manifests that the basic results in Table 5 are robust. At the same time, all the F statistics were higher than 10, indicating that the weak instrument variable test had been passed. For the instrumental variables constructed in this paper, which is highly correlated with ENPU at the prefecture-level city level, and has nothing to do with other indicators that affect pollution emissions, which satisfies the premise of using instrumental variables.

5 Conclusions and policy implications

This paper selects 460 newspapers from the CNKI newspaper database from 2001 to 2016 as the data source and uses the text analysis method and the construction method of economic policy uncertainty index proposed by Baker et al. (2016) to construct China's national, provincial and prefecture-level EPUI for the first time. The results show that China's EPUI has obvious stage characteristics and regional characteristics. Among them, the EPUI of China from 2012 to 2016 is higher than that from 2001 to 2011, and the EPUI of northern provinces is significantly higher than that of southern

TABLE 8 The regression results of using GMM and Instrument varible as robustness checks.

Variables	GMM	GMM	IV first	IV second	IV second
	ln SO_2	ln CO_2	ln $ENPU_{i,t-1}$	ln SO_2	ln CO_2
ln $ENPU_{i,t-1}$	−0.250***	−0.0641***		−0.140***	−0.0534***
	(0.0543)	(0.0136)		(0.0386)	(0.0131)
IV			5.945**		
			(2.552)		
DP	−0.00119	0.000115	−0.000120	−0.00278**	−0.00149**
	(0.000891)	(0.000371)	(0.000646)	(0.00108)	(0.000628)
ES	4.47e-05	2.91e-05**	2.39e-05	−5.76e-05	−4.82e-05**
	(3.80e-05)	(1.42e-05)	(5.42e-05)	(4.95e-05)	(2.02e-05)
ln PFE	−0.172	0.137***	0.126	0.571*	0.202**
	(0.116)	(0.0294)	(0.169)	(0.297)	(0.0933)
ln PGDP	−0.288*	0.0650*	0.0959	0.00307	0.149**
	(0.154)	(0.0362)	(0.146)	(0.182)	(0.0633)
TI	0.134	−1.496***	0.475	−0.291	−1.813***
	(0.681)	(0.319)	(0.921)	(1.428)	(0.534)
GL	−1.284***	−0.0926	0.132	−1.489***	0.266*
	(0.470)	(0.144)	(0.409)	(0.516)	(0.151)
F statistic			16.38		
Observations	1,114	1,562	1,822	1,502	1,803
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

provinces. From 2001 to 2016, the distribution of EPUI at provincial and prefecture level in China shows obvious regional transfer characteristics, that is, high EPUI gradually shifts from western China to central, eastern, and northeastern China. By applying the Chinese city-level EPUI to the field of urban pollution reduction, we have obtained an important finding that the increase of environmental policy uncertainty will reduce pollutant emissions such as urban industrial sulfur dioxide and carbon dioxide, but at the expense of the development of urban secondary industry.

Based on the conclusions obtained in this article, we propose the following policy recommendations: firstly, when policymakers of government at all levels introduce environmental protection policies, they should have a thorough understanding of local natural resource endowment, geographic location and climate, economic development level and other factors. They need to pay attention to maintaining the consistency and continuity of environmental protection policies in the time dimension, instead of making frequent changes when the environmental protection policies are introduced. At the same time, it is necessary to eliminate the environmental policy confusions caused by divided policies from various sources, and control the uncertainty of environmental policy within a reasonable range. Secondly, although the continuous promulgation and revision of environmental protection policies can effectively reduce urban industrial sulfur dioxide and carbon dioxide emissions, it should be noted that such emission reduction comes at the expense of economic development. How to strike a balance between environmental protection and economic development is a key consideration for policymakers. In the meantime, while continuously improving environmental protection standards in the economically backward central and western inland areas, it is recommended that the central government carry out a certain scale of transfer payments between eastern and western provinces and cities in order to help those inland cities to eliminate the worries of continually improving standards. Finally, the national, provincial, and prefecture-level EPUI constructed in this paper has important application prospects in energy structure transformation and cultivating a low-carbon economy. It also has positive policy guidance for the early realization of the dual carbon goals. Therefore, governments at all levels need to increase funding for various types of basic data research and continuously increase policy support for basic research.

The deficiency of this study is that the application of EPUI only stays at the city level. And the transmission channel through which environmental policy uncertainty affects urban pollutant emissions is only concentrated on the scale of secondary industry, without considering other transmission channels (such as technological

innovation) or policy dividends or spillover effects brought to neighboring cities by the introduction or revision of environmental policies. In the future, we would apply the EPUI to more scenarios (such as at enterprise level or household level), or use the spatial econometric regression method to study the spillover effect of environmental policy changes in different regions.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Materials, further inquiries can be directed to the corresponding author.

Author contributions

RL and JH designed the research. RL helped organize the manuscript. JH performed the analysis. RL and JH revised the manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1203318/full#supplementary-material

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Digital economy and private donation behavior: an empirical analysis based on the CFPS data

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With the development of digital economy, especially the Mobile payment, the lifestyles such as the private donation, is undergoing accelerated changes in the last decades. Based on the China Family Panel Studies 2018 data, this paper systematically investigated the donation models, empowered by digital technology, have realized economy system refinement and intelligent development. Compared with residents who do not use the Internet, residents who use the Internet are about 10% more likely to donate, and the amount of donations will increase by about 56%. After considering the potential endogeneity problem, results still hold with Propensity Score Matching (PSM) and Instrumental Variable. The mechanism analysis shows that the searching cost and information asymmetry play an important role. The research of this paper has enlightening that the widespread use of digital technologies can effectively change the private donation behavior and penetrate energy consumption via dramatically decreasing searching cost.

KEYWORDS

digital economy, private donation, searching cost, information asymmetry, energy consumption

1 Introduction

With the development of Internet and Mobile Payments, there are around 800 million Mobile payment users according to the Statistical Report on Internet Development in China released by the China Internet Network Information Center in Figure 1. At the same time, according to the China Charitable Giving Report, the total amount donated by private has sharply increased from 267 billion yuan to 524 billion yuan in the last decade, showing an increasing trend in private donations but a relatively stable trend in social charities from enterprises (Figure 2). Coincident events hint at whether there is a relationship between them. This paper aims to explore the possible link between these two trends and investigate the factors that may influence individual donation behaviors in the digital age.

Recent literatures show that information asymmetry (Chen, 2021) and donation cost (Liu et al., 2021), such as transportation cost and time cost, are the main obstacles to private donations. Even though the Internet and Mobile payment can help us cross the above hurdles, there are also traps in online donations. Take Waterdrop as an example, this platform was officially established in July 2016. By the end of 2021, about 394 million users had donated over 48.4 billion yuan ($6.94 billion) to nearly 2.4 million seriously ill patients through the platform. Unfortunately, however, the Waterdrop was exposed by the media last year for its "gray chain" problem[1]. It was

1 Refer to the website here: https://m.thepaper.cn/baijiahao_19561245.

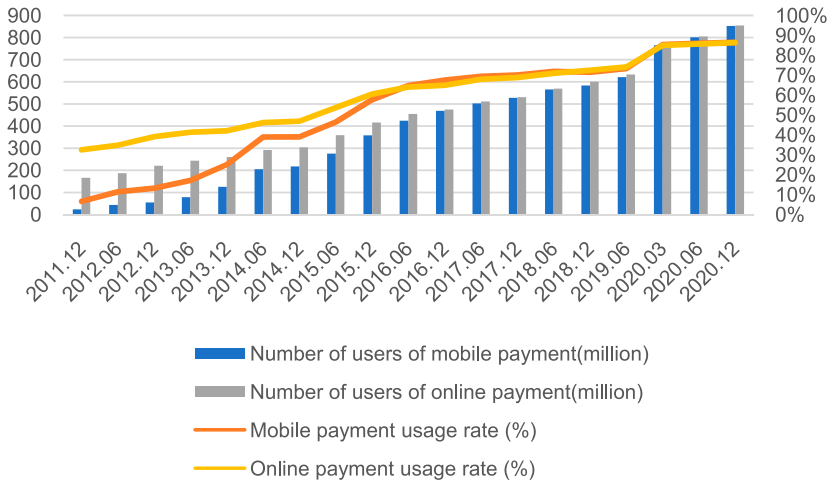


FIGURE 1
The scale and usage rate of online/mobile payment users in China (2011–2020). Source: The Statistical Report on Internet Development in China released by the China Internet Network Information Center (CNNIC) over the years.

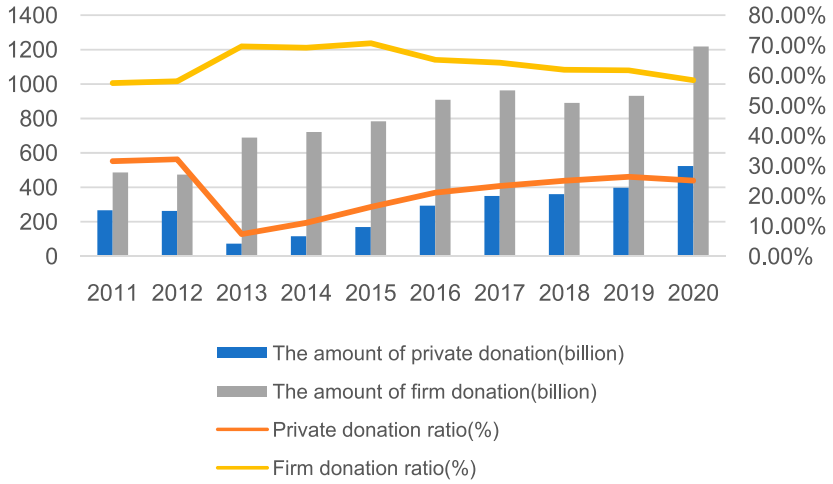


FIGURE 2
The amount and ratio donated by private and firms in China (2011—2020). Source: The China Charitable Giving Report, which is an annual series of reports on China's charitable giving commissioned by the Ministry of Civil Affairs.

reported that intermediaries on Waterdrop were conducting malicious promotions with commission rates of 30%–70% on fundraising intermediaries. Therefore, it is unclear whether the effect of the Internet on personal donation is significantly positive or not.

On the one hand, the popularity of the Internet has *a positive impact* on charitable fundraising in terms of both openness and convenience. Firstly, as for openness, digital technology upgrading has provided diverse channels for charitable organizations to disclose information, which helps solve the trust challenges faced by traditional charitable giving (Gandia, 2011; Blouin et al., 2018). The specific content of donation projects, including the number of donations, the number of donors, the progress of donation projects, the source and destination of funds, and other information can be disclosed in real-time through the Internet, which also makes it timelier and more convenient for all kinds of the government sectors to grasp the situation, so as to monitor more effectively. Secondly, as for convenience, mobile payments such as Alipay and WeChat have broken through the geographical, spatial, and crowd restrictions of traditional charity fundraising (Zheng, 2020), greatly facilitating the operation of donations by residents. Participation enthusiasm is reinforced, due to the ease and convenience of use (Boden et al., 2020). In addition, against the important backdrop of addressing climate change and achieving sustainable development (Yu et al., 2021; Guo et al., 2023; Wang et al., 2023), the popularization and promotion of mobile payment can promote the development of a low-carbon economy, further promoting low-carbon living.

On the other hand, the popularity and widespread use of the Internet may have *a negative impact* on donations. Firstly, there are

frequent incidents or suspected incidents of fraudulent or deceptive use of crowdfunding on the internet (Zenone and Snyder, 2019), especially in China. Because China's existing Charity Law does not cover the activity of Internet fundraising and current crowdfunding platforms generally have low requirements for originators' qualifications (Ke, 2017). Secondly, because of the anonymity and rapidity of information dissemination on the Internet, the cost of creating and spreading rumors is greatly reduced (Vosoughi et al., 2018; Zhang et al., 2022). It is difficult to figure out rumors. Residents' enthusiasm to make charitable donations are reinforced.

Overall, the development of the Internet has had a significant impact on residents' charitable activities, but its ultimate impact remains to be studied in depth. The role of digital technologies in influencing residents' willingness to donate has been explored in the literature, but mainly in the context of population-specific studies of donation behavior and willingness (Andreoni et al., 2003; Bryant et al., 2003; Meer and Rosen, 2013; Meer and Priday, 2021), or using experimental methods for analysis (Chen et al., 2005; Ingenhoff and Koelling, 2009; Castillo et al., 2014), which did not include the analysis of large-scale, more representative samples. And the reliability of the study's conclusions still needs further verification. In particular, the paper of Gao and Wang (2021) is similar to the topic of this paper, but they use data from the 2012 Chinese General Social Survey (CGSS) and find that using the Internet makes residents more willing to give and that residents' volunteer participation, social networks, and sense of giving all play moderating roles in charitable giving. It is important to note that, first, the data used in this paper are from 2012, which is relatively outdated compared to the booming Internet philanthropy, because neither the coverage of the Internet, nor the application of various charity APPs and official accounts is comparable to today[2], and the impact of Internet use on residents' giving has not yet been fully revealed. Second, they do not explore the mechanism by which Internet use affects residents' donation behavior. Therefore, it is necessary to conduct a more in-depth study of this issue using more representative and current data in order to draw more accurate conclusions.

For the above reasons, this paper systematically investigates the impact of Internet use on residents' giving behavior using micro-data from the China Family Panel Studies (CFPS) 2018 to draw more precise and relevant conclusions. The results of the study, which control for endogeneity issues, show that residents who use the Internet are about 10% more likely to donate and the number of donations will increase by about 56%. This effect is more pronounced for Internet users who are highly educated, working, and non-retired. Further analysis suggests that Internet use acts on personal donation behavior primarily through two major mechanisms: searching cost and information asymmetry.

This paper may have three marginal contributions in comparison to existing literature. First, we detect the causal effect of digital economy on private donation behavior, which extends our understanding the impact of the digital technologies on residents' lifestyle, which extends the literature related to the effect of the digital economy and the causal factors of the private donation. Second, this study figures out that possible mechanisms by which using Internet affects residents' donation behavior. Third, based on the mechanism analysis, we find reducing the transportation cost is a benefit from the development of the digital economy, which is important evidence to sustain the widespread use of digital technologies can effectively penetrate energy consumption.

The remaining part of the paper proceeds as follows. Section 2 contains a literature review; Section 3 describes the data and the identification strategy used in the analysis; Section 4 presents the empirical results as well as the robustness tests followed by heterogeneity analysis; Section 5 further explores the mechanisms involved; and Section 6 concludes.

2 Literature review

It has been shown that people's willingness and behavior to donate can be influenced by numerous factors. According to the literature, we can classify these influences into two categories: individual and environmental factors.

Individual factors mainly refer to the personal characteristics of the donor, including gender, age, education, income and wealth, and many other aspects. For gender, Andreoni et al. (2003) found that for single households, there was a significant difference between men and women in terms of the amount donated. Böhm and Regner (2013) conducted a real-effort task experiment and found that male subjects increased donation performance in the public setting for the purpose of status-seeking. Lee et al. (2016) verified that donation attitudes were more positive among female than male students and this phenomenon could be interpreted using altruism theory. For age, the empirical literature generally finds that both the probability and amount of donation decrease when the elderly are getting old. Meer and Rosen (2013) confirmed that under the same assumptions, the manner in which older adults die also had an impact on donation. For education, Bryant et al. (2003) observed that individuals with high human capital were more willing to donate based on the survey data from 1994. For income and wealth, Meer and Priday (2021) used panel data on income to empirically test that donation behavior increases as individuals' income and wealth increase.

Environmental factors, on the other hand, emphasize that the external environment in which individuals live plays a role in influencing donation behavior through structural forces such as infiltration or coercion. These factors include family environment, cohort effect, social capital, and geographical proximity. For the family environment, Lee et al. (2016) identified the relative impact of parent-related factors, including parents' donation activity and volunteer work, on middle school students' donation attitudes. For the peer effect, Meer (2011) focused on it in the solicitation, looking at whether people give more if the ask comes from someone they know. Smith et al. (2015) empirically verified donors were significantly influenced by the donations of their peers in the context of individual online fund-raising. For social capital, Brown and Ferris (2007) found a strong correlation between social capital on philanthropy through a field experiment, i.e., the higher the stock of

2 Online fundraising platforms are currently an important way for residents to donate, and were only approved by the Ministry of Civil Affairs starting in 2016.

individual social capital, the higher the level of donation. Saxton and Benson (2005) showed that by controlling for other relevant social, political, and economic factors, communities with higher levels of social capital experience more extensive growth in their nonprofit sectors. For geographical proximity, the sense of geographical proximity believing that recipients come from the same area had a strong correlation with an individual's donation behavior (Guéguen et al., 2018).

In terms of the research topic of this paper, there are a number of studies. However, the literature studying charitable giving from the Internet perspective has mainly focused on experimental studies rather than empirical studies. This is because the popularity of the Internet provides a more convenient platform and channel for conducting donation experiments (Chen et al., 2005). Chen et al. (2005) implemented the first web-based online fundraising experiment to test the effectiveness of various fundraising mechanisms. Ingenhoff and Koelling (2009) used charitable fundraising nonprofit organizations (NPOs) experiments to demonstrate that the Internet increases the likelihood of public participation in dialogue by providing a two-way communication channel for NPOs to communicate with the public. Castillo et al. (2014) implemented a field experiment embedded in an online giving organization's web page to further explore the impact of incentives on the willingness to fundraise.

It is noteworthy that experiments used to study charitable giving suffer from some common drawbacks. Firstly, the participant pool in experiments is often limited, which restricts the number of variables that can be controlled simultaneously. Secondly, most experiments utilize homogenous samples of students, casting doubt on the external validity of findings based on student populations. Research studies based on random population samples, on the other hand, tend to have large and well-represented samples, which can offset the limitations of experimental research. Nonetheless, there are few studies in this area, with the exception of Gao and Wang (2021). Therefore, this paper utilizes the latest 2018 China Family Panel Studies (CFPS) data to re-examine the impact of Internet use on residents' donation behavior and provide an in-depth analysis of the relevant mechanisms to bridge the gap in this area.

3 Data and identification strategy

3.1 Data

The data used in the paper are from the China Family Panel Studies (CFPS), which is a biennial survey conducted from 2010 to 2020 and covers 162 counties in 25[3] of 31 provinces. The sample is nationally representative of Chinese communities, households, and individuals. The explanatory variable in this study is personal donation behavior. In the CFPS individual-level questionnaire, the donation-related questions are asked only in 2018, we have to use the 2018 survey data for benchmark empirical analysis.[4] We limit the study to the adult questionnaire and ultimately retain a sample of 30,169 after removing missing values for key variables.

Personal donation behavior—The dependent variable is the donation behavior of residents. We use two indicators to characterize this. Firstly, we construct a dummy variable for whether residents have made a donation, based on the question in the CFPS questionnaire: " In the past 12 months, have you ever made any donation to any individual or organization?" The dummy variable *if_donate* was constructed to indicate whether or not the resident had made a donation. If the answer is yes, then the variable takes the value of 1, otherwise, it takes the value of 0. Secondly, we constructed the continuous variable *ln_donation*[5] to characterize the amount of money donated by residents based on their responses to the question "What is the total amount of donation in the past 12 months? ". What's more, if the question is limited to "in the past 12 months", it will be 1 year backward from the survey time. Therefore, the donation data used in the benchmark regression in this study refers specifically to the time period from June 2017 to June 2018. The CFPS data does not record each individual's donation transactions, but report each's donation decision and total amount in the last 12 months. (Supplementary Table A2).

Internet service - The independent variable is the Internet usage of residents, which is a dummy variable. Based on two questions "Do you use mobile devices (e.g., mobile phone, tablet PC) access to the Internet?" and "Do you use computer access to the Internet?", if the respondent answer "yes" for either of above two questions, this variable is assigned the value of 1, otherwise, this dummy variable is set a value of 0.

Other control variables - According to the previous literature (Bronars and Lott, 1997; Yang et al., 2020; Andreoni et al., 2003; Meer and Rosen, 2013; Bryant et al., 2003; Meer and Priday, 2021), we also controlled for a range of personal and household characteristics variables in order to exclude other influences. The personal characteristics variables include the respondent's gender (1=male; 0=female), age, years of schooling (refer to the highest level of education completed[6]), marital status (1=unmarried, divorced or widowed; 0=married or cohabiting), work status (1=employed; 0=unemployed, including withdrawal from the labor market), self-rated health status (1=very good; 0=very poor), usual place of residence (0=rural; 1=urban), annual income level (logarithmic form), CCP member (1= the member of Communist Party of China; 0=not), public sector[7] (1=public sector; 0=private sector), and retirement status (1=retired; 0=not). What's more, *Personality traits* are a more comprehensive portrayal of a person's traits (Almlund et al., 2011; Heckman, 2011) and these may be important variables.

3 Tibet, Qinghai, Xinjiang, Ningxia, Inner Mongolia, Hainan, Hong Kong, Macau, and Taiwan are not included.

4 We also conduct a robustness analysis later by using household panel data.

5 This variable is processed by adding 1 and then taking the logarithm form.

6 0=Illiterate/semi-literate 6=Primary school 9=Junior high school 12=Senior high school/Vocational School 15=3-year college 16=4-year college/Bachelor's degree 19=Master degree 22= Doctoral degree.

7 Public sector refers to working in Government, Party, People's organization, Military, State-owned, or Collectively-owned public institution, State-owned, or State-controlled enterprise.

TABLE 1 Summary statistics of individual cross-sectional data.

Variables	Note	Mean	Minimum	Maximum	Standard deviation	Observation
Internet		0.528	0	1	0.499	30169
if_donate		0.225	0	1	0.417	30169
ln_donation		1.107	0	13.12	2.160	30095
male	gender	0.497	0	1	0.500	30169
age		46.71	16	96	16.87	30169
urban	usual place of residence	0.507	0	1	0.500	29890
health	self-rated health status	0.706	0	1	0.456	30169
edu_year	the highest level of education completed	7.652	0	22	5.003	30169
single	marital status	0.212	0	1	0.409	30169
employment	work status	0.713	0	1	0.453	30169
party	CCP member	0.0955	0	1	0.294	30169
tizhi	Public sector	0.0943	0	1	0.292	30169
ln_income	annual income level	9.839	0	15.01	1.363	30015
retire	retirement status	0.180	0	1	0.384	30169
con	conscientious	3.603	0.714	5	0.563	30168
ext	extraversion	4.165	1	5	0.833	30156
agr	agreeableness	2.875	1	5	0.754	30166
neu	neuroticism	2.619	1	5	0.531	30168
ope	openness	1.884	1	5	1.124	30123
ln_assets	household assets	7.088	0	16.17	4.786	29913

We constructed five major personality trait variables, namely conscientious, extraversion, agreeableness, openness, and neuroticism based on the NEO personality trait revision questionnaire developed by Costa and McCrae (2008) and the questions from the British Household Panel Study (BHPS) (Brown and Taylor, 2014), and then add 'Big five' personality trait in the main model.[8] Household characteristics variables are then added by using household assets (containing cash, savings, and financial products, in logarithmic form).

Table 1 presents the summary statistics of individual cross-sectional data. As shown in Table 1, 53% of residents accessed the internet via computer or mobile. This figure is largely consistent with the Internet penetration rate of 59.6% in 2018 published by CNNIC, indicating that the use of CFPS data to study internet use is relatively representative. In addition, in terms of donation behavior, nearly a quarter (22.5%) of respondents made donations in 2018, with the average donation amount of all samples being 99.97 yuan ($14.36), accounting for 0.69% of individual income.[9]

3.2 Identification strategy

In the baseline regression, this paper uses a Probit model to investigate the effect of Internet use on whether residents make donations. The model was set up as follows.

$$probit\left(if_donate_i = 1 \middle| internet_i, X_i, \alpha_c\right) = \Phi\left(\beta_0 + \beta_1 internet_i + \beta_2 X_i + \alpha_c\right) \quad (1)$$

In Equation 1, the explanatory variable if_donate_i indicates whether resident i makes a donation or not. The explanatory variable $internet_i$ denotes whether resident i use the internet. X_i denotes a set of control variables, including individual characteristics and household characteristics. α_c denotes county-level fixed effects. β_1 is the coefficient of interest in this paper, which indicates the effect of Internet use on donation behavior. If the coefficient is positive, it shows that internet use increases the probability of donation among residents, and if it is negative, it means that Internet use decreases the probability of donation among residents.

For the amount of donation, this paper uses ordinary least squares (OLS) for estimation. The model is set up as follows.

$$ln_donation_i = \gamma_0 + \gamma_1 internet_i + \gamma_2 X_i + \alpha_c + \varepsilon_i \quad (2)$$

In Equation 2, the explanatory variable $ln_donation_i$ represents the donation amount of resident i, ε_i is a random disturbance term, and other variables have the same meaning as in Equation 1.

8 The specific criteria for the classification of 'Big Five' personality traits can be found in the Supplementary Table A1.

9 The average donation amount of the donor sample was 448.52 yuan($64.43).

TABLE 2 The impact of internet use on donations: baseline estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	Probit	Probit	Probit	OLS	OLS
VARIABLES	if_donate	if_donate	if_donate	if_donate	if_donate	ln_donation
internet	0.213***	0.115***	0.104***	0.104***	0.108***	0.562***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.040)
gender		0.006	−0.007	−0.007	−0.011**	−0.032
		(0.005)	(0.005)	(0.005)	(0.005)	(0.026)
age		−0.002***	−0.002***	−0.002***	−0.002***	−0.004**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
urban		0.025***	0.019**	0.019**	0.019**	0.127***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.043)
health		0.000	−0.006	−0.006	−0.006	−0.024
		(0.006)	(0.006)	(0.006)	(0.006)	(0.029)
edu_year		0.012***	0.008***	0.008***	0.008***	0.050***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
single		−0.047***	−0.021***	−0.021***	−0.010	−0.090**
		(0.007)	(0.008)	(0.008)	(0.007)	(0.036)
employment			0.049***	0.049***	0.049***	0.338***
			(0.007)	(0.007)	(0.006)	(0.030)
party			0.064***	0.064***	0.076***	0.493***
			(0.008)	(0.008)	(0.010)	(0.056)
tizhi			0.079***	0.078***	0.118***	0.687***
			(0.009)	(0.009)	(0.012)	(0.066)
ln_income			0.016***	0.016***	0.014***	0.099***
			(0.003)	(0.003)	(0.002)	(0.012)
retire			−0.013	−0.012	−0.013	−0.098**
			(0.011)	(0.011)	(0.008)	(0.042)
con			0.022***	0.022***	0.017***	0.085***
			(0.006)	(0.006)	(0.006)	(0.030)
ext			0.009***	0.009***	0.010***	0.058***
			(0.003)	(0.003)	(0.003)	(0.018)
agr			0.006*	0.006*	0.004	0.017
			(0.004)	(0.004)	(0.003)	(0.017)
neu			0.014***	0.014***	0.016***	0.097***
			(0.005)	(0.005)	(0.005)	(0.023)
ope			0.006**	0.006**	0.007***	0.034***
			(0.002)	(0.002)	(0.003)	(0.013)
ln_assets				−0.000	−0.000	0.000
				(0.001)	(0.001)	(0.003)

(Continued on following page)

TABLE 2 (*Continued*) The impact of internet use on donations: baseline estimates.

VARIABLES	(1) Probit if_donate	(2) Probit if_donate	(3) Probit if_donate	(4) Probit if_donate	(5) OLS if_donate	(6) OLS ln_donation
County FE	YES	YES	YES	YES	YES	YES
Observations	29,497	29,261	29,079	29,024	29,633	29,562
R-squared	-	-	-	-	0.160	0.177

Note: Standard errors are clustered at the county level. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Probit regressions report average marginal effects; OLS regressions report estimated coefficients. Notes to subsequent tables are the same as in Table 2 unless otherwise stated.

4 Empirical results

4.1 Baseline estimates

We present the baseline specification in Table 2, which demonstrates the impact of internet usage on personal charitable giving behavior. The dependent variables are the probability of donating and the amount donated, while the independent variables are internet usage and other control variables. Columns 1–5 of Table 2 display the results for whether an individual made a donation in 2018. The regression analysis demonstrates that the coefficient for internet usage remains significantly positive at the 1% level, even after controlling for individual demographic characteristics, work characteristics, wealth characteristics and personality traits one at a time. This suggests that the positive effect of internet usage on the likelihood of donating is robust. Column 4 of Table 2 shows that residents who use the internet are about 10.4% more likely to donate compared to those who do not use the internet. This figure represents 0.46 times the 2018 average probability of donation (22.5%), which is a highly economically significant result. The results in column 5 are obtained using a linear probability model, and the significance of the estimates is consistent with the Probit model. Column 6 examines the impact of internet usage on the amount donated by individuals in 2018. The regression analysis shows that residents who use the internet donate approximately 56.2% more compared to those who do not use the internet.

4.2 Endogeneity issues

To ensure the reliability of our findings, we implemented several methods to address potential endogeneity concerns. We employed three different techniques to tackle endogeneity issues.

4.2.1 Propensity score matching

Self-selection bias is a bias that is introduced into a research project when participants choose whether or not to participate in the project, and the group that chooses to participate is not equivalent (in terms of the research criteria) to the group that opts out. The treatment groups and control groups are observed in this study. In this study, the donation group is not equivalent to the nonparticipant group because of unobserved characteristics, such as the donation preference or culture. Therefore, the estimation results may be biased, and the baseline regression may overestimate the effect of internet use on donation behavior. To ensure the reliability of the core findings of this study and better reveal the causal relationship between internet use and individual donation behavior, we employed the propensity score matching (PSM) method for handling and compared the difference in donation behavior between these two groups of individuals, namely Average Treatment Effect (ATT), to determine the effect of Internet use on personal donation behavior.

The results of the balance test showed that the differences between the control variables in the experimental group and the control group were significantly reduced after matching, and most of the covariates' significance disappeared, meeting the requirement of covariate balance between groups. Table 3 reports the results of the ATT calculated using the nearest neighbor matching method. It can be seen that compared with residents who do not use the Internet, Internet use increases the probability of donation by approximately 10.2% and 11.5%. The effect of Internet use on donation behavior remains siginificant at the 1% level after using PSM for matching, consistent with the conslusion in Table 2. The results indicate that the problem of self-selection bias does not have a significant impact on the regression results.

4.2.2 Measurement errors

To address the issue of potential measurement errors, we removed questionnaires with low credibility scores. Based on the observations of the CFPS interviewers, the respondents' impatience with the interview was scored on a scale of 1 (very low) to 7 (very high) to measure the credibility of the sample. We used a mean score of 4 as the criterion to determine whether the respondent was impatient, and if the score was higher than 4, the value of "*Credible*" was set to 0. This is because if the interviewer gave a score higher than 4, it means that the respondent is more likely to choose quick answers in the preceding questions, rather than providing truthful answers. For example, when asked "Do you use a computer to access the internet," if the respondent answers "yes," further questions will be asked about the frequency of internet use for study and work, but if the respondent answers "no," there will be no related follow-up questions. Therefore, it is possible that the quality of the information provided by the respondent may be compromised due to impatience with the interview, leading to measurement errors.

On the basis of the baseline regressions, we removed samples with scores greater than 4, representing approximately 15% of the total sample. The results in columns 1 and 2 of Table 4 validate the

TABLE 3 Propensity score matching.

ATT	(1) nearest-neighbor PSM 1:1	(2) nearest-neighbor PSM 1:4
Internet	0.102***	0.115***
	(0.016)	(0.015)
Controls	YES	YES
Observations	29,633	29,633
Pseudo R2	0.432	0.432

Note: Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. The dependent variable was donation behavior *if_donate*. The control variables include personal characteristics gender, age, education, marital status, work status, health status, usual place of residence, income level, CCP member, public sector, retirement status, and household assets.

TABLE 4 Removal of samples with low credibility.

VARIABLES	(1) if_donate	(2) ln_donation	(3) if_donate	(4) ln_donation
internet	0.105***	0.569***	0.104***	0.561***
	(0.008)	(0.043)	(0.008)	(0.044)
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Interviewer FE	**NO**	**NO**	**YES**	**YES**
Credible	**YES**	**YES**	**YES**	**YES**
Observations	24,673	25,158	24,526	25,158
R-squared	-	0.183	-	0.211

TABLE 5 Instrument variable.

VARIABLES	(1) IV-Probit	(2) IV-2sls
Panel A the Second Stage		
internet	0.176**	0.181**
	(2.567)	(2.384)
Panel B the First Stage		
IV	0.392***	0.359***
	(0.037)	(10.423)
Controls	YES	YES
Prov FE	YES	YES
Observations	29,394	29,394
R-squared	-	0.117
The first stage F statistic		501.25{0.000}
Wald test		5.69{0.012}

Note: Standard errors are clustered at the county level. Significance levels: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. IV-Probit regressions report average marginal effects; IV-2sls regressions report estimated coefficients. The dependent variable was donation behavior *if_donate*. As the Wald test for IV-Probit requires an assumption of homoskedasticity (no robust or cluster), we can't get the *p*-value of the Wald test in IV-probit.

TABLE 6 Expenditure on gifts for social relations.

VARIABLES	(1) if_donate	(2) ln_donation
internet	0.102***	0.558***
	(0.008)	(0.041)
ln_fexpense_gift	0.010***	0.043***
	(0.001)	(0.006)
Controls	YES	YES
County FE	YES	YES
Observations	28,693	29,227
R-squared	-	0.181

robustness of our conclusions. The measurement errors are unlikely to drive our estimates spuriously.

Besides, to address concerns about comparability of subjective scoring across interviewers, we also control the interviewer fixed effect, the results in columns 3 and 4 of Table 4 are still robust.

4.2.3 Instrument variable

If generous donors are inherently more likely to be online, then distinguishing whether Internet use increases giving behavior or whether Internet use is due to generous giving will be very difficult. To eliminate this potential endogeneity problem, we introduce the instrumental variable, drawing on the idea of constructing instrumental variables from Gao and Wang (2021). We selected the average internet usage of all respondents within the same county excluding the respondent himself/herself as the instrumental variable for respondents' internet usage. The level of Internet access and utilization in a region has a significant impact on individuals' decisions to access the Internet, and the regional use of the Internet is strongly exogenous to residents' donation behavior, so it is reasonable to use the regional average Internet use as an instrumental variable. Based on the characteristics of the explanatory variables, we conducted IV-Probit regression and IV-2sls regression respectively, and the regression results are shown in Table 5.

The result of the first-stage estimates is reported in Panel B of Table 5. It can be seen that as the explanatory variable, the first-stage regression coefficient of internet use is significantly positive at the 1% level, indicating a significant positive impact of average Internet use in county areas on whether individuals use the internet. Therefore, the instrument variable has a strong correlation. The first-stage F-values were 501.25. According to Stock and Yogo (2005), the critical value of the F-value is 16.38 under the assumption that the bias level is less than 10%, which further demonstrates the explanatory power of regional average Internet usage for whether individuals use the internet, and there is no weak instrument problem. The second stage results from Table 5 report that the regressions using instrumental variable are generally consistent with the baseline estimates: a 17.6% increase in the probability of donation for residents who use the internet in the IV-probit regression; and a 18.1% increase in the probability of donation for residents who use the internet in the IV-2sls regression.

4.3 Robustness tests

4.3.1 Expenditure on gifts for social relation

Expenditure on gifts for social relations, as the cost of interaction between people, has the function of maintaining long-term relationships between acquaintances. This is different from the act of donation, but it is easy to confuse household favor expenditure with donation expenditure. In particular, favor expenditure from wealthy families to poorer families may have both social capital attributes and donation attributes, unlike general donation expenditure. Therefore, in order to exclude the effect of this type of expenditure on the conclusions, we selected the corresponding question from the CFPS household questionnaire, "In the past 12 months, what was the total amount of money your family spent on gifts for social relations? " to measure Expenditure on gifts for social relations and included this control variable *ln_fexpense_gift* in the main model. The regression results in Table 6 report that the internet's ability to significantly increase the probability and amount of giving still holds after controlling for household spending on favors. Our main findings remain unchanged.

4.3.2 Household panel data

It has been proved that charitable giving tends to be made by households as a unified economic entity, with joint decision-making by couples being the dominant way (Wiepking and Maas, 2009). The giving behavior we see may not only be the individual decisions, but also the behavior of households. Therefore, we use the household panel data below to analyze the impact of internet use on giving behavior.

In the CFPS household-level questionnaires, the household donation information and internet usage are recorded in 2014, 2016, and 2018. So, this panel data from these three periods is conducted to make the robust test. The final sample contained 40,580 observations after removing missing key variables. Referring to the study by Yang et al. (2022) and Guo (2020), we examined household internet use in two dimensions. The first variable *if_internet* is whether the household uses the Internet, taking a value of 1 to indicate that at least one person in the household uses the Internet and 0 to indicate that no one in the household uses the Internet; the second variable *ratio_internet* is the household Internet usage rate, which is the ratio of the number of people using the Internet to the number of all people in the household. We constructed the continuous variable *ln_donation*[10] based on the responses to the economic questionnaire " In the past 12 months, how much social donation did your family make in cash and in kind (e.g., food and clothes)?". The continuous variable was used to characterize the amount donated by households. The dummy variable *if_donate* was constructed to indicate whether or not the household made a donation. The control variables include the personal characteristics of the household financial manager and

10 This variable is processed by adding 1 and then taking the logarithm form.

TABLE 7 Summary statistics of household panel data.

Variables	Mean	Minimum	Maximum	Standard deviation	Observation
wave	2016	2014	2018	1.634	40580
if_internet	0.559	0	1	0.497	40580
ratio_internet	0.378	0	1	0.385	40580
if_donate	0.187	0	1	0.390	40580
ln_donation	0.981	0	10.82	2.133	40467

TABLE 8 The impact of internet use on donations: household panel data.

	(1)	(2)	(3)	(4)
VARIABLES	if_donation	ln_donation	if_donation	ln_donation
if_internet	0.041***	0.204***		
	(0.005)	(0.025)		
ratio_internet			0.075***	0.508***
			(0.007)	(0.044)
Controls	YES	YES	YES	YES
County FE	**YES**	**YES**	**YES**	**YES**
Year FE	YES	YES	YES	YES
Observations	37,400	37,734	37,400	37,734
R-squared	-	0.149	-	0.152

TABLE 9 Heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	if_donate	ln_donation	if_donate	ln_donation	if_donate	ln_donation
internet	0.080***	0.101	0.081***	0.225***	0.112***	0.636***
	(0.012)	(0.070)	(0.010)	(0.048)	(0.008)	(0.044)
internet*edu_year	0.003***	0.061***				
	(0.001)	(0.007)				
internet*employment			0.029**	0.442***		
			(0.012)	(0.052)		
internet*retire					−0.051***	−0.432***
					(0.016)	(0.089)
Controls	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	28,974	29,510	28,974	29,510	28,974	29,510
R-squared	-	0.181	-	0.180	-	0.179

TABLE 10 Mechanism analysis.

VARIABLES	(1) if_donate	(2) ln_donation
internet	0.039***	−0.010
	(0.013)	(0.045)
internet*impinternet	0.018***	
	(0.003)	
internet*phone		0.114***
		(0.044)
Controls	YES	YES
County FE	YES	YES
Observations	28,947	28,974

household characteristics, including gender, age, education, marital status, work status, CCP member, public sector, annual household income, household assets, time fixed effect and county fixed effect. Table 7 reports summary statistics for the main variables at the household level.

Table 8 presents the results of the effect of household-level Internet use on giving behavior. The results in column 1 of Table 8 show that Internet use increases the probability of household giving by 4.1%. The results in column 2 indicate that households using the Internet are 20.4% more likely to donate compared to households not using the Internet. This suggests that the positive impact of internet use on donation behavior remains robust even at the household level. The regression results in columns 3 and 4 of Table 8 also report that an increase in household internet usage rate increases the probability of giving and the amount given by households.

4.4 Heterogeneity analysis

The benchmark regression results show that internet usage can increase the probability of residents' donations, but differences in individual characteristics may lead to variations in this relationship. Based on the benchmark regression, we introduced interaction terms between years of education, employment status, retirement status, and internet usage, respectively, to investigate whether the impact of internet usage on resident donation behavior varies significantly due to differences in human capital and income.

Columns 1 and 2 of Table 9 show that highly educated Internet-using individuals are 0.3% more likely to give than less educated Internet-using ones and give approximately 6.1% more; columns 3 and 4 examine that working Internet-using residents are 2.9% more likely to give than non-working Internet-using ones and the number of donation are 44.2% higher; columns 5 and 6 indicate that retired Internet users are 5.1% less likely to give than non-retired Internet users, and money donated is 43.2% less. As expected, Internet use has a greater positive impact on the giving behavior of highly educated, working, and non-retired residents. These differences may be explained by the fact that better-educated residents are more likely to be influenced by information on the Internet to give because of their mindset and values, and that working and non-retired Internet users are more likely to donate because of their financial abundance.

5 Mechanism analysis

As discussed in Section 4, Internet use has a significant positive impact on personal donation behavior. In this section, we will specifically examine the mechanisms through which the Internet promotes giving. From the perspective of the Internet's own functions, its underlying mechanisms for influencing giving include the following two, namely information asymmetry and searching cost.

5.1 Information asymmetry

Information asymmetry between donors and recipients is an important factor limiting the development of charitable fundraising (Chen, 2021). Before the popularity of the Internet, it was often difficult for donors to know details about donation projects, including the number of donations, the progress of donation projects, the source and destination of funds, or even where potential recipients were located. In December 2011, there were 446,000 registered civil society organizations in China, with less than 5% of public welfare organizations able to disclose information comprehensively and on time.[11] The rapid development of the Internet has provided low-cost and diversified channels for information disclosure for charitable organizations, greatly alleviating the information asymmetry phenomenon (Gandia, 2011; Blouin et al., 2018). Taking the One Foundation initiated by Jet Li as an example, it has disclosed various reports such as annual audit reports on its official website. In addition, donors can check the use of donations and the implementation of projects in real-time on the One Foundation's official website. Each donor can also apply for invoices on the website. Therefore, we believe that the information mechanism that alleviates information asymmetry is the first mechanism through which the Internet influences individuals' giving behavior.

5.2 Searching cost

Access to the Internet has largely reduced the information searching cost of donors (Daurer et al., 2012) which can address information asymmetry to some extent. Besides, the popularity of the Internet can also reduce the participation cost of donations, including time, transportation, and transaction costs, making charitable giving more efficient. Both searching cost and participation cost can be seen as opportunity costs of giving, and when such opportunity costs are too high, donors may eventually choose not to give. However, the internet

11 Refer to the website here: http://epaper.zqcn.com.cn/content/2013-05/14/content_14514.htm.

can greatly reduce the opportunity cost of giving and thus facilitate giving behavior. We refer to this mechanism as searching cost.

In order to test the validity of these two mechanisms, we introduced two interaction terms in the main model. Firstly, we introduced an interaction term of two dummy variables, which are the importance of the Internet and Internet use, to test the validity of the information asymmetry mechanism. The individuals' responses to the question "How important is the Internet as a communication path for you?" is used to construct the dummy variable to characterize the importance of the Internet. All respondents were asked about the importance of the Internet, even individuals who did not use it. Around 12.78% of the individuals who do not use the Internet point out that the Internet is an important source of access to information (Supplementary Table A3). The logic is that if the Internet is more important to a resident's access to information, then the role of the Internet in mitigating information asymmetries will be greater for him/her, and the marginal impact of the Internet on personal donation behavior should be greater.

Second, there are differences in the convenience level between computer accessing to the Interne and mobile phone accessing to the Internet. Straightforwardly, the searching cost is different. In this part, we include the interaction term between the dummy variable Internet usage and the dummy variable phone usage. We can separate study sample into four groups: mobile internet users, mobile non-internet users, non-mobile internet users, and non-mobile non-internet users.

The estimates for the two mechanisms are presented in Table 10. The coefficients of all the interaction terms are significantly positive, indicating that the information asymmetry mechanism and the searching cost mechanism are indeed all significantly present. The result in column 1 of Table 10 shows that among individuals who use the internet, those who regard the Internet as important are more likely to donate. It can also be observed that among individuals who use the internet, using a mobile phone can significantly increase their probability of making donations (Column 2 of Table 10).

6 Conclusion

With the widespread of digital economy, the number of Mobile payment users and the amount of private donation increased simultaneously in the last decades. The donation models, empowered by digital technology, have realized more openness and more convenience. But the popularity and widespread use of the Internet may have a negative impact on donations in terms of both incidents and rumors. Therefore, the study of residents' new lifestyle, such as donation behavior, has important practical significance and theoretical value. Based on the China Family Panel Studies (CFPS) data, we systematically investigate the impact of digital technologies on residents' donation behavior and explores its mechanisms. The research in this paper finds that Internet use largely increases the probability of donation and the amount of donation among respondents. Residents who use the Internet are 10% more likely to donate and approximately donate about 56% more than residents who do not use the Internet. This effect was more pronounced for highly educated, and working users, as well as those who are non-retired. Further, we propose and validate two mechanisms by which the Internet influences residents' donation behavior: searching cost and information asymmetry, in terms of the basic functions of the Internet. The research of this paper has enlightening that the widespread use of digital technologies can effectively change the private donation behavior and penetrate energy consumption via dramatically decreasing searching cost.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: http://www.isss.pku.edu.cn/cfps/index.htm.

Author contributions

XL, YS, and TT contributed to conception and design of the study. TT organized the database. YS performed the statistical analysis. TT wrote the first draft of the manuscript. XL and YS wrote sections of the manuscript. All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Digital transition and the clean renewable energy adoption in rural family: evidence from Broadband China

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Introduction: The increasing digital transformation and the global need for sustainable energy solutions have sparked considerable interest in the examination of digital technologies' impact on the adoption of clean renewable energy. However, limited research focuses on energy consumption in rural households, especially in developing countries such as China.

Methods: This study leverages the quasi-natural experiment provided by the Broadband China Policy (BCP) and utilizes data from the China Labor-force Dynamics Survey (CLDS) spanning 2012 to 2016. Our investigation aims to understand the effect of the digital transition on the adoption of clean renewable energy within rural families. We employ staggered Difference-in-Difference (DID) and Doubly Robust Staggered DID estimators to assess this impact, allowing us to explore regional heterogeneity.

Results: Our findings reveal that implementing the BCP significantly influences clean renewable energy adoption, although this effect varies across different regions. Specifically, in the middle region, the BCP results in a notable 5.8% increase in clean renewable energy adoption compared to non-pilot cities. However, in the east and west regions, the BCP is associated with a decrease of 12.6% and 13.5%, respectively, in clean renewable energy adoption. Dynamic effect analysis further indicates that the east region had already experienced high clean renewable energy adoption prior to the BCP's implementation, while the BCP positively influences clean renewable energy intentions in the west region.

Discussion: Our analysis identifies three significant channels through which the BCP affects clean renewable energy adoption: population size, economic size, and income level. Larger populations and greater economic size enhance the BCP's impact on clean renewable energy adoption. These findings provide empirical evidence for developing countries that seek to harness digital development for technological advancement, industrial upgrading, and carbon emission reduction.

KEYWORDS

digital transition, clean renewable energy, rural family, Broadband China, Difference-in-Difference

1 Introduction

In recent years, the world's attention on environmental issues and climate change has grown significantly, leading to proactive efforts in exploring strategies to combat pollution and reduce greenhouse gas emissions. The excessive use of fossil fuels and inefficient energy structures have been identified as significant contributors to these pressing environmental challenges (Zhang and Bai, 2017; Lv et al., 2021; Li and Zhao, 2023). Reinforcing the situation's urgency, the International Energy Agency (IEA) recently released a report highlighting the concerning trends. In 2021, global coal power generation witnessed a worrisome increase of 9%, while carbon emissions from energy combustion and industrial processes grew by 6%. Particularly alarming is the staggering amount of 15.3 billion tons of CO_2 emissions resulting from coal consumption, accounting for over 40% of the total incremental emissions. Disturbingly, the IEA projects a further 0.7% rise in global coal consumption in 2022. Given these critical developments, nations worldwide are prioritizing socioeconomic sustainability by promoting and advancing clean, renewable energy sources.

The significance of sustainable energy in mitigating pollution and improving environmental conditions has sparked significant scholarly interest in comprehending the factors influencing individuals' adoption of such energy sources. Existing literature explores multiple avenues of inquiry, encompassing various dimensions. One prominent line of research delves into demographic factors such as age, education, income, and social status (Zografakis et al., 2010; Willis et al., 2011; Eshchanov et al., 2021; Irfan et al., 2021). Furthermore, scholars have explored subjective attitudes and psychological elements, including the acceptance of sustainable energy, trust, and risk perception (Zografakis et al., 2010; Upton and Snyder, 2015; Irfan et al., 2021). In addition, scholars have closely examined macro variables, such as economic development (Eren et al., 2019; Razmi and Janbaz, 2020; Wang et al., 2021), economic incentives, and energy policies (Asante et al., 2020); the development of the clean renewable energy industry (Molnarova et al., 2012; Ge et al., 2022); and environmental pollution (Zhang et al., 2021). These issues underscore the need to devise strategies for measuring and addressing the challenges associated with innovation and the adoption of clean renewable energy.

Digital technology has emerged as a potential solution to the aforementioned challenges, as noted by numerous scholars. The advent of digital technologies has transformed the way both businesses and individuals operate, ushering in a digital transition (El Hilali et al., 2020). Key elements of this transition include 5G, artificial intelligence, the Internet of Things (IoT), and information and communication technology (ICT). These evolving digital technologies have the potential to reshape the energy consumption patterns of corporations (Ren et al., 2021). However, there has been relatively limited research focusing on the energy consumption of residents.

ICT, with broadband as one of its foundational components, has already delivered significant economic benefits (Bertschek et al., 2015). Moreover, broadband is one of the most immediate and tangible aspects of the digital transition that directly affects the lives of residents. In China, for instance, urban dwellers predominantly use natural gas as a domestic fuel, whereas fossil fuels remain the primary source of energy in rural areas. Against this backdrop, it becomes particularly intriguing to investigate the causal effects of broadband connectivity on the adoption of clean renewable energy among rural residents.

We propose three potential pathways through which digital transition may promote household clean renewable energy adoption (CREA). Firstly, governance participation and pollution control play a crucial role. Improved internet accessibility resulting from the Broadband China Policy (BCP) enables the dissemination of information and knowledge (Chen et al., 2022b). It also provides a platform for rural residents to voice their opinions on environmentally friendly policies, encouraging the government to invest in and develop clean renewable energy infrastructure. This, in turn, can facilitate a shift in the energy consumption structure of households towards cleaner sources. Secondly, the availability of job opportunities and increased salary income can influence clean energy adoption in rural households. Internet access opens up new avenues for rural residents to access job opportunities and entrepreneurial platforms (Cheng et al., 2021). Higher-income levels, resulting from these opportunities, can positively impact the adoption of clean energy technologies by making them more affordable and accessible to households (Commander et al., 2011). Lastly, the process of industrial upgrading stimulated by the BCP can significantly affect clean energy adoption. As industries undergo technological advancements and upgrades, local economies are likely to experience growth. This economic growth can provide the local government with resources and the ability to invest in clean technology infrastructure (do Valle Costa et al., 2008; Yu et al., 2015). Moreover, increased income levels resulting from industrial upgrading can enable households to afford and adopt clean renewable energy solutions.

China's BCP, initiated in 2013, 2014, and 2015, presents a unique opportunity to investigate the role of broadband in promoting the adoption of clean renewable energy among rural families. This policy exhibits three distinctive features that facilitate our empirical analysis. Firstly, the BCP pilot cities are directly designated by the China central government, and while local governments can seek qualification as BCP cities, they lack the authority to decide their inclusion in the BCP list. As a result, the BCP represents an exogenous event for both local governments and residents, providing a natural experimental setting. Secondly, China's household registration system (Hukou) and the escalating real estate prices impose significant restrictions on migration between rural areas and cities. This limited mobility between regions further emphasizes the localized impact of the BCP on rural residents. Finally, the investment in broadband infrastructure, prompted by the BCP pilot cities, is temporary. After the establishment of essential infrastructure such as station towers, the primary investment in BCP tends to reduce.

We conducted a comprehensive study by hand-collecting county-level data for the "Broadband China" pilot cities in 2013, 2014, and 2015, and merged this dataset with the individual-level data from the China Labor-force Dynamics Survey (CLDS). Employing a staggered Difference-in-Difference with two-way

fixed effects (TWFE DID) and dynamic staggered DID methodology proposed by Callaway and Sant'Anna (2021), our research reveals compelling insights into the impact of the BCP on CREA, while also identifying regional variations in this effect. In the middle region, the implementation of the BCP results in a noteworthy 5.8% increase in CREA compared to non-pilot cities. However, contrasting trends are observed in the east and west regions, where the BCP is associated with a decrease of 12.6% and 13.5% in CREA. Further analysis using dynamic effects demonstrates that the east region had already witnessed a high level of CREA prior to the BCP's implementation, while the BCP positively influences clean renewable energy intentions in the west region. Moreover, we investigate the role of natural gas, a clean energy source in China, and find that the BCP contributes to a 1.38% increase in natural gas usage specifically in the east region.

The identification strategy of TWFE-DID relies on the parallel assumption, which states that, in the absence of any intervention, trends in CREA should not be related to the intensity of the treatment represented by the BCP. Our findings provide evidence supporting this assumption. We employed two main approaches to confirm this premise. Firstly, we utilized an event study strategy to compare the outcome trends of the treatment group and the control group before the treatment group received the BCP. This analysis revealed no significant pre-treatment differences between the two groups.

Secondly, we thoroughly examined the potential influences of specific local characteristics, such as the level of sunshine duration and local government efforts to decrease pollution, as well as the impact of other contemporaneous historical events like green finance initiatives, the digital country program, and the innovation cities project. We found that the BCP's implementation was independent of these factors, further affirming the parallel assumption. During the study period of BCPs, the Chinese government intensified its efforts to combat environmental pollution, leading to the rapid expansion of CREA, such as the adoption of natural gas in families and solar power in manufacturers since the late 2010s. To control for this confounding factor, we collected province-by-year information on CREA. Despite the influence of pollution control policies and the expansion of renewable energy adoption during the study period, our estimation coefficients on the BCPs remained stable, indicating that the BCPs had a distinct and independent effect on CREA. Additionally, we accounted for local pollution levels in the district and the level of green finance in each city, further ensuring the robustness of our analysis.

Our study highlights the significant consequences of the digital transition on CREA among rural families, shedding new light on the role of digital transformation in promoting environmental protection and sustainable economic growth in China. While existing research has explored the macro effects of digital transition on renewable energy consumption in China, little attention has been paid to the individual level, particularly in rural areas where fossil fuel adoption is predominant. In this paper, we bridge this gap by merging individual-level and macro-level data to examine the effects of digital transition on CREA in rural areas. Our analysis primarily focuses on rural families affected by the digital transition during the late 1990s and the 21st century. This period was characterized by significant industrialization and urbanization reforms, which enabled the rural labor force to seek employment opportunities outside their hometowns. Additionally, the reform and opening up policies provided opportunities for rural residents with basic education to find work abroad, leading to higher income and improved access to better infrastructure compared to living in rural areas. Many of them took up jobs as manufacturing workers or in the flourishing Township and Village enterprises. As a result of these economic opportunities, a considerable portion of rural families now reside in cities or overseas, while still sending income back to their families living in rural areas. This interaction has facilitated the exchange of ideas and concepts, including the promotion of environmentally friendly energy consumption practices. Building on these observations, our empirical findings suggest a potential link between the increase in CREA, driven by the digital transition and the rapid expansion of internet infrastructure in China, and the country's overall economic growth during the reform era.

Our study mainly contributes to two strands of literature. The first examines the channels of digital transition and energy consumption, especially the energy consumption in a rural family. Surveys show that digital technology increased labor productivity, promoted the reorganization of the supply chain, and reduced energy consumption (Hertin and Berkhout, 2001). With the availability of digital technology adoption data, economists conduct a lot of empirical research on digital transition and energy consumption; internet technology adoption is one of the main driving forces behind economic growth, and it also promotes energy product efficiency (Atkinson and McKay, 2007). The rapid spread of internet technology changes the energy use intensity and renewable energy cost; therefore, it reduces carbon emissions and energy resource consumption (Moyer and Hughes, 2012); specifically, ICT significantly improves the electricity adoption efficiency in European manufacturing companies (Ishida, 2015). These studies focus on the macroeconomic effects of digital technology on renewable energy adoption, mainly based on the macro-level data. In contrast, our results demonstrate that increasing local digital technology adoption significantly promotes renewable energy adoption in rural families. Moreover, the development of the local economy is an important channel through which BCPs improve renewable energy adoption in a rural family. Additionally, digital technology adoption will increase electricity usage, and according to the rebound effect, the digital transition may increase energy consumption. In developed countries, electricity is important in the causal effect path between digital technology adoption and economic growth. Empirical evidence based on OECD panel data shows that internet technology adoption not only promotes the development of the economy but also increases the quantity of electricity consumption both in the short and long term (Salahuddin and Alam, 2016). In developing countries, the digital transition significantly positively increases both electricity consumption and energy consumption. Even in China, the biggest developing country, digital transition increases the total energy consumption at the province level (Ren et al., 2021). Unlike the existing literature, our paper examines the individual-level renewable energy adoption in a rural area of the

biggest developing country. We also investigate the intermediate effects of other factors, such as electricity adoption in families, social connection to the neighborhoods, economic foundation, and industrial structure in the local area. Furthermore, we compare the effect of BCPs on family renewable energy adoption in cities, the developed area, and the county, the developing area. Our empirical results show that electricity consumption has a significantly positive intermediate effect on the causal path between BCP and renewable energy adoption, and the BCPs have shown more significant effects in the rural family rather than in the citizen family.

The second literature investigates the economic impact of digital transition policy, especially internet communication technology. Economists have studied this topic from a lot of perspectives including GDP (Jorgenson, 2001), economic growth rate (Czernich et al., 2011), innovation performance (Paunov and Rollo, 2016), green technology innovation and adoption (Tang et al., 2021), and financial market (Cheng et al., 2021). However, the digital transition policy impact on rural individual-level outcomes remains understudied, and our study contributes to the economic consequence of digital transition policy in two ways. First and foremost, we uncover the mechanisms by which economic growth and infrastructure improvements due to digital technology adoption affect residential energy preferences; therefore, we extend the economic impact of digital transition from the macro level to the individual level and explored the potential mechanism between macro factors and individual behavior.

Therefore, our study makes notable contributions to the existing literature by exploring the microlevel effects of digital transition on CREA within rural families, particularly in the context of China's BCP. Unlike previous research that mainly focused on macroeconomic effects, our investigation specifically targets rural areas, where fossil fuel adoption remains prevalent. Leveraging the unique exogenous nature of the BCP, a centrally designed policy, we offer compelling evidence on the causal impact of broadband connectivity on renewable energy adoption. Additionally, our paper goes beyond direct effects and examines intermediate factors, including electricity adoption, social connections, local economic foundation, and industrial structure, to unravel the mechanisms underlying the relationship between the BCP and CREA. Notably, we identify regional variations, highlighting diverse outcomes in China's east, west, and middle regions. Our comprehensive empirical analysis, combining individual-level and macro-level data with advanced econometric techniques, sheds new light on the role of digital technology in promoting sustainable energy adoption, and its potential contribution to China's environmental protection and sustainable economic growth goals.

The remainder of this paper is organized as follows. *Section 2* is the literature review. *Section 3* briefly reviews the institutional background of Broadband China. *Section 4* presents a mechanism analysis of digital transition and renewable energy adoption in rural China. *Section 5* introduces datasets and econometric setups. *Section 6* represents the empirical results of how digital transition affects renewable energy adoption in Chinese rural families. *Section 7* provides the conclusions and policy implications.

2 Literature review

The synergies between digital transition and renewable energy adoption have become central to discussions surrounding sustainable development, particularly in rural areas. This comprehensive review of recent literature aims to unearth the depth and breadth of research conducted on these topics, analyzing the impact of digitalization on renewable energy adoption among rural families.

2.1 Digital transition

The transformational influence of digital technologies is perceptible in both urban and rural environments, particularly concerning economic growth, family income, and energy consumption structures. Draca et al. (2009) scrutinized the role of digital technology in promoting productivity, deducing that access to precise and extensive information is integral to productivity growth. Koutroumpis (2009), using data from OECD countries between 2002 and 2007, explored the relationship between broadband adoption and GDP growth, confirming that broadband utilization significantly bolsters GDP growth. Furthermore, broadband adoption has a substantial positive impact on employment, annual payroll, and the establishment of businesses (Kandilov and Renkow, 2010; Mack and Faggian, 2013; Mack and Rey, 2014; Castellacci and Vinas-Bardolet, 2019), although internet growth seems unrelated to wage growth (Forman et al., 2012).

Whitacre et al. (2014) leveraged county-level data in the US from 2001 to 2010 to determine a causal link between fixed residential broadband availability/adoption and rural economic development. Their findings show that counties with higher levels of broadband adoption experienced faster growth in median household income and reduced growth in unemployment, while counties with lower levels of broadband adoption endured slower growth in employment and number of firms. Wang et al. (2022) employed macro-level data in China to investigate the causal relationship between digital transition and electricity consumption. Their findings suggest that digital transition fosters the progression of the energy consumption structure.

2.2 Renewable energy adoption

The transition towards renewable energy is shaped by a multitude of factors spanning socioeconomic and environmental aspects (Mensah, 2019). Significant research has underscored the pivotal role that energy efficiency plays in the context of environmental pollution, underlining the detrimental impact of economic activities on our ecosystems (Khan et al., 2021). Areas characterized by relative energy poverty stand to benefit significantly from the adoption of renewable energy, which has the potential to alleviate energy scarcity while also reducing income inequality, thereby fostering sustainable development (Nguyen and Nasir, 2021; Zhao et al., 2022).

However, despite the lower cost profile of renewable energy compared to traditional fossil fuels (Masterson, 2021), non-renewable sources remain the dominant form of energy in developing regions (Noor et al., 2023). This dominance is expected to wane as a country's level of development progresses, leading to increased adoption of renewable energy (Guney, 2019). Moreover, the literature illustrates an inverse relationship between GDP growth and the adoption of non-renewable energy (Chen et al., 2022a). A study that delved into public acceptance of renewable energy underscored the importance of government engagement in the decision-making process and stressed the need for awareness about the direct benefits of renewable energy for the environment and the people (Guney and Kantar, 2020).

Similarly, Wei and Huang (2022) conducted an exploration into the economic ramifications of renewable energy adoption by looking into adjusted national savings. They concluded that renewable energy technologies can confer significant economic advantages and act as a catalyst for sustainable development. However, the initial financial burden and technology constrain associated with adopting renewable energy may deter families under financial constraints from its adoption (Khan et al., 2023). Thus, policy interventions to reduce the initial cost of renewable energy systems could significantly bolster their adoption in rural areas.

When examining environmental factors, D'Adamo et al. (2023) conceptualized renewable energy adoption as an ecological transition, discovering a strong association between environmental consciousness and the uptake of renewable energy technologies. Interestingly, even with the adoption of renewable energy, total energy consumption continues to maintain a negative correlation with environmental protection and sustainable development (Gasimli et al., 2022). This highlights a trend among rural families with higher environmental consciousness who are more likely to adopt renewable energy technologies. Consequently, it underscores the need for persistent environmental education initiatives to bolster the adoption of renewable energy technologies.

The existing literature undeniably underscores the integral role digital technologies hold in numerous dimensions of economic development. However, it is critical to acknowledge that the digital transition profoundly influences consumer behavior at the individual level. Furthermore, considerable room remains for exploring the intricate interplay between digital technologies, industry structures, pollution levels, and family income, among other factors, particularly in the context of CREA and sustainable economic growth.

The complexity of these interactions poses intriguing questions for future research. How does digital transformation influence the energy consumption choices of individuals? In what ways do industry structures and pollution levels interact with digital technologies to impact energy consumption patterns? How does the family income level shape the influence of digital transition on CREA? Perhaps most importantly, how can these insights be leveraged to inform effective policy design?

Exploring these questions could enrich our understanding of the multifaceted relationships between digital technologies and various economic and environmental factors. This deeper understanding, in turn, could empower policymakers to more effectively employ digital technologies as a tool for promoting economic prosperity and sustainability across diverse contexts. This pursuit also aligns with the global agenda for sustainable development, particularly in light of the increasing importance of clean energy for tackling climate change and ensuring economic resilience.

3 Institutional background

3.1 The "Broadband China" Policy: a brief history

Broadband China is an ambitious initiative launched by the Chinese government to promote the development and development of high-speed broadband infrastructure across the country. Recognizing the crucial role that broadband connectivity plays in driving economic growth, social progress, and technological innovation, China has taken significant steps to bridge the digital divide and create a digitally inclusive society.

The origins of the "Broadband China" Policy can be traced back to August 2013, and the primary objective of it is to provide universal access to high-quality broadband services for all citizens, regardless of their geographic location. In this plan, the local governments play a crucial role, not only to build broadband infrastructure but also to introduce relevant policies supporting the implementation of broadband. More specifically, according to this plan, in these pilot cities, significant progress has to be made in the implementation of urban fiber-optic connectivity, extending from building to homes, as well as in the expansion of broadband access in rural areas by 2015, including villages. The penetration rate of fixed broadband in households is supposed to reach 50%; furthermore, the adoption rate of third-generation mobile communications, along with its long-term evolution technology (3G/LTE), is supposed to stand at 32.5%. Broadband access in administrative villages, whether through wired or wireless methods, is supposed to achieve a remarkable coverage of 95%. Moreover, broadband connectivity is supposed to be effectively established in educational institutions, libraries, hospitals, and other public facilities. The average broadband access speed in urban and rural households is supposed to reach approximately 20 megabits per second (Mbps) and 4 Mbps, respectively, with certain advanced cities even attaining speeds of up to 100 Mbps. To achieve these goals, during 2013–2015, the Chinese government selected 117 pilot cities to implement broadband in China in three batches. Figure 1 presents the Broadband China pilot cities in 2014, 2015, and 2016.

3.2 Digital transition in Broadband China pilot cities

Our paper uses "Broadband China" as a proxy variable for digital transition in China. The key variation used in this paper comes from the different batches of Broadband China pilot cities. The exogenous nature of broadband expansion in China about

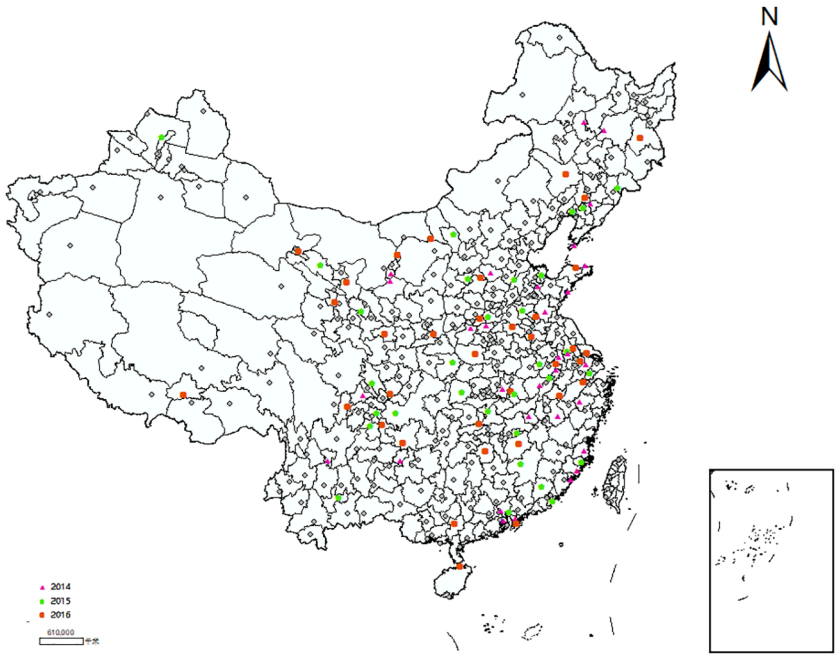


FIGURE 1
Broadband China Policy pilot cities.

household clean energy usage allows the identification strategy employed in this paper to effectively capture the causal relationship.

The broadband network serves as a crucial public infrastructure for China's economic and social development in the contemporary era. Its progress and expansion play a significant role in stimulating productive investment, fostering information consumption, facilitating the transition of development models, and constructing a prosperous society. Internationally, the broadband network is propelling a new wave of information-driven advancements, prompting numerous countries to prioritize its development as a strategic imperative. It is considered a vital measure to secure a competitive advantage in international economic, scientific, technological, and industrial arenas. Over the past years, China has witnessed a continuous expansion in broadband network coverage, augmentation of transmission and access capacities, notable strides in broadband technology innovation, and the establishment industrial ecosystem. The level of application services has improved, leading to the flourishing of emerging industries such as e-commerce, software outsourcing, cloud computing, and the IoT. Concurrently, efforts have been made to enhance network information security. However, certain challenges persist within China's broadband network landscape, including the ambiguous positioning of broadband as a public infrastructure, disparities in regional and urban–rural development, inadequate application services, limited original technological capabilities, and an imperfect development environment. These issues demand urgent attention and resolution.

To address the aforementioned challenges, BCP focuses on four key areas of intervention and improvement. Firstly, Broadband China recognizes the significance of robust infrastructure for delivering high-speed and reliable broadband services. The initiative emphasizes the expansion and enhancement of telecommunications infrastructure across the country. This includes the deployment of fiber-optic networks, the development of advanced 4G and 5G mobile networks, and the utilization of satellite communication systems. The government is investing in the construction of backbone networks, last-mile connectivity, and rural broadband infrastructure to ensure comprehensive coverage, particularly in underserved areas.

Secondly, Broadband China aims to make broadband services affordable and accessible to all citizens. To achieve this, the initiative employs various strategies, such as price regulation, subsidy programs, and encouraging healthy competition among service providers. These efforts aim to reduce the cost of internet access, ensuring that even low-income households and rural communities can afford and benefit from broadband connectivity. Additionally, the initiative encourages the development of public access points, such as community centers and libraries, to provide internet access in areas with limited infrastructure or financial constraints.

Thirdly, Broadband China is committed to bridging the digital divide and promoting digital inclusion. The initiative focuses on providing equal access to educational resources, e-government services, healthcare facilities, and e-commerce platforms. Efforts are made to support underprivileged communities, including rural areas, ethnic minorities, and people with disabilities, by implementing targeted programs and policies. Capacity-building programs are also initiated to enhance digital literacy and skills, ensuring that citizens can fully participate in the digital economy and benefit from digital services and opportunities.

Finally, BCP recognizes the transformative potential of broadband technology and its impact on economic growth and industrial development. The initiative encourages research and development in the field of ICT and promotes collaboration

between academia, industry, and government. By fostering innovation, entrepreneurship, and the development of digital industries, such as e-commerce, cloud computing, artificial intelligence, and the IoT, Broadband China aims to create a thriving digital ecosystem that drives economic prosperity and technological advancement.

By focusing on these four key aspects, BCP strives to build a comprehensive and inclusive broadband network that empowers individuals, enhances social services, promotes economic growth, and positions China as a global leader in the digital age. The busy-time weighted average available download rate for network downloads for fixed broadband users in China was 9.46 Mbit/s by the first quarter of 2016, an 84.77% increase compared to the first quarter of 2015. This metric reflects the average download speed experienced by users during peak hours when network traffic is typically higher. It indicates the performance and capacity of the fixed broadband networks in delivering data to users. Figure 2 presents the busy-time weighted average available download rate for network downloads for fixed broadband users in each province in the first quarter of 2016. It indicates that the municipalities directly under the Central Government exhibit higher broadband speeds compared to the national average, even though the rate of most provinces is lower than the national average; the lowest download rate is larger than an impressive level of 7 Mbit/s.

4 Methodology

4.1 Data source

Our study incorporates two sets of data: information on renewable energy adoption in Chinese households and data on BCP pilot cities. Firstly, we collected data on renewable energy adoption in Chinese households from the CLDS. Secondly, we collected data from the Chinese Ministry of Industry and Information Technology, while macroeconomic data for prefecture-level cities were sourced from the China City Statistical Yearbook.

The CLDS serves as the primary data source for this study, with the objective of capturing the changes in social structure, labor force dynamics within communities and families, and the interplay among communities, families, and individuals. Notably, the CLDS is a nationally representative longitudinal survey that focuses on the Chinese labor force (Ma et al., 2022). The survey encompasses both urban and rural areas across 29 mainland provinces and municipalities in China. Respondents in the CLDS consist of individuals aged 15 to 64, as well as those aged 65 and above who are actively employed within their respective households.

The data for the CLDS were collected by the Center for Social Science Survey at Sun-Yat-sen University in Guangzhou, China, employing a multistage random sampling methodology. For our study, we utilized three waves of CLDS data, specifically from the years 2012, 2014, and 2016. This dataset offers comprehensive information on various cooking fuel usage, along with demographic characteristics and socioeconomic indicators. The extensive nature of the survey's data aligns well with the research topic under investigation.

To process the data, several operations were conducted. Firstly, to ensure consistency in coding strategies, the survey data from 2012 and 2014 were merged since the coding strategy in 2012 differed from the subsequent year. Following the data cleaning guidelines outlined in the CLDS manuscript, we constructed panel data by combining individual surveys, family surveys, and county surveys. Secondly, in order to maintain consistent identification, the

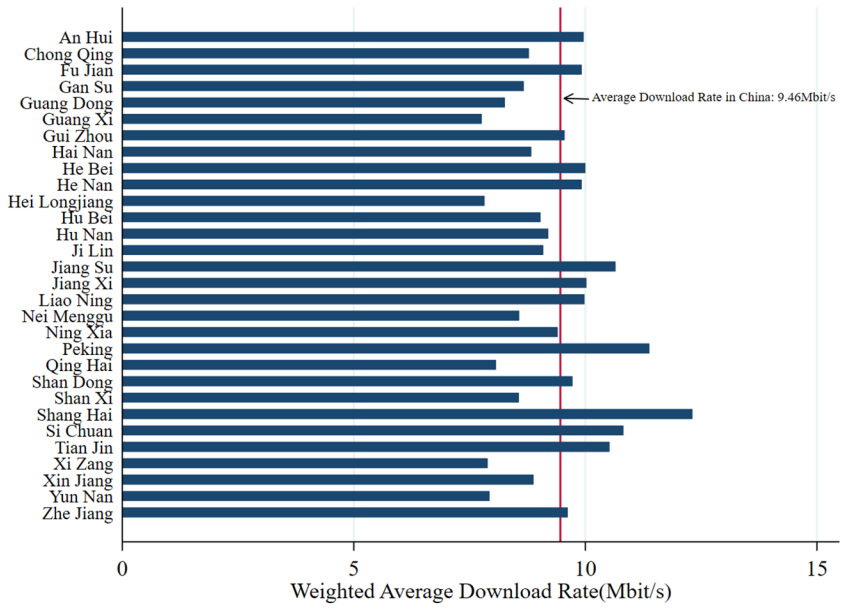


FIGURE 2
Weighted average download rate in each province.

panel data were assigned identification codes based on the coding strategy employed in the 2016 wave. Thirdly, any missing values were dropped from the dataset, and we only kept the rural residents' sample, resulting in 34,566 observations. Lastly, we obtain the macro data from the China Statistical Yearbook and combine it with CLDS based on the province code.

4.2 Variables

4.2.1 Household clean renewable energy adoption

The dependent variable in this study is household CREA. The CLDS database captures household renewable energy use for cooking through the question, "What is the main fuel used for cooking in your home?"; the available options include firewood, coal, gas (LPG), solar, biogas, electricity, and natural gas. Among these options, firewood, solar energy, and biogas are considered renewable energy sources, while the latter two are specifically categorized as clean renewable energy sources. To operationalize the explained variable, we assign a value of 1 to CREA when clean renewable energy sources are utilized, and 0 otherwise.

4.2.2 Broadband China

The explanatory variable in this paper is Broadband China pilot cities, and BCP is used as a proxy variable. In the framework of the empirical models, we defined the core explanatory variable BCP as 1 if the city was formally rated as the BCP pilot city from a given date, and 0 otherwise. Broadband China encompassed a total of 139 pilot cities, which were introduced in three separate batches. The first batch of pilot cities became operational on 1 August 2013. The second batch followed on 5 November 2014, and the third batch was implemented on 9 October 2015. Table 1 reports the details of the Broadband China pilot city.

4.2.3 Control variables

Considering that household energy adoption is significantly influenced by household member characteristics such as income, social security, working experience, and other relevant factors, it is crucial to control for these characteristics in both the treatment and control groups (Zografakis et al., 2010; Willis et al., 2011; Eshchanov et al., 2021; Irfan et al., 2021). This control is necessary to ensure comparability in terms of renewable energy adoption between the two groups. By controlling for household member characteristics, we can better isolate the impact of the treatment (BCP) on renewable energy adoption and draw more accurate conclusions from the analysis.

Moreover, it is important to note that the community environment in which residents reside significantly influences energy adoption patterns. Rapid urbanization poses a considerable threat to the environment and human health, primarily due to high levels of pollution. Industries such as iron and steel, and chemical and energy industries, known for their significant pollution output, have contributed to severe environmental pollution issues (Feroz et al., 2021). The detrimental effects of such pollution can hinder clean energy adoption and have broader implications for sustainable development. Indeed, we control the industrial structure and the pollution status of the community. According to Ren et al. (2021) and Wang et al. (2022), the energy consumption is closely related to economic development; we control the GDP and fiscal structure.

4.2.4 Descriptive statistics

The descriptive statistics presented in Table 2 provide an overview of the dataset used in this study. The table includes various variables related to CREA and its potential determinants. Starting with the dependent variable, CREA, the sample consists of 37,146 observations. The mean CREA adoption rate is 0.39649, indicating that, on average, approximately 39.65% of households in the sample have adopted clean renewable energy technologies. The standard deviation of 0.489175 suggests a considerable variation in CREA adoption levels across the sample. Moving to the explanatory variables, we find that the variable BCP, representing the availability of a specific policy intervention, has a mean value of 0.144403, indicating that the policy is present in a relatively small proportion of the sample. The standard deviation of 0.351503 suggests some heterogeneity in the implementation of the policy across regions.

Further examining the regional distribution, we observe that the middle region has a mean value of 0.291768, indicating a moderate presence of households in this region. The east region has a higher mean of 0.445835, suggesting a relatively greater concentration of households with access to clean renewable energy technologies.

TABLE 1 Broadband China pilot cities.

Policy Release Date	Broadband China Pilot Cities
2014 BCP Cities 2013/8/1	Beijing, TianJin, Shanghai, Changsha, Zhuzhou, Shi Jiazhuang, Dalian, Benxi, Yanbian, Haerbin, Daqing, Qingdao, Zibo Weihai, Linyi, Zhengzhou, Luoyang, Wuhan, Wuhu, Anqing, Nanjing, Suzhou, Zhenjiang, Kunshan, Jinhua Fuzhou, Xiamen, Quanzhou, Nanchang, Shangrao, Guangzhou, Shenzhen Zhongshan Chengdu, Pan Zhihua, Aba, Guiyang, Yinchuan, Wuzhong, A Laer
2015 BCP Cities 2014/11/5	Taiyuan, Hu Hehaote, Eer Duosi, Anshan, Panjin, Baishan, Dongying, Jining, Dezhou, Xinxiang, Yongcheng, Huangshi, Xiangyang, Yichang, Shiyan, Suizhou, Yueyang, Hefei, Tongling, Yangzhou, Jiaxing, Putian, Xinyu, Ganzhou, Shantou, Meizhou, Dongguan, Chongqing Jiangjin and Rongchang District, Mianyang, Neijiang, Yibin, Dazhou, Yuxi, Lanzhou, Zhangye, Guyuan, Zhongwei, Kelamayi
2016 BCP Cities 2015/10/9	Yantai, Zaozhuang, Shangqiu, Jiaozuo, Nanyang, Ezhou, Hengyang, Yiyang, Wuxi, Taizhou, Nantong, Hangzhou, Suzhou, Huangshan, Ma Anshan, Ji'an, Yulin, Haikou, Hong Kong Jiulongpo District, Chongqing Beipei District, Ya'an, Luzhou, Nanchong, Zunyi, Wenshan, Lasa, Linzhi, Weinan, Wuwei, Jiuquan, Tianshui, Xining, Yangquan, Jinzhong, Wuhai, Baotou, Tongliao, Shenyang, Mu Danjiang

TABLE 2 Descriptive statistics of variables.

Variable	Obs	Mean	SD	Min	Max
Dependent Variable					
CREA	37,146	0.39649	0.489175	0	1
Explanatory Variable					
BCP	37,146	0.144403	0.351503	0	1
Middle Region	37,146	0.291768	0.454582	0	1
East Region	37,146	0.445835	0.497064	0	1
West Region	37,146	0.262397	0.439943	0	1
Heterogeneity					
Low-Income District	37,146	0.142223	0.349283	0	1
GDP Mean Group	37,146	0.319819	0.466413	0	1
Mid GDP Mean Group	37,146	0.436009	0.495895	0	1
East GDP Mean Group	37,146	0.218785	0.413428	0	1
West GDP Mean Group	37,146	0.499596	0.500007	0	1
Mean Popu	37,146	0.46853	0.499015	0	1
Mechanism					
Pollution	37,146	0.233861	0.423291	0	1
Family Salary Income	20,629	8.906139	3.446237	−6.90776	15.76142
Industry Structure	33,438	1.032445	0.509438	0.272344	4.757226
Control Variable					
Age	37,146	48.09807	17.08312	3	114
Gender	37,146	0.482367	0.499696	0	1
Marriage	37,146	0.127335	0.333353	0	1
Health	35,860	2.388846	1.01141	1	5
Minority	37,146	0.126124	0.331994	0	1
Family Expense	36,692	10.17263	1.037794	0.336472	15.42495
Social Security	37,146	0.10063	0.300842	0	1
House Value	37,092	183565.4	5278747	0	1.00E+09
Electric Consumption	37,146	2659.899	15599.28	0	99999
Internet Usage	37,146	3.045146	1.049114	0	4
GDP	34,679	1.051193	0.507415	0.226896	3.712207
Fiscal Expense Ratio	36,762	0.203236	0.123192	0.065621	0.686978

Conversely, the west region has a lower mean of 0.262397, indicating a lower prevalence of CREA adoption compared to the other regions.

Considering heterogeneity factors, the presence of low-income districts is captured by the variable "Low Income District", which has a mean value of 0.142223, indicating a relatively small proportion of low-income districts in the sample. The mean values of the GDP Mean Group variables provide insights into the economic conditions of different regions. Specifically, the mean values for Mid GDP Mean Group, East GDP Mean Group, and West GDP Mean Group are 0.436009, 0.218785, and 0.499596, respectively, suggesting varying levels of economic development across these regions.

In terms of the mechanisms that might influence CREA adoption, the pollution variable indicates the extent of pollution in the sample. With a mean value of 0.233861, the data suggest that pollution is present to some degree across the observed areas. The variable "Family Salary Income" represents the natural logarithm of family salary income, which has a mean value of 8.906139. This indicates that, on average, households in the sample have a relatively high salary income. Additionally, the industry structure

variable has a mean value of 1.032445, suggesting a diverse industrial landscape in the observed areas.

Moving on to the control variables, we find that the mean age of individuals in the sample is 48.09807, indicating a relatively mature population. The gender variable, with a mean value of 0.482367, suggests a nearly equal distribution of men and women. The marriage variable has a mean value of 0.127335, indicating a relatively low proportion of married individuals. The mean health score, represented by the variable "Health", is 2.388846, suggesting a moderate health status in the sample. The minority variable, with a mean value of 0.126124, indicates a relatively low proportion of minority groups in the observed areas. Other control variables include family expenses, social security, house value, electric consumption, internet usage, GDP, and fiscal expense ratio. These variables exhibit varying means and standard deviations, reflecting the diversity of economic and socio-demographic factors present in the sample.

4.3 Empirical strategy

4.3.1 Benchmark regression

The impact of digital transition on the adoption of clean renewable energy in rural households encounters identification challenges due to potential confounding factors, as the city-level digital transition policy is exogenous to household behavior. This study employs a quasi-natural experiment approach by considering the BCP as the treatment group, enabling the estimation of the causal effect of digital transition on CREA through the construction of a staggered DID model. Specifically, the cities selected as part of the BCP are treated as the treatment group, while the cities not selected as part of the BCP during the sample period serve as the control group. The disparity in the change in clean renewable adoption between the two groups following the implementation of the BCP serves as an indicator of the net effect of the BCP. Therefore, we start our analysis using the following equation:

$$CREA_{it} = \alpha_0 + \alpha_1 BCP_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \quad (1)$$

where the dependent variable $CREA_{it}$ refers to the clean renewable energy adoption, BCP_{it} represents a dummy variable that indicates whether city i is designated as BCP city in year t, the X refers to the control variables, μ_c refers to the province-level fixed effect, γ_t refers to year-level fixed effect, and ϵ_{it} refers to the error term. Moreover, considering the significant economic development disparity across various regions in China, we stratify the sample cities based on their provinces, dividing cities into four distinct regions. To account for time-varying factors specific to each region, such as the influence of place-based policies, we also introduce an interaction term, denoted as θ_{rt}, between region r and year t. This interaction term allows us to capture the nuanced effects of regional characteristics over time within the analysis.

4.3.2 Parallel trend assumption test

After estimating the staggered DID model, as Beck et al. (2010) recommended, we employ the event study approach to examine the validity of the parallel trend assumption. This approach not only helps assess the assumption but also captures the dynamic effects of the BCP. The model can be represented as follows:

$$CREA_{it} = \alpha_0 + \sum_{s=1}^{3} \alpha_{pres} BCP_{pres} + \alpha_{current} BCP_{current} + \sum_{s=1}^{2} \alpha_{posts} BCP_{posts} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \quad (2)$$

where BCP_{pres} presents the specific year preceding the inclusion of a pilot city in the BCP (Before BCP implementation), $BCP_{current}$ represents the city after its inclusion in the BCP (During BCP implementation), and BCP_{posts} represents the specific year following the inclusion of a pilot city in the BCP (After BCP implementation). The duration of the pre-treatment and post-treatment periods varies across the treatment group cities. The longest observed post-treatment duration in the sample is 2 years (corresponding to the initial batch of the 2014 BCP), while the longest pre-treatment duration in the sample is 4 years (corresponding to the third batch of the 2016 BCP). For the purposes of our analysis, we consider the 3-year pre-treatment period as the baseline. If the coefficients of BCP_{pres} are found to be statistically insignificant, it suggests that the parallel trend assumption holds. In turn, the coefficients of BCP_{posts} reflect the dynamic effects of the BCP on CREA in rural families.

4.3.3 Extend staggered DID estimator

The analysis follows a commonly used methodology known as the two-way fixed effects (TWFE) staggered DID regression. However, to ensure unbiased estimation of the coefficient ϵ_{it}, three conditions must be satisfied. Firstly, the treatment can only increase over time and change once. In other words, the treatment is not reversible, and once a unit enters the treatment group, it remains there. Secondly, the treatment is binary, indicating that it is a dichotomous variable with two possible values (treated and untreated). These two conditions imply that units in the treatment group can only transition from being untreated to being treated. Thirdly, there is no variation in treatment timing across the units being analyzed (De Chaisemartin and d'Haultfoeuille, 2020).

In this study, it is challenging to satisfy the aforementioned conditions. Specifically, if we use the TWFE approach, we need to impose stricter assumptions than just the parallel trend assumption to account for the dynamic effects that may be correlated with the estimation of the average treatment effect (ATT), denoted as β_{it}. For instance, if the treatment effect is constant, $TE_{it} = \delta$ for all (i,t), and the treatment effect does not systematically differ based on different weights assigned to β_{it}, then the estimator $\hat{\beta}_{it}$ is unbiased for the ATT [as shown in Corollary 2 in De Chaisemartin and d'Haultfoeuille (2020)].

However, in the analysis of the CLDS survey data, this assumption of "no correlation" is implausible due to respondents' mobility between cities. For example, a household might have lived in Beijing, the capital of China, in 2012, but moved to Guangzhou in 2013, where BCP was promoted, and in 2013, this household moved back to its hometown, Yan Bian, which is a remote city in China. During these 4 years, the household lived in both a developed city affected by BCP and non-BCP, developing area. To address this concern, we introduce the DID with multiple matching estimators

proposed by De Chaisemartin and d'Haultfoeuille (2020). This estimator is a weighted average of the DID with positive treatment (DID_+) and DID with negative treatment (DID_-), specifically designed for cases with two periods and binary treatment. The DID_+ estimator is given by:

$$DID_+ = \frac{1}{N_{0,1}} \sum_{g:D_{g,1}=0,D_{g,2}=1} (Y_{g,2} - Y_{g,1}) - \frac{1}{N_{0,0}} \sum_{g:D_{g,1}=0,D_{g,2}=0} (Y_{g,2} - Y_{g,1}) \quad (3)$$

and DID_- is given by:

$$DID_- = \frac{1}{N_{1,1}} \sum_{g:D_{g,1}=1,D_{g,2}=1} (Y_{g,2} - Y_{g,1}) - \frac{1}{N_{1,0}} \sum_{g:D_{g,1}=1,D_{g,2}=0} (Y_{g,2} - Y_{g,1}) \quad (4)$$

where $N_{a,b}$ refers to the number of units for which $D_{g,1} = d_1$ and $D_{g,2} = d_2$, and the DID_+ estimator refers to the DID estimator that compares units transitioning from the control group to the treatment group between periods t_1 and t_2. Under the parallel trends assumption, this estimator is unbiased for estimating the treatment effect for units transitioning into the treatment group. On the other hand, the DID_- estimator compares units transitioning from the treatment group to the control group between periods t_1 and t_2. It is important to note that in the original definition, the control group and treatment group have the same group size. However, we extend the DID_M (Difference-in-Difference with Multiple Matching) estimator to accommodate different group sizes. This extension allows for a more flexible analysis when the treatment is binary and staggered. One advantage of using the DID_M estimator is its robustness to dynamic effects. By accounting for the different group sizes and considering staggered treatment, the DID_M estimator provides a more reliable estimate of the treatment effect while addressing concerns related to dynamic effects.

Since 2012, the first interview, there is the possibility of respondents moving between cities in the follow-up surveys. Additionally, the Broadband China pilot policy was proposed in three separate batches in 2014, 2015, and 2016. Consequently, some respondents may have been exposed to the treatment multiple times. For example, a respondent who lived in Changsha in 2014, where the first batch of Broadband China was proposed, and later moved to Taiyuan in 2015, where the second batch was proposed, would have received the treatment twice. To address this scenario, previous studies have proposed various estimators. Graham and Powell (2012) introduced an estimator that compares the outcome evolution of movers and quasi-stayers. However, this method relies on the assumption of a linear treatment effect and does not account for the period one treatment. De Chaisemartin and d'Haultfoeuille (2020) implemented a relabeling strategy to extend the DID_M estimator. However, when there are no true stayers in both the treatment and control groups, it becomes necessary to choose a bandwidth to identify the quasi-stayers. In our study, the estimator proposed by Callaway and Sant'Anna (2021) is more suitable. They define the treatment effect (TE) as:

$$TE_{c,c+1} = E[\hat{Y}_{c,c+l}(0_{c-1}, 1_{l+1}) - \hat{Y}_{c,c+l}(0_{c+l})] \quad (5)$$

where $\hat{Y}_{c,c+l}$ refers to the average outcome at period t across the treatment groups belonging to cohort c, c denotes the cohort, t denotes the periods, and $l \in 1,\ldots,t$; this estimator accounts for the multiple treatments and does not rely on the assumption of true stayers, making it well-suited for our analysis. Moreover, in terms of the average effect of having been treated for $l + 1$ period in the cohort treated at period c, the DID estimator is given by:

$$DID_{c,l} = \hat{Y}_{c,c+l} - \hat{Y}_{c,c-l} - (\hat{Y}_{n,c+l} - \hat{Y}_{n,c-l}) \quad (6)$$

This estimator extends the staggered DID estimator in several important ways. Firstly, it provides a more aggregated estimation approach. Secondly, it utilizes the not-yet-treated group as the control group instead of the never-treated group. This is particularly useful in our study, as in the case of the third batch of Broadband China, where a large proportion of individuals have already been treated by the policy; it becomes challenging to identify a never-treated group. However, this method can still estimate the causal effects of the third batch of Broadband China. Furthermore, even if there are individuals who have never been treated throughout the entire study period, the presence of a substantial not-yet-treated group can lead to more precise estimations. Another important aspect of this estimator is its reliance on a conditional parallel trend assumption. This assumption is crucial for obtaining unbiased treatment effect estimates. To address concerns regarding this assumption, Callaway and Sant'Anna (2021) propose robust placebo estimators to heterogeneous effects. These placebo tests can be used to assess the validity of the parallel trend assumption underlying their estimator. In light of these considerations, after presenting a TWFE staggered DID approach, we employ the DID_M estimator and the $DID_{c,l}$ estimator to re-estimate the causal inference of the Average Treatment Effect on the Treated (ATT). Additionally, we provide parallel assumption tests and placebo tests based on these estimators to further evaluate the validity of the parallel trends assumption.

Our estimator should be interpreted as a conservative estimate of the effect of digital transition on family financial behavior. In our study, the digital transition is represented by the external shock known as Broadband China, and we define the cities that actively promoted this transition as the treatment group. However, even if respondents did not reside in these specific cities, they may have still benefited from the digital transition through what we refer to as the overflow effect. This effect implies that the impact of the digital transition may extend beyond the treatment group and affect individuals in neighboring areas or the broader region. Furthermore, individuals outside the treatment group may also be influenced by fellow townspeople or acquaintances who reside in the cities where Broadband China was implemented. This peer effect can result in indirect exposure to the digital transition and its associated effects.

Because of these factors, our estimation may underestimate the true effect of Broadband China on the treatment group. The overflow and peer effects introduce additional channels through which the digital transition indirectly affects individuals outside the treatment group. Therefore, it is important to consider that our estimates reflect a conservative assessment of the impact of Broadband China on family financial behavior, as they may not fully capture the overall influence of the digital transition on a wider scale.

4.3.4 Heterogeneity

To mitigate the estimation bias induced by the structure of energy consumption and regional disparities, we initially incorporate natural gas utilization and coal gas adoption as the dependent variables, and the model is given by:

$$\mathbf{Y}_{it} = \alpha_0 + \alpha_1 BCP_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \quad (7)$$

where Y_{it} refers to (*natural gas, coal gas*). Should the coefficient α_1 exhibit a significant positive value, this would suggest that the BCP markedly catalyzes the adoption of natural gas and/or coal gas. This interpretation would be contingent on the premise that an increased value in α_1 signifies a stronger influence of the BCP on promoting alternative energy sources.

Furthermore, we incorporate an interaction term between the *BCP* variable and dummy variables to assess regional heterogeneity. This approach enables us to estimate the nuanced variations across different geographical areas, and the model is given by:

$$CREA_{it} = \alpha_0 + \alpha_1 BCP_{it} \times Heterogeneity_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \quad (8)$$

where $Heterogeneity_{it}$ represents the distinct dummy variables associated with heterogeneity, each reflecting unique attributes or characteristics of the various regions under study. The estimation of the parameter α_1 serves as an indication of the heterogeneous effects associated with BCP. This interpretation suggests a differential impact of the BCP across diverse geographical regions or contexts.

4.3.5 Mechanism

The association between the promotion of renewable energy adoption and the BCP presents a conundrum. To explore the underlying mechanisms connecting CREA and BCP, we employ a strategy analogous to Chen et al. (2020) and Braguinsky et al. (2021), wherein we integrate an interaction term into the benchmark regression. The resulting formulation is as follows:

$$CREA_{it} = \alpha_0 + \alpha_1 BCP_{it} + \alpha_2 BCP_{it} \times Mechanism_{it} + \beta \boldsymbol{X} + \mu_c + \gamma_t + \theta_{rt} + \epsilon_{it} \quad (9)$$

where $Mechanism_{it}$ refers to the mechanism variables.

5 Results and discussion

5.1 Benchmark regression

Table 3 elucidates the influence of the BCP initiative on CREA within rural households, as specified by Model (1). The table comprises several columns, each illustrating a different model specification. From columns (1) to (4), control variables at the individual, familial, and macroeconomic levels are sequentially incorporated. In the scenario where province fixed effects are not accounted for [columns (1) to (4)], the coefficients of BCP are significantly positive, with a statistical significance at the 1% level (0.155, 0.153, 0.147, and 0.0873, respectively). These observations indicate that the BCP significantly fosters the promotion of CREA among rural households, aligning with the results from Wang et al. (2021), which evaluated the causal impact of digital transitions on the energy consumption structure at the macroeconomic level.

In column (5), province-level fixed effects are introduced. Even with this additional layer of complexity, the coefficients of BCP retain their significantly positive status (0.0668, with statistical significance at the 5% level), albeit exhibiting a reduced magnitude compared to column (1). This pattern implies that the BCP continues to positively affect CREA in rural households, despite considering the inherent heterogeneity at the province level.

In column (6), which controls for both province-level and year-level fixed effects, the coefficient of BCP is significantly negative (−0.0764, with statistical significance at the 5% level). This outcome suggests that the influence of the BCP varies considerably across different regions within China. Notably, this finding deviates from existing well-regarded research, such as that conducted by Wang et al. (2022) and Ren et al. (2021). This discrepancy underlines the complex and dynamic nature of policy impact analysis, and may indicate unique regional factors at play in the context of this study.

From these findings, it becomes evident that the digital transition's causal effects on energy consumption, particularly as observed through individual-level data, can vary significantly. Importantly, to gain a comprehensive understanding of the policy's impacts, it is crucial to account for potential heterogeneity across both provinces and years in the estimation. This awareness of regional and temporal diversity facilitates a more nuanced interpretation of the policy's effectiveness and can better inform future policy adjustments and implementations.

Table 4 showcases the results derived from partitioning the sample into three geographic divisions: middle, east, and west, based on the respective provinces, and subsequently incorporating interactive fixed effects for region and year, as specified by model (8). The table comprises different columns, each corresponding to a unique model specification.

In column (1), the model used in column (6) of Table 3 is adjusted to introduce the interactive fixed effect of region and year. Notably, despite this adjustment, the coefficient of BCP continues to be significantly negative (−0.0804, with statistical significance at the 5% level). This result suggests that the BCP has a negative influence on CREA, a pattern that persists even when the interactive fixed effects of region and year are accounted for. This indicates that regional variations and time dynamics may not fully explain the observed negative impact of the BCP on CREA, pointing towards other potentially influential factors that warrant further investigation.

Upon examination of column (2), the interaction term *BCP* × *Middle Region* is introduced as an explanatory variable, while concurrently controlling for individual-level, family-level, and macroeconomic-level attributes. Furthermore, province fixed effects, year fixed effects, and the interactive fixed effect of region and year are accounted for. In this specific model specification, the coefficient of *BCP* × *Middle Region* is 0.0580, with statistical significance at the 1% level. This result demonstrates that the BCP exerts a significantly positive impact on CREA in the central region of China.

In contrast, columns (3) and (4) see the introduction of *BCP* × *East Region* and *BCP* × *West Region* as explanatory variables, respectively. In both scenarios, the coefficients are significantly negative, with statistical significance at the 1% level [−0.126 for

TABLE 3 The effect of BCP on CREA in rural family.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA	(5) CREA	(6) CREA
BCP	0.155***	0.153***	0.147***	0.0873***	0.0668**	−0.0764**
	[0.009]	[0.009]	[0.009]	[0.010]	[0.030]	[0.035]
Age		0.000102	5.47E-05	0.000199	0.00300***	0.00331***
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Gender		0.0312	0.0256	0.0706	0.00792**	0.00586
		[0.086]	[0.086]	[0.094]	[0.004]	[0.004]
Marriage		0.0533	0.0619	0.0757*	0.0481***	0.0455***
		[0.039]	[0.040]	[0.043]	[0.010]	[0.009]
Health		0.0230***	0.0231***	0.0225***	0.0516***	0.0507***
		[0.005]	[0.005]	[0.005]	[0.004]	[0.004]
Minority		−0.0377	−0.0353	−0.0345	2.07E-05	−0.00489
		[0.035]	[0.036]	[0.037]	[0.035]	[0.033]
Family Expense		0.00656	0.00275	−0.0387***	−0.0439***	
			[0.005]	[0.005]	[0.005]	[0.005]
Social Security		0.0139	0.0125	−0.122***	−0.0519***	
			[0.024]	[0.025]	[0.014]	[0.011]
House Value		2.53E-08	−6.26E-09	−1.13e-09***	−1.21e-09***	
			[0.000]	[0.000]	[0.000]	[0.000]
Electric Consumption		3.92E-07	4.39E-07	−2.57E-08	2.02E-07	
			[0.000]	[0.000]	[0.000]	[0.000]
Internet Usage		−0.00473	0.0015	0.0856***	0.0580***	
			[0.005]	[0.005]	[0.006]	[0.006]
GDP				0.213***	−0.0870***	−0.0927***
				[0.032]	[0.029]	[0.029]
Fiscal Expense Ratio			1.741***	1.127***	0.697***	
				[0.240]	[0.220]	[0.212]
Cons	0.374***	0.293***	0.237***	−0.337***	0.118	0.344***
	[0.002]	[0.046]	[0.067]	[0.079]	[0.076]	[0.077]
N	37,146	35,860	35,392	33,009	33,009	33,009
Province Fixed Effect	No	No	No	No	Yes	Yes
Year Fixed Effect	No	No	No	No	No	Yes
Cluster	No	No	No	No	Family	Family

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

column (3) and −0.135 for column (4)]. This indicates that the BCP contributes to a reduction in CREA in both the east and west regions of China. The results thus highlight a region-specific effect of the BCP on renewable energy adoption, underscoring the necessity of context-sensitive policy implementation and analysis.

The observed differences in the effects of BCP across regions can be attributed to various factors. In the economically developed east region, many rural young people migrate to work in coastal cities and do not reside in rural areas (Wang and Mesman, 2015). Moreover, the use of gas and natural gas as a living fuel is widespread among the elderly population (Zou et al., 2018). In the west region, the economy is less developed and rural residents often choose to work in the east region or middle region cities. Additionally, the availability of abundant natural gas resources in

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TABLE 4 The region heterogenous effect of BCP on CREA in rural family.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
BCP	−0.0804** [0.035]			
BCP		0.0580***		
Middle Region		[0.015]		
BCP			−0.126***	
East Region			[0.011]	
BCP				−0.135***
West Region				[0.016]
Age	0.00330***	0.00334***	0.00328***	0.00334***
	[0.000]	[0.000]	[0.000]	[0.000]
Gender	0.00566	0.00555	0.00548	0.00561
	[0.004]	[0.005]	[0.005]	[0.005]
Marriage	0.0451***	0.0450***	0.0448***	0.0451***
	[0.009]	[0.007]	[0.007]	[0.007]
Health	0.0501***	0.0498***	0.0498***	0.0499***
	[0.004]	[0.002]	[0.002]	[0.002]
Minority	−0.00658	−0.0139	−0.0136	−0.00595
	[0.033]	[0.010]	[0.010]	[0.010]
Family Expense	−0.0436***	−0.0440***	−0.0435***	−0.0439***
	[0.005]	[0.002]	[0.002]	[0.002]
Social Security	−0.0514***	−0.0540***	−0.0493***	−0.0545***
	[0.011]	[0.008]	[0.008]	[0.008]
House Value	−1.18e-09***	−1.19e-09***	−1.20e-09***	−1.17e-09***
	[0.000]	[0.000]	[0.000]	[0.000]
Electric Consumption	1.69E-07	1.54E-07	1.59E-07	1.73E-07
	[0.000]	[0.000]	[0.000]	[0.000]
Internet Usage	0.0584***	0.0579***	0.0580***	0.0580***
	[0.006]	[0.003]	[0.003]	[0.003]
GDP	−0.0873***	−0.0985***	−0.0868***	−0.0982***
	[0.029]	[0.006]	[0.006]	[0.006]
Fiscal Expense Ratio	0.646***	0.739***	0.718***	0.638***
	[0.210]	[0.042]	[0.041]	[0.043]
Cons	0.382***	0.364***	0.358***	0.393***
	[0.078]	[0.032]	[0.032]	[0.032]
N	33,009	33,009	33,009	33,009
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

the west region leads to a preference for natural gas as living energy resource.

In contrast, the middle region exhibits a relatively homogeneous industry and is rich in natural resources such as biogas and solar energy. Rural residents in this region have access to various energy resources, including firewood, biogas, and solar energy (Wang et al., 2016; Wang et al., 2017). Some residents even generate electricity from solar panels and sell it to the local government.

Overall, these findings highlight the regional variations in the effects of the BCP on CREA in rural areas of China, with positive effects observed in the middle region and negative effects observed in the east and west regions.

5.2 Parallel trend test

The validation of the benchmark regression and the parallel trend assumption is crucial in assessing the reliability of the results. In addition to the baseline estimates, model (2) employs the event study approach to examine the parallel trend assumption and provide insights into the dynamic effects of the BCP on CREA in rural families.

The event study model allows for a more detailed analysis of the treatment effects over time, capturing the dynamic of the BCP's impact on CREA. By examining the coefficients of the BCP variable across different periods relative to the policy implementation, we can assess whether the parallel trend assumption holds. Furthermore, the event study model provides valuable information on the dynamic effects of the BCP on CREA in rural families. It allows us to observe how the treatment effect evolves, providing insights into any lagged or cumulative effects of the policy. This helps us understand the long-term implications and sustainability of the BCP in promoting CREA. By incorporating the event study approach, the analysis goes beyond the average treatment effect captured by the baseline model. It provides a more nuanced understanding of the temporal patterns and dynamic effects of the BCP on CREA in rural families, allowing for a comprehensive assessment of the policy's impact. Figure 3 presents the estimation results for the parallel trend assumption test, providing evidence to support the validity of the parallel trend assumption in our specification. The graph illustrates that the renewable energy adoption of rural families in the BCP pilot cities is not statistically different from that in the non-pilot cities before the implementation of the BCP. This indicates that the treatment and control groups had similar trends in renewable energy adoption before the policy intervention, validating the parallel trend assumption.

Moreover, Figure 3 also displays the dynamic effects of BCP on CREA over time. It demonstrates that the policy's effect diminishes gradually as time progresses. Specifically, the estimated coefficient for the BCP variable is not statistically significant in the year preceding the policy implementation. However, in the year of implementation and the subsequent year, the coefficient becomes statistically significant, indicating a positive effect of the BCP on CREA during these periods. It is important to note that the magnitude of the coefficient decreases in the 2 years following the implementation, suggesting a diminishing effect of the policy over time.

These findings provide valuable insights into the temporal dynamics of the BCP's impact on CREA in rural families. They suggest that the policy's effect is most pronounced in the year of implementation and the immediate aftermath, highlighting the importance of early policy implementation for promoting CREA. However, the diminishing effect observed in the subsequent years highlights the need for continuous policy support and potential challenges in sustaining the initial positive impact over time.

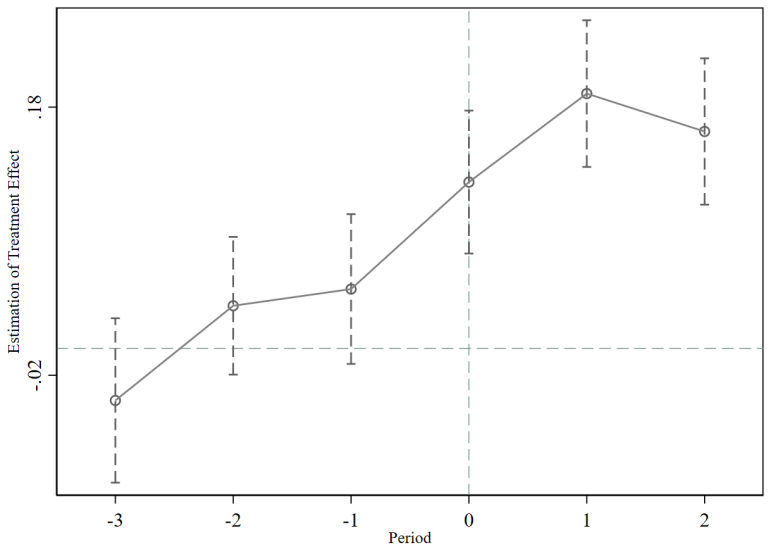


FIGURE 3
Parallel test.

5.3 Robustness test

5.3.1 Propensity score matching

While our benchmark regression aligns with the parallel trend assumption, it is important to acknowledge that the selection process for BCP may not be completely exogenous. The choice of pilot cities could be influenced by various external factors, including economic foundations, internet development, residents' living conditions, and fiscal conditions. Consequently, disparities between pilot cities and non-pilot cities may result in divergent trends concerning the adoption of clean renewable energy over time. To alleviate the potential estimation bias caused by sample selection, we apply the propensity score matching (PSM) method to re-estimate the baseline staggered DID regression model. We first take the relevant characteristics, including GDP, family total income, the ratio of fiscal expense and income, family expense, internet adoption, family electric consumption, house value, health condition, and age, as covariate variables and use the logit model to calculate the propensity score of each city in our entire sample. Figure 4 illustrates the results of the PSM test. The analysis reveals that the treatment group and control group exhibit a comprehensive distribution, implying a reasonable comparison between the two groups.

Subsequently, we utilize the weighted sample, samples with support, and the weighted average samples to re-estimate the staggered DID model. This approach allows us to account for the varying weights of the observations and focus on the samples that satisfy the common support condition. We aim to obtain more robust and reliable estimates for the staggered DID model with a PSM sample by employing these methods.

Table 5 presents the results of our analysis; we control for the control variables as in the benchmark regression, incorporating province fixed effects, year fixed effects, and region and year fixed effects. Additionally, we cluster the standard errors at the family level. The table includes several rows of interest; in the full sample row, we utilize BCP as the explanatory variable and CREA as the dependent variable, considering the entire sample. In the middle region row, we introduce the interaction term *BCP* × *Middle Region* as the explanatory variable, focusing specifically on the middle region. In the east region row, we employ the interaction term *BCP* × *East Region* as the explanatory variable, concentrating on the east region. In the west region row, we use the interaction term *BCP* × *West Region* as the explanatory variable, focusing on the west region. By analyzing the coefficients and statistical significance of these explanatory variables in each row, we can elevate the sample selection bias and gain insights into the impact of the BCP on CREA in different regions.

The estimation results align with the benchmark regression, showing a marginal increase in the policy effect. This suggests that any underestimation of the effect due to potential sample selection bias is minimal. Overall, the analysis reveals heterogeneous effects of the BCP across regions. Specifically, in the middle region of China, the BCP significantly increases CREA in rural families. However, in the east and west regions of China, the BCP significantly reduces CREA in rural families.

5.3.2 Robust staggered DID estimator with multiple periods

Figure 5 presents the estimation results of the re-estimated staggered DID model using a doubly robust staggered DID

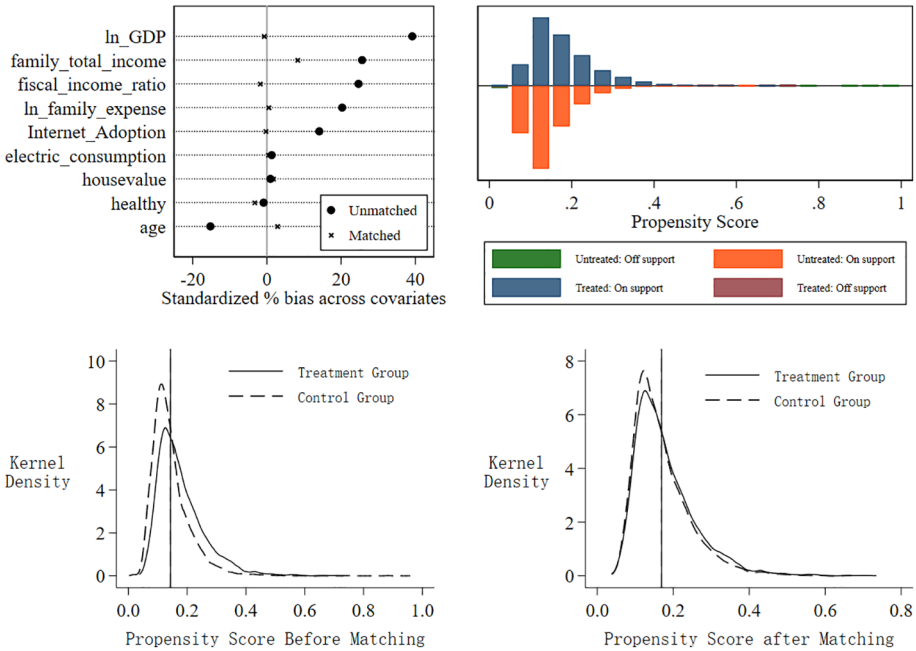


FIGURE 4
Propensity score balance test.

TABLE 5 The effect of BCP on CREA using PSM-DID estimation.

Method Variable	Weighted Sample CREA	Support Sample CREA	Weighted Average Sample CREA
Full sample			
BCP	−0.0890**	−0.143***	−0.0782**
	[0.036]	[0.036]	[0.036]
_cons	0.415***	0.453***	0.387***
	[0.105]	[0.024]	[0.106]
Middle Region			
BCP × Middle Region	0.0491**	0.119***	0.0500**
	[0.021]	[0.019]	[0.020]
_cons	0.343***	0.368***	0.323***
	[0.058]	[0.002]	[0.052]
East Region			
BCP × East Region	−0.102***	−0.191***	−0.0856***
	[0.016]	[0.050]	[0.014]
_cons	0.357***	0.433***	0.339***
	[0.058]	[0.023]	[0.052]
West Region			
BCP × West Region	−0.206***	−0.203***	−0.193***
	[0.023]	[0.069]	[0.020]
_cons	0.447***	0.444***	0.416***
	[0.059]	[0.023]	[0.052]
N	12,305	32,934	15,179
Control Variable	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes
Cluster	Family	Family	Family

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

estimator specified in Equation (6). As mentioned above, this estimator addresses the potential biases arising from residents migrating across regions, being treated multiple times, and transitioning between treatment and control groups. The results align with the benchmark regression, which suggests that the findings are robust and reliable. This consistency strengthens the validity of the estimated treatment effects of the BCP on CREA.

It is worth noting that the impact of BCP on CREA demonstrates a greater magnitude within the full sample compared to the benchmark regression. Moreover, the adverse effect of BCP on CREA exhibits increased significance when considering two lagged periods. Notably, the reduction in CREA is particularly pronounced in the east region, characterized by a pre-existing high utilization of clean domestic energy before the implementation of the BCP. Subsequently, residents in this region displayed a decreased inclination toward employing clean renewable energy after the policy enactment. In the central region, BCP exerts a noteworthy driving force on CERA, albeit with a diminishing impact observed after a two-period lag. Conversely, the west region reveals a negative regression coefficient for BCP. However, BCP fosters an inclination among residents to embrace clean renewable energy.

There are four possible reasons. Firstly, the varying impacts of the BCP on CREA across different regions could be attributed to pre-existing economic disparities (Zhang and Bai, 2017). The east region, having a relatively high utilization of clean renewable energy before the policy implementation, might indicate greater availability of alternative energy sources or a stronger market for renewable energy. Consequently, residents in this region may have been less motivated to adopt clean renewable energy after the policy was

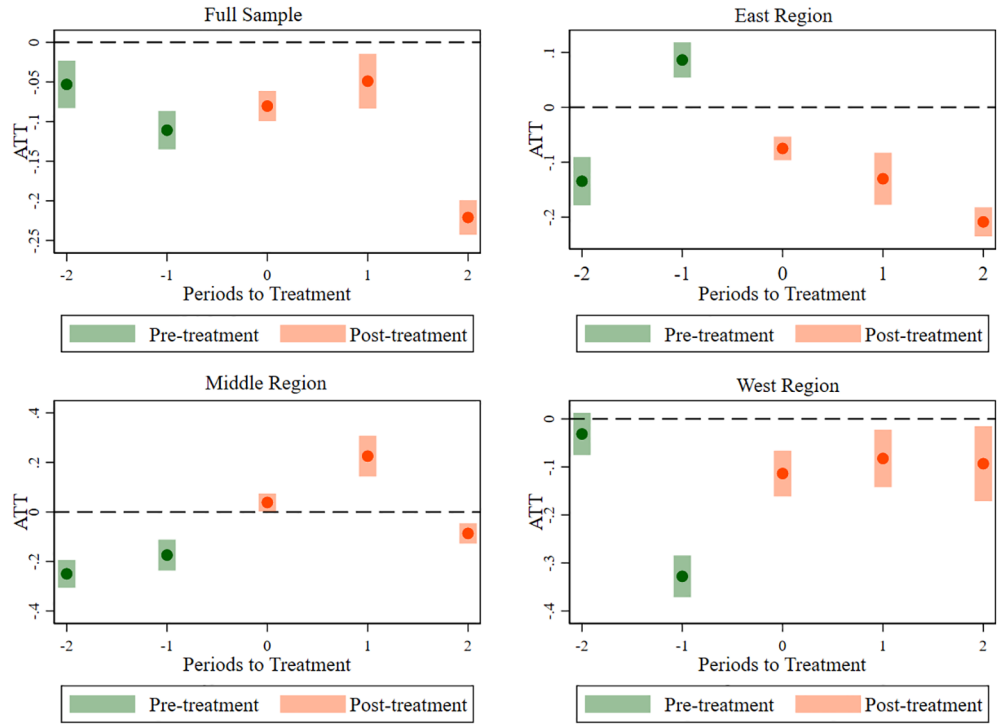


FIGURE 5
Doubly robust staggered DID estimator.

enforced. In contrast, the central and west regions may have had lower levels of clean renewable energy usage initially, leading to different responses to the BCP. Secondly, the effectiveness of the BCP in driving CREA could be influenced by variations in infrastructure and accessibility across regions. The east region, with its established clean energy infrastructure (Liu et al., 2011), may have faced fewer barriers in utilizing alternative energy sources. In contrast, the central and west regions might have encountered challenges related to infrastructure development, making it more difficult for residents to adopt clean renewable energy, particularly after the initial period.

Thirdly, economic factors such as market incentives and cost considerations play a vital role in CREA. The higher prevalence of clean renewable energy usage in the east region before BCP implies that residents may have already taken advantage of existing incentives or enjoyed relatively lower costs associated with CREA (Schulte et al., 2016; Feng et al., 2017). Consequently, the policy implementation may have had a diminishing effect on CREA in this region, as residents may have perceived fewer economic benefits compared to other regions.

Finally, regional differences in the composition of industries and economic activities can also influence the response to the BCP and CREA. For instance, if the east region had a greater concentration of industries or economic sectors that heavily relied on clean renewable energy, the impact of BCP on CREA might have been mitigated due to the existing utilization of renewable sources.

5.3.3 Clean energy in China: natural gas and coal gas

To address concerns surrounding regional heterogeneity and potential estimation bias caused by variations in energy consumption structure, a revised analysis is proposed. This re-estimation modifies the dependent variable to include the adoption of natural gas and coal gas, as suggested by Zou et al. (2018). Notably, while most existing studies focus on macro-level energy consumption, our emphasis is on the individual level, which we argue is crucial for sustainable development.

In China, natural gas is considered a clean energy source and its adoption has been actively promoted by the government in the east region over the past three decades. In contrast, gas and firewood are still the dominant sources of energy for rural families in the middle and west regions. By incorporating these variables, a staggered DID model can be utilized to study the impact of the BCP initiative on natural gas and coal gas adoption across different regions (Beck et al., 2010). This revised approach offers insights into how the policy influences the adoption of cleaner energy sources (natural gas) versus traditional energy sources (coal gas) in diverse geographical areas. Moreover, by comparing changes in natural gas and coal gas consumption, as well as CREA before and after the BCP implementation, within and across regions, it becomes possible to untangle the specific impact of the policy on each energy source. The regression results of this analysis are reported in Table 6.

After including the control variables, province fixed effects, year effects, and the interactive fixed effect of region and year, the revised analysis reveals notable findings. The BCP appears to have a significant positive impact on clean energy adoption in the middle and east regions of China, as evidenced by coefficients of 0.0138 at the 1% significance level for the middle region and 0.0109 at the 10% significance level for the east region. Conversely, in the west region, the policy seems to hinder the adoption of natural gas (with a coefficient of −0.0327 at the 1% significance level) while significantly reducing coal gas adoption (with a coefficient of −0.0563 at the 1% significance level).

A potential explanation for the observed reduction in clean energy adoption in the west region may lie in the migration of rural residents to more developed regions in China, a phenomenon suggested by both Zou et al. (2018) and Wang et al. (2016). Rural residents, especially those with internet access, might be able to find online job opportunities and subsequently leave their hometowns. This migration could result in a decreased demand for clean energy adoption in the west region, as the population engaged in energy consumption declines due to outmigration. This finding underscores the importance of considering broader socioeconomic factors and regional dynamics when analyzing the impact of policies on energy adoption. In this case, employment opportunities, internet access, and rural–urban migration patterns seem to play a role in shaping energy consumption patterns and moderating the effectiveness of the BCP in promoting clean energy adoption in the west region.

5.3.4 Placebo test

To address concerns related to sample selection bias and potential estimation bias caused by unobservable confounders, a placebo test is conducted following a non-parametric permutation method similar to the approach used by Ferrara et al. (2012). The purpose of this test is to examine whether the baseline regression results are affected by unobservable variables.

The placebo test involves the random selection of 106 cities from the entire sample, designating them as the false treatment group, while the remaining cities serve as the false control group. For each city in the false treatment group, a random year between 2007 and 2016 is assigned as the false policy implementation year. This process is repeated 500 times, resulting in 500 sets of estimated coefficients obtained from the random assignments. Figure 6 illustrates the kernel density distributions of these 500 estimated coefficients. The distribution closely approximates a normal distribution, and the average value of the coefficients is close to zero. These findings indicate that the impact of the BCP on CREA is unlikely to be driven by omitted unobservable variables. Therefore, the robustness of the baseline estimates is supported.

6 Mechanism

In this section, we analyze the mechanism underlying the impact of Broadband China Policy (BCP) on the adoption of clean renewable energy (CREA) in rural households. As previously discussed, this impact is multifaceted and encompasses various dimensions of economic activities.

One of the primary objectives of the BCP initiative is to enhance broadband adoption. Through the implementation of BCP, rural residents have gained improved affordability and faster internet speeds, enabling them to access online resources more readily. This improved internet accessibility plays a crucial role in facilitating the dissemination of information and knowledge concerning clean

TABLE 6 The effect of BCP on natural gas and gas.

	(1) Natural Gas	(2) Natural Gas	(3) Natural Gas	(4) Coal Gas	(5) Coal Gas	(6) Coal Gas
BCP × Middle Region	0.0138*			−0.0153		
	[0.008]			[0.015]		
BCP × East Region		0.0109*			−0.0330***	
		[0.006]			[0.011]	
BCP × West Region			−0.0327***			−0.0563***
			[0.009]			[0.016]
_cons	−0.0665***	−0.0647***	−0.0594***	0.351***	0.347***	0.360***
	[0.018]	[0.018]	[0.018]	[0.033]	[0.033]	[0.033]
N	33,009	33,009	33,009	33,009	33,009	33,009
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family	Family	Family

Robust standard errors are in parentheses; * and *** denote significances at 10% and 1% levels, respectively.

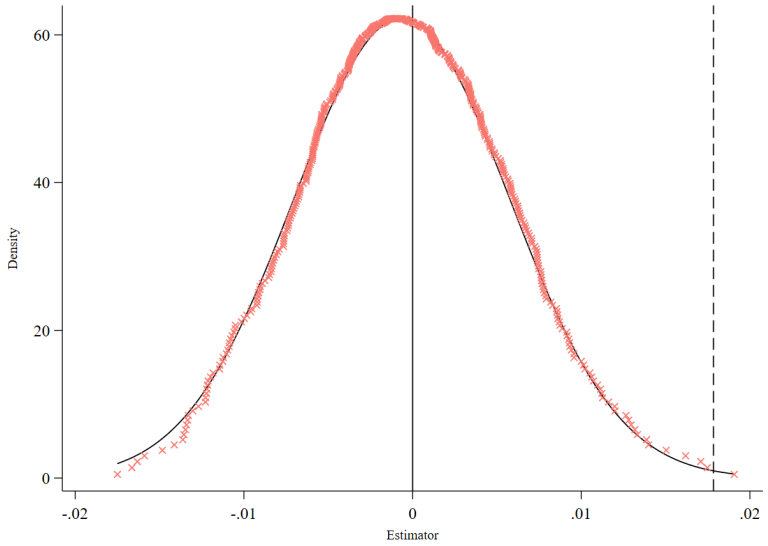


FIGURE 6
Placebo test.

energy technologies and practices. The internet serves as a valuable platform for educational resources, providing rural residents with access to relevant information (Zaharov et al., 2018; Jang and Song, 2022), case studies, and success stories related to clean renewable energy. By leveraging these resources, individuals can make informed decisions regarding the adoption of clean renewable energy (CREA). Consequently, internet accessibility serves as a vital channel connecting BCP to CREA, as it enhances awareness and understanding of the benefits and feasibility associated with CREA. Therefore, we propose three distinct avenues through which BCP can facilitate the promotion of CREA in rural families.

6.1 Governance participation and pollution

The accessibility of the internet not only empowers rural residents to voice their concerns, provide feedback, and actively participate in discussions related to pollution control and clean energy policies but also plays a crucial role in facilitating effective governance and policy reforms (Flew et al., 2019; Haggart, 2020). By harnessing the power of the internet, residents can engage in environmental issues, express their opinions, and advocate for sustainable practices, thereby exerting pressure on local governments to allocate more resources to pollution control efforts.

Moreover, the advent of new digital technologies has revolutionized environmental monitoring and management. Real-time monitoring systems, remote sensing technologies, and advanced data analysis tools have become invaluable assets in the identification and mitigation of pollution sources (Cheng et al., 2021; Chen et al., 2022b). These digital innovations enable authorities to promptly detect and address environmental hazards, leading to the implementation of more stringent regulations and the enhancement of enforcement mechanisms.

Furthermore, the internet acts as a catalyst for promoting clean renewable energy alternatives. Digital platforms provide a space for knowledge sharing, where information regarding the benefits and feasibility of clean energy technologies can be disseminated (Jang and Song, 2022). Online resources such as case studies, success stories, and educational materials are readily accessible, enabling rural residents to make informed decisions regarding clean energy adoption. The availability of such information not only raises awareness but also enhances the understanding of clean energy solutions, further driving the shift toward sustainable practices.

The digital transition also brings about increased government investment and efficiency in addressing environmental challenges. With the aid of digital tools and technologies, governments can streamline administrative processes, facilitate data-driven decision-making, and improve resource allocation. This results in more effective and targeted interventions to combat pollution and promote clean energy. Additionally, the transparency and accountability enabled by digital platforms foster trust between governments and citizens, creating a conducive environment for collaboration and the implementation of sustainable policies.

6.2 Job opportunities and salary income

The accessibility of the internet opens up avenues for rural residents to access a wider range of job opportunities, fostering economic empowerment and financial stability (Stevenson, 2008; Maurer-Fazio, 2012; Suvankulov et al., 2012; Castellacci and Vinas-Bardolet, 2019). With the advent of digital platforms and online marketplaces, individuals residing in rural areas can engage in remote work or venture into entrepreneurship, regardless of their geographic location. This expanded economic activity not only provides individuals with additional sources of income but also

enhances their financial capacity to invest in various aspects of their lives, including clean energy technology.

By leveraging digital platforms, rural residents can participate in remote work arrangements (Ghislieri et al., 2022), such as freelancing, consulting, or telecommuting. This flexibility allows individuals to harness their skills and expertise, serving clients and organizations worldwide (Sako, 2021). Additionally, online marketplaces offer opportunities for rural entrepreneurs to showcase and sell their products or services to a global customer base, transcending traditional geographical limitations. This newfound economic potential provides rural residents with a pathway toward financial independence and improved livelihoods.

The increased income and financial stability resulting from these digital opportunities can indirectly impact the adoption of clean renewable energy (CREA) in rural areas. As individuals' economic circumstances improve, they gain the means to invest in clean energy technologies for their households or businesses. This could involve installing solar panels, purchasing energy-efficient appliances, or implementing sustainable farming practices. The availability of reliable and sustainable income sources enables individuals to allocate resources towards environmentally friendly solutions, gradually transitioning towards a cleaner and more sustainable energy future.

Moreover, the economic empowerment facilitated by internet accessibility can have wider community benefits. As rural residents engage in remote work or establish online businesses, they contribute to local economic development and job creation. This virtuous cycle stimulates economic growth within rural communities, fostering a supportive ecosystem for the adoption of clean energy. Local businesses, service providers, and community organizations may also respond to the growing demand for clean energy solutions, further promoting the uptake of CREA.

However, with the development of the internet and the increase in income, online platforms provide multiple products and delivery services with coupons (Duan et al., 2022). This convenience and attractive pricing often lure residents to order take-out meals instead of cooking at home (Jiang et al., 2021). Furthermore, residents may choose to purchase more advanced electrical equipment due to their increased purchasing power. While these trends may seem beneficial, they have the potential to reduce the utilization of renewable energy sources. To address this issue, it is crucial to examine the impact of these factors on the energy consumption patterns of residents. Firstly, the widespread adoption of online platforms for food delivery can lead to a higher demand for transportation and logistics services. The increased frequency of delivery vehicles on the roads can result in greater fuel consumption and emissions, indirectly contributing to environmental pollution. This aspect needs to be considered when evaluating the overall energy efficiency of the online food delivery system.

Secondly, the availability of coupons and discounts on online platforms can influence consumer behavior (Duan et al., 2022). By offering reduced prices for take-out meals, online platforms encourage residents to order food instead of cooking at home. This shift in behavior can lead to increased energy consumption, as households relying on take-out meals are likely to use more electricity for lighting, refrigeration, and other related purposes. Consequently, the energy demand may rise, potentially placing additional strain on non-renewable energy sources.

Furthermore, the affordability of advanced electrical equipment, made possible by increased income, can also impact energy consumption patterns. While these appliances may provide convenience and improved functionality, they often require substantial amounts of energy to operate. If the trend of purchasing such energy-intensive equipment continues, it could contribute to higher overall energy demand, possibly relying more heavily on non-renewable energy sources.

6.3 Industrial upgrading

The adoption of the internet and digital technologies, including IoT devices, smart systems, and data analytics, plays a pivotal role in optimizing energy usage, monitoring emissions, and integrating renewable energy sources across industrial and household sectors (Ishida, 2015; Lahouel et al., 2021; Chen et al., 2022b). This process of digital transition catalyzes industrial upgrading, leading to the adoption of cleaner production processes and promoting the adoption of clean renewable energy solutions in daily life.

By leveraging IoT devices and smart systems, industries and households can enhance their energy efficiency and reduce their environmental impact (Wang et al., 2021; Chen et al., 2022b). Smart grids enable real-time monitoring and control of energy consumption, allowing for more efficient allocation and utilization of resources. Industrial processes can be optimized through data analytics, identifying areas for improvement, and implementing energy-saving measures. This optimization not only reduces energy waste but also minimizes emissions and environmental pollutants. Furthermore, the integration of renewable energy sources is facilitated by digital technologies. IoT devices and data analytics enable the seamless integration of renewable energy systems, such as solar panels and wind turbines, into existing infrastructure. These technologies provide real-time monitoring and management of renewable energy generation, ensuring efficient utilization and grid integration. The intelligent control systems allow for dynamic load balancing, storage management, and demand response mechanisms, optimizing the overall energy mix and promoting the use of clean energy sources.

The impact of BCP is significant in this context as it accelerates the digital transition and promotes the widespread adoption of these technologies. Improved internet accessibility through BCP facilitates the dissemination of digital innovations, enabling industries and households to embrace energy-efficient practices and renewable energy solutions. By enhancing energy efficiency and reducing environmental impacts within industries and households, BCP contributes to the wider availability and adoption of clean energy sources.

In summary, the adoption of the internet and digital technologies empowers industries and households to optimize energy usage, monitor emissions, and integrate renewable energy sources. This digital transition, supported by initiatives like Broadband China, drives industrial upgrading and promotes the

adoption of cleaner production processes and clean renewable energy solutions. Ultimately, it improves energy efficiency, reduces environmental impact, and paves the way for a more sustainable and clean energy future.

6.4 Mechanism analysis

To test the mechanisms discussed above, we have introduced the interactive terms of BCP with pollution, industry structure, and family salary income in our baseline regression, as specified in model (9). The results of these regressions are presented in Table 7.

In column (1), the interaction term between BCP and pollution, represented as *BCP* × *Pollution*, is introduced. The coefficient corresponding to this interaction term is quantified as 0.0238, demonstrating statistical significance at the 10% level, and is decidedly positive. This empirical evidence suggests that the local district's pollution levels modulate the relationship between BCP and CREA.

The positive coefficient affiliated with the *BCP* × *Pollution* interaction term is concordant with the hypothesis that BCP avails residents with expanded avenues for expressing their perspectives and concerns about pollution. Through the medium of online platforms, residents are empowered to articulate their sentiments and advocate for an enhanced environmental living standard.

The positive coefficient also denotes that as pollution escalates, the positive influence of BCP on CREA becomes increasingly discernible. This finding infers that the digital transition, embodied by online platforms, equips residents with the tools necessary to champion and strive for betterment in their living conditions, specifically regarding the reduction of pollution.

In column (2), we incorporate the interaction term between BCP and Industry Structure, denoted as *BCP* × *Industry Structure*. Relative to the baseline model, there are significant alterations in the coefficients and subsequent interpretations. Primarily, the coefficient associated with BCP becomes statistically significant and positive (0.043 at a 1% significance level), thereby signifying that BCP profoundly fosters CREA among rural families when industry structure is factored in. This indicates that the utilization of online platforms, including BCP, exerts a positive influence on the economic welfare of rural families, considering the distinct characteristics of the industry structure.

Contrastingly, the coefficient for the interaction term *BCP* × *Industry Structure* is statistically significant yet negative (−0.117 at a 1% significance level). This observation intimates that the relationship between BCP and CREA is shaped by the proportion of tertiary industry in the region. As the proportion of this industry, characterized by a dominance of service-oriented sectors such as hospitality and restaurants, swells, the effect of BCP on CREA appears to decline or even reverse, becoming negative.

This discovery is supported by the analysis delineated earlier, although it diverges from macro-level analyses, as cited in previous studies. When the tertiary industry dominates the local industrial structure, residents may prefer dining in restaurants as opposed to home cooking, thereby reducing both traditional and clean renewable energy usage. Simultaneously, this shift may incite an increase in electricity consumption due to the availability of more accessible and affordable electrical devices. Such a transition in consumption habits can potentially negate the positive effect of BCP on CREA.

TABLE 7 Mechanism analysis.

	(1) CREA	(2) CREA	(3) CREA
BCP	−0.0822***	0.0453***	0.444***
	[0.008]	[0.016]	[0.168]
BCP × Pollution	0.0238* [0.014]		
BCP × Industry Structure		−0.117*** [0.012]	
BCP × Family Salary Income			−0.0508*** [0.016]
_cons	0.344***	0.300***	0.177**
	[0.031]	[0.033]	[0.085]
N	33009	30398	19259
Control Variable	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes
Cluster	Family	Family	Family
Adjust R^2	0.2893	0.2982	0.2606

Robust standard errors are in parentheses; *, **, and *** denote significances at 10%, 5%, and 1% levels, respectively.

In column (4), we incorporate the interaction term between BCP and family salary income, denoted as *BCP* × *Family Salary Income*. The coefficients corresponding to BCP and the interaction term yield significant insights into the tripartite relationship among digital transition, familial income, and consumption structure.

In a manner analogous to the preceding model, the coefficient associated with BCP is significantly positive (0.444 at a 1% level) in column (4). This implies that BCP has a beneficial influence on CREA in rural families when we account for family income. The digital transition facilitates economic activity, contributes to the economic wellbeing of households, and fosters CREA among rural families. Contrarily, the coefficient for the *BCP* × *Family Salary Income* term is significantly negative (−0.0508 at a 1% level). This indicates that as family salary income escalates, the relationship between BCP and CREA is negatively impacted.

Elevated income levels induce changes in consumption habits, such as a predilection for meal delivery services or restaurant dining, over home cooking. Specifically, the rise in family income may enable households to afford more convenient food options, instigating a departure from traditional home cooking. This shift in consumption behavior may precipitate a reduction in traditional energy costs but an uptick in electricity consumption due to the utilization of more contemporary, energy-demanding devices. Thus, the negative coefficient for the *BCP* × *Family Salary Income* interaction term underscores the importance of considering income's role in understanding BCP's impact on consumption patterns and energy usage. Heightened family income levels may attenuate the positive influence of BCP on CREA due to consumption behavior changes engendered by increased affordability and convenience.

These findings highlight the importance of various factors and the diverse effects of BCP on CREA. They imply that policymakers and stakeholders should be cognizant of the differing impacts of digital transition on various industries, household financial circumstances, and consumption behavior. This understanding is pivotal for nurturing sustainable economic growth and promoting energy efficiency in rural locales.

7 Heterogeneity and alternative interpretation

7.1 Heterogeneity

According to the analysis presented earlier, it is evident that the impact of BCP on CREA is influenced by multiple economic factors. Additionally, the considerable gap in economic development across different regions in China introduces significant heterogeneity in the causal inference between BCP and CREA. In this section, we delve further into this heterogeneity to gain a deeper understanding of the nuanced dynamic at play.

7.1.1 Heterogeneity of real estate district

Real estate holds significant importance for Chinese families, serving as both a living space and an investment asset (Ren et al., 2012). However, the high prices of real estate and the traditional cultural significance of owning a home create substantial financial burdens for families (Deng et al., 2012). Many Chinese families find themselves stretching their financial resources to meet the expenses associated with purchasing a house, often having to exhaust their savings and rely on various sources of funding.

It is worth noting that the heterogeneity in the types of housing available in China further contributes to the financial diversity across families. The CLDS survey includes a question that provides an opportunity to identify this heterogeneity by asking respondents about the type of district they reside in. The responses include non-reformed old districts, districts for workers in mining enterprises, districts for government officials and state-owned enterprise employees, social welfare housing communities, general commercial housing districts, upscale commercial housing communities, districts for rural-to-urban migrants, and shantytowns.

The majority of families residing in districts other than commercial housing districts and districts for government officials and employees of state-owned enterprises often face financial challenges, particularly those in rural areas. These families struggle with mandatory expenses such as food, education, and housing rent. Moreover, owing to the lack of comprehensive social security coverage, residents are often required to make upfront payments for medical treatment, and some may even find themselves unable to afford hospital bills. Consequently, the financial strain they face makes it difficult for them to afford the costs associated with adopting clean renewable energy sources. Moreover, the financial constraints experienced by families living in poverty or facing economic hardships underscore the challenges they encounter in adopting clean renewable energy technologies. Access to affordable and clean energy sources is crucial for sustainable development and environmental conservation. However, the financial limitations faced by these families restrict their ability to invest in renewable energy solutions, which often require upfront costs and infrastructure investments.

To examine the impact of low-income districts on the relationship between BCP and CREA, we introduce a dummy variable called "Low Income District", which takes a value of 1 if residents live in a low-income district, and 0 otherwise. Additionally, we incorporate the interaction term between BCP and Low-Income District, denoted as *BCP* × *Low Income District*, into the baseline model. To capture the heterogeneity across different regions, we divide the sample into the middle region, east region, and west region.

The results presented in Table 8 demonstrate that all of the coefficients of the interaction term, *BCP* × *Low Income District*, are statistically significant and negative. This indicates that rural families residing in low-income districts across China are likely to experience a reduction in CREA. These findings highlight the adverse impact of living in low-income districts on the relationship between BCP and CREA, regardless of the geographical region. The negative coefficients suggest that the combination of BCP usage and residing in a low-income district has an amplifying effect on the reduction of CREA. This outcome is noteworthy as it indicates that the potential benefits of BCP adoption in promoting CREA are diminished in low-income districts. The financial constraints and challenges faced by families in these districts hinder their ability to invest in clean and renewable energy

TABLE 8 Heterogeneity of Real Estate District.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
	Full Sample	Middle Region	East Region	West Region
BCP × Low Income District	-0.223***	-0.182**	-0.177***	-0.504***
	[0.056]	[0.084]	[0.066]	[0.105]
_cons	0.324***	0.350**	0.419***	0.142
	[0.077]	[0.169]	[0.107]	[0.137]
N	33009	9782	15668	7559
Control Variable	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	No	No	No
Adjust R^2	0.2917	0.2908	0.2307	0.3071

Robust standard errors are in parentheses; ** and *** denote significances at 5% and 1% levels, respectively.

technologies, ultimately impacting their CREA levels. Furthermore, the results indicate that the heterogeneity across different regions does not significantly alter the causal inference of BCP on CREA in low-income districts. Regardless of whether the sample consists of the middle region, east region, or west region, the coefficients of the interaction term remain consistently negative and statistically significant. This suggests that the detrimental impact of low-income districts on the relationship between BCP and CREA extends throughout China.

The findings underscore the need for targeted interventions and policy measures to address the challenges faced by rural families living in low-income districts. Such measures should aim to alleviate financial constraints, improve access to affordable clean energy solutions, and promote sustainable development in these areas. By implementing policies that specifically target low-income districts, policymakers can help bridge the gap and ensure that the benefits of BCP and clean renewable energy are accessible to all, irrespective of their income levels or geographical location. In conclusion, the inclusion of a dummy variable for low-income districts and the corresponding interaction term in the analysis reveals that rural families living in low-income districts experience a reduction in CREA across China. This highlights the importance of addressing the financial constraints and challenges faced by these families in adopting clean and renewable energy technologies. The consistent findings across different regions emphasize the need for targeted policies to promote sustainable energy practices and mitigate the adverse effects of low-income districts on CREA.

7.1.2 Heterogeneity of population size

Population size plays a significant role in determining the level of public infrastructure, public services, and economic foundation in Chinese cities. Larger population centers tend to have more extensive public facilities and services to cater to the needs of a larger number of residents. Moreover, the larger population base offers attractive investment opportunities and a target market for both the government and enterprises. As a result, these areas are more likely to attract investments in green technology research and development, clean technology applications, and clean renewable energy infrastructure.

The heterogeneity arising from population size has several implications. Firstly, cities with larger populations often have a higher demand for energy and resources. This increased demand necessitates the development of robust and sustainable energy systems to meet the needs of the population. Consequently, policymakers and stakeholders are more inclined to invest in clean and renewable energy infrastructure in these areas to ensure a reliable and environmentally friendly energy supply.

Secondly, the availability of a large population provides a more significant market for clean technology products and services. With a large group, companies and entrepreneurs are motivated to develop and commercialize clean technologies to cater to the needs and preferences of a diverse consumer base. This, in turn, drives innovation and fosters the growth of the clean technology sector in these populous areas.

Furthermore, the concentration of the population in larger cities facilitates knowledge exchange, collaboration, and the sharing of best practices. These cities often serve as hubs for research and development, attracting skilled professionals and experts in the field of clean renewable energy. The presence of a knowledgeable workforce and a vibrant intellectual environment accelerates technological advancements and the adoption of clean renewable energy solutions.

However, it is crucial to consider the potential drawbacks and challenges associated with large population centers. Rapid urbanization and population growth can strain existing infrastructure and resources, leading to increased energy consumption and environmental pressures. Managing the energy demands of a large population requires careful planning efficient resource allocation, and sustainable urban development strategies.

To investigate the impact of population size on the relationship between BCP and CREA, we introduce a dummy variable called

"Mean Popu". This variable takes a value of 1 if the population of the city is larger than the mean population across China, and 0 otherwise. Additionally, we divide the sample into the middle region, east region, and west region to capture the regional heterogeneity. Incorporating the interaction term between BCP and Mean Popu, denoted as *BCP* × *Mean Popu*, into the baseline model, we present the results in Table 9. The coefficients of *BCP* × *Mean Popu* are found to be statistically significant and positive. This indicates that in cities with larger populations, the presence of BCP significantly promotes CREA.

Comparing these results to the baseline model, it becomes evident that population size introduces significant heterogeneity across China. Larger cities not only attract migration but also attract technological advancements and investment. The concentration of population in these cities creates an environment that fosters the adoption and utilization of BCP, leading to a positive impact on CREA. On the other hand, smaller cities may face challenges associated with a declining population and limited investment opportunities. These factors may hinder the adoption of BCP and limit the potential benefits for CREA in these areas.

The findings highlight the importance of considering population size and its impact on the effectiveness of BCP in promoting CREA. Policy interventions and strategies should take into account the varying dynamics across cities of different sizes. It is crucial to support smaller cities in overcoming barriers and creating an enabling environment for the adoption of BCP and clean renewable energy technologies. Furthermore, the regional heterogeneity observed in the results emphasizes the need for tailored approaches in different regions. Middle, east, and west regions may have unique characteristics and specific challenges that require region-specific policies and initiatives to enhance CREA. By understanding and addressing the specific needs of each region, policymakers can foster sustainable economic growth, encourage investment in clean energy technologies, and promote energy efficiency.

In conclusion, the inclusion of the dummy variable "Mean Popu" and the corresponding interaction term *BCP* ×*Mean Popu* provides insights into the relationship between population size and the impact of BCP on CREA. The positive and statistically significant coefficients suggest that in cities with larger populations, BCP has a significant positive effect on CREA. This underscores the importance of considering population size and its associated heterogeneity when designing policies and interventions to promote sustainable energy practices and enhance CREA in different regions of China.

7.1.3 Economic size

The gaps in economic development across regions pose another important consideration in understanding the impact of BCP on CREA. In China, the east region holds a pivotal role in the country's economy, fiscal income, foreign communication, and technology innovation. On the other hand, the middle region and the west region are still in the process of development. To explore the potential heterogeneity resulting from economic size, we calculate the mean total GDP to be 3,617.536 billion. Furthermore, the mean GDP in the east region is 5,424.964 billion, that in the middle region is 2355.583 billion, and that in the west region is 1900.047 billion. These figures indicate substantial disparities in economic size across the regions.

Given these disparities, it is reasonable to expect that the impact of BCP on CREA may vary significantly across regions. The larger economic size of the east region, coupled with its advanced technological capabilities and greater investment opportunities, may create a more conducive environment for the adoption and utilization of BCP. The positive impact of BCP on CREA in the east region is likely to be more pronounced compared to the middle and west regions. However, as discussed above, the residents living in the east region will change their consumption structure due to the developed economic and digital transition; as a result, the BCP

TABLE 9 Heterogeneity of population size.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
	Full Sample	Middle Region	East Region	West Region
BCP × Mean Popu	0.0719**	0.141***	0.0354***	0.105***
	[0.031]	[0.016]	[0.012]	[0.023]
_cons	0.121	0.154***	0.247***	−0.169***
	[0.075]	[0.060]	[0.045]	[0.064]
N	33,009	9,782	15,668	7,559
Control Variable	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	No	No	No
Adjust R^2	0.2582	0.2655	0.1938	0.2597

Robust standard errors are in parentheses; ** and *** denote significances at 5% and 1% levels, respectively.

shows a lower impact on CREA in rural families residing in the east region.

Conversely, the middle and west regions, characterized by lower economic sizes and relatively less developed infrastructure, may face challenges in realizing the full potential of BCP for promoting CREA. The limited resources and investment in these regions could hinder the adoption and utilization of BCP, leading to a relatively weaker impact on CREA. To comprehensively understand the heterogeneity resulting from economic development gaps, it is crucial to conduct further analysis and regression models that explicitly account for regional economic factors. This would enable a more nuanced examination of the relationship between BCP and CREA, considering the varying economic sizes across regions and their impact on the adoption and effectiveness of BCP.

To further investigate the heterogeneity related to economic size, we introduce a dummy variable called "GDP Mean Group". This variable takes a value of 1 if the GDP of a region is larger than the mean GDP across all regions, and 0 otherwise. Additionally, we introduce the dummy variables "Mid GDP Mean Group", "East GDP Mean Group", and "West GDP Mean Group" based on the means of GDP in the middle, east, and west regions, respectively. Table 10 presents the results of the regression analysis. We find that GDP plays a significant role in determining the impact of BCP on CREA across China. The coefficients of the interaction term between the BCP and GDP Mean Group are statistically significant and positive in the full sample. Comparing these results to the baseline model, it becomes evident that economic development amplifies the impact of BCP on CREA. Regions with higher levels of economic development tend to experience a stronger positive effect of BCP on CREA.

Furthermore, when we examine the results for specific regions, we observe some interesting findings. In the middle and west regions, the coefficients of the interaction term are statistically significant and positive, indicating that the impact of BCP on CREA is amplified in these regions. This aligns with our previous analysis, highlighting the challenges faced by less-developed regions and their potential to benefit from BCP adoption. Surprisingly, in the east region, the coefficient of the interaction term is not statistically significant. This suggests that the relationship between BCP and CREA may be influenced by other factors in the east region, such as advanced technological infrastructure and higher levels of investment. These factors may overshadow the specific impact of BCP on CREA in the east region.

Furthermore, when we examine the results for specific regions, we observe some interesting findings. In the middle and west regions, the coefficients of the interaction term are statistically significant and positive, indicating that the impact of BCP on CREA is amplified in these regions. This aligns with our previous analysis, highlighting the challenges faced by less-developed regions and their potential to benefit from BCP adoption. Surprisingly, in the east region, the coefficient of the interaction term is not statistically significant. This suggests that the relationship between BCP and CREA may be influenced by other factors in the east region, such as advanced technological infrastructure and higher levels of investment. These factors may overshadow the specific impact of BCP on CREA in the east region.

7.2 Alternative interpretation

7.2.1 Social study

In order to examine the potential influence of social study on the impact of BCP on CREA, we introduce the interaction term *BCP* × *Social Study* into the analysis. The frequency of social study

TABLE 10 Heterogeneity of economic size.

	(1) CREA	(2) CREA	(3) CREA	(4) CREA
	Full Sample	Middle Region	East Region	West Region
BCP × GDP Mean Group	0.0540*** [0.009]			
BCP × Mid GDP Mean Group		0.0739*** [0.017]		
BCP × East GDP Mean Group			0.00823 [0.012]	
BCP × West GDP Mean Group				0.0343*** [0.010]
_cons	0.114***	0.102*	0.244***	0.251***
	[0.031]	[0.060]	[0.045]	[0.045]
N	33,009	9,782	15,668	15,668
Control Variable	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	No	No	No
Adjust R^2	0.2575	0.2608	0.1934	0.194

Robust standard errors are in parentheses; * and *** denote significances at 10% and 1% levels, respectively.

activities, as reported by the respondents in the CLDS survey, serves as a proxy for their engagement in acquiring knowledge, training, and technical support related to clean renewable energy technologies. Additionally, we consider the role of natural gas, another important source of energy in China, to test whether social study has a greater impact on promoting CREA compared to BCP. This allows us to assess whether social study activities have a specific influence on the adoption of clean renewable energy technologies, independent of the overall impact of BCP and other energy sources.

In columns (1) and (2) of Table 11, we observe that the coefficients of the interaction terms between BCP and Social Study are statistically insignificant and positive. This implies that the frequency of social study activities, as reported by the respondents, does not appear to have a significant influence on the relationship between BCP and CREA. These results suggest that while social study activities may provide channels for rural residents to access clean renewable energy knowledge and training, it does not significantly enhance the impact of BCP on the adoption of clean renewable energy technologies in rural areas. Other factors or mechanisms might be more influential in driving the adoption of CREA.

It is important to interpret these findings cautiously and consider the potential limitations of the analysis. Other factors not captured in the model or variations in the sample characteristics could also contribute to the insignificant relationship between BCP, social study, and CREA. Further research and analysis may be required to explore additional factors or alternative explanations for the observed results.

Overall, the analysis suggests that social study activities alone may not be a significant determinant of the impact of BCP on CREA. Policymakers and stakeholders should consider other strategies and interventions to promote CREA in rural areas, taking into account the specific context and characteristics of the target population.

7.2.2 Energy conservation and emission reduction pilot city

To address concerns regarding potential confounding factors, we examine the impact of other policies related to clean energy adoption, such as the Energy Conservation and Emission Reduction Pilot City (ECERP) program. The ECERP program aims to enhance energy conservation and emission reduction efforts in selected cities, integrating various fiscal policies to achieve China's targets

TABLE 11 Alternative interpretation.

	(1) CREA	(2) Natural Gas	(3) CREA	(4) CREA	(5) CREA	(6) CREA
	Full Sample		Exclude the ECERP pilot City			
BCP × Social Study	0.000685	0.0129				
	[0.007]	[0.008]				
BCP			-0.0487***			
			[0.009]			
BCP × Middle Region				0.0598***		
				[0.016]		
BCP × East Region					-0.0764***	
					[0.013]	
BCP × West Region						-0.116***
						[0.017]
_cons	0.368***	-0.0654	0.325***	0.305***	0.311***	0.336***
	[0.079]	[0.050]	[0.036]	[0.036]	[0.036]	[0.036]
N	33009	33009	29061	29061	29061	29061
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes
Province Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Family	Family	Family	Family	Family	Family
Adjust R^2	0.2901	0.3342	0.2763	0.2759	0.2764	0.2767

Robust standard errors are in parentheses; *** denotes significance at 1% level.

in these areas. The program was initiated in 2011, with additional cities being promoted in 2013 and 2014, totaling 28 cities. To eliminate the potential influence of ECERP on our baseline estimation, we exclude the ECERP cities from the total sample and re-estimate the baseline model. Columns (3) to (6) in the analysis report the results. By excluding the ECERP cities, we can isolate the specific impact of the BCP on CREA, independent of any potential effects resulting from the ECERP program. This allows us to examine the true relationship between BCP and CREA, without the confounding influence of this particular policy intervention. The coefficients of BCP and the interaction terms are statistically significant. Compared to the baseline model, the coefficient is smaller, which suggests that the ECERP has affected the adoption of renewable energy in rural family, and it also supports the idea that the BCP has a significant impact on CREA, and it shows heterogeneity across regions.

The results of the analysis in columns (3) to (6) indicate that the coefficients of BCP and the interaction terms remain statistically significant, even after excluding the ECERP cities from the sample. However, it is observed that the magnitude of the coefficients is smaller compared to the baseline model. This finding suggests that the presence of the ECERP program has affected the adoption of renewable energy in rural families. The program may have influenced the overall energy conservation and emission reduction efforts in the ECERP cities, which could have indirectly affected the adoption of clean renewable energy technologies in these areas. Nonetheless, the significance of the coefficients of BCP and the interaction terms, even in the absence of the ECERP cities, supports the idea that BCP has a significant impact on CREA. It further reinforces the notion that BCP plays a vital role in promoting the adoption of clean renewable energy technologies in rural areas.

Additionally, the presence of heterogeneity across regions is observed, indicating that the impact of BCP on CREA varies across different parts of China. This regional variation suggests that factors such as economic development, policy environment, and infrastructure may influence the effectiveness of BCP in promoting CREA.

Overall, by excluding the ECERP cities and observing the significance of the coefficients in the remaining sample, we can conclude that the BCP has a significant impact on CREA, even after accounting for the potential influence of the ECERP program. The presence of heterogeneity across regions underscores the need for tailored policies and strategies to effectively promote CREA in rural areas across different parts of China.

8 Conclusion

The ongoing digital transition and the urgent need to address global warming have brought attention to the energy consumption patterns in rural families. However, there is currently a lack of theoretical frameworks and empirical research focusing on this specific context. Furthermore, the impact of digital transition on the adoption of clean renewable energy in rural families remains understudied. This paper aims to fill these research gaps by utilizing Broadband China Policy (BCP) as a quasi-natural experiment and analyzing data from the CLDS spanning the years 2012 to 2016. To assess the impact of digital transition on CREA in rural families, the study employs a staggered DID approach and the Doubly Robust Staggered DID estimator. The use of a traditional staggered DID estimator allows for a rigorous examination of the causal relationship between digital transition and CREA, by analyzing the CLDS datasets, which provide valuable insights into the energy consumption patterns of rural families, and the study aims to shed light on the potential effects of digital transition on CREA in this specific context. By applying a robust statistical method, the study seeks to provide reliable and accurate estimates of the impact of digital transition on CREA; moreover, it also provides the chance to analyze its dynamic effects. This rigorous analysis contributes to the existing literature on energy consumption patterns and the role of digital technology in promoting sustainable energy practices.

Our findings demonstrate that the digital transition has a significant impact on the adoption of clean renewable energy in rural families, with notable heterogeneity across regions. Specifically, the implementation of the BCP resulted in a significant increase in CREA in the middle region, with a 5.8% increase compared to non-pilot cities. However, in the east and west regions, the BCP led to a reduction in CREA, with a 12.6% decrease in the east region and a 13.5% decrease in the west region. Furthermore, our dynamic effect analysis reveals interesting patterns in the causal relationship between the BCP and CREA. In the east region, we observe that CREA was already high before the implementation of the BCP, suggesting that other factors may have played a significant role in driving adoption in this region. In contrast, in the west region, the BCP had a positive impact on the intention to adopt clean renewable energy after its implementation, indicating the potential for the BCP to facilitate adoption in this region.

Additionally, considering natural gas as a clean energy source in China, we find that the BCP led to a 1.38% increase in natural gas usage in the east region. This suggests that the BCP may have influenced the choice of clean energy sources, with a shift towards natural gas in this particular region. Furthermore, our analysis reveals that the impact of the BCP on CREA operates through three channels: population size, economic size, and income level. Cities with larger populations and greater economic size experience a more significant impact of the BCP on CREA in rural families. However, low-income families tend to prefer using fossil energy rather than clean renewable energy following the implementation of the BCP.

These findings provide empirical evidence for countries, particularly developing nations, that aim to leverage digital development for technological progress and industrial upgrading to reduce carbon emissions, increase CREA, and improve the welfare of residents. By understanding the heterogeneity of the effects and the underlying channels through which digital transition impacts CREA, policymakers can design targeted interventions and policies to promote sustainable energy practices and enhance overall societal wellbeing.

9 Further research direction

Building upon the findings of this study, future research should aim to further delineate the nuanced relationships between BCP and consumer behavior. The digital transition's varied impact on different industries and diverse household income levels, as well as consumption behaviors, warrants further exploration. Specifically, a deeper understanding of how digital tools like BCP can be optimized to stimulate CREA in different socioeconomic and industrial contexts is imperative.

Furthermore, it would be beneficial to expand the scope of this research to a broader geographical context. This study predominantly focused on rural families; however, the impacts of BCP and digital transitions might differ in urban settings due to contrasting living conditions, industry structures, and income levels. Cross-regional comparisons would provide comprehensive insights into the generalizability of the current findings.

In addition, the role of government policy in influencing and possibly amplifying the positive effects of BCP on CREA should not be overlooked. Policymakers should consider incentives to encourage the use of online platforms to promote energy efficiency and sustainable practices among citizens. Therefore, future research could examine how different policy interventions affect the relationship between BCP and CREA.

Lastly, it would be intriguing to examine the long-term impacts of changes in consumer behavior on energy consumption patterns. As income levels rise and consumption habits shift, what are the long-term implications for traditional and renewable energy usage? Unraveling the potential impacts of these dynamics could provide valuable insights into sustainable economic growth strategies and the promotion of energy efficiency in both rural and urban areas.

Data availability statement

The datasets presented in this study are a result of the combination of three separate datasets, namely: China Labor-force Dynamics Survey (CLDS), Data from Chinese Ministry of Industry and Information Technology, and China City Statistical Yearbook. These datasets have been integrated and summarized in the Supplementary Material.

Author contributions

JY: original writing and revision. JL: data collection. XL: data collection and polishing the paper. YL: supervision and polishing the paper. All authors contributed to the article and approved the submitted version.

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Supplementary material

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The impact of industrial structure upgrading and digital economy integration on China's urban carbon emissions

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This paper is based on the research hypothesis that the development of the digital economy can enable urban carbon emission reduction. We use the panel data of 275 prefecture-level cities in China from 2011 to 2019, the static panel-data interaction-effect model, and the panel-threshold model to verify the non-linear impact mechanism and heterogeneity of the digital economy in industrial structure upgrading affecting urban carbon emissions. The results demonstrate the following insights. First, due to the heterogeneity of industries, an increase in the proportion of the tertiary industry cannot reduce urban carbon emissions. Second, the digital economy has an inverted U-shaped adjustment effect on the process of industrial structure upgrading, affecting urban carbon emissions. Consequently, the integration and development of the tertiary industry and the digital economy can achieve urban carbon emission reductions. Finally, the digital economy has a double threshold effect on the process of industrial structure upgrading, affecting urban carbon emissions. The carbon-emission-reduction effect of industrial structure upgrading only appears after the scale of the digital economy crosses the first threshold. As the scale of the digital economy continues to increase, the carbon-emission-reduction effect of industrial structures is likely to continue increasing significantly. We recommend that local governments achieve urban carbon reduction by encouraging the development of high-end service industries and strengthening digital infrastructure.

KEYWORDS

carbon-emission intensity, industrial structure, digital economy, panel threshold model, nonlinear relation

1 Introduction

The global warming caused by carbon emissions is seriously threatening human survival and sustainable development; it is one of the major global challenges facing humanity today. Reducing carbon emissions and responding to increasingly severe climate change have become key issues of common concern to the international community. China's industry accounts for a relatively large proportion of the national economy, with problems of high energy consumption, high emissions, and low efficiency coexisting. According to data from the National Energy Administration and the Bureau of Statistics of China, China's energy consumption and carbon emissions in 2020 were 4.98 billion tce and 10.25 billion t CO_{2e}, making China the country with the largest energy consumption and carbon emissions in the world. China's energy consumption per unit of gross domestic product (GDP) is 3.4tce/10,000 US dollars, and its carbon emissions per unit of GDP are 6.7t/10,000 US dollars, which are 1.5 times and 1.8 times the world average annual level, respectively. As such, China is not only one of the world's largest emitters (Irfan et al., 2021) of greenhouse gases but also plays a crucial role in global climate governance. It is urgent that green development characterized by energy conservation and emission reduction be promoted. The 2022 report of the 20th National Congress of the Communist Party of China emphasizes that promoting green and low-carbon economic and social development is the key to achieving high-quality development. In this process, it is necessary to speed up the adjustment and optimization of industrial, energy, and transportation structures; improve the market-oriented allocation system of resources and environmental elements; accelerate the research and application of advanced energy-saving and carbon-reducing technologies; advocate green consumption; and promote the formation of green and low-carbon production patterns and lifestyles. The traditional view holds that the most direct path to carbon emission reduction is energy-utilization technology progress and energy-consumption structure adjustment (Lin and Jiang, 2009; Sarkodie and Strezov, 2019; Li and Wang, 2022). However, pure technological progress cannot solve the problem of carbon emissions caused by energy consumption. On the contrary, technological progress may create an "energy rebound effect" (Sorrell et al., 2020). Considering China's resource endowment status of being rich in coal, poor in oil, and low in gas, it will likely be difficult to change the energy consumption structure dominated by coal for many years (Lin and Li, 2015). Determining how to reduce excessive dependence on energy through industrial upgrading and industrial structure adjustment is the top priority. The research has shown that, based on accelerating the application and innovation of carbon-emission-reduction technologies, industrial restructuring is an effective way for China to achieve carbon emission reduction.

Following the traditional agricultural economy and the modern industrial economy, the digital economy, as a new economic form, has comprehensively reshaped and upgraded social production methods and people's consumption concepts. In addition, the digital economy has provided a key engine and driving force for China's economy to achieve high-quality development. Simultaneously, the digital economy is also an important driver and catalyst for industrial structure upgrading (Xuan, 2017; Li et al., 2021). The digital economy and upgrading of industrial structures promote one another, and their integrated development is likely to solve the problems of high pollution and emissions caused by energy dependence and the improper allocation of resources. According to the "White Paper on China's Digital Economy Development" (CAICT, 2021), China's digital economy will likely achieve a growth rate of more than three times the GDP from 2020, accounting for 38.6% of the GDP, and its scale has also achieved a historic breakthrough in reaching 39.2 trillion yuan. This demonstrates that the digital economy has become a fundamental driving force behind the steady growth of China's economy. In addition, the scale of digital industrialization and industrial digitization in 2020 reached 7.5 trillion yuan and 31.7 trillion yuan, respectively, accounting for 19.1% and 80.9% of the digital economy and 7.3% and 31.2% of the GDP. Some literature claims the digital economy can not only integrate and develop with traditional industries but also integrate and innovate with the fields of resources, energy utilization, and environmental protection (Shi, 2022). Whether the digital economy plays an effective role in the realization of China's "dual carbon" goals and how the role operates are questions worth exploring.

Scholars have conducted considerable research on the impact of changes in industrial structures on carbon emissions. Early scholars mainly focused on the distribution of production factors among different industries and related relationships and their impact on carbon emissions (Zhang and Choi, 2013; Lin and Benjamin, 2017; Hu and Sun, 2022). In this type of research, the measurement of industrial structures generally uses the proportion of the secondary or tertiary industry as a proxy variable. This research has shown that an increase in the proportion of the tertiary industry is conducive to the improvement of regional carbon emissions (Pao et al., 2011; Dong et al., 2018). Following this work, the research perspectives of scholars shifted from the proportion of industrial output to the impact of the evolution and upgrading of industrial structures on carbon emissions (Du et al., 2019). Such studies explored the evolution of primary, secondary, and tertiary industries in addition to changes in carbon-emission intensity during the process of industrial evolution. In other words, they analyzed the impact of advanced industrial structures on carbon emissions (Zhang et al., 2020; Wu et al., 2021; Xu et al., 2021). To explain the impact of industrial restructuring on carbon emissions more comprehensively, some scholars have begun to draw on the ideas of the Theil index and Lorenz curve to construct the industrial structure rationality and industrial structure high-level index (Zhang et al., 2022). This helps such scholars explore industrial restructuring's impact on carbon emissions from multiple perspectives, such as industry proportion, concentration, and reasonable distribution (Liang et al., 2021; Zhang and Xu, 2022).

In recent years, however, the digital economy has flourished and become a new engine of economic growth, and scholars have now begun to study the impact of the digital economy on carbon emissions. Research on the impact of digital economy development on regional carbon emissions is mainly carried out

from three perspectives. The first is to explore the impact of the digital economy on high-quality economic development from a macro perspective and based on qualitative research methods (Li et al., 2022; Zhang et al., 2022; Zhu X et al. 2022). The second relates to perspectives of technological progress (Kuang et al., 2020), urbanization processes (Li et al., 2021), inclusive finance (Dong et al., 2022), imports and exports (Ma et al., 2022; Zhong et al., 2022), and government intervention (Lin and Huang, 2022). These studies explore the impact of the path of digital economy development on regional carbon emissions. Finally, the third perspective mainly revolves around the energy-saving and emission-reduction potential of the digitization of industrial processes (Zhu Z et al., 2022; Wang et al., 2022).

In summary, scholars have conducted considerable and valuable research on the impacts of industrial structures and the digital economy on carbon emissions, which has laid a solid theoretical foundation for the writing of this paper. However, the digital economy does not directly affect carbon emissions. Instead, it indirectly affects carbon emissions through intermediate variables such as industrial structure and technological progress (Wang et al., 2019). As such, the aim of this paper is to investigate the non-linear effects and regional heterogeneity of the digital economy's impact on industrial upgrading and urban carbon emissions. This study focuses on 275 prefecture-level cities in China, where we initially computed the carbon-emission intensity of each city from 2011 to 2019 and examined its spatiotemporal pattern evolution. Next, we developed a panel-data fixed-effects model, which included interactive terms, to investigate the joint effects of the digital economy and industrial upgrading on changes in urban carbon emissions. Furthermore, we constructed a panel-threshold model to explore the threshold effect of the digital economy on the influence of industrial upgrading on urban carbon emissions and to analyze the heterogeneity of this impact in different threshold ranges. Finally, we proposed targeted policy recommendations, based on our conclusions, to effectively facilitate the transformation of urban economic growth and industrial structure upgrading, thus promoting the attainment of the carbon peaking and carbon neutrality goals. This paper answers the following three questions: First, does the digital economy have a regulating effect on the carbon-emission-reduction effect of industrial structure upgrading? Second, if there is a regulating effect, how do we determine the threshold interval of its effect? Third, within the range of different threshold intervals, what kind of heterogeneity exists in the direction and strength of the effects?

In addition, this study demonstrates innovation in three main areas. First, it verifies, from both theoretical and empirical perspectives, the moderating effect of the digital economy on the relationship between industrial upgrading and urban carbon emissions. This expands the research field of the low-carbon economy by considering the digital economy as a factor influencing carbon emissions. Second, this study uses a panel-threshold model to test the threshold effect of the digital economy on the relationship between industrial upgrading and urban carbon emissions and explore the mechanism and heterogeneity of this relationship in different threshold ranges. Third, this paper challenges how existing research has primarily focused on the impact of industrial upgrading on urban carbon emissions and has only provided theoretical guidance at the industry level for carbon emission reduction. This study instead highlights the joint impact of the digital economy and industrial upgrading on carbon emissions and proposes differentiated policy recommendations to promote urban carbon reduction through industrial upgrading at different levels of digital economic development.

The remaining sections of this article are structured as follows. Section 2 introduces the theoretical mechanism and research hypotheses. Section 3 outlines the methods and data utilized in this study. Section 4 presents and discusses the empirical analysis results. Section 5 discusses the research findings. The final section summarizes the conclusions and presents policy implications.

2 Theoretical analysis and hypothesis development

2.1 Industrial structure upgrading and carbon emissions

Existing research on the upgrading of industrial structures, whether from the perspective of industrial structure rationality or the industrial structure high-level index, is conducted around the proportion of the added value of the three industries. Scholars believe that the core content of industrial structure adjustment and upgrading is the joint transformation of primary and secondary industries into the tertiary industry, which ultimately leads to an increase in the proportion of the tertiary industry. In China, heavy industry means that it is the leading industry that provides the material and technological foundation for all sectors of the national economy. Among the three industries, the secondary industry has the most characteristics of energy dependence and carbon-emission intensity. Therefore, the upgrading of industrial structures helps to reduce the proportion of the secondary industry, especially heavy industry such as steel, energy, chemicals, and materials, and reduce the massive consumption of traditional fossil energy (Lin and Du, 2015). The development of China's economy in recent years has mainly been driven by investment, and its emphasis on industrial output inevitably increases its dependence on the input of production factors. This eventually leads to the characteristics of "high pollution, high energy consumption and low efficiency" in economic growth (Crompton and Wu, 2005). Encouraging and promoting the development of the tertiary industry can help reduce energy consumption in the production process, break through the rigid demand for energy in the economic system, improve the quality of economic growth, and reduce energy intensity and total carbon emissions. Moreover, the previous development of China's industry chose a capital-biased path, resulting in the industrial system's high dependence on chemical energy and hindering the optimization of energy consumption structures and the use of low-carbon clean energy (Wang et al., 2022). Vigorously developing the service industry, especially the producer- and technology-service industries, can promote the service-oriented transformation of industrial enterprises, improve production efficiency, reduce energy consumption per unit of product while producing high-value-added products, and ultimately achieve energy conservation

and emission reduction. Based on the above analysis, this paper presents the following hypothesis:

H1: An increase in the proportion of the tertiary industry will help reduce the energy dependence of the economic system and reduce the intensity of carbon emissions.

2.2 Tertiary industry heterogeneity and carbon emissions

Existing studies believe that the carbon-emission-reduction effect of industrial structure upgrading is also related to the nature of subdivided industries within the tertiary industry (Sun et al., 2021). According to the gap in technology intensity and per capita output value of different industries, the tertiary industry is usually divided into high-end, middle-end, and low-end industries. High-end industries generally include the financial industry, the computer service and software industry, technical services, and the geological prospecting industry. Middle- and low-end industries include transportation and postal services, wholesale and retail, leasing, and business services. Furthermore, different types of industries have different service targets. High-end industries generally target technology-intensive and high-end manufacturing industries, while low-end industries generally target labor-intensive and capital-intensive manufacturing industries. The varied proportions of different types of industries in the tertiary industry can directly affect the carbon-emission-reduction effect of the tertiary industry. The technology-intensive and high-end manufacturing industry is at the upstream end of the industrial chain, and the energy consumption and carbon-emission intensity per unit product are both relatively low. Therefore, if such industries account for a large proportion of the tertiary industry, the "economy of scale effect," "industrial structure upgrading effect," and "technology spillover effect" of industrial structure upgrading may be effectively introduced (Crompton and Wu, 2005). An increase in the proportion of the tertiary industry, especially the rapid development of the environmental governance industry and the public facilities management industry, is conducive to reducing the cost of environmental governance for enterprises. This makes it possible to centralize carbon-emission control and helps reduce carbon-emission intensity (Liang et al., 2021). In contrast, labor- and capital-intensive industries are at the middle and low ends of the industrial chain, respectively, and their energy consumption and carbon-emission intensity per unit of product are both relatively high. The increasing share of such industries in the tertiary sector is not conducive to carbon reduction and even inhibits the reduction of carbon-emission intensity (Wu et al., 2021). Therefore, this paper proposes the following hypothesis:

H2: The carbon-emission-reduction effect of the tertiary industry is affected by the heterogeneity of its internal industries. A large proportion of high-end industries will help reduce carbon-emission intensity; conversely, a large proportion of low-end industries will inhibit the reduction of carbon-emission intensity.

2.3 Industrial structure upgrading, digital economy, and carbon emissions

In contrast to traditional industries, the digital economy, as an emerging economic form, has an impact on the macroeconomic system through its technical and structural attributes (Chen et al., 2023). In addition to the widespread discovery that the development of the digital economy has accelerated an increase in the proportion of tertiary industries (Xu et al., 2022), within the tertiary industry, integration of the digital economy will likely reduce both the energy consumption per unit of product and the carbon-emission intensity of the industry, regardless of whether it serves low-end or high-end industries (Dong et al., 2022). As an emerging economic element, the digital economy has optimized or reshaped the way value is created after being fully integrated into the tertiary industry. For instance, it accelerates the process of upgrading industrial structures and reduces the carbon emissions of the secondary industry. Moreover, it directly reduces the carbon emissions of the tertiary industry. Therefore, it is expected that a greater level of digital industrialization and industrial digitization will lead to a larger scale of the digital economy and be more conducive to the exploration and carbon reduction effects of industrial structure upgrading.

First, the larger scale of the digital economy makes it more conducive to the energy-saving development of the tertiary industry. From the perspective of technical attributes of the digital economy, the rapid development of information technologies such as big data, cloud computing, and 5G intelligence has improved the speed and accuracy of business connections among enterprises in different industries and significantly reduced transaction and time costs among enterprises (Wen et al., 2022). For example, the rapid development of cloud computing and the Internet of Things has improved the calculation accuracy of transportation nodes and routes in the logistics industry. The rapid connection between the transportation industry and other industries, as well as the optimization of transportation routes, is expected to greatly reduce energy consumption during transportation and carbon-emission intensity (Zhao et al., 2022). Furthermore, the larger scale of the digital economy makes it more conducive to the development of environmentally friendly industries. Due to the structural attributes of the digital economy, the integration of information technology has accelerated the transformation and upgrading of traditional industries from extensive development to an environmentally friendly direction. Within the tertiary industry, industrial structures have changed from being labor and capital intensive to being technology intensive (Wen et al., 2023). Simultaneously, the digital economy has also spawned many emerging industries, most of which are technology-oriented and environmentally friendly while also promoting sustainable development. Emerging industries not only alleviate social employment pressure but also meet the requirements of the era of green development (Wang et al., 2022).

In summary, the development of the digital economy not only reduces the energy consumption of low-end industries at the

technical level but also reduces carbon emissions. At the structural level, the development of the digital economy can continuously promote the optimization of the internal industry structure of the tertiary industry. The optimization of industry structures significantly enhance the economic benefits per unit of energy, which then plays a role in promoting and improving carbon-emission intensity. Figure 1 has been drawn to describe the mechanism of the digital economy's impact on carbon emissions.

In view of these insights, this paper posits the following theoretical hypothesis:

H3: The carbon-emission-reduction effect of the tertiary industry is affected by the digital economy, and the carbon-emission-reduction effect of the digital economy can only appear when it reaches a certain scale.

In the following sections, we will use econometric methods to verify the validity of the above research hypothesis. Briefly, we will use the panel-threshold model to examine the nonlinear mechanism by which the digital economy moderates the impact of industrial structure on carbon emissions. Additionally, a series of robustness tests will be performed.

3 Materials and methods

3.1 Baseline regression model

According to the previous theoretical analysis, the scale of the digital economy has an impact on the carbon-emission-reduction effect of the tertiary industry. This section first constructs a static panel-data model to test whether the scale of the digital economy has a moderating effect on the carbon emission reduction of the tertiary industry. To reduce the influence of heteroscedasticity on the model, the following logarithmic processing is performed on all variables:

$$\ln CI_{it} = \alpha_0 + \alpha_1 \ln Str_{it} + \beta_i X_{it} + \mu_i + \nu_t + \epsilon_{it} \quad (1)$$

$$\ln CI_{it} = \alpha_0 + \alpha_1 \ln Str_{it} + \alpha_2 \ln Digital_{it} + \alpha_3 \ln Str_{it} \times \ln Digital_{it} + \beta_i X_{it} + \mu_i + \nu_t + \epsilon_{it} \quad (2)$$

Among these variables, i represents the city, t represents the year, ϵ_{it} represents the random disturbance item, CI_{it} represents the carbon-emission intensity, Str_{it} represents the industrial structure, X_{it} represents a set of control variables, μ_i represents regional fixed effects, and ν_t represents a fixed time effect. Formula (1) is a basic econometric model that simply examines the impact of industrial structure on carbon-emission intensity. To verify the regulating effect of the digital economy on the carbon-emission-reduction effect of the industrial structure, formula (1) is extended to include the interaction term between the digital economy and the industrial structure. In formula (2), $\ln Digital_{it}$ represents the scale of the digital economy, $\ln Str_{it} \times \ln Digital_{it}$ represents the interaction effect between the scale of the digital economy and the industrial structure, μ_i represents regional fixed effects, and ν_t represents a fixed time effect.

3.2 Panel-threshold regression model

If the scale of the digital economy has a regulating effect on the carbon-emission-reduction effect of the industrial structure, a reasonable range for the scale of the digital economy must be determined. For this reason, this section continues to build a panel-threshold regression model to examine the threshold value of the different adjustment effects of the scale of the digital economy on the carbon-emission-reduction effect of the industrial structure. The regression equation is as follows:

$$\ln CI_{it} = \alpha_0 + \alpha_{11} \ln Str_{it} \times d(q \le Digital_{it}) + \alpha_{12} \ln Str_{it} \times d(q > Digital_{it}) + \beta_i X_{it} + \epsilon_{it} \quad (3)$$

Compared with formulas (1) and (2), the meaning of the response variable in formula (3) has changed. Among the formula's variables, d(.) is the indicative function, Digital_{it} is the threshold variable, and α_{11} and α_{12} represent the elastic coefficients of the industrial structure to carbon-emission intensity at $q \le Digital_{it}$ and $q > Digital_{it}$, respectively. If the threshold is chosen reasonably, the estimates or signs of α_{11} and α_{12} should be significantly different. Formula (3) only analyzes the single-threshold effect. Given that the analysis process of multiple thresholds is similar to the single-threshold effect, it is not repeated. In the empirical analysis section, this paper conducts multiple-threshold verification and analysis.

3.3 Variable selection and description

(1) Interpreted variable: carbon-emission intensity (*CI*)

This paper uses the ratio of urban carbon emissions to GDP to represent carbon-emission intensity. It is worth emphasizing that urban carbon emissions are obtained according to the latest energy-data revisions (2015) of the National Bureau of Statistics of China. These values are then combined with the official websites of local energy bureaus from 2011 to 2018. Due to the use of different methods, the results obtained by using the apparent emissions accounting method and the sectoral method sometimes do not fully align.

(2) Core explanatory variable: industrial structure (*Str*)

Given that the explained variable in this paper is carbon-emission intensity, a high level of industrial structure is not selected to ensure the consistency of the data quality. However, the proportion of the added value, in GDP, of the tertiary industry in prefecture-level cities over the years is selected as the proxy variable.

(3) Threshold variable: digital economy (*Digital*)

Referring to the research results of Guo et al. (2020), based on the data of the inclusive finance index, the number of people in the computer service and software industry of information transmission, the number of internet broadband access users, the number of mobile phone users, and the telecom business income of each prefecture-level city over the years, this paper adopted the coefficient-of-variation method and the principal-component

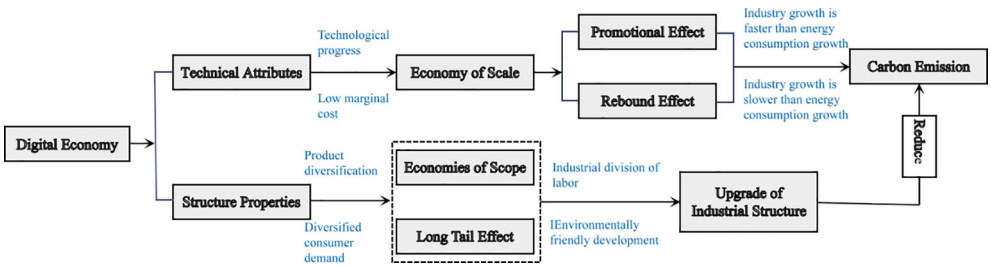


FIGURE 1
Transmission mechanism of carbon-emission-reduction effects in digital economy.

analysis method to calculate the scale of the digital economy as the proxy variable of the digital economy.

(4) Other control variables

An important control variable is energy efficiency under carbon-emission constraints (*CEE*). The improvement of energy utilization efficiency will likely reduce energy consumption, thereby promoting the reduction of carbon-emission intensity. This paper takes the energy consumption, employees, and capital stock of prefecture-level cities over the years as the input, the GDP as the desired output, and carbon dioxide as the non-consensual output. *CEE* is calculated using the super-efficiency SBM model. Population density (*Pd*) is measured by dividing the population of prefecture-level cities by the area of the administrative region. This variable indicates the impact of differences in the scale of population activities in each city. The degree of openness (*Open*) selects the ratio of the total import and export trade of the region to the GDP as a proxy indicator of the degree of openness. Government intervention (*Gi*) uses the proportion of regional fiscal budget expenditures in GDP over the years as a proxy indicator. Enterprise size (*Scale*) uses the ratio of the added value of enterprises above the designated size in prefecture-level cities in every previous year to the GDP as a proxy indicator.

Considering the integrity of the data and the impact of establishing or cancelling some prefecture-level cities on the balance of panel data, this paper excludes data from cities such as Danzhou, Bijie, Tongren, and Pu'er. Finally, this paper selects 275 prefecture-level cities in China from 2011 to 2019 as the research sample. It should be emphasized that we used data before 2020 for two reasons. On the one hand, China's economic data after 2020 has been deeply affected by COVID-19, resulting in large outliers in macroeconomic data. On the other hand, the urban traffic barring caused by COVID-19 epidemic control has had a significant impact on urban carbon emissions, which is difficult to include in the control variables, and the endogenous problem caused by omitted variables may be very serious. The data in this paper mainly derives from the "China Statistical Yearbook 2012–2020" (National Bureau of Statistics of China, 2012–2020a), "China City Statistical Yearbook 2012–2020" (National Bureau of Statistics of China, 2012–2020b), "China Energy Statistical Yearbook 2012–2020" (National Bureau of Statistics of China, 2012–2020c), "EPS database & WIND database"[1] and "China Energy Statistical Yearbook 2012–2020" (National Bureau of Statistics of China, 2012–2020d). Supplementary explanation: Some missing values of urban variables are filled in using the interpolation method. The specific indicators, data descriptions, and statistical descriptions are shown in Table 1.

4 Results

4.1 Kernel density estimation

The authors selected the data on carbon-emission intensity, industrial structure, and digital economy in 2011, 2013, 2015, 2017,

1 http://www.epschinadata.com/

TABLE 1 Variable definitions and descriptive statistics.

Variable	Definition	Sample size	Mean	Std. dev.
ln*CI*	Carbon-emission intensity	2,475	1.112	0.391
ln*Str*	Industrial structure	2,475	0.417	0.089
ln*Digtial*	Digital economy	2,475	8.631	0.954
ln*CEE*	Energy efficiency	2,475	0.424	0.122
ln*Open*	The degree of openness	2,475	1.221	0.426
ln*Scale*	Enterprise size	2,475	6.606	1.082
ln*Fi*	Government intervention	2,475	0.194	0.094
ln*Pd*	Population density	2,475	5.776	0.901

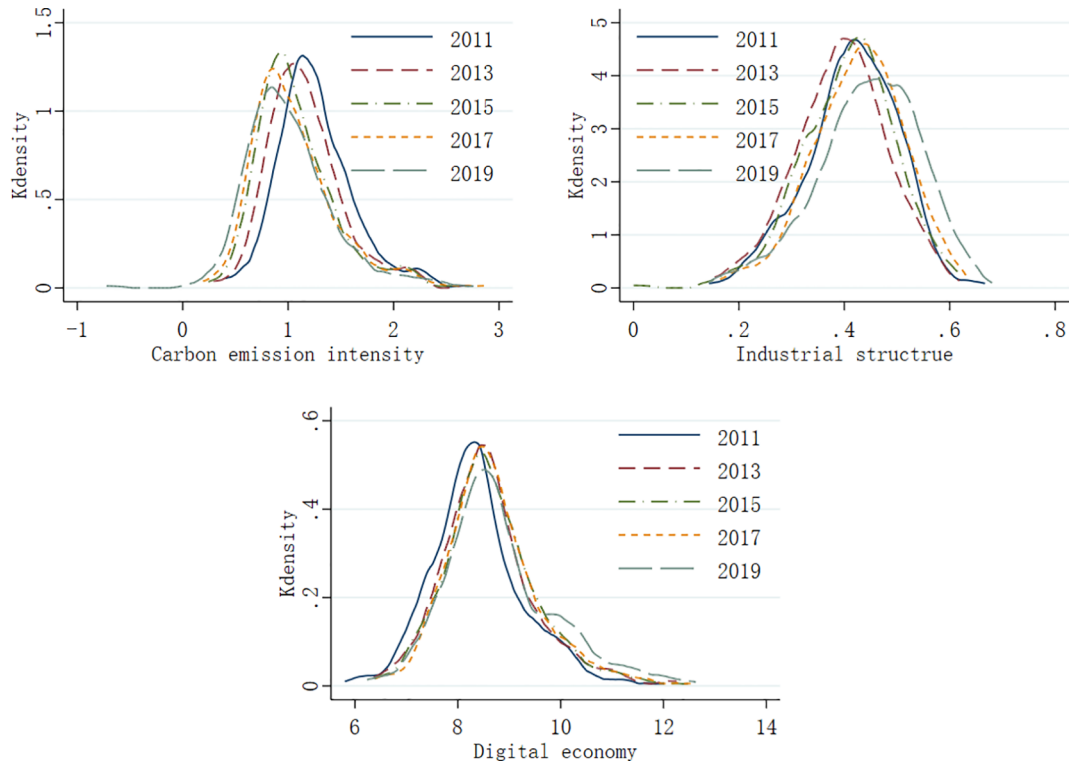


FIGURE 2
Variables' kernel density estimation.

and 2019, and we drew the kernel density map as shown in Figure 2. The results illustrate that urban carbon-emission intensity presents a unimodal distribution during the sample period. Furthermore, after 2015, the kurtosis gradually decreases, indicating that the regional differences in carbon-emission intensity are gradually shrinking. From the perspective of skewness, the kernel density curve of carbon-emission intensity in the sample period gradually tends to be left-biased and has a long tail to the right, indicating that the city's carbon-emission intensity is decreasing year by year. However, there are still high-emission areas. The kernel density curves for industrial structure and the digital economy also show a unimodal distribution. In terms of kurtosis, the industrial structure shows a downward trend during the sample period, while the digital economy shows an upward trend. This indicates that the differences in the industrial structure between cities are gradually shrinking, while the differences in the scale of the digital economy are gradually increasing. In terms of skewness, the industrial structure gradually shifts to the right and has a long tail to the left, while the digital economy gradually shifts to the right and has a long tail to the right. This shows that the proportion of the tertiary industry and the scale of the digital economy are increasing each year, but there are still areas with low proportions in the industrial structure. Moreover, areas with high-scale digital economies are also increasing each year.

4.2 Baseline regression

This paper uses the individual-time two-way fixed-effect model. In addition, it uses the urban carbon-emission intensity as the explained variable and the urban industrial structure as the core explanatory variable for regression analysis. The results are shown in Table 2.

Columns (1) and (2) in Table 2 are baseline regressions that do not consider other factors. These results indicate that industrial structure adjustment has a significant positive impact on urban carbon emissions. This conclusion is inconsistent with the research results of Jiang and Sun (2023), who found that the increase in the proportion of the tertiary sector of the economy is conducive to reducing urban carbon emissions. The main reason is that Jiang and Sun (2023) may have ignored the impact of tertiary sector industry heterogeneity on carbon emissions. The increase in the proportion of middle- and low-end industries in the tertiary sector of the economy cannot curb carbon emissions, while digital economy development has a significant negative impact on urban carbon emissions. Column (3) reflects the combined impact of industrial structure adjustment and digital economy development on urban carbon emissions, and the magnitude and direction of the two factors' coefficients show no significant changes. Column (4) builds on column (3) by adding the interaction term of industrial structure and digital economy development. The results indicate that the direction of digital economy development on urban carbon emissions has changed from the original negative impact to a positive impact, and the interaction between industrial structure and the digital economy has a significant negative impact on urban carbon emissions. Column (5), based on (4), adds control variables such as energy efficiency, government intervention, enterprise scale, degree of openness, and population density. The results show that industrial structure and digital economy development have a significant positive impact on

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TABLE 2 Regression results of the impact of industrial structure on carbon emissions.

	lnCI				
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Ln*Str*	0.647*** (0.099)		0.643*** (0.060)	2.556*** (0.598)	1.842*** (0.565)
Ln*Digtial*		−0.017* (0.009)	−0.015** (0.006)	0.085*** (0.030)	0.064** (0.030)
ln*Str* × ln*Digtial*				−0.223*** (0.065)	−0.162** (0.063)
Ln*CEE*					−0.162*** (0.063)
Ln*Fi*					0.760*** (0.182)
Ln*Scale*					−0.115*** (0.018)
Ln*Open*					−0.019* (0.011)
Ln*Pd*					−0.107** (0.054)
City fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
_cons	0.990*** (0.043)	1.397*** (0.080)	1.113*** (0.087)	0.258 (0.275)	1.881*** (0.393)
N	2475	2475	2475	2475	2475
R^2	0.439	0.411	0.441	0.447	0.553

Standard errors are in parentheses; * significant at 10%, ** significant at 5%, *** significant at 1%.

urban carbon emissions, with impact coefficients of 1.842 and 0.064, respectively. Furthermore, the interaction term between the two has a significant negative impact on urban carbon emissions, with an impact coefficient of −0.162. This shows that the digital economy has played a mitigating role in the process of increasing carbon emissions due to industrial restructuring. This result is consistent with the research conclusion of Hu (2023), who also found that the development of the digital economy has a positive regulatory effect in the process of exacerbating carbon emissions due to changes in industrial structures.

Among the control variables, government intervention has a significant positive impact on urban carbon emissions, with a coefficient of 0.760. Energy efficiency, enterprise scale, degree of openness, and population density all have significant negative effects on urban carbon emissions, with coefficients of −0.162, −0.115, −0.019, and −0.107, respectively. The results in columns (4) and (5) show that the digital economy has a significant moderating effect on the process of industrial structure affecting carbon emissions, and this effect is explained further in the threshold-effect analysis below.

4.3 Endogeneity discussion

There may be a specific endogenous relationship between industrial structure upgrading and urban carbon emissions. On the one hand, the transformation of the industrial structure from the secondary industry to the tertiary industry has created a reduction in energy dependence and consumption, thereby reducing urban carbon emissions. On the other hand, the constraints of urban carbon-emission targets may lead to government intervention, which in turn will promote the adjustment of industrial structure. Therefore, there may be an endogenous problem of reverse causality between industrial restructuring and carbon emissions. In the following, the instrumental variable method is used to solve the endogeneity problem in the model. We use the logarithm of the number of employees in the tertiary industry and its lag one period as well as the logarithm of the green coverage rate of prefecture-level cities and its lag one period as the instrumental variables of the industrial structure. The regression results for the instrumental variables are shown in Table 3.

The results show that the Durbin-Wu-Hausman (DWH) test results of all models rejected the null hypothesis at the significance level of 1%, indicating that the selected exogenous instrumental variables were correlated with the endogenous explanatory variables and could be identified. Among them, the Cragg-Donald Wald F statistic values of the weak instrumental variables test were 132.788, 141.104, and 119.233 respectively. All these values were significantly greater than the critical value of 16.85 at the significance level of 5%, rejecting the null hypothesis of weak instrumental variables. Simultaneously, in the regression results, the coefficient size, sign, and significance of the core explanatory variable and each control variable were also consistent with the benchmark regression. Based on the above analysis, it is determined that there is no endogeneity problem in the regression results statistically.

TABLE 3 Regression results of instrumental variable method.

	lnCI		
	Model (6)	Model (7)	Model (8)
ln*Str*	0.980*** [0.178]	0.894*** [0.158]	0.566*** [0.190]
ln*Digtial*		−0.076*** [0.008]	−0.057*** [0.009]
Control variable	No	No	Yes
City fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
RKF test	132.788	141.104	119.233
DWH p-value	108.092 (0.000)	107.652 (0.000)	89.059 (0.000)

The t statistics are in square brackets; * significant at 10%, ** significant at 5%, and *** significant at 1%.

4.4 Robustness check

The robustness of the model is tested by changing the control variable, reducing the control variable, increasing the control variable, and changing the time span. The results are shown in Table 4.

Model (9) uses the number of patent applications (ln*Tp*) in prefecture-level cities as the proxy variable of technological progress

TABLE 4 Robustness check.

	lnCI				
	Model (5)	Model (9)	Model (10)	Model (11)	Model (12)
Ln*Str*	1.842*** (0.565)	1.741*** (0.573)	1.292** (0.514)	1.913*** (0.581)	1.258* (0.715)
Ln*Digtial*	0.064** (0.030)	0.067** (0.031)	0.051* (0.028)	0.066** (0.031)	0.025* (0.039)
ln*Str* × ln*Digtial*	−0.162** (0.063)	−0.161*** (0.063)	−0.118** (0.058)	−0.171*** (0.064)	−0.069** (0.075)
ln*CEE*	−0.162*** (0.063)		−0.127** (0.059)	−0.229*** (0.065)	−0.288*** (0.092)
ln*Fi*	0.760*** (0.182)	0.850*** (0.204)	0.423*** (0.129)	0.774*** (0.184)	0.594*** (0.170)
ln*Scale*	−0.115*** (0.018)	−0.119*** (0.019)	−0.054*** (0.018)	−0.120*** (0.018)	−0.092*** (0.023)
ln*Open*	−0.019* (0.011)	−0.024** (0.011)	−0.010 (0.009)	−0.017 (0.011)	−0.017 (0.012)
ln*Pd*	−0.107** (0.054)	−0.126** (0.056)	−0.195*** (0.053)		−0.073 (0.054)
ln*Tp*		−0.013 (0.008)			
ln*Pgdp*			−0.274*** (0.041)		
City fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
_cons	1.881*** (0.393)	5.030*** (0.611)	5.227*** (0.543)	1.273*** (0.298)	1.753*** (0.462)
N	2475	2475	2475	2475	1925
R^2	0.553	0.542	0.604	0.551	0.377

Standard errors are in parentheses; * significant at 10%, ** significant at 5%, *** significant at 1%.

to replace ln*CEE* in the original model. Model (10) adds the control variable of economic development level based on the original model (5) (per capita GDP of prefecture-level cities is used as the proxy variable). Model (11) is based on the original model (5), and the control variable of population density is eliminated. Model (12) is based on the original model (5), and the sample years are shortened to 2013–2019. In the transformed models (9)–(12), the industrial structure, digital economy development, and their interaction terms saw no significant changes in the direction of effect or the magnitude of the coefficients, indicating that the original model is robust.

In addition, this paper draws on the research of Tang and Yang (2023), takes the "Broadband China" demonstration cities as quasi-natural experiment conditions, and assigns values to cities according to the 2016 "Broadband China" demonstration cities list published by the Ministry of Industry and Information Technology of China. We assign a value of 1 to the year and subsequent years when a certain city conducts the construction of the "Broadband China" demonstration city; otherwise, it will be 0. Due to the announcement of the three batches of demonstration city lists in the second half of the year, this article defines the year following the release of the "Broadband China" demonstration city list as the year of policy implementation and estimates the policy effects. The analysis is conducted according to the following model:

$$Y_{it} = \alpha_0 + \beta policy_{it} + \delta X_{it} + \mu_i + \nu_t + \epsilon_{it} \quad (4)$$

In the equation, Y_{it} is the dependent variable, representing the carbon-emission level of city i in year t. ν_t represents a fixed time effect, μ_i represents the individual fixed effects of each city, and ϵ_{it} is a random error term. X_{it} is a series of variables that may have an impact on the carbon emission levels of a region. $policy_{it}$ is the core explanatory variable, representing the dummy variable of the "Broadband China" demonstration city, and its coefficient β is used to measure the impact of the construction of "Broadband China" demonstration cities on carbon emissions. If β is negative and significant, it indicates that the construction of "Broadband China" demonstration cities can reduce carbon emissions levels. The specific results are shown in Table 5.

The results in column (1) of Table 5 show that the estimated coefficient of $policy_{it}$ is −0.041, which is significant at the 1% significance level without adding control variables. This result indicates that, compared to non-pilot cities, the implementation of the "Broadband China" pilot policy has reduced the carbon-emission intensity of pilot cities by 4.1%. The main reasons for this are twofold. On the one hand, the implementation of the "Broadband China" pilot policy has improved the level of internet infrastructure and accelerated the digitization process. On the other hand, the popularization of internet broadband has produced the digital economy. The inclusiveness of the digital economy is conducive to the surrender of funds from enterprises and individual investors to environmentally friendly industries, enabling widespread support for green technology and reducing carbon-emission intensity. In columns (2) and (3) of the table, industrial structure variables and other control variables were added in sequence, and the regression results were still significantly negative, in line with the expected assumptions.

The use of the Differences-in-Differences method for policy-effect evaluation must satisfy the premise that the control group and

TABLE 5 Differences-in-Differences regression results.

	lnCI		
	Model (13)	Model (14)	Model (15)
$policy_{it}$	−0.041*** (−3.971)	−0.039*** (−3.882)	−0.035*** (−3.491)
ln*Str*		0.918*** (0.215)	0.524*** (0.115)
ln*CEE*			−0.385*** (0.076)
ln*Fi*			0.553*** (0.148)
ln*Scale*			−0.158*** (0.018)
ln*Open*			−0.023 (0.012)
ln*Pd*			−0.013* (−1.74)
City fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	2475	2475	2475
R^2	0.227	0.231	0.312

*, *** represent significance at the level of 10% and 1%, respectively.

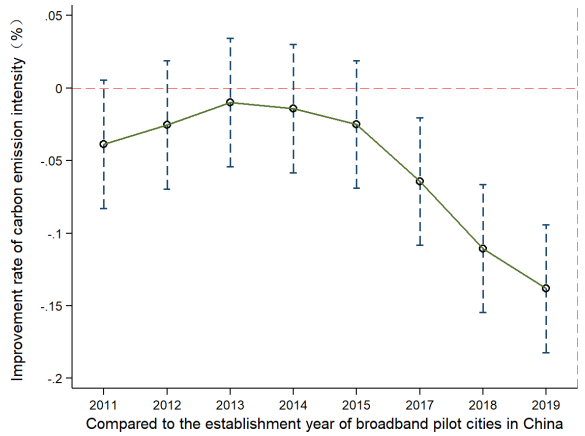


FIGURE 3
Parallel trend test results.

the experimental group have a common trend. Therefore, this article uses the dynamic Differences-in-Differences method for parallel trend testing, and the results are shown in Figure 3. Meanwhile, although the regression in Table 5 controls for a series of urban characteristic factors that affect carbon-emission intensity, there may still be some unobservable factors that change over time and location, which may affect the estimation results and lead to estimation errors. Therefore, this article uses an indirect placebo test to randomly select pilot cities for "Broadband China." According to the regression model in Table 5, 500 simulated regressions were repeated, and the results are shown in Figure 4.

The results in Figure 3 show that before the implementation of the "Broadband China" pilot policy, there was no systematic and significant difference in carbon-emission intensity between pilot cities and non-pilot cities. After the implementation of the policy, the differences between the two were significant, meeting the assumption of parallel trends, and the use of Differences-in-Differences is reasonable and effective. Similarly, the results in Figure 4 show that the P value distribution and the regression coefficient kernel density distribution of 500 simulated regressions essentially follow the normal distribution, which also indicates that the regression results are robust.

4.5 Digital economy threshold estimation

Building on the research of Wang and Li (2022), this paper uses the panel-threshold model to test the threshold effect of variables, and the results are shown in Table 6. The results indicate that, with the digital economy (lnDigtial) as the threshold variable, the single-threshold test is passed at a significance level of 1%. Furthermore, the double-threshold test is passed at a significance level of 5%, and the triple-threshold test does not pass the significance test.

After the threshold effect self-sampling inspection, the threshold value of the panel threshold model must be estimated and tested, and the results are shown in Table 7 and Figure 5. Table 7 illustrates the estimated values and confidence intervals of the two thresholds of the digital economy. Combined with the likelihood ratio function figure in Figure 5, the construction process of the estimated values and confidence intervals of the two thresholds of the digital economy can be understood more intuitively and clearly. When the likelihood ratio statistic LR takes a value of 0, the estimated values of the double thresholds corresponding to the digital economy are 8.366 and 9.237, respectively. The dotted line in Figure 5 indicates that, under the 95% confidence interval, all LR values of the two threshold estimates of the digital economy are less than the critical value (7.350) at the 5% significance level. Therefore, the digital economy development

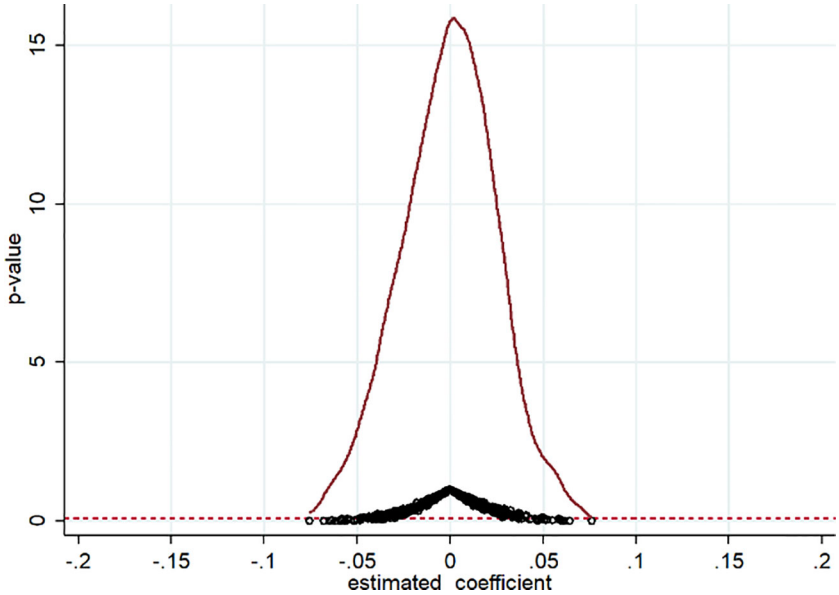


FIGURE 4
Placebo test results.

TABLE 6 Threshold effect self-sampling test.

Threshold variable	Explained variable	Threshold	*F*	*P*	BS times
Ln*Digtial*	ln*CI*	1	70.32***	0.007	300
		2	44.63**	0.050	300
		3	18.46	0.900	300

*significant at 10%, **significant at 5%, ***significant at 1%.

of China's 275 prefecture-level cities during the sample period can be divided into three levels: areas with a low level of digital economy development (lnDigtial < 8.366), areas with a medium level of digital economy development (8.366 ≤ lnDigtial ≤ 9.237), and areas with a high level of digital economy development (9.237 < lnDigtial).

The impact of different types of regional industrial structures on carbon-emission intensity is shown in Table 8. The results demonstrate that the industrial structure of prefecture-level cities in China had different impacts on carbon-emission intensity under different development levels of the digital economy during the sample period. In the low-level digital economy development area, although the significance test is not passed, the industrial structure has a positive impact on carbon-emission intensity, with a coefficient of 0.025. In the middle level of the digital economy development area, the impact of industrial structure on carbon-emission intensity has changed from positive promotion to negative inhibition, with a coefficient of −0.121, and the test is passed at a significance level of 10%. At the high level of digital economy development, the inhibitory effect of industrial structure on carbon-emission intensity is further increased, with a coefficient of −0.307, and the test is passed at a significant level of 1%.

The results demonstrate that the impact of industrial structure on carbon-emission intensity, along with the development level of digital economy, presents an inverted U-shaped action path of "first promotion, then inhibition, and then strong inhibition." This result aligns with the findings of Liu and Zhang (2023), who empirically examine the impact of the digital economy on carbon emissions as well as the mediating and threshold effects of different innovation modes. They found that the effect of the digital economy on carbon emissions has a threshold feature, with an inverted U-shaped relationship between the two, and that an increase in autonomous innovation and imitation innovation can enhance the digital economy's carbon-reduction effect. This impact path emerges because the increase in the proportion of the tertiary industry may have a restraining effect on carbon-emission intensity, and the quality of the tertiary industry is affected by the development of the digital economy. More specifically, as online sales are favored by consumers, the rapid development of the logistics industry is promoted. Without reaching a certain scale of the digital economy, the rapid development of the logistics industry inevitably leads to a sharp increase in energy consumption and thus carbon emissions. When the development of the digital economy reaches an ideal scale, the technical attributes of the digital economy will likely directly affect low-end industries, reducing their energy dependence and moderately reducing carbon emissions. When the digital economy reaches a larger scale, its structural attributes will likely affect the proportion of industries within the tertiary industry. The service objects of the industry are expected to gradually change from being labor and capital intensive to more advanced-technology intensive. Moreover, the energy dependence of the tertiary industry will likely decrease rapidly, thereby improving carbon-emission intensity significantly.

In summary, we have completed the empirical test of the three hypotheses proposed in Section 2. We found that developing tertiary industries does not reduce urban carbon emissions, and only when the scale of the digital economy reaches a certain level can the tertiary industry effectively reduce urban carbon emissions. In the following discussion section, we will review the main conclusions, research contributions, and limitations of this paper in detail.

In addition, this article defined three intervals for the development level of urban digital economy: ln*Digtial* < 8.366 is the first interval, 8.366 ≤ ln*Digtial* ≤ 9.237 is the second interval, and 9.237 < ln*Digtial* is the third interval. Subsequently, three years of 2011, 2015, and 2019 were selected for cluster analysis of cities in the eastern, central, and western regions of China in different years. The specific results are shown in Figure 6.

The results in Figure 6 indicate that the eastern, central, and western regions of China have converged over time in the three levels of digital economy development. The number of cities in the first region gradually decreased, while the number of cities in the second and third regions constantly increased. However, the proportion of cities suggests that the number of cities in the central and western regions increased significantly in the second and third intervals, especially in the third interval, compared to the eastern region. This indicates that the digital economy has had a more significant effect on regulating the carbon reduction effect of industrial upgrading in the central and western regions of China.

TABLE 7 Threshold estimation results.

Threshold	Estimated value	95% confidence interval
First threshold	8.366	[8.336, 8.371]
Second threshold	9.237	[9.206, 9.245]

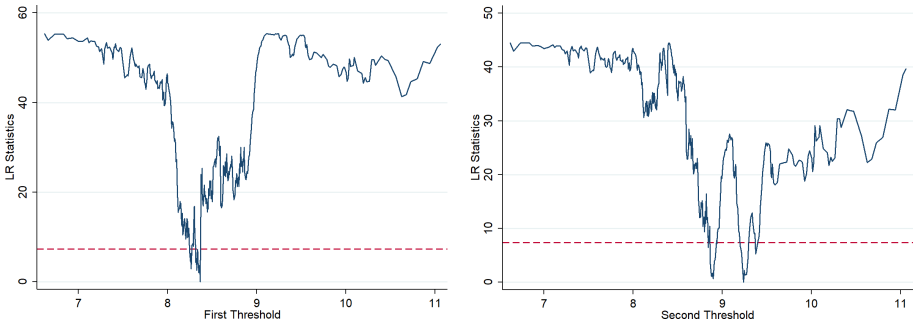


FIGURE 5
Double threshold estimation results and confidence intervals.

This also confirms that the digital economy mentioned above is different from the traditional economy and has the characteristics of "inclusive improvement" in carbon-emission reduction.

5 Discussion

This paper examines the current state of the digital economy, industrial upgrading, and carbon emissions across 275 prefecture-level cities in China from 2011 to 2019. It investigates the moderating influence of digital economy development on the effects of industrial upgrading on carbon emissions and employs the digital economy as a threshold variable to analyze the mechanisms and variations in the effects of industrial upgrading on carbon emissions within different threshold ranges. While this study focuses on prefecture-level cities in China, the methodology can be applied to explore the moderating and threshold effects of digital economy development on carbon emissions in other countries worldwide. Furthermore, this study introduces a new research paradigm for investigating energy conservation and carbon-emission reduction in urban areas. The detailed contributions of this paper are as follows.

First, this paper refines the scale of research on the impact of industrial upgrading on urban carbon emissions from the provincial to the prefecture level. Additionally, the spatiotemporal characteristics of the digital economy, industrial upgrading, and urban carbon emissions at the prefecture level are explored using kernel density estimation. The results demonstrate that the levels of digital economy development, industrial upgrading, and carbon-emission intensity in cities all exhibit a unimodal distribution during the sample period. Furthermore, the kurtosis of industrial upgrading and carbon-emission intensity exhibits a decreasing trend each year, indicating that the gap between cities in industrial upgrading and carbon-emission intensity is gradually narrowing. However, the skewness of the level of digital economy development shows an increasing trend each year, suggesting that the gap between cities in the level of digital economy development is widening. In terms of skewness, carbon-emission intensity and the level of digital economy development show a right-skewed trend, while industrial upgrading indicates a left-skewed trend. This suggests that there are still high-emission areas and areas with backward industrial upgrading in prefecture-level cities in China. These findings are consistent with the research conclusions drawn by Zhu Z et al. (2022).

Second, this paper uses a panel-data two-way fixed-effects model, including interaction terms, to analyze the moderating effect of the digital economy on the relationship between industrial upgrading and urban carbon emissions. Endogeneity exploration and robustness tests are conducted to ensure that the analysis results are scientific and accurate. The findings show that

TABLE 8 Estimation results of the digital economy double-threshold parameters.

Variable		$lnCI$		
		Coefficient	t value	95% confidence interval
ln*Str*	ln*Digtial* < 8.366	0.025	0.37	[−0.110, 0.160]
	8.366 ≤ ln*Digtial* ≤ 9.237	−0.121*	−1.76	[−0.256, 0.014]
	9.237 < ln*Digtial*	−0.307***	−4.31	[−0.446, −0.167]
Control variable		Yes	–	–
_cons		4.638***	16.68	[4.093, 5.184]
R^2		0.247	–	–
N		2475	2475	2475

*Significant at 10%, ***significant at 1%.

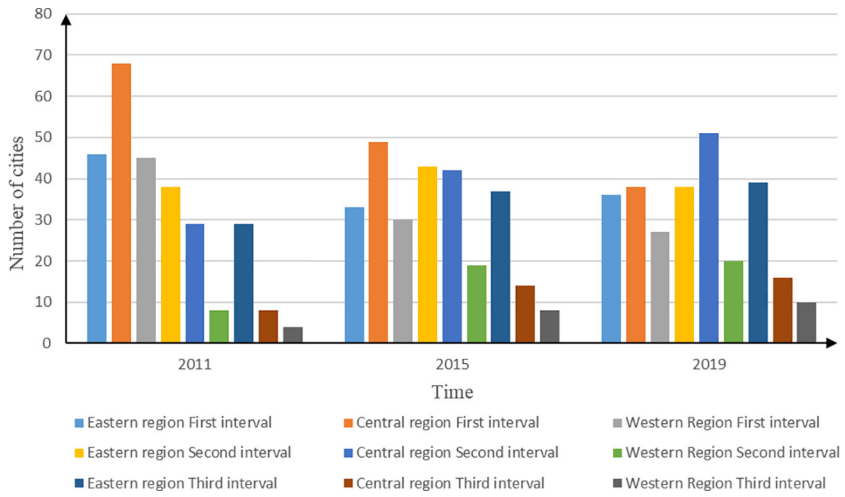


FIGURE 6
Cluster analysis of cities in different years and intervals.

both industrial structure and digital economy development have a significant positive impact on urban carbon emissions, with impact coefficients of 1.842 and 0.064, respectively. However, the interaction term between the two has a significant negative impact on urban carbon emissions, with an impact coefficient of −0.162. This indicates that the digital economy can mitigate the negative impact of industrial structural adjustments on carbon emissions. These results align with the findings of Zhang et al. (2022).

Finally, this study constructs a panel threshold model to test the threshold effect of the digital economy on the impact of industrial upgrading on urban carbon emissions. This model aims to explore the mechanisms and heterogeneity of the impact of industrial upgrading on urban carbon emissions at different threshold levels of digital economic development. The findings reveal a double-threshold effect of the digital economy on the impact of industrial upgrading on urban carbon emissions, with threshold values of 8.366 and 9.237. The results also demonstrate significant heterogeneity in the mechanisms of industrial upgrading of urban carbon emissions within different threshold ranges. More specifically, when the level of digital economic development is below the first threshold value, the industrial structure has a positive effect on carbon-emission intensity, with a coefficient of 0.025. After surpassing the first threshold, the effect of the industrial structure changes from a positive promotion to a negative suppression, with a significant coefficient of −0.121 at the statistical level of 10%. When the level of digital economic development surpasses the second threshold, the suppression effect of the industrial structure on carbon-emission intensity further increases, with a significant coefficient of −0.307 at the statistical level of 1%. Therefore, the authors conclude that the impact of the industrial structure on carbon-emission intensity follows a pathway of "first promotion, then suppression, and finally strong suppression" with the increase in the level of digital economic development.

This study has several limitations that should be acknowledged. First, the digital economy is a multifaceted concept, and the evaluation indicators used in this paper, such as the inclusive finance index, the number of people in the information transmission computer service and software industry, the number of internet broadband access users, the number of mobile phone users, and the revenue of the telecommunications industry, may not cover all aspects of the digital economy. Therefore, the indicator system used in this study may require further refinement. Second, the proxy variable used for industrial upgrading – the proportion of the added value of the tertiary industry to GDP – may not fully capture the direction of changes in the industrial structure. To ensure consistency in variable calculation across different cities, this proxy variable was used instead of more direct measures of industrial upgrading. This limitation suggests the need for further research to develop more comprehensive and accurate indicators of industrial upgrading.

6 Conclusions

Building a digital powerhouse and achieving the goals of "carbon peaking and carbon neutrality" are new consensus measures to promote high-quality economic development in the new era. Fully tapping into the energy-saving and emission-reduction "dividends" of the digital economy under the "dual carbon" goal is crucial for breaking the constraints of energy and environment while achieving the modern development of harmonious coexistence between humans and nature. To explore whether the digital economy is a "dividend" or a "negative benefit" for urban energy conservation and emission reduction, this paper used the panel data of 275 prefecture-level cities in China from 2011 to 2019. We adopted the static panel-data interaction-effect model and panel-threshold model to verify the path and heterogeneity of the digital economy to improve urban carbon emissions, which was based on the research hypothesis that the development of the digital economy

reduces urban carbon emissions. The main research conclusions are as follows. (1) Affected by the differences in industry characteristics within the tertiary industry, simple industrial restructuring cannot achieve urban carbon emission reduction. On the contrary, an increase in the proportion of tertiary industries will likely further worsen urban carbon emissions. As the object of this study is urban carbon emissions, this conclusion is not completely consistent with the conclusions of existing studies (Pao et al., 2011; Dong et al., 2018). This conclusion indicates that merely increasing the proportion of tertiary industries does not necessarily reduce carbon emissions and achieve green development in urban economies. The key lies in whether the secondary industry with high pollution is reduced and the proportion of high-tech, environmental protection, and high-end tertiary industries is increased (Han and Xie, 2017). (2) The digital economy has a significant inverted U-shaped regulatory effect on the carbon-emission-reduction effect of industrial structure adjustment, and the integrated development of the digital economy and the tertiary industry can achieve urban carbon emission reduction. Existing studies have found that the digital economy and industrial structure upgrading have a synergistic effect on carbon emission reduction (Zhu X et al., 2022; Wang et al., 2022), but the specific effect is still unclear. This conclusion explains why carbon emissions have increased in many places after the development of the digital economy. In addition, this conclusion shows that only when the digital economy develops to a certain extent and fully empowers the upgrading of industrial structures can it play a role in promoting carbon emission reduction. (3) The digital economy has a double-threshold effect in the process of industrial structure adjustment to promote carbon emission reduction, and the thresholds are 8.366 and 9.237, respectively. Based on how existing studies have recognized that industrial digitalization has a positive impact on energy conservation and emission reduction (Li and Huang, 2022; Zhang and Li, 2022), this conclusion further clarifies that industrial digitalization has a threshold effect in achieving carbon-emission reduction. Only when the digital economy reaches a certain scale can the adjustment of industrial structure exert its carbon-emission-reduction effect. With the continuous expansion of the scale of the digital economy, the carbon-emission-reduction effect of industrial structure adjustment will likely continue to increase significantly.

Based on the research conclusions of this paper, the authors offer the following policy recommendations. First, in the process of upgrading industrial structures, all regions should not only increase the proportion of the service industry but also encourage the development of high-end service industries. In other words, under the "dual carbon" goal and in the process of adjusting industrial structures and transforming economic growth modes, all regions should further increase the proportion and development speed of high-end industries in the tertiary industry. These regions should also promote the embedding of high-end industries in the manufacturing value chain and the transformation of the manufacturing industry from high energy dependence and high emissions to low emissions and low energy dependence. This suggestion can also provide a reference for other developing countries. Second, drawing on the experience of developed countries in Europe and America, local governments should pay attention to the coordinated development of digital industrialization and industrial digitalization. In other words, based on strengthening the innovation of digital technology, the integration of big data, AI, cloud computing, block chain, and other digital technologies with medium- and low-end industries in the tertiary industry should be strengthened. This creates opportunities regarding the technical-attribute dividends of the digital economy, further saves energy consumption in medium and low-end industries, and realizes energy conservation and emission reduction. Third, the spillover effect of the digital economy on carbon emissions reduction should be expanded. The digital economy can achieve cross-spatial trade cooperation and knowledge sharing, drive the joint development of upstream and downstream enterprises in the industry, and promote the dissemination and diffusion of green and low-carbon concepts. It not only has a significant impact on local carbon emissions but also significantly reduces the carbon-emission intensity of neighboring countries or regions. Finally, it creates opportunities for the synergistic effect of government and market in the low-carbon development of the industrial economy. On the one hand, efforts should be made to change the unbalanced distribution of digital infrastructure among cities. On the other hand, digital technologies, especially energy-saving and emission-reduction digital technologies, should be shared among cities to break through the "digital economic divide" between cities and realize the "inclusive improvement" of overall carbon emissions in cities.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

All authors contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by HJ, ZHC, and YL. The first draft of the manuscript was written by HJ and ZHC, and by ZYC. WZ, DL, and ZYC commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Can digital technology reduce carbon emissions? Evidence from Chinese cities

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Introduction: Global warming presents significant challenges to the sustainable development of human society. Accelerating the achievement of carbon peak and neutrality is the vision for creating a global ecological community with a shared future. The development of digital technology provides us with the direction of action.

Methods: Based on panel data from 276 cities in China from 2011 to 2020, principal component analysis was used to measure the basic state of digital technology at the city level, and the twoway fixed effects model and instrumental variable method to verify the impact of digital technology on carbon emissions from the perspective of technology diffusion.

Results: The results show that the deep diffusion of digital technology in the real economy sector is helpful to improve productivity and carbon efficiency, thus significantly reducing carbon emissions. The role of digital technologies in reducing carbon emissions is heterogeneous. The results of the sub-sample test show that digital technology has a stronger emission reduction effect in large-scale cities, resource-based cities, smart cities and emission trading policy pilot areas. Digital technology can reduce carbon emissions by improving energy efficiency, promoting green technology innovation, and promoting virtual agglomeration.

Discussions: The contribution of this paper is that it not only reveals that digital technology can reduce carbon emissions but also analyzes the emission reduction path of digital technology from a new perspective. The conclusion of this paper has implications for accelerating the diffusion of digital technology in the real economy sector to accelerate the realization of green production and cope with climate change.

KEYWORDS

digital technology, carbon neutrality, energy efficiency, green technology innovation, virtual agglomeration, technology diffusion

1 Introduction

The problem of climate warming caused by greenhouse gas emissions has become increasingly prominent. Dealing with climate change and controlling greenhouse gas emissions has become a common global challenge. According to World Bank data, global carbon emissions (CE) have increased 1.67 times in the past 30 years, from 20,625 (ten million tons) in 1990 to 34,344 (ten million tons) in 2019; At the same time, the global per capita GDP has increased by 2.63 times. As can be seen from Figure 1, there is a high correlation between economic development and CE.

According to the *AR6 Synthesis Report: Climate Change 2023* (IPCC, 2023), the global surface temperature in 2011–2020 is 1.1°C higher than in 1850–1900. Continued greenhouse gas emissions will further increase the global temperature rise. In the scenarios and model paths considered, the best estimated global temperature rise will reach 1.5°C in the near future (2021–2040) (IPCC, 2023). With the increase of global warming, the current feasible and effective adaptation measures will be limited, and the effect will be reduced. According to the World Bank, China's carbon emissions (CE) reached 9.899 billion tons in 2020, making it one of the world's highest carbon emitters. In 2020 alone, China's CO_2 emission reached 9.8 billion tons, accounting for about 31% of the global total (World Bank, 2022). As a result, China has become the focus of global efforts to reduce carbon emissions. In response to the deteriorating ecological environment, the Chinese government put forward the "dual-carbon" goal of peaking carbon neutrality at the 75th session of the United Nations General Assembly and incorporated "a steady decline in carbon emissions after peaking" into the 2035 vision goal. The 14th Five-Year Plan further defines an action plan to reach the carbon peak by 2030 while committing to reduce CO_2 intensity by 60% to 65% compared with 2005 and striving to achieve carbon neutrality by 2060.

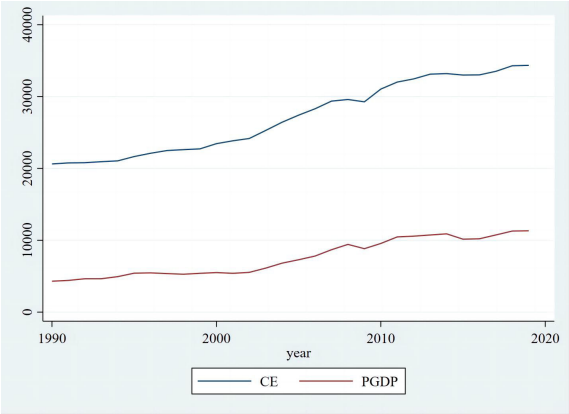


FIGURE 1
Global per capita GDP and carbon emission concentration from 1990 to 2019. Data Source: compiled by the author based on the open data of the World Bank. https://data.worldbank.org.cn/indicator?tab=all.

Digital technology (DT), a general term for emerging general technologies, including the Internet of Things (IoT), big data, cloud computing, and artificial intelligence, has been regarded as essential to promoting the "fourth industrial revolution." The steady advancement of DT in various fields has become an essential means to promote economic growth and a new way to promote industrial transformation. In the "digital" era, most cities face new opportunities for low-carbon development. According to *The Enablement Effect: The impact of mobile communications technologies on carbon emission reductions* jointly released by the Global System for Mobile Communications Association (GSMA) and the Carbon Trust, the application of mobile Internet technology in intelligent energy, smart agriculture, smart manufacturing, and smart cities has reduced global greenhouse gas emissions by about 21.35 tons in 2018 (GSMA and the Carbon Trust, 2019). Moreover, according to the SMARTer2030 report released by the Global E-Sustainability Initiative (GeSI), DT could reduce global carbon emissions by 20% over the next ten years by integrating with the enterprise and industry (GeSI, 2015).

As a representative of universal technology, the impact of DT on carbon emissions has attracted worldwide attention, but existing studies have yet to reach a consistent conclusion. Some studies believe that DT, as a force of creative destruction, can promote green technological innovation (GTI) and production process innovation and restrain CO_2 emissions (Aghion et al., 2021; Zhang Q. et al., 2022; Hu, 2023). Some other studies believe that DT is built based on electricity, and the development and operation of cloud, blockchain, data center, and other infrastructure require more and more energy-intensive infrastructure, which will cause more carbon emissions to some extent (Dhar, 2020; Noussan and Tagliapietra, 2020). Some other studies believe there may be a nonlinear relationship between DT and carbon emissions, which is affected by technology scale and diffusion speed. As one of the general-purpose technology (GPT), compared with the direct application of technology, the diffusion effect of DT in other fields deserves more attention. Different from the existing research, we not only discuss the direct technical effect of DT, but also pay attention to the carbon reduction effect produced by the technology diffusion process. On the basis of defining the concept of DT, an index system for measuring DT is constructed, and the panel data of 276 cities in China from 2011 to 2020 are used to further explore the impact of DT on carbon emissions and its mechanism from the perspective of technology diffusion, which can provide theoretical support and a practical basis for China to achieve the goal of carbon peaking and carbon neutrality.

This paper has the following research objectives:

(i) Establishing an evaluation index system for DT;

(ii) Estimating the impact of DT on CE based on measuring the level of carbon emissions at the city level;

(iii) Based on technology diffusion theory, to identify the mechanisms by which DT affect urban CE, which include potential direct and indirect mechanisms, among which, identify the important mechanisms of virtual agglomeration.

2 Literature review

2.1 Estimation study of CE

Since no exact data on carbon emissions are published, many scholars have done a lot of research on carbon emission measurement, and various measurement methods have been derived for different research objects and data. Currently, the three mainstream methods are the input–output method, which is applicable to calculate CE from single products or projects, the life-cycle evaluation method, which calculates CE from different industries, and the CO_2 emission factor method, which calculates CE at national, provincial and regional levels.

The input–output approach is to develop input–output tables to reflect the relationship between various sectors of the economic system, which can track direct and indirect energy use and CE of product production. For example, Zhang et al. (2021) combined the input–output method with the carbon emission factor method to measure the CE of 30 provinces and eight industries in China in 2018, and found that the thermal power generation and industrial emissions far exceeded the remaining six industries. The input–output method is comprehensive, but the method is less time-sensitive because input–output tables are compiled every five years in China. The carbon emission factor method involves summing the carbon emission factors of each energy source based on the product of the corresponding energy consumption to obtain the CE (Yang et al., 2021; Li and Wang, 2022). Alam et al. (2012) based on the IPCC method, calculated the relationship between energy consumption, electricity consumption, carbon emissions and economic growth; Chang et al. (2022) studied the changes in carbon emissions from 2003 to 2017 through the consumption side in China's national and regional power sectors using the log-average index (LMDI) model and estimated the carbon emissions from the power sector in each region through the production and consumption accounting principles, using two-factor ANOVA and one-factor ANOVA. The differences in regional power sector carbon emissions were compared by two principles; Feng et al. (2022) used the annual panel data of China from 1997 to 2017 to first analyze the spatial and temporal evolution process of CE, and then developed a spatial Durbin model and partial derivative method based on direct, indirect and total EKC, which yielded a positive spatial autocorrelation of CE with the center of gravity shifting westward. However, this method is difficult to calculate CE in the absence of carbon emission factor data, and the carbon emission factors may be affected by the level of technology, production status, energy use and process with large uncertainties. The life cycle approach is used to evaluate carbon emissions over the product life cycle, measuring the CE of a product from the time of resource extraction until the end of product disposal (Luo et al., 2022). This method can account for the direct or implied CE of a product, process, or production activity, but accounting is costly and time-consuming. Gustavsson et al. (2010) analyzed the carbon emissions of an eight-story wood-frame apartment building using the life cycle evaluation method and found that building operations used the largest share of life cycle energy use, and this share increased as the life of the building increasingly.

2.2 Study on the influencing factors of CE

Regarding the factors influencing CE, in terms of economic growth, Grossman and Krueger (1991) put forward the Environmental Kuznets Curve (EKC), which shows an inverted U-shaped relationship between economic growth and environmental pollution. However, Dogan and Turkekul (2016) showed that the increase in real output in the United States improved the ecological environment, and this finding does not support the EKC hypothesis. Wang et al. (2013) used the extended STIRPAT model to show that factors such as population, level of urbanization, level of industrialization, and level of services lead to an increase in CE, while technological progress, energy consumption structure, and degree of foreign trade leads to a decrease in CE. Recent studies suggest that the digital economy is also an important factor influencing CE (Liao et al., 2023). Kong et al. (2022) used the logarithmic mean divisia index model (LMDI) to analyze the influencing factors of China's carbon emissions. According to the empirical results, in the long run, technological innovation is essential for China to meet its carbon reduction commitments. Slower economic growth will delay the peak in carbon emissions and increase carbon intensity. Optimizing the industrial structure, reducing the size of the population, and adjusting the energy structure can reduce China's peak and carbon emissions, but the effect is negligible. Inah et al. (2022) studied the trend of CE and its reduction potential in the manufacturing sector in Nigeria from 2010 to 2020. They decomposed the changes in CE into pre-determined factors using the LMDI approach and concluded that energy intensity and equity-funded production were the main drivers of increased emissions, while productive capacity utilization reduced emissions; Yılmaz (2023) applied Granger causality tests and cointegration methods to explore the role of trade openness and energy use on CE in 30 countries in sub-Saharan Africa, showing that energy use has a significant long-term effect on the increase of CE while there is a positive bivariate causality between trade openness and CE.

2.3 Study on the impact of digital technology on CE

With the disruptive changes brought by DT and the rise of digital economy, more and more scholars have paid attention to the environmental effects brought by DT, and most of the studies have pointed out that DT plays a pivotal role in the environment, but there are different findings on the specific effects.

The positive effects are reflected in the following: At the macro level, Lahouel et al. (2021) based on Tunisia 1970–2018, pointed out that ICT technology is a key factor in mitigating climate change by reducing CE while promoting economic growth. Shahnazi and Shabani (2019) studied further stated that ICT technologies also have spillover effects, as local ICT technologies can effectively boost the demand for ICT products and services in neighboring regions while reducing the demand for traditional products, thus contributing to the reduction of CO_2 emission levels in

neighboring regions. At the industry level, the development of DT promotes digital industrialization, and digital technological innovation also promotes the continued emergence of green recycling and recovery models such as idle exchange, shared transportation, and waste recycling, as well as accelerates the breakthrough and application of renewable energy technologies, thereby reducing CE (Wang et al., 2021). At the micro level, Zhang (2023) pointed out that DT can facilitate the development of enterprise information and the application of new technologies to improve resource utilization, reduce environmental pollution, and improve the environment to some extent; DT also contribute to low-carbon formation through system integration, demand substitution for high-emitting products such as coal, and optimization of resource management and decision-making processes (Zhu et al., 2022).

The opposite opinion is that although DT advances are closely related to the solution of environmental pollution, the widespread use of DT inevitably leads to corresponding negative impacts. For example, Al-Mulali and Sab (2012) conducted an empirical analysis with data from 30 sub-Saharan African countries and found that under the influence of DT, energy consumption played an important role in the economic growth and financial development of the economies investigated, but the increased energy consumption also had high pollution consequences. Noussan and Tagliapietra (2020) assessed the impact of transportation digitization on energy consumption and found that the application of DT to transportation will increase the demand for transportation and expand the scale of transportation trips, resulting in more energy consumption. Dong et al. (2022) used data on the change and intensity of CE for 15 countries worldwide from 2000 to 2014 and found that the ICT industry is an important industry contributing to carbon emissions, where the manufacturing of computer, electronic and optical products accounted for 82.83% of global ICT implied CE.

There are also studies found a non-linear relationship between DT and CE. Li et al. (2021) introduced DT as a technological advancement into the Solow growth model and use fixed effects model to test empirically based on global panel data for 190 countries from 2005 to 2016, and the study found that there is an inverse relationship between CE and DT have an inverted U-shaped relationship, and argued that this inverted U-shaped relationship validates the EKC hypothesis. Li and Wang8 introduced digital factors as endogenous factors promoting technological progress into the production function, and study shows an inverted U-shaped relationship between DT and carbon dioxide emissions.

2.4 Research gap

In conclusion, there is no consistent answer regarding the specific impact of DT on CE, which may stem from differences in the selection of proxy variables for DT on the one hand, which are multidimensional and a combination of information, computing, communication, and connectivity technologies (Bharadwaj et al., 2013) and differences in carbon emission measurement methods on the other hand. In addition, the results of the study may have been influenced by regional heterogeneity. For example, estimates based on developed countries may differ from those in emerging countries, where DT is still in a period of rapid development; estimates should also differ in regions where environmental incentives have been adopted, where DT is more likely to promote (Akcigit et al., 2018).

At the same time, the discussion of the mechanisms by which DT affect CE is very inadequate. Existing studies are mainly based on the EKC hypothesis proposed by Grossman and Krueger (1991), which summarizes the mechanism of DT to reduce carbon emissions as technology effect and structural effect, such as Chen et al. (2023) and Wang H. et al., (2023), which identify the mechanism of green technological innovation or industrial structure upgrading; or summarizes the mechanism of DT to increase CE is summarized as the scale effect, i.e., DT makes enterprises improve production efficiency and expand production scale, which in turn increases carbon emissions, such as Zhang J. et al. (2022) and Li and Wang (2022). However, in fact, there are other mechanisms worth discussing for the effect of DT on CE, which is important for enriching the study of DT effects on CE and proposing the optimization path of CE in the digital economy era.

However, these discussions are all based on the impact of the development of DT itself on carbon emission reduction, and pay little attention to the diffusion of DT. In fact, the diffusion process of DT also has an important impact on carbon emission reduction, especially in the spatial change of industrial characteristics, which is very important for us to identify the mechanism of DT affecting carbon emission reduction. Based on the multidimensional definition of spatial agglomeration, this study is of great value in constructing the measurement index system of spatial agglomeration, discussing the impact of spatial agglomeration on urban carbon emission, and innovatively identifying the virtual agglomeration mechanism from the process of technology diffusion.

3 Theoretical mechanism and research hypothesis

Technology diffusion refers to the widespread and large-scale imitation and adoption of innovative outcomes after technological innovation (Tirole, 1988). The theory of technology diffusion was first proposed by American sociologist Everett M. Rogers in 1962 and was elaborated in his classic work, *Diffusion of Innovations*. Rogers (1962) discussed the behavioral patterns and characteristics of different types of individuals, such as innovators, early adopters, early majority, late majority, and laggards, in accepting and adopting new technologies. He also explored the factors and mechanisms that influence technology diffusion, providing an important intellectual foundation for subsequent research and practice. Subsequently, the theory of technology diffusion has been widely applied and developed, becoming an important tool and theoretical framework for studying social transformation, technological innovation, and market promotion.

As a new technology, DT can change existing high-energy production methods and factor structures in multiple aspects, achieving decarbonization effects, which is one of the direct

impacts of technology. On the other hand, DT is a typical general-purpose technology, which can also trigger imitation and innovation in other fields during the diffusion process: from the perspective of enterprises, it can stimulate them to improve energy efficiency and conduct environmentally-friendly green innovation based on digital technology innovation, thereby reducing urban carbon emissions; from an external perspective, knowledge spillovers brought about by the diffusion of DT will promote the optimization of factor allocation within a spatial range, thereby having a significant impact on urban carbon emissions reduction. Based on this framework, the theoretical logic of this paper is illustrated in Figure 2.

3.1 Direct impact of digital technology on CE

The main material carriers of DT are the Internet, AI and Quantum Computing and other high-tech services, which can facilitate faster information transfer and break the "data islands" formed by information asymmetry, therefore promoting the rational distribution of resources and energy, improving total factor productivity and helping to reduce CE. The purpose of promoting the construction of new digital infrastructure is to open the era of industry Internet, drive the digital transformation of transportation, industry and energy, and empower the green digital economy. DT can promote energy optimization, cost optimization, risk foresight and decision control in traditional industries, and overall realize energy saving and cost reduction as well as efficiency and quality improvement (Shen and Zhang, 2023).

Firstly, the new generation of DT provides new solutions for industrial green transformation and helps traditional manufacturing industries to "jump out of the factory" to develop green production. DT can be widely used in the industrial field of energy-saving transformation, material saving, accurate matching of supply and demand, logistics line optimization, material recycling and other production and circulation links. More and more industrial enterprises are using internet of things (IoT) to integrate sensors and devices into various environmental monitoring systems, and using DT such as supercomputers and cloud computing to integrate IoT in the environmental field to achieve environmental management and decision-making in a more refined and dynamic way. This not only helps to optimize the ultimate carbon handling technology for enterprises, but also helps to accurately measure the carbon footprint and thus track and monitor CE. For example, the Industrial Internet Identifier resolves the key issues of data reliability and data traceability in the field of carbon management, helping enterprises to set, adjust and achieve carbon emission targets more accurately. In addition to promoting the greening of industrial production, DT will also empower carbon management in the industrial sector. The integration of DT innovation management system through data resources provides strong support for building a powerful, extensive and accurate carbon data service platform and digital network system, which greatly reduces the cost of carbon information retrieval, classification and calculation, and improves the government's information sharing and intelligent management of carbon emissions, carbon sinks and other data resources. Improving the carbon trading market through DT helps eliminate the discrepancies between verified data and carbon emissions reported by enterprises on their own, enabling ecological and environmental departments to accurately and efficiently make carbon emission quotas among enterprises, while allowing enterprises with higher energy use efficiency to sell their excess emission rights to other enterprises, and it is DT that has developed carbon trading to encourage enterprises to take the initiative in energy saving and emission reduction.

Secondly, the carbon reduction effect of DT is reflected as a form of creative destruction, which can stimulate enterprises to GTI. DT can effectively break the path dependence of enterprise technological innovation, promote technological innovation in the direction of green, low-carbon, energy-saving and emission-reducing development and progress, which helps to enhance the level of GTI and promote the transformation of low-carbon economy. DT can reduce the transaction cost and information retrieval, effectively break the barriers to the flow of production factors between regions, therefore accelerating the flow of factors and providing multi-source knowledge for GTI. It can provide financial support for enterprise R&D by improving the availability of innovation and financial resources; the use of DT in the financial sector can also reduce the cost and threshold of financial services and ease the financing cost of enterprise innovation in many ways

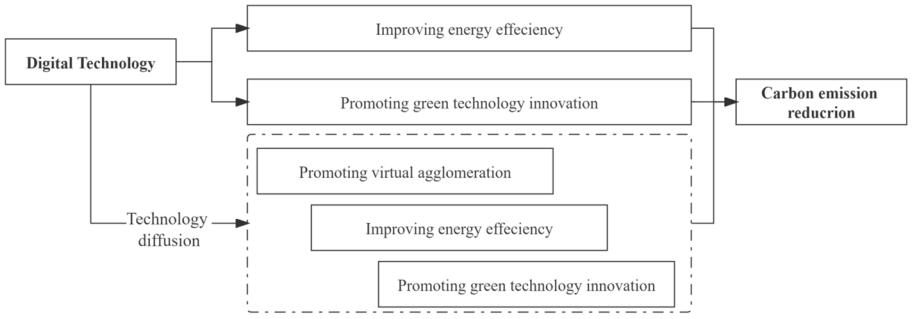


FIGURE 2
The theoretical framework of the paper.

(Aghion et al., 2021). On the other hand, DT is conducive to reducing search and transaction costs and therefore breaking the boundaries of enterprises, promoting frequent learning exchanges and knowledge sharing among R&D workers (Akcigit et al., 2018), and facilitating enterprises to accelerate the pace by improving the level of innovation cooperation. The carbon reduction effect brought about by GTI is reflected in the fact that innovative technologies such as clean production technologies and pollutant control technologies in GTI will help governments, enterprises, and residents to achieve efficient use of energy, therefore reducing the CE generated per unit of energy demand or increasing the economic benefits generated per unit of energy demand. For example, the development of new energy public transportation systems will improve the energy efficiency of public transportation by using cleaner fuels, especially in congested urban areas. On the other hand, the economic effects of GTI, while not having a direct impact on CE, can help maintain a steady growth in regional GDP by strengthening the technological frontier of society as a whole.

Thirdly, the carbon reduction effect of DT is also reflected in its ability to improve energy efficiency as a technological innovation. The application of DT can promote further integration of ICT into the real economy, accelerate R&D, optimize resource allocation, and improve energy efficiency. Data as a new factor can reduce the use of other factors, such as developing the value of data elements and optimizing the efficiency of factor allocation both to improve energy efficiency. A sharing economy based on DT can also improve energy trade and resource allocation efficiency by facilitating specific trade among energy market participants through multilateral platforms. Sharing platforms can match supply and demand data through big data, cloud computing and other technologies, optimize resource allocation through scale operations, reduce vehicle idling rates, reduce fuel consumption and lower CE. DT is also a reliable backing for renewable energy. At this stage, China's economic development process of energy demand is still increasing, subject to the influence of resource endowment characteristics, China's energy consumption products for a long time to coal-based. New energy applications face problems such as high operation and maintenance costs, difficulties in solving them, and unstable production, while DT can help the innovative development of new energy technologies, i.e. DT can help the change of new energy production management and marketing model, change the production chain and supply chain of new energy, and reduce the cost of operation and maintenance of new energy enterprises. In addition, the use of DT can also reduce the loss of new energy in the process of transmission, conversion and storage, achieve efficient allocation of energy through intelligent scheduling, and maximize energy efficiency. The application of DT reduces the cost of developing and using renewable energy and provides technical support for the large-scale use of renewable energy. In addition, through the control and restraint of DT informatization and intelligence, it can significantly reduce unnecessary energy consumption in economic activities and help solve the problems of energy crisis and environmental pollution. DT such as AI and deep learning can help energy producers achieve real-time monitoring and parameter control of the production process, thus improving the efficiency of energy production, energy transportation, energy distribution and energy storage, reducing the energy consumption of the production process and improving total factor energy efficiency. At the energy trading end, the platform economy based on DT can effectively solve the problem of information asymmetry between supply and demand, reduce the time inequality between supply and demand, and new generation DT such as LoT, 5G, and big data optimize the signal transmission process between energy supply and demand, reducing avoidable energy losses in the energy trade process. Moreover, higher energy efficiency means accomplishing the same tasks or production activities with less energy consumption. A considerable number of study has proven that when energy efficiency improves, the energy consumption required for the same amount of economic output decreases, leading to a reduction in carbon emissions (Hens et al., 2001; Hasanbeigi et al., 2013; Tajudeen et al., 2018; Na et al., 2022). The improvement of energy efficiency also implies the optimization of the factor structure within enterprises. As intermediate producers, these enterprises will reduce the procurement of high-emission energy and shift towards cleaner and lower-carbon renewable energy sources (Özbuğday and Erbas, 2015). This transition will transmit through the supply chain to other businesses, thereby driving the entire industry towards a green transformation and promoting carbon emissions reduction. Therefore, there exists a theoretical logic that digital technologies can exert a decarbonization effect by enhancing energy efficiency.

Based on the above analysis, this paper proposes the following research hypothesis:

H1: DT can reduce CE emissions.

H2: DT can reduce CE through mechanisms of improving EE and promoting GTI.

3.2 The mechanism of virtual agglomeration of industries

As Chandler (1962) points out, "The industrial revolution is inevitably accompanied by organizational change." The history of industry and technology also shows that every major technological change leads to a major change in the organization of production. The revolution in information technology has led to a spatial extension of the production and value chains of enterprises. Virtual agglomeration is based on the integration of DT domains, and production factors are clustered in virtual space with resource allocation optimization, empowering traditional cluster networks and eventually forming a borderless production network (Wang and Liang, 2022). It not only has the function of geographic agglomeration, but also has unique advantages in optimizing resource allocation and sharing knowledge and information interaction. The impact of industrial agglomeration on technology diffusion can be described by the "borehole model", which means that the process of industrial agglomeration accelerates the spontaneous flow of technology and other resources and promotes industrial technology diffusion.

According to Schumpeter's (1912) innovation theory, the innovation activity of enterprises is an important driving force for

economic restructuring and transformation of development mode. The mechanism of "creative destruction" caused by technological progress can help improve production efficiency and optimize industrial structure, laying a solid industrial and technological foundation for energy saving and emission reduction. Generally speaking, the labor pool, intermediate input sharing and knowledge spillover in industrial agglomeration are indispensable drivers of scale and technology effects (Hou and Zhou, 2023). For example, shared labor pools can deepen the division of labor specialization and improve the fit between the agglomeration and the labor force to improve production efficiency and resource utilization, and reduce energy consumption and carbon emissions. Upstream and downstream industry chain integration is conducive to saving production costs for agglomeration enterprises, promoting circular economy and achieving green economic growth.

With the development of a new generation of ICT, new infrastructures, as physical support for industrial digitization record the traces of economic activities such as production, exchange as well as flow of various resources in the physical space inside the cyberspace, break through the dependence of traditional industrial geographic agglomeration on spatial location, and promote the formation of a new organizational form of industrial virtual agglomeration based on close coupling between the real and the virtual. On the one hand, DT breaks the time and space constraints (Goldfarb and Tucker, 2019), reduces transaction costs, promotes the circulation of factors and resources, and provides a platform for clean industries to agglomerate in virtual space. The development of DT significantly reduces transaction costs and improves information asymmetry, builds a platform for energy trading and the interconnection of factors between regions and enterprises, and promotes the effective flow and rational allocation of various factors of production, such as knowledge, labor, and energy, in the virtual space. A typical example is the one-way bidding (online trading) in the carbon trading market, which promotes the clustering of emission reduction enterprises in the virtual space to sell excess allowances or produce CERs with higher efficiency, and emission control enterprises can also find more suitable trading partners on the virtual platform, which is supported by the development of DT such as Blockchain. DT also builds a platform for knowledge spillovers. DT promotes the rapid flow of data and knowledge, which can facilitate the subjects to break the boundaries of enterprises and form clusters in the virtual space; through the interaction with the star enterprises in the virtual space, it accelerates the knowledge dissemination and enhances the scale of virtual clustering and knowledge spillover (Chen et al., 2023).

The green transformation of a certain enterprise in the virtual space will form a knowledge spillover effect on other enterprises, therefore promoting the green transformation and industrial structure upgrading. For example, the China Industrial Enterprise Energy Control Center, by establishing a data exchange and fusion interface, realizes the sharing of enterprise data resources and information fusion, helps the efficient use of energy big data, promotes the virtual agglomeration of using energy enterprises, and also promotes the development of carbon trading, carbon finance and other industries. DT will also promote further specialization division of labor and advance the ICT industry in virtual space clustering, forming the so-called specialization clustering. As DT is a modular hierarchical architecture, the development of a certain module requires the cooperation of other modules. In order to reduce the cost of communication and cooperation between modules, each module can form a virtual agglomeration effect in the form of interface. virtual agglomeration of ICT industry can bring into play the scale effect of digital industry, so that industrial enterprises can obtain the DT they need to introduce at a lower search cost and reduce the fixed capital investment of using DT for green transformation. When virtual agglomeration reduces the technology investment cost for green transformation of industrial enterprises, it can further expand the scale of agglomeration by exerting Metcalfe effect, and even promote the transformation of virtual agglomeration to physical agglomeration. At the same time, according to Krugman's (1991) opinion, industrial agglomeration has technology diffusion effect, and there is a self-reinforcing relationship between the two that is interlinked and mutually reinforcing. Virtual agglomeration also has the same effect, that is, DT on the one hand enhances the level of virtual agglomeration; on the other hand, the development of virtual agglomeration can accelerate the speed of technology diffusion, promote the application and dissemination of DT in industrial enterprises, break the path dependence of enterprise green innovation, and thus enhance the enthusiasm of enterprise green innovation and promote energy conservation and emission reduction. Accordingly, this paper proposes research hypothesis 3:

H3: DT can reduce CE by increasing the virtual agglomeration of industries.

4 Research design and data sources

4.1 Variable setting

4.1.1 Explained variable

Carbon emission (CE). CE is measured using carbon emission intensity per unit of GDP. Given the availability of data related to CE at the city level, this paper uses the apparent emission accounting method to measure carbon dioxide emissions. In general, urban CE include both CE from direct energy consumption, such as gas and LPG, and CE from electrical and thermal energy consumption. Therefore, the carbon sources for measuring carbon emissions at the city level in this paper are mainly four types of energy consumption: natural gas, lp-gas (LPG), coal electricity and thermal energy. Drawing on the approaches of existing studies (Shan et al., 2022; Jing et al., 2023), the basic equation for carbon accounting provided by the IPCC 2006 Guidelines for National Greenhouse Gas Inventories is used to obtain the total CE of cities by multiplying the amount of activities that result in carbon emissions from production or consumption with the CO_2 emission conversion factor (IPCC, 2006).

The direct energy types include LPG and natural gas. The measurement process is to calculate the CE from direct energy consumption of the city with the carbon conversion factors published by the IPCC (2006). Indirect energy consumption is

electrical energy and thermal energy, where the CE from electrical energy consumption are directly calculated using the corresponding carbon conversion factors, while thermal energy is supplied in different ways and most of them use raw coal for heating. In this paper, according to Wu and Guo (2016), the thermal efficiency value is chosen as 70% and the average low level heat of raw coal is chosen as 20908 kJ/kg, and then the CE from heat supply are first converted into the required amount of raw coal according to the total amount of heat supply, and then calculated according to the carbon conversion factor of raw coal published by the IPCC (2006). Finally, CE from direct energy consumption and indirect energy consumption were summed up to get the total CE of each city.

4.1.2 Core explanatory variable

Digital technology (DT). Cloud computing, artificial intelligence, big data, the Internet of Things, and blockchain technology form the fundamental support of digital technology and provide solid technical support for various digital application scenarios. Digital application is a specific item of technology in the economy and society, which can effectively reflect the integration degree of digital technology with physical enterprises and daily life (Liu et al., 2022). Digital activities represented by digital industry sector, digital service application and e-commerce are different stages in the era of digital economy (Bukht and Heeks, 2018). The digital industry represents the development direction and latest achievements of the new generation of digital industry sectors, reflecting the industrialization characteristics of the digital economy, including the proportion of computer services and software employees and the level of digitalization of enterprises. Similar to the telephone penetration rate symbolizing the service subject of digital applications, digital finance is the concrete manifestation of digital platforms and digital services. The methods used in existing studies to measure the degree of digital technology are mainly the compilation of relevant indices, the construction of satellite accounts, and the accounting of value added. The compilation of relevant indices compilation is widely used in studying the social effects of digital economy by virtue of its high data availability, breadth of content coverage, and accounting treatment of indicators, which is more advantageous (Zhao et al., 2020; Ma et al., 2022; Zhang K. et al., 2022; Zhao et al., 2023). According to the published articles, we use the comprehensive index evaluation method to measure the level of digital technology development at the city level (Chen et al., 2022; Wang J. et al., 2023; Liu et al., 2022; Vărzaru, 2022; Chen Y. et al., 2023; Wang H. et al., 2023). Combining the availability of city-level data, this paper measures the comprehensive development level of digital technology in each city from five aspects: broadband Internet foundation, mobile Internet foundation, information industry factor inputs, telecommunication industry output, and digital inclusive finance. To achieve comparability of the comprehensive index across periods, this paper uses the global factor analysis method to calculate the DT development level. This method can well cover all characteristics of the original data, avoiding the subjectivity caused by artificially determined weights, and eliminating the bias of results caused by overlapping information of indicators. The evaluation index system of DT and its description are shown in Table 1.

4.1.3 Mediating variables

Energy efficiency (EE). Influenced by the characteristics of resource endowment, most of China's urban energy consumption products are mainly coal for a long time, and a large amount of energy consumption will inevitably be accompanied by the generation of a large amount of carbon emissions. Improving the EE use is one of the important ways to achieve carbon emission reduction. If we can reduce energy consumption and improve energy efficiency and utilization rate of renewable energy with the same output, we will be able to effectively mitigate the rising trend of carbon emission intensity. In this paper, the energy intensity of each prefecture-level city is used to measure its energy efficiency, which is the energy consumption per unit of GDP. Lower values of this variable indicate higher energy efficiency.

Green technological innovation (GTI). GTI is the general term for low or even zero pollution technologies, processes and products that follow ecological principles and ecological economic laws, save resources and energy, avoid, eliminate or mitigate ecological pollution and damage, and minimize negative ecological effects, and are innovative technologies that help save resources, improve energy efficiency, prevent and control pollution, and achieve sustainable development, mainly including innovative technologies in alternative energy, environmental materials, energy conservation and emission reduction, pollution. It mainly

TABLE 1 Digital technology evaluation index system.

Indicators	Secondary Indicators	Indicator Description
DT	Broadband Internet Foundation	Internet broadband access subscribers per 100 people
	Mobile Internet Foundation	Number of cell phone subscribers per 100 people
	Information industry factor input	The proportion of the number of employees in the information transmission, computer services and software industry to the total number of employees in urban units
	Telecommunications industry output	Telecommunications business income per capita
	Digital Inclusive Finance	Peking University Total Digital Inclusive Finance Index

includes innovative technologies in alternative energy, environmental materials, energy conservation and emission reduction, pollution control and management, recycling, etc. R&D investment as a sunk cost is not an output efficiency, and the use of this indicator to measure the potential innovation capability of enterprises lacks relevance and precision, while the number of patents can visually reflect the technological innovation capability of enterprises (Fang and Na, 2020). Green invention patents are breakthrough innovations in products or processes that help enterprises achieve energy saving and carbon reduction goals. In this paper, the number of invention patents and utility patents related to environmental protection applied by enterprises in each prefecture-level city is selected to measure GTI.

Virtual agglomeration (VA). VA among enterprises is the process of system coordination. The geographical agglomeration and virtual agglomeration of upstream and downstream associated enterprises in the industrial chain have intertwined coupling relationship, which is a cyclic mechanism of mutual promotion and symbiosis. The important realization carrier of virtual agglomeration is Internet and information technology. Although the digital content and network services of enterprises are themselves realized through the cloud, the digital content and services formed by virtual agglomeration are essentially the concrete results of resource input and output, not virtual. The digital services are realized through the medium of products such as big data, expertise, creative design, and blockchain. In this paper, we use the locational entropy method to calculate the virtual agglomeration of industries in each city based on the idea of existing literature (Zhang and Ru, 2021). In general, the more people employed in a particular industry in a region means the more developed the industry is. Therefore, this paper uses information transmission, computer service and software employees as important indicators of virtual agglomeration and uses the locational entropy method to measure them. Because virtual agglomeration is less restricted by geographic space, it will often have spillover effects on surrounding cities through virtual network space. However, the traditional industries integrated into the virtual agglomeration platform are the foundation of the cluster, so the spillover effects also have spatial "distance attenuation." By using the potential market model and adding inverse geographical distance weight to the location entropy method, virtual agglomeration can be better distinguished from traditional agglomeration (Liu et al., 2023). The calculation method of VA is as follows:

$$VA_{it} = \sum_i \left(\frac{ICT_{it}}{Total_{it}} \Big/ \frac{ICT_t}{Total_t} \right) d_{ij}^{-1} \quad (1)$$

In Eq. (1), d_{ij}^{-1} is the weight of the spherical geographical distance between city i and city j, calculated by GIS software. ICT_{it} is the number of people employed in the information transmission, computer services and software industries of City i in year t; $Toatl_{it}$ is the total number of jobs in city i in year t; ICT_t is the total number of people employed nationwide in the information transmission, computer services and software industries; $Total_t$ is the total number of jobs in all industries nationwide. Finally, in order to eliminate the causal relationship between industries and the development of science and technology, this study calculated the direct consumption coefficient of digital factors of each industry at the national level based on the data of the OECD input–output table and used the direct consumption coefficient of digital factors at the industry level to match with the micro-data of the first national economic census at the industry level. Then, the proportion of industry output in each city during the initial period of the study sample is taken as the weight, and the digital service input at the industry level is weighted at the city level.

4.1.4 Control variables

Since there are many external factors affecting CE, according to published articles on the impact of carbon reduction (Chen et al., 2016; Han et al., 2017; Guo et al., 2022; Xu et al., 2022; Luo et al., 2023; Shen and Yang, 2023), six control variables were selected to minimize the problem of bias in the model fitting results.

Population density. Energy consumption increases as population increases, which brings about an increase in overall carbon emissions. In this paper, the population density is measured by dividing the year-end population of each prefecture-level city by the year-end administrative area of that prefecture-level city.

Level of financial development. Credit supply can exacerbate energy consumption by stimulating consumption and industrial investment, which in turn increases CE. But at the same time, finance can reduce CE by supporting technological innovation and promoting the transformation of traditional industries into cleaner ones. In this paper, the total financial deposits and loans of each prefecture-level city in the past years are used to measure the level of financial development of a city.

Foreign direct investment (FDI). FDI is beneficial to both economic growth and the introduction of carbon-reducing technologies and equipment to drive local enterprises to innovate on their own and improve energy efficiency, thereby reducing carbon emissions. However, the purpose of FDI into the host country may be to transfer the high energy consumption and pollution-intensive industrial enterprises in the home country, and there is a "pollution sanctuary" effect, which aggravates carbon emissions. In this paper, the total amount of actual FDI utilized by each prefecture-level city is used to measure the openness of a city.

Government spending. The tangible hand of the government is an important channel to influence economic development and ecological environment. Local governments will make economic construction a key point of fiscal spending to attract enterprises to invest and set up factories locally by vigorously building infrastructure, lowering or exempting taxes and fees, and reducing environmental regulation. Local governments' eagerness to attract investment may weaken regional environmental quality standards and indirectly connive at enterprises' CE. In this paper, we measure the level of regional government spending by the share of local fiscal spending in urban GDP.

Infrastructure. Driven by the demand for infrastructure development, emerging economies have played an important role in increasing global production capacity in recent years, and their carbon emissions have increased rapidly, becoming the main driver of the increase in CE from major energy infrastructure.

Infrastructure development in cities will play an important role in promoting zero-carbon energy development as a key technology vehicle for achieving carbon neutrality goals. This paper uses road area per capita to measure the level of infrastructure in cities.

Industrial structure. According to the new structuralist economic theory, the industrial structure is both a "resource converter" of various factor inputs and outputs and an "environmental controller" of various pollutant types and quantities (Yu, 2017). The type of combination and intensity of adjustment of factors in different sectors within an industry determine the economic efficiency and energy use efficiency of the industry, which has an indirect impact on resource consumption and environmental pollution. In this paper, the ratio of regional tertiary industry output value to secondary industry output value is used to measure the industrial structure of cities.

4.2 Econometric model

Based on the aforementioned theoretical assumptions, the following econometric model is constructed to test the direct impact of DT on carbon emissions:

$$CE_{it} = a_0 + a_1 DT_{it} + \sum a_2 X_{it} + \nu_i + \mu_t + \varepsilon_{it} \quad (2)$$

In Eq. (2), the subscripts i and t are city individuals and time, respectively, and X denotes the set of information on a series of control variables. ν_i denotes individual fixed effects, μ_t denotes the time fixed effects, ε_{it} denotes the error term that obeys the white noise process, a_0 denotes the constant term, and a_1 and a_2 are the regression coefficients of digital technology and control variables, respectively, where the coefficients of significance and sign direction are the focus of this paper. If the sign is negative and passes the significance test at least at the 10% level, it indicates that hypothesis H1 is valid and DT can reduce CE. On the basis of Eq. (2), combined with the method and operation process of the mediating effect test recommended by Jiang (2022), the article constructs the following three models to test whether research hypotheses H2 and H3 are valid:

$$EE_{it} = b_0 + b_1 DT_{it} + \sum b_2 X_{it} + \nu_i + \mu_t + \varepsilon_{it} \quad (3)$$

$$GTI_{it} = c_0 + c_1 DT_{it} + \sum c_2 X_{it} + \nu_i + \mu_t + \varepsilon_{it} \quad (4)$$

$$VA_{it} = d_0 + d_1 DT_{it} + \sum d_2 X_{it} + \nu_i + \mu_t + \varepsilon_{it} \quad (5)$$

In Eq. (3) to (5), the b_0, c_0, d_0 are the constant terms, b_1, c_1, d_1 denote the numerical technical regression coefficients, and b_2, c_2, d_2 denote the regression coefficients of the control variables, and the meanings of the remaining symbols and letters remain the same as in Eq. (2).

4.3 Data sources

Following the principles of data availability and comparability, the article eliminates the sample of cities with more changes in city level and missing values, such as Bijie, Tongren, Laiwu, and Chaohu, which are affected by the policy of "abolishing counties and establishing districts", and the cities of Altay, Riqaze, and Linzhi, which have serious missing data, and finally selects the panel data of 276 cities in China from 2011 to 2020 as the statistical sample. The panel data of 276 cities in China from 2011 to 2020 were selected as the statistical sample. The original source of each data item is various statistical yearbooks published by the National Bureau of Statistics. The data on energy consumption, electricity consumption and transportation for calculating carbon emissions and their conversion factors are mainly derived from the China Urban Statistical Yearbook, China Statistical Yearbook, China Urban Construction Statistical Yearbook, IPCC 2006 Guidelines for National Greenhouse Gas Inventories, and China Regional Grid Baseline Emission Factor Report. The data for measuring DT-related indicators are derived from the Digital Inclusive Finance Index of Peking University and the China Urban Statistical Yearbook. The data for the remaining indicators are mainly derived from the China City Statistical Yearbook, the China Regional Economic Statistical Yearbook, the National Economic and Social Development Statistical Bulletin of each city, and the Bureau of Statistics, the China Academy of Information and Communication Research, and the China National Intellectual Property Administration (CNIPA). Very few missing values are filled in using the linear interpolation method of yes. In addition, to reduce sample fluctuations, all variables are logarithmized in this paper. The descriptive statistical analysis of each variable is shown in Table 2.

5 Empirical analysis

5.1 Baseline regression

Due to the acceleration of global digital transformation and the growth of demand for computing power, as well as the broader application of 5G, the vigorous development of information infrastructure, and the growth of energy demand and carbon emissions, the energy consumption of information and communication industry cannot be ignored. It is urgent to take the road of green and low-carbon development. To verify whether DT can reduce CE, the impact of DT on city-level CE is estimated based on 2,760 observations, combining research hypothesis H1 and Eq. (2). According to the results of the F-tests and Hausman tests, the p-values of both significantly reject the original hypothesis, indicating that the fixed effects model is most suitable for the sample data in this paper. In order to eliminate possible estimation bias caused by time and region differences, the two-way fixed effects model is used as the baseline regression. In addition, the article uses the Driscoll-Kraay method to adjust the standard errors to alleviate the heteroskedasticity, cross-sectional correlation, and autocorrelation. The results are shown in Table 3. Among them, columns (1) and (3) are estimated from the model without control variables; columns (2) and (4) are estimated from the model with control variables.

TABLE 2 The descriptive statistics of the variables.

Variables	Code	Mean	Std. dev.	Min.	Max.
Carbon emissions	CE	−4.557	0.855	−7.650	−0.904
Digital technology	DT	2.301	0.059	2.211	2.794
Population Density	PD	5.752	0.937	1.629	9.086
Financial Development Level	FDL	0.904	0.515	−0.531	3.644
Foreign Direct Investment	FDI	−5.042	2.634	−23.026	−1.553
Fiscal Expenditure	FE	−1.638	0.490	−3.126	−0.001
Traffic Infrastructure	TI	2.782	0.428	0.314	4.096
Industrial Structure	IS	−0.095	0.473	−2.175	1.677
Energy Efficiency	EE	−13.501	0.862	−17.013	−8.236
Green technological innovation	GTI	0.181	0.429	0.001	5.101
Virtual Agglomeration	VA	−0.283	0.304	−1.015	2.839

As can be seen from Table 3, the results of column (1) without any control variables show that the regression coefficient of DT on CE is -0.510 and significant at the 10% level, indicating that DT can reduce CE. The results of column (4) with control variables, time fixed effects and individual fixed effects show that the regression coefficient of DT on CE is −0.44 and significant at the 5% level. The result is similar to that of published research (Lee et al., 2022; Bai et al., 2023; Hu et al., 2023), the result of this paper also indicates that DT can reduce CE and the findings are robust. Research hypothesis H1 was verified. At this stage, insufficient technological innovation, information asymmetry and external diseconomies of CE are the main blockages in the process of achieving the dual carbon goal. With the rapid development of new-generation information technology and Internet technology, DT evolved from automation can provide information technology support for the environmental management work of city managers

TABLE 3 Baseline regression results.

Variables	(1)	(2)	(3)	(4)
DT	−0.510* (−1.68)	−0.401 (−1.44)	−0.485* (−1.97)	−0.448** (−2.730)
FE		0.069 (0.97)	0.055 (0.75)	0.057 (0.760)
DFL		0.155* (2.15)	0.139* (1.94)	0.137* (2.180)
TI			−0.056*** (−4.30)	−0.050*** (−4.000)
IS			0.111 (1.50)	0.113 (1.680)
FDI				−3.378** (−3.310)
PD				−0.016 (−0.210)
_cons	−3.320*** (−4.81)	−3.162*** (−4.52)	−s3.162*** (−5.24)	−3.100*** (−6.550)
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	2760	2760	2760	2760
R^2	0.5754	0.0746	0.0782	0.0889
F-tests	3.16**	44.63***	14.96***	15.04***
Hausman Tests	48.09***	109.26***	114.77***	80.59***

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively; t-statistics are reported in parentheses.

and corporate subjects to enhance economic efficiency while taking into account the ecological environment. Through the digital platform, enterprises can plan the production process accurately and control the production process intelligently, optimize the end of carbon emission management and energy-saving control measures in real time, which will lead to a significant increase in green total factor productivity and ultimately realize lean production and cost reduction. DT, with its timely and convenient data sharing and information dissemination functions, can effectively eliminate the problem of incomplete information among enterprises in various parts of the industry chain, help to weaken or even eliminate the technical barriers among innovation subjects, and promote the participation of multiple parties to the research and development of common technologies and cooperation to achieve GTI and clean production. Through DT, the enterprise's capital flow, goods flow, commercial flow, logistics and other flow space elements are integrated and summarized in order to guide the flow of limited green financial resources to the environmentally-friendly high-tech industries. Most importantly, DT such as artificial intelligence, big data analysis and digital twin provide arithmetic support and data foundation for carbon trading cities, enabling accurate measurement, monitoring, reporting and verification of CE, and empowering efficient operation of carbon markets and carbon finance as well as scientific decision-making in urban ecological sectors.

5.2 Robustness test

To verify the robustness of the baseline regression results, the article uses four methods.

The first is to replace the core explanatory variable. The study used two methods to substitute proxy variables for digital technologies. First is to use the lagged term of CE as explanatory variable to test the time-lagged effect of DT. The second method uses the number of digital technology patents filed by listed companies. Since the IPC information of patents can accurately depict the technical field characteristics of innovation activities, this paper combined the Statistical Classification of Digital Economy and its Core Industries (2021) and the Reference Relation Table of International Patent Classification and Industry Classification of National Economy (2018) issued by the National Bureau of Statistics. To construct the corresponding relationship of "core industry classification code of digital economy – four-digit code of national economy industry classification (SIC4) – IPC Subgroup", identify the technical field of digital technology innovation and its corresponding IPC code to identify the digital technology innovation patents applied by enterprises at the level of IPC group. Further, from the three dimensions of "enterprise – year – city," the digital technology invention patents were summed up to construct the digital technology innovation measurement index at the city level. Since Chinese listed companies gradually paid more attention to the patents on digital technology after 2013, the number of applications before 2013 was relatively small (Tao et al., 2023). Therefore, the time window used in this method is 2013–2020.

The second is to add omitted variables. Rapidly advancing urbanization objectively requires better municipal infrastructure and basic public services such as transportation, electricity, and medical care, which brings about rapid economic development while also causing an increase in greenhouse gas emissions. Cities contribute about 75% of CE (Zhang et al., 2023). However, the high concentration of population and economic activities in urban areas also gives rise to economies of scale and process-oriented production patterns, which help to improve resource allocation efficiency and achieve optimal dispatch of materials, reducing CE. The business credit environment in a given region is an important factor affecting sustainable economic development (Shen et al., 2022). Under the joint incentive mechanism of trustworthiness, by focusing on improving the business credit environment and the red list system will motivate enterprises to focus on environmental protection and inspire green transformation. At the same time, the "reputation effect" generated by the strengthened business credit environment makes enterprises more actively take social responsibility to build a good image and reduce the emission of environmental pollution. Based on this, this paper adds two control variables, urbanization and business credit environment, to Eq. (2). Green finance is emerging with the primary purpose of coping with climate change, improving environmental quality, and saving and efficient use of resources. It can inject more capital into the green and environmental protection field through green credit, bonds, and other policy tools, which will substantially impact "carbon reduction" activities. Different from command-based or market-based regulatory policies, the establishment of green finance reform and innovation pilot zones will promote the pilot areas to accelerate the improvement of green development policies and green finance top-level design, including environmental policies, green finance systems, organizational systems, market operation mechanisms, product service systems, support, and safeguard measures. Green finance, for example, has significant signaling effects. Through leverage and credit support, limited green financial capital can quickly attract more social capital "green" and highly implement carbon reduction activities. At this time, green finance has a pronounced inhibition effect on high-carbon investment, which weakens investment in energy-intensive industries and limits interest-bearing debt financing and new investment in heavily polluting enterprises. Based on the research direction of the existing literature (Shi et al., 2022), we take the green finance policy implemented in 2017 as a new control variable.

Thirdly, the econometric model is replaced. In addition to using robust standard errors to control for the heteroskedasticity, within-group autocorrelation and between-group contemporaneous correlation present in the nuisance terms, feasible generalized least squares estimation (FGLS) can be used to eliminate them. Given the large regional variability in resource endowment, industrial structure and data characteristics of cities, in order to ensure the accuracy of the regression results, this paper selects comprehensive FGLS estimation with different autoregressive coefficients for each individual to corroborate the robustness of the benchmark regression results.

Finally, the potential two-way causality endogeneity problem is addressed. In the context of the "double carbon" target-oriented

policy, the city administrations will implement more stringent carbon emission control mechanisms to force enterprises to implement GTI and cleaner production. Technological advances with a green bias will influence the development of DT through spillover effects and knowledge spillover, i.e., DT is more advanced in cities with lower carbon emissions and advanced economies. In order to avoid the interference of endogeneity issues on the model regression calculation, this paper draws on the research ideas from the existing literature (Yi and Zhou, 2018; An et al., 2023) and conducts the estimation of instrumental variables by constructing Bartik instrumental variables with some exogeneity (the product of the lagged and differential terms of DT). Because strictly exclusive instrumental variables are rare, digital technology, in particular, has some correlation with many aspects of socioeconomic affairs. Under the premise of the "unclean" instrumental variable assumption, the estimation results of the traditional instrumental variable method become unreliable. Therefore, we draw on the idea of Conley et al. (2012) to relax the exclusion constraint and use a Plausibly exogenous instrumental variable estimation method for robust inference, assuming that the estimated coefficients of instrumental variables affecting the explanatory variables through other channels are approximately zero, in order to estimate the regression coefficients of the core explanatory variables assuming the strict exclusion constraint of the relaxed instrumental variables. This method is also widely used to analyze the relationship between industrial robots and carbon emissions (Yu et al., 2023). To enhance the rigor of such research in causal inference, this study also uses the time-varying DID method to calculate the potential of digital technology in carbon emission reduction. Specifically, the "Broadband China" strategy, implemented in three batches from 2014–2016, provides a good quasi-natural experiment for this research (Wen et al., 2022). In the process of new infrastructure construction, the General Purpose Technology (GPT) of broadband networks has been applied in a large area and may stimulate the development of a digital economy and industrial structure optimization, thereby reducing urban carbon emissions.

As can be seen from Table 4, the results of all four methods show that the regression coefficients of DT are significantly negative and the significance only changes slightly, indicating that the conclusion that DT can reduce CE obtained from the baseline regression part is robust and reliable. In addition, the results of Method 4 based on the causal inference perspective show that the regression coefficient of DT on CE is −5.250 and passes the 5% significance test. This result shows that the conclusion that DT reduces CE still holds after eliminating the endogeneity problem. The conclusion that DT reduce CE is not a simple statistical relationship, but more in line with the causal logic between economic facts. H1 is strongly validated.

6 Mechanism test

The above results showed that the development of DT does significantly curb the CO_2 emission intensity of cities. However, it would be more revealing to reveal the mechanisms through which DT reduces CE. According to the research hypothesis and mechanism test equation above, this paper still uses the two-way fixed effects model to do the regression analysis, and the results are shown in Table 5.

As shown in Table 5, the regression coefficients of DT on EE and GTI are −0.537 and 0.850, respectively, and significant at the 5% and 10% levels, respectively, showing that DT can reduce CE through mechanisms of improving enterprises' GTI capacity and reducing energy consumption intensity. H2 is verified. DT is a specific practice

TABLE 4 Results of robustness tests.

Variable	Method 1	Method 2	Method 3	Method 4	Method 5	Method 6
DT	−0.534*** (−3.90)	−0.391*** (3.02)	−0.451** (−2.70)	−0.925*** (−6.76)	−5.250** (−2.11)	−0.0473* (−1.89)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Ys	Yes	Yes	Yes	Yes
N	2,484	2,208	2,760	2,760	2,760	2,760

** and *** indicate significant at the 5% and 1% levels, respectively; in Methods 1 and 2, the t-statistic is reported in parentheses; in Methods 3 and 4, the z-statistic is reported in parentheses.

TABLE 5 Results of mechanism tests.

Variables	EE	GTI	VA
DT	−0.537** (−2.590)	0.850* (2.160)	0.046*** (11.38)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively; t-statistics are reported in parentheses.

of advanced productivity, which itself has the role of technological progress and green attributes. The ever-changing technology carriers and rapidly evolving ICTs bring about iterative renewal of production equipment. For example, the digital transformation of enterprises makes online meetings and cloud offices possible, indirectly promoting the optimization of production operations, organizational coordination and management control, and improving the production lines and processes of enterprises. DT highlights the universality of "Davidson's Law", which is constantly replacing low-energy-consuming equipment with high-energy-consuming equipment, forcing the elimination of outdated production capacity and transformation and upgrading, therefore reducing energy consumption per unit of GDP. At the same time, under the influence of Metcalfe's law, DT improves the efficiency of information search, expands the channels and scope of information dissemination, and accelerates the association of production factors at the spatial level and network externality spillover, which improves the technological innovation capacity and output efficiency of each production node (Zhang and Wei, 2019). In addition, the open and inclusive characteristics of DT can promote the sharing of enterprise innovation knowledge, provide a sharing platform and channel to alleviate resource mismatch and inefficient operation, and enable the flow of innovation factors and high-quality resources to high-efficiency industries, which can reduce CE.

The regression coefficient of DT on virtual agglomeration (VA) is 0.046 and passed the 1% significance test, indicating that DT can reduce CE through the mechanism of promoting industrial virtual agglomeration. H3 was verified. The new technological paradigm reduces the original production and transaction costs, which inevitably leads to a change in the shape and structure of production organization. With the deep development of DT, especially the popularity and application of machine learning, big data technology, digital twin and smart manufacturing, the evolution of organizational form has been given new dynamics and paths (Feng, 2018). Based on the new technology network, more and more industries break through the barriers of physical space, and the associated collaboration among enterprises is less dependent on geographic space, and various subjects in the value. The externalities of agglomeration are multiplied by the increase of participating subjects. First of all, DT represented by cloud computing and industrial Internet provide virtual space and technical carriers for the circulation and aggregation of data elements, which help big data realize low-cost and high-efficiency real-time exchange through the network platform. Data elements are stored in a distributed manner in the virtual network space and linked by the network, and data demanders implement extraction and analysis of data resources through the massive storage network. This can optimize the spatial layout of data elements, promote the modularization and standardization of service elements, and enhance the transparency of element circulation and the coupling and coordination of production demands. Furthermore, through the virtual space aggregation platform of technical resources, tacit knowledge, which was difficult to be copied and disseminated in the past, can be realized through the network platform to achieve knowledge overflow in multiple points in time and multiple dimensions. The virtual cyberspace turns the tacit knowledge that cannot be digitized into explicit, stable knowledge that can be coded and disseminated over long distances, and reduces the spatial stickiness of knowledge, effectively shortens the time lag of technology diffusion, and bursts the technology welfare effects (Zhang and Ru, 2021). Finally, DT enables the subjects clustered in cyberspace to quickly disseminate information on the output of final goods while also obtaining more efficiently any number of intermediate goods inputs that exist in the market. The output and services of each node of the industry chain will face a wide market demand, and the market effect of intermediate inputs will be infinitely enlarged at this time. At the same time, DT weakens the specialization of productive service inputs in the traditional geographical agglomeration. The non-tradable productive services in traditional industrial agglomeration will become tradable under the role of virtual agglomeration, and the convenience of obtaining intangible intermediate inputs in virtual agglomeration is much greater than that in traditional industrial agglomeration. The DT has reduced the possibility of technology dormancy by promoting the characteristics of knowledge diffusion in a network. It breaks the linear closed technology transfer mode of traditional upstream and downstream industries, converts the "point-to-point" technology diffusion into a "one-to-many" network structure, and shrinks or blurs the industrial boundary line. Therefore, DT helps to improve the fineness of professional division of labor and the concentration of different industries or similar industries in virtual space. chain achieve agglomeration and division of labor in the virtual space of infinity (cloud) (Chen et al., 2021).

7 Heterogeneity analysis

7.1 Heterogeneity test of urban resource endowment

Considering the unbalanced regional economic development in China, this paper divides the sample according to city scale and whether it is a resource-based city to assess whether the carbon emission reduction effect of DT is heterogeneous depending on the resource endowment. For the sample division of city scale, this paper divides the new first-tier and first-tier cities into large cities and the second-tier, third-tier, fourth-tier and fifth-tier into middle-sized and small cities based on the New Grading List of Chinese Cities published by the New First-Tier Cities Institute in 2020 (The Rising Lab, 2020). For the sample classification of resource-based cities, this paper mainly refers to the classification criteria of the National Sustainable Development Plan for Resource-based Cities issued by the State Council in 2007 (The State Council of the People's Republic of China, 2008). As shown in Table 6, the regression coefficients of DT in large cities and middle-sized and small cities are −1.289 and −0.552, respectively, and both pass the significance test at the 5% level. Comparing the two coefficients, we can find that the regression coefficients of DT are significantly larger in large cities than in middle-sized and small cities, indicating that DT plays a more significant role in CO_2 emission reduction in areas with high economic density and good business conditions. The potential reasons are that large cities have more complete Internet

TABLE 6 Heterogeneity test of urban resource endowment.

Variables	Large Cities	Middle-sized and Small Cities	Resource-based Cities	Non-resource-based Cities
DT	−1.289** (−3.00)	−0.552** (−2.26)	−2.350** (−2.92)	0.154 (0.85)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	190	2570	1130	1630

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively; t-statistics are reported in parentheses.

infrastructure and policy measures, the application scenarios and usage frequency of DT is broader, and the coupling and integration of advanced technologies with the traditional real economy is higher. At the same time, compared with middle-sized and small cities, large-scale cities have more sufficient funds, more advanced DT and better talents, and the scale of digital economy is also larger, with a higher level of agglomeration conditions and resource allocation, and the investment and pace of digital transformation is larger, which can more effectively enhance urban productivity and thus suppress more CE, and the effect of reducing carbon emission intensity will be more obvious.

What can also be found from Table 6 is that the regression coefficient of DT in resource-based cities is −2.350 and passes the significance test at the 5% level; in non-resource-based cities, the regression coefficient of DT is 0.154 and does not pass the significance test. The potential reason for this result is that the economic development pattern of resource-based cities is mainly characterized by factor inputs and primary processing of products, and the industrial structure is dominated by heavy industry. Compared with agriculture and service industries, heavy industries are characterized by high consumption and high pollution, and the crude economic development mode results in high CE. The popular application of DT can accelerate the transformation, upgrading and clean development of traditional industries such as coal, iron and steel, cement and chemical industry, dissolve the excess capacity of coal, and boost the low-carbon transformation and circular development of industries in old industrial base cities (Zhang J. et al., 2022). Industrial digital transformation can significantly improve enterprise production efficiency and improve production processes, optimize the combination of factor allocation, and the marginal effect of carbon emission reduction by DT is more significant. Meanwhile, in the Opinions on Promoting the Sustainable Development of Resource-based Cities issued by the State Council in 2007 (The State Council of the People's Republic of China, 2008), governments at all levels are required to increase support for the sustainable development of resource-based cities and establish institutional mechanisms conducive to the sustainable development of resource-based cities as soon as possible. Aided by strict environmental regulations to improve the ecological environment for the comprehensive, coordinated and sustainable economic and social development of resource-based cities, resource-based cities are in a better position to give full play to the role of DT in leading demonstrations. Local governments can build an intelligent, precise and comprehensive management system to shape a favorable development environment for the green transformation of urban industries, help the regional economy develop in a green and high-quality way, and reduce carbon emission intensity. In addition, resource-based cities have more room for progress in DT development and develop more rapidly, which can accelerate the rational allocation of resource factors and the synergistic division of labor among industries, and more easily promote the coordinated and rational industrial structure and green transformation of cities, improve energy efficiency and reduce carbon emissions. The economic development of non-resource-based cities does not depend on resource processing and energy consumption, and the industrial structure is more inclined to agriculture or service industry. DT has been deeply integrated with other industries by virtue of the network incremental effect of Merkauf's law, and thus the marginal effect of carbon emission reduction decays. At the same time, DT is dependent on electricity consumption. The large-scale application of machines and network facilities will increase the CE of the power sector.

7.2 Heterogeneity test of urban policy

Existing literatures have divided cities into different types according to China's geographical location to conduct heterogeneity test. However, this method only considers physical geography and resource endowment, and the conclusions obtained are not targeted enough for administrative departments or enterprise managers to formulate management strategies, nor can they stimulate the subjective initiative of market subjects (Yang et al., 2022; Yi et al., 2022; Sun and Wu, 2023). The Chinese government is firmly committed to promoting ecological environmental protection and green development. The carbon emission reduction role of DT may be influenced by macro-level policy regulation, and ignoring regulatory policies for environmental governance in China may lead to biased empirical estimates. Therefore, this paper selects two policy regimes related to digital infrastructure and environmental regulation, respectively, to test the heterogeneity of DT in carbon emission reduction.

A smart city is an intelligent management and operation and maintenance path that can be sensed, seen, measured, analyzed and controlled based on the overall digitalization of the city, which includes digital infrastructure such as urban networks, sensors, and

computing resources. This paper divides the 276 samples into two samples based on the Assessment Report on the Development Level of China's Smart Cities published by the State, with a view to assessing the heterogeneous impact of DT on CE in cities with different degrees of development of DT facilities. As shown in Table 7, the regression coefficient of DT in the pilot cities is −0.579 and significant at the 5% level, while in the non-pilot cities, although DT can still reduce CE but the reduction effect is not significant. The potential reason is that in the pilot cities of smart cities, new DT such as big data, IoT, cloud computing, next-generation Internet, and AI can be widely used in various digital infrastructures to achieve cross-sectoral, cross-level, cross-regional, cross-institutional, and cross-path network collaboration, and better play their own impact role. It can be seen that DT development significantly contributes to the reduction of carbon emission intensity in smart cities, but does not effectively curb the carbon emission intensity in non-smart cities.

The carbon pilot policy requires cities to adopt low-carbon economy as the development model and direction, citizens to adopt green and low-carbon living as the concept and action mode, and government management to adopt low-carbon society as the governance model and construction blueprint. Therefore, this paper uses the low-carbon city pilot policy to divide the sample in order to verify the heterogeneous effects of DT in regions with different strengths of environmental regulation. As shown in Table 7, the regression coefficients of DT in pilot and non-pilot areas of low-carbon city policy are −3.058 and −0.391, respectively, and they pass the significance tests of 1% and 10%, respectively. Comparing the magnitudes of the two coefficients, it can be found that the coefficients of DT in the pilot low-carbon city areas are significantly larger than those in the non-pilot areas, even by several times, indicating that the carbon reduction effect played by DT is more obvious and prominent in areas with stronger environmental regulation, verified the Potter Hypothesis. The potential reason is that environmental regulation through digital media is more capable of guiding the public to form a green concept, leading a green life and mitigating urban CE. In addition, a strong external regulatory force can apply the law of "survival of the fittest" to enterprises. Some resource-intensive and labor-intensive enterprises cannot afford the cost of green innovation and process transformation in a short period of time, so they will move to other regions or temporarily reduce their production capacity to control CE. Based on the pollution data provided by DT, government departments will also discipline highly polluting enterprises by "shutting down and closing down". As a result, the cleanliness of the industrial structure of the whole region will be significantly improved with the support of DT and environmental regulations to achieve carbon emission reduction.

8 Conclusions and policy implications

8.1 Conclusions

Peak carbon dioxide emissions and carbon neutrality an urgent need to solve the significant problems of resource and environmental constraints and realize sustainable development, conform to the trend of technological progress and promote the transformation and upgrading of economic structure, and meet the people's growing demand for the beautiful ecological environment and promote the harmonious coexistence between man and nature. DT is used in all sectors of economic and social development, and the application and support of DT is indispensable to achieve carbon peaking and carbon neutrality goals. In the new form of digital economy, the green transformation of industries empowered by DT has become the key to efficiently promote and achieve the low-carbon emission reduction milestones (Shen and Yang, 2023).

Based on the technology diffusion theory, the article first systematically compares the theories and mechanisms of carbon emission reduction by DT, and then empirically tests the impact of DT on carbon emission based on panel data of 276 cities in China from 2011 to 2020, using a two-way fixed effects model and instrumental variables method. Consistent with the findings of published papers (Liu et al., 2022; Shen et al., 2023; Xu et al., 2023), this paper found that DT significantly reduces CE in cities. This conclusion still holds after robustness tests by replacing the explanatory variables, eliminating endogeneity and adding omitted variables. In the post-pandemic era, "digitalization" and "greening" have become the main themes of global economic recovery. Digital technology is essential in helping the global response to climate change. Digital technology can deeply integrate with energy, power, industry, transportation, buildings, and other key carbon emission fields, effectively improve the use efficiency of energy and resources, and realize the double improvement of production efficiency and

TABLE 7 Heterogeneity test of urban policy.

Variables	Smart City		CE Trading System	
	Pilot Cities	Non-pilot Cities	Pilot Cities	Non-pilot Cities
DT	−0.579** (−2.46)	−0.585 (−1.52)	−3.058*** (−4.51)	−0.391* (−2.07)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	1260	1500	330	2430

***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively; t-statistics are reported in parentheses.

carbon efficiency. Digital is becoming an essential technological path for China to achieve carbon neutrality. DT has highly convergent, permeable and synergistic characteristics, and its deep integration with the real sector can bring into play the positive externalities of technology in reducing carbon emissions. It's different from published research (Yang et al., 2022; Wang and Chen, 2023), the contribution of this study, of course, is to reveal new paths for DT to reduce carbon emissions, especially the role of VA. In addition, the heterogeneity of carbon emission reduction by digital technologies revealed in this study is also helpful in ecology because it considers the resource endowment of cities themselves rather than simply classifying them according to geographical location. Mechanism tests show that DT can reduce CE through mechanisms of improving energy efficiency, promoting virtual agglomeration of industries, and stimulating GTI of enterprises. DT is more effective in promoting carbon emission reduction in large cities and resource-based cities, that is, there is heterogeneity in the role of DTs in reducing CE. In addition, the policy system is also an important factor influencing the reduction of CE by DT. Specifically, the carbon emission reduction role played by DT is more evident in smart cities and pilot areas of carbon emission trading policies. Developing advanced industrial structure is an important way to reduce environmental pollutants (Kong et al., 2023). Specialized agglomeration and diversified agglomeration of different industries on the Internet information platform are conducive to giving play to the advantages of advanced industrial structure. The unique theoretical contribution of this paper lies in that it not only reveals that digital technology has great potential in reducing carbon emissions and promoting sustainable development but also innovatively brings virtual industrial agglomeration into the path mechanism of digital technology to reduce carbon emissions, which is helpful to enrich the theoretical research perspective. In addition, the paper verifies the heterogeneity of digital technology emission reduction from the perspective of environmental regulation policy and digital infrastructure policy, which is helpful for relevant subjects to take corresponding actions in time to achieve carbon emission reduction. Therefore, this study is a useful exploration under the background of a new round of technological revolution and carbon neutrality. On the one hand, the research conclusion of this paper expands the channels of reducing carbon emissions by digital technology in theory, and on the other hand, it also helps policymakers to take corresponding actions in practice to conform to the laws of global economic development.

8.2 Policy recommendations

(1) Improve resource allocation and seize the digital economy dividend. Digital infrastructure has the role of early capital, and upgrading the investment in digital infrastructure construction, especially new infrastructure such as 5G and 6G, as well as accelerating the improvement of digital industry-related infrastructure, can also create a favorable environmental atmosphere for the development of DT. Local governments should improve Internet data exchange platforms, Internet of Things and other network infrastructures, strengthen the comprehensive integration of big data mechanisms, cloud computing and artificial intelligence, etc., deeply tap into the Internet development space and release digital dividends.

(2) Focus on the development differences between regions and promote the progress of lagging regions. Compared with the "advanced" regions, some of the "backward" regions are still relatively underdeveloped in DT and have developed relatively late. Therefore, local communities need to learn from the experience of DT development in "advanced regions", strengthen the exchange of experience, and seize the development opportunities brought by DT in a timely and proactive manner. The government should build a platform for inter-regional knowledge and technology communication, strengthen inter-regional digital innovation exchange and cooperation, enhance digital scale, promote green, intelligent, coordinated and sustainable development of regional transportation, and coordinate regional differences in DT. While learning from the experience of DT development in "advanced zones", local communities should also pay close attention to the characteristics of local development, so that DT can be better applied to the local market and truly contribute to the economic development of the area. Combining the regional industrial structure and resource endowment, using DT to transform traditional industries in an all-round and whole-chain manner, enhancing the adaptability of the digital economy to the industrial restructuring of cities with different industrial attributes and resource endowment, accelerating the cultivation of new industries and new models based on new DT, accelerating technological progress and GTI, promoting low-carbon technological innovation and digital transformation of resource-based industries, and breaking the structural energy and resource "curse", and continuously release the vitality of digital construction to empower urban low-carbon transformation, so as to realize the coordinated symbiosis of digital transformation and green development of old industrial bases and resource-based cities.

(3) We should create a good policy environment, introduce policies and regulations related to GTI, improve the legal and regulatory system of green innovation technology and intellectual property rights system, solidify the guarantee of green development system, establish an all-round and multi-dimensional fair competition environment and policy system, and encourage enterprises to actively carry out GTI; meanwhile, we can also encourage enterprises to reduce carbon tax by introducing advanced DT and equipment. Encourage the research and development of green, clean and low-carbon technologies, accelerate the transformation and application of advanced technological achievements, and cultivate new momentum for the green and low-carbon transformation of China's cities In addition, talents are also the key to strengthening GTI, and it is necessary to cultivate a team of green and low-carbon talents, and the construction of GTI platforms should be encouraged, while the government should increase the procurement of GTI products, and strengthen the GTI achievements in industry, agriculture. At the same time, the government should increase the procurement of GTI products

and strengthen the wide application of GTI results in various fields such as industry, agriculture, construction and transportation, so as to effectively promote the development of energy saving and emission reduction and ultimately help the low carbon transformation of the city.

8.3 Research limitations

This study evaluated whether DT can reduce carbon emissions. The methods used were more focused on statistical inference of statistical models. However, economic research focuses more on the causal relationships between economic variables. In future research, it will be beneficial to use the list of intelligent manufacturing demonstration enterprises and the policy of industrial intelligent demonstration parks and use the double-difference method and breakpoint regression to make the research conclusions more consistent with causality. Measuring the efficiency of resource utilization can better reflect the ecological and social values of various essential resources (Yuan et al., 2023). In future research, researchers should pay attention to the path mechanism of digital technology to reduce carbon emissions and the role of digital technology in improving carbon efficiency because it will directly affect ecological accounts and resource liabilities. In future research, it will be beneficial to combine econometrics with natural science methods such as game theory, operational research, and management science to evaluate the impacts of DT on CE from an interdisciplinary perspective.

Data availability statement

Publicly available datasets were analyzed in this study. Proper sources are cited in the text. The data used to support the findings of this study are available from the corresponding author upon request.

Author contributions

YS and HL, conceptualization, formal analysis, and writing–original draft. YS, funding acquisition, resources, and supervision. LW and HL, investigation, data curation and methodology. YS, project administration, software, and visualization. HL and LW, validation and writing–review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Regional differences and evolution trends of China's industrial green transformation

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Green and low-carbon development is the direction of the current technological revolution and industrial transformation, while China is still in the historical stage of deep industrialization and has yet to completely break away from the high-input, high-consumption, and high-emission development method, and is still facing serious challenges in terms of improving the efficiency of resource utilization and reducing pollution emissions. To effectively promote China's industrial green transformation, it is necessary to accurately grasp its development connotations and scientifically realize the measurement of industrial green transformation. Therefore, this paper measures the efficiency of China's industrial green transformation, based on the directional distance function and the Global Malmquist-Luenberger (GML) index, to portray its distribution dynamics, regional differences and further identify its growth drivers. The results found that the overall efficiency of China's industrial green transformation has been steadily increasing, and that the regional pattern is characterized by northwestern, northeastern, central, eastern and southwestern regions, in that order. The Markov chain estimates show that industrial green transformation efficiency is most likely to remain in its original state, with probabilities of 88.31%, 63.54%, 42.86%, and 75.61% for low, medium-low, medium-high, and high levels respectively, but also has a jump shift characteristic, with a certain possibility of falling back from the high-efficiency state to the low state. Dagum Gini coefficient estimation results show that differences between groups in the five major regions are the main source of the widening differences in the overall industrial green transformation, with the contribution remaining at around 60%. Further research suggests that economic growth, technological progress, foreign trade, and foreign direct investment (FDI) may lead to a widening of the efficiency gap in industrial green transformation, while the industrial structure and outward foreign direct investment (OFDI) help to reduce spatial differences to some extent. Based on the above conclusions, this paper proposes some countermeasures to promote the overall improvement and coordinated development of China's industrial green transformation.

KEYWORDS

industrial green transformation, dynamic evolution, regional differences, influencing factors, China

1 Introduction

Environmental degradation is closely related to the productive life of human society and directly affects the quality of economic and social development, which, if left unchecked, will have a serious and destructive impact on natural ecosystems and economic and social systems (Wang and Wang, 2023). Since the Industrial Revolution, the rapid growth of the global economy has met the material needs of humankind, and the development of the real economy, represented by the industrial sector, has been the fundamental engine of economic growth, but it has also left countries facing great challenges in terms of resources and the environment. The transformation of the original traditional extensive growth mode has become a global consensus, and the green transformation of industry is imperative. The Organization for Economic Cooperation and Development (OECD, 2005) suggests that in order for industry to achieve a green economy, it must rise to the level of "green transformation", which connotes the realization of the transformation of the economy from unsustainable to sustainable development, the transformation of the "black" or "brown" economy to a green economy, as well as the transformation of low-quality development to a high-quality development model. Against the backdrop of tightening global pressure on both resources and the environment, the United Nations has proposed the 2030 Sustainable Development Goals, advocating that developing countries should follow a sustainable development path and avoid the "pollute first, treat later" development approach of developed countries.

With the reform and opening up and active integration into the international cycle, China's industrial system has gradually improved and its industrial volume has expanded rapidly, making it the world's number one industrial and trading nation (Yang et al., 2017; Shao et al., 2019; Wang et al., 2020a). However, a status quo that cannot be ignored is that the share of new technology and high-tech industrial sectors is relatively low, the economic growth drivers are still dominated by traditional industrial sectors, and the crude development model has not been fundamentally changed. Although spectacular economic growth has been achieved, the long-term expansionary use of resources has also pushed industrial economic growth close to the boundaries of ecological constraints, and the resource dividend is gradually being depleted (Yao et al., 2019; Gao and Yuan, 2022a). According to the Chinese Statistical Yearbook, industrial value added accounted for 31.0% of total GDP in 2020 but consumed 66.1% of final energy and emitted 79.8% of sulfur dioxide and 85.1% of carbon dioxide. Under the development trend that the green economy has become a new engine of global economic growth and a new advantage in international competition, China's new industrialization process is bound to be affected. Thus, it is urgent to accelerate the green transformation of China's industry (Chen et al., 2022a; Li et al., 2018). However, most current studies only cut in from a certain perspective to study its specific impact on industrial green transition, such as Hou et al. (2018) examined the impact of technological progress on industrial green transition, and Liu et al. (2022a) examined the impact of economic growth on industrial green transition. Yet fewer studies have examined industrial green transformation in depth from its own perspective.

To effectively promote China's industrial green transformation, it is necessary to accurately grasp its development connotation and scientifically quantify the industrial green transformation. Therefore, this paper measures the efficiency of China's industrial green transformation based on the directional distance function and GML index, portrays its distribution dynamics and regional differences in both time and space dimensions, and further identifies its growth drivers. The main contributions of this paper can be summarized as follows. Firstly, drawing on scholars such as (Cheng and Zervopoulos, 2014; Gao et al., 2021), this paper constructs a directional distance function based on a slack measure and GML index model to measure the efficiency of industrial green transformation, and incorporates CO2 in the non-desired output to demonstrate China's industrial green transformation that takes into account the carbon attainment and carbon neutrality targets. Secondly, considering that the traditional three major regions may not accurately reveal the regular characteristics of China's industrial green transformation, this paper combines natural, economic, and social development characteristics to regroup China's 30 provinces into five major regions. Then we combine the use of kernel density estimation, Markov chains, and Dagum Gini coefficients to paint a more detailed picture of the evolutionary characteristics and spatial differences of China's industrial green transformation, providing reference ideas for promoting the overall improvement of industrial green transformation in each region. Thirdly, a quantile model is used to examine the role of economic development, industrial structure, technological progress, foreign trade, FDI, and OFDI, to identify the key influencing factors of China's industrial green transformation at different levels, and then to target the potential green values driving the industrial green transformation.

The rest of this paper is structured as follows. Section 2 reviews the literature on industrial green transformation. Section 3 introduces the methodology and data. Section 4 presents the measured results and evolutionary trends of industrial green transformation. Section 5 details the regional differences in industrial green transition and the sources of the differences. Section 6 discusses the factors influencing the industrial green transition. Finally, Section 7 draws conclusions and policy implications.

2 Literature review

2.1 Definition of industrial green transformation

Since the industrial revolution, the rapid growth of the global economy has met the material needs of human beings, but it has also left countries facing huge challenges in terms of resources and the environment, such as the global warming problem caused by massive greenhouse gas emissions threatening sustainable economic development (Jordaan et al., 2017; Wang et al., 2020b), environmental pollution seriously affecting human health (Wei et al., 2018; Li et al., 2020), extreme weather reducing wheat production (Elahi et al., 2021) and Water stress in agriculture

(Razzaq et al., 2022). Given the increasing resource depletion and environmental pollution, it has become a global consensus to change the original traditional extensive growth mode, and a green transformation of industry is imperative. The Organisation for Economic Co-operation and Development (OECD) suggests that for the industry to achieve a green economy, it must rise to the level of a "green transition", which includes a shift from an unsustainable to a sustainable economy, a shift from a "black" or "brown" economy to a green economy, and a shift from a low-quality to a high-quality development model (OECD, 2005). Graedel et al. (2012) believes that the green transformation of industry connotes a shift in industrial development from crude to intensive and from highly polluting to less polluting. Kemp and Never (2017) state that industrial green transformation is an industrial green production process from unsustainable to sustainable, which is characterized by reduced environmental impact, reduced pollution emissions, increased production efficiency, increased resource utilization rate, and sustainable development (Du et al., 2021). Ran et al. (2023) argue that fundamental to China's industrial green transformation is the promotion of sustained improvements in industrial green total factor productivity. Ren et al. (2022a) identify industrial green transformation as a series of shifts based on the transformation of the production function from one characterized by natural factor inputs to one characterized by green factor inputs, with the underlying growth drivers stemming from institutional change and technological change (Mao et al., 2019).

2.2 Measurement of industrial green transformation

The existing measurement methods can be divided into two categories: the evaluation system method and the indicator selection method, where the indicator selection method can be divided into single-factor indicators and total-factor indicators.

In terms of constructing the evaluation system, scholars have used hierarchical analysis and entropy methods to fit the multi-dimensional evaluation system to quantify industrial green transformation. For example, Yuan et al. (2020b), Han et al. (2020), and Gao and Yuan (2022b), based on China's Industrial Green Development Plan (2016–2020) and the Green Development Indicator System, build an evaluation index system for industrial green transformation from the aspects of industrial economic development, resource and environmental carrying capacity, and industrial structure optimization, etc. The advantage of the index system is that it has a wide coverage, but the tertiary indicators are mainly derived through subjective screening, which tends to duplicate information (Cao et al., 2021).

In terms of single factor indicators, Mensah et al. (2019) measure the industrial green transformation of OECD countries from three indicators: total CO2 emissions, production-side carbon emissions, and demand-side carbon emissions. Yu et al. (2018) and Mao et al. (2019) quantify the greening degree of industrial structure with the proportion of highly polluting industries. Liu and Chen (2022) directly take the number of green patent applications as the proxy variable of industrial green transformation. Such indicators visualize a particular feature of industrial green transformation, but also ignore the quality of economic growth and fail to capture the desirable outputs and undesirable outputs generated by energy consumption (Cheng et al., 2020).

In terms of total factor indicator, improving green total factor productivity (GTFP) is an important way to achieve industrial green transformation (Zhang et al., 2020). Since GTFP can reflect both desired and undesired outputs and the harmony between economic and ecological development, a large number of scholars have chosen this indicator to measure industrial green transformation (Wu et al., 2022; Yu et al., 2022; Zeng et al., 2023). In addition, some other scholars believe that the root of China's industrial green transformation is to promote the continuous improvement of industrial green total factor productivity through technological innovation. Subsequently, based on this definition, many scholars have chosen industrial green total factor productivity as an indicator for measuring industrial green transformation. For example, Cheng et al. (2020) use the global Malmquist-Luenberger index to measure green total factor productivity to analyze the green transformation in 30 Chinese provinces. Qu et al. (2020) use NDDF and DEA methods to measure the green transformation efficiency of manufacturing industries in China. Tian et al. (2022) calculate the green transformation efficiency of enterprises in heavily polluting industries in China by using super-efficient SBM. Ran et al. (2023) measure China's industrial green transition using industrial green total factor productivity calculated by the super-efficient SBM.

2.3 Influencing factors of industrial green transformation

Domestic factors of industrial green transformation include economic level (Gao and Yuan, 2022b; Liu et al., 2022b), industrial structure (Lin and Wang, 2023; Lin and Xie, 2023), technological progress (Wu and Zhang, 2020; Yan et al., 2020), and environmental regulation (Hou et al., 2018; Guo and Yuan, 2020). In terms of influence of the economic level, Gai et al. (2022) believe that economic development is the direct driving force for the efficiency of industrial green development. Chen et al. (2022b) further find that this positive effect has a significant spatial spillover effect. In terms of industrial structure optimization, Yuan et al. (2020a) find that the impact of manufacturing agglomeration on green economic efficiency shows a positive U-shaped characteristic of first inhibiting and then promoting and emphasize that to achieve high-quality manufacturing development requires promoting industrial structure upgrading and reducing the congestion effect generated by industrial agglomeration. Similarly, Yang et al. (2023) points out that at this stage, China's industrial green transformation needs to focus on the efficiency and quality of industrial development, rather than blindly pursuing quantity. In terms of R&D investment and technological progress, Li et al. (2019) and Fu et al. (2020) argue that the slow progress of green technology is an important limiting factor for the improvement of

industrial green development, and that increasing investment in science and technology innovation and environmental protection can effectively improve industrial green development. In terms of environmental regulation, Zhai and An (2020) believe that it helps to achieve industrial green transformation. However, Sun et al. (2022) find that strict environmental regulation inhibits the contribution of technological progress to industrial green transformation in the eastern provinces of China. Yuan and Xiang (2018) and Li (2019) suggest that environmental regulation has not contributed to China's industrial green development.

Under closed conditions, technological advancement depends only on the domestic stock of intellectual capital, whereas under open conditions, intellectual capital is characterized by cross-country diffusion (Pan et al., 2020), trade openness, foreign direct investment, and outward foreign direct investment all influence industrial green transformation. For trade opening, some scholars argue that trade liberalization will facilitate the spillover and diffusion of advanced and clean technologies, helping to promote industrial green transformation (Hao et al., 2021). For example, Ding et al. (2022) find that trade openness has contributed to the green transformation of Chinese industry using provincial panel data from China. The opposing view is that trade expansion increases production, which requires more energy to be consumed, thus increasing pollution emissions (Xu et al., 2020). For example, Yu et al. (2022) use cross-country panel data to find that imports and exports contribute to green productivity in high-income countries, but not in low-income countries. Ren et al. (2014) find that a widening trade surplus is an important cause of increased industrial pollution emissions in China. In terms of foreign direct investment, Liu et al. (2022a) discuss the impact of FDI on industrial green transformation in terms of both quantity and quality using a provincial panel in China. They find that FDI quality has no significant effect on industrial green transformation and that FDI quantity inhibits industrial green transformation in neighboring areas. Qiu et al. (2021) finds that the impact of FDI on industrial green transformation has both pollution halo and pollution paradise effects, and that environmental regulation and policy guidance can weaken the negative effect of FDI. Hu et al. (2018) develop a discussion that foreign direct investment entry has a promoting effect on the green transformation of industrial sectors that are greener but has a restraining effect on less green industries. In terms of outward foreign direct investment, through cross-border M&As and greenfield investment, OFDI not only broadens the international market for multinational enterprises, but also enables them to gain access to key technologies in the host country, thus forming reverse technological spillovers, promoting the productivity and technological innovation capacity of the home country and influencing the high industrial green transformation (Piperopoulos et al., 2018; Hao et al., 2020). For example, Kong et al. (2021) find that market-seeking OFDI provides a channel for the transfer of gradually saturated production capacity in home countries, which in turn provides more scope for domestic production segments to adjust to higher value-added segments, helping to promote industrial green transformation. Zhang (2022) believes that in the face of high environmental standards in developed countries, multinational companies will continue to develop and innovate new technologies to achieve green production to gain a more stable market share, and that the application of R&D results in home countries will help to achieve industrial green transformation. Peng et al. (2023) point out that OFDI can improve the sustainable productive capacity of Chinese industrial firms, but the impact is heterogeneous depending on the absorptive capacity in terms of human capital, R&D intensity, and technology gaps.

3 Methodology and data

3.1 Methodology

3.1.1 Directional distance function and GML index

Industrial green transformation should balance production efficiency and environmental quality. It is difficult for a single indicator to measure both factors simultaneously, while an evaluation system built through subjectivity tends to duplicate information (Cao et al., 2021), therefore, referring to Cheng and Zervopoulos (2014); Gao et al. (2021), this paper quantifies industrial green transformation using industrial green total factor productivity measured by the DDF-GML method.

Firstly, construct an undesired output efficiency model and an expected output efficiency model based on the DDF. According to Chung et al. (1997), assuming that there are n DMUs, each with i inputs $x = (x_1, x_2, \cdots, x_i) \in R_i^+$, yielding j desired outputs y = $(y_1, y_2, \cdots, y_j) \in R_j^+$ and m non-desired outputs $b = (b_1, b_2, \cdots, b_m) \in R_m^+$, and let the directionality vector be $g = (g_y, g_b)$ and t(t = $1, 2, 3 \cdots, T$) represent each period, the DDF for period t is:

$$D^t(x^t, y^t, b^t; g) = \sup\{\gamma | (y^t + \gamma g_y, b^t - \gamma g_b) \in P^t(x^t)\} \quad (1)$$

where x^t is a vector of capital, labor, and energy inputs; y^t and b^t denote the vector of desired and undesired outputs, respectively; and γ is the value of the directional distance function that maximizes desired output and minimizes undesired output $P^t(x^t)$ is the set of production possibilities, which includes both desired and undesired outputs, and the undesired outputs are weakly disposable.

Secondly, propose the non-desired output efficiency model and desired output efficiency model by specifically varying the above directional vectors. The non-desired output efficiency model is:

$$s.t. \begin{cases} \alpha^* = \min \alpha \\ x\lambda \le x_k, y\lambda \ge y_k, b\lambda = \alpha b_k \\ \lambda \ge 0 \end{cases} \quad (2)$$

where a is the optimal solution of the non-desired output efficiency model; x, y, and b denote the factor input, desired output, and non-desired output values respectively; and c is a vector of weight coefficients relative to the DMU being evaluated in the effective DMU portfolio. α is the ratio of the potential optimal non-desired output to the actual non-desired output of the decision unit under the given conditions of factor inputs and desired

outputs. The higher the value of α, the lower the potential for a reduction in the undesired outputs of the DMU.

And the desired output efficiency model is:

$$s.t.\begin{cases}\beta^{*}=\min\beta\\ x\lambda\le x_k, y\lambda\ge(1+\beta)y_k, b\lambda=b_k\\ \lambda\ge 0\end{cases} \tag{3}$$

where β is the desired output expansion potential under the non-desired output constraint, the higher the value of β, the greater the desired output expansion potential of the DMU.

Finally, the GML index analysis method is used to measure the efficiency under environmental constraints. According to Oh (2010), the GML index from period t to t+1 is defined as:

$$GML^{t,t+1}(x^t,y^t,b^t,x^{t+1},y^{t+1},b^{t+1})=\frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \tag{4}$$

If industrial activities produce more desired output and less undesired output, then $GML^{t,t+1}>1$, indicating higher productivity and contributing to industrial green transformation; if they produce less desired output and more undesired output, then $GML^{t,t+1}<1$, indicating lower productivity and inhibiting industrial green transformation.

3.1.2 Dagum Gini coefficient

The Dagum Gini coefficient method is used to systematically analyze the regional differences in China's industrial green transformation. According to Dagum (1997), the inter-group Gini coefficient can be calculated as Eq.(5):

$$G_{hk}=\frac{\sum_{i=1}^{n_h}\sum_{l=1}^{n_k}|y_{hi}-y_{kl}|}{n_h n_k(\overline{y_h}+\overline{y_k})} \tag{5}$$

where h and k are two different regions, n_h and n_k are the number of provinces in each region, y_{hi} and y_{kl} denote the level of industrial green transformation of province i in region h and province l in region k, respectively, $\overline{y_h}$ and $\overline{y_k}$ denote the mean value of the level of industrial green transformation of all provinces in the corresponding region. When the two provinces involved in the calculation are in the same region, the result is the intra-group Gini coefficient (G_{hh}).

Further, assuming the existence of n provinces divided into m regions and defining $p_h=n_h/n$, $s_h=n_h\overline{y_h}/n\overline{y}$, the overall Dagum Gini coefficient is calculated as follows:

$$G=G_w+G_{nb}+G_t \tag{6}$$

$$G_w=\sum_{h=1}^{m}G_{hh}p_h s_h \tag{7}$$

$$G_{nb}=\sum_{h=1}^{m}\sum_{k\neq h}G_{hk}p_h s_k D_{hk} \tag{8}$$

$$G_t=\sum_{h=1}^{m}\sum_{k\neq h}G_{hk}p_h s_k(1-D_{hk}) \tag{9}$$

where G_w is the total contribution of intra-regional variation to the overall industrial green transition variation, $G_{nb}+G_t$ is the total contribution of all inter-regional variation to the overall variation; D_{hk} is the relative influence of the level of industrial green transition between two different regions, calculated as:

$$D_{hk}=\frac{d_{hk}-p_{hk}}{d_{hk}+p_{hk}} \tag{10}$$

$$d_{hk}=\int_0^{\infty}dF_h(y)\int_0^{y}(y-x)dF_k(x) \tag{11}$$

$$p_{hk}=\int_0^{\infty}dF_k(y)\int_0^{y}(y-x)dF_h(x) \tag{12}$$

In the Eq.(10)–(12), d_{hk} represents the total influence between the industrial green transformation of region h and region k. p_{hk} is the hypervariable first order moment between region h and region k. $F_h(\cdot)$ and $F_k(\cdot)$ are the cumulative distribution functions of industrial green transformation in region h and region k.

3.1.3 Markov chain probability transition matrix

Markov chain is a horizontal space of a stochastic process that reflects the distribution and evolutionary trends at different types of time and states by dividing continuous discrete values into N types. For any period t and possible types i, j, and j_k (k=0,1,…, t-2), the Markov chain satisfies Eq.(13), from which it can be argued that the probability of an industrial green transition efficiency being of type i in period t+1 depends only on its type in period t.

$$\begin{aligned}&P\{X_{t+1}=i|X_t=j,X_{t-1}=j-1,\ldots,X_0=j_0\}\\&=P\{X_{t+1}=i|X_t=j\}=P_{ji}\end{aligned} \tag{13}$$

Then, the quartile method is used to divide all industrial green transformation efficiency values in the sample period into four levels: low, medium-low, medium-high, and high, on average according to their magnitudes, and a dimensional probability matrix of industrial green transformation type transfer can be obtained through Markov chains, as in Eq.(14).

$$P=P_{jt}=\begin{vmatrix}P_{11}&P_{12}&P_{13}&P_{14}\\P_{21}&P_{22}&P_{23}&P_{24}\\P_{31}&P_{32}&P_{33}&P_{34}\\P_{41}&P_{42}&P_{43}&P_{44}\end{vmatrix} \tag{14}$$

where P_{jt} represents the probability that a region is of type j in period t and shifts to type i in period t+1. The shifting probability is calculated by using a maximum likelihood estimate, calculated as in Eq.(15):

$$P_{jt}=k_{ji}/k_j \tag{15}$$

where k_{ji} represents the number of times that industrial green transition efficiency shifted from type j to type i during the observation period, and k_j is the total number of occurrences of type j.

3.1.4 Quantile model

The quantile regression method is more precise than OLS in describing the effects of explanatory variables on the range of variation in the explanatory variable and the shape of the conditional distribution. Following the cross-sectional quantile, Koenker (2004) proposed a panel quantile, combining the

quantile regression method with a panel data model, further extending the application of the quantile regression method. To investigate the underlying causes of the spatial and temporal evolutionary characteristics of China's industrial green transition, a fixed effect panel quantile model was used, following Powell (2022), and an adaptive Monte Carlo method was selected for estimation, with five representative quantile levels estimated: 10%, 25%, 50%, 75%, and 90%.

3.2 Data and variables

Based on data completeness and comparability, this paper finally uses data for 30 Chinese provinces for the period 2004-2020 from the *China Industrial Statistics Yearbook*, the *China Energy Statistics Yearbook*, the *China Environment Yearbook*, the *CEADs* database, the *China Statistical Yearbook*, and the *Foreign Direct Investment Statistics Bulletin*[1].

For the calculation of the industrial green transition indicator, the industrial sectors of each Chinese province from 2003 to 2020 are used as the production decision unit. The input factors are labor, capital, and energy. And labor input is measured using the average number of workers employed by industrial enterprises above the scale, capital input is measured using the average annual balance of net fixed assets, and energy input is measured using industrial end-use consumption. Desired output is measured using industrial sales output. Undesired outputs include industrial emissions of sulfur dioxide, chemical oxygen demand in wastewater, solid waste, and carbon dioxide. Using 2003 as the base period, capital input is deflated using the fixed asset investment price index and the desired output is deflated using the ex-factory industrial price index, in order to exclude price factors.

For the analysis of the factors influencing the spatial and temporal evolution of the industrial green transition, two types of indicators are selected. The first category is domestic factors, including economic growth, industrial structure, and technological progress. The second category is international factors, including foreign trade, foreign direct investment, and outward foreign direct investment. Specific definitions are listed in Table 1.

4 Measurement results and trend evolution of industrial green transformation

4.1 Measurement results of industrial green transformation

The results of the industrial green transition efficiency calculations for each province in China are shown in Table 2, based on matlab2021. From an overall perspective, the efficiency of China's industrial green transformation shows a steady upward growth trend, with the national average rising from 1.0107 in 2004 to 1.2922 in 2020, an average annual increase of 1.65%, indicating that China's industrial green transformation has steadily advanced and made some progress. In terms of regional comparisons, the Northwest region has the highest industrial green transition efficiency with an in-sample mean of 1.2559, followed by the Northeast, Central, Eastern, and Southwest, and the Southwest region with a mean of 1.0806[2]. In terms of comparison of transformation among provinces, the top three industrial green transformation efficiency rankings in 2004 are Tianjin, Hebei, and Guangdong, distributed in the eastern region; by 2020, the top three are Qinghai, Beijing, and Jilin, distributed in the northwest, east and northeast regions respectively; furthermore, Qinghai, Gansu, and Inner Mongolia ranked the top three in terms of the annual average of industrial green transformation efficiency, distributed in the northwest region. The change in the ranking of the transformation indicates that China's industrial green transformation is characterized by a "geese formation" with the eastern part leading the way and other regions following, that is, a gradient transformation.

4.2 Trend evolution of industrial green transformation

To further investigate more precisely the dynamic evolution of the distribution of industrial green transformation, a kernel density map is drawn to portray the overall shape of the efficiency of China's industrial green transformation. According to Figure 1, the dynamic evolution of the distribution is characterized by three aspects. Firstly, the distribution of industrial green transition efficiency shifted to the right overall, indicating that industrial green transition efficiency in each region has gradually improved. Secondly, the height of the wave decreases, becomes flatter, and becomes wider, indicating a gradual widening of the gap in industrial green transformation efficiency across regions. Thirdly, the distribution of industrial green transition efficiency extends and widens, meaning that the gap between the extremes and the mean within the region does not gradually narrow, with some provinces and municipalities maintaining higher or lower industrial green transition efficiency. The task of China's industrial green transformation has remained arduous, possibly because China is in the mid-to-late stages of industrialization, with higher levels of energy consumption due to greater resource dependence on the one hand, and lower value added due to a lower industrial chain on the other.

To predict the trend characteristics of China's industrial green transformation, the quartile method is first used to classify

1 Since the statistical caliber of Hong Kong, Macao, and Taiwan Province is inconsistent, and the data of Xizang Province is seriously missing, this paper selects 30 provinces in mainland China as research samples.

2 Based on the natural, economic, and social development characteristics of China, this paper divides China's 30 provinces into five regions, namely the Eastern, Central, Northeast, Southwest, and Northwest. The provinces included in each region are shown in Table 2.

TABLE 1 Explanatory variables definitions.

Variables	Symbol	Definition	References
economic growth	lnpgdp	logarithm of GDP per capita	Chen et al. (2022a); Gao and Yuan (2022a)
industrial structure	stru	value added tertiary sector/value added secondary sector	Gao and Yuan (2022b); Sun et al. (2022)
technological progress	tech	logarithm of the number of patent applications granted	Li et al. (2021); Chen et al. (2022b)
foreign trade	trade	exports and imports of goods/GDP	Ren et al. (2022b); Ran et al. (2023)
foreign direct investment	lnfdi	logarithm of foreign direct investment	Gao et al. (2022b); Zhang and Wu (2021)
outward foreign direct investment	lnofdi	logarithm of outward foreign direct investment	Mahadevan and Sun (2020); Ren et al. (2022a)

TABLE 2 Measurement results of China's industrial green transformation.

Region	Province	2004	Rank	2012	Rank	2020	Rank	Annual average	Rank	Average growth rate
Nationwide	—	1.0107	—	1.2297	—	1.2922	—	1.1775	—	1.65%
Eastern	Beijing	1.0109	17	1.1993	19	1.4239	2	1.2266	8	2.31%
	Tianjin	1.0583	1	1.2310	15	1.2437	22	1.2080	11	1.08%
	Hebei	1.0556	2	1.1840	22	1.2668	20	1.1458	23	1.22%
	Shanghai	1.0151	15	1.1958	21	1.3288	13	1.1689	19	1.81%
	Jiangsu	1.0003	22	1.1314	27	1.1520	27	1.1000	27	0.95%
	Zhejiang	0.9881	25	1.0899	29	1.1115	29	1.0680	29	0.79%
	Fujian	1.0408	4	1.2378	14	1.3445	9	1.2094	10	1.72%
	Shandong	1.0234	12	1.2410	12	1.2052	24	1.1587	21	1.10%
	Guangdong	1.0411	3	1.1584	24	1.2733	18	1.1687	20	1.35%
	Hainan	1.0070	21	1.2463	11	1.3684	6	1.2001	12	2.07%
	mean	1.0240	—	1.1915	—	1.2718	—	1.1654	—	1.46%
Central	Shanxi	1.0104	18	1.1619	23	1.1884	25	1.0967	28	1.09%
	Anhui	1.0220	13	1.2270	16	1.2672	19	1.1835	16	1.44%
	Jiangxi	1.0290	7	1.3077	6	1.3281	14	1.2354	6	1.72%
	Henan	1.0083	20	1.2047	17	1.1349	28	1.1524	22	0.79%
	Hubei	0.9653	29	1.2410	13	1.3133	16	1.1755	18	2.07%
	Hunan	1.0400	5	1.2494	10	1.3390	10	1.2248	9	1.70%
	mean	1.0125	—	1.2319	—	1.2618	—	1.1780	—	1.48%
Northeast	Liaoning	1.0307	6	1.3902	3	1.3894	4	1.2588	4	2.01%
	Jilin	0.9960	24	1.3001	7	1.3941	3	1.2282	7	2.27%
	Heilongjiang	1.0289	8	1.1993	20	1.3381	11	1.1782	17	1.77%
	mean	1.0185	—	1.2965	—	1.3739	—	1.2217	—	2.02%
Southwest	Guangxi	0.8978	30	0.8453	30	0.8798	30	0.8540	30	-0.13%
	Chongqing	1.0149	16	1.1370	26	1.1797	26	1.1001	26	1.01%
	Sichuan	0.9978	23	1.1565	25	1.2744	17	1.1413	24	1.64%
	Guizhou	0.9771	27	1.1055	28	1.2326	23	1.1117	25	1.56%
	Yunnan	1.0250	10	1.2646	9	1.3591	8	1.1961	13	1.90%

(Continued)

TABLE 2 Continued

Region	Province	2004	Rank	2012	Rank	2020	Rank	Annual average	Rank	Average growth rate
	mean	0.9825	—	1.1018	—	1.1851	—	1.0806	—	1.26%
Northwest	Inner Mongolia	0.9723	28	1.3629	5	1.3885	5	1.2683	3	2.40%
	Shaanxi	1.0088	19	1.2037	18	1.3160	15	1.1862	14	1.79%
	Gansu	1.0188	14	1.4048	2	1.3602	7	1.2693	2	1.95%
	Qinghai	1.0238	11	1.5406	1	1.7785	1	1.3803	1	3.75%
	Ningxia	0.9864	26	1.2869	8	1.2558	21	1.1838	15	1.62%
	Xinjiang	1.0277	9	1.3866	4	1.3310	12	1.2476	5	1.74%
	mean	1.0063	—	1.3642	—	1.4050	—	1.2559	—	2.25%

industrial green transformation efficiency into four levels, low (L), medium-low (ML), medium-high (MH), and high (H). And the five regions are similarly graded. The Markov chain method is then used to obtain a probability transfer matrix as shown in Table 3. The results show that:

There is a general club convergence effect in China's industrial green transformation efficiency across the country and the five regions, and a "low-level trap" and "high-level monopoly" phenomenon. In the national probability transfer matrix, the probability values on the main diagonal are greater than the values on the non-main diagonal, and the probabilities of low, medium-low, medium-high, and high-level provinces maintaining their status one year after industrial green transformation are 88.31%, 63.54%, 42.86% and 75.61% respectively, indicating that the different levels of industrial green transformation efficiency are more stable and there is a club convergence effect. The eastern, northeast, and northwest show club convergence in all four categories. The central region shows club convergence in three categories except for the high-level group. And the southwest region only has the characteristic of club convergence in the low and middle-low levels. In addition, the probabilities of the low-level industrial green transformation group maintaining its status in the whole country and five regions are 88.31%, 90.27%, 89.66%, 76.00%, 93.94%, and 80.43%, respectively, all of which are much higher than the probability of upward shift, indicating the existence of a "low-level trap". The probabilities of high-level industrial green transformation group maintaining their status are 75.61%, 85.71%, and 81.48% for the whole country, eastern and northwestern regions respectively, while the central, northeastern, and southwestern regions have a lower number of high-level industrial green transformation efficiency and a lower transfer probability. This indicates that industrial green transformation on the whole is characterized by a "high-level monopoly", which originates from the higher level of green transformation in some provinces in the eastern and northwestern regions.

The level of industrial green transformation is characterized by a "leapfrog" shift and a long-term growth trend, but care needs to be taken to prevent a regression in industrial green transformation. From the whole nation, the transfer not only occurs between adjacent levels, but also exists a "leapfrog" transfer from low level to medium-high level or even high level. This transfer comes from the leap in the north-western provinces, such as Qinghai, Gansu, and Xinjiang, which have jumped from medium to high levels nationally. At the same time, the probabilities of shifting to the right

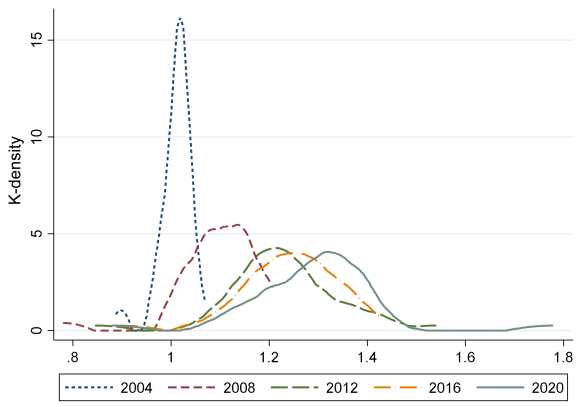


FIGURE 1
Kernel density map of China's industrial green transformation.

TABLE 3 Markov probability transfer matrix of China's industrial green transformation.

Region	t/t+1	L	LM	MH	H
Nationwide	L	0.8831	0.1006	0.0032	0.0130
	ML	0.1354	0.6354	0.1979	0.0313
	MH	0.0000	0.2571	0.4286	0.3143
	H	0.0000	0.0488	0.1951	0.7561
Eastern	L	0.9027	0.0973	0.0000	0.0000
	ML	0.1212	0.7273	0.1515	0.0000
	MH	0.0000	0.1429	0.4286	0.4286
	H	0.0000	0.0000	0.1429	0.8571
Central	L	0.8966	0.1034	0.0000	0.0000
	ML	0.0800	0.6800	0.2400	0.0000
	MH	0.0000	0.2727	0.5455	0.1818
	H	0.0000	0.0000	1.0000	0.0000
Northeast	L	0.7600	0.2400	0.0000	0.0000
	ML	0.2727	0.2727	0.3636	0.0909
	MH	0.0000	0.2500	0.3750	0.3750
	H	0.0000	0.0000	0.5000	0.5000
Southwest	L	0.9394	0.0606	0.0000	0.0000
	ML	0.0833	0.8333	0.0833	0.0000
	MH	0.0000	0.0000	0.0000	1.0000
	H	0.0000	0.0000	0.0000	1.0000
Northwest	L	0.8043	0.0870	0.0217	0.0870
	ML	0.2000	0.4667	0.2000	0.1333
	MH	0.0000	0.3750	0.3750	0.2500
	H	0.0000	0.0741	0.1111	0.8148

of the main diagonal are greater than the probability of shifting to the left, implying a long-term growth trend in industrial green transformation. Further, the probabilities of upward transfer after one year are 11.69%, 22.92%, and 31.43% for low, medium-low and medium-high levels respectively, which shows that the probability of upward transfer of China's industrial green transformation increases after crossing the low level. While the probabilities of downward transfer after one year are 13.54%, 25.71%, and 24.39% for medium-low, medium-high, and high levels respectively. This indicates that there is a certain risk that the level of China's industrial green transformation will fall and may drop from a high level to a medium-low level in a "precipitous" manner. Therefore, all provinces should be alert to the risk of a downward transfer, prevent a reversal of industrial green transformation, keep the existing development results solid and strive to achieve an upward transfer. From the perspective of the five regions, the eastern, central, and southwestern regions do not have the characteristics of "leapfrog" transfer. In the northeast, the probability of downward transfer is higher than the probability of upward transfer, while the opposite is true in the northwest.

5 Regional difference analysis of industrial green transformation

5.1 Overall variation

In order to more intuitively grasp the regional differences, the Dagum Gini coefficient analysis method is used to calculate and decompose the overall variation of China's industrial green transformation from 2004 to 2020. As can be seen from the line graph presented in Figure 2, the overall variation in China's industrial green transformation over the sample period shows an upward trend. Specifically, the overall variation of the industrial green transformation is only 0.0155 in 2004, and after reaching its first peak in 2011, it has remained high, showing a fluctuating and rising "W"-shaped trend. By 2020, the overall variation is 0.0538, an increase of 2.47 times, indicating that the gap in China's industrial green transformation among the provinces is widening. The bar chart shows the decomposition of the overall difference in China's industrial green transformation. It can be seen from the changing trend that the between-group variation accounts for a relatively

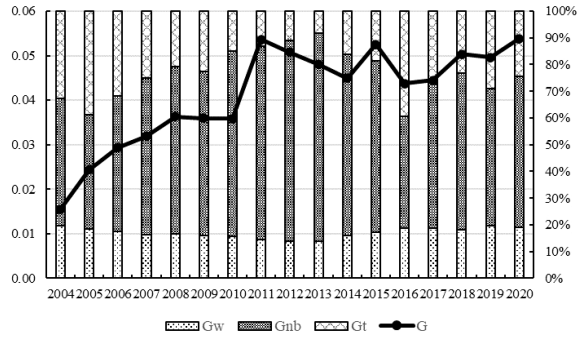


FIGURE 2
Evolution of the overall Gini coefficient and its decomposition.

high proportion, suggesting that the change of the overall variation may depend more on between-group variation. The intra-group variation remained essentially at the same level, indicating a small variation within the region. And the supervariable density function tends to decline after a "W" pattern of "gentle decline–rapid upward movement–gentle downward movement", indicating that the overlap between regions has less impact on the overall variation. Comparing the development of the contribution rates of the three variations, although the percentages of the three have shown a tendency to change over the sample period, the contribution rate of between-group variation to the overall variation has always remained around 60%, except for a few years, which exceeds the total contribution rate of within-group variation and supervariable density, thus indicating that the spatial differences in the level of China's industrial green transformation mainly come from the differences among the five regions, and how to narrow the transformation gap among regions is a key direction for future efforts. This result is similar to the findings of Zhang et al. (2022). They concluded that the key to improving industrial competitiveness in China is also to reduce inter-regional differences.

5.2 Within-group variation

There is regional heterogeneity in the upward trend of variation within the five regions. As shown in Table 4, in general, the within-group differences all exhibit a fluctuating upward trend of variation. The largest increase in intra-group variation is observed in the northwest, followed by the eastern, southwest, and central regions, with the smallest increase in the northeast. In terms of values, the intra-group variation in the southwest is consistently the largest among the five regions, indicating a high degree of imbalance in Southwest provinces' industrial green transformation. For example, Yunnan's industrial green transformation efficiency in 2020 is 1.3591, while Guangxi in the same year is only 0.8798, a large gap between the two. The northwest ranks second, but unlike the southwest, the intra-group variation in the northwest has undergone an upward trend from low to high, especially since 2018, evolving in a "sharp upward" trend. Besides, the differences within the northeast region are relatively small, compared with the eastern and central regions. It may be that the provinces and cities in the eastern and central regions show a "wild goose mode" of industrial development, with both "star" provinces and relatively "mediocre" provinces. While the three provinces in the northeast have the same industrial base, are closely linked and have a faster technology transfer. This comparison shows that attention should be paid to the coordinated development within the eastern and central regions.

5.3 Between-group variation

Figure 3 plots the Between-group variation in industrial green transformation among the five regions. In terms of the overall trend, the gradual increase in the shaded area in the figure indicates that the level of industrial green transformation among China's five regions is differentiated, with some provinces able to rapidly advance their industrial green transformation in terms of both optimizing industrial structure and fostering or introducing new technologies for green production, while other regions are constrained by the historical baggage of slow progress. In terms of differences between regions, the differences between the eastern, central, and northeast are small, with the difference between the eastern and central is the lowest in the full sample, with a mean value of 0.0300. Large values of differences are all derived from the southwest and other regions. For example, the difference between the southwest and northwest has the largest value in the sample period, with a mean of 0.0758, twice as large as the difference between the eastern and central. In terms of time-varying trends in inter-regional differences, the most significant increases in differences between the northwest and other regions, such as 10.28%, 9.92%, and 9.64% between central and northwest, southwest and northwest, and eastern and northwest, respectively, ranked among the top three increases in differences between regions.

TABLE 4 Estimations of within-group variation.

Region	Mean Gini coefficient	2004	2008	2012	2016	2020	Average growth rate
eastern	0.0268	0.0126	0.0228	0.0228	0.0318	0.0415	7.76%
central	0.0271	0.0123	0.0284	0.0198	0.0366	0.0327	6.32%
northeast	0.0206	0.0076	0.0129	0.0327	0.0332	0.0091	1.12%
southwest	0.0556	0.0238	0.0581	0.0646	0.0541	0.0711	7.08%
northwest	0.0311	0.0110	0.0188	0.0420	0.0365	0.0566	10.77%

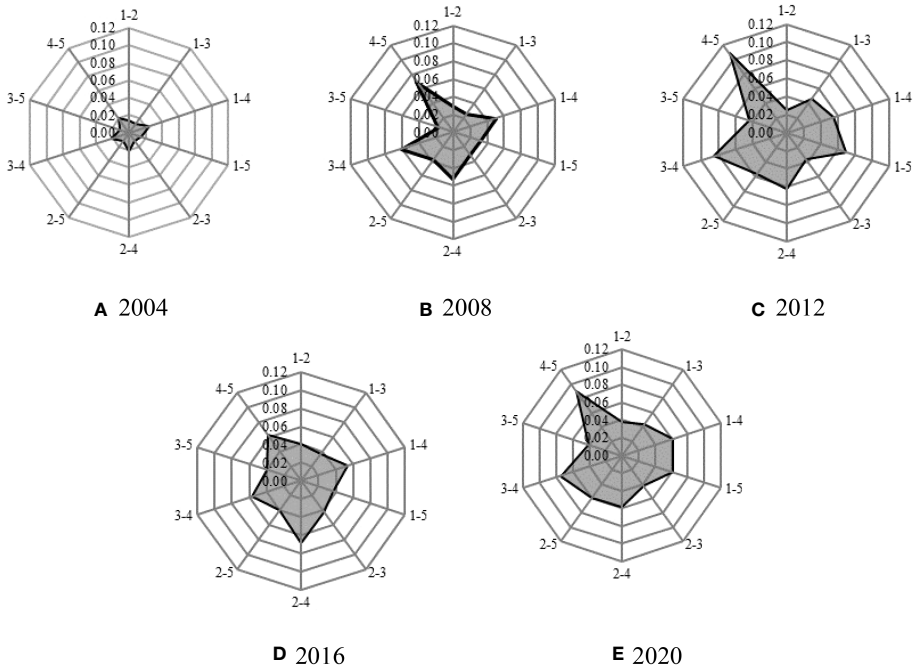


FIGURE 3
Between-group variation in the year 2004 **(A)**, 2008 **(B)**, 2012 **(C)**, 2016 **(D)** and 2020 **(E)**.

6 Analysis of factors affecting industrial green transformation

For investigating the deep-seated reasons for the spatial-temporal evolution characteristics of China's industrial green transformation, the results were examined with the help of a quantile model, as shown in Table 5.

In terms of domestic factors, the estimated coefficients of *lnpgdp*, *stru*, and *tech* are significantly positive in all quartiles, indicating that economic development, industrial structure optimization, and technological progress significantly improve industrial green transformation efficiency. However, the manifestations of the improving effect are different. The coefficient of *lnpgdp* is positive at all quantile levels and shows an

TABLE 5 Estimations of quantile models.

Variable	Q10	Q25	Q50	Q75	Q90
lnpgdp	0.0703***	0.0747***	0.0735***	0.1038***	0.1369***
	(0.0016)	(0.0131)	(0.0027)	(0.0004)	(0.0127)
stru	0.0074***	0.0148***	0.0294***	0.0105***	0.0196**
	(0.0021)	(0.0016)	(0.0005)	(0.0004)	(0.0097)
tech	0.0214***	0.0312***	0.0352***	0.0310***	0.0084**
	(0.0011)	(0.0011)	(0.0003)	(0.0005)	(0.0039)
trade	-0.0303***	-0.0228***	-0.0442***	-0.0491***	-0.0816***
	(0.0045)	(0.0018)	(0.0006)	(0.0007)	(0.0080)
lnfdi	-0.0581***	-0.0574***	-0.0498***	-0.0571***	-0.0424***
	(0.0013)	(0.0030)	(0.0002)	(0.0004)	(0.0063)
lnodis	0.0266***	0.0160***	0.0102***	0.0163***	0.0161***
	(0.0008)	(0.0017)	(0.0004)	(0.0003)	(0.0032)
fixed effect	Y	Y	Y	Y	Y
obs	510	510	510	510	510

*p<0.1, **p<0.05, and ***p<0.01.

increasing trend as the quantile level increases, implying that economic development contributes more significantly to provinces with more efficient industrial green transformation. The coefficient of *stru* undergoes an "inverted U-shaped" process of change, which means that there is an optimal interval for the promotion of industrial green transformation by adjusting the ratio of the third sector to the second sector. And the promotion of industrial green transformation by industrial structure is more obvious when the efficiency of industrial green transformation is at an intermediate level. The magnitude of the coefficient of *tech* is second only to *lnpgdp*, indicating that technological progress is an important driver of industrial green transformation, but the value of the coefficient falls back at the 90 percentiles, probably because the contribution of science and technology carried by the number of patents granted gradually falls back when the green transformation of industry is more efficient. At this time, more attention should be paid to the development and application of green technology. As found by Qing et al. (2022), proactive green innovation, including process innovation and product innovation, has a significant positive effect on improving corporate earnings.

In terms of international factors, the estimated coefficients of *trade* and *lnfdi* are significantly negative at all quartiles, and the coefficient of *lnofdi* is significantly positive, indicating that foreign trade and foreign direct investment inhibit China's industrial green transformation, while outward foreign direct investment promotes it. Specifically, the coefficient of trade is at a low level until the 75 percentiles, but the inhibiting effect increases significantly at the 90 percentiles. The possible reason is that China used to be in a low position in the international division of labor system, which to some extent led to the restructuring of import and export trade inhibiting the green transformation of industry. The magnitude of the coefficient of *lnfdi* gradually decreases with the quantile, probably because foreign investors have transferred some highly polluting enterprises to China, but as the efficiency of China's industrial green transformation continues to increase, such enterprises gradually increase their green output under the influence of competitive effects, reducing the inhibiting effect on industrial green transformation. Unlike the other two factors, the estimated coefficient of *lnofdi* is positive at all quartiles, contributing to the industrial green transformation and showing a "U-shaped" change characteristic of first decreasing and then increasing.

7 Conclusion and policy implications

Industrial green transformation is an important element in achieving Chinese-style modernization and has attracted extensive attention from scholars, but a review of the literature reveals a relative lack of research on the evolution of trends, regional differences, and causes. Therefore, this paper uses China's provincial panel data from 2004-2020 to measure the efficiency of industrial green transformation adopting the directional distance function and the GML index and carries out systematic verification and analysis based on kernel density estimation, Markov chain analysis, the Dagum Gini coefficient, and the quantile model. The following main findings are obtained: (1) From the measurement results, the efficiency of China's industrial green transformation has steadily increased over the sample period, showing a decreasing distribution of the northwest, northeast, central, eastern, and southwest in that order. The northwestern and northeastern provinces have the highest annual average value increase, making the top three provinces shift from being exclusively shared by the east to being shared by the northwest, east and northeast. (2) From the distribution characteristics, the industrial green transformation efficiency shows the characteristics of " transformation efficiency increasing and absolute difference expanding". In addition, there is a "low-level trap" and a "high-level monopoly" in China's industrial green transformation, and it is most likely to remain in its original state, but it also has the characteristic of "jumping" transfer. There is also a certain risk that the industrial green transition will fall in rank, especially if the medium-high rank is reduced to a medium-low rank. (3) From the regional differences, the overall Gini coefficient shows a fluctuating upward "W" trend, highlighting the widening gap in industrial green transformation efficiency among provinces. The decomposed results show that the differences are mainly between groups that is, the differences between the five regions, and the intra-group differences are also increasing. (4) From the influencing factors, the absolute values of the estimated coefficients of economic growth, technological progress, foreign trade, and FDI expand as the quantile point increases, suggesting that the factors above may pull the industrial green transformation efficiency to achieve rapid improvement (reduction) in higher level provinces, while relatively slow improvement (reduction) in lower level provinces, thus leading to the expansion of overall spatial differences to a certain extent. The estimated coefficients of industrial structure and OFDI help to narrow the spatial differences.

According to the research conclusion, we obtain the following policy implications: (1) we should face up to the shortcomings in the process of industrial green transformation and prevent the efficiency of industrial green transformation from "backtracking". Provinces should focus on the relationship between "quantity" and "quality" in the process of promoting industrial green transformation, as the two are not separate. In particular, for provinces locked in low levels of transformation efficiency and at risk of declining grades, it is all the more important to achieve a significant improvement in quality while maintaining quantitative growth. (2) Pay attention to regional differences in the process of industrial green transformation, especially the development differences among the five major regions. In the process of building a unified domestic market, exchanges and cooperation between regions should be further strengthened, resources should be rationally allocated, a synergy of industrial green transformation should be formed, and regional development imbalances should be prevented from further widening. Although the efficiency of industrial green transformation has increased fastest in the northwest, the eastern provinces have strong economic strength and always have a leading edge, so the eastern region needs to take on more tasks of tackling cutting-edge technologies and the cost of pilot tolerance. The southwest region, on the other hand, has the lowest efficiency of transformation, so the priority is to improve the efficiency of transformation by learning from successful transformation experiences. (3) Make full use of both domestic and international markets and resources to promote industrial

green transformation. Based on the identification of key influencing factors at different sub-levels of industrial green transformation, will help provinces to introduce policies to promote industrial green transformation according to the characteristics of the region. For provinces with a higher industrial green transformation efficiency, they can increase investment in green technology research and development and adjust their industrial structure, which will not only help them realize their industrial green transformation, but also generate spillover effects and play a leading role. For provinces and cities with a lower efficiency rating, they can develop their economies and raise their GDP per capita, and in addition, they can increase OFDI, which will help accelerate the industrial green transformation to a higher value.

Although this paper discusses the evolutionary characteristics and influencing factors of China's industrial green transformation, there are still some limitations that deserve further study. Firstly, this paper uses kernel density estimation, Markov chain method and Dagum Gini coefficient to demonstrate the evolution trend, transfer probability and regional differences of China's industrial green transformation, but neglects the convergence analysis between regions, which is worthy of further discussion. And in the future, it can be combined with the measure of spatial convergence to examine the convergence of industrial green transformation under the condition of spatial interconnection. In addition, this paper analyzes China's industrial green transformation only at the regional level, however, China has many industrial sub-divisions, which can be classified as labor-intensive, capital-intensive, and technology-intensive, so further attention can be paid to the green transformation of different types of industrial sectors in the future.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: the China Industrial Statistics Yearbook, the China Energy Statistics Yearbook, the China Environment Yearbook, the CEADs database, the China Statistical Yearbook, and the Foreign Direct Investment Statistics Bulletin.

Author contributions

CL: Conceptualization, Writing – review & editing, Writing – original draft. JX: Writing – review & editing, Methodology, Validation, funding acquisition. JZ: Conceptualization, Formal analysis, Writing – review & editing.

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Can the development of digital construction reduce enterprise carbon emission intensity? New evidence from Chinese construction enterprises

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Introduction: With the rapid development of digital technology and its deep integration with the engineering and construction field, digital construction has become an effective way for low-carbon transformation in the construction industry. However, there is a gap of empirical research between digital construction and carbon emissions.

Methods: This paper empirically investigates the impact of digital construction level on carbon emission intensity and the mechanism of action by using the two-way fixed effects model and mechanism testing based on the panel data of 52 Shanghai and Shenzhen A-share listed companies in China's construction industry from 2015 to 2021.

Results: The findings indicate that the improvement of digital construction level can significantly decrease the carbon emission intensity of construction enterprises, and the conclusions still hold after robustness tests and discussions on endogeneity issues such as replacing core explanatory variables, replacing models, using instrumental variables method, system GMM model and difference in differences model. According to a mechanism analysis, digital construction can curb carbon emission intensity by enhancing the R&D innovation capacity and total factor productivity of enterprises. Furthermore, the heterogeneity analysis shows that the improvement of digital construction level in state-owned enterprises as well as civil engineering construction enterprises can better contribute to reducing carbon emission intensity.

Discussion: This paper will provide a reference for the synergistic optimization of digital construction development and carbon emissions reduction in construction enterprises. The research conclusions are going to promote the digital transformation of the construction industry to accelerate the achievement of the carbon peaking and carbon neutrality goals.

KEYWORDS

construction enterprises, digital construction, carbon emission reduction, R&D innovation capability, total factor productivity

1 Introduction

Since the industrial revolution, carbon dioxide (CO_2) emissions have proliferated, and the global climate has gradually warmed because of the massive global consumption of fossil energy. The Paris Agreement, signed by 175 countries in 2016, aimed to limit global warming far below 2°C, ideally to 1.5°C, relative to pre-industrial levels (Hu et al., 2023). As a major carbon-emitting country, China attaches great importance to achieving peak carbon and carbon neutrality. The Chinese government's high sense of responsibility and determination to achieve high-quality development is reflected in the pledge made by Chinese leaders to achieve China's carbon peak and carbon neutral "3060 goals", as well as in the Chinese Government Report in 2023, which mentioned "working toward the targets of peak carbon emissions and carbon neutrality with well-conceived and systematic steps".

The construction industry is a pillar industry of China's national economy, with a gross output value of 31.2 trillion dollars and an added value of 8.3 trillion dollars, accounting for 6.9% of GDP, which has made a great contribution to the high-quality development of China's economy in 2022. However, the traditional construction industry also has the following factors and characteristics that constrain its high-quality development: first, as an energy-intensive industry, it suffers from high resource consumption and serious energy wastage; second, it has a poor construction environment, more problems with building quality, and the industry suffers from low productivity and high labor costs; and third, it has a slow process of industrialization of the construction industry, with a low degree of application of informatization and digitization of the construction process. As a consequence, the building sector has become one of the top three industries in terms of global CO_2 emissions (Chen et al., 2020). The 2022 China Building Energy Consumption and CO_2 Emissions Research Report shows that the proportion of the total life-cycle carbon emissions of buildings in the country is 50.9% in 2020. At the same time, the building sector also has the most significant potential for energy savings, with urban commercial buildings contributing 45% by 2050 and urban residential buildings contributing 49% (Zhou et al., 2018). Consequently, how to promote the carbon emission reduction of the construction industry and then put forward corresponding strategic suggestions is an urgent problem to be solved to achieve the "dual carbon" goal of China's construction industry.

Meanwhile, a new generation of information technology is featured by digitalization, networking and intelligence to the subversive changes brought to the manufacturing industry, which triggered the industrial transformation is gradually affecting the traditional construction industry. However, unlike the manufacturing industry, the digital transformation of the construction industry has its own characteristics such as the manufacturing industry can usually manufacture products in the assembly line, the production tools are relatively fixed, while the location of the building in the construction industry is unchanged, the construction tools have a greater dynamic (Ding, 2020). In addition, the digitalization of the construction industry is also characterized by the following features: informatization and intelligence of the entire construction lifecycle supported by engineering software, enhanced upstream and downstream collaboration and information sharing in the construction supply chain, timely completion of key project milestones, and control of project costs and reduction of exceeding the project budget (Yilmaz et al., 2023). "A Program for the Overall Layout of China's Digital Development" pointed out that the construction of digital China is an essential engine for promoting the Chinese path to modernization in the digital era in February 2023, and digital construction is an essential portion of the realization of digital China construction, which will effectively solve the pain points of the traditional building industry such as extensive production methods, low production efficiency, and large resource consumption. At the same time, the "Digital Building Development White Paper" published by the China Academy of Information and Communications Technology (CAICT, 2022) proposed that the global building digitization market size was about $9.8 billion in 2019. It is predicted to reach $29.1 billion by 2027, with a CAGR of 18.2%, which is in a rapid growth trend. It can be seen that the combination of engineering construction and digital technologies such as machine learning, building information modeling (BIM), blockchain, and big data will become a novel power for the transformation and high-quality development of the construction industry.

Construction enterprises play a crucial role in the use of digital construction technology and the realization of carbon emission intensity reduction as the carrier of digital construction technology implementation and the micro-unit to realize carbon peaking and carbon neutrality goals of the construction industry. From the existing literature, the carbon emission decrease effect of digital construction technology has sparked the interest of the academic community. It has been shown that Building 4.0 can improve productivity and economic efficiency (Forcael et al., 2020), promote technological progress and technological innovation, and enhance sustainability in the construction industry through new technologies and processes (Baduge et al., 2022). The overall green building analysis capability of BIM facilitates the design of sustainable buildings and the rational selection of materials (Liu et al., 2022b), and automation and robotics in intelligent construction help minimize waste in construction, providing the construction industry with opportunities to improve accuracy, keep project costs down and reduce waste, resulting in enabling efficient use of resources and reducing carbon emissions (Adepoju et al., 2022). In the articles above, instead of fully testing the impact of digital construction at a comprehensive level on CO_2 emissions and mechanism, the scholars have only analyzed the impact of carbon emission with a few specific digital construction technologies.

In this context, this study aims to respond to the following questions: Can digital construction effectually reduce the CO_2 emissions of construction enterprises? If digital construction can empower construction enterprises to reduce carbon emissions, what is its mechanism of action? What actions should be taken by relevant government departments and construction companies to promote the synergistic development of digital construction and carbon emission reduction?

Accordingly, the research objectives of this paper are as follows:

(1) Focusing on the construction industry, this research measures the digital construction level index scientifically

and comprehensively and analyzes the impact of the digital construction level on the carbon emission of construction enterprises from the micro-enterprise level.

(2) We systematically analyze the micro-internal mechanism of digital construction affecting the carbon emission intensity of enterprises and examine the heterogeneity of the level of digital construction on carbon emission reduction in terms of the nature of business and the sub-industry types to which it belongs.

(3) We propose corresponding policy recommendations based on the theoretical analysis and empirical test results.

As a consequence, from the perspective of micro-enterprises, this paper innovatively measures the digital construction level index using the entropy weight method from the input, governance, and output dimensions of digital construction and empirically tests the influence of digital construction level on the carbon emission intensity of enterprises and its mechanism of action based on a sample of 52 listed companies in the construction industry from 2015–2021. The results of the study provide a theoretical basis for government departments to formulate leading policies on digital construction technology and carbon emission reduction policies in the construction industry and offer a reference for carbon emission reduction management decisions of construction enterprises.

The remainder of the paper is laid out as follows. Section 2 is a literature review. Section 3 presents the research hypotheses. The materials and methods are presented in Section 4. Section 5 discusses the empirical findings. Section 6 consists of conclusions and policy recommendations.

2 Literature review

A number of scholars have studied digital technology and its development extensively, with the tremendous changes it has produced in human production and lifestyle as well as the important role it plays in helping the global process of combating climate change. According to the research theme of this paper, the literature involved is mainly reviewed from the following three aspects: the first is the application of digital technology in the area of engineering construction, that is, the related research of digital construction, the second is the research related to building carbon emissions, and the third is the study on the influence of digital technology on carbon emissions.

2.1 Related research of digital construction

Disruptive digital technologies have driven the evolutionary adaptation of the construction industry through historical socio-technical processes (Woodhead et al., 2018). Digital construction is a new engineering construction mode that uses digital technology for architectural design, construction and operation under the background of a new round of scientific and technological revolution (Ding, 2020). Similarly, some scholars have drawn analogies to the theory of Industry 4.0, where the increasing automation of manufacturing environments and the creation of digital value chains derive the concept of Construction 4.0 (Craveiro et al., 2019), which can then be called a new era for construction (Chen et al., 2022). Construction 4.0 will contribute to the transformation of the construction industry into a technologically innovative industry and align it with manufacturing in terms of productivity and performance improvement (Oesterreich and Teuteberg, 2016). In view of this, scholars have conducted extensive research on how to apply digital construction technologies. Dou et al. (2023) summarized and analyzed the overall application of the top ten emerging digital technologies in the architecture, engineering and construction sectors from 2011 to 2020, including BIM, radio frequency identification, 3D printing, big data, digital twins, blockchain, IoT, virtual reality and artificial intelligence. Zhang et al. (2022) proposed a digital twin framework for building site monitoring by combining the multiple levels of detail of BIM, which can enhance the process monitoring of construction sites, improve quality, efficiency and construction safety, as well as the integration of digital twin and BIM can also support the implementation of net-zero carbon buildings (Shen et al., 2022). Regarding the future trend of digital construction, efficient construction, value-driven computational design and user-driven built environments are emerging visions for digital transformation in the building industry (Ernstsen et al., 2021).

2.2 Research related to building carbon emissions

The current research on building carbon emissions involves the calculation of carbon emissions and the path to achieve carbon reduction and carbon neutrality related to this study. Regarding the accounting of carbon emissions, at the macro level, one method is to adopt the carbon emission factor method proposed by IPCC in 1996 to measure the national carbon emissions from the construction industry (Chi et al., 2021); the other is to apply the input–output model (Leontief, 1970) and combine it with the LCA method to measure the carbon emissions of the construction industry (Onat et al., 2014). In contrast, there is no systematic methodology at the micro-firm level, which is mainly obtained directly through ESG reports etc., or estimated with the help of firm and industry main operating cost (Chapple et al., 2013). Furthermore, scholars have analyzed the building life cycle and emission reduction measures at various stages in the path to achieving carbon emissions reduction in buildings. Du et al. (2023b) pointed out that reasonable profit distribution based on carbon emission reduction is crucial to promote the implementation of low-carbon initiatives by construction supply chain firms. Zhang et al. (2019) developed the China Building Construction Model (CBCM) based on the production and transportation of building materials and on-site construction processes, indicating that it may be possible to reduce future carbon emissions associated with the building construction sector with the promotion of new low-carbon building structures and the improvement of productivity. Li et al. (2022) assessed the changes in carbon emission reductions from commercial building operations in various provinces of China, which provides a reference for local

governments and other economies to improve energy efficiency during the operation phase. In addition, it can promote carbon reduction in the construction industry by rationally managing the construction waste generated in the construction process during the building demolition phase and utilizing this resource (Liu et al., 2023a).

2.3 Research on the impact of digital technology on carbon emissions

At present, numerous studies have been undertaken to explore the influence of the digital economy or digitalization on CO_2 emissions, and digital technology can provide digital and intelligent technical means for the green development of society, contributing to promoting the decrease of overall energy consumption and CO_2 emissions in society (CAICT, 2021). Some scholars have studied the correlation between the digital economy and carbon emissions in various cities in China and found that the growth of the digital economy can decrease urban CO_2 emissions (Yu et al., 2022) through strengthening environmental supervision and promoting green innovation (Pan et al., 2023), while positively influencing carbon emission reduction by exerting a "spillover effect" on neighboring cities (Liu et al., 2022a). Lu (2018) found that information and communication technologies significantly curbed CO_2 emissions based on a sample of 12 Asian nations from 1993 to 2013. Danish (2019) also came to the same conclusion using data from 59 nations along the Belt and Road from 1990 to 2016. However, other academics contend that as digital technology depends on energy (Yang et al., 2022), using electricity will intensify the extraction and consumption of resources, resulting in more carbon emissions, but it will gradually suppress CO_2 emissions with the deepening of the use of digital technology, displaying a nonlinear connection with an inverted U shape (Li et al., 2021; Miu et al., 2022). For example, Li et al. (2023b) found that the coefficient of the influence of the digital economy on 3E (energy–environment–economy) efficiency changed from negative to positive when per capita GDP exceeded the threshold based on data from 24 EU nations from 2011 to 2019, illustrating that as the continuous maturity of the digital economy, the sustainability of economic growth progressively rose and the energy intensity decreased step by step.

Further focusing on the micro-enterprise level research perspective, Shang et al. (2023) took listed companies in China from 2012 to 2020 as a sample, and revealed that company digital transformation can dramatically lower enterprise carbon emission intensity by enhancing internal control abilities and technological innovation capability. In addition, other scholars have discovered that enterprise digital transformation can also decrease corporate CO_2 emissions by improving energy utilization efficiency (Yang et al., 2023), resource allocation capacity (Chen and Kim, 2023), green innovation capability (Liu et al., 2023c) and other factors.

2.4 Comment on the research literature

In conclusion, it can be found that domestic and international scholars have achieved stage-by-stage results in the research related to digital construction and carbon emission in the construction field based on the organization and review of domestic and international literature. However, some problems still need to be solved:

(1) The study on the impact of digital technology on CO_2 emissions is mostly concentrated at the macro level of countries, regions and industries, but there are fewer studies at the micro-enterprise level. Especially for construction enterprises, existing studies mainly focus on the specific application of digital construction technology to the various stages of the building life cycle, but few studies have measured the comprehensive level of digital construction of construction enterprises; therefore, there are fewer empirical studies on the impact on carbon emissions of enterprises.

(2) In the path of building carbon emission reduction, scholars primarily analyze emission reduction measures based on the industry level in the building life cycle and its various stages, in which digital construction provides new opportunities for low-carbon transformation for construction enterprises. However, the current research only stays in the stage of qualitative analysis, and few researches have systematically analyzed and explored the intrinsic mechanism of carbon emission reduction of construction enterprises by digital construction through empirical tests.

In view of the gaps and deviations of the above studies, this study draws on the way scholars measure the digital economy or enterprise digitization and combines the digital characteristics of engineering construction itself, to construct the digital construction level index of construction enterprises from a brand-new dimension. Then, we study its impact on corporate carbon emission reduction and the internal mechanism from both theoretical and empirical perspectives.

3 Theoretical analysis and research hypotheses

3.1 Digital construction and carbon emissions

As an emerging construction mode in the construction industry, digital construction provides new strategic opportunities and scientific and technological support for the low-carbon transformation of the construction industry (Wang et al., 2023a), and promotes the carbon emission reduction of construction enterprises from the following aspects. To begin with, the application of digital construction technology can achieve real-time collection, monitoring, transmission and analysis of energy data and guide energy factors to realize efficient allocation (Yao et al., 2023); at the same time, according to the theory of supply and demand, it can also effectively promote the coordination of the supply and demand side of production factors in construction enterprises, so that enterprises can achieve higher energy

efficiency under the same conditions (Veskioja et al., 2022; Zhao and Ren, 2023) to promote carbon emission reduction. Furthermore, in accordance with the project management life cycle theory (Ma et al., 2018), the carbon emission reduction empowered by digital construction technology is also reflected in the use of digital elements by enterprises to strengthen the control of the whole life cycle process of construction. In the project design stage, construction enterprises can virtualize the construction process by using construction virtual prototype technology and mixed reality technology, which aims to provide visual means for carbon emission prediction and minimization of construction projects so as to find methods to decrease carbon emissions by taking preventive or corrective measures before the project starts (Wong et al., 2013). During the construction phase, the materials used in the use of 3D concrete printing technology can emit 80% less CO_2 than the production of traditional concrete materials (Nematollahi et al., 2018). In the construction operation and management phase, companies generate fewer carbon emissions in future construction activities by applying industrial IoT to collect past data from the construction process and using digital twin architecture to monitor real-time architectural situations (Shen et al., 2022) to compose models and predict their future behavior (Metallidou et al., 2022). Finally, the application of digital construction technology can enhance the ability of information interaction and sharing within enterprises, such as the use of data creation and sharing, cross-temporal information dissemination and other channels to transmit, flow green emission reduction technology and other aspects of information (Lyu et al., 2023), for the purpose of reducing unnecessary activities, in addition, big data technology can offer data support for enterprise carbon emission reduction by improving the integration of data information such as energy input structure and CO_2 emissions (Zhang et al., 2021). Based on the above, a hypothetical H1 is proposed.

H1: The development of digital construction level can contribute to the reduction of carbon emission intensity of enterprises.

3.2 Digital construction, enterprise R&D innovation capability and carbon emissions

For the construction industry, the process of integrating traditional engineering construction activities with digital technology is an innovative activity (Ding, 2020), such as China State Construction Engineering Corporation Limited established the first China National Digital Construction Technology Innovation Center and independently developed AECMate domestic 3D engineering image software. On the one hand, digital innovation theory holds that firms will invest more in innovation activities among themselves in order to make better products in the digital economy (Wen et al., 2022a; Wen et al., 2022b). In order to implement innovation-driven development strategies and enhance their competitive advantages in the industry, construction enterprises will inevitably increase their R&D efforts and investments in digital construction technology and other key core technologies (Wu et al., 2021), thereby enhancing innovation output (Kim, 2019). Pecking order theory states that since the cost of external financing is higher than the cost of internal financing, the company can only rely heavily on internal financing, resulting in underinvestment (Myers and Majluf, 1984). The implementation of digital construction technology in construction enterprises also releases a benign signal to the outside world to actively respond to the national strategy, implying high-quality development in the future, which means that it is conducive to facilitating the trust of external financial backers (Bertani et al., 2020; Zhang and Dong, 2023), so as to provide financial support for enhancing R&D innovation capabilities (Ding et al., 2022). It has been shown that for China, increased R&D investment directly curbs carbon intensity (Wang and Zhang, 2020) and can play a moderating role between digitization and CO_2 emissions (Ma et al., 2022).

On the other hand, transaction cost theory holds that cost reduction is an essential way for firms to obtain heterogeneous innovation resources (Hennart, 1988). Digital technologies such as the Internet and artificial intelligence have the advantage of facilitating the sharing of explicit and tacit knowledge resources, which can help enterprises break down information silos (Wu et al., 2022), alleviate information asymmetry (Liu et al., 2023b) and improve the transmission efficiency and accuracy of internal and external information and knowledge (Goldfarb and Tucker, 2019; Fang et al., 2022; Wen et al., 2022a). It can also increase the efficiency of resource allocation of companies (Sousa-Zomer et al., 2020), and allocate key resources to core technologies and innovation activities (Li et al., 2023a), thus reducing the cost of companies in the process of information acquisition and avoiding the misallocation of resources and energy waste, and reducing CO_2 emissions. In addition, digital technology also helps to enhance the green development capability of enterprises when R&D cooperation and experience exchange of reducing carbon emission among companies in the construction industry (Wang et al., 2018; Zhang et al., 2021); and it promotes collaboration and knowledge sharing between enterprises and institutions such as universities and research institutes (Zhang, 2019) and open innovation of enterprises (Mubarak et al., 2021), resulting in reducing the R&D trial and error costs of digital construction technologies, shortening the R&D design cycle, and improving innovation efficiency (Shang et al., 2023). Based on the above, a hypothetical H2 is proposed.

H2: The development of digital construction level can reduce the carbon emission intensity by improving the R&D innovation capability of enterprises.

3.3 Digital construction, total factor productivity and carbon emissions

Total factor productivity is part of the output that cannot be interpreted by the number of inputs used in production, and more is the growth brought about by intangible factors such as technological progress and technological efficiency (Comin, 2010). The theory of technological progress argues that the margins of productivity factors can be raised in the identical ratio by technological progress to bring

down energy intensity, thus achieving carbon emissions reduction (Cheng et al., 2021). Correspondingly, in the long run, it is increasingly becoming a consensus in Chinese society to achieve low-carbon economic development with technology (Wang et al., 2022). On the one hand, digital construction technologies can boost total factor productivity by increasing construction efficiency on the construction site; specifically, when building concrete walls with complex geometry using a robot on the construction site, productivity increases significantly compared to traditional forms of construction (García De Soto et al., 2018). Moreover, a construction site digital process platform built upon the foundation of IoT, cloud computing, and 5G mobile communication technologies can improve productivity in the construction process (Zhou et al., 2020) by addressing the complexity of the construction site environment and enhancing collaboration between different project participants such as contractors, construction workers, machinery and equipment, and material suppliers on the construction site (Oesterreich and Teuteberg, 2016). On the other hand, digital construction can also provide technical support for lean construction, such as the development of construction sites VisiLean (Dave et al., 2011) and BeaM! (Schimanski et al., 2021) production management systems integrated with BIM, IoT and lean construction, which can be applied to the entire project lifecycle, enabling the realization of lean principles from planning and design, construction and post-construction phases (Dave et al., 2016), with the aim of minimizing waste and uncertainty in the building construction process and thus increasing total factor productivity. Further, the increase in total factor productivity can yield desirable outputs such as meeting project schedules, cost and quality targets with sufficiently few construction inputs such as materials, energy and labor (Hu and Liu, 2017), which can improve energy efficiency and reduce carbon emission intensity (Amri et al., 2019; Altinoz et al., 2021; Lahouel et al., 2021). For instance, Zhu et al. (2019) found that technological progress (measured by total factor productivity) decreased the energy consumption intensity of the Chinese building industry at an average rate of 7.1% per year by constructing a model of the building process, hence contributing to carbon productivity (i.e., the inverse of carbon intensity) (Fan et al., 2021; You and Zhang, 2022). Based on the above, a hypothetical H3 is proposed.

H3: The development of digital construction level can reduce the carbon emission intensity of enterprises by improving total factor productivity.

Through the above theoretical analysis, the theoretical transmission mechanism is shown in Figure 1.

4 Materials and methods

4.1 Econometric model

To test the effect of digital construction on the carbon intensity of construction enterprises, the following benchmark regression model is constructed in this paper, as shown in Equation (1):

$$CEI_{i,t} = \alpha_0 + \alpha_1 DIGC_{i,t} + \alpha_2 controls_{i,t} + \lambda_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

where, the enterprise, t denotes the year, $CEI_{i,t}$ denotes the carbon emission intensity of the enterprise i in t year, $DIGC_{i,t}$ denotes the digital construction level index of the enterprise, $controls_{i,t}$ represents the control variable, as well as $\varepsilon_{i,t}$ is the random error term; in addition, the model also controls the enterprise fixed effect λ_i, the year fixed effect δ_t. For the sake of making the test results more robust, this paper defaults to the clustering robustness standard error.

4.2 Variables

4.2.1 Explained variables: enterprise carbon emission intensity

Enterprise carbon emission intensity (CEI) is determined by accounting for carbon emissions, which indicates the CO_2

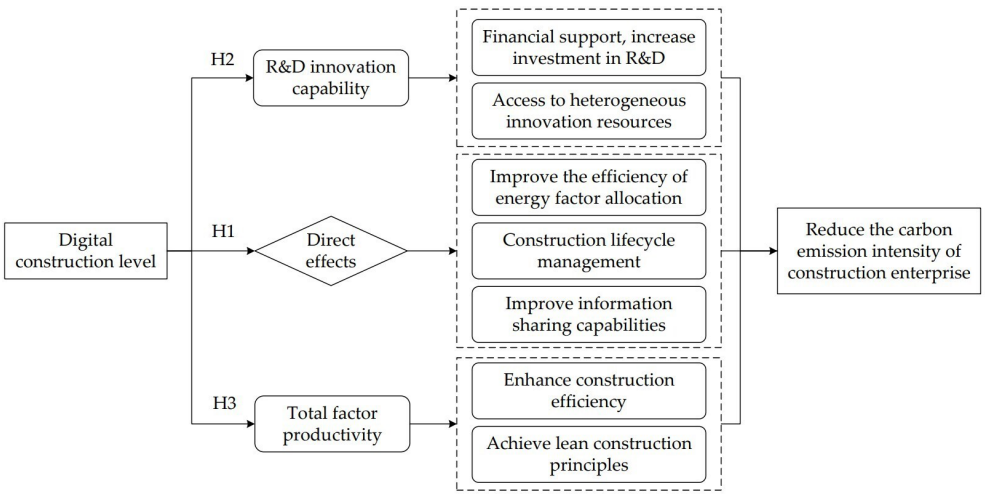


FIGURE 1
The theoretical transmission mechanism.

emissions produced per unit of production value, and the reduction of carbon emission intensity reflects, to some extent, the improvement of enterprises' CO_2 emission reduction ability. This paper evaluates carbon emission intensity by the proportion of enterprise CO_2 emissions to main business income in light of the data accessibility, as described by Chapple et al. (2013). The amount of directly available data is very limited since the Chinese government currently does not mandate companies to disclose CO_2 emissions data in their annual reports or environmental, social, and governance (ESG) reports. Hence, research uses the way of Shang et al. (2023) to estimate the carbon emissions of companies using industry carbon emissions with the help of the main business cost, which is calculated as shown in Equation (2):

$$\boldsymbol{emissions_i} = \frac{\boldsymbol{cost_i}}{\boldsymbol{cost_{in}}} \times \boldsymbol{E_{CO_2}} \tag{2}$$

where $emissions_i$ denotes enterprise CO_2 emissions, $cost_i$ denotes the main business cost of company, $cost_{in}$ denotes the industry main business cost and E_{CO_2} denotes industry CO_2 emissions. The carbon emission behaviors of the construction enterprise include the carbon emission generated by the process of completing the construction of various sub-elements and implementing various measures of the project, as well as the various types of energy power consumed by mechanical equipment used in the demolition phase. In other words, the CO_2 emission is mainly due to the energy consumption, i.e., the combustion of fossil fuels, and therefore the industry's CO_2 emissions are measured according to the energy consumption. When we check the "China Energy Statistical Yearbook", there are 11 main types of energy consumption involved in the construction industry, mainly including raw coal, coke, kerosene, fuel oil, gas oil, diesel oil, crude oil, LPG, natural gas, heat and electricity, of which the CO_2 emissions from the depletion of the first nine types of energy are direct emissions from the combustion of fossil fuels, and the electricity and heat purchased by enterprises outside are indirect emissions. The CO_2 emissions of the industry can be calculated according to Equation (3):

$$\boldsymbol{E_{CO_2}} = \boldsymbol{E_f} + \boldsymbol{E_{eh}} \tag{3}$$

where, E_f denotes CO_2 emissions due to the burning of consumed fossil fuels, E_{eh} denotes CO_2 emissions due to the burning of electricity and heat by enterprises.

Equations (4) and (5) can be used to compute CO_2 emissions from fossil fuel burning using the emission factor approach described in the 2006 IPCC Guidelines for National Greenhouse Gas Inventories:

$$\boldsymbol{E_f} = \sum_{i=1}^{n} (\boldsymbol{FC_i} \times \boldsymbol{EF_i}) \tag{4}$$

In Equation (4), FC_i denotes the quantity of fossil fuel consumed, and EF_i denotes the CO_2 emission factor.

$$\boldsymbol{EF_i} = \boldsymbol{NCV_i} \times \boldsymbol{CC_i} \times \boldsymbol{OF_i} \times \boldsymbol{\rho} \tag{5}$$

In Equation (5), NCV_i stands for the average low-level calorific value of the fossil fuel, CC_i for its carbon content per unit calorific value, OF_i for its carbon oxidation rate, and ρ denotes the proportion of CO_2 to the molecular weight of carbon, which is 44/12. Table 1 displays the values of each variable and data source.

For the measurement of CO_2 emissions from electricity and heat, it can be calculated according to Equation (6):

$$\boldsymbol{E_{eh}} = \boldsymbol{AD_e} \times \boldsymbol{EF_e} + \boldsymbol{AD_h} \times \boldsymbol{EF_h} \tag{6}$$

where AD_e and AD_h denote the consumption of electricity and heat respectively, EF_e and EF_h denote the CO_2 emission factors of electricity and heat respectively, both adopt the recommended values of the Ministry of Ecology and Environment, and the CO_2 emission factors of electricity in 2015–2020 and 2021 are calculated as 0.6101 tCO_2/MWh and 0.518 tCO_2/GJ respectively, and the CO_2 emission factor of heat is 0.11 tCO_2/GJ.

4.2.2 Core explanatory variables: digital construction level index

How to measure the digital construction level index (DIGC) of construction enterprises is a complex and systematic difficulty. As

TABLE 1 CO_2 emission reference factors for various energy sources.

Energy Type	Average low-level calorific value	Carbon content Per unit calorific value	Carbon oxidation rate	CO_2 emission factor
	NCV_i	CC_i	OF_i	EF_i
Raw Coal	20934 kJ/kg	26.37 tC/TJ	0.94	1.9027 kg-CO_2/kg
Coke	28470 kJ/kg	29.5 tC/TJ	0.93	2.8639 kg-CO_2/kg
Crude Oil	41868 kJ/kg	20.1 tC/TJ	0.98	3.0240 kg-CO_2/kg
Fuel Oil	41868 kJ/kg	21.1 tC/TJ	0.98	3.1744 kg-CO_2/kg
Gas Oil	43124 kJ/kg	18.9 tC/TJ	0.98	2.9287 kg-CO_2/kg
Kerosene	43124 kJ/kg	19.6 tC/TJ	0.98	3.0372 kg-CO_2/kg
Diesel Oil	42705 kJ/kg	20.2 tC/TJ	0.98	3.0998 kg-CO_2/kg
LPG	50242 kJ/m^3	17.2 tC/TJ	0.99	3.1052 kg-CO_2/m^3
Natural Gas	38979 kJ/m^3	15.3 tC/TJ	0.99	2.1649 kg-CO_2/m^3

NCV_i is derived from the Basic Guidelines for Calculating Total Energy Consumption; CC_i and OF_i are derived from the Guide to Provincial Greenhouse Gas Inventory Preparation.

digital construction is in the initial phase, scholars are gradually exploring and improving the concepts and theories, and there is a dearth of academic research on the measurement of the digital construction level of construction enterprises. At the same time, with the advent of the digital economy era, many scholars measure the digital economy or digital transformation of enterprises with various methods. Therefore, this paper draws on the relevant digital index measurement methods and combines the digital characteristics of engineering construction itself to make a comprehensive estimation of the digital construction level of construction enterprises.

In this paper, we will measure the digital construction level index in three dimensions: input, governance and output of construction enterprises in digital construction, whose conceptual diagram is shown in Figure 2, and synthesize the index by using the entropy value method.

(1) Referring to Xiao et al. (2022), this paper uses the proportion of digitization-related portion of intangible assets in the breakdown of intangible assets to total assets as a proxy variable for firms' digital construction input. Specifically, the use of software in construction enterprises mainly includes BIM, engineering management information systems, virtual design and construction, simulation calculation and process planning. As a consequence, the items with intangible asset line items, including "software", "computer software", "computer software", "software use rights", "software systems", "intelligent platforms" and other digital technology-related keywords are regarded as "digital construction intangible assets", and then their proportion to the total assets of the year is calculated, which is the digital construction input of the enterprise.

(2) Digital construction technology, as a key point for the transformation and upgrading of construction enterprises, its characteristic information is more likely to be represented in the annual reports of enterprises. The vocabulary usage in annual reports can reflect the strategic features and future view of enterprises, and to a large extent, it also manifests the management concepts promoted by enterprises and the development path guided by this philosophy (Wu et al., 2021). Consequently, this paper refers to Wu et al. (2021) and Zhao and Wang (2021) to extract the keywords of "digital construction technology" from the annual reports of construction enterprises and conduct word frequency statistics as a variable for the digital construction governance of companies.

Following are the precise steps. In the first step, the annual reports of listed enterprises in the construction industry from 2015–2021 were collected from Giant Tide Information Network and converted to text format through Python's "pdfplumber" function. In the second step, a feature thesaurus of digital construction technology was formed on the basis of policies and research reports such as the "Digital Construction Development White Paper (2022)" and the "Several Comments on Accelerating the Development of New Construction Industrialization", as shown in Figure 3, with a total of 96 feature words in six dimensions. In the third step, based on the self-built feature lexicon, the Jieba function of Python was used to split words for all samples and remove intonation words, auxiliary words and punctuation that have no practical meaning in the text, making it more meaningful to do word frequency statistics. The fourth step was to search, match and count word frequencies depending on the feature thesaurus based on the annual report in the company text format. In the fifth step, because the Jieba function had certain limitations on the word segmentation function of English words, such as part of word frequency statistics of "AR", "VR", "AI" and "CIM", which had nothing to do with digital construction technology, these were eliminated after identification to form the final total word frequency of digital construction of construction enterprises.

(3) The output of digital construction is expressed by using the patents applied by construction companies in the area of digital construction technology. The calculation method is as below. In the first step, obtain the IPC subdivision classification numbers of patents applied for inventions and utility models by construction enterprises for each year from the China Research Data Service Platform (CNRDS). In the second step, patents in the field of

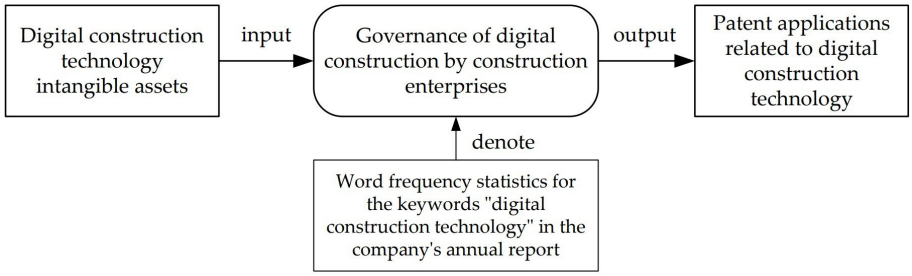


FIGURE 2
Conceptual diagram of digital construction technology.

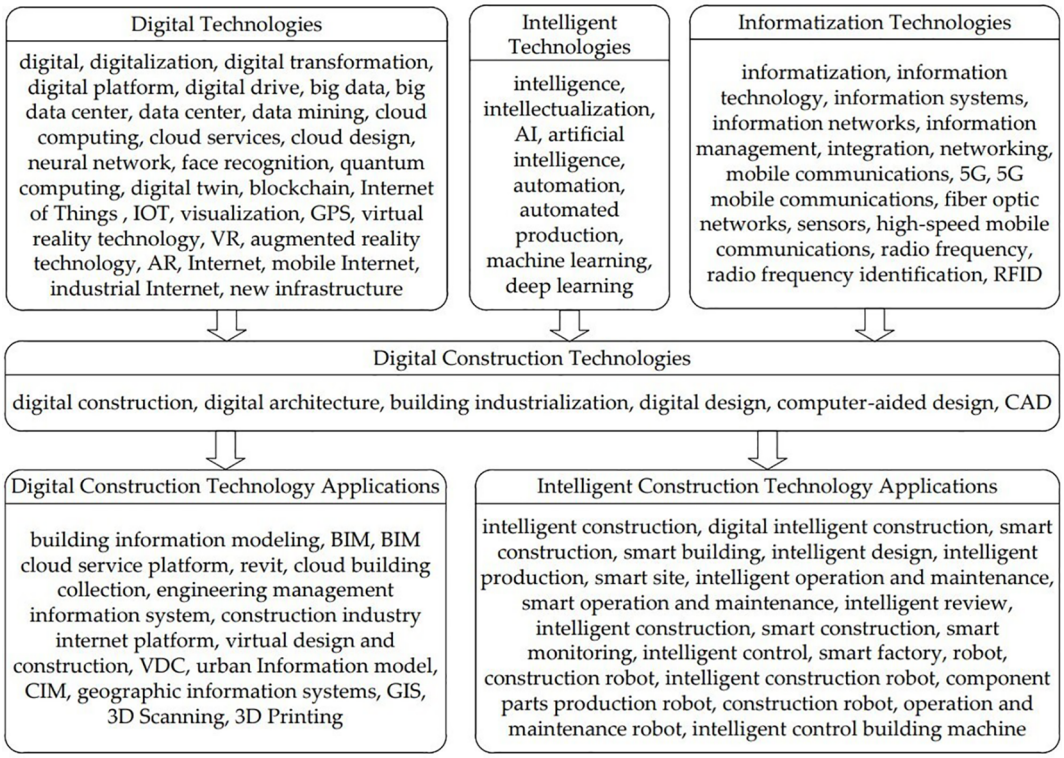


FIGURE 3
Feature thesaurus for digital construction technology.

digital construction are matched according to the "International Patent Classification and National Economic Industry Classification Reference Relationship Table (2018)" (China National Intellectual Property Administration, 2018) and the "Statistical Classification of Digital Economy and Its Core Industries" issued in China in 2021.

Finally, the proportion of digital construction input, i.e., the enterprise's investment in digital construction intangible assets is 35.6% in the establishment of the digital construction level index. The weight of digital construction governance is 16%, which may be influenced by the quality of the company's annual report and the construction of the characteristic word database, and there may be some deviation in the results, so the weight is reasonable. The weight of digital construction output, i.e., digital construction technology patents, accounts for nearly half of the weight since the patent applications are generated by construction enterprises in the process of engineering construction, which can best reflect the digital construction level of companies. Consequently, the weights of each sub-index of the digital construction level index are scientific and reasonable.

4.2.3 Control variables

To increase the study's accuracy, this paper draws on previous studies (Shen et al., 2020; Zhang and Dong, 2023) and combines the research practice of this paper to add the control variables. Enterprise size (Size) and enterprise age (Age) are the basic situations of the enterprise. The larger the size of the enterprise, the more likely it is to have the energy to implement low-carbon behaviors and governance. The enterprise age may reflect the life cycle in which the firm is located, with longer-established firms likely to be in decline and less able to govern low-carbon behaviors. Reducing greenhouse gas emissions demands a great deal of additional management in day-to-day operations, as it requires a complex design of green governance processes within the company, so good corporate governance enables companies to integrate internal resources to promote carbon reduction (Kock et al., 2012). Therefore, this paper controls corporate governance factors from board size (Board), equity multiplier (EM), current ratio (CR) and operating capacity (ET), in which the board of directors makes the final decision on the extent to which the firm implements carbon reduction strategies; equity multiplier reflects the financial leverage of the enterprise, and excessive leverage is not conducive to the enterprise's carbon emission reduction; current ratio reflects the enterprise's solvency, and the value of which to a certain extent will affect the decision on the carbon emission reduction; and the operating capacity embodies the enterprise's efficiency of the use of assets to support the business activities. In addition, the disclosure of environmental and sustainable development (Sus) reflects a company's environmental awareness and social responsibility. Specific variables are defined in Table 2.

4.3 Sample selection and data sources

We have combed through China's important national policies on the development of digitization and informatization in the construction industry in recent years and found that the state has been vigorously promoting digital construction-related technologies as well as the wide-scale application of digital construction technologies by construction enterprises since 2015. Therefore, in this paper, 52 listed companies in Shanghai and Shenzhen A-shares in the construction industry from 2015–2021 are used as the initial sample, and the listed companies in the construction industry are determined according to the industry categories stipulated by the China Securities Regulatory Commission in 2012. According to the needs of the study, the samples are screened as follows: (1) exclude samples listed after 2015; (2) exclude samples listed in ST, *ST and delisted from 2015–2021; (3) exclude samples undergoing major asset restructuring from 2015–2021; (4) exclude samples changing from other industries to the construction industry from 2015–2021. After the above screening, we finally obtained 364 company-annual observations. The original data used in this study are obtained from China Energy Statistical Yearbook, China City Statistical Yearbook, CSMAR Database, China Economy Information NET Database, RESSET Database and CNRDS, and the annual reports of enterprises are compiled from Giant Tide Information Network.

5 Empirical results and discussion

5.1 Descriptive statistics

The results of descriptive statistics are presented in Table 3, in which the mean value of carbon emission intensity (CEI) is 46.313, indicating that construction enterprises produce 46.313 kg of CO_2 emissions per 10,000 yuan of business income on average, and the standard deviation of 4.921 with the maximum values is 59.9 and the minimum values is 31.085, indicating that there are large differences in the carbon emission intensity of different enterprises. The mean value of the Digital Construction Level Index (DIGC) is 2.514, the standard deviation is 0.543, and the maximum and minimum values are 3.730 and 0.796, respectively, which means that the development level of digital construction of different construction enterprises varies greatly, some construction enterprises have a higher development level and application of digital construction, but some construction enterprises have not yet made effective use of digital construction technology. The mean value of Sus is 0.885, and the standard deviation is 0.320, indicating that most construction enterprises disclose environmental and sustainability-related information in their annual reports or ESG reports. The distribution characteristics of the remaining control variables are roughly the same as in previous studies and will not be repeated.

5.2 Benchmark regression

The benchmark regression findings of the effect of the level of digital construction on the CO_2 emission intensity of construction companies are shown in Table 4. This study adopts the progressive regression method in the benchmark regression, and after gradually introducing fixed effects and control variables, the influence of digital construction on carbon intensity is always negative. Column (1) reports the regression results of the explanatory variables and core explanatory variables only, and the coefficient of the digital construction level index (DIGC) is −3.283, which passes the 1% statistical significance test, indicating that the improvement of digital construction level of construction enterprises can significantly reduce carbon emission intensity. Although column (2) controls for firm and year fixed effects based on column (1), the coefficient for DIGC is still statistically negative at the 1% level at −1.982. Columns (3) and (4) add control variables to column (1) and control for firm and year fixed effects in turn, and it can be found that the R^2 of the model is increasing and the DIGC coefficient is gradually decreasing, indicating that it may be

TABLE 2 Description of main variables.

Variable Category	Variable Name	Symbol	Variable Description
Explained variable	Enterprise carbon emission intensity	CEI	Ratio of enterprise CO_2 emissions to main business income
Core explanatory variable	Digital construction level index	DIGC	Synthesize it from three dimensions of input, governance and output of construction enterprises in digital construction using entropy method
Control variables	Enterprise size	Size	Natural logarithm of total corporate assets
	Enterprise age	Age	Year of enterprise −year of establishment + 1
	Board size	Board	Natural logarithm of the number of board members
	Equity multiplier	EM	Total corporate assets/total shareholders' equity
	Current ratio	CR	Current assets/current liabilities
	Operating capacity	ET	Expressed as shareholders' equity turnover ratio, operating income/average shareholders' equity
	Whether to disclose environmental and sustainability	Sus	Enterprises disclosed in the year to take 1, not disclosed to take 0

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TABLE 3 Descriptive statistical characteristics of main variables.

Variable	N	Mean	S.D.	Min	Max
CEI	364	46.313	4.921	31.085	59.9
DIGC	364	2.514	0.543	0.796	3.730
Size	364	10.383	0.766	9.160	12.378
Age	364	20.346	6.072	7	38
Board	364	0.9186	0.083	0.699	1.176
EM	364	4.128	2.911	1.397	45.016
CR	364	1.316	0.353	0.612	3.774
ET	364	2.439	1.496	0.124	11.001
Sus	364	0.885	0.320	0	1

because some factors affecting the intensity of carbon emissions have been absorbed after the inclusion of control variables and fixed effects, but the significance has not changed. In conclusion, the data above demonstrates that the level of digital construction has a considerable negative effect on the intensity of carbon emissions, and that the carbon emission intensity decreases with increasing levels of digital construction in construction enterprises, and the research hypothesis H1 is supported by the empirical evidence.

TABLE 4 Benchmark regression results.

	CEI	CEI	CEI	CEI
	(1)	(2)	(3)	(4)
DIGC	−3.283***	−1.982***	−1.443***	−1.426***
	(0.466)	(0.523)	(0.535)	(0.542)
Size			−3.794***	−3.736***
			(0.747)	(0.771)
Age			−1.615***	−1.689***
			(0.0784)	(0.0923)
Board			5.173***	5.607***
			(1.908)	(1.924)
EM			−0.00850	0.000617
			(0.0219)	(0.0210)
CR			−1.477***	−1.486***
			(0.517)	(0.524)
ET			0.743***	0.713***
			(0.147)	(0.147)
Sus			0.885*	0.916**
			(0.458)	(0.464)
_cons	54.57***	57.67***	140.5***	142.1***
	(1.190)	(1.274)	(6.574)	(6.750)
FIRM FE	N	Y	Y	Y
YEAR FE	N	Y	N	Y
N	364	364	364	364
R^2	0.131	0.888	0.904	0.905

*, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively. The brackets represent the clustering robustness standard errors. The following tables are identical unless specified differently.

5.3 Robustness test

In order to enhance the robustness and validity of the core findings, this paper chooses to replace the core explanatory variables and replace the model for robustness testing.

5.3.1 Replacing core explanatory variables

In this paper, the digital construction level of construction enterprises is remeasured in the following way: the enterprise's governance of digital construction indicator is replaced by the frequency of digital construction keywords in the annual reports of enterprises as the ratio of the total number of keyword disclosures to the total number of words in the annual report of the corresponding year, and then it is re-synthesized into the digital construction level index with the digital construction input and output indicators using the entropy value method, which is denoted as DIGC_1. The test finding is reported in column (1) of Table 5, where it is discovered that DIGC_1's coefficient is considerably negative at the 1% level, which demonstrates that the main finding of the study still holds after changing the measurement of digital construction level, further validating the research hypothesis of this paper.

5.3.2 Replacing the model

To address the possible heteroskedasticity and autocorrelation in the panel data, this paper draws on Cai et al. (2022) to estimate the model using FGLS, and the findings are shown in column (2) of Table 5, where the regression coefficient of DIGC is still dramatically negative at the 1% level.

The findings of all the aforementioned robustness tests do not differ noticeably from the sign and degree of significance of the primary explanatory variables based on the fixed-effects model, demonstrating the robustness of the estimates of the fixed-effects model.

TABLE 5 Regression results of robustness test.

	Replacing Core Explanatory Variables	Replacing the Model
	(1)	(2)
	CEI	CEI
DIGC_1	−1.534***	
	(0.565)	
DIGC		−1.321***
		(−3.44)
_cons	83.18***	–
	(6.610)	–
Controls	Y	Y
Firm FE	Y	Y
Year FE	Y	Y
N	364	364
R^2	0.906	–

*** represents statistical significance at the 1% level. R^2 is not analytically significant in FGLS regression and is not reported. FGLS regression shows the Z value in parentheses.

5.4 Endogenous Problems

The endogeneity problem due to reverse causality may exist in the empirical study of this article (Zhao and Wang, 2021), in other words, enterprises with low carbon emission intensity are more focused on improving digital construction. To mitigate the endogeneity problem, we control for time effects and firm effects in the baseline model, furthermore, the instrumental variables approach, the system GMM model and the difference in differences model are applied to discuss the endogenous problem.

5.4.1 Instrumental variable method

The basic approach to solving the endogeneity problem is to select appropriate instrumental variables for the core explanatory variables, and effective instrumental variables fulfill the basic requirements of correlation and exogeneity. This study utilizes the historical data with the lagged terms of the core explanatory variables as a solution to the endogeneity problem. Specifically, this paper selects the postal and telecommunication data in 1984 of the province where the firm is located as an instrumental variable drawing on Wang et al. (2023b), Du et al. (2023a) and Xue et al. (2022). Since the post and telecommunication data are cross-sectional data and cannot be directly used in the econometric analysis of panel data, we refer to Nunn and Qian (2014), Wang et al. (2023b) and Xiao et al. (2022) for the treatment of this issue, and introduce the time-series variable of the number of Internet broadband access subscribers in the previous year to construct the panel instrumental variable. Finally, instrumental variables for the level of digital construction in this study are the interaction terms of the number of Internet broadband access subscribers in the previous year with the number of landline telephones per 100 people in the province where the construction firms were registered in 1984, respectively, as well as the first-order lagged terms of the core explanatory variables. The model is re-tested using the two-stage least squares (2SLS) method.

Theoretically, for historical postal data, on the one hand, digital construction technology is based on BIM, Internet, big data, digital twin and other digital technologies; meanwhile, post and Internet provide specific carriers for digital construction technology applications in construction enterprises, so the tool variables satisfy the relevance condition; on the other hand, the development of post and mobile Internet itself does not produce the massive CO_2 emissions and will not have a direct effect on the carbon emission intensity of enterprises, in this sense, the selected instrumental variables satisfy the condition of exogeneity. For the lagged terms of the core explanatory variables, on the one hand, the core explanatory variables are correlated with their first-order lagged variables, and on the other hand, the lagged variables are exogenous because they have already occurred and are therefore "pre-determined", and may not be correlated with the current period's disturbance terms.

The result of the second-stage estimation of the instrumental method is shown in column (1) of Table 6. The Kleibergen-Paap rk LM statistic is 22.254, which significantly rejects the original hypothesis of non-identifiability at the 1% level. The Cragg-Donald Wald F statistic is greater than the Stock-Yogo test at 10% critical value of 19.93, rejecting the original hypothesis of weak instrumental variables. The Hansen J test p-value is 0.338, which is greater than 0.1, indicating that all instrumental variables are exogenous. The above indicators show that the instrumental variables are reasonably reliable. The coefficient of the digital construction level of the enterprise (DIGC) is extremely negative at the 1% level in the second-stage regression, indicating that the main conclusion of this paper holds again.

5.4.2 System GMM model

Next, a system GMM model is used with reference to Xie and Kuang (2020), and the level lagged terms of key variables are introduced as instrumental variables in the regressions for testing. The core explanatory variable DIGC regression coefficient is dramatically negative, according to the result in column (2) of Table 6, which is similar to the prior estimation and shows that the conclusion of this study is robust.

5.4.3 Difference in differences model

In this study, the difference in differences model (DID) is chosen to further overcome the endogeneity problem by referring to the studies of Wu et al. (2021) and Wang et al. (2023b). When constructing the digital construction level index using the entropy value approach, its subindex, the quantity of applications for digital construction patents, has the largest weight and best reflects the digital construction level of construction enterprises, so it is used to judge whether the digital construction technology has been effectively applied according to the digital construction patent applications of enterprises in each year. If a construction enterprise has applied for a digital construction patent during the sample period, it means that there is a substantial application of digital construction technology, and this type of enterprise is used as an experimental group (du=1); if there has been no application for a digital construction patent, it means that there is no substantial application of digital construction technology, and this type of enterprise is used as a control group (du=0); furthermore, the period dummy variable dt is set, and dt is assigned to 1 if the enterprise adopts digital construction technology in the current and subsequent years, otherwise it is 0. Accordingly, the following difference in differences model is established to examine how the level of digital construction of construction enterprises affects carbon intensity:

$$CEI_{i,t} = \varphi_0 + \varphi_1 du_{i,t} + \varphi_2 dt_{i,t} + \varphi_3 (du_{i,t} \times dt_{i,t}) + \varphi_4 controls_{i,t} + \varepsilon_{i,t} \quad (7)$$

where φ_3 reflects the change in carbon emission intensity before and after the adoption of digital construction technology by enterprises and is the parameter to be estimated for the key variable. Considering that the application of digital construction technology by construction companies is an incremental behavior with time continuity, the sample of enterprises whose digital

TABLE 6 Regression results of the endogenous test.

	IV	System GMM	DID	
	(1)	(2)	(3)	(4)
	CEI	CEI	CEI	CEI
DIGC	−2.791**	−4.530**		
	(1.390)	(1.697)		
$du \times dt$			−4.788***	−0.714**
			(0.561)	(0.335)
_cons	142.9***	–	38.11***	113.9***
	(14.18)	–	(5.544)	(6.308)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	N	Y
Year FE	Y	Y	N	Y
Kleibergen-Paap rk LM	22.254***			
Cragg-Donald Wald F	26.504			
Hansen J test p-value	0.338			
Hansen test p-value		0.170		
N	312	208	343	343
R^2	0.888	–	0.343	0.911

** and *** represent statistical significance at the 5% and 1% levels, respectively.

construction level is greater than 0 in the current year but 0 in the subsequent years is excluded from this paper.

Further, to verify the robustness of the difference in differences model again, the above model is tested again after focusing on regulating for firm fixed effects λ_1 and year fixed effects δ_t, as shown in Equation (8):

$$CEI_{i,t} = \varphi_0' + \varphi_1' du_{i,t} + \varphi_2' dt_{i,t} + \varphi_3' (du_{i,t} \times dt_{i,t}) + \varphi_4' controls_{i,t} + \lambda_i + \delta_t + \varepsilon_{i,t} \quad (8)$$

In columns (3) to (4) of Table 6, the empirical findings based on the difference in differences model tests are displayed. Column (3) is tested with Equation (7), and the coefficient of $du_{i,t} \times dt_{i,t}$ is −4.788, which is significantly negative at the 1% level, again indicating that the carbon intensity of construction enterprises was significantly reduced after adopting digital construction technology. Column (4) shows the results of the test in Equation (8), adding firm and year fixed effects, and finds that the coefficient of $du_{i,t} \times dt_{i,t}$ shrinks significantly to −0.714, but remains significant at the 5% level. The above findings indicate that after mitigating the endogeneity of the model using the difference in differences model, the improvement in the level of digital construction still significantly reduces the carbon emission intensity.

The difference in differences model should satisfy the parallel trend assumption condition, i.e., the carbon emission intensity of the experimental group samples and the control group samples should have the same trend of change before the implementation of digital construction by the construction enterprises. For this reason, we carry out the parallel trend test, and the test results are shown in Figure 4.

In Figure 4, current denotes the time variable of the first implementation of digital construction technology by a construction enterprise, which is taken as the time base, and pre_i and post_i denote the time variable of the ith year before and after the implementation of digital construction technology by a construction enterprise, respectively. Let pre_3 denote the time variable 3 years before and before the implementation of digital construction technology by the enterprises, and post_5 denote the time variable 5 years after and after the implementation of digital construction technology by the enterprises. As can be seen in Figure 4, the estimated coefficients for all periods are significantly around 0 before the implementation of digital construction technology in construction firms, indicating that the experimental group is not significantly different from the control group and the parallel trend assumption is satisfied. After the implementation of digital construction technology, the estimated coefficients show a significant downward trend, which indicates that digital construction has a significant inhibitory effect on the carbon emission intensity of construction enterprises.

5.5 Heterogeneity analysis

The disincentive influence of digital construction on carbon emission intensity may vary among different types of enterprises, so this paper will classify construction enterprises according to the nature of business and the industry segment to which they belong for heterogeneity analysis.

5.5.1 Heterogeneity of the nature of business

This paper separates the sample into state-owned and non-state-owned firms based on the kind of business, and lines (1) to (2)

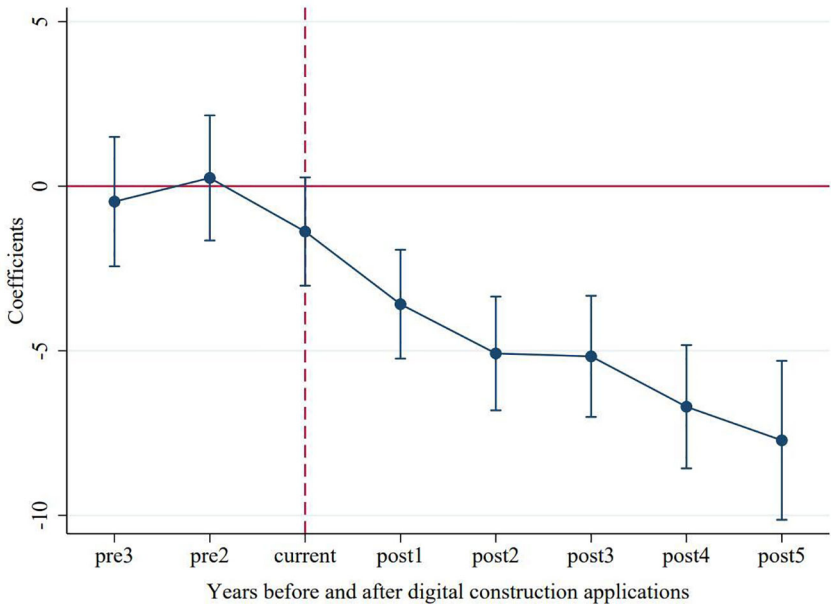


FIGURE 4
The parallel trend test.

of Table 7 analyze the carbon emission reduction impact of businesses with various business natures. The study discovers that the effect of digital construction level on carbon emission intensity in the group of state-owned enterprises is significantly negative at the 5% level, and its coefficient is −2.234; while the regression coefficient of digital construction on carbon emission intensity for the group of non-state-owned companies is also negative (−1.068), but it fails the statistical significance test, and its coefficient is also significantly lower than that of the state-owned enterprises' group, indicating that the digital construction level of non-state-owned companies is relatively less effective in curbing carbon emission intensity compared to state-owned companies. The reason for this difference may be that, for one thing, state-owned companies need to consider social benefits in addition to economic benefits when formulating their own development strategies, and take more social responsibilities than non-state-owned companies, as well as consider the overall development of society and actively respond to the strategy of the carbon peaking and carbon neutrality goals proposed by China, so they play a greater role in carbon emission reduction in the building sector. For another thing, the implementation of digital construction technology in construction enterprises requires large-scale investment in software such as BIM, virtual design and construction and digital twin, or high-end equipment such as construction robots and intelligent factories. State-owned enterprises not only have more advantages in terms of capital and technology but also have access to more preferential policies, resource support and institutional guarantees, which can provide sufficient conditions for the rapid development of digital construction technologies, thus empowering enterprises to reduce carbon emissions.

5.5.2 Heterogeneity of sub-industry types

In this paper, the sample is divided into civil engineering construction enterprises and non-civil engineering construction enterprises according to the differences in the sub-sectors and main business of construction enterprises, and the influence of digital construction on carbon emission intensity is examined for both types of enterprises, and the results are indicated in lines (3) to (4) of Table 7. It has been discovered that digital construction technology significantly decreases the intensity of carbon emissions for civil engineering construction companies (the regression coefficient is −1.900 and passes the 1% statistical significance test). In contrast, for non-civil engineering construction enterprises, including landscape, building decoration and other construction enterprises, the coefficient of DIGC does not pass the statistical significance test, indicating that civil engineering construction enterprises are more able to promote carbon emission reduction by adopting digital construction technology compared to non-civil engineering construction enterprises. The reason for this difference may be that the adoption of digital construction technology is more focused on the field of engineering construction, which can realize the refinement, wisdom and efficiency of the whole life cycle management of the construction process, such as architectural design, construction and operation, for example, the use of the IoT and intelligent construction platform can realize fine construction, so that logistics scheduling, construction scheduling and other information flow automatically, and reduce the cost and increase the efficiency of engineering projects, while for landscape, building decoration and other construction industry enterprises, the use of digital construction technology is more limited, so civil engineering construction enterprises will suppress carbon emission intensity to a greater extent based on the extensive use of digital construction technology.

5.6 Mechanism testing

On the basis of the previous theoretical analysis, the implement of digital construction in construction enterprises can decrease carbon emission intensity and promote carbon emission

TABLE 7 Regression results of heterogeneity analysis.

	CEI	CEI	CEI	CEI
	(1)	(2)	(3)	(4)
Types	SOEs	non-SOEs	civil engineering	non-civil engineering
DIGC	−2.234**	−1.068	−1.900***	0.419
	(0.965)	(0.707)	(0.678)	(0.977)
_cons	93.23***	75.52***	85.29***	92.91**
	(15.81)	(19.99)	(13.01)	(42.53)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	196	168	217	147
R^2	0.926	0.889	0.932	0.865

** and *** represent statistical significance at the 5% and 1% levels, respectively.

reduction in enterprises by improving R&D innovation capability and total factor productivity. In order to verify this mechanism of action, the following mechanism testing models are utilized to analyze the R&D innovation capacity effect and the total factor productivity effect, based on the methodology of Huang et al. (2023):

$$CEI_{i,t} = \alpha_0 + \alpha_1 DIGC_{i,t} + \alpha_2 controls_{i,t} + \lambda_i + \delta_t + \varepsilon_{i,t} \quad (9)$$

$$Mec_{i,t} = \beta_0 + \beta_1 DIGC_{i,t} + \beta_2 controls_{i,t} + \lambda_i + \delta_t + \varepsilon_{i,t} \quad (10)$$

where $Mec_{i,t}$ is the mechanism variable, denoting enterprises' R&D innovation capability (RDI) and total factor productivity (TFP), $\varepsilon_{i,t}$ is random error terms, λ_i is firm fixed effects, and δ_t is year fixed effects.

In this study, we assess the R&D innovation capability of companies on the basis of two factors: R&D input and innovation output (Hall and Lerner, 2010), where R&D input is expressed by the annual R&D investment funds of enterprises; the innovation output of enterprises primarily consists of invention, utility model and design patents. The quantity of patent applications is a more timely indicator of an organization's potential for innovation because patents typically take a long time to be granted (Zhang and Dong, 2023). Finally, utilizing the enterprise's R&D expenditure and the quantity of annual patent applications, the proxy variables of the enterprise's R&D innovation capabilities are synthesized using the entropy method. Then, the total factor productivity of companies is determined using the LP approach based on the research of Levinsohn and Petrin (2003) and Lu and Lian (2012).

5.6.1 R&D innovation capability mechanism

The regression result in line (1) of Table 8 shows that the regression coefficient of digital construction level is significantly negative, indicating that the use of digital construction in construction enterprises can lower carbon emission levels; the use of digital construction is advantageous for enhancing the R&D innovation capability of construction firms, as shown by the regression coefficient of R&D innovation capability in line (2) of Table 8 being statistically significant in the positive direction at the 1% level. On the one hand, the use of digital construction technology prompts construction enterprises to make extensive use of emerging digital technologies and break down information silos, obtain heterogeneous innovation resources and advanced technologies and management tools from more channels, optimize the allocation of resources (Huang et al., 2023), and reduce the waste of resources, which improves the R&D and innovation capability and at the same time reduces the carbon emissions of enterprises. On the other hand, construction companies are bound to adopt more digital construction technologies, increase R&D investment, improve R&D and innovation capacity, and generate new and more productive energy efficient technologies through the innovation process (Petrović and Lobanov, 2020), in order to improve efficiency and reduce costs in the planning, design, construction and building operation phases. An increase in R&D investment reduces CO_2 emissions through direct and indirect effects (rebound effects, spillover effects) (Fernández Fernández et al., 2018). As a result of the above analysis, there is a mechanism of "digital construction development → enterprise R&D innovation capability improvement → carbon emission intensity reduction", and hypothesis H2 is verified.

5.6.2 Total factor productivity mechanism

According to the regression coefficient in line (3) of Table 8, which is dramatically positive at the 1% level, the growth of digital construction is favorable to increasing the total factor productivity of construction enterprises. Digital construction technology can increase total factor productivity by improving productivity and efficiency in the construction process and maximizing the elimination of waste and uncertainty of resources. The enhancement in total factor productivity implies technological progress and technological revolution, which can enable

TABLE 8 Regression results of mechanism testing.

	CEI	RDI	TFP
	(1)	(2)	(3)
DIGC	−1.426***	0.125***	0.177***
	(0.542)	(0.0427)	(0.0684)
_cons	142.1***	−3.934***	−5.647***
	(6.750)	(0.528)	(1.346)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N	364	364	364
R^2	0.905	0.938	0.973

*** represents statistical significance at the 1% level.

construction companies to obtain the desired output with sufficiently few construction inputs such as materials, energy and labor, and the efficiency of energy utilization has been improved, thus reducing the intensity of carbon emissions. Technological advances have been widely recognized as the most promising approach to curbing China's current carbon emissions (Huang et al., 2020), which could lead to CO_2 reductions through carbon efficiency improvements (You and Zhang, 2022). After the above analysis, there is a mechanism of "digital construction development → total factor productivity increase → carbon emission intensity reduction" in this study, and hypothesis H3 is verified.

6 Conclusions and policy recommendations

6.1 Conclusions

The continuous development of digital construction provides a significant opportunity for the low-carbon transformation of the construction industry. This paper constructs the digital construction level index of construction enterprises from three dimensions, and empirically analyzes and examines the impact and mechanism of digital construction on the carbon intensity of enterprises by using the two-way fixed effects model based on the panel data of 52 listed companies in China's building industry from 2015 to 2021. The results of the study show that:

(1) The improvement of digital construction level can significantly reduce the carbon emission intensity of construction enterprises, and for every 1 unit increase in digital construction level, the carbon emission intensity of construction enterprises will decrease by 1.426 units. The conclusions are still valid after a battery of robustness tests and discussions on endogeneity issues such as replacing core variables, replacing models and using instrumental variables method, system GMM model and difference in differences model.

(2) This paper reveals the intrinsic mechanism between digital construction and the carbon emission intensity of construction enterprises, in which digital construction can significantly reduce the carbon emission intensity by improving the R&D and innovation capability and total factor productivity.

(3) From the point of view of the nature of enterprises, state-owned enterprises are more able to curb carbon emission intensity than non-state-owned enterprises in terms of improving the level of digital construction, which is mainly due to the fact that state-owned enterprises need to assume more social responsibility and have more resources and institutional safeguards, and therefore the leading role of state-owned enterprises should be played.

(4) In terms of the industry type of the enterprises, digital construction of civil engineering construction enterprises can significantly reduce carbon emission intensity due to their more extensive application of digital construction technology, while digital construction of non-civil engineering construction enterprises is not significant to carbon emission intensity.

This study further extends the application of project management life cycle theory, digital innovation theory, transaction cost theory and technological progress theory, and makes up for the lack of research on the impact of digital transformation of the construction industry on the carbon emission intensity of enterprises. The conclusions of this paper can provide a reference for the carbon emission reduction management decisions of construction enterprises, have practical guiding significance for future construction enterprises to implement digital change and integrate digital technology into all stages of project construction, and provide theoretical guidance for promoting the transformation and upgrading of the construction industry and for the introduction of relevant policies by the government.

6.2 Policy recommendations

According to the preceding research and conclusions, this paper provides the following policy recommendations:

(1) The government ought to speed up the formulation of leading policies for digital construction technology in the construction industry, encourage to fully incorporate of digital technology and engineering construction, guide each construction enterprise to recognize that digital construction is the best path to achieve carbon emission reduction, and also introduce a series of preferential policies and incentive policies to strengthen the digital technical support efforts and financial support for non-state construction enterprises and small and medium businesses, so as to stimulate the green innovation behavior and CO_2 emission reduction potential of enterprises. Similarly, it is essential to actively cultivate compound talents in digital construction and carbon management of construction enterprises, and invest more resources in talent training. To this end, we should vigorously promote the construction of composite disciplines in colleges and universities and connect with the needs of the industry. Furthermore, it is also crucial to establish and robust a system for environmental information disclosure that complies with legal requirements, as well as to encourage enterprises to do so, as a result, strengthen enterprises' environmental awareness and consciously and proactively promote green transformation and development.

(2) Construction enterprises ought to pay attention to and make full use of digital construction technologies and engineering wisdom management platforms such as blockchain technology, BIM technology, digital twin, 3D printing, construction robots, Internet of Things, VR and construction industry Internet platforms in construction projects, integrate the vision of green development into the whole process of construction and daily management, effectively reduce resource consumption and environmental pollution, and achieve a higher level of green and low-carbon. Simultaneously, they are also supposed to play the leading role of corporate champions, such as state-owned and central enterprises in the construction field, drive other enterprises to implement digital, networked and intelligent changes, vigorously develop digital construction, enhance the sense of social responsibility and promote green development of enterprises.

(3) Construction enterprises should implement the national innovation-driven development strategy, pay attention to improving R&D innovation capacity, increase R&D investment, strengthen cooperation with higher education institutions or other enterprises, obtain information through multiple channels, break information silos, effectively integrate the advantages of all parties, and focus superior resources on breaking through the key core technologies, engineering software and major equipment of digital construction, so as to provide green transformation for the construction industry. In the meanwhile, they should also focus on improving total factor productivity, taking the implementation of digital construction technology as an opportunity to advance the technological progress and technical efficiency of companies, improve energy utilization efficiency and decrease resource waste so as to maximize the carbon emission reduction effect of digital construction.

6.3 Limitations and research prospects

This paper explores and innovatively investigates the impact and mechanism of digital construction level on carbon emission of construction enterprises, but there are some limitations: firstly, this study examines the causal connection between an enterprise's level of digital construction and its ability to reduce CO_2 emissions, as well as the role that R&D and innovation capacity and total factor productivity play in that relationship, but there may be other ways and mechanisms that can be further explored; secondly, as a result of the shortage of data, this article solely takes Chinese listed companies in the construction industry as the sample, but there are still a sizable number of businesses left out and they can all be included in the sample for further exploration; finally, since most construction enterprises do not disclose the detailed data of carbon emissions, this paper obtains them indirectly, and with the improvement and implementation of the system related to environmental information disclosure of enterprises, this data will be available directly in the future, so that the data will be more accurate.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

XY: conception, design of the study, validation, writing—review and editing, supervision and funding acquisition. GL: conception, design of the study, validation, writing—original draft preparation, data curation, visualization and software. XW: data curation, visualization, software and investigation. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2023.1250593/full#supplementary-material

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Study on the coupling and coordination relationship between the digital economy and green development: evidence from Guangdong province in China

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The digital economy city and green development of China are important engines with important backgrounds. This paper takes 21 prefecture-level cities in Guangdong Province as the research object. By constructing the index system of the digital economy and green development, this paper discusses the external spatial pattern and internal temporal evolution characteristics of the coordinated development of the digital economy and green development from the two perspectives of intercity and inner city. The results show that: 1) From the perspective of intercity, there is a large gap between the development level of the digital economy and the green development level of all cities, only Guangzhou and Shenzhen have the digital economy development level ahead of the green development level. The coupling level of the two systems presents an unbalanced pattern of "centre-edge," and "Guangzhou-Foshan-Shenzhen-Dongguan" becomes the core pole of the coupling development of the two systems in the province. The coordinated horizontal cascade distribution of the two systems is obvious, showing a spatial pattern of decreasing step by step from the first circle to the third circle. 2) From the perspective of inner city, the digital economy level and green development level of all cities showed an upward trend from 2013 to 2019. The coupling level shows a two-stage development trend: the stable development stage from 2013 to 2016, and he accelerated development stage from 2016 to 2019, and the internal interaction of the two systems is deepening. The coordination level of all cities improved significantly in 7 years, and in 2019, 21 cities all reached the level of moderate coordination or high coordination. Based on above research conclusions, in order to promote the positive interaction between digital economy and green development, this paper proposes to optimize resource allocation based on regional differences, and adhere to innovation-driven policy proposals to activate the potential of green development.

KEYWORDS

digital economy, green development, coupling coordination, China, entropy method

1 Introduction

China's economy is at a crucial stage of replacing old growth drivers with new ones and achieving high-quality development. Problems such as the dual economic structure, increasing labour costs, increasing demand for resources, and extensive development mode still exist. At present, the economic cycle is not smooth, development is not coordinated, and the green transition is facing greater pressure. At the same time, the global economic landscape is being reshaped by the geopolitical landscape, the COVID-19 pandemic, the new round of technological revolution and industrial transformation, and the digital economy has become the main direction for countries to seize the commanding heights of the new global economic landscape. "The digital economy, as an emerging economic development mode, is gradually becoming an important pillar of China's national economic growth. Through the research and development of digital information technology, we can cultivate new drivers, promote the development of green industries, and achieve a fundamental improvement of ecological environment" the 14th Five-Year Plan for The digital economy Development points out. The report of the 20th National Congress of the Communist Party of China further pointed out "Accelerating the building of digital China." It can be seen that the booming digital economy not only brings opportunities for China to build new competitive advantages but also provides an important path for China's green development (Li et al., 2022).

As the vanguard of China's economy and the experimental area of reform and opening up, Guangdong has profound economic deposits, and the level of economic development has always ranked first in China. In 2021, the value-added scale of Guangdong's digital economy reached 5.9 trillion yuan, ranking first in China for five consecutive years. In the digital economy index, Guangdong province also consistently ranks among the top. However, the proportion of traditional industries in Guangdong is large, and problems such as inadequate green governance and ecological protection are still prominent. A large number of facts show that digital economy and green development have a logical correlation mechanism that promotes each other: On the one hand, the digital economy itself is a low-carbon circular economy, which can promote the upgrading of industrial structure and the improvement of resource allocation efficiency through technology empowerment, and provide digital momentum for green development; On the other hand, green development stimulates the demand of enterprises and individuals for the digital economy, expands the application scenarios of the digital economy, enricfies the business formats of the digital economy, and achieves the expansion of the scale of the digital economy. Therefore, how to realize the integration of digital economy and green development has become an important issue at present. The analysis of the coupling and coordination relationship between digital economy and green development has important theoretical and practical significance for understanding the internal logical correlation between digital economy and green development and realizing the positive interaction between digital economy and green development. In view of this, this paper takes Guangdong, which is at the forefront of the digital economy and green development in

TABLE 1 The digital economy and green development index system construction.

Index system	First-order index	Secondary index	Units	Attribute
The digital economy	Digital business scale	Total volume of telecommunication service	Hundred million yuan	+
		Share of employees in information transmission, software and information technology services	%	+
	Digital infrastructure	Mobile phone subscriber	Ten thousand households	+
		Number of Internet broadband access users	Ten thousand households	+
	Digital technology innovation	Percentage of R&D expenditure in GDP	%	+
		Number of patent applications granted	Piece	+
		Output value of high-tech products	Hundred million yuan	+
		Number of high-tech enterprises	Unit	+
Green development	Environmental governance	Urban sewage treatment rate	%	+
		Rate of harmless disposal of municipal solid waste	%	+
	Urban ecology	Standard number of urban buses in operation	one	+
		Urban *per capita* park green space	Square meter	+
	Energy conservation and emission reduction	Electricity consumption	Hundred million kilowatt hours	-
		Discharge of industrial wastewater	Hundred million tons	-
		Total industrial dust emissions	Ten thousand tons	-
		Production of industrial solid wastes	Ten thousand tons	-

China, as an example, constructs an indicator system, and discusses the external spatial pattern and internal temporal evolution characteristics of the coupled and coordinated development of digital economy and green development from the perspectives of intercity and inner city, to provide experience and reference for the high-quality development of global economy.

2 Review of relevant literature

In recent years, the digital economy and green development have become hot topics that governments all over the world pay close attention to. The academic circle has also carried out multi-dimensional research on it. In the field of the digital economy, the research mainly focuses on connotation characteristics, influencing factors, development level measurement and so on. On the basis of sorting out the origin and evolution of the digital economy, Han and Chen (2022) proposed the connotation and characteristics of the digital economy from the four aspects of technology, industry, scene application and governance. Ge et al. (2022) discussed the driving factors of the digital economy from the perspectives of international cooperation, factor accumulation, regulatory system, macro policy, and new infrastructure construction. Li and Han (2022) construct the development level index of the digital economy from the aspects of digital infrastructure, digital industrialization, industrial digitalization, etc., and find that China's digital economy is growing rapidly, and predict that the growth level of the digital economy will continue to increase in the future. Niftiyev (2022a) discoveries economic growth, government effectiveness, and the public services index would positively impact E-government development. Wu and Wang (2022) point out that although China's digital economy industry develops rapidly, the regional imbalance is expanding. Sadik-Zada et al. (2022) reveals that e-government offers one of the greatest opportunities for socio-economic development and improves the efficiency and effectiveness of public administration. Niftiyev (2022b) noted the need to improve economic reforms and policies to keep pace with regions driven by FDI and successfully integrated into global value chains.

In the field of green development, the existing researches mainly focus on the internal logic of green development and the measurement of green development level. Wang and Gao (2016) made a comprehensive review and study on the status and policies of green development since China's reform and opening up. Wu and Zhang (2017) sorted out the internal logic of the green development concept and predicted the future trend of green development. Huang and Li (2017) take urban agglomerations in China as the research object and find that the level of green development fluctuates, rises and diverges. Chen and Xu (2019) focused on the 11 provinces of the Yangtze River Economic Belt, and built an index system from five dimensions, including environmental carrying capacity, environmental management ability, environmental friendliness, environmental stress resistance and environmental stability, and pointed out that the overall level of green development in these provinces is improving.

With the increasing importance of the digital economy and green development, in recent years, scholars have begun to pay attention to the relationship between the digital economy and green development. The research mainly focuses on the following two aspects:

(1) The impact of the digital economy on green development. Han et al. (2022) pointed out that digital economy can trigger a comprehensive green revolution from production factors to productivity and production relations, and realize the all-round empowerment of green development. Wei and Hou (2022) carried out research using efficiency analysis and the entropy value method and pointed out that there were obvious regional differences between the digital economy and green development level in prefecture-level cities, and the digital economy could improve the green development level of cities. Different scholars also try to explore from different perspectives. Liu et al. (2022) measured and analyzed the level of economic development from two dimensions industrial digitalization and digital industrialization. Liu and Kong (2021) take 110 prefecture-level cities in the Yangtze River Economic Belt as examples to explore the effect mechanism of the digital economy on urban green transformation, and the results show that the digital economy exerts a positive effect in promoting urban green transformation. From the perspective of space, some scholars adopted the spatial Dubin model to study 30 provinces in China during 2006–2019 and found that the digital economy development has direct and spillover effects on green total factor productivity, and the promotion effect of central and western China is stronger than that of eastern China (Wu et al., 2022). Zhang (2022) found a significant spatial correlation between urban digital economy development and green total factor productivity.
(2) Research on the coordinated development of the digital economy and green development. Hu et al. (2022) proved that China's digital economy and green development have been effectively coordinated, showing a good trend year by year. Zheng et al. (2021) explored and found that the coordination level of public coupling between the digital economy and green development presents a spatial feature of "high in the east and low in the central and western regions" from two aspects of public coupling and content coupling. Li et al. (2022) proved that the digital economy, technological innovation and their interaction can positively promote green development.

After a comprehensive analysis of existing literature, it can be found that the academic circle has made a relatively comprehensive exploration in the research on the impact of the digital economy on green development and the measurement of the two, but the existing research on the interaction between the two systems still needs to be expanded and deepened. First, the relationship between the digital economy and green development is more than a single function. Clarifying the interaction between the two will provide a useful reference for China's high-quality development. Second, Guangdong is an important growth pole of China's digital economy and the vanguard of green development. The selection of Guangdong as a research object is typical and representative and can provide a reference for the construction of the Guangdong-Hong Kong-Macao Greater Bay Area and China's digital economy and green development. Based on the above analysis, this paper

takes Guangdong as an example to deeply explore the dynamic evolution process of the coupling and coordinated relationship between the digital economy and green development, in order to provide theoretical support and a decision-making basis for China's high-quality development.

3 Research design

3.1 Index selection

To ensure the accuracy of the evaluation system of the digital economy and green development, the index system of the digital economy and green development is constructed by referring to the existing research results and following the principles of systemization, hierarchy and accessibility. The digital economy system includes eight specific indicators from three dimensions: digital business scale, digital infrastructure and digital technology innovation. The green development system includes eight indicators from three dimensions: energy conservation and emission reduction, environmental governance and urban ecology as shown in Table 1.

3.2 Data source

This paper takes 21 cities in Guangdong Province as the research object to explore the relationship between the digital economy and green development. Based on data availability, the study spans from 2013 to 2019. The data on the digital economy and green development evaluation index are mainly collected from the China Statistical Yearbook of Science and Technology, the China Urban Statistical Yearbook, the Guangdong Statistical Yearbook, and the statistical yearbook and bulletin of each municipality. The year data of some cities are missing, and the interpolation method is used to complete them.

3.3 Research method

3.3.1 Entropy method

Since there are dimensional and order of magnitude differences among the index data, to facilitate the calculation and accuracy of each index, the design index is standardized:

$$\text{Positive index: } Y_{mij} = \frac{X_{mij} - X_{min}}{X_{max} - X_{min}} + 0.00001 \quad (1)$$

$$\text{Negative index: } Y_{mij} = \frac{X_{max} - X_{mij}}{X_{max} - X_{min}} + 0.00001 \quad (2)$$

where X_{min} and X_{max} represent the minimum and maximum values of the j-th index respectively. X_{mij} and Y_{mij} respectively represent the original value and the standardized value of the index, m represents the year, i represents the region, and j represents the index number.

3.3.2 Coupling coordination degree model and type division

In view of the validity reduction caused by the uneven distribution of C values calculated by the traditional coupling degree model, the following coupling degree model is constructed by referring to the research of Wang et al. (2021):

$$C = \sqrt{\left[1 - \sqrt{(U_2 - U_1)^2}\right] \times \frac{U_1}{U_2}} = \sqrt{\left[1 - (U_2 - U_1)\right] \times \frac{U_1}{U_2}} \quad (3)$$

Where, the C value is the coupling degree, U_1 and U_2 are the comprehensive level of the digital economy system and green development, respectively. The more the C value approaches 1, the higher the coupling degree of the two systems.

The coupling degree can only reflect the interaction between the two systems. To further explore the coordination of the interaction between the two systems, the coordination degree model is introduced as follows:

$$T = \alpha U_1 \times \beta U_2 \quad (4)$$

$$D = \sqrt{C \times T} \quad (5)$$

Meanwhile, referring to the research of Han et al. (2019), the classification standards of coupling degree and coordination degree are set as shown in Table 2 below:

4 Empirical analysis

Because the coupling degree C value and the coordination degree D value measured by the coupling model are only relative values within a certain year or a certain region, rather than absolute values, the comparability is limited (Wang et al., 2021). Therefore, this paper will take the two perspectives of intercity and inner city as the entry point, based on the construction of an index system and entropy method, and calculate the comprehensive development level of the digital economy and green development of 21 cities in Guangdong from 2013 to 2019. The coupling degree model and coupling coordination degree model were used to measure the coupling degree and coordination degree of the two systems, and ArcGIS software was used for spatiotemporal analysis.

4.1 Evolution of the comprehensive development level of the digital economy and green development

4.1.1 A view from an intercity perspective

To more intuitively analyze the evolution path of the digital economy and green development, the comprehensive development level data of the two systems in 2013, 2016 and 2019 are selected in this paper to draw Figure 1. As can be seen from Figure 1, there is a large gap between the comprehensive level of the digital economy and the comprehensive level of green development among cities. The development level of the digital economy in Guangzhou and Shenzhen is ahead of the level of green development while lagging behind the level of green development in other cities.

From the perspective of geographical space, the digital economy level of Guangzhou and Shenzhen is significantly higher than that of other regions, mainly because Guangzhou and Shenzhen, as the two core cities of Guangdong Province, have superior digital economy development environments. The specific manifestations are as follows: first, Guangzhou and Shenzhen have many high-tech

TABLE 2 Coupling level and coordination level classification criteria.

C	0 < C ≤ 0.2	0.2 < D ≤ 0.4	0.4 < D ≤ 0.6	0.6 < D ≤ 0.8	0.8 < D ≤ 1
Coupling level	Uncoupling	Low coupling	Antagonistic coupling	Run-in coupling	Highly coupled
D	0 < D ≤ 0.2	0.2 < D ≤ 0.4	0.4 < D ≤ 0.6	0.6 < D ≤ 0.8	0.8 < D ≤ 1
Coordination level	Serious dissonance	Moderate dissonance	Basic coordination	Moderate coordination	Highly coordinated

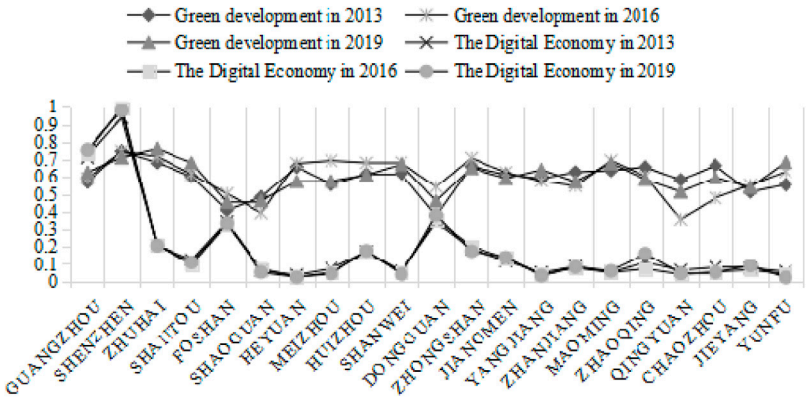


FIGURE 1
The trend of the digital economy system and green development system in 21 cities of Guangdong Province from the perspective of intercity from 2013 to 2019. Note: The author collated and calculated according to the relevant data of the Guangdong Statistical Yearbook, China City Statistical Year, China Science and Technology Statistical Yearbook, and various city statistical yearbooks and bulletins.

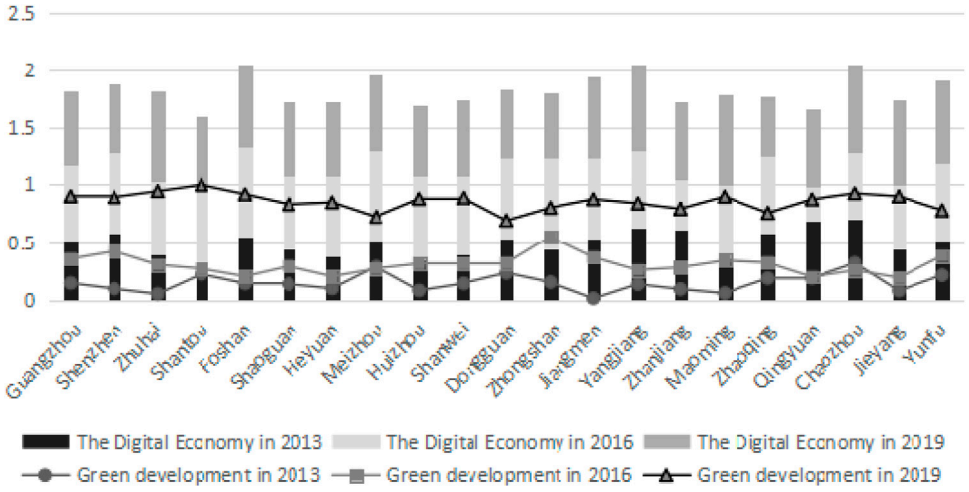


FIGURE 2
The changing trend of the digital economy system and green development system in 21 cities of Guangdong Province from the perspective of inner-city from 2013 to 2019. Note: The author collated and calculated according to the relevant data of the Guangdong Statistical Yearbook, China City Statistical Year, China Science and Technology Statistical Yearbook, and various city statistical yearbooks and bulletins.

industries and open markets, which have brought a good foundation for the transformation of achievements in the digital economy. Second, the two cities have a large number of universities and talent, which can provide a steady stream of high-quality talent for the development of the digital economy. In terms of green development, the gap between cities is relatively small. Foshan,

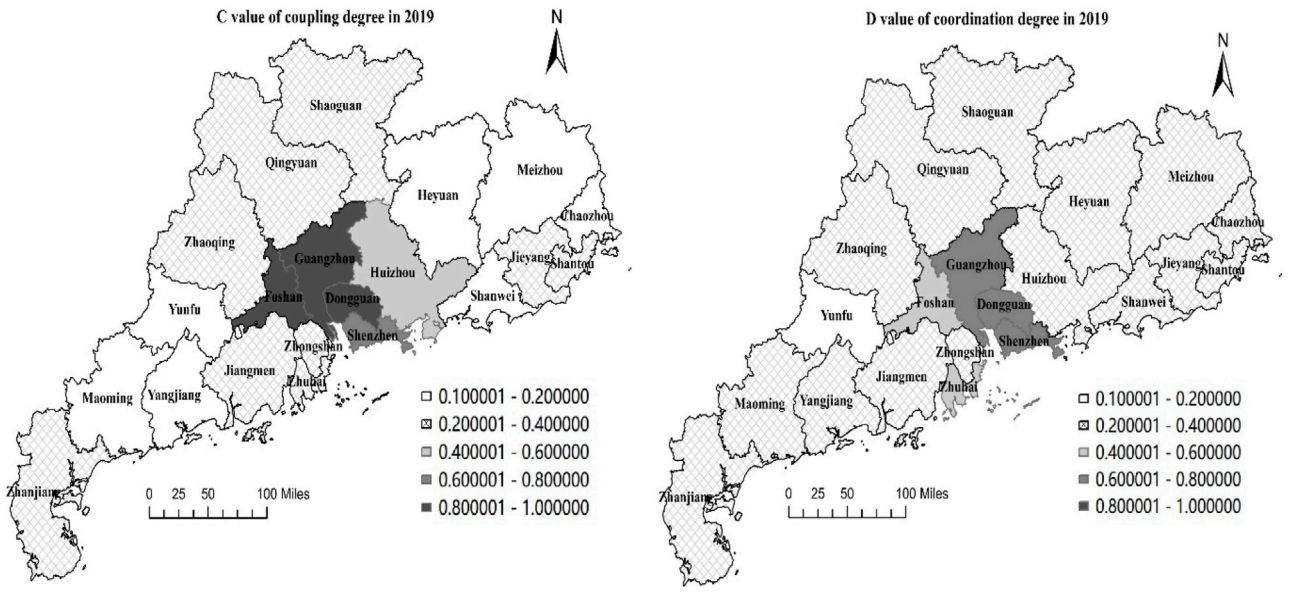


FIGURE 3
Coupling degree and coordination degree of the digital economy and green development in 21 cities of Guangdong Province in 2019 Note: The author collated and calculated according to the relevant data of the Guangdong Statistical Yearbook, China City Statistical Year, China Science and Technology Statistical Yearbook, and various city statistical yearbooks and bulletins.

Dongguan, Shaoguan and Qingyuan have a relatively low overall trend, with the comprehensive level of green development being 0.454, 0.461, 0.462 and 0.513 respectively in 2019, which is closely related to the development patterns and leading industries of the above cities. Among them, the industrial pattern of Foshan and Dongguan dominated by manufacturing and processing trade inhibits the green development space to a certain extent. Shaoguan and Qingyuan have received much of the heavy industry and high energy consumption capacity transferred from the Pearl River Delta region, which has a certain inhibiting effect on green development.

4.1.2 A view from an inner-city perspective

From 2013 to 2019, the level of the digital economy and green development in 21 cities in Guangdong showed an increasing trend. The development level of the digital economy in cities has been rising rapidly, especially in the 3 years from 2016 to 2019. Compared with the level of the digital economy, the level of green development is improved slowly and fluctuates significantly from year to year, showing a trend of fluctuating development as shown in Figure 2.

4.2 Analysis of the degree of coupling and coordination between the digital economy and green development

4.2.1 A view from an intercity perspective

By calculating the coupling degree and coordination degree of the digital economy and green development in 21 cities of Guangdong from 2013 to 2019, we find that: The interannual variation of the coupling degree and coordination degree of the two systems in each city is not obvious. Therefore, the calculation results of 2019 are selected, and ArcGIS software is used for spatial visualization processing to form the spatial distribution map of the coupling degree and coordination degree of the digital economy and green development in 2019 (as shown in Figure 3).

In terms of the coupling degree of the two systems, the coupling degree of the digital economy and green development in 21 cities in Guangdong presents an unbalanced pattern of "centre-edge." "Guangzhou-Foshan-Shenzhen-Dongguan" has become the core pole of the coupling development of the two systems in the province, and the C values are 0.85, 0.804, 0.729 and 0.872, respectively. Except Shenzhen is in the run-in coupling stage, the other three cities are in the highly coupled stage. The coupling degree of Huizhou was 0.404, which was in the antagonistic stage. Other cities in the Pearl River Delta have reached the low coupling stage, which is mainly due to the spillover effect of core cities. In the west, east and north of Guangdong, Qingyuan, Shaoguan, Zhanjiang, Jieyang and Shantou are at the low coupling stage, while other cities are at the uncoupling stage. The east and west of Guangdong are regions with rapid economic growth but mainly rely on resource-consuming industries and have prominent green weaknesses, so the industrial ecology still needs to be improved. Due to its geographical location, northern Guangdong has low accessibility and is less attractive to technical talents and foreign enterprises. The digital economy develops slowly, with a single industrial structure and a large number of high-emission and high-pollution industries. However, as a green ecological barrier in northern Guangdong, a good interaction between the digital economy and green development can be realized by improving resource utilization efficiency.

In terms of the coordination degree of the two systems, the spatial evolution and coupling degree are close to the same level, and the regional differences are significant. The coordination level of

TABLE 3 Coupling degree and coordination degree index of the digital economy and green development in Guangdong Province.

	Coupling degree C			Coordination degree D		
	2013	2016	2019	2013	2016	2019
Guangzhou	0.428	0.610	0.752	0.372	0.556	0.767
Shenzhen	0.293	0.646	0.698	0.313	0.605	0.723
Zhuhai	0.292	0.561	0.845	0.254	0.514	0.857
Shantou	0.790	0.528	0.661	0.462	0.486	0.740
Foshan	0.392	0.317	0.786	0.366	0.398	0.800
Shaoguan	0.462	0.553	0.812	0.364	0.505	0.777
Heyuan	0.433	0.378	0.789	0.320	0.413	0.769
Meizhou	0.673	0.395	0.926	0.514	0.460	0.800
Huizhou	0.418	0.496	0.726	0.297	0.511	0.737
Shanwei	0.512	0.537	0.762	0.371	0.518	0.768
Dongguan	0.547	0.534	0.897	0.458	0.521	0.763
Zhongshan	0.496	0.717	0.731	0.383	0.695	0.706
Jiangmen	0.105	0.594	0.823	0.170	0.562	0.808
Yangjiang	0.331	0.467	0.907	0.355	0.468	0.849
Zhanjiang	0.272	0.726	0.867	0.308	0.513	0.797
Maoming	0.327	0.620	0.900	0.263	0.548	0.874
Zhaoqing	0.441	0.565	0.752	0.410	0.527	0.699
Qingyuan	0.364	0.784	0.799	0.400	0.436	0.789
Chaozhou	0.523	0.535	0.814	0.518	0.476	0.825
Jieyang	0.335	0.468	0.839	0.295	0.417	0.831
Yunfu	0.534	0.630	0.944	0.441	0.577	0.844

Note: The author collated and calculated according to the relevant data of the Guangdong Statistical Yearbook, China City Statistical Year, China Science and Technology Statistical Yearbook, and various city statistical yearbooks and communique.

cities is as follows: there are 3 cities with moderate coordination level, 2 cities with basic coordination level, 15 cities with moderate dissonance level, 1 city with serious dissonance level, and no city reaches high coordination level. It can be seen that the synergistic interaction between the two internal indexes of each city still needs to be further improved. The coordination degree of Guangzhou, Shenzhen and Dongguan has always been at a high level, and the D value of the coordination degree reached 0.767, 0.786 and 0.606 respectively, which is in the moderate coordination stage and classified as the first level. This is closely related to its superior geographical location, rich resources, diversified industrial structure, convenient transportation and policy support. Driven by the radiation of core cities, the economic interaction of surrounding cities increased, and the spillover effect is obvious. The D values of Foshan and Zhuhai reached 0.563 and 0.411 respectively, which were at the basic coordination stage. Fifteen cities, including Zhongshan, Huizhou, Jiangmen, Shaoguan, Qingyuan, Zhaoqing, Jieyang, Shanwei and Zhanjiang, were in the moderate dissonance stage. These cities are classified as the second level. Yunfu City is the only city in the serious dissonance stage, with a D value of 0.191, which is classified into the third level. On the whole, the coordination level of 21 cities in Guangdong showed a descending spatial pattern from the first level to the third level.

4.2.2 A view from inner-city

To analyze the inter-annual variation trend of the coupling and coordination degree of the digital economy and green development in Guangdong cities, this paper further measures from the time series dimension and the results are shown in Table 3. The results show that the C value of the coupling degree between the two systems from 2013 to 2019 is between 0.105 and 0.999, with a large span. It indicates that the coupling degree between the digital economy and green development varies greatly from year to year. The coupling degree of each city shows an overall fluctuation rising trend. Some cities such as Shantou, Heyuan and Meizhou showed a "U-shaped" development trend, and the development was relatively slow from 2013 to 2016. After 2016, the coupling degree accelerated and the coupling trend became better year by year. In 2019, all cities reached the running-in coupling and highly coupling stages, indicating that with the timing development, the digital economy system and the green development system within each city began to

promote each other and check each other, showing the characteristics of the ordered development of resonance coupling. The main reason is that China is committed to accelerating the development of high-tech industries and strategic emerging industries, and many major scientific and technological achievements have reached the world's advanced level. In green development, new progress has been made in promoting an ecological civilization. Functional zones have been gradually improved, the discharge of major pollutants has been steadily reduced, and energy conservation and environmental protection have been significantly improved. Cities have responded to national policies and made positive contributions to the digital economy and green development.

Further analysis of the coordination degree between the digital economy and green development in Guangdong shows that the fluctuation of the D value of the coordination degree of all cities increased from 2013 to 2019, showing a good development trend. In 2013, D values of coordination degree ranged from 0.170 to 0.518, spanning three levels of serious dissonance, moderate dissonance and basic coordination. Six cities, including Shantou and Meizhou, reached the basic coordination level, accounting for about 29% of the overall proportion. Fourteen cities, including Guangzhou, Shenzhen and Zhuhai, were in the moderate dissonance level, accounting for 66% of the total. Only Jiangmen City is in the serious dissonance stage, accounting for about 5%. In 2016, the overall coordination degree of each city showed a slight increase, and the D value ranged from 0.398 to 0.695. Except for Foshan, whose coordination degree was 0.396, which was in the stage of moderate dissonance, the other cities reached the level of basic coordination and moderate coordination. In 2019, the coordination degree of all cities increased significantly, with the D value exceeding 0.7. There were 14 cities at moderate coordination level, accounting for 67% of the whole. There were 7 highly coordinated cities, accounting for about 33%. This shows that the digital economy level of the 21 cities in Guangdong province has been effectively improved, and the green development level has also achieved good results.

5 Conclusion and policy recommendations

This paper constructs an evaluation index system of the digital economy and green development to measure and analyze the comprehensive development level of the digital economy system and green development system in 21 cities of Guangdong province during 2013–2019 from the perspectives of intercity and inner city. This paper also reveals the spatiotemporal evolution characteristics of the coupling and coordination degrees of the two systems. The research in this paper shows that:

The characteristics of urban spatial pattern from the perspective of intercity. 1) Characteristics of comprehensive development level: From the perspective of intercity, there is a large gap between the digital economy development level and the green development level of each city. The digital economy development level of Guangzhou and Shenzhen is ahead of the green development level, while other cities lag behind the green development level, showing obvious regional differences. 2) Coupling characteristics: the coupling degree of the digital economy and green development in each city presents an unbalanced pattern of "centre-edge," and "Guangzhou-Foshan-Shenzhen-Dongguan" has become the core pole of the coupled development of the two systems in the province. 3) Coordination characteristics: the coordination degree of the two systems presents echelon distribution. Guangzhou, Shenzhen and Dongguan are the first levels; Fifteen cities, including Foshan, Zhuhai, Zhongshan, Huizhou, Jiangmen, Shaoguan, Qingyuan, Zhaoqing, Jieyang, Shanwei and Zhanjiang, are in the second level. Yunfu City is the third level.

Characteristics of temporal development from the perspective of the inner city. 1) Characteristics of comprehensive development level: The digital economy level and green development level of 21 cities in Guangdong showed an increasing trend from 2013 to 2019; while the digital economy is accelerating rapidly, the level of green development shows a fluctuating trend. 2) Coupling characteristics: The coupling degree of the digital economy and green development within each city can be roughly divided into two stages: steady development before 2016 and accelerated development after 2016. The coupling trend is getting better year by year, which indicates that the functions of the two systems within the city are deepening. 3) Coordination characteristics: From 2013 to 2019, the D value of the coordination degree between the digital economy and green development in each city increased, showing a good development trend. In 2013, the coordination degree was in three levels: serious dissonance, moderate dissonance and basic coordination. In 2019, the coordination degree of each city increased significantly, with the D value exceeding 0.7, which was between moderate coordination and high coordination.

Based on the above research conclusions, this paper puts forward the following policy recommendations:

5.1 Optimize resource allocation based on regional differences

Since the coupling level and coordination level of the digital economy and green development between different cities are significantly different, each city should implement a regional differentiation development strategy, based on its own reality, comprehensively consider the existing advantages and weaknesses, and make overall layout and scientific planning. On the one hand, efforts should be made to strengthen the leading role of Guangzhou, Shenzhen and the Pearl River Delta urban agglomeration, give full play to its advantages in the field of the digital economy, strengthen cooperation and exchanges with other cities in the field of the digital economy and green development, exert spillover effect, stimulate the development of surrounding cities, and eliminate the digital divide between regions. On the other hand, for the cities with weak digital economy foundation and dominated by traditional industries in the east, west and north of Guangdong, the government should give some support to the digital economy development in these areas, actively guide enterprises to use digital technologies to transform and upgrade traditional businesses in a multi-directional and whole-chain way, and promote enterprises to realize digital and intelligent transformation. At the same time, the government should encourage enterprises to adopt the concept of green production and green consumption, accelerate the promulgation of relevant policies and regulations, deepen the supervision system of ecological and environmental protection, implement the responsibility system of environmental governance, make green development

standardized and strict, and force enterprises to carry out green transformation.

5.2 Pursue innovation-driven development and unleash the potential for green development

Science and technology innovation is the foundation of the digital economy and an important driving force of green development. Therefore, scientific and technological innovation has become a breakthrough for the problem of disconnection between the digital economy and green development. Due to the long R&D cycle and slow benefits of technological innovation in the green field, problems such as insufficient endogenous impetus and insufficient innovation are prominent in the R&D of digital technologies in the green field. Therefore, colleges and universities should constantly improve training mechanisms, not only to cultivate senior R&D talents with the spirit of exploration, but also to focus on the training of senior technicians in related fields, integrate the green scientific spirit and green innovative thinking into education, and guarantee the talents for the green development. Enterprises, especially leading enterprises, should increase investment in green technology research, strengthen innovation in resource utilization technology, pollution control technology and clean energy development, promote digital and green development of enterprises, and build a green and circular production system. Finally, enterprises can cooperate with universities, scientific research institutions, industrial parks, etc., to jointly conduct technology research and development, jointly overcome the difficulties in green technology, and jointly promote the coordinated development of digitalization and greenization.

Due to the limitation of the length of this paper, this paper only discusses the dynamic evolution characteristics of the coupling and coordination relationship between digital economy and green development before the outbreak of COVID-19. However, it is well known that the digital economy has become an important driver of economic development in the post-epidemic era, and the interactive relationship between the digital economy and green development will also show new characteristics in the post-epidemic era. Therefore, to explore the differences and reasons of the coupling and coordination relationship between digital economy and green development before and after the epidemic, and to comprehensively examine the impact of COVID-19 on the interaction between digital economy and green development, is an important direction for further research in the future.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary Material.

Author contributions

XZ: Writing–original draft, Writing–review and editing. ZC: Writing–original draft, Writing–review and editing. BP: Writing–original draft, Writing–review and editing. TC: Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Carbon reduction effect of ESG: empirical evidence from listed manufacturing companies in China

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Against the backdrop of global climate change, corporate carbon emissions have increasingly become a focal point, making carbon reduction by companies a pivotal issue. Based on data from Chinese listed manufacturing companies from 2010 to 2020, this paper explores the impact of ESG performance on carbon reduction. The results indicate that ESG performance significantly reduce corporate carbon emissions. Green technology innovation, corporate efficiency, and managerial short-sightedness are vital channels through which ESG promotes corporate carbon reduction. For companies with different environmental regulations, industry competition intensities, and capital intensities, the relationship between ESG performance and carbon reduction varies significantly. Notably, we found that in companies with strict environmental regulations, intense industry competition, and high capital intensity, the carbon-reducing effect of ESG performance is more pronounced. Furthermore, digital transformation positively moderates the relationship between ESG performance and carbon reduction. This study not only provides new empirical evidence for understanding the impact of ESG performance on carbon reduction but also offers valuable insights for businesses and policymakers to promote corporate efforts in carbon reduction and achieve China's "Dual Carbon" goals.

KEYWORDS

ESG, manufacturing company, corporate carbon reduction, mechanism verification, digital transformation

1 Introduction

With the climate change and issues of income inequality on the rise recently, sustainability has taken center stage in the growth of the world. All facets of society should take notice as serious concerns to human health, social cohesiveness, and economic growth are posed by issues of environmental degradation. Corporations,

which are vital to economic activity, have a duty to push society toward sustainable development. This means that businesses must develop business models that balance economic efficiency and sustainable growth while pursuing profit maximization, actively adopting the ESG (Environmental, Social, and Governance) concept. ESG is the idea of incorporating environmental, social, and corporate governance considerations into financial and operational choices. It acts as a benchmark for businesses to track and manage their performance and a crucial criterion for investors to gauge and assess the social responsibility and capacity for sustainable development of businesses (Pulino et al., 2022; Zhou et al., 2023). In delving deeper into the ESG framework, it is essential to understand how each of its components—Environmental, Social, and Governance—uniquely contributes to carbon reduction and sustainable development. The environmental aspect of ESG emphasizes a company's role in stewarding natural resources and minimizing ecological footprints, directly impacting carbon emissions through practices like energy efficiency, waste reduction, and sustainable resource utilization. The social dimension focuses on a company's management of relationships with employees, suppliers, customers, and communities where it operates, indirectly affecting carbon emissions by promoting a broader culture of sustainability and responsible consumption. Lastly, the governance component, involving management structures, policies, and procedures, ensures accountability and transparency in environmental and social practices, supporting carbon reduction goals through sustainable decision-making processes.

The basic tenet of ESG stresses that businesses should prioritize social responsibility, environmental protection, and improved corporate governance in addition to pursuing financial goals like profit. Additionally, it tries to help investors assess a company's sustainability to make wise investment choices. The ESG idea is currently growing quickly in the business, regulatory, and financial sectors worldwide (Agliardi et al., 2023; Liu et al., 2023; Zhang et al., 2023b). Global ESG assets were predicted to be at $22.839 trillion in 2016 and will rise to $35.3 trillion in 2020, a rise of 54.56 percent from 2016. This is according to the Global Sustainable Investment Alliance (GSIA). In addition, the number of parties who have ratified the PRI (Principles for Responsible Investment) and the size of managed assets both keep expanding. 3,826 institutions signed the PRI as of 2021, controlling $121.3 trillion in total assets. In contrast, only 890 institutions signed the PRI in 2011 and only $24 trillion worth of assets were under their management (Mao and Wang, 2023).

Since the proposal of the "carbon peak and carbon neutrality" goals, China's emphasis on ESG has increased as society has become more aware of the ESG performance of corporations. The China Securities Regulatory Commission (CSRC) amended the "Corporate Governance Guidelines for Listed Businesses" in 2018, which stipulates that listed companies must disclose information about corporate governance, social responsibility, and environmental protection. ESG data is one of the items for communication between listed firms and investors in investor relations management, according to the "Guidelines for Investor Relations Management of Listed Companies" published by the CSRC in April 2022. Statistics from the China Listed Businesses Association on information disclosure show that over 1,700 companies produced and disseminated ESG-related reports for 2022, accounting for 34%, a major increase from the prior year. The economic performance and social implications of ESG will be more apparent as Chinese companies increase their focus on it, which will help to improve their long-term competitiveness and reputation abroad. The "dual carbon" strategy and high-quality development goals of China are also closely aligned with ESG, which is a key factor in accelerating China's sustainable economic development and achieving the "carbon peak" and "carbon neutrality" targets (Yan et al., 2020; Li et al., 2023a; Zheng et al., 2023).

Addressing global climate change and achieving low-carbon development are shared goals of the international community. The "14th Five-Year Carbon Reduction Action Plan" clearly states that promoting low-carbon technology innovation and industrial upgrading during the "14th Five-Year Plan" period is the core task for realizing green development and building an ecological civilization. It's also a crucial path to practice the concept of sustainable development and advance the global ecological civilization construction (Wen et al., 2023). The report of the 20th National Congress of the Communist Party emphasizes the need to vigorously develop a green, low-carbon economy, improve energy efficiency, and strive to achieve carbon peak and carbon neutrality goals. The "Government Work Report" of 2022 further points out the necessity to accelerate the green, low-carbon transition, deepen the national carbon emission rights trading market and promote adjustments in industrial and energy structures to achieve carbon emission reductions. In this context, the ESG performance of enterprises plays a pivotal role in their efforts towards carbon reduction and addressing climate change. Companies with good ESG performance typically excel in areas like environmental protection, resource utilization, and energy efficiency, helping them reach carbon reduction goals (Sun et al., 2023; Li et al., 2023c). These companies also tend to have more investment and financing opportunities, as many investors and financial institutions now lean towards supporting businesses with commendable ESG records (Long et al., 2023; Xu et al., 2023; Zhang et al., 2023b). However, despite the widely acknowledged importance of ESG, how companies can ensure effective carbon reduction and other ESG goals while pursuing economic gains remains a challenge in practice. Moreover, there may be significant disparities in carbon reduction and ESG practices across different companies, industries, and regions. Thus, against the backdrop of China's pursuit of carbon neutrality and sustainable development goals, it's imperative to explore how corporate ESG performance assist in achieving carbon reduction targets, enhance energy efficiency, provide robust support for a low-carbon economy, and contribute to social and economic development. This article will delve into this critical topic, combining theoretical frameworks with empirical data.

ESG is rapidly developing globally and has received widespread attention from scholars both domestically and internationally. ESG performance significantly impacts corporate value and performance (Yu and Xiao, 2022), reduces corporate financing costs (El Ghoul

et al., 2011; Fang and Hu, 2023; Ning and Zhang, 2023), lowers corporate risks (Albuquerque et al., 2019; Yu and Xiao, 2022), and promotes foreign direct investment (Zhang et al., 2022). Although corporate social responsibility and sustainable development topics have garnered widespread attention, research on whether and how ESG performance influence corporate carbon reduction remains relatively limited. In terms of carbon reduction research, most existing literature focuses on the impact of policy tools and technological advancement on corporate carbon emissions. In contrast, literature related to the environmental factors in the ESG topic primarily focuses on the relationship between environmental performance and corporate performance. For instance, Pei et al. examined the impact of environmental regulations on corporate carbon emission efficiency (Pei et al., 2019); and Zhang et al. (2022) explored the potential impact of corporate social responsibility on carbon reduction. Nevertheless, these studies did not systematically explore the impact of ESG performance on corporate carbon reduction. Therefore, this research aims to investigate from a fresh perspective of ESG performance, utilizing data from Chinese listed manufacturing companies from 2010 to 2020, to deeply examine how ESG performance impact corporate carbon reduction behaviors and their underlying mechanisms. This research helps reveal the role of ESG performance in propelling corporations to achieve carbon neutrality, providing strategic recommendations for governments and corporations. Simultaneously, it offers a novel theoretical and empirical perspective on the relationship between ESG and corporate carbon emissions.

Compared to existing research, this paper may have made marginal contributions in the following areas.

Firstly, this paper is among the first to explore how ESG performance influence corporate carbon reduction behaviors. Although ESG in relation to corporate sustainability and social responsibility has become a hot research topic, most literature mainly focuses on how ESG impacts corporate value, performance, financing costs, risks, and foreign direct investments, among others (El Ghoul et al., 2011; Albuquerque et al., 2019; Wu et al., 2022; Xie et al., 2022; Xie et al., 2022; Li et al., 2023a; Wang et al., 2023a). The specific impact of ESG performance on corporate carbon reduction behaviors remains largely unexplored. Thus, from the perspective of corporate carbon reduction behaviors, this paper provides new insights into the relationship between ESG and climate change.

Secondly, this paper further enriches and enhances research on carbon reduction and corporate behaviors. Most relevant to the research theme is how sustainable or green development affects corporate carbon emissions. However, most literature typically discusses the impact of green development on carbon emissions indirectly from a macro perspective, such as from the angle of environmental regulatory policies (Chen, 2022; Cong et al., 2022; Cahyono et al., 2023; Chen et al., 2023; Chen et al., 2023; Deng et al., 2023). Unlike the aforementioned literature, this paper directly analyzes the impact of corporate ESG performance on their carbon reduction behaviors from a micro perspective. More importantly, most existing literature usually only focuses on the environmental factors (E) in ESG, while the core metric in this paper (ESG performance) encompasses corporate performances in environmental protection, social responsibility, and corporate governance, offering a more comprehensive and systematic perspective for the research on carbon emissions and corporate behaviors.

Thirdly, in terms of influencing mechanisms, although some literature has explored from various angles how ESG impacts corporate carbon reduction, these studies mainly concentrate on a single or dual dimensions. In contrast, this paper systematically delves into how ESG performance influence corporate carbon reduction behaviors from three core dimensions: financing constraints, innovation efficiency, and risk-taking. Specifically, this paper discovers that ESG performance can promote corporate carbon reduction goals by alleviating corporate financing constraints, enhancing innovation efficiency, and rationalizing risk-taking. The exploration of these three mechanisms helps to understand more comprehensively and deeply the intrinsic connection between ESG performance and corporate carbon reduction behaviors.

Fourthly, in addition to exploring the impact of ESG performance on corporate carbon reduction behaviors, this paper further investigates from the perspective of digital transformation how ESG assists corporations in achieving low-carbon goals in the digital age. With the rapid development of digital technology, corporations face different carbon emission pressures and opportunities compared to traditional models. This paper finds that ESG performance not only enable corporations to better utilize digital technologies to optimize their operations and production, thereby achieving carbon reduction but also help ensure continuity and consistency of their low-carbon strategies during digital transformation. This part of the research provides a fresh perspective and empirical evidence on how to maintain low-carbon development in the digital age.

Lastly, in terms of policy implications, facing the dual challenges of deepening ecological civilization construction in China and implementing strict carbon peak and carbon neutrality goals, deeply exploring how ESG performance assist corporate carbon reduction holds profound practical and strategic significance. This paper confirms the positive role of ESG performance in reducing corporate carbon emissions, revealing that by actively fulfilling their environmental, social, and governance responsibilities, corporations can not only enhance their sustainability and social responsibility but also make significant contributions to national and even global carbon reduction goals. This implies that for China in the process of achieving the "dual carbon" goals, strengthening corporate ESG practices and enhancing their ESG levels are vitally important. Simultaneously, this also provides crucial policy recommendations for the government and decision-makers on how to promote national carbon reduction and low-carbon development goals by encouraging and supporting corporations to strengthen ESG practices.

In summary, this paper primarily contributes by articulating how ESG performance impacts corporate carbon reduction behaviors and examining the mechanisms behind this impact. While the influence of ESG on aspects such as corporate value,

performance, and risk has garnered extensive attention, research specifically addressing how ESG performance affects corporate carbon reduction is relatively sparse. This study fills this gap by analyzing data from Chinese listed manufacturing companies from 2010 to 2020, revealing that ESG performance positively influences corporate carbon reduction behaviors through multiple channels such as alleviating financing constraints, enhancing innovation efficiency, and rationalizing risk-taking decisions. Additionally, this paper explores how digital transformation moderates the relationship between ESG performance and carbon reduction in the current digital era, offering new insights and empirical evidence for understanding low-carbon development against a backdrop of digitalization. Moreover, our research delves into the heterogeneity of the ESG performance and carbon reduction relationship across companies with different environmental regulatory intensities, industry competition, and capital intensities, thereby enriching the understanding of how ESG performance impacts corporate carbon reduction.

The remainder of the paper is organized as follows: Section 2 provides a comprehensive literature review and develops the research hypotheses. Section 3 details the research methodology and the data sources utilized in the study. Section 4 reports on the empirical results and conducts a thorough analysis of the findings. Section 5 explores the mechanisms and heterogeneity of ESG impacts, while Section 6 investigates the moderating role of digital transformation in this context. Finally, Section 7 concludes the paper, summarizing the main findings and discussing their policy implications, limitations, and avenues for future research.

2 Theoretical analysis and research hypothesis

2.1 Impact effect analysis

ESG performance play a crucial role in connecting businesses with the market, providing effective market-driven governance impetus for corporate carbon reduction (Zhang et al., 2022; Zhang, 2023). With the increasing severity of global climate change, corporate carbon emissions have become a societal focal point (Lee et al., 2022). The carbon reduction behaviors of companies directly relate to the global effectiveness of addressing climate change (Pei et al., 2019). ESG performance emerged in this context. They not only measure corporate performance in environmental, social, and governance aspects but more importantly, they provide businesses with a clear direction to emphasize environmental protection and commitment to carbon reduction while pursuing economic benefits. On the one hand, ESG performance promote the operation of market incentive mechanisms, driving businesses to take the initiative in carbon reduction (Apergis et al., 2022; Wang et al., 2022; Zheng et al., 2023; Ren et al., 2023a). In the capital market, as investors increasingly focus on sustainable investments, companies with high ESG performance tend to attract more investments. Such companies are seen as having better management and reduction strategies against climate risks (Cho, 2022; Bai et al., 2023). Additionally, financial institutions in credit decisions also favor companies that excel in ESG performance because these companies are more likely to have a competitive edge in future environmental regulations.

On the other hand, ESG performance strengthen the supervisory role of stakeholders, compelling businesses to undertake carbon reduction. When a company emits excessive carbon or lacks action in reduction, a low ESG rating quickly sends a negative signal to the market. Such transparency can prompt investors, consumers, and other stakeholders to reassess their relationships with that company and might attract public attention and criticism (Cong et al., 2022; Ge et al., 2022; Pan et al., 2022). In conclusion, ESG performance, through both market incentives and stakeholder supervision mechanisms, effectively drive companies to take proactive measures for carbon reduction, thereby enhancing the long-term sustainability and competitiveness of companies. Based on this, we propose the following Research Hypothesis. Furthermore, drawing on the research by Li and Wen (2023), we should also consider the impact of cultural and social factors, such as local government and public participation, on corporate low-carbon behavior. The policy of civilized cities, as a mechanism to promote local government and public engagement in green development, underscores the significance of these factors in driving low-carbon practices in businesses. Thus, in addition to the direct mechanisms of market incentives and stakeholder supervision, our study extends to exploring the potential indirect influences on corporate carbon emissions through cultural and social mechanisms.

Hypothesis 1. ESG performance can promote corporate carbon reduction.

2.2 Impact mechanism analysis

With the increasing severity of global climate change and environmental issues, corporate ESG performance has garnered widespread attention. Many scholars and practitioners believe there is a close relationship between a company's ESG practices and its carbon emissions. However, the nature and mechanism of this relationship remain unclear. To better understand how ESG impacts corporate carbon emissions, this paper delves deep into the effects of green technology innovation, corporate efficiency improvement, and curbing managerial short-sightedness from three different angles.

2.2.1 Green technology innovation effect

First, from the perspective of signal transmission theory, showcasing good ESG performance sends a message to the public and stakeholders about the company's commitment to environmental responsibility and its willingness to invest in green technologies (Ma et al., 2022; Xie and Lv, 2022; Zheng et al., 2023). Such positive environmental performance not only helps establish a leading position for the company in environmental protection but also attracts more consumers and investors who increasingly value green and sustainable practices of companies (Li et al., 2023b). This

positive market feedback further encourages companies to invest in green technology research and innovation. Secondly, based on stakeholder theory, the interaction and relationships between a company and its employees, customers, suppliers, government, and other stakeholders play a crucial role in driving green technology innovation (Yuan et al., 2022). As described by Lin et al. (2021), Freeman's view in 1984 emphasized the importance of maintaining good relationships with stakeholders (Lin et al., 2021). Especially for environmental issues and notably for reducing carbon emissions, establishing close cooperation with external stakeholders such as governments, environmental organizations, and research institutions can provide companies with more resources for green technology and innovation (Cho, 2022). Resource sharing and collaboration expedite the development of green technology, advancing technological progress, leading to effective carbon emission reduction (Xu et al., 2023). Furthermore, with the deepening of green technology innovation and application, companies can directly reduce their carbon emissions and, by improving production efficiency and reducing energy and resource consumption, achieve dual growth in economic and environmental benefits (Li et al., 2023b; Wang et al., 2023b). In this way, companies not only contribute to global carbon reduction goals but also lay a solid foundation for their long-term development and competitive advantage. Therefore, we propose the following hypotheses:

Hypothesis 2. ESG performance can significantly reduce companies' carbon emission intensity by fostering green technology innovation.

2.2.2 Corporate efficiency improvement effect

Corporate efficiency is an essential factor affecting the level of corporate carbon emissions. Exceptional ESG performance can drive companies to improve their operational efficiency, which in turn has a positive effect on carbon emissions (El Ghoul et al., 2011; Xie and Lv, 2022; Xiao et al., 2023). The reason is that, from the perspective of signal transmission theory, companies with good ESG performance actively convey their advantages in areas such as environment, society, and governance to the external world. This can attract more investors and partners, thereby helping the company gain more resources and technological support, enhancing production and operational efficiency (Hu and Guo, 2023). Firstly, according to signal transmission theory, companies with excellent ESG performance are more inclined to actively disclose their achievements in green technology and energy-saving emissions reduction, signaling their commitment to low-carbon, environmental protection, and sustainable development to the public and investors. Research has also pointed out that ESG information disclosure can increase corporate transparency, attracting more investors and consumers concerned about the environment and sustainable development (Lin et al., 2021). This will bring more financial and technological support to companies, boosting their production efficiency and reducing carbon emissions. Secondly, based on resource dependency theory, companies with high ESG performance are more likely to obtain external resources like funding, technology, and partners. These resources positively impact the production and operational efficiency of companies, leading to reduced carbon emissions (Garel and Petit-Romec, 2022). For instance, companies might acquire more efficient production technologies, advanced energy-saving equipment, or engage in green collaborations. Moreover, under the broader backdrop of the Chinese government's encouragement of low-carbon, green, and sustainable development, companies with good ESG performance are more likely to receive government support and favorable policies. This further aids companies in enhancing their efficiency and reducing carbon emissions (Houston and Shan, 2022). An improvement in corporate efficiency means producing more products or services with fewer resources, directly leading to a reduction in carbon emissions. Researches also indicates that enhancing corporate efficiency can reduce production costs, subsequently decreasing carbon emissions (Hu et al., 2021; Zhong and Ma, 2022).

Therefore, from the perspective of corporate efficiency, ESG performance can directly or indirectly promote companies to reduce carbon emissions, driving low-carbon and sustainable development.

Hypothesis 3. ESG performance can significantly reduce companies' carbon emission intensity by enhancing operational efficiency.

2.2.3 Managerial myopia curtailment effect

The decision-making orientation of managers largely determines the level of corporate carbon emissions. Compared to traditional short-term profit orientations, good ESG performance often reflects a company's commitment to long-term and sustainable development. Managerial myopia can lead to the neglect or delay of necessary green technology investments and updates, thereby increasing carbon emissions (Hu et al., 2021; Wang et al., 2022; Xu et al., 2023). Firstly, according to behavioral finance theory, managerial myopia often causes them to have exaggerated expectations of immediate returns, overlooking or inadequately considering long-term and sustainable investments. In contrast, companies with good ESG performance tend to adopt a long-term perspective, focusing on investments in environmental, social, and governance areas, which helps reduce the company's carbon footprint. Secondly, based on agency theory, there might be a conflict of interest between managers and shareholders, especially concerning carbon emissions and environmental protection investments. However, when a company implements robust ESG measures, it can serve as a mechanism to ensure the long-term commitment of managers to environmental and social issues, thereby reducing carbon emissions (Cong et al., 2022). Additionally, for large enterprises operating globally, the international pressures and expectations they face make ESG performance especially crucial. International organizations and multinational companies are increasingly demanding that members of their supply chains meet strict ESG standards, further prompting companies to reduce carbon emissions to meet these standards and expectations. overall, the effect of managerial myopia might increase corporate carbon emissions, while good ESG performance can alleviate this effect. This assists companies in adopting more sustainable strategies and actions, reducing carbon

emissions. In summary, this paper further proposes the following research hypotheses.

Hypothesis 4. ESG performance can significantly mitigate companies' carbon emission intensity by curtailing managerial myopia, facilitating the adoption of long-term, sustainable carbon reduction strategies.

2.3 Moderating role of digital transformation

Digital transformation is a critical trend in today's corporate development, involving a fundamental transformation of a company's operational model, production processes, and organizational structure through the application of technology and data. Against the broader context of sustainable development and environmental management, digital transformation gains a new dimension of importance. In regions like Pakistan, where agricultural practices and water management are central to both the economy and ecological sustainability, digital innovation plays a crucial role in shaping sustainable practices (Rajpar et al., 2019). As highlighted in recent studies, the interaction between technology and sustainable practices can significantly influence the environmental impact of economic activities (Saqib et al., 2020; Razzaq et al., 2022a; Razzaq et al., 2022b).

Against the backdrop of ESG promoting corporate carbon reduction, digital transformation may play a pivotal moderating role. Firstly, digital transformation can help companies monitor, manage, and report their carbon emission data more accurately (Chen and Zhang, 2023). Through advanced sensor technology, the Internet of Things, and big data analysis, companies can obtain detailed real-time data on their carbon emissions, allowing for more accurate calculations of their carbon footprint, ensuring accurate reflection of their efforts in carbon reduction. Secondly, digital transformation can optimize a company's production and supply chain management, thereby reducing carbon emissions (Ma and Yang, 2023). For example, advanced supply chain optimization algorithms can reduce unnecessary logistics activities, subsequently reducing carbon emissions. Additionally, digital transformation can help companies better predict market demands, reducing overproduction and waste, and further lowering carbon emissions. Lastly, digital transformation can also promote innovation and R&D in companies, leading to the development of more eco-friendly products and services (Zhang et al., 2023a). Through digital technologies, such as machine learning and artificial intelligence, companies can accelerate product prototyping and testing, speeding up the R&D and commercialization process of green technologies. Therefore, while ESG itself already aids corporate carbon reduction, this effect might be further strengthened in the context of digital transformation. Specifically, digital transformation might enhance the positive impact of ESG on corporate carbon reduction. Based on the above analysis, we propose the following hypothesis.

Hypothesis 5. Digital transformation has a positive moderating role in the promotion of corporate carbon reduction by ESG.

3 Research design

3.1 Model specification

This study aims to examine the impact of ESG performance on corporate carbon emissions. Following the approach used in similar studies (Lee et al., 2022; Li and Wen, 2023), we set up the following basic regression model:

$$Carbon_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 X_{it} + \mu_i + \vartheta_t + \epsilon_{it} \quad (1)$$

In Equation 1, i and t respectively represent the company and the year; *Carbon* represents the intensity of corporate carbon emissions; *ESG* represents the ESG performance; X is a series of company-level control variables selected in this study; μ_i and θ_t respectively indicate that the model controls for individual fixed effects and time fixed effects, and ϵ_{it} is the random error term. Among them, β_1 is the core result that this study focuses on. If β_1 is significantly less than zero, then H1 will be verified, implying that ESG can significantly inhibit the increase in the carbon emission intensity of manufacturing companies.

To explore the mechanism by which ESG affects the carbon emission intensity of manufacturing companies, we utilize the mediation effect model as suggested by Liu and Lyu (2022) and Qing et al. (2022):

$$Inter_{it} = \rho_0 + \rho_1 ESG_{it} + \rho_2 X_{it} + \mu_i + \vartheta_t + \epsilon_{it} \quad (2)$$

$$Carbon_{it} = \gamma_0 + \gamma_1 ESG_{it} + \gamma_2 Inter_{it} + \gamma_3 X_{it} + \mu_i + \vartheta_t + \epsilon_{it} \quad (3)$$

In Equations 2 and 3, *Inter* represents the mediating variable, and the meanings of the other variables are the same as in formula (1). In the case where ρ_2 is discernibly positive, it can be inferred that there is a positive correlation between ESG performance and the intermediary variable. Conversely, a significantly negative γ_2 underscores the inverse relationship between the intermediary variable and corporate carbon emissions. Collectively, these findings suggest a mechanism through which ESG performance attenuates corporate carbon emissions intensity, mediated by its influential role on the intermediary variable.

To further examine the moderating effect of digital transformation on the suppression of carbon emissions by ESG, we introduced an interaction term between ESG and digital transformation (Dig) into the baseline regression model, as recommended by Luo et al. (2023):

$$Carbon_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 X_{it} + \beta_3 ESG \times Dig + \mu_i + \vartheta_t + \epsilon_{it} \quad (4)$$

In Equation 4, if β_3 is observed to be significantly negative, it provides evidence that digital transformation exerts a moderating effect in the relationship under study.

3.2 Variable selection

(1) Dependent variable: Corporate carbon emission intensity (*Carbon*). When evaluating the carbon emission level of

companies in this study, it was found that few companies voluntarily disclose carbon emission data in their annual reports. Due to the limitations of the availability of micro-level company data, this study adopts the research method of (Lee et al., 2022; Cahyono et al., 2023), estimating the corporate carbon emissions based on the proportion of operating costs.

(2) Explanatory variable: ESG performance. The core explanatory variable in this study is the corporate ESG performance, which is measured using the Huazheng Index's ESG rating. The development of the Huazheng ESG rating involved an extensive analysis of ESG practices specific to the Chinese market, incorporating a balance of environmental, social, and governance factors tailored to local corporate contexts. The Huazheng ESG evaluation data has characteristics such as being close to the Chinese market, having a wide coverage, and high timeliness. Currently, this index has been widely recognized and applied by both the industry and academia (Chen and Zhang, 2023; Zhang et al., 2023b). For data updates, the Huazheng ESG index adopts a combination of quarterly regular evaluations and dynamic tracking for data adjustments, classifying corporate ESG into 9 levels: C, CC, CCC, B, BB, BBB, A, AA, AAA. Following the method of Liu and Zhang (2023), this study assigns values from 1 to 9 in ascending order according to the ratings. A higher value indicates a greater ESG performance of the listed company. Compared to other ESG metrics in the literature, the Huazheng Index's strength lies in its real-time adaptability and comprehensive scope, while its limitation might be its relative novelty and focused applicability primarily within the Chinese market.

(3) Control variables. Control variables are used to further improve research accuracy. Based on previous literature, this study selects a series of control variables suitable for listed manufacturing companies. These include: (1) Company size (Size) represented by the logarithm of the company's total annual operating income; (2) Company age (Age), represented by the logarithm of the length of time since the company's establishment; (3) Profitability (ROE), the company's annual return on net assets; (4) Debt repayment ability (Lev), the company's debt-to-asset ratio, representing the level of the company's financial leverage; (5) Shareholding concentration (Top1), measured by the shareholding ratio of the largest shareholder of the listed company; (6) Shareholding stability (Top2), represented by the difference in shareholding ratios between the second-largest and the largest shareholder. Generally, the smaller this difference, the higher the possibility that the second-largest shareholder could replace the largest shareholder, indicating a more unstable shareholding structure of the listed company; (7) R&D investment (RD), represented by the ratio of company's R&D investment to its operating income.

(4) Mediator Variables: This study examines the role of Green Technology Innovation (GTI), measured by green patent authorizations, Firm Efficiency (Efficiency), indicated by total factor productivity, and Managerial Myopia (Myopia), an index reflecting short-term focus in management. These mediators help understand how ESG performance impacts corporate carbon emissions.

(5) Moderating Variable: The study also considers Digital Transformation (Dig), represented by the digitalization index of manufacturing enterprises, as a moderating factor. This examines the influence of digitalization on the effectiveness of ESG strategies in reducing carbon emissions.

A detailed definition of all the variables involved in this study is provided in Table 1.

TABLE 1 Definition of main variables.

Variable Type	Variable Name	Variable Code	Variable Meaning
Explained Variable	Enterprise Carbon Emission Intensity	Carbon	Carbon emissions per unit of revenue
Explanatory Variables	ESG Score	ESG	The ESG performance of listed companies are assigned from 1 to 9 in descending order
Control Variables	Enterprise Size	Size	Logarithm of total business revenue of the enterprise in the current year
	Enterprise Age	Age	ln(current year − year of listing + 1)
	Profitability	ROE	Return on total assets
	Asset–liability ratio	Lev	Total liabilities/total assets
	Shareholding Concentration	Top1	The shareholding ratio of the largest shareholder of the listed company
	Equity Stability	Top2	Difference between the shareholding ratio of the second largest shareholder and the first largest shareholder
	R&D Investment	RD	R&D investment as a percentage of operating revenue
Mediating variable	Green Technology Innovation	GTI	Logarithm of the number of green patent authorizations
	Firm Efficiency	Efficiency	Total factor productivity of the enterprise
	Managerial myopia	Myopia	Index of managerial myopia
Moderating variable	Digital Transformation	Dig	Digitalization index of manufacturing enterprises

3.3 Data sources and processing

Given the relatively large number of listed companies in the industrial sector, their longer listing duration, and the abundance and completeness of data available in their annual reports, this study selects listed manufacturing companies from the Shanghai and Shenzhen A-shares from 2010 to 2020 as the research subjects. The choice of the manufacturing sector is due to its significant contribution to China's economy and the stable, comprehensive data it offers. The period from 2010 to 2020 encompasses a crucial phase in China's economic development, providing a valuable temporal scope for analysis. The data processing involves the following steps: (1) Excluding companies labeled ST, ST*, and PT. (2) To ensure consistency across all variable data, the financial metrics published in the annual consolidated reports of listed companies are used. Companies with obviously unreasonable financial metrics are also excluded. (3) Considering the accessibility of data from the Tibet region, companies with their registered offices in Tibet are excluded. (4) To mitigate the impact of outliers on the regression results, a 1% and 99% tail-trimming process is applied to all continuous variables at the company level.

Ultimately, the study focuses on 28 industries, encompassing 1,825 companies, amounting to 11,431 company-year observations. This extensive dataset from a key sector over a significant period allows for a robust analysis of trends and practices that are indicative of wider economic conditions. The primary raw data at the company level used in this study mainly comes from the CSMAR database and WIND database. The descriptive statistics for the main variables used in this study are detailed in Table 2.

4 Empirical results and analysis

4.1 Baseline result analysis

Table 3 reports the baseline regression results of the impact of ESG performance on corporate carbon emission intensity. In column (1), while controlling for company fixed effects and year fixed effects, only the core explanatory variable ESG is added. The results indicate that the coefficient of ESG performance is −0.031, and it is significantly negative at the 1% significance level. This suggests that a higher ESG rating is significantly negatively associated with a lower carbon emission intensity. In column (2), after other control variables are incorporated, the coefficient of ESG performance is −0.029 and remains significantly negative at the 1% significance level. Specifically, holding other conditions constant, for every one-level increase in the ESG rating, the company's carbon emission intensity will decrease by approximately 2.9%. When benchmarking these findings against comparable literature, several similarities and differences emerge. Studies such as Cong et al. (2022) and Lee et al. (2022) have also observed a negative relationship between ESG performance and carbon emission intensity. Cong et al. reported a slightly lower effect size (1.5% decrease in emissions per ESG rating increase), potentially due to their sample including companies from a broader range of sectors with varying ESG maturity levels. This further confirms the significant negative relationship between ESG performance and corporate carbon emission intensity, demonstrating the crucial role of ESG performance in reducing corporate carbon emissions.

Regarding the control variables, the coefficient for company size (Size) is significantly positive, implying that larger companies tend to have higher carbon emission intensities. The coefficient for profitability (ROE) is significantly negative, suggesting that companies with stronger profitability often have lower carbon

TABLE 2 Descriptive statistical analysis of variables.

Variables	N	Mean	SD	Min	Max	Corr with ESG
ESG	11431	3.739	1.122	1	8	1
Carbon	11431	1.748	1.336	0.001	6.045	−0.511
Size	11431	21.626	1.354	18.536	25.136	0.361
Age	11431	2.047	0.853	0	3.222	0.392
ROE	11431	0.051	0.136	−0.765	0.333	0.153
Lev	11431	0.610	0.196	0.054	0.867	−0.182
Top1	11431	35.264	14.533	9.180	75.100	0.164
Top2	11431	25.237	17.344	0.040	73.010	0.225
RD	11431	3.845	4.790	0	251.130	−0.191
GTI	11431	0.5381	0.958	0	4.189	0.422
Efficiency	11431	6.640	0.880	4.070	8.850	0.386
Myopia	11431	0.113	0.092	0.000	1.214	−0.263
Dig	11431	0.185	0.354	0.021	0.425	0.289

TABLE 3 Benchmark regression results.

Variables	(1)	(2)
	Carbon	Carbon
ESG	−0.031***	−0.029***
	(−3.551)	(−3.882)
Age		−0.422***
		(−4.224)
Lev		0.257
		(1.633)
ROE		−1.898***
		(−6.223)
Size		0.776***
		(4.174)
Top1		−0.012
		(−1.335)
Top2		−0.024
		(−1.253)
RD		−0.427***
		(−4.224)
Firm FE	YES	YES
Year FE	YES	YES
N	11431	11431
adj. R2	0.336	0.428

*** p<0.01, ** p<0.05, * p<0.1 represent significance at the 1%, 5%, and 10% levels respectively. Numbers in parentheses are t-values.

emission intensities. The coefficient for company age (Age) is significantly negative, indicating that as the company's age increases, its carbon emission intensity decreases. The coefficient for R&D investment (RD) is significantly negative, implying that companies with higher R&D investments typically have lower carbon emission intensities. For instance, the negative coefficient of R&D investment on carbon emissions is in line with research by Fang and Hu (2023), reinforcing the notion that investment in innovation is crucial for reducing environmental impact. Overall, these results support our research hypothesis, namely, that a company's ESG performance can significantly reduce its carbon emission intensity. This further reflects the positive impact of corporate attention and investment in environmental, social, and corporate governance aspects on carbon emission reduction.

4.2 Endogeneity treatment

Endogeneity is a prominent issue in economic research, mainly arising from omitted variable bias and mutual causality. To address this, our study employs a two-stage least squares (2SLS) approach using a suitable instrument variable. Following the methodology of (Xie and Lv, 2022), we chose the number of "ESG investment funds" holding the firm (Fundnumber) as the instrumental variable for the company's ESG performance. Regarding the relevance of this instrument, institutional investors such as fund companies can participate in a company's decision-making process and optimize its governance structure, thus positively influencing its overall performance. A study by Wu et al. (2022) shows a clear positive relationship between the equity of institutional investors and the ESG performance of firms. This relationship might be due to institutional investors expressing their preference for enhanced ESG performance through direct communication with firms. This establishes the relevance between ESG investment funds and a company's ESG performance. From an exogeneity perspective, the establishment and shareholding information of ESG investment funds are based on independent decisions by fund companies and fund managers, unrelated directly to the employment level of companies. Such funds aim to integrate the three factors of Environment (E), Social Responsibility (S), and Corporate Governance (G) into investment analysis to assess firms' sustainability and societal benefits, thereby achieving long-term stable returns. Given our study's endogenous variable ESG, we chose the number of "ESG investment funds" holding the firm (i.e., Fundnumber) as its instrumental variable.

Table 4 presents the 2SLS regression results using Fundnumber as the instrumental variable, aiming to mitigate potential endogeneity between ESG performance and corporate carbon emission intensity. Endogeneity could arise from omitted variable bias, simultaneity bias, or bi-directional causality. Column (1) showcases the first-stage regression results. This stage mainly examines the relationship between the instrumental variable Fundnumber (the lagged value of the number of "ESG investment funds" holding the firm) and the endogenous explanatory variable ESG. The results indicate that the coefficient of Fundnumber is 0.025, significantly positive at the 1% level. This suggests a significant positive association between firms held by more "ESG investment funds" and their higher ESG performance. Column (2)

TABLE 4 Instrumental variable regression results.

Variables	(1)	(2)
	First-stage regression	Second-stage regression
	ESG	Carbon
Fundnumber	0.025***	
	(3.884)	
ESG		−0.028*** (−3.763)
Control Variables	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
N	11431	11431

*** p<0.01, ** p<0.05, * p<0.1 represent significance at the 1%, 5%, and 10% levels respectively. Numbers in parentheses are t-values.

displays the second-stage regression results. In this stage, we use the ESG values predicted from the first stage as the explanatory variable to estimate the effect of ESG performance on corporate carbon emission intensity. The results show that the coefficient for ESG is −0.028, significantly negative at the 1% level. This further confirms our primary finding: that there's a significant negative relationship between ESG performance and corporate carbon emission intensity. Overall, the 2SLS estimates using Fundnumber as an instrumental variable further substantiate the significant negative effect of ESG performance on corporate carbon emission intensity. This implies that our main conclusion remains valid when considering potential endogeneity issues.

4.3 Additional robustness tests

To ensure the stability of our research findings, we conducted the following series of tests: (1) We utilized the Wind ESG performance and composite scores to measure a company's ESG performance. (2) To minimize the impact of extreme values, we adjusted the dependent variable at both 1% and 5% levels. (3) We modified the fixed effects controls by adding regional-year and industry-year FE. (4) We handled the standard errors with various clustering methods, including clustering at the regional and industry levels. (5) In the regression analysis, we incorporated more control variables, such as the scale of the company's fixed assets, the shareholding ratio of the top ten shareholders, and the company's profitability rate. The related results are presented in Table 5. In conclusion, all these tests consistently confirm the robustness of our research findings.

5 Mechanism test and heterogeneity analysis

5.1 Mechanism test

Following the theoretical analysis presented earlier, we will now delve into the mechanisms through which ESG impacts carbon emission reduction in manufacturing companies from three perspectives: Green technology innovation, firm efficiency, and managerial perspective. The detailed results are presented in Table 6.

5.1.1 Green technology innovation effect

Following the research strategy similar to that of Liu and Zhang (Liu and Zhang, 2023), this study uses ESG performance to investigate its impact on green technological innovation. In column (1), the coefficient for ESG on green technological innovation is 0.002, which is positively related at the 5% significance level. This implies that an ESG advantage might promote green technological innovation. Data analysis across multiple sectors shows a trend where companies with higher ESG ratings consistently increase their investments in sustainable technologies and green product development, leading to notable advancements in eco-friendly innovations.

In column (2), we see that the coefficient for green technological innovation on carbon emissions is −0.001, which is negatively related at the 5% significance level. This means that green technological innovation helps reduce carbon emissions. An aggregate analysis of industry data indicates a clear trend: companies with higher investments in green technologies report a more significant reduction in carbon emissions over time. Overall, the ESG performance not only promotes green technological innovation but also this innovation further assists companies in reducing their carbon emissions (Qing et al., 2022).

5.1.2 Firm efficiency effect

This study estimates the total factor productivity of companies using the LP method, serving as a proxy for firm efficiency. The data reveal a correlation between higher ESG scores and improvements in operational efficiency metrics, such as reduced waste and lower energy consumption. In column (3), the coefficient for ESG on efficiency is 0.025, which is positively related at the 1% significance level. This suggests that an ESG advantage can enhance a firm's operational efficiency. In column (4), the relationship between improved efficiency and carbon emissions is −0.005, which is negatively related at the 1% significance level, indicating that improved efficiency helps reduce carbon emissions. This is further supported by data showing that companies with enhanced efficiency metrics tend to have a lower carbon footprint. These results further validate our theoretical anticipation that a firm's ESG performance can reduce carbon emissions by enhancing efficiency (Cho, 2022).

5.1.3 Managerial perspective effect

Referring to the approach of Hu et al. (2021), we conduct a textual analysis of the MD&A section in the annual reports, identify a set of short-term horizon words, and then use a lexicon-based method to construct an indicator for managerial myopia (Hu et al., 2021). In column (5), the coefficient for ESG on managerial myopia is −0.012, which is negatively related at the 1% significance level. This means that companies with an ESG performance are more likely to have managers adopting a long-term perspective. In column (6), the relationship between managerial myopia and carbon emissions is 0.025, which is positively related at the 5% significance level, suggesting that managerial myopia might lead to higher carbon emissions. These findings align with our previous theoretical expectations, i.e., a firm's ESG performance can reduce its carbon emissions by mitigating managerial short-sighted behaviors.

5.2 Heterogeneity analysis

5.2.1 Environmental regulation intensity

Carbon emission reduction, as a significant challenge faced by businesses, is closely related to their environmental regulations. When analyzing the relationship between ESG and carbon

TABLE 5 Robustness tests.

Variables	(1)	(2)	(3)	(4)	(5)	
	Replacement of explanatory variables	Shrinking of carbon at 1%	Shrinking of carbon at 5%	City & Industry FE	SE clustered by City & Industry	Addition of control variables
ESG	−0.026***	−0.029***	−0.027***	−0.029***	−0.028***	−0.016**
	(−4.681)	(−3.642)	(−3.663)	(−3.785)	(−3.891)	(−4.254)
Control Variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	11431	11431	11431	11431	11431	11431
adj. R2	0.468	0.445	0.358	0.432	0.467	0.532

*** p<0.01, ** p<0.05, * p<0.1 represent significance at the 1%, 5%, and 10% levels respectively. Numbers in parentheses are t-values.

reduction for companies under different environmental regulatory intensities, we used the proportion of environmental vocabulary in the region where the company is located as a proxy for environmental regulation and classified accordingly (Pei et al., 2019). As shown in column (1) of Table 7, for companies in areas with strong environmental regulations, the ESG performance significantly reduces their carbon emissions. This may be because, under stricter environmental regulations, companies pay more attention to environmental protection and take more measures to reduce carbon emissions to meet government environmental requirements and avoid associated economic penalties. However, for companies in areas with weaker environmental regulations, as shown in column (2), the relationship between ESG and carbon reduction is not significant. This implies that in areas with more lenient environmental oversight, companies may not value their ESG performance as much, and thus the impact of ESG performance on carbon reduction is not as pronounced as in areas with stricter regulations.

5.2.2 Industry competition intensity

Drawing from past studies (Bai et al., 2023), the industry competition intensity (HHI) is usually measured using the Herfindahl-Hirschman Index, calculated as $HHI = \Sigma(\frac{X_i}{X})^2$, where XX is the total main business income of all companies in the industry, and XiXi is the main business income of company i in the industry. The larger the HHI value, the lower the competition intensity of the industry. Industry competition has a significant impact on a company's business strategy and behavior, especially in

TABLE 6 Impact mechanism test.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	GTI	Carbon	Efficiency	Carbon	Myopia	Carbon
ESG	0.002** (2.564)	−0.0026*** (−3.461)	0.025*** (4.553)	−0.0027*** (−3.774)	−0.012*** (−3.773)	−0.0022*** (−4.223)
Green Technology Innovation		−0.001** (−2.582)				
Efficiency				−0.051*** (−3.665)		
Managerial myopia						0.025** (2.444)
Control Variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	11431	11431	11431	11431	11431	11431
adj. R2	0.328	0.436	0.565	0.498	0.324	0.437

*** p<0.01, ** p<0.05, * p<0.1 represent significance at the 1%, 5%, and 10% levels respectively. Numbers in parentheses are t-values.

TABLE 7 Heterogeneity test.

Variables	(1) Strong environmental regulation	(2) Weak environmental regulation	(3) Strong industry competition	(4) Weak industry competition	(5) Highly capital intensive	(6) Minorly capital intensive
ESG	−0.013*** (−3.078)	−0.008 (−1.484)	−0.008*** (−2.965)	−0.004 (−1.215)	−0.011** (−2.516)	−0.005 (−0.861)
Control Variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	7231	4200	6927	5134	3876	7555
adj. R2	0.409	0.368	0.412	0.279	0.388	0.369

*** p<0.01, ** p<0.05, * p<0.1 represent significance at the 1%, 5%, and 10% levels respectively. Numbers in parentheses are t-values.

carbon emission management. As shown in column (3) of Table 7, for companies in competitive industries, the ESG performance significantly reduces their carbon emissions. This might be because, in competitive industries, companies are more inclined to adopt more environmentally friendly strategies to gain a competitive market edge and attract more consumers and shareholders. However, as shown in column (4), for companies in less competitive industries, the relationship between ESG and carbon reduction is not significant. This may be because companies in these industries might focus more on their core business rather than environmental responsibility.

5.2.3 Capital intensity

Capital intensity represents the degree to which a company relies on fixed assets (calculated as fixed assets/total assets) and is closely related to the company's operational strategy and carbon emission strategy. As shown in column (5) of Table 7, in companies with high capital intensity, the relationship between ESG performance and carbon reduction is negative and relatively significant. This might be because, in these companies, environmental responsibility and social responsibility are crucial for their long-term success and profitability. However, as shown in column (6), for companies with low capital intensity, the relationship between ESG and carbon reduction is not significant. This suggests that companies with low capital intensity might focus more on their current assets and short-term returns rather than long-term environmental responsibilities.

6 Further research: the moderating role of digital transformation

Recent studies have highlighted the critical role of digital transformation in enhancing corporate sustainability and environmental strategies. For instance, Ren et al. (2023a) argued that digital transformation offers new pathways for companies to improve their environmental performance by facilitating more efficient resource utilization and enabling the adoption of cleaner technologies. Similarly, Luo et al. (2023) found that companies undergoing digital transformation were better positioned to integrate their ESG goals into their business models, leading to more effective sustainability practices. These findings align with the notion that digital transformation can significantly impact how companies approach and implement their ESG strategies, especially in the context of carbon emissions reduction. Building on this foundation, our research aims to empirically test how digital transformation moderates the relationship between ESG investment and corporate carbon emissions.

As companies increasingly invest in and prioritize environmental, social, and governance (ESG) factors, the rapid advancement of technology and the deep integration of the global economy have made digital transformation a core topic for business development. Digital transformation refers to the fundamental changes in internal and external business, culture, and customer experience brought about by the use of digital technology. With the rise of the internet, big data, artificial intelligence, and other technologies, companies must rethink their business models and operational strategies to adapt to the demands of this digital age. The reasons for this transformation vary and include changes in consumer demand, technological innovation, and intensified global competition. Against this backdrop, digital transformation not only helps companies improve efficiency and create new sources of value but may also impact their sustainability strategies, especially strategies related to carbon emissions and environmental protection. Therefore, when examining the relationship between ESG investment and corporate carbon emissions, it is crucial to introduce digital transformation as a moderating mechanism into the analysis. This is because digital transformation may influence the extent to which companies prioritize ESG and the intensity of their actions in carbon reduction. For instance, through advanced data analytics and technology, companies might more easily identify their carbon footprint and discover effective methods to reduce carbon emissions. Similarly, digital transformation may facilitate better communication with stakeholders, allowing companies to better address their environmental and social responsibilities.

In Model (1) of Table 8, the coefficient of ESG is −0.031 and is significant at the 1% level, indicating that as companies increase their ESG investments, their carbon emissions significantly decrease. This result is consistent with expectations, as when companies place greater emphasis on environmental and social responsibilities, they will take more measures to reduce their carbon footprint to meet the expectations and needs of various stakeholders.

In Model (2) of Table 8, we further added an interaction term between ESG and digital transformation. The coefficient of this interaction term is −0.231 and is significant at the 1% level. This suggests that in the context of digital transformation, the role of ESG in reducing carbon emissions becomes even more pronounced. In other words, digital transformation amplifies the negative impact of ESG on carbon emissions. This might be because digital transformation aids companies in managing their resources and operations more effectively (Ma and Yang, 2023), further reducing their carbon emissions. Additionally, digital transformation might also encourage companies to adopt cleaner technologies and solutions, reducing their reliance on fossil fuels (Ren et al., 2023b). In summary, our results demonstrate that ESG investments have a distinct positive effect on reducing corporate carbon emissions, and this effect is further strengthened in the context of digital transformation. This provides a crucial insight for companies: digital transformation can serve as an effective tool and strategy when pursuing sustainability and carbon reduction goals.

7 Conclusions and policy implications

Faced with the challenges of global climate change, corporate carbon emissions have become a central issue of global concern. Against this backdrop, this study delves into the actual impact of ESG performance on corporate carbon reduction by analyzing data from listed manufacturing companies in China from 2010 to 2020. After an in-depth research analysis, we arrive at several core conclusions: First, ESG performance have a significant positive effect on reducing corporate carbon emissions. Secondly, green technology innovation, corporate efficiency, and managerial shortsightedness have all been proven to be key channels through which ESG performance promote carbon reduction. Furthermore, our heterogeneity tests reveal significant variations in the relationship between ESG performance and carbon reduction under different environmental regulations, industry competition, and capital intensity contexts. Notably, the positive moderating role of digital transformation in the relationship between ESG performance and carbon reduction provides companies with a new perspective: enhancing their ESG performance through digital transformation to better tackle the challenges of carbon reduction.

TABLE 8 The moderating role of digital transformation.

Variables	(1)	(2)
ESG	−0.031***	−0.026***
	(−3.883)	(−4.227)
ESG×Dig		−0.231***
		(−3.977)
Control Variables	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
N	11431	11431
adj. R2	0.336	0.445

*** p<0.01, ** p<0.05, * p<0.1 represent significance at the 1%, 5%, and 10% levels respectively. Numbers in parentheses are t-values.

To strengthen our conclusions, it is valuable to compare our findings with relevant studies conducted in other major economies. For instance, research conducted in the European Union (EU) and the United States shows similar trends, where companies with higher ESG scores are more likely to engage in practices that reduce carbon emissions. A study by Asl et al. (2022) in the EU context found a comparable effect of ESG performance on carbon emissions, underscoring the global relevance of ESG in corporate environmental responsibility. However, there are differences too. For example, in the US, the integration of ESG into corporate strategy has been more market-driven, whereas in China, it is more policy-driven. This difference in drivers could affect the implementation and impact of ESG initiatives.

The conclusions of this study have important policy implications. The climate change and environmental pollution issues have heightened the emphasis on ESG both domestically and internationally. ESG has become a crucial force in promoting corporate adherence to new development concepts and achieving sustainable development. The report from the 20th National Congress of the Communist Party of China proposes accelerating the green transformation of development modes, stressing that greening and decarbonizing economic and social development are key to achieving high-quality development. At present, as China has entered a stage of high-quality development, establishing and perfecting an ESG system suitable for China's national conditions will help achieve the "dual carbon" goals and sustainable development. Additionally, with the accelerated internationalization of ESG, it has become an essential content of international market cooperation. Therefore, advancing the construction of the ESG policy system will not only help China promote global sustainable development and build a community with a shared future for humanity but will also benefit China's foreign trade and investment. This study reveals the positive impact of ESG performance on promoting corporate carbon reduction, which has significant policy implications for corporations to actively fulfill their social responsibilities, promote China's high-quality development, and assist the country in achieving its "dual carbon" goals.

7.1 Policy implications

From a policy implication perspective, this study offers the following suggestions for policymakers and corporate decision-makers: (1) Policy Support and Guidance: Government

departments should further strengthen support and guidance for corporate ESG practices, such as providing tax incentives, subsidies, and other motivating measures, encouraging companies to enhance green technology innovation and improve operational efficiency. Additionally, the government can formulate specific market incentives, like carbon credits and environmental rewards, to encourage improvement in ESG performance. These incentives can help businesses secure better financing conditions in capital markets, enhancing their competitive advantage. (2) Perfecting ESG Information Disclosure System: The government should establish and perfect the ESG information disclosure system to ensure transparency and authenticity, guiding companies to better fulfill their social responsibilities. Furthermore, raising investor awareness of ESG investments and emphasizing their focus on corporate social responsibility and environmental sustainability can be achieved through investor education campaigns and publicity, thus increasing capital market recognition of high ESG performing companies. (3) Promoting Digital Transformation: Encourage enterprises to undergo digital transformation, using advanced technological means to monitor and manage carbon emissions while strengthening corporate ESG practices. (4) Industry and Corporate Collaboration: Strengthen collaboration among the government, industries, and corporations, jointly promoting the deepening of ESG practices, thereby better addressing the challenges of global climate change. (5) Internal Training and Capacity Building in Enterprises: Encourage businesses to strengthen internal staff understanding and training on ESG to improve overall ESG management levels. This includes providing training on sustainable development, environmental protection, and social responsibility, as well as expertise in ESG reporting and analysis. (6) Integrating ESG and Financial Performance: Encourage businesses to more closely align ESG performance with financial performance assessment, demonstrating the impact of ESG investments on long-term company value. This involves developing and using more sophisticated tools to assess the direct and indirect effects of ESG performance on financial outcomes.

7.2 Limitations and future research

The study's scope, primarily focused on China's manufacturing sector from 2010 to 2020, poses a limitation to its applicability in other geographical contexts and time periods. This geographic and temporal confinement might not fully capture the diverse global landscape of ESG impacts. Additionally, the exclusive concentration on the manufacturing industry may not adequately represent the varied ESG challenges and opportunities present in other sectors, each with its unique environmental footprint.

A significant limitation of this study is the reliance on carbon emissions proxies in lieu of directly reported emissions data from the sampled firms. This approach, while necessary due to data availability constraints, may not accurately capture the true carbon emissions of each company. Proxies, based on industry averages or standardized metrics, might lead to over- or under-estimation of actual emissions, thus impacting the precision of our conclusions regarding ESG performance and carbon emission intensity.

Future research should aim to broaden the scope, both in terms of industry and geography. Exploring a variety of sectors will provide a more holistic understanding of how ESG performance influences carbon reduction across different business landscapes. Moreover, extending the research to include longitudinal studies across a wider range of countries and time frames is crucial. Such studies would capture the evolving nature of ESG standards and their varied impacts on corporate carbon reduction strategies in a global context. Incorporating directly reported emissions data, where available, would significantly enhance the accuracy and relevance of future research in this field.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

JY: Conceptualization, Formal Analysis, Supervision, Writing – review & editing. WX: Methodology, Software, Writing – original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Financial openness and energy structure transformation

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Energy structure transformation is the only way for China to achieve the "dual carbon" goal, and one of the difficulties faced by energy transformation is financing. In the context of China's steadily promoting the high-level opening-up of financial industry, this paper uses the panel data of China's provincial level from 2010 to 2019 to systematically examine the impact of financial opening-up on the transformation of energy structure. The results show that: 1) Financial openness has a significant positive impact on the energy structure transition; 2) In different stages of energy structure transformation, as the main driving force in the initial stage of energy structure transformation is the government's policy support, with the continuous maturity of energy structure transformation, the impact of financial openness on energy structure transformation gradually increases; 3) With different levels of economic development, the driving effect of financial openness is also different. The lower the level of economic development is, the stronger the driving effect of financial openness on energy structure transformation is due to the lack of financing channels. This paper provides a theoretical basis for China's energy structure transformation, and also provides rich policy implications for promoting China's financial industry to open up at a high level.

KEYWORDS

financial openness, transformation of energy structure, "dual carbon" targets, heterogeneity, China

1 Introduction

The "dual goals" of carbon peak by 2030 and carbon neutrality by 2060 are an inevitable requirement for China to cope with climate change and an important deployment for China to formulate its medium—and long-term development strategy. The consumption of coal, oil and other petrochemical energy is the main source of global greenhouse gases. In order to achieve the goal of "dual carbon," it is necessary to accelerate energy transformation, transform the coal-based energy structure, and promote the development of non-fossil energy.

Although the overall trend of energy structure transformation is optimistic and positive, in order to achieve the "dual carbon" goal and control climate change, the field of energy structure transformation needs a lot of financial support. According to the Global Energy Transition Outlook report of the International Renewable Energy Agency, in order to achieve the goal of the Paris Agreement and control the increase in global average temperature above pre-industrial levels to less than 1.5°C, the global energy transition will require investment of 570 million US dollars per year by 2030, showing that the funding gap for energy transition is huge. For China, there is also a huge gap in green investment and financing. According to the Green Finance for Carbon Neutrality released by China International Capital Corporation Limited, in order to achieve carbon neutrality, China's

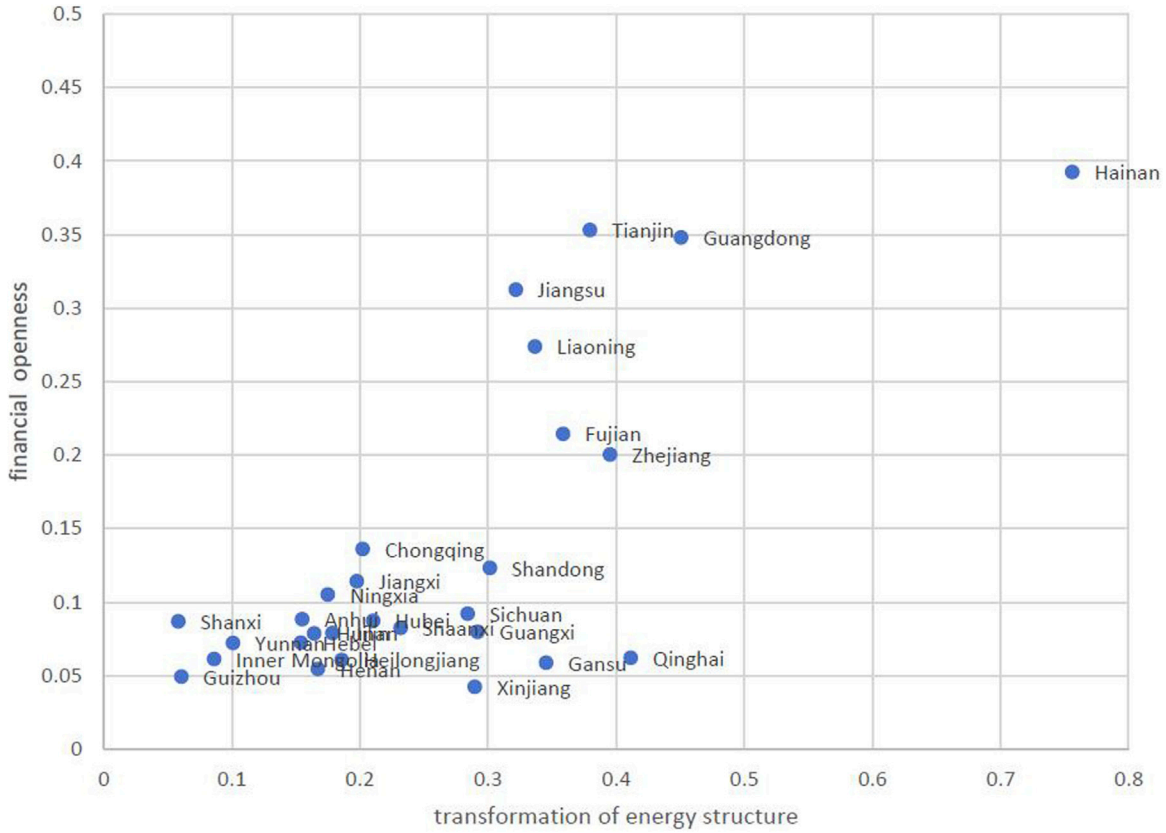


FIGURE 1
Relationship between financial openness and energy structure transformation.

green investment and financing gap is about 540 billion yuan per year from 2021 to 2030. In the absence of policy intervention, the investment and financing gap for renewable energy will rise rapidly to 310 billion yuan per year after 2031. Such a huge demand for investment and financing has become a severe challenge for the transformation of energy structure under the "dual carbon" goal.

Figure 1 provides an intuitive description of the relationship between financial openness and the transformation of the energy mix. The horizontal and vertical coordinates in Figure 1 are measured by the energy structure transformation index and the financial openness level constructed in Section 3.2, which are the average energy structure transformation index and the average financial openness level of 30 provinces in China from 2010 to 2019, respectively. As can be seen from Figure 1, there is a significant positive correlation between the level of financial openness and the energy structure transformation of 30 provinces in China. Whether financial openness is conducive to energy structure transformation, and whether this effect varies in different stages of energy structure transformation and different levels of economic development, need more rigorous demonstration. In order to better answer the previous questions, this paper uses the panel data of 30 provinces in China from 2010 to 2019 to analyze the internal relationship between financial openness and energy structure transformation at the provincial level, as well as whether there is heterogeneity in the relationship between the two.

The existing research mainly focuses on the impact of policy factors, carbon emissions, economic development and other factors on the energy structure transition, but there is still a lack of discussion on the impact of financial openness on the energy structure transition. Therefore, this paper will take China's provincial data as the research object, explore the impact of financial openness on energy structure transformation, and conduct regional heterogeneity analysis. Its main contributions include: 1) Using China's provincial data to study the impact of financial openness on energy structure transformation, it can more accurately observe the impact of financial openness in China, and realize the comparison of characteristics in different regions. 2) In quantitative research, we distinguish different stages of energy structure transformation and different levels of economic development to explore the dynamic evolution of the driving effect of financial openness, and use the panel threshold model to study the evolution characteristics of the marginal effect of financial openness. The driving factors of energy structure transformation are multi-dimensional and dynamic, so the discussion by development stage can be more consistent with the reality and the law of industrial development. 3) The research conclusions provide empirical evidence for steadily expanding the institutional opening of the financial sector, improving the facilitation of cross-border investment and financing, and attracting more foreign financial institutions and long-term capital to facilitate the transformation of

energy structure; At the same time, it provides policy inspiration for deepening international cooperation in green finance, improving the green financial system, and helping to achieve the goal of "dual carbon," which has strong practical significance.

The rest of this paper is arranged as follows: the second part is literature review and research hypothesis; The third part, empirical design, variables and data; The fourth part, benchmark regression, robustness test and heterogeneity results analysis; Finally, conclusions and policy recommendations are presented.

2 Literature review and research hypotheses

2.1 Influencing factors of energy structure transformation

In the context of the "dual carbon" target, many scholars have carried out quantitative research on the influencing factors of energy structure transformation. Although the conclusions are not consistent, the research on the influencing factors mainly focuses on the following five aspects: economic factors, policy factors, environmental factors, energy factors and social factors. 1) Policy factors. The change in production technology represented by the steam engine was the driving force of the first energy transition, the invention and promotion of the internal combustion engine was the driving force of the second energy transition, and policy factors may be one of the main driving forces of this energy transition (Cansino et al., 2010; Bai et al., 2023; Yu et al., 2023a; Liu and Peng, 2022); 2) Energy factors. Some scholars believe that the price of fossil energy and national energy endowment will affect the transformation of energy structure (Sadorsky, 2009b; Su and Tan, 2023; Yu et al., 2023b; Guo et al., 2023); 3) Environmental factors. Environmental factors mainly refer to that the emission of carbon dioxide, sulfur dioxide and other exhaust gases will affect the transformation of energy structure Bai et al. (2023), and Werner and Lazaro, (2023) believes that environmental regulation will affect the transformation of energy structure. 4) Economic factors. Most scholars believe that economic development can promote the transformation of energy structure Bai et al. (2023), and Tian et al. (2022) studied the impact of economic recovery on the transformation of energy structure; 5) Social factors. Rosenbloom et al. (2018) believed that public education would improve people's awareness of environmental protection and help promote energy structure transformation, while Kuamoah (2020) believed that the lack of infrastructure was one of the obstacles to energy transformation. It is worth noting that although the role of finance in the transformation of energy structure has gradually attracted the attention of scholars, the research mainly focuses on the impact of domestic financial development on it and the qualitative risk level.

Most existing studies have found that financial development has a positive impact on the transformation of energy structure (Ding et al., 2023), and its driving effect on finance only stays at the level of financial development, without considering financial openness. Although financial openness brings benefits such as lowering financing costs and improving risk aversion, cross-border capital may also bring disadvantages such as economic and financial turbulence. Then, for the energy structure transformation with a long investment cycle and a large amount of financial support, what is the impact of foreign capital on it? This is a question worth investigating. This paper will take China's provincial-level data as samples to study the impact of financial openness on energy structure transition, and further explore the heterogeneity of financial openness driving effect in different energy transition stages and different levels of economic development.

2.2 Mechanism and heterogeneity driven by financial openness

(1) The working mechanism driven by financial openness.

Compared with traditional fossil energy, non-fossil energy depends more on financial development. The main reason is that compared with fossil energy, the production cost of non-fossil energy has its uniqueness, which is mainly reflected in the following aspects: 1) The production technology of non-fossil energy is still very immature, many production fields still need further exploration and innovation, and the research and development of technology has a lot of uncertainties, that is, great risks. In addition to the government's financial support, it also needs financial support from the financial sector to make up for the shortage of funds; 2) Non-fossil energy construction not only has a relatively large initial investment scale, but also has a relatively high operating cost, which requires a lot of financing needs and support from the financial field; 3) Although compared with fossil energy, the investment cycle and time span of non-fossil energy are greatly shortened, it still belongs to the investment with a long cycle. Such financing services such as medium - and long-term loans are easier to obtain from foreign banks to ensure smooth project implementation.

The impact of financial openness on the transformation of energy structure is mainly reflected in the following three aspects: 1) Expand financing channels. On the one hand, the flow of international capital can effectively relieve the pressure of capital shortage in the process of local economic development; On the other hand, the entry of foreign financial institutions and the intensification of competition in the financial industry can provide more abundant financial products and provide more capital services and financing opportunities for energy transition enterprises. 2) Improve the return on investment. On the one hand, abundant financial products and financing channels can improve the anti-risk ability of energy transition enterprises; On the other hand, a perfect financial market can help enterprises better integrate resources and promote the efficient operation of investment activities. 3) Increase R&D investment of enterprises. Funds in the financial market tend to flow to technical fields with high or potential returns, while R&D of energy transition enterprises requires long-term sustainable and stable investment; therefore, relatively sufficient sources of funds will affect the R&D investment decisions of energy transition enterprises and increase R&D investment. Based on this, this paper proposes:

Hypothesis 1: Financial openness is conducive to promoting the transformation of energy structure.

(2) Heterogeneity driven by financial openness in different stages of energy structure transition

Although there are differences in the paths and ways of energy structure transformation in China's provinces, the government's policy support is still the initial driving force for China's energy structure transformation. The supporting policies for energy structure transformation can be roughly divided into two types: the first is the supply-side driven policy, which leads to the R&D input for energy structure transformation from the supply side, such as the establishment of power system adapted to new energy generation, the development of smart grid and electric vehicles, and the subsidy policy for renewable energy development. The second is demand-pull policy, which leads to capacity investment in renewable energy from the demand side and indirectly promotes the transformation of energy structure. For example, Renewable energy quota system and Tax Credit policies (including Production Tax Credit and Investment Tax Credit), tax subsidies, etc.

In the early stage of energy structure transformation, the market mechanism is certainly immature at this time, and the development of renewable energy mainly depends on the policy support of the government. It is difficult for financial openness to play a role through the market mechanism, and the role driven by financial openness is quite limited (Aklin and Urpelainen, 2013; Kim and Park, 2018). In the initial stage, the main problem of non-fossil energy development is that the use cost is too high due to the lack of technological innovation, which makes non-fossil energy maintain a high price and cannot compete with traditional petrochemical energy in the market. Therefore, the initial stage of non-fossil energy development is faced with the problems of market failure and insufficient funds. Government support is particularly important at this stage. At the same time, in the early stage of energy structure transformation, on the one hand, due to the high uncertainty of non-fossil energy technology innovation and high investment risk, the profit-driving behavior of financial institutions will turn to the less risky areas for investment, which will also have a "crowding out effect" on non-fossil energy; On the other hand, under the condition of market failure, it is also difficult for financial subjects to play their financing mechanism in the transformation of energy structure. Under the effect of dual forces, financial openness may have an inhibitory effect on energy structure transformation in the early stage.

In the growth and maturity stages of energy structure transformation, the market mechanism is gradually improved, and the strength of government support policies is gradually weakened, while the role of finance through perfect market mechanism can better promote energy structure transformation (Amuakwa-Mensah and Nasstrom, 2022). At this time, the technological progress of non-fossil energy gradually reduces the use cost, and its price can compete with the traditional fossil energy in the energy market. With the continuous improvement of cost competitiveness, the large-scale production of non-fossil energy is gradually realized, and the consumption of non-fossil energy accounts for a higher and higher proportion in the total energy consumption. Therefore, in this stage, the role of the market is gradually enhanced, and the government support policy is gradually weakened. In a sound market mechanism, financial subjects can create diversified financing channels to serve the development of non-fossil energy, reduce its financing costs, and continuously promote the transformation of energy structure. Based on this, this paper proposes:

Hypothesis 2: In the initial stage of energy structure transformation, the main driving force of energy structure transformation is government policy support, while the driving effect of financial openness is weak, and may even be inhibiting; In the growth and maturity stages of the energy structure transformation, the market mechanism is constantly improved, and the financial openness may have a significant positive impact on the energy structure transformation, and with the deepening of the energy structure transformation, this promoting effect will be strengthened.

(3) Heterogeneity driven by financial openness at different levels of economic development

Provinces with different levels of economic development have different impact paths and ways of financial openness on energy structure transformation. On the one hand, the process of energy structure transformation from research and development to investment and construction needs a lot of financial support; On the other hand, compared with the economically developed regions, the financial industry in the economically underdeveloped regions is relatively backward. Both the banking industry and the securities industry have relatively small overall scale, low level of development, imperfect financial system, extensive development mode, low operation quality and imperfect market mechanism. This makes the need for funds for energy structure transformation in less economically developed regions more urgent. To a certain extent, financial openness can break the barriers of sino-foreign trade financing, reduce financing costs, help to increase the rate of foreign direct investment, and thus promote the process of energy structure transformation. At the same time, from the perspective of economics, financial opening is conducive to the improvement of financial system and market mechanism, and helps to provide a good financial environment and better financial support for the energy structure transformation in economically underdeveloped regions. Based on this, this paper proposes:

Hypothesis 3: The financing capacity of less developed regions is greatly insufficient, but the transformation of energy structure needs a large amount of financial support. Therefore, the need for financial openness is more urgent in economically underdeveloped regions, that is, the lower the level of economic development is, the greater the impact of financial openness on the transformation of energy structure is.

3 Empirical design, variables and data

3.1 Model specification

In order to verify the relationship between financial openness and energy structure transformation, this paper constructs a two-way fixed effect model of time and region. The model is set as follows:

$$ZX_{i,t} = \alpha + \theta FO_{i,t} + \beta' X_{i,t} + \mu_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

Where i represents province and t represents year; $ZX_{i,t}$ represents the transformation degree of energy structure; $FO_{i,t}$ represents the level of financial openness; $X_{i,t}$ represents a series

of control variables, including economic factors, energy factors, policy factors and environmental factors; μ_i represents provincial fixed effects; γ_t represents the time fixed effect; $\varepsilon_{i,t}$ represents the disturbance term. In Eq. 1, θ represents the impact of financial openness on the transformation of energy structure.

In order to verify the heterogeneous impact of financial openness on energy structure transition, artificially dividing the interval of the variable "energy structure transition (or economic development level)" will cause estimation errors. The threshold panel model proposed by Hansen (1999) divides the interval of the variable according to the characteristics of the data itself. This endogenous interval division method can avoid artificial subjective factors and make the estimation more accurate. Therefore, this section uses the method proposed by Hansen (1999) to study the differences in the impact of financial openness on energy structure transition in different energy structure transition levels (or economic development levels).

Firstly, we introduce the most basic threshold panel model, that is, the setting of single threshold panel model, which is expressed as follows:

$$ZX_{it} = \vartheta_i + \gamma_1 FO_{it}\left(g_{it} \le \lambda\right) + \gamma_2 FO_{it}\left(g_{it} \ge \lambda\right) + \delta' X_{it} + v_{it} \quad (2)$$

Where i represents province and t represents year; ZX_{it} is the explained variable, indicating the transformation of energy structure; FO_{it} is the core explanatory variable, indicating the level of financial openness; X_{it} represents a group of control variables that may have a great impact on energy structure transformation, including economic factors, energy factors, policy factors and environmental factors; g_{it} represents the threshold variable, which in this paper refers to the energy structure transition level and the economic development level respectively, and λ represents the specific threshold value. $I(\cdot)$ is the indicator function, ϑ_i is used to reflect the individual effects of provinces, such as unobservable factors such as location characteristics and development endowments, and v_{it} is the random interference term.

According to econometric theory, it is possible for models to have multiple threshold values. As for the multi-threshold panel model, this paper first extends to the double-threshold panel model for a brief introduction, which is expressed as:

$$\begin{aligned} ZX_{it} = {} & \vartheta_i + \gamma_1 FO_{it}\left(g_{it} \le \lambda_1\right) + \gamma_2 FO_{it}\left(\lambda_1 < g_{it} \le \lambda_2\right) \\ & + \gamma_2 FO_{it}\left(g_{it} > \lambda_2\right) + \delta' X_{it} + v_{it} \end{aligned} \quad (3)$$

On this basis, the panel models with more thresholds can be extended, which will not be described here.

3.2 Variables and data description

(1) Explained variable: energy structure transition (ZX). The transformation of energy structure is a dynamic process and system engineering of continuous optimization and adjustment of various leading energy sources in the process of mutual substitution and complementation. Different types of energy have very different carbon emission capabilities. Therefore, changes in carbon emissions are closely related to changes in energy consumption structure. In order to realize the transformation of energy consumption structure characterized by "pollution and high carbon" to "clean and low carbon," it is imperative to promote the dual transformation of "oil and gas replacing coal and non-fossil energy replacing fossil energy". Therefore, this paper uses the dual substitution index of energy consumption structure to measure the transformation of energy structure, that is, the unit of consumption of coal, oil, natural gas and non-fossil energy is converted into standard coal by the discounted standard coal coefficient. The oil and gas substitution index (OG) is quantified by the ratio of total consumption of oil and natural gas to coal consumption. Non-fossil energy substitution index (RE) is quantified by the ratio of non-fossil energy consumption to fossil energy consumption, and the dual substitution index of energy structure is the geometric mean of the product of oil and gas substitution index and non-fossil energy substitution index.

$$ZX = \sqrt{OG \times RE} = \sqrt{\frac{\left(E_O + E_g\right) \times E_n}{E_C \times \left(1 - E_n\right)}} \quad (4)$$

Where E_O、E_g、E_n、E_c represent the ratio of oil, natural gas, non-fossil energy and coal consumption to total energy consumption, respectively.

(2) Explanatory variable: financial openness (FO). For example, Fernández et al. (2016) used the proportion of FDI in GDP to measure the level of financial openness, but this method cannot reflect the degree of financial service openness of a country. Some scholars specially describe the financial services from the perspective, but this is only theoretical elaboration without specific measurement. This paper adopts the idea of Zhang Xiaobo et al., from the two-way quantification of "bring in" and "go global." Based on the actual situation and the availability of data in various regions of China, the measurement formula of financial openness is expressed as:

$$FO_{it} = \alpha_1 \times \frac{FDI_{it}}{GDP_{it}} + \alpha_2 \times \frac{OFDI_{it}}{GDP_{it}} + \alpha_3 \times \frac{FDL_{it}}{TDL_{it}},\ (\alpha_1 + \alpha_2 + \alpha_3 = 1) \quad (5)$$

Where FO_{it} represents the degree of financial openness, FDI_{it} represents the stock of foreign direct investment, $OFDI_{it}$ represents the stock of foreign direct investment, FDL_{it} represents the total foreign currency deposits and loans of financial institutions, and TDL_{it} represents the total domestic and foreign currency deposits and loans of financial institutions. Let $\alpha_1 = 0.4$、$\alpha_2 = 0.3$、$\alpha_3 = 0.3$.

(3) Control variables. 1) Policy factor (ZC). The investment amount of pollution control projects completed this year is used to measure the policy factors (Unit: 100 billion yuan), which can reflect the government's emphasis on environmental pollution control, and then reflect the government's demand for energy consumption structure transformation; 2) Economic factors (JJ). Per capita GDP is used to measure economic factors (Unit: ten thousand yuan), mainly because existing studies have shown that the level of economic development is an important driving factor for energy transition (Sadorsky, 2009a). 3) Energy factor (NY). Energy consumption is selected to measure the endowment basis of energy resources (Unit:

TABLE 1 Descriptive statistics of variables.

Variables	Meaning	Obs.	Mean	S.D.	Min	Max
JJ	Economic factors	300	5.2635	2.6287	1.3119	16.4222
ZC	The policy factor	300	0.0223	0.0215	0.0004	0.1416
NY	The Energy factor	300	1.4781	0.882	0.1359	4.139
HJ	Environmental factors	300	0.0049	0.004	0.00002	0.1827
FO	Level of financial openness	300	0.1612	0.1572	0.0255	0.8085
ZX	Transformation of energy structure	300	0.2947	0.2521	0.0321	2.6732

Billion tons of standard coal). 4) Environmental factors (*HJ*). Previous studies have found that concern for the environment, especially pollutant emissions, will be conducive to energy transition, and so^2 emissions (Unit: 100 million tons) are selected to measure environmental factors.

The data in this paper are the panel data of 30 provinces in China from 2010 to 2019. Due to the serious lack of data in Tibet, the data of this province were excluded, and individual missing data were supplemented by interpolation method. The data mainly come from the "China Financial Database," "China Macroeconomic Database," "China Energy Database" and "China Environment Database" in EPS data platform. The descriptive statistics of the variables are shown in Table 1. As can be seen from Table 1, the minimum, maximum and average values of energy structure transformation are 0.0321, 2.6732 and 0.2947, respectively, indicating that the level of energy structure transformation among provinces in China is generally low and the gap is large. The minimum, maximum and average values of financial openness are 0.0255, 0.8085 and 0.1612 respectively, indicating that China's financial openness also has problems of low overall level and large gap between regions.

4 Analysis of empirical results

4.1 Status quo of China's energy structure transformation

The energy structure transformation level of 30 provinces in China during 2010–2019, calculated according to the energy structure transformation index constructed in Section 3.2, is shown in Table 2. As can be seen from Table 2: From the perspective of time trend, the energy structure transformation level of each province is basically gradually improved with the passage of time, which intuitively indicates that all parts of China are steadily promoting the energy structure transformation; From the horizontal point of view, the highest is Beijing, Beijing as the capital of China, the energy structure transformation should be at the forefront. Shanghai, Zhejiang, Guangdong and Hainan also have a high level of energy structure transformation, all above 0.5. These provinces are located in coastal areas and can make full use of their geographical advantages to achieve energy transformation, such as offshore wind power generation. Shanxi and Inner Mongolia have the lowest level of energy structure transformation, both below 0.1. These two places are China's large coal-power provinces and also the provinces with the highest net energy output. In the past, a large amount of resources were consumed in economic construction, leading to environmental degradation, and the economic growth model needs to be changed urgently. For a long time, China's economic and social development depends on coal resources, coal has become an important basic energy and industrial raw materials, reliable type of energy security. Although, in recent years, the proportion of coal consumption has declined, but the rich coal, poor oil, less gas energy resource endowment and non-fossil has not been reliable alternative to the *status quo* of traditional resources have determined that the coal-based energy structure is difficult to change in the short term, coal will still be the "ballast stone" "stabilizer" of energy supply. Therefore, the transformation degree of energy structure in these regions is not high.

4.2 Average impact of financial openness on energy structure transition

Columns (1)–(3) of Table 3 respectively report the impact of financial openness on energy structure transition without adding control variables, adding control variables and two-way fixed effects. From the estimation results, it can be seen that there is a significant positive relationship between financial openness and energy structure transition. It can be seen from Column (3) of Table 3 that the average effect of financial openness on the energy structure transition is 0.58, which is significant at the level of 1%. That is, for every 1 unit increase in financial openness, the energy structure transformation will increase by 0.58 units. The above structure shows that in the process of energy consumption structure transformation, the openness of the financial industry is conducive to energy structure transformation, that is, Hypothesis 1 is verified.

4.3 Robustness test

In the part of robustness test, this paper mainly uses the replacement of core explanatory variables, the addition and reduction of control variables and the random effect model to test the robustness of the empirical results.

(1) Replacing core explanatory variables. In order to further eliminate the impact of the measurement error of financial openness index on the empirical results, this paper uses the

TABLE 2 The energy structure transformation level of 30 provinces in China from 2010 to 2019.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.49	0.52	0.56	0.59	0.70	0.92	1.10	1.50	2.15	2.67
Tianjin	0.32	0.32	0.30	0.34	0.34	0.37	0.39	0.44	0.48	0.49
Hebei	0.13	0.13	0.13	0.13	0.14	0.15	0.15	0.16	0.19	0.22
Shanxi	0.05	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.07
Inner Mongolia	0.07	0.06	0.06	0.09	0.09	0.09	0.10	0.10	0.10	0.09
Liaoning	0.30	0.30	0.30	0.32	0.32	0.32	0.35	0.35	0.39	0.41
Jilin	0.15	0.14	0.16	0.16	0.16	0.19	0.20	0.21	0.21	0.22
Heilongjiang	0.19	0.18	0.18	0.19	0.18	0.18	0.20	0.19	0.19	0.18
Shanghai	0.38	0.38	0.41	0.46	0.46	0.51	0.52	0.53	0.54	0.57
Jiangsu	0.27	0.26	0.26	0.29	0.30	0.32	0.33	0.37	0.40	0.41
Zhejiang	0.34	0.35	0.35	0.38	0.39	0.39	0.39	0.43	0.44	0.50
Anhui	0.12	0.13	0.12	0.14	0.16	0.16	0.16	0.18	0.19	0.19
Fujian	0.28	0.25	0.27	0.30	0.38	0.40	0.43	0.42	0.41	0.44
Jiangxi	0.16	0.16	0.17	0.18	0.17	0.19	0.22	0.23	0.24	0.25
Shandong	0.21	0.21	0.22	0.25	0.27	0.30	0.34	0.38	0.41	0.43
Henan	0.13	0.13	0.16	0.17	0.16	0.16	0.17	0.18	0.20	0.21
Hubei	0.15	0.14	0.14	0.20	0.21	0.23	0.23	0.25	0.26	0.27
Hunan	0.12	0.14	0.15	0.17	0.16	0.18	0.17	0.16	0.19	0.20
Guangdong	0.39	0.37	0.39	0.43	0.44	0.46	0.48	0.49	0.52	0.53
Guangxi	0.16	0.24	0.28	0.27	0.30	0.32	0.31	0.34	0.35	0.35
Hainan	0.77	0.75	0.73	0.68	0.74	0.78	0.80	0.74	0.76	0.81
Chongqing	0.13	0.13	0.14	0.18	0.19	0.23	0.24	0.24	0.26	0.27
Sichuan	0.20	0.21	0.20	0.20	0.25	0.32	0.32	0.35	0.37	0.40
Guizhou	0.03	0.03	0.03	0.04	0.05	0.06	0.07	0.07	0.10	0.11
Yunnan	0.03	0.04	0.04	0.04	0.05	0.06	0.06	0.16	0.26	0.27
Shaanxi	0.25	0.24	0.23	0.23	0.22	0.22	0.22	0.23	0.24	0.24
Gansu	0.34	0.35	0.33	0.35	0.33	0.34	0.33	0.36	0.36	0.36
Qinghai	0.40	0.41	0.39	0.38	0.41	0.43	0.37	0.42	0.45	0.47
Ningxia	0.16	0.13	0.20	0.20	0.19	0.19	0.21	0.18	0.15	0.15
Xinjiang	0.29	0.29	0.28	0.30	0.32	0.29	0.29	0.28	0.28	0.28

proportion of FDI in GDP to measure financial openness for robustness test, and the results are still robust.

(2) Increase or decrease of control variables. In order to test whether different control variables will affect the empirical estimation results, this paper adopts the stepwise regression method, gradually adding control variables for regression, and the results of the core explanatory variable financial openness are still robust.

(3) Random effect model. In order to test whether the adoption of different panel models will affect the empirical estimation results, this paper uses the random effect model for estimation, and the results are still robust.

4.4 Analysis of heterogeneity

4.4.1 The effect of financial openness in different development stages of energy structure transition

On the basis of Table 3, we further explore the average effect of financial openness in different stages of energy transition. The higher the energy structure transition index is, the higher the proportion of oil and gas replacing coal and non-fossil energy replacing fossil energy in this region is, and the more mature the energy transition in this region is. In this paper, the threshold panel model of Hansen (1999) is used to divide the interval of variables according to the characteristics of the data itself for parameter estimation.

TABLE 3 Benchmark regression results.

Variables	(1)	(2)	(3)
FO	0.98***	0.49***	0.58***
JJ		0.07***	0.09***
ZC		−0.73	−0.61
NY		−0.21***	−0.18***
HJ		6.9**	−0.5
Province fixed effects	Yes	Yes	Yes
Time fixed effects	No	No	Yes
Samples	300	300	300
Adj R^2	0.44	0.42	0.46

Note: ***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Since the threshold value and its number in the threshold model are unknown, in order to determine the form of the model, this section first determines the possible number of thresholds and their values through the corresponding algorithms and procedures according to the characteristics of the data. The regression results show that the double threshold model should be used for analysis. The two threshold estimates for the dual threshold model are 0.25 and 0.53, respectively. According to these two threshold values, the energy structure transformation of each province can be divided into three types: the initial stage of transformation, the growth stage of transformation and the maturity stage of transformation. Column (1) of Table 4 shows the regression results of the model under the double threshold.

It can be seen from Column (1) of Table 4 that in the early stage of energy structure transition, the estimated coefficient of financial openness is significant at the significance level of 1%, and its value is −0.71. In the growth period of energy structure transformation, the estimated coefficient of financial openness is significant at the 1% significance level, and its value is 0.36. In the mature period of energy structure transition, the estimated coefficient of financial openness is significant at the 1% significance level, and its value is 1.17. Obviously, 1.17 > 0.36>−0.71, which indicates that with the continuous maturity of energy structure transformation, the impact of financial openness on energy structure transformation is gradually enhanced. That is, Hypothesis 2 is verified.

4.4.2 The effect of financial openness at different levels of economic development

On the basis of Table 3, we further explore the average effect of financial openness at different levels of economic development. The threshold panel model of Hansen (1999) is still adopted, and the regression results show that the double threshold model should be used for analysis. The two threshold estimates for the dual threshold model are 4.11 and 7.63, respectively. According to these two threshold values, we can divide the economic development level of each province into three types: underdeveloped, moderately developed and developed. Column (2) of Table 4 shows the regression results of the model under the double threshold.

It can be seen from Column (2) of Table 4 that in economically underdeveloped regions, the estimated coefficient of financial openness is significant at the 1% significance level, and its value is 2.38. In the growth period of energy transition, the estimated coefficient of financial openness is significant at the 1% significance level, and its value is 1.08. In the maturity period of energy transition, the coefficient estimate of financial openness is significant at the 1% significance level, and its value is 0.72. Obviously, 2.38 > 1.08>0.72, which indicates that the more backward the economy is, the stronger the driving effect of financial openness on energy structure transformation is. That is, Hypothesis 3 is verified.

5 Conclusion and policy recommendations

This paper uses the panel data model of 30 provinces in China from 2010 to 2019 to examine the impact of financial openness on

TABLE 4 Parameter estimation results of heterogeneity analysis.

Variables	(1)	(2)
JJ	0.04***	0.08***
ZC	−0.92	−0.63
NY	−0.02	−0.04
HJ	1.47	9.84***
ZX − 1	−0.71***	
ZX − 2	0.36***	
ZX − 3	1.17***	
JJ − 1		2.38***
JJ − 2		1.08***
JJ − 3		0.72***
$Adj - R^2$	0.68	0.52

Note: *ZX* − 1, *ZX* − 2 and *ZX* − 3 represent the *FO* of small, medium and large energy structure transition level intervals, respectively; *JJ* − 1, *JJ* − 2 and *JJ* − 3 represent the *FO* of small, medium and large economic development levels, respectively; ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.

the transformation of energy structure, in order to provide theoretical support and policy reference for promoting the steady opening of financial market and helping to achieve the goal of "dual carbon". The results show that: 1) From the current situation of China's energy structure transformation, it can be seen that coastal cities have a higher level of energy transformation, while resource-based cities such as Shanxi have a lower level of energy transformation; 2) In general, financial openness is conducive to energy structure transformation; 3) In the initial stage of energy structure transformation, the main driving force of energy structure transformation is government policy support, while the driving effect of financial openness is weak, and may even be inhibiting; In the growth and maturity stages of the energy structure transformation, the market mechanism is constantly improved, and the financial openness may have a significant positive impact on the energy structure transformation, and with the deepening of the energy structure transformation, this promoting effect will be strengthened. 4) The financing capacity of less developed regions is greatly insufficient, but the transformation of energy structure needs a large amount of financial support. Therefore, the need for financial openness is more urgent in economically underdeveloped regions, that is, the lower the level of economic development is, the greater the impact of financial openness on energy structure transformation is. Based on this, this paper puts forward the following policy suggestions:

(1) Opening up the financial market in a steady and orderly manner. Adhering to the equal emphasis on "bringing in" and "going global," by promoting the high-level opening up of the financial industry, it can promote the deepening reform of China's financial industry, make the power of long-term capital and institutional investors continue to grow, attract overseas institutions and investors to participate in the transformation of energy structure, which will help enrich the participants of the financial market and optimize the financial supply. Provide rich financing channels for the transformation of energy structure and help further deepen the transformation of energy structure.
(2) Enhance innovation and diversity of financial products and broaden financing channels for energy structure transformation. In the process of energy structure transformation, one of the biggest problems is the difficulty of financing, which is more difficult for economically underdeveloped regions. The financing problem should not only rely on the guidance and incentive of the government, but also play the role of the financial market, especially foreign capital. First, actively promote the growth of green credit business for the transformation of energy structure. We will encourage financial institutions to invest more capital in green industries through tax cuts and targeted RRR cuts. Second, we will continue to deepen international cooperation in green finance, actively participate in the formulation of international standards in relevant fields, jointly incubate pilot and test projects, and explore the construction of a green finance market ecosystem.
(3) Give full play to the complementary advantages of government policies and financial institutions. In the initial stage of energy structure transformation, the main driving force of energy structure transformation is government policy support. However, with the deepening of the transformation of energy structure, it is necessary to make full use of the advantages of financial institutions, promote government-bank cooperation, give full play to the advantages of both sides in policy, information, resources and capital, explore diversified financial cooperation models, and jointly contribute to the transformation of energy structure.
(4) Pay attention to the reduction and withdrawal of traditional industries in resource-based areas to make up for the vacancy. Most industries in resource-based areas are closely related to fossil energy. On the one hand, resource-based areas should rely on local resource endowments, establish a multi-energy complementary comprehensive energy supply industry chain, establish and improve the exit compensation mechanism, and guide the steady transformation of industries. On the other hand, resource-based areas can reduce the risk of transition to a greater extent through the coordinated development of fossil energy and renewable energy.
(5) Both supply and demand sides should make concerted efforts to promote the transformation of energy structure. On the one hand, from the supply side, we should vigorously develop new and renewable energy such as wind power, hydropower, photovoltaic power generation and nuclear power, and zero and low-carbon energy production bases such as natural gas. We should promote various new energy projects, build a multi-energy complementary, safe and efficient energy system, and effectively lead the green transformation of energy. On the other hand, from the demand side, we should actively transform the growth drivers, change the growth mode, adjust the industrial structure, and limit the development of industries with high energy consumption. On the micro level, under the premise of comprehensive consideration of safety, economy, environmental protection and other factors, consumers' lifestyle and consumption mode should be guided to shift to the direction of low energy consumption, low pollution and low emissions. Supply and demand sides work together to promote the transformation of energy structure.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

XJ: Conceptualization, Methodology, Resources, Validation, Writing–review and editing. WX: Data curation, Software, Writing–original draft. KW: Supervision, Writing–review and editing.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1346594/full#supplementary-material

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The impacts of digital value chain embeddedness on trade-related carbon emissions intensity

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Objective: Digitalization supported by digital technology presents a potential solution for improving the efficiency of resource utilization. However, the impacts of digitalization on trade-related carbon emissions intensity have not been studied systematically.

Methods: Based on panel data of 41 countries and regions over the period 2000–2014, this study examines how different types of digital value chain embeddedness can affect carbon emissions intensity using a semi-parametric partially linear model.

Results: Research findings indicate that there is an inverted U-shaped relationship between digital domestic value chain embeddedness and carbon emissions intensity embodied in domestic trade; only when digitalization reaches a threshold of approximately 0.88, does the effects on carbon emissions intensity become negative. In addition, the impacts of digital global value chain embeddedness on carbon emissions intensity embodied in import trade and export trade are recognized as being non-linear; the thresholds of digitalization are approximately 0.1 and 0.3 for import trade and approximately 0.03 and 0.21 for export trade. Although participating in global value chains is conducive to accelerating digital technology diffusion, the actual environmental effects are constrained by a country's absorptive capacity and high economic system complexity. Compared with developed countries, developing countries lag behind in entering the downward stage of the inverted U-shaped curve, thereby gaining environmental benefits from digital value chain embeddedness. Moreover, in terms of utilizing digital value chain embeddedness to improve energy efficiency, measures include optimizing trade conditions, adjusting energy structure, and increasing trade scale, which can play an active role.

Value: This study sheds light on the exploration of the potential of digitalization and the facilitation of economic development in a more environmentally friendly manner.

KEYWORDS

CO_2 emissions, global value chain, carbon intensity, digital embeddedness, panel model

1 Introduction

The advent of global value chains (GVCs) has significantly changed international trade patterns (Meng et al., 2018). Depending on comparative advantages, the production of a commodity can be undertaken in different regions, and intermediate products may be traded across borders many times (Grossman and Rossi-Hansberg, 2008; Baldwin and Venables, 2013; Antràs and Gortari, 2020). Under the trend of international production fragmentation, some side effects arise from trade activities, especially environmental issues such as increased carbon dioxide (CO_2) emissions. It is estimated that approximately a quarter of global carbon emissions are derived from international trade, with a serious asymmetry in environmental costs between developed and developing countries (Peters et al., 2011; Huang and Zhang, 2023). Therefore, participating in GVCs in a more environmentally friendly way is becoming increasingly important, among which improving energy efficiency is regarded as key to balancing steady economic growth and carbon emissions reduction (Sun et al., 2019; Li et al., 2022; Zhang et al., 2023).

Digitalization supported by digital technology has been considered as a potential driver for sustainable economic development (Gouvea et al., 2020; Ren et al., 2021). Encouraging and promoting cleaner production is conducive to reducing carbon emissions (Nguyen et al., 2020). On the other hand, some researchers argue that environmental degradation may also occur (Moyer and Hughes, 2012). In recent years, with the continuous penetration of digital technology into the real economy, GVCs have undergone drastic changes. A new channel of digitally driven globalization has arisen (van der Marel, 2021; Blazquez et al., 2022), which is defined as digital value chain embeddedness in this study. Concerning the interaction between digital technology and GVCs, a large body of research has been carried out to analyze the impacts of digitalization on productivity, economic growth, and GVC specialization (Niebel, 2018; Szalavetz, 2019; Lahouel et al., 2021; Banga, 2022). However, there has only been a very limited attempt to link digitalization, GVCs, and carbon emissions intensity together (Wiedmann and Lenzen, 2018). With the rapid digital transformation of GVCs, carbon emissions embodied in international trade might be altered due to the change in trade patterns. Moreover, as domestic trade accounts for a considerable proportion of overall trade in some countries, the environmental effects of digitalization along domestic value chains have also yet to be investigated. In this regard, the study aims to clarify the impacts of digital value chain embeddedness on carbon emissions intensity, which is critical for fully utilizing the energy-saving effects of digitalization and identifying the probable pressures during a low-carbon transition process.

Although digitalization is generally perceived as an engine for a low-carbon economy, controversy remains about the role of digitalization in trade-related carbon emissions (Danish, 2019; Lin and Huang, 2023). According to the study of Copeland and Taylor (1994); Antweiler et al.(2001), the environmental effects of trade bring into play due to trade scale, trade embedded technique and trade composition. One view suggests that digitalization induces large-scale data trading, and the supporting operation of digital industries increases carbon consumption (Jones, 2018; Xiao et al., 2020; He and Xie, 2022). The direct effects of a cyclic process of digitalization, as well as the indirect effects of an expanding economy, tend to increase carbon emissions (Lange et al., 2020). Moreover, the rebound effect also leads to a surge in carbon-intensive product consumption (Peng et al., 2023). By contrast, another view supporting the emission reduction effects of digitalization suggests that through technological progress, learning by exporting, and trade barrier pushback (Banga, 2022), it will bring significant energy savings. In addition, several studies have confirmed that digitalization promotes technological innovation and further optimizes energy utilization structures (Ollo-López and Aramendía-Muneta, 2012; Usman et al., 2015; Bastida et al., 2019; Xu et al., 2022), which contribute to carbon emissions reduction. From the perspective of countries of different economic development levels, developing countries are at a disadvantage in terms of the trade environment (Wang et al., 2021), and even become a "pollution refuge" by taking part in global production networks (Peng, 2020; Li et al., 2021). Although the relationship between digital value chain embeddedness and carbon emissions intensity is intricate, most scholars identify with the energy saving effects for developed countries (Danish et al., 2019; Qayyum et al., 2021; Shi et al., 2022). Furthermore, apart from the above two opposite propositions on the carbon emission effects of digitalization, it is also argued that the relationship between digitalization and environmental performance is probably non-linear (Higon et al., 2017). However, based on the viewpoint of energy efficiency, the potential non-linear relationship between digitalization and carbon emissions intensity has been investigated less (Bekaroo et al., 2016; Li and Wang, 2022).

A challenge to achieving a consensus on the relationship between digitalization and energy efficiency is the accounting framework. A large body of literature has applied the "consumption-based carbon accounting" method to compute carbon emissions, which is a modification of the conventional "territorial-based carbon accounting" method (Su et al., 2010; Liddle, 2018). Both measures are based on gross trade statistics, which would give rise to the issue of double counting and non-conformity with the System of National Accounts. As an improvement, the accounting method of value-added trade provides powerful tools for calculating carbon emissions embodied in trade (Meng et al., 2018). On this ground, existing efforts have been made to trace the carbon footprint from the point of life-cycle assessment, and the methods are mainly based on bilateral trade input-output models or single regional input-output models (Fan et al., 2021). Additionally, some scholars have conducted research on GVCs and carbon emissions embodied in trade separately (Dolter and Victor, 2016; Pothen, 2017; Jiborn et al., 2018). However, these attempts did not distinguish the carbon content difference between imported and domestic intermediate goods, causing the measurement results to deviate from the actual situation (Xu et al., 2011; Liu et al., 2013). With the worldwide prevalence of intra-product trade, applying multiregional input-output models (MRIOs) to track carbon emissions back to the production sector is gradually becoming mainstream. As Jin et al. (2020) have pointed out, although CO_2 emissions are probably increasing year-on-year, the energy utilization efficiency indicator characterized by carbon emissions intensity might show different results and more convincingly evaluate the performance of energy conservation.

Overall, there is room for improvement in existing studies. In terms of measurement, digital value chain embeddedness is not clearly

reflected by the statistical indicators, such as the digital input ratio and digital development index. These pertinent measures provide a limited reference for the real level of digital value chain embeddedness. As for the potential non-linear relationship between digital value chain embeddedness and carbon emissions intensity, it has received less attention, and the evolvement of the marginal effect has not been investigated either. Furthermore, the phenomenon of the digital divide across countries is probably an influential factor in mediating the effects of digitalization on energy efficiency, which needs to be further verified. In this study, based on panel data of 41 economies over the period 2000–2014, we construct the carbon emissions intensity indicator to reflect adversely on domestic and international trade-related energy efficiency. In addition, we identify digital economy sectors from all sectors and establish the measurement and decomposition framework of digital value chain embeddedness. Furthermore, we use a semi-parametric partially linear model to test the non-linear effects of digital value chain embeddedness on carbon emissions intensity, with the purpose of emphasizing the evolvement of the marginal impact concerning different digital development levels. Compared with other econometric models, on the one hand, it avoids the weakness of setting a specific functional relationship subjectively and can better grasp the true impacts of digital value chain embeddedness on carbon emissions intensity; on the other hand, the marginal effect graph can directly show the effects of the core explanatory variable on the dependent varible. The empirical results prove that there is an inverted U-shaped relationship between digital domestic value chain embeddedness and carbon emissions intensity. We identify a threshold of 0.88 that divides the range of digitalization into two intervals; when it is in the low range of digital domestic value chain embeddedness, its marginal effect on carbon emissions intensity is positive; when it is in the higher range, the impact is reversed. Comparatively, we recognize two thresholds in the case of digital GVC embeddedness, which are 0.1 and 0.3 for import trade and 0.03 and 0.21 for export trade. This reveals that a country's pertinent absorptive capacity lags behind in digital technological development as the enhancement of the adaptive capability needs to take a dynamic process.

The marginal contributions of this study are reflected in three aspects: first, compared with the single indicator of CO_2 emissions that is based on the absolute quantity perspective, in this study, we construct carbon emissions intensity indicators to reflect adversely on energy efficiency. Specifically, through the lens of value chains, we focus on carbon emissions intensity embodied in domestic trade, import trade, and export trade. Additionally, the digital domestic value chain embeddedness and digital GVC embeddedness are measured. This study provides statistical backing for the research fields of digitalization and its environmental effects. Second, in the era of the digital economy, the relationship between value chain activities and environmental impacts may shed some new light. However, relevant research that combines digitalization, GVCs, and carbon emissions intensity is still lacking. By integrating them into a unified framework, this study provides a novel insight into boosting decarbonization through digital value chain embedding while enhancing steady economic growth. Third, different from existing studies that focus on the linear environmental effects of digitalization, based on theoretical analysis of probable non-linear effects, this study applies a semi-parametric partially linear model to explore the non-linear relationship between different types of digital value chain embeddedness and carbon emissions intensity. The findings reveal that only when digital value chain embeddedness reaches a certain value, it has virtual impacts on energy saving. Targeted policy implications are thus put forward, especially that each economy should adjust its digital transformation strategy based on its stage of economic development and the technology absorptive capacity.

2 Theoretical analysis

Compared with conventional industries, digital industry is much more environmentally friendly, with the advantages of high energy efficiency (Amri et al., 2019). It is well-recognized that digitalization provides a new impetus for technological progress. As intermediate inputs, digital elements contribute to upgrading conventional manufacturing industries and improving the efficiency of R&D. Thus, digitalization is conducive to reducing carbon emissions intensity. However, the effectiveness of digitalization is constrained by its connectivity characteristics (Lin and Huang, 2023). Conditional on different levels of digital value chain embeddedness, both the energy consumption impact and the energy saving benefit of digitalization take effect. The net impact depends on which mechanism prevails, and a simple linear assumption would not be valid (Ren et al., 2021). To inspect the win-win influence of digitalization in facilitating economic growth and carbon emissions reduction (Xu et al., 2022), the indicator of carbon emissions intensity is chosen to manifest the environmental performance, which is more comprehensive than that of the absolute carbon emissions indicator. Concerning the mixed effects of digitalization, we refer to the studies of Lange et al. (2020) and Azam et al. (2021) and propose that digital value chain embeddedness has a complex non-linear relationship with carbon emissions intensity.

From a perspective of technology adoption life cycle, the process of digital technology diffusion takes place gradually (Rao and Kishore, 2010). As Bai et al. (2023) have pointed out, there are innovators, early adopters, early majority, late majority, and laggards according to the adoption stages. While it is in a low range of digital value chain embeddedness, the construction of digital supportive resources is insufficient. The host country's absorption capacity is limited because of the low degree of digital embedding (Huang et al., 2022). To sustain digital connectivity, many energy-intensive applications, such as data centers, electronic equipment, and data transmission networks, require massive energy consumption (Galvin, 2015; Bieser and Hilty, 2020). Owing to a high dependence of digital infrastructure on electric power, carbon emissions and carbon intensity increase when digital value chain embeddedness is in the early development stage (Morley et al., 2018; Jin and Yu, 2022). In addition, the rebound effect that refers to the production expansion of other industries incurred by digitalization poses another threat to energy efficiency endeavors (Joyce et al., 2019; Lin and Zhu, 2021). Additionally, digital trade operations have reshaped traditional trade models by expanding market reach and enhancing trade efficiency, which promotes economic growth (Zheng et al., 2023). In this regard, we conclude that digital value chain embeddedness indirectly increases carbon emissions intensity by broadening the economy.

As digital technology progresses, the ability of host countries to make use of advanced technologies is enhanced, and it will result in a declining trend in energy consumption. The deep integration of digital elements with conventional industries can decrease carbon emissions

intensity by facilitating technological innovation, alleviating resource distortion, upgrading industrial structures, and accelerating the accumulation of human capital (Lin and Zhou, 2021; Zhong et al., 2022; Zhang et al., 2023). Based on innovation and signaling theory, participating in GVCs enhances the flow of digital elements, which is beneficial for technology spillovers. Positive externalities of internal and external communications about the knowledge-intensive technology provide impetus for the low-carbon transformation. From the perspective of manufacturing industry servicing, digitally enabled services can be traded by overcoming the constraints of geographical distance (Zhou et al., 2018; Blazquez et al., 2023). More varieties of high-quality services are available for manufacturers to make use of, which not only contributes to the growth of value-added trade but also enhances the environmental benefits.

Overall, owing to the overlap of direct and indirect environmental influences of digital value chain embeddedness, there may be an intricate relationship between digital value chain embeddedness and carbon emissions intensity. Energy consumption is often larger than the energy savings in the early stage of digitalization, and the energy saving effect takes precedence when the digitalization surpasses a certain level during its exponential growth path. Given the abovementioned analysis, we put forward the first hypothesis:

H1. There is an inverted U-shaped relationship between digital value chain embeddedness and carbon emissions intensity.

In addition to the threshold environmental effect of digital value chain embeddedness, developing and developed countries may exhibit significant differences in practice. Depending on their contrastive ways of embedding GVCs, developing countries typically take part in GVCs through backward embedding, which puts them in a position to generate more carbon emissions (Zhang et al., 2017). Participation in GVCs provides developing countries with opportunities to obtain advanced technologies and knowledge (Hummels et al., 2001; Wang et al., 2021). However, as developing countries are constrained to the lower end of the value chain, they are disadvantaged in upgrading industrial structures because they lack key technologies. There are significant gaps in digital technology between developing and developed countries. Compared with conventional production technology, it is more difficult to learn digital technology through demonstration and observational learning. Under the conditions of the core technologies grasped by developed countries (Huang et al., 2022), developing countries have to strengthen their absorption capacity, which depends on the accumulation of human capital, R&D ability, and the institutional environment.

Based on the standpoint of "pollution heaven" (Copeland and Taylor, 1994), pollution-intensive industries are shifted from developed countries to developing countries. Through importing intermediate products and exporting high-pollution final goods, developing countries generally gain low additional value and become net exporters of carbon embodied in trade (Xing, 2018; Liu et al., 2020). To cope with the pressure of carbon emissions reduction while realizing economic growth, improving environmental efficiency is more urgent for developing countries. In the global production network, long-term dependence on gaining technology spillovers from developed countries means it is difficult for developing countries to form independent intellectual property rights. As the application of digital technology requires substantial catch-up cosst for developing countries, it is challenging to improve GVCs by relying on the introduction of digital technology (Huang and Zhang, 2023). Furthermore, when confronted with digital technical blockades, such as digital patent protection strategies (Sun et al., 2019), developing countries lag further behind in exploiting the potential of digitalization. As a result, the risks of locking in low-end value chains are magnified in the digital era. In summary, we put forward the second hypothesis:

H2. Compared with developing countries, developed countries take the initiative in utilizing the energy-saving effects of digitalization.

3 Measurement

3.1 Measurement of carbon emissions intensity

We calculate trade-related carbon emissions intensity following the MRIO framework. In a global multi-regional input-output table comprising G countries, with each having N sectors, the basic row balance relation can be expressed as (Leontief, 1936):

$$X = AX + Y \Rightarrow X = (I - A)^{-1}Y = BY \tag{1}$$

where X is the gross output, a $GN \times 1$ vector; A represents the direct consumption coefficient matrix, a $GN \times GN$ matrix; Y denotes the demand for the final goods, a $GN \times G$ matrix; and I is an identity matrix with the same dimensions of $GN \times GN$. Define $B = (I - A)^{-1} = (I + A + A^2 + \cdots)$, which is the Leontief inverse matrix.

To measure the transfer of carbon emissions embodied in domestic and international trade, this study set the coefficient vector of carbon emissions as follows:

$$CR_i = \left\{CR_i^k\right\} = CE_i^k \Big/ X_i^k \tag{2}$$

where CE_i^k and X_i^k denote the direct carbon emissions and gross output of sector k in country i, respectively. The coefficient CR_i^k refers to the carbon emissions embodied in the unit gross output of sector k in country i. According to the study by Peters et al. (2011), by considering the indirect carbon flow induced by the demand for intermediate and final goods, a carbon flow matrix $\{C_{ir}\}$ can be constructed. For simplicity, referring to the study by Fan et al. (2021), we selected three economies (economies 1, m, and G) as an example to show the following relationship:

$$\begin{pmatrix} C_{11} & C_{1m} & C_{1G} \\ C_{m1} & C_{mm} & C_{mG} \\ C_{G1} & C_{Gm} & C_{GG} \end{pmatrix} = \begin{pmatrix} (CR_1)' & 0 & 0 \\ 0 & (CR_m)' & 0 \\ 0 & 0 & (CR_G)' \end{pmatrix} \times \begin{pmatrix} B_{11} & B_{1m} & B_{1G} \\ B_{m1} & B_{mm} & B_{mG} \\ B_{G1} & B_{Gm} & B_{GG} \end{pmatrix} \begin{pmatrix} Y_{11} & Y_{1m} & Y_{1G} \\ Y_{m1} & Y_{mm} & Y_{mG} \\ Y_{G1} & Y_{Gm} & Y_{GG} \end{pmatrix} \tag{3}$$

In Eq. 3, C_{m1} refers to the carbon emissions of country m induced by the final demand of country 1. The first subscript denotes the exporting country, and the second subscript represents the importing country. By categorizing traded goods into intermediate goods and final goods, we distinguished the carbon emissions embodied in exported and imported trade along GVCs, as shown in the following equations:

$$C_i^{import} = \sum_{r \neq i} C_{ri}^{import} = \underbrace{\sum_{r \neq i} (CR_r) B_{rr} A_{ir} X_i}_{imported\ carbon\ of\ intermediate\ goods} + \underbrace{\sum_{r \neq i} (CR_r) B_{rr} Y_{ir}}_{imported\ carbon\ of\ final\ goods} \quad (4)$$

$$C_i^{export} = \sum_{r \neq i} C_{ir}^{export} = \underbrace{(CR_i) B_{ii} \sum_{r \neq i} A_{ir} X_r}_{exported\ carbon\ of\ intermediate\ goods} + \underbrace{(CR_i) B_{ii} \sum_{r \neq i} Y_{ir}}_{imported\ carbon\ of\ final\ goods} \quad (5)$$

Thus, the net carbon flow of a country is given as:

$$C_i^{net} = C_i^{export} - C_i^{import} \quad (6)$$

Similar to the construction of carbon flow matrix, when the matrix of CR_i in Eq. 2 is replaced by the value-added factor matrix V_i, which refers to the value-added per unit of the gross output. Accordingly, we could obtain a global value-added flow matrix $\{VA_{ir}\}$. As the carbon flows can be categorized into three types, carbon flow in the local region (C_{ii}), carbon flow of import trade (C_i^{import}), and carbon flow of export trade (C_i^{export}), according to the flow direction (Yan et al., 2020; Chen et al., 2022), the related carbon intensity indicators were constructed, respectively.

$$CI_i^{local} = C_{ii} \Big/ VA_{ii} \ \ (i = 1, 2, \cdots G) \quad (7)$$

$$CI_i^{import} = C_i^{import} \Big/ \sum_{r \neq i} VA_{ri} \ \ (i, r = 1, 2, \cdots G) \quad (8)$$

$$CI_i^{export} = C_i^{export} \Big/ \sum_{i \neq r} VA_{ir} \ \ (i, r = 1, 2, \cdots G) \quad (9)$$

where CI_i^{local} denotes carbon emissions intensity of local region I and CI_i^{import} and CI_i^{export} represent carbon emissions intensity incurred by the import and export trade of region i, respectively.

3.2 Measurement of digital value chain embeddedness

Based on where goods are consumed, the direct consumption coefficient matrix (A) could be divided into $A^D = \{a_{ii}\}$ and $A^F = \{a_{ij}, i \neq j\}$. Thus, the gross output of a country could be expressed as $X = A^D X + Y^D + A^F X + Y^F$, where $A^D X + Y^D$ represents a country's domestic use and $A^F X + Y^F$ represents a country's gross exports.

With reference to the study by Ma et al. (2023), by using superscript to separate the digital (d) sectors from the non-digital (n) sectors of an economy, the domestic direct consumption coefficient matrix was given as $A^D = \begin{bmatrix} a_{11}^{dd} & a_{11}^{dn} & \cdots & 0 & 0 \\ a_{11}^{nd} & a_{11}^{nn} & & \vdots & \vdots \\ 0 & 0 & \ddots & 0 & 0 \\ \vdots & \vdots & & a_{GG}^{dd} & a_{GG}^{dn} \\ 0 & 0 & \cdots & a_{GG}^{nd} & a_{GG}^{nn} \end{bmatrix}$. Moreover, for the purpose of emphasizing the purely digital or non-digital sectors of the domestic economy, we defines a matrix A^{DD} that was denoted by $A^{DD} = \begin{bmatrix} a_{11}^{dd} & 0 & \cdots & 0 & 0 \\ 0 & a_{11}^{nn} & & \vdots & \vdots \\ 0 & 0 & \ddots & 0 & 0 \\ \vdots & \vdots & & a_{GG}^{dd} & 0 \\ 0 & 0 & \cdots & 0 & a_{GG}^{nn} \end{bmatrix}$. The element on the diagonal of matrix A^{DD} is a_{ii}^{kk}, where k represents a digital or non-digital sector and i denotes the specific country. Based on the definition of matrix A^D, we defined the domestic Leontief inverse matrix $L = (I - A^D)^{-1} = \begin{bmatrix} l_{11}^{dd} & l_{11}^{dn} & \cdots & 0 & 0 \\ l_{11}^{nd} & l_{11}^{nn} & & \vdots & \vdots \\ 0 & 0 & \ddots & 0 & 0 \\ \vdots & \vdots & & l_{GG}^{dd} & l_{GG}^{dn} \\ 0 & 0 & \cdots & l_{GG}^{nd} & l_{GG}^{nn} \end{bmatrix}$, which reflects the technological-economic linkages between domestic sectors. Therefore, the gross output of a country could be simplified as $X = LY^D + LE$. Referring to the economic implications of matrix A^{DD}, the matrix L could be further decomposed into H and L-H, where $H = \left(I - A^{DD}\right)^{-1} = \begin{bmatrix} h_{11}^{dd} & 0 & \cdots & \cdots & 0 \\ 0 & h_{11}^{nn} & & & 0 \\ \vdots & & \ddots & & \vdots \\ \vdots & & & h_{GG}^{dd} & \vdots \\ 0 & 0 & \cdots & \cdots & h_{GG}^{nn} \end{bmatrix}$ and $L - H = \begin{bmatrix} l_{11}^{dd} - h_{11}^{dd} & l_{11}^{dn} & \cdots & 0 & 0 \\ l_{11}^{nd} & l_{11}^{nn} - h_{11}^{nn} & & \vdots & \vdots \\ 0 & 0 & \ddots & 0 & 0 \\ \vdots & \vdots & & l_{GG}^{dd} - h_{GG}^{dd} & l_{GG}^{dn} \\ 0 & 0 & \cdots & l_{GG}^{nd} & l_{GG}^{nn} - h_{GG}^{nn} \end{bmatrix}$. Simply put, the matrix H was constructed to reflect the intrasectoral production linkages in the purely digital sectors or non-digital sectors, whereas the matrix L-H was used to represent the intersectoral production linkages. Therefore, the expression of the value-added vector could be reorganized as:

$$\begin{aligned} VA &= VLY^D + VLE = VLY^D + VL\left(A^F X + Y^F\right) \\ &= VLY^D + VL\left(A^F BY + Y^F\right) \\ &= VHY^D + V(L - H)Y^D + VHA^F BY + V(L - H)A^F BY \\ &\quad + VHY^F + V(L - H)Y^F \\ &= VHY^D + V(L - H)Y^D + VHY^F + V(L - H)Y^F + VHA^F LY \\ &\quad + V(L - H)A^F LY + VLA^F(B - L)Y \end{aligned} \quad (10)$$

According to the nature of the sector that is digital or non-digital, domestic value added by country i could be divided into digital domestic value added (VA_i^d) and non-digital domestic value added (VA_i^n). Taking VA_i^d as the analysis object, it includes two main components: the direct and indirect value-added effect of the digital economic sectors. Referring to the study by He and Xie (2022), we divided each component into four parts as follows:

(1) the digital value added by final goods to meet domestic demands ($VA1$)

$$direct_VA1_i^d = V_i^d h_{ii}^{dd} Y_{ii}^d \quad (11)$$

$$indirect_VA1_i^d = V_i^d \left[\left(l_{ii}^{dd} - h_{ii}^{dd}\right) Y_{ii}^d + l_{ii}^{dn} Y_{ii}^n\right] \quad (12)$$

The direct $VA1$ ($direct_VA1_i^d$) and indirect $VA1$ ($indirect_VA1_i^d$) correspond to the first and second components of Eq. 10, respectively. The lowercase variables, including h_{ii}^{dd}, l_{ii}^{dd}, and l_{ii}^{dn}, represent the according element of matrixes H, L, and L, respectively (similarly hereinafter).

(2) The digital value added by exports of final goods ($VA2$)

$$direct_VA2_i^d = V_i^d h_{ii}^{dd} \sum_{j \neq i}^{G} Y_{ij}^d \tag{13}$$

$$indirect_VA2_i^d = V_i^d \left[\left(l_{ii}^{dd} - h_{ii}^{dd} \right) \sum_{j \neq i}^{G} Y_{ij}^d + l_{ii}^{dn} \sum_{j \neq i}^{G} Y_{ij}^n \right] \tag{14}$$

The direct $VA2$ ($direct_VA2_i^d$) and indirect $VA2$ ($indirect_VA2_i^d$) correspond to the third and fourth components of Eq. 10, respectively, where Y_{ij}^d denotes the export of digital final goods from country i to country j, and Y_{ij}^n represents that of non-digital final goods.

(3) The digital value added that returns to the domestic country ($VA3$)

$$direct_VA3_i^d = V_i^d h_{ii}^{dd} \sum_{j \neq i}^{G} \sum_{r \in \{d,n\}} a_{ij}^{dr} \sum_{m \in \{d,n\}} l_{jj}^{rm} Y_{ji}^m \tag{15}$$

$$\begin{aligned} indirect_VA3_i^d = V_i^d \Bigg[& \left(l_{ii}^{dd} - h_{ii}^{dd} \right) \sum_{j \neq i}^{G} \sum_{r \in \{d,n\}} a_{ij}^{dr} \sum_{m \in \{d,n\}} l_{jj}^{rm} Y_{ji}^m \\ & + l_{ii}^{dn} \sum_{j \neq i}^{G} \sum_{r \in \{d,n\}} a_{ij}^{nr} \sum_{m \in \{d,n\}} l_{jj}^{rm} Y_{ji}^m \\ & + \sum_{r \in \{d,n\}} l_{ii}^{dr} \sum_{j \neq i}^{G} \sum_{s \in \{d,n\}} a_{ij}^{rs} \sum_{k=1}^{G} \sum_{m \in \{d,n\}} \left(b_{jk}^{sm} - l_{jj}^{sm} \right) Y_{ki}^m \Bigg] \end{aligned} \tag{16}$$

The direct $VA3$ ($direct_VA3_i^d$) corresponds to part of the fifth component of Eq. 10, and the indirect $VA3$ ($indirect_VA3_i^d$) corresponds to part of the sixth and seventh component of Eq. 10. $VA3$ manifests exports of intermediate goods that are traded across multiple countries and eventually go back to the producer country i.

(4) The digital value added that meets the foreign market demand ($VA4$)

$$direct_VA4_i^d = V_i^d h_{ii}^{dd} \sum_{j \neq i}^{G} \sum_{r \in \{d,n\}} a_{ij}^{dr} \sum_{m \in \{d,n\}} l_{jj}^{rm} \sum_{p \neq i}^{G} Y_{jp}^m \tag{17}$$

$$\begin{aligned} indirect_VA4_i^d = V_i^d \Bigg[& \left(l_{ii}^{dd} - h_{ii}^{dd} \right) \sum_{j \neq i}^{G} \sum_{r \in \{d,n\}} a_{ij}^{dr} \sum_{m \in \{d,n\}} l_{jj}^{rm} \sum_{p \neq i}^{G} Y_{jp}^m \\ & + l_{ii}^{dn} \sum_{j \neq i}^{G} \sum_{r \in \{d,n\}} a_{ij}^{nr} \sum_{m \in \{d,n\}} l_{jj}^{rm} \sum_{p \neq i}^{G} Y_{jp}^m \\ & + \sum_{r \in \{d,n\}} l_{ii}^{dr} \sum_{j \neq i}^{G} \sum_{s \in \{d,n\}} a_{ij}^{rs} \sum_{k=1}^{G} \sum_{m \in \{d,n\}} \left(b_{jk}^{sm} - l_{jj}^{sm} \right) \sum_{p \neq i}^{G} Y_{kp}^m \Bigg] \end{aligned} \tag{18}$$

The direct $VA4$ ($direct_VA4_i^d$) corresponds to part of the fifth component of Eq. 10, and the indirect $VA4$ ($indirect_VA4_i^d$) corresponds to part of the sixth and seventh component of Eq. 10. Different from $VA3$, $VA4$ denotes exports of intermediate goods that satisfy the foreign market demand.

In a similar way, the value added from the non-digital sector in country i could also be categorized into eight parts, denoted as $direct_VA1_i^n \sim direct_VA4_i^n$ and $indirect_VA1_i^n \sim indirect_VA4_i^n$, respectively. To fully reflect the development of digitalization in country i, both the direct digitalization of the digital sectors and the indirect digitalization of the non-digital sectors should be considered. According to which component belongs to the domestic value chain or the category of GVC, it is meaningful to account for the ratio of digital value added to a country's total value added (Peng et al., 2023). This study further constructed the indicators of digital domestic value chain embeddedness (DC_i^d) and digital GVC embeddedness (DC_i^g), which could be expressed as:

$$DC_i^d = \frac{direct_VA1_i^d + direct_VA2_i^d + indirect_VA1_i^d + indirect_VA2_i^d}{VA_i} \tag{19}$$

$$\begin{aligned} DC_i^g = & \frac{direct_{VA3_i^d} + direct_{VA4_i^d} + indirect_{VA3_i^d} + indirect_{VA4_i^d}}{VA_i} \\ & + \frac{indirect_{VA3_i^n} + indirect_{VA4_i^n}}{VA_i} \end{aligned} \tag{20}$$

In light of the connotation of digital economy, and the availability of related data, this study referred to the study by Lyu et al. (2020) about digital economy sector classification. The digital economy was categorized into three parts: digital infrastructure, digital media, and digital trading; the details are shown in Table 1.

4 Empirical design

4.1 Model setting

As illustrated above, there is no specific functional relationship between digital value chain embeddedness and carbon emissions intensity. If a parameter estimation method is applied, a prior parameter model needs to be determined. Thus, the parameter method is very sensitive to the selected model, which may lead to the misspecification of the problem (Li and Wang, 2019; Du et al., 2020). In this regard, the non-parametric method has attracted increasing attention due to its flexibility and accuracy, and its specific functional form does not need to be determined in advance. However, it should be noted that this highly data-dependent method easily leads to an overfitting phenomenon, which, in particular, incurs the issue of the "curse of dimensionality" (Li and Racine, 2006).

In view of this, we selected the semi-parametric model to analyze the non-linear effects. As both linear parameter and non-parametric components are included in the model, it can improve the explanatory power of the model and effectively overcome the drawbacks of overfitting (Härdle et al., 1998). The most commonly used semi-parametric models are semi-parametric partially linear models, which have some additional advantages (Li and Liang, 2015): First, they allow for a more flexible model that can adapt to different types of data and relationships. Second, they offer a wider range of link functions and analytical forms compared with traditional parametric or non-parametric models. Third, the smoothing parameters can be estimated using generalized cross-validation techniques, which is a robust method for parameter estimation.

This study constructed the following semi-parametric partial linear model to test the impacts of digital value chain embeddedness on carbon emissions intensity:

TABLE 1 Digital economy sectors of the WIOD.

Industrial classification	Coverage	WIOD sector code	WIOD sectors
Digital infrastructure	Computer hardware	C26	Manufacture of computers, electronic and optical products
		C27	Manufacture of electrical equipment
	Telecommunication equipment and service	J61	Telecommunications
	Computer software	J62_J63	Computer programming, consultancy and related activities; information service activities
Digital media	Internet publishing	J58	Publishing activities
	Internet transmission	J59_J60	Motion picture, video and television program production, sound recording and music publishing activities; programming and broadcasting activities
Digital trading	Wholesale and retail	G46	Wholesale trade, except of motor vehicles and motorcycles
		G47	Retail trade, except of motor vehicles and motorcycles
	Financial services	K64	Financial service activities, except insurance and pension funds
	Other auxiliary services	H53	Postal and courier activities
		M69_M70	Legal and accounting activities; activities of head offices; management consultancy activities
		M72	Scientific research and development

$$CI_{it} = G(DC_{it}) + \beta X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{21}$$

where $G(DC_{it})$ is an unknown function that measures the marginal effect of digital value chain embeddedness, X_{it} represents the collection of control variables, and λ_i and μ_t denote country effects and year effects, respectively. By using the series estimation method, this study followed the specific steps for estimating this semi-parametric partial linear model as follows:

Using a p^*1 vector of base functions $q(DC_{it}) = [q_1(DC_{it}), \cdots, q_p(DC_{it})]'$ and a p^*1 vector of unknown parameters $\theta = [\theta_1, \cdots, \theta_p]'$ to approximate the coefficient function $G(DC_{it})$:

$$q(DC_{it})'\theta = \left[q_1(DC_{it}), \cdots, q_p(DC_{it})\right]\begin{bmatrix}\theta_1\\ \vdots\\ \theta_p\end{bmatrix} \tag{22}$$

Referring to the research by Du et al. (2020), we employed a B-spline method to approximate the unknown functions, as well as apply the least-squares cross-validation to determine the number of knots.

By rearranging Eq. 21, we obtained:

$$CI_{it} = q(DC_{it})'\theta + \beta X_{it} + \lambda_i + \mu_t + \delta_{it} \tag{23}$$

where $\delta_{it} = \varepsilon_{it} + v_{it}$ and $v_{it} = CI_{it} - q(DC_{it})'\theta$, denoting the sieve approximation error.

Taking the first-time difference of Eq. 23 to eliminate the fixed effects, we then obtained:

$$\Delta CI_{it} = \Delta\left((DC_{it})'\right)\theta + \beta\Delta X_{it} + \Delta\delta_{it} \tag{24}$$

Applying the least square estimator to estimate Eq. 24, we defined:

$$(\beta, \theta) = \left[\Delta\tilde{X}'\Delta\tilde{X}\right]^{-1}\Delta\tilde{X}'\Delta\tilde{CI} \tag{25}$$

Estimate the functional coefficients as follows:

$$\widehat{G}(DC_{it}) = q(DC_{it})'\widehat{\theta} \tag{26}$$

On the basis of the benchmark model, the mechanisms through which digital value chain embeddedness can affect trade-related carbon emissions intensity need to be further explored. Among the factors influencing carbon emissions intensity, the facility of advanced green knowledge and technology being transferred through international trade is essential for promoting cleaner production (Lee et al., 2022). In addition, the rise of tertiary industry may explain the decoupling of economic growth and carbon emissions (Xie et al., 2024). Additionally, trade scale is usually regarded as an indirect factor in explaining the variations in a country's carbon emissions (Liu et al., 2020).

Based on the analyses, we build the following model to investigate the terms of trade effect, structural effect, and export trade scale effect:

$$CI_{it} = G(DC_{it}) + \alpha DC_{it} \cdot M_{it} + \beta X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \tag{27}$$

where M_{it} indicates the variables corresponding to the above three effects. Eq. 27 includes the interaction term $DC_{it} \cdot M_{it}$. By examining the sign and significance of the coefficient α, we can figure out feasible ways to effectively reduce carbon emissions intensity.

4.2 Variables

The explained variable is the carbon intensity indicator (CI_i^{local}; CI_i^{import}; CI_i^{export}), which is measured based on the accounting

TABLE 2 Descriptive statistics of major variables.

Variable	Obs	Mean	Std.dev	Min	Max
CI_i^{local}	615	0.513	0.589	0.030	4.529
CI_i^{import}	615	0.891	0.436	0.405	2.061
CI_i^{export}	615	0.880	1.054	0.041	9.095
DC_i^D	615	0.634	0.172	0.061	0.928
DC_i^G	615	0.183	0.100	0.011	0.608
forest	615	0.361	0.170	0.011	0.737
lnpgdp	615	9.858	0.980	6.627	11.630
renewable	615	0.170	0.139	0.000	0.602
open	615	0.913	0.571	0.196	3.334
urban	615	0.711	0.140	0.277	0.978
r&d	615	0.014	0.010	0.000	0.043
financial	615	0.489	0.489	0.000	3.219
industrial	615	0.265	0.069	0.100	0.481

framework of trade in value-added. The core explanatory variable is digital value chain embeddedness (DC_i^d, DC_i^g), as Eqs 19 and (20) have shown the specific measurement. It needs to be emphasized that when the explained variable is CI_i^{local}, the corresponding explanatory variable is DC_i^d, and when the explained variable is CI_i^{import} or CI_i^{export}, the corresponding explanatory variable is DC_i^g.

With reference to the studies by Du et al. (2020) and He and Xie (2022), the control variables in this study were: (1) the forest area proportion (denoted as *forest*), which was used to reflect the impact of forest resources; (2) income level (denoted as *lnpgdp*), which was represented by the real GDP *per capita*, and take log of it; (3) the renewable energy share (denoted as *renewable*), which represented the energy consumption structure to some extent; (4) trade openness (denoted as *open*), which was calculated by adding up the exports of goods and services (percentage of GDP) and imports of goods and services (percentage of GDP); (5) urbanization level (denoted as *urban*), which was measured by 1 minus the ratio of the rural population to the total population; (6) research and development intensity (denoted as *r&d*), which was the ratio of research and development expenditure to GDP, which was used to manifest the roles of technological innovation; (7) financial development (denoted as *financial*), which was measured by the market capitalization of listed domestic companies (percentage of GDP); and (8) industrial development (denoted as *industrial*), which was proxied by the proportion of industrial added value in the GDP.

4.3 Data source and descriptive statistics

This study used balanced panel data for 41 countries (or regions) spanning from 2000 to 2014, excluding the Netherlands, Taiwan, and the rest of the world due to the lack of available and consistent data. The input-output data used for calculating digital value chain embeddedness were obtained from the World Input-Output Database (WIOD), the original data for CO_2 emissions were obtained from the Environmental Accounts published by the WIOD in 2016, and data on control variables was obtained from World Development Indicators (WDI). Descriptive statistics for major variables are illustrated in Table 2.

5 Results and discussion

5.1 Overview of CO_2 emissions in global value chains

The CO_2 emissions embodied in the total global intermediate goods trade and global final goods trade over the period 2000–2014 are shown in Figure 1, 2, respectively. There is a higher growth rate of CO_2 emissions embodied in global intermediate goods trade than that embodied in global final goods trade. It reveals a slight decrease in CO_2 emissions embodied in the global intermediate goods trade in 2009 because of the economic crisis, which conforms with the findings of Fan et al. (2021). Meanwhile, for both the global intermediate goods trade and final goods trade, the carbon embodied in international trade is far larger than that in domestic trade. The findings indicate that world economic development and trade networks are closely related to CO_2 emissions. In the long term, CO2 emissions embodied in global trade still shows an upward trend. Thus, putting more emphasis on decreasing carbon intensity is a more important concern.

Figure 3 shows a comparison among carbon intensities that are related to the domestic trade, import trade, and export trade of the sample countries. In this study, we extend the time range to 2014. Compared with the research by Fan et al. (2021), this study shows that for most developed countries, the carbon intensity embodied in import trade is higher than that in export trade, and is higher still than that in domestic trade; Australia (AUS) is not an exception. In addition, for some transitional economies, such as Russia (RUS), India (IND), Bulgaria (BGR), and China (CHN), the carbon intensity of their export trade is considerably higher than the average of the sample. Based on the findings, there are significant differences in the three types of carbon intensity, not only within a country but also from the perspective of countries with different levels of economic development. Additionally, the findings signify that developing countries have experienced higher negative externalities from export trade than developed countries; this revelation is consistent with the research by Dorninger et al. (2021). As a result, developing countries are under greater pressure to reduce carbon emissions intensity.

5.2 Benchmark analysis of digital value chain embeddedness on carbon emissions intensity

The estimation results with CI_i^{local}, CI_i^{import}, CI_i^{export} as the explained variables and DC_i^D, DC_i^G, DC_i^G as the core explanatory variables are presented in columns (1)–(3) of Table 3. The marginal effects of each core explanatory variable on the corresponding explained variable are shown in Figures 4–6, respectively. By observing the estimation results, we have discovered an inverted U-shaped relationship between digital domestic value chain

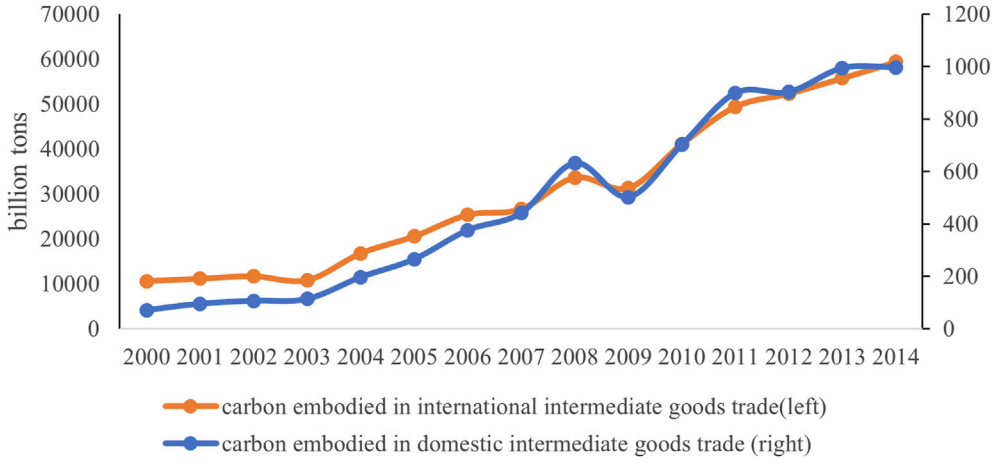


FIGURE 1
CO_2 emissions of global intermediate goods trade from 2000 to 2014.

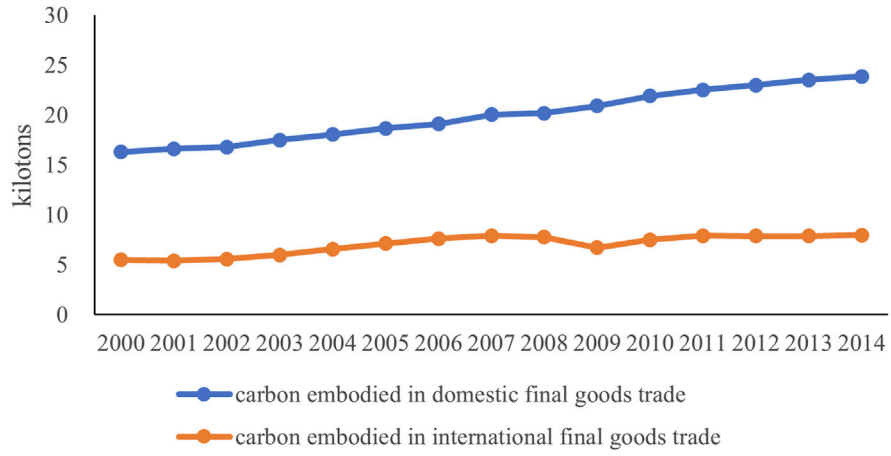


FIGURE 2
CO_2 emissions of global final goods trade from 2000 to 2014.

embeddedness and carbon intensity embodied in domestic trade, which verifies H1. With the improvement in digital domestic value chain embeddedness, the carbon intensity embodied in domestic trade increases first and then decreases, and the threshold of DC_i^d is approximately 0.88. Additionally, there is a non-linear relationship between digital GVC embeddedness and carbon intensity embodied in international trade, which is divided into two types: import trade and export trade. The marginal impact first rises in a deceleration, then falls, and finally rises after the inflection point. Furthermore, the thresholds of DC_i^g affecting the carbon intensity embodied in import trade are approximately 0.1 and 0.3, and the thresholds of DC_i^g affecting carbon intensity embodied in export trade are approximately 0.03 and 0.21. Thus, we can conclude that participating in export trade can realize the environmental benefit of digital value chain embeddedness earlier.

The possible explanations for the non-linear relationship between different types of digital value chain embeddedness and the carbon emissions intensity may be that, on the one hand, the process of digital value chain embedding is accompanied by the continuous integration of digital technology and conventional industries. However, the cultivation of digital ability is not synchronized, and it requires vast amounts of upfront investment. From a dynamic process perspective, adaptive capacity is built on the basis of the improvement of data analysis, data operation, and data empowerment (Yang et al., 2023). Therefore, there is a transitional period of digital transformation. It is necessary to cross the first threshold of digital value chain embeddedness; then, the benefits of digitally empowering low-carbon development can be exploited significantly. On the other hand, under the condition that some experience has been accumulated during the digital transformation, and the synergy between digital technology and other input factors in the economic system is strengthened, digitalization can improve the input-output efficiency of an economy and obtain environmental benefits.

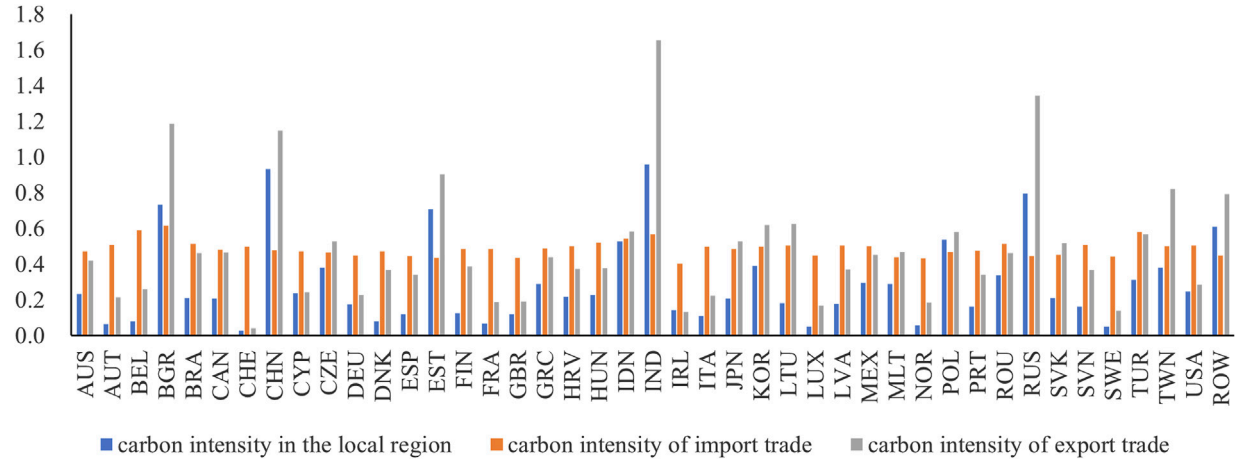


FIGURE 3
Carbon intensities of sample economies in 2014.

TABLE 3 Estimation results of the partially linear functional-coefficient panel model.

	(1) CI_i^{local}	(2) CI_i^{import}	(3) CI_i^{export}
DC_i^D	see Figure 4		
DC_i^G		see Figure 5	see Figure 6
forest	−11.640*** (2.418)	−5.812** (2.796)	−24.507*** (5.394)
lnpgdp	−1.712*** (0.103)	−1.355*** (0.119)	−2.979*** (0.229)
renewable	−1.078*** (0.283)	−0.639** (0.328)	−2.260*** (0.632)
open	0.204*** (0.057)	−0.072 (0.061)	0.390*** (0.118)
urban	0.774 (1.030)	−7.992*** (1.191)	2.708 (2.297)
r&d	0.069 (0.630)	−0.747 (0.731)	0.124 (1.410)
financial	0.014 (0.016)	0.023 (0.020)	0.005 (0.039)
Industrial	0.981*** (0.347)	1.238*** (0.401)	0.793 (0.773)
Year effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
N	615	615	615
R^2	0.436	0.406	0.337

Comparing the thresholds of digital value chain embeddedness as for the trade types of export trade, import trade and domestic trade, i.e., 0.03 < 0.1 < 0.88. For digital GVC embeddedness, as a large amount of cross-border trade of intermediate goods accelerates the spillover and diffusion of digital technology, the impacts on reducing carbon emissions intensity are manifested. In addition, it should be noted that the continuous increase in the degree of digital GVC embeddedness will eventually follow the law of diminishing marginal effect. With the bottlenecks of digital technology upgrading and industrial structure optimization, when the digital GVC embeddedness surpasses the second threshold, the environmental burden will be aggravated if the complexity of the economic system is high.

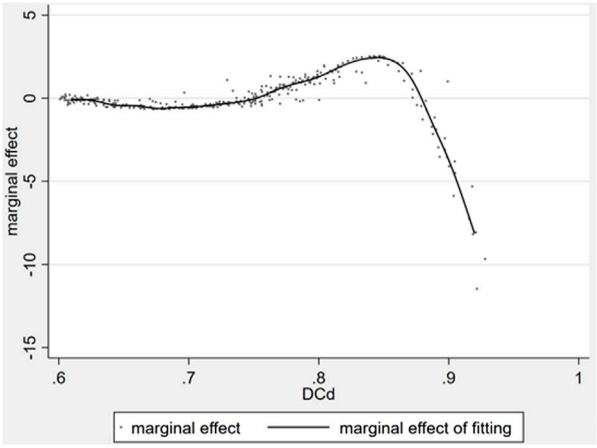


FIGURE 4
Marginal effect of DCd on local CI.

5.3 Further analysis concerning differences in economic development

Considering the possible digital divide between economies at different stages of economic development, this study divides the sample into high-income economies (*ECON* = 1) and middle- and low-income economies (*ECON* = 0) according to the World Bank's classification. The economies in the *ECON* = 0 group in this sample are mostly developing countries. The estimation results are shown in Table 4, and the estimation of the marginal effect of each core explanatory variable is shown in Figures 7–9. The results show that in different subsamples, there is a non-linear relationship between digital value chain embeddedness and carbon emissions intensity. When comparing the thresholds of digital value chain embeddedness in different sample groups, the thresholds of high-income economies are lower than those of middle- and low-income economies, indicating that high-income economies take precedence over middle- and low-income economies in terms of obtaining environmental benefits,

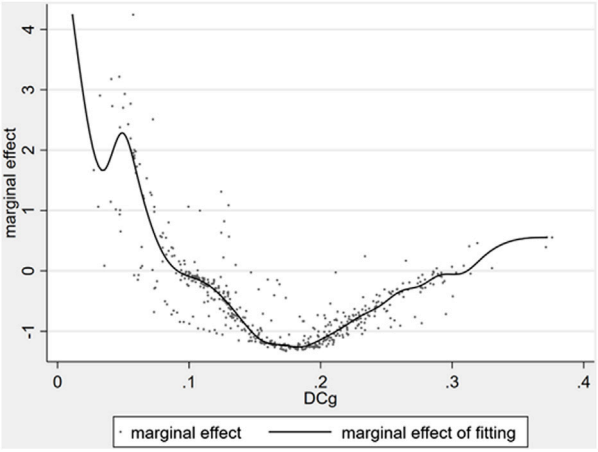


FIGURE 5
Marginal effect of DCg on import CI.

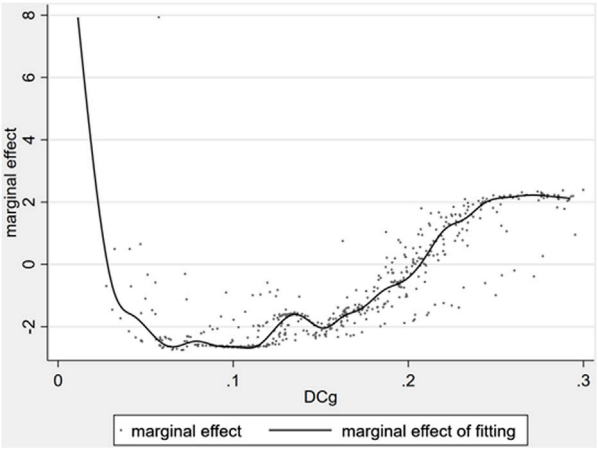


FIGURE 6
Marginal effect of DCg on export CI.

which verifies H2. When many high-income economies have been at the stage of reducing carbon emissions intensity through digitalization, most middle- and low-income economies still bear the pressure of increasing environmental pollution, which is in conformity with the findings of Huang and Zhang (2023). The reason for this is that high-income economies have the first-mover advantage in the development of digital technology and are motivated to implement trade restrictions to hinder the spillover of core digital technology, which slows down the pace of green and low-carbon development in middle- and low-income economies.

5.4 Heterogeneity analysis

5.4.1 Heterogeneity analysis based on the terms of trade

Among the indicators that can reflect the convenience of trade, compared with the trade openness index or transaction costs indicator of international trade (Bogmans, 2015; Murshed, 2020), this study innovatively selects the net barter terms of the trade index released by the World Bank WDI database to reflect the terms of trade (*FC*). The index represents the number of imported products that can be obtained by exporting one unit product, where an *FC* of 100 in the year 2000 is used as the benchmark value. The higher the index value, the more advantageous it is for international trade. This study takes the logarithm and includes it in the empirical model in the form of an interaction term. The empirical results are shown in Table 5. The coefficient of the interaction term is significantly negative in the types of carbon intensity embodied in domestic trade and export trade. It indicates that optimizing terms of trade and reducing trade barriers are conducive to promoting digital value chain embeddedness and improving environmental quality. This may be due to a close communication of digital technology through trade activities, which is very important for improving green production capacity. Comparatively, the interaction coefficient in column (2) of Table 5 is not significant, which reveals that the net barter terms of the trade index focus on the measurement from the perspective of exports; therefore, it is unlikely to have a significant impact on the carbon intensity embodied in import trade.

5.4.2 Heterogeneity analysis based on structural effects

Concerning the industrial upgrading process which increases the supply of low-energy consuming products, the transformation promotes the need of skilled labor with environmental awareness and the ability to reduce existing carbon emissions (Mahmood et al., 2019). To further test the role of the structural effect in the process of digital value chain embedding, this study takes the ratio of tertiary industry output to GDP as the index of structural effect (*ST*), and includes it in the model in the form of an interaction term. The empirical results are shown in Table 6. The interaction coefficient is negative in the three types of carbon intensity, and it is significant in the type of carbon intensity embodied in domestic trade. This is because as the energy consumption of the tertiary industry is significantly lower than that of the secondary industry, which represents the main direction of industrial upgrading, the higher the ratio of the tertiary industry output to GDP, resulting in the optimization of the energy structure. The empirical results reveal that adjusting energy structure is an important mechanism for an economy utilizing digital value chain embeddedness to achieve environmental improvement.

5.4.3 Heterogeneity analysis based on the scale effect

According to the study by Yan et al. (2023), the export scale effect is an important mechanism affecting trade-embodied carbon emissions. With the purpose of examining the scale effect, this study uses the actual value of a country's total exports to reflect the scale effect (*SC*) and includes it in the benchmark model in the form of an interaction term. The empirical results are shown in Table 7. The interaction coefficient is significantly negative in the types of carbon intensity embodied in domestic trade and import trade. In addition, it is negative in the type of carbon intensity embodied in export trade, revealing that the scale effect is also the mechanism of the green and low-carbon development of digital empowerment. The existing research applying the absolute amount of carbon emissions embodied in trade generally holds that the scale effect is a main mechanism for environmental degradation.

TABLE 4 Estimation results concerning differences in economic development.

	CI_i^{local}		CI_i^{import}		CI_i^{export}	
	(1) *ECON* = 1	(2) *ECON* = 0	(3) *ECON* = 1	(4) *ECON* = 0	(5) *ECON* = 1	(6) *ECON* = 0
DC_i^D	see Figure 7					
DC_i^G			see Figure 8		see Figure 9	
forest	−9.682*** (2.443)	−11.728** (5.501)	−15.950*** (3.576)	7.809* (4.352)	−11.354** (4.913)	−32.409** (12.583)
lnpgdp	−1.260*** (0.087)	−3.517*** (0.382)	−1.571*** (0.126)	−1.199*** (0.312)	−2.087*** (0.173)	−7.513*** (0.903)
renewable	−0.859*** (0.231)	−2.741** (1.128)	−0.055 (0.338)	−0.595 (0.887)	−1.688*** (0.465)	−5.793** (2.565)
open	0.151*** (0.045)	0.358 (0.254)	0.047 (0.060)	−0.639*** (0.189)	0.222*** (0.083)	0.669 (0.546)
urban	0.636 (1.019)	10.177*** (3.369)	−12.923*** (1.486)	−4.356 (2.723)	0.290 (2.042)	29.905*** (7.872)
r&d	−0.047 (0.459)	−0.598 (8.282)	−0.676 (0.676)	−0.175 (6.558)	−0.116 (0.928)	4.205 (18.962)
financial	0.014 (0.013)	0.044 (0.080)	0.022 (0.020)	−0.027 (0.051)	0.006 (0.028)	−0.052 (0.148)
Industrial	0.589* (0.307)	2.089** (0.966)	1.515*** (0.448)	−0.099 (0.780)	0.833 (0.615)	1.591 (2.256)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	Yes	Yes	Yes	Yes	Yes	Yes
N	495	120	495	120	495	120
R^2	0.413	0.595	0.485	0.476	0.324	0.548

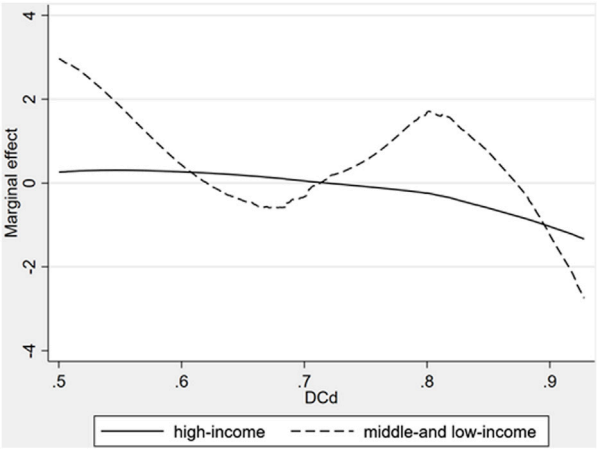


FIGURE 7
Marginal effect of DCg on local CI based on economic development.

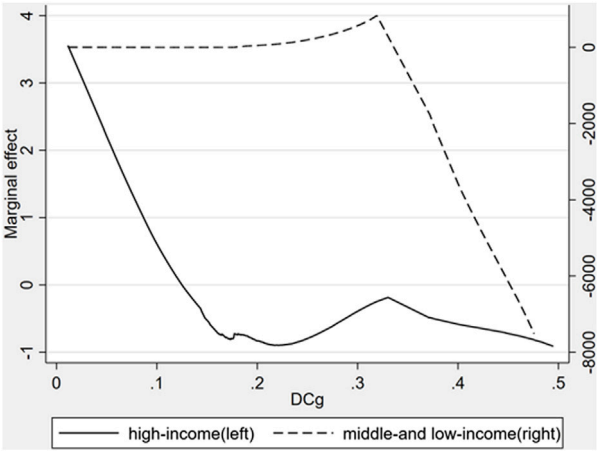


FIGURE 8
Marginal effect of DCg on import CI based on economic development.

From the perspective of carbon intensity, this study confirms that promoting economic growth and improving carbon emission reduction capacity can go hand in hand. By reducing carbon intensity, it is beneficial to balance the dual pressures between a country's economic slowdown and total carbon emissions.

5.5 Discussion

In this study, we focused on measuring digital value chain embeddedness, as well as discussing the impacts of different types of digital value chain embedding on trade-related carbon emissions intensity. Previous studies have investigated the relationship between digital progress and environmental performance, GVCs and carbon emissions embodied in trade, and digitalization and GVCs. However, studies concerning the three aspects are rare and limited to the absolute carbon emissions indicator, neglecting the value-added dimension of trade activities. By unifying digital value chain embeddedness and carbon emissions intensity, it is recognized that in the early stage of digital domestic value chain embeddedness, the marginal effect on carbon emissions intensity is positive. When it is larger than a

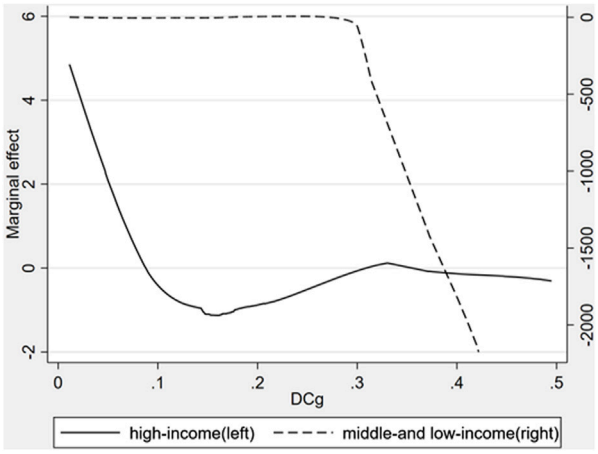


FIGURE 9
Marginal effect of DCg on export CI based on economic development.

TABLE 5 Heterogeneity test results based on the terms of trade.

	(1) CI_i^{local}	(2) CI_i^{import}	(3) CI_i^{export}
DC_i^D	omitted		
DC_i^G		omitted	omitted
$DC_i^D \times FC$	−0.435*** (0.105)		
$DC_i^G \times FC$		0.123 (0.297)	−1.865*** (0.568)
forest	−11.864*** (2.400)	−5.631** (2.813)	−24.052*** (5.378)
lnpgdp	−1.685*** (0.102)	−1.360*** (0.119)	−2.954*** (0.227)
renewable	−1.045*** (0.280)	−0.633** (0.328)	−2.212*** (0.628)
open	0.155*** (0.058)	−0.076 (0.063)	0.322*** (0.120)
urban	0.678 (1.033)	−7.820*** (1.212)	2.650 (2.316)
r&d	0.250 (0.623)	−0.759 (0.732)	0.256 (1.400)
financial	0.008 (0.016)	0.022 (0.020)	0.015 (0.038)
Industrial	1.144** (0.480)	0.923* (0.563)	0.885 (1.076)
Year effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
N	615	615	615
R^2	0.453	0.407	0.349

TABLE 6 Heterogeneity test results based on structural effects.

	(1) CI_i^{local}	(2) CI_i^{import}	(3) CI_i^{export}
DC_i^D	omitted		
DC_i^G		omitted	omitted
$DC_i^D \times ST$	−1.008* (0.557)		
$DC_i^G \times ST$		−0.353 (1.156)	−1.344 (2.184)
forest	−11.381*** (2.391)	−5.825** (2.801)	−24.851*** (5.293)
lnpgdp	−1.704*** (0.101)	−1.348*** (0.119)	−2.908*** (0.225)
renewable	−1.056*** (0.279)	−0.634** (0.328)	−2.185*** (0.620)
open	0.136** (0.058)	−0.082 (0.062)	0.278** (0.118)
urban	0.840 (1.025)	−8.019*** (1.194)	2.219 (2.257)
r&d	0.193 (0.620)	−0.711 (0.735)	0.450 (1.389)
financial	0.010 (0.016)	0.021 (0.020)	−0.011 (0.038)
Industrial	0.857** (0.423)	1.227*** (0.464)	1.322 (0.876)
Year effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
N	615	615	615
R^2	0.457	0.407	0.364

TABLE 7 Heterogeneity test results based on scale effects.

	(1) CI_i^{local}	(2) CI_i^{import}	(3) CI_i^{export}
DC_i^D	omitted		
DC_i^G		omitted	omitted
$DC_i^D \times SC$	−0.279*** (0.039)		
$DC_i^G \times SC$		−0.204*** (0.071)	−0.131 (0.137)
forest	−10.643*** (2.335)	−6.068** (2.811)	−25.186*** (5.474)
lnpgdp	−1.268*** (0.115)	−1.281*** (0.122)	−2.900*** (0.238)
renewable	−0.973*** (0.275)	−0.703** (0.333)	−2.168*** (0.648)
open	0.339*** (0.059)	−0.064 (0.063)	0.393*** (0.122)
urban	1.619 (1.012)	−7.550*** (1.219)	2.724 (2.375)
r&d	0.263 (0.610)	−0.829 (0.739)	0.183 (1.439)
financial	−0.010 (0.016)	0.005 (0.021)	−0.002 (0.040)
Industrial	0.907** (0.349)	1.195*** (0.421)	0.673 (0.820)
Year effects	Yes	Yes	Yes
Country effects	Yes	Yes	Yes
N	615	615	615
R^2	0.482	0.412	0.334

certain level, the impact is reversed. This is generally consistent with the findings of Wang et al. (2021) and Ma et al. (2023), indicating that the carbon emission effect appears until the tipping point of digitalization is reached.

The new finding in this study is that compared with the single threshold associated with digital domestic value chain embeddedness, we have discovered two thresholds in the case of digital GVC embeddedness. The explanation may be that as digitalization is in the high range, a country's corresponding absorptive capacity is not synchronized with digital technological development, resulting in the aggravation of pollution (Huang et al., 2022). In the era of the knowledge-based economy, soft power,

especially human capital, plays a very influential role in providing innovation impetus (Haini, 2018). Thus, strengthening the awareness of environmental protection is closely related to the cultivation of high-quality human capital.

This study also explores the heterogeneous impacts of digital value chain embeddedness on carbon emissions intensity in countries of different economic development, which reveals new empirical proof for the digital divide between developed and developing countries. In reality, developed countries take the initiative in utilizing digital technologies. With the purpose of maintaining the dominant position in GVC embedding, they usually control the outflow of high-tech products or services, which poses a greater environmental pressure from the global perspective. In this regard, developing countries have to cultivate their own digital innovation ability (Yang et al., 2023) and strive to get rid of the digital technology barriers in the long term.

6 Conclusion

Based on the panel data of 41 countries and regions from 2000 to 2014, this study investigated the non-linear impacts of digital value chain embeddedness on trade-related carbon emissions intensity. The empirical results show that: (1) the impact of digital domestic value chain embeddedness on carbon intensity embodied in domestic trade is an inverted U-shape. The integration of digital technology and conventional industries requires a transitional period. As the digital domestic value chain embeddedness crosses the threshold, which is approximately 0.88, it can promote the green and low-carbon development of the economy. (2) Digital GVC embeddedness has a non-linear effect on carbon intensity embodied in import and export trade, which first rises in a deceleration, then falls, and finally rises after the inflection point. Although participating in GVCs can strengthen the spillover and diffusion of digital technology, when digital GVC embeddedness is higher than the second threshold, it is also necessary to be alert to the bottlenecks encountered in the re-upgrading of technology. (3) The impacts of digital value chain embeddedness on carbon emissions intensity are closely related to economic development levels. Developed countries still dominate in digital value chain embeddedness, and developing countries lag behind developed countries in the environmental benefits of digital technology utilization. (4) Optimizing the terms of trade, adjusting the energy structure, and increasing the scale of trade are conducive to promoting the environmental benefits of digital empowerment. When there is an economic slowdown and energy consumption pressure, making more efforts to reduce carbon intensity is an important starting point for a country attempting to achieve sustainable economic development.

The findings of this study contain crucial policy recommendations. To improve energy efficiency and promote economic growth, it is essential to implement incentive measures to fully utilize digital technology. At the moment, the digital divide between developed economies and developing economies hinders the spread of new energy technology via digital spillover effects. As participating in GVCs provides opportunities for learning through trade, especially for the main carbon-emitting countries, overcoming the shortcomings in digital technology and strengthening cross-border cooperation in R&D can help achieve sustainable development. In addition, instead of focusing exclusively on digital value chain embedding, developing economies should pay much more attention to nurturing and refining the technology absorptive capacity of conventional industries. Although the digital transformation process might take a long time, it can be regarded as a long-term environmentally friendly investment, which is beneficial for cultivating the ability to develop independently. Furthermore, accelerating domestic digital R&D is fundamental for improving a country's GVC competitiveness when economic development surpasses a certain stage. Additionally, it has been suggested that energy efficiency can be boosted by promoting scale effects and the learning mechanism to the utmost extent.

Owing to data availability, this study only covers a time span from 2000 to 2014. Future research might discover more countries over a longer period. Moreover, contrasting more industrialized categorizations in depth is also an extension research project.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

YL: Conceptualization, Funding acquisition, Project administration, Validation, Visualization, Writing–review and editing. YX: Methodology, Resources, Software, Writing–original draft. DW: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Glossary

AUS	Australia
AUT	Austria
BEL	Belgium
BGR	Bulgaria
BRA	Brazil
CAN	Canada
CHE	Switzerland
CHN	China
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
EST	Estonia
FIN	Finland
FRA	France
GBR	United Kingdom
GRC	Greece
HRV	Croatia
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ITA	Italy
JPN	Japan
KOR	Korea
LTU	Lithuania
LUX	Luxembourg
LVA	Latvia
MEX	Mexico
MLT	Malta
NOR	Norway
POL	Poland
PRT	Portugal
ROU	Romania
RUS	Russian Federation
SVK	Slovak Republic
SVN	Slovenia
SWE	Sweden
TUR	Turkey
TWN	Chinese Taipei
United States	United States
ROW	Rest of the World

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Resource dependence and enterprise ESG performance: an empirical study based on A-share listed companies

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The impact of resource dependence on social economy and environment lacks empirical evidence at the micro level. This article uses data from A-share listed companies from 2011 to 2020 to construct an econometric model to empirically test the impact of resource dependence on ESG performance of enterprises. We find that the corporate ESG scores in regions with high resource dependence will decline. After a series of robustness tests such as replacing the dependent variable, controlling province time fixed effect, eliminating extreme effects, and eliminate provinces with high resource dependence, the conclusion of this article still holds. In addition, we alleviate the endogeneity problem caused by OLS estimation by constructing a dynamic panel model. Further analysis indicates that there are differences in the effect of resource dependence on enterprises sub-scores, with a significant negative impact on the environmental dimension and social dimension, and no significant impact on the governance dimension. It has a greater impact on the ESG score of SOEs and has no significant impact on non-SOEs. The empirical results of this paper enrich the research on the influencing factors of enterprise ESG performance, and further expand the research framework of the socio-economic consequences of enterprise resource dependence.

KEYWORDS

resource dependence, enterprise ESG score, enterprise sustainable development, China, A-share listed companies

1 Introduction

For a long time, economists have launched a series of theoretical and empirical investigations on the "gospel theory" and "curse theory" of natural resource endowment. The "gospel theory" advocates that abundant natural resources are an important factor for economic growth, which is conducive to the rapid development of regional economy and the rapid accumulation of capital. According to the theory of new economic geography, the

development of resource industries will attract the agglomeration of their upstream and downstream industries. The spatial agglomeration of industries saves transaction costs and helps to generate economies of scale, thereby promoting economic growth. Feyrer et al. (2017) used US data and found that resource extraction has a positive spillover effect on related industries. The benefits brought by the mining industry to the local area are higher than the mining costs. Resources are not a curse, but a blessing. Allcott and Keniston (2018) used micro data on the US manufacturing industry from 1969 to 2014 and found that resource prosperity contributes to the development of related manufacturing enterprises, while having no significant impact on non-related manufacturing enterprises. Asher and Novosad (2014) used data from India's three economic censuses and instrumental variable method to study and found that the economic growth effect brought about by resource prosperity is extensive, with a positive spillover effect on surrounding towns 50km away from mines. The "curse theory" believes that regions with abundant resources will cause serious negative effects on long-term economic growth through intermediary crowding out effects (Gylfason, 2001), institutional deterioration effects (Bodea et al., 2016) and price fluctuation effects (Leong and Mohaddes, 2011; Su et al., 2023), which are not conducive to the sustainable development of local enterprises. On the other hand, the over-exploitation of natural resources will bring a series of environmental problems such as ecological environment damage and natural environment deterioration, and the efficiency of environmental pollution management varies greatly among regions (Zhao et al., 2022). Therefore, as the main body of pollution discharge and treatment, enterprises face many challenges in their development (Lin et al., 2021; Qin et al., 2022; Su et al., 2022a). In 2020, China has proposed the social and economic development goal of carbon peaking and carbon neutrality. In this context, higher demands are placed on corporate sustainability (Su et al., 2022b; Su et al., 2022c). Investors also incorporate the performance of enterprises in environmental and social aspects into their investment decision-making functions. Enterprise ESG index is the concrete embodiment of this emerging investment concept.

Enterprise ESG indicators are obtained by combining the performance of enterprises in three aspects: environmental, social and governance. In recent years, companies have shifted from the short-term goal of profit maximization to the long-term goal of sustainable ESG performance (Min and Mentzer, 2004; Studer et al., 2006). Stakeholder theory suggests that ESG emphasizes the coordinated development of economy, environment, and society, advocates long-term goal orientation, promotes the pursuit of maximizing social value by enterprises, and helps to build trust in uncertain environments; At the same time, enterprises actively practice the concept of sustainability, increase corresponding investments, and form ESG advantages, which have a strong externality on their own business development. ESG performance of enterprises has been a hot topic studied by many scholars in the past decade (Halbritter and Dorfleitner, 2015; Van Duuren et al., 2016; Gillan et al., 2021; Pedersen et al., 2021). The current empirical research on corporate ESG mainly focuses on two aspects: the economic impact of corporate ESG and the various factors that affect corporate ESG performance. Several studies showed that ESG has become an important source of corporate risk that can directly or indirectly affect a company's financial performance as well as profitability (Friede et al., 2015; Aouadi and Marsat, 2018; Byun and Oh, 2018; Broadstock et al., 2021; Wong et al., 2021). For example, research by Cheng et al., (2014) and Ghoul et al. (2017) found that companies that focus on environmental, social and governance development are more likely to obtain financial resources needed for operating activities at a lower cost. In terms of factors influencing corporate ESG performance, some researchers have studied from the perspectives of socio-cultural and legal systems (Alsayegh et al., 2020; Chen et al., 2022) and internal corporate management factors (Cucari et al., 2018; McBrayer, 2018). The former includes factors such as the level of economic development (Cai et al., 2016), market liberalization (Chemmanur et al., 2020; Yang et al., 2022), social and media attention (Garcia et al., 2017; Burke, 2022), and the legal system (Liang and Renneboog, 2017). The latter includes factors as the board and CEO (Cronqvist and Yu, 2017; Hegde and Mishra, 2019), institutional investors (Dyck et al., 2019; Chen et al., 2020), and management tenure (McBrayer, 2018). For example, Doran and Ryan (2016) found that regulation and customer pressure are feasible mechanisms to encourage enterprises to fulfill social and environmental responsibilities, thus improving their ESG performance. This paper attempts to empirically study the relationship between resource dependence and corporate ESG performance from the perspective of the company's external environment, that is, the resource dependence of the region where the company is located.

There is a large branch of literature revolving around the relationship between resource endowments and economic growth. Among them, the findings of Sachs and Warner, (1995) are the most representative. They selected the country-level variables of natural resources and economic growth, and studied the relationship between the two variables, finding that natural resources and economic growth were surprisingly negatively correlated, which overturned the traditional perceptions. Subsequently, Gylfason (2001); Papyrakis and Gerlagh, (2004) also found a monotonic negative relationship between resource stocks and economic growth in the long run for countries that use natural resources solely for economic development. There are also scholars who take a different view. For example, Boschini and Roine, (2007), Same (2008), and Haseeb et al. (2021) argue that natural resources are not the direct cause of the conundrum of economic growth problems in resource-based regions. A few studies have explored this issue from the perspective of corporate behavior. Torvik (2001) argues that in resource-rich countries, firms tend to engage in unproductive economic activities and benefit through rent-seeking, which is detrimental to economic growth. Lim and Morris (2022) found that state-owned enterprises can achieve higher-scale economies through production links with natural resources departments. In general, the existing research mainly verifies two questions: whether the resource curse exists and why it occurs. However, when investigating whether there is a resource curse in resource-based regions, we should not only consider the economic growth factor, the environmental consequences should be also included in the scope of the study (Boschni and Pettersson,

2007). Based on this, this paper comprehensively considers economic and environmental factors, and examines the impact of regional resource dependence caused by abundant resources on the ESG of its enterprises from the micro level.

The marginal contribution of this article is mainly reflected in the following aspects. Firstly, due to the fact that research on corporate ESG is still in its early stages, most studies on factors affecting corporate ESG are focused on the internal environment of the company. We discussed the impact of the external environment faced by the company, namely the resource dependence of the region where the company is located, on the ESG performance of the enterprise. This article explores the impact of enterprise resource dependence on its ESG performance from the perspective of enterprise resource acquisition, based on the theory of resource dependence. This article provides new empirical evidence for the literature on factors that affect corporate ESG performance. Secondly, current empirical studies on regional resource endowments and economic growth are mostly based on macro-level perspectives such as cross-country and domestic regions, while studies on resource endowments on micro-firm performance are still very limited. These studies have mostly focused on the economic performance of firms and rarely consider the environmental as well as social performance of firms. This paper provides micro-level evidence on this issue from the perspective of resource dependence on firm ESG performance. Last but not least, this paper further expands the research framework of the social and economic consequences of enterprise resource dependence. As an important consideration when making strategic decisions, resource dependence affects corporate social and environmental behavioral decisions, which in turn directly affects corporate ESG performance and has direct economic consequences.

Section 2 develops the theoretical hypothesis. Section 3 introduces the setting of the measurement model and the selection of variables. Section 4 shows the benchmark regression results and robustness test. Section 5 is a further analysis, exploring the impact of resource dependence on corporate ESG sub-score and the heterogeneity of the nature of enterprise ownership. Section 6 summarizes and puts forward policy recommendations and research prospects.

2 Theoretical hypothesis

"Resource curse" theory suggests that abundant natural resources do not show a significant contribution to economic development, but rather a hindering effect. Numerous studies have shown that the crowding out effect of natural resources on investment in technology innovation and human capital leads to the occurrence of the resource curse (Gylfason, 2001). Due to the economic division of labor and long-term path dependence, regions with higher natural resource abundance are more likely to move towards a resource-dependent economic development path. The more resource-rich regions have labor-intensive attributes, and the local production is characterized by low-technology content (Ethier, 1985). Resource-dependent firms tend to aim for high revenues in the short term by engaging in production activities that consume large amounts of natural resources, such as extraction the primary processing. These firms are usually less exposed to low growth and technology, and thus less motivated to invest in technology development (Li et al., 2020). The high income of the resource sector attracts more labor and capital, accelerating the transfer of funds from R&D to the primary product sector, causing the aggravation of the resource mismatch problem, which is not conducive to the technological innovation of enterprises, and to a certain extent hinders the green development of enterprises. Fulfillment of social, environmental and governance responsibilities by enterprises is an activity with significant externalities and high costs, and investors' investment decision was made based on corporate ESG performance (Crifo et al., 2015; Alsayegh et al., 2020). Sufficient production resource guarantee enables enterprises to obtain higher revenues and achieve rapid development in the short term, with little demand for external investors. Therefore, enterprises with strong resource dependence lack the incentive to fulfill their social, environmental and governance responsibilities. On the other hand, resource-dependent enterprises usually adopt a crude production model with high input, high consumption, high pollution and low technological level. And their production activities are often accompanied by greater environmental destructiveness and difficulty in safe production, with high environmental management costs (Song et al., 2022). In areas of low resource abundance and dependence, firms are limited in their activities to obtain resources from external sources and rely more on resource accumulation and internal capital allocation, as well as technological innovation and organizational change to create opportunities (Zhang et al., 2022). At the same time, the low abundance and low dependence environment intensifies competition. At a time when low carbon development and environmental issues are widely emphasized, companies need to actively fulfill their social and environmental responsibilities and improve their ESG performance to gain an advantageous position in the market. Based on the above analysis, the rising dependence of companies on resources is not conducive to enhancing the fulfillment of integrated social, environmental and governance performance. Therefore, hypothesis one of this paper is proposed.

Hypothesis 1: The dependence of enterprises on resources is mainly characterized by the "resource curse", which has a negative impact on the environmental, social and governance performance of enterprises.

Resource dependency is mainly reflected in the degree of importance and intensity of influence of resource-based industries on the industrial structure, employment structure, level of technological progress, development speed and direction of the regional economy, which means the level of status and role of resource-based industries in the regional economic development. Although natural resources can bring direct or indirect benefits to society (Pan et al., 2022), excessive dependence on natural resources and resource-based industries can create a "resource curse" effect (Gylfason and Zoega, 2006; Brunnschweiler and Bulte, 2008), and the long-term dependence of the production process on resources will squeeze out R&D activities and cause the outflow of technological factors, which is not conducive to the innovation of energy-saving

and environmental protection technologies. In addition, in terms of the regional distribution characteristics of natural resources in China, the degree of marketization in areas with high resource dependence is relatively low, so in terms of marketization environment, compared to areas with low resource dependence, enterprises in areas with high resource dependence have less incentive to innovate and their technological innovation level is relatively low. On the other hand, the crude production of resource-dependent enterprises is accompanied by a large amount of pollution emissions, and the technological base is not sufficient to compensate for the environmental management costs of the enterprises; therefore, the resource dependence of enterprises is not conducive to the fulfillment of their environmental responsibilities.

Enterprises are the main body of social responsibility. Social responsibility refers to the active engagement in socially responsible behavior that goes beyond the economic and legal requirements of the firm (Wood, 1991), and refers to the need for firms to take social responsibility for employees, consumers, suppliers, communities, and the environment in addition to generating profits and taking economic responsibility for shareholders (Clarkson, 1995), The resource-based theory suggests that whether a company takes more social responsibility depends on its own resources and capabilities (Barney, 1991; Grant, 1991; Hart, 1995), and that it is difficult for a company to meet the demands of all stakeholders at the same time due to limited financial resources. Resource dependence theory suggests that among many stakeholders, a firm will first focus on and deal with the interests of those who hold key resources to ensure its continued survival, and effective corporate governance is a necessary factor in the firm's goal of maximizing profits. For resource-dependent enterprises, in addition to improving the efficiency of corporate governance, their long-term path dependence on resources as the main factor for production, as well as the high income of the resource sector itself is more attractive to factors of production such as labor, social responsibility-related interest holders will not affect the development of the enterprise to a certain extent, therefore, enterprises lack the motivation and incentive to fulfill social responsibility. Moreover, the pollution effect generated by the crude development mode of resource-dependent enterprises has strong negative externality and adversely affects the living environment of the surrounding residents; therefore, the increase of resource dependence has a hindering effect on the performance of corporate social responsibility. Based on the above analysis, the increase of resource dependency of enterprises will reduce the environmental and social performance of enterprises, while the effect on corporate governance is not obvious. Therefore, the second hypothesis of this paper is proposed.

Hypothesis 2: The inhibitory effect of increased resource dependence on corporate ESG performance is mainly reflected in the hindering effect on corporate fulfillment of social and environmental responsibilities.

State-owned enterprises (SOEs) are the mainstay of the national economy and an important subject responding to various national policies. Their main purpose is not to maximize corporate profits, but to maximize the welfare of the whole society. As important bearers of social responsibility, they are responsible for society and the environment in the process of production and operation, and maximize the creation of comprehensive economic, social and environmental value to promote the sustainable development of the national economy. However, SOEs are owned by the local government, which makes it easier to obtain rent-seeking benefits and reduces the motivation of enterprises to build their own capabilities. Therefore, they are less efficient than non-SOEs (Nie and Jia, 2011). Moreover, most SOEs belong to energy industries such as power supply industry, oil and gas extraction industry, which consume more resources and emit more pollution. They enjoy government guarantees and financial support, and have many ways to obtain resources with less difficulty. Therefore, it is easier to form a resource-dependent development path and lack the motivation for technological innovation and green transformation. For non-SOEs, social, environmental and governance performance are important factors in attracting investors. In the fierce market competition, non-SOEs whose main goal is profit maximization have an accumulating effect (Huang et al., 2022), which makes them more motivated to fulfill their social and environmental responsibilities and improve their corporate governance efficiency. Based on the above analysis, the negative effect of resource dependence on the ESG rating of enterprises is mainly reflected in SOEs. Therefore, the third hypothesis of this paper is proposed.

Hypothesis 3: The effect of resource dependence on ESG performance is non-consistent for firms with different ownership properties, and the negative effect is particularly pronounced for state-owned enterprises.

3 Empirical strategy and data sources

3.1 Data sources

This paper uses the data of China's A -share listed companies as a research sample. Among them, the corporate ESG data comes from Bloomberg Financial Terminal, and the rest of the data comes from the Wind database, China Stock Market & Accounting Research Database (CSMAR) and national statistics Bureau, etc. Before the empirical analysis, preliminary screening and processing of sample data are carried out: companies in the financial industry are excluded; ST companies are excluded; companies whose ESG scores are missing values are excluded; companies whose main financial management data are missing values are excluded. Based on data availability and excluding the impact of the 2008 financial crisis, this article has chosen 2011-2020 as the research interval for this article.

3.2 Model and variables

Using the data of all A-share listed companies from 2011 to 2020, this paper constructs the following measurement model to examine the relationship between resource dependence and corporate ESG scores. The baseline estimation model used in this paper is as follows:

$$y_{i,t} = \beta_0 + \beta_1 \ln Resourse_{i,t} + \beta_2 X_{i,t}^{c} + \sigma_j + t + \varepsilon_{i,t} \quad (1)$$

Among them, $y_{i,t}$ indicates ESG score of corporate i in year t, using Bloomberg ESG score. Since 2009, Bloomberg has collected information on environmental, social and governance disclosures of listed companies, and based on this, a comprehensive ESG score and three sub-scores have been formed, representing the overall ESG performance of listed companies and the sub-performance of environmental, social and governance. Bloomberg ESG scores range from 0-100, representing a scale from "disclosing the least amount of ESG data points" to "disclosing every ESG data point collected by Bloomberg". The higher the score, the better the corporate ESG performance. $\ln Resourse_{i,t}$ represents the resource dependence at the provincial level. Previous studies have used indicators such as the proportion of fixed asset investment in the extractive industry (Xu and Wang, 2006) and the proportion of the mining industry in the total population (Li and Zou, 2018) to measure resource dependence. Drawing on Hu and Yan, (2019), we use the ratio of the employed population in the mining industry to the total urban employed population as a proxy variable. In order to avoid potential heteroscedasticity and skewness problems, we take the logarithm of this ratio. σ_j is the industry fixed effect, and t is the year dummy variable. $X_{i,t}^{c}$ represents the control variables at the enterprise level. This paper draws on the research of Harjoto and Wang (2020) and selects the control variables according to other factors that may affect the ESG performance of enterprises: enterprise age, enterprise size, return on equity, asset-liability ratio, enterprise ownership nature, board size, proportion of female directors in the board of directors, proportion of independent directors in the board of directors, and separation rate of two positions. The definitions of the variables are shown in Table 1.

TABLE 1 Definition and description of main variables.

Type	Variable name	Symbol	Description
Explained variable	Corporate ESG Score	ESG	Bloomberg ESG Score
Explanatory variables	resource dependency	Resource	Mining Employment/ Urban Employment
	business age	Age	2022-year of establishment of the company
	Enterprise size	Size	Total assets
	Roe	Roe	Net Profit/Total Owner's Equity
	Assets and liabilities	Lev	Total Liabilities/ Total Assets
Control variable	nature of ownership	Sate	1=state-owned enterprise, 2=private, 3=foreign capital, 4=other
	Board size	Board	Board of Directors
	Proportion of women on the board	Woman	Number of women on board/Number of board members
	Proportion of independent directors in the board of directors	Indep	Number of Independent Directors/ Number of Board of Directors
	Separation rate of two jobs	Dual	Separation rate of two jobs

4 Empirical results

4.1 Descriptive statistics

The descriptive statistics of the variables are shown in Table 2. In all samples, the mean value of corporate ESG score is 1.240, which is far lower than the median of 19.835, indicating that the ESG evaluation of sample companies is average and needs to be further improved. At the same time, the maximum value of the ESG score of the sample companies is 64.115, the minimum value is 1.240, and the standard deviation is 7.023. It can be seen that there are great differences in the ESG scores among the sample companies.

4.2 Benchmark regression results

This part conducts regression analysis on the correlation between enterprise ESG score and resource dependence according to Equation 1, and the results are listed in Table 3. Column (1) is the regression result that only controls the industry-fixed effect. The regression result shows that resource dependence has a significant negative impact on the ESG score of enterprises. Column (2) further controls the year-fixed effect, and the coefficient of resource dependence is still significantly negative at the 5% level. Column (3) adds a series of control variables, and the coefficient is still significantly negative at the 1% level. The benchmark regression results show that resource dependence has a strong explanatory power on corporate ESG scores, that is, companies in areas with high resource dependence have worse ESG performance and sustainable development. From Table 3, the estimated value of the coefficient for resource dependency is 0.420, it means for every 10% increase in resource dependence, the ESG score of the enterprise decreases by 0.04%.

As far as the coefficients of the control variables are concerned, the coefficient of lnSize is positive and significant at the 1% level, indicating that larger firms are more likely to have the advantage of economies of scale and thus perform better in ESG scores. The coefficient of lnAge is significantly positive at the level of 1%, which indicates that the older the enterprise is, the stronger its motivation to pursue sustainability and the better its ESG performance. The coefficient of lnROE is significantly positive, which indicates that good company operations are conducive to improving a corporate ESG performance. The coefficient of lnLev is significantly negative at the level of 1%, which indicates that the higher the ratio of total liabilities to total assets, the less incentive a company has to improve its ESG performance. In addition, the significant positive correlation between Indep and the ESG score of the company

TABLE 2 Variable definitions and descriptive statistics.

variable	N	mean	sd	min	p50	max
ESG	9892	20.698	7.023	1.240	19.835	64.115
Resource	9892	0.020	0.031	0.000	0.006	0.222
Age	9892	23.846	5.256	6.000	24.000	55.000
Size	9892	16.750	84.040	0.003	3.577	2733.000
Roe	9892	0.090	5.372	-207.397	0.068	713.204
Lev	9892	0.438	0.524	-0.195	0.418	63.971
State	9892	1.664	0.600	1.000	2.000	4.000
Board	9892	8.582	1.707	0.000	9.000	18.000
Woman	9892	0.146	0.130	0.000	0.111	0.800
Indep	9892	0.376	0.056	0.167	0.364	0.800
Dual	9892	4.632	7.533	-7.640	0.000	56.109

indicates to some extent that independent directors play an important role in the long-term development of the company.

4.3 Robustness test

4.3.1 Replace the measurement of the explained variable

In order to test the reliability of the relationship between resource dependence and enterprise ESG score, we replace the measurement method of the explained variable to test the robustness. We use the ESG rating data of SynTao Green Finance as the proxy variable of enterprise ESG. Due to data availability, the time frame here is 2015-2020. Since 2015, SynTao Green Finance's ESG rating has been used to rate the ESG performance of listed companies based on the public information of listed companies and the announcement documents of regulatory authorities. It is constructed from 3 primary indicators (environmental, social and governance), 13 secondary indicators and multiple tertiary indicators, which can comprehensively reflect the ESG performance of listed companies. The rating of SynTao Green Finance consists of ten grades: A+, A, A-, B+, B, B-, C+, C, C-, and D. We assign 1-10 to these ten grades from low to high. The first column of Table 4 is the regression result of SynTao Green Finance ESG rating as the explained variable. The regression result shows that the coefficient of resource dependence is still significantly negative, which is consistent with the benchmark regression result.

4.3.2 Controlling province-time fixed effect

Although we control for a range of control variables at the firm level, provincial-level influences on corporate ESG performance may still be missed in the benchmark regression analysis because our explanatory variables are resource-dependent data at the provincial level. Provinces may have different economic development trends and social environments over time. For example, provincial-level environmental regulations may impose energy-saving and emission reduction constraints on local enterprises, thereby affecting their ESG performance. Therefore, we will incorporate provincial-level environmental regulations (ER, ER is measured by the chemical oxygen demand emissions in the province where the enterprise is located) into the model for regression analysis. In addition, to avoid the impact of other provincial level economic and social environments that change over time on corporate ESG, we further add the interaction term of province and year to the model for regression analysis. The results in column (2) of Table 4 show that after controlling for the ER and province-year fixed effect, the coefficient of resource dependence is still significantly negative at the 1% level.

4.3.3 Eliminating extreme effects

Winsorization is a commonly used method for robustness testing, which replaces values beyond the set percentile with values at the percentile to effectively avoid the impact of extreme values on the model estimation results. This article winsorize 1% and 5% for continuous variables, and then re-regresses using the winsorized variable values. According to the regression results in columns (3) and (4) of Table 4, the estimated coefficient of resource dependence is significantly negative at the 1% level. Therefore, the conclusion that resource dependence has a negative impact on corporate ESG performance is still robust and reliable after eliminating extreme effects.

4.3.4 Eliminate provinces with high resource dependence

China has a vast territory, and the distribution of natural resources is very unbalanced among regions. There are many resource-based cities in the central and western regions. At the same time, from the descriptive statistical results, there is a large gap between the median and the maximum resource dependence level. In order to avoid the influence of extreme values on the benchmark regression results, we exclude resource-dependent provinces from the sample. The criteria for the exclusion of resource-based provinces here are first to select the first few provinces in

TABLE 3 Benchmark regression results.

variable	(1) ESG	(2) ESG	(3) ESG
ln*Resource*			-0.501***
-0.349**			-0.420***
	(0.148)	(0.169)	(0.128)
ln*Size*			2.253***
			(0.169)
ln*Age*			2.506***
			(0.762)
ln*Roe*			0.598*
			(0.336)
ln*Lev*			-2.650**
			(1.134)
ln*Board*			0.834
			(0.835)
Woman			-1.437
			(1.001)
Indep			3.731**
			(1.608)
Dual			0.0046
			(0.0138)
State			-0.836**
			(0.339)
Industry fixed effects	YES	YES	YES
year fixed effect	NO	YES	YES
Observations	9588	9588	8966
R^2	0.114	0.164	0.320

The values in parentheses are the standard errors of clusters at the provincial level; ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively.

descending order of the proportion of the mining industry in urban employment, and then refer to the list of national resource-based cities in the National Sustainable Development Plan for Resource-based Cities (2013-2020). Provinces with more resource-based cities and districts are supplemented. Finally, we exclude Shanxi, Liaoning, Xinjiang, Qinghai, Inner Mongolia, Heilongjiang, Guizhou, Shaanxi, and Ningxia for regression. The regression results are shown in Column (5) of Table 4. We can find that the coefficient of resource dependence is still significantly negative at the 1% level.

5 Further analysis

5.1 Dynamic panel model

Due to the impact of previous ESG performance on current ESG performance, we use a dynamic panel model to measure the relationship between resource dependence and enterprise ESG performance through generalized moment estimation, in order to reduce estimation bias. In Equation 2, $\varnothing_1$ is the estimation coefficient, and $y_{i,t-1}$ represents a period of lag in the enterprise's ESG, this variable can be set to control for the endogeneity caused by lagging ESG; β_1 is the estimated coefficient we are interested in. From the results in Table 5, the econometric results of generalized moment estimation show that the impact of resource dependence on firm's ESG is still negative and significant.

$$y_{i,t} = \beta_0 + \beta_1 \ln Resourse_{i,t} + \varnothing_1 y_{i,t-1} + \beta_2 X^c_{i,t} + \sigma_j + t + \varepsilon_{i,t} \quad (2)$$

5.2 The sub-item impact of resource dependence on ESG

Enterprise ESG indicators are composed of three aspects: environment, society and governance. Therefore, in order to uncover the black box of the impact of resource dependence on ESG performance, we regressed the three sub-indicators to resource

TABLE 4 Robustness test regression results.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG
lnResource	-0.506**	-0.381***	-0.426***	-0.462***	-0.345**
	(0.232)	(0.113)	(0.128)	(0.141)	(0.157)
Enterprise Control Variables	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES
year fixed effect	YES	YES	YES	YES	YES
Province-Year Fixed Effects	NO	YES	NO	NO	NO
ER	NO	YES	NO	NO	NO
Observations	2773	8966	8966	8966	7901
R^2	0.167	0.323	0.312	0.280	0.337

The values in parentheses are the standard errors of clusters at the provincial level; *** and ** represent the significance levels of 1% and 5%, respectively.

TABLE 5 Dynamic panel.

Variable	(1) ESG	(2) ESG	(3) ESG
lnResource	-0.072**	-0.063**	-0.098***
	(0.030)	(0.030)	(0.030)
lESG	0.938***	0.918***	0.901***
	(0.008)	(0.010)	(0.010)
Enterprise Control Variables	NO	YES	YES
Industry fixed effects	YES	NO	YES
year fixed effect	YES	YES	YES
Observations	8516	7958	7958
R^2	0.839	0.841	0.844

The values in parentheses are the standard errors of clusters at the provincial level; *** and ** represent the significance levels of 1% and 5%, respectively.

dependence. The sub-item data of corporate ESG adopts the data of Bloomberg Financial Terminal, and the sample interval is 2011-2020. Referring to the method of Harjoto and Wang (2020), we construct the econometric model as Equation 3:

$$y_{i,t}(E,S,G) = \alpha_0 + \alpha_1 \ln Resourse_{i,t} + \alpha_2 X_{i,t}^{c} + \sigma_j + t + \varepsilon_{i,t} \quad (3)$$

The explained variables are the sub-score of corporate environment, sub-score of corporate society and sub-score of corporate governance, and the control variables are the same as the benchmark regression model. The itemized regression results are shown in Table 6.

Column (1) of Table 6 is the regression result of ESG comprehensive score on resource dependence. Columns (2) - (4) are the regression results of the sub-scores of environment, society and governance on the resource dependence, respectively. The regression result in Column (2) is significantly negative and the absolute value of the coefficient is larger than that in Column (1), which indicates that the environmental performance of enterprises in regions with high resource dependence is poor. Similarly, the regression result of Column (3) is also significantly negative, and the absolute value of the coefficient is greater than the first two columns, indicating that corporate social performance in regions with higher resource dependence is worse. This may be due to the fact that firms in these regions face greater challenges in environmental and social dimensions. The coefficient in Column (4) is not significant, which shows that resource dependence has no impact on the corporate governance dimension, indicating that corporate governance is still more affected by internal factors.

5.3 Heterogeneity in enterprise ownership

Compared with non-SOEs, SOEs are more affected by the local resources and environment, and thus the ESG performance of SOs may be more vulnerable to the impact of resource dependence. Based on this, this paper further explores the heterogeneous impact of resource dependence on ESG performance from the perspective of the nature of enterprise ownership. Column (1) of Table 7 shows the regression results of SOEs. It shows that the coefficient of resource dependence is significantly negative at the level of 1%, which indicated the ESG performance of SOEs is more affected by the local resource endowment. As for non-SOEs, they are more affected by market competition, and therefore pay more attention to their investment value. Non-SOEs are more motivated to win the favor of investors through good ESG performance. Therefore, investors' attention to enterprise ESG performance will encourage non-SOEs to improve their ESG scores.

6 Conclusion

This article uses data from A-share listed companies from 2011 to 2020 to find that the higher the resource dependence of the company's location, the worse the ESG performance of the enterprise. This conclusion still holds after a series of robustness tests. Through regression analysis of regional resource dependence from three dimensions: environment, society, and governance, it was found that resource dependence has a significant negative impact on environmental and social performance. In areas with high resource dependence, the negative impact on enterprises may outweigh the growth effect brought by resources. The sub sample regression results based on the nature of enterprise ownership indicate that the resource dependence of state-owned enterprises has a significant negative impact on their ESG scores. However, no significant correlation was found in the sample of non-state-owned enterprises. The reason may be that non-state-owned

TABLE 6 Itemized regression results.

Variables	(1) ESG	(2) E	(3) S	(4) G
ln*Resource*	-0.421***	-0.436***	-0.751***	-0.199
	(0.128)	(0.149)	(0.168)	(0.117)
Enterprise Control Variables	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
year fixed effect	YES	YES	YES	YES
Observations	9588	9588	9588	9588
R^2	0.164	0.114	0.166	0.907

The values in parentheses are the standard errors of clusters at the provincial level; *** represents the significance levels of 1%.

TABLE 7 Regression results grouped by nature of ownership.

Variable	(1) ESG	(2) ESG
lnResource	-0.492***	-0.317
	(0.074)	(0.237)
Enterprise Control Variables	YES	YES
Industry fixed effects	YES	YES
year fixed effect	YES	YES
Observations	4829	4137
R^2	0.353	0.235

The values in parentheses are the standard errors of clusters at the provincial level; *** represents the significance levels of 1%; the state variable is not included in the Enterprise Control Variables.

enterprises are more actively seeking the comprehensive development of ESG due to fierce market competition and financing pressure, offsetting the negative impact of resource dependence.

Based on the above analysis, we propose the following suggestions: Firstly, the particularity of the development of resource dependent regions determines that we cannot rely solely on market tools to enhance the enthusiasm and initiative of enterprises to fulfill social and environmental responsibilities. Government support and policy guidance are the practical conditions for promoting green transformation of enterprises. At the macro policy level, it is necessary to further enhance the stability of policies, form a foreseeable long-term benefit driven mechanism for the green transformation and development of enterprises, make improving social and environmental performance a consensus for the development of resource-based enterprises, and reduce the short-term risks and costs of companies fulfilling social and environmental responsibilities. At the micro policy level, in the short term, it is necessary to reduce the costs, risks, and uncertainties of implementing green transformation and fulfilling social and environmental responsibilities for high resource dependent enterprises through tilted allocation of production factors, tax incentives, and subsidies, so as to provide stable profit margins for enterprises that actively fulfill social and environmental responsibilities. At the local government level, it is necessary to continuously improve the software and hardware infrastructure of resource-based areas, actively promote the development of non resource-based enterprises, and reduce the resource dependence of regional development and the opportunity cost of green development for enterprises. Secondly, from the perspective of the capital market, relevant financial institutions should further improve their ESG ratings to provide investors with a reliable value investment foundation, thereby pointing the direction for the sustainable development of enterprises. Again, from the perspective of enterprises, resource-based state-owned enterprises are the economic mainstay of resource-based regions and the guarantee of national resource and energy strategic security. They will inevitably undertake new historical missions in the context of low-carbon transformation. On the one hand, resource-based state-owned enterprises need to improve resource utilization efficiency, enhance resource recycling level, achieve green transformation, and better fulfill social and environmental responsibilities. On the other hand, resource-based state-owned enterprises are large and strong. They should effectively drive the social and environmental performance of industries, improve the efficiency of industrial green transformation, drive the development of resource-based regional green transformation, and improve the regional environment through the positive externalities generated by their own green transformation.

This article attempts to analyze in depth the impact of resource dependence on corporate social and environmental performance when studying the relationship between resource dependence and corporate behavior. Some conclusions have been drawn, which are consistent with the research results of relevant literature and provide reference for future research ideas and directions. With the deepening of research on enterprise resource dependence and social environmental behavior, it is necessary to improve research methods and incorporate more influencing factors, mechanism channels, and situational factors into the analysis framework. For example, the micro mechanism of the impact of resource dependence on corporate ESG performance can be explored through field research. In addition, the theoretical model of resource dependent corporate behavior still needs further expansion. The vast majority of literature typically only considers one type of corporate behavior, and there are few studies that comprehensively consider the comprehensive impact of multiple corporate behaviors. Therefore, establishing a unified theoretical framework that considers the interaction between resource dependent corporate behavior from three aspects: social, environmental, and corporate governance, and measuring its relative importance, is an important direction for future research.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

YF: Formal Analysis, Methodology, Software, Writing – original draft. LF: Investigation, Software, Writing – review & editing. ZL: Methodology, Supervision, Validation, Writing – review & editing. WL: Conceptualization, Data curation, Writing – original draft.

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Conflict of interest

Authors YF, LF, and ZL were employed by Huzhou Power Supply Company, State Grid Zhejiang Electric Power Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Sustainable development in the context of pandemic: the impact of COVID-19 pandemic on green investment

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Promoting green investment is the inevitable choice for sustainable economics against climate change. We examine how the COVID-19 pandemic affected corporate green investment. Using a sample of publicly listed firms in China, we document the negative and significant effect of the COVID-19 pandemic on corporate green investment. Further analyses suggest that the COVID-19 pandemic impeded corporate green investment by exacerbating firms' financial constraints. We also find that the COVID-19 pandemic had no significant effect on total investment, suggesting that the pandemic shock only changed investment structure. In summary, our findings reveal the real effects of the COVID-19 pandemic on green development at the firm level.

KEYWORDS

COVID-19 pandemic, green investment, total investment, financial constraints, sustainable development

1 Introduction

Global health crises such as COVID-19, SARS, or MERS seriously threaten the economy (Ferguson et al., 2006; Chen et al., 2020; Hassan et al., 2023; Ru et al., 2020). For example, the COVID-19 pandemic is predicted to shrink the global economy by 3% (International Monetary Fund, 2020). This decline is described as the worst since the Great Depression in the 1930s. Meanwhile, the outbreak of the pandemic has once again triggered people to think about the relationship between human beings and nature. Green and low carbon have become inevitable choices for sustainable development. The outbreak of the COVID-19 pandemic has raised urgent questions about the real effects of the pandemic on the green economy.

As a large economy-wide and unexpected shock, the pandemic has attracted a great deal of attention from economists and policymakers (e.g., Fan, 2003; Chen et al., 2005; Ferguson et al., 2006; Keogh-Brown and Smith, 2008; Chen et al., 2020). However, little research has explored the effect of pandemics on firms' green investments. Corporate green

investment contributes to combating climate change and promoting sustainable economic development. Zheng and Jin (2023) find firms' green investments help to reduce carbon emissions. We address this gap by examining how the COVID-19 pandemic affected firms' investment decisions. In particular, we ask the following questions: How did firms determine their green investment in response to the COVID-19 pandemic shock? Which channels can explain the relation? By addressing these questions, we hope to enhance the understanding of the impact of the pandemic and appropriate policy responses.

We focus on exploring the effects of the COVID-19 pandemic on corporate green investment. The main reasons are: first, the environment is closely related to human health. It has been proved that large-scale epidemics, such as SARS, originate from animal-to-human transmission. Improving the environment can reduce public health risks; secondly, the pandemic has rekindled people's concern for environmental safety and the need for sustainable development. We argue that the direction of the pandemic's impact on green investment is uncertain. On the one hand, we posit that the COVID-19 pandemic negatively influenced green investment through financial constraints. In terms of financial restrictions, the heightened uncertainty linked to the spread of the disease and governmental responses during the pandemic may have made banks more risk-averse, reducing the supply of capital or raising its costs (Easley and O'Hara, 2010; Shleifer and Vishny, 2010). On the other hand, the pandemic resulted in many provincial interventions, such as restricted business hours, cancellation of the May Day holiday, and bans on public gatherings. Thus, the COVID-19 pandemic has changed people's lifestyles (Chen et al., 2020), such as telecommuting and virtual meetings, bringing opportunities for firms to go green. At the same time, the pandemic has increased the attention to green development. Enterprises may actively promote green transformation to gain long-term profits and growth. The COVID-19 pandemic may positively influence green investment.

Using a sample of Chinese listed firms in 2020-2021, we find that the COVID-19 pandemic significantly negatively impacts green investment, suggesting that the COVID-19 pandemic reduces firms' willingness to invest in green. In other words, the COVID-19 pandemic stalls the process of greening the economy. The main results are robust to tests that address endogeneity concerns. We further investigate the channel through which the pandemic affects corporate green investment. We find that the negative effect of the COVID-19 pandemic on green investment is more substantial for firms with a younger age, with no dividends, with a higher WW index, or ownership by non-government entities, supporting the financial constraints channel. Meanwhile, the results show the effect of the COVID-19 pandemic on total investment is not significant.

Given the similarity between the coronaviruses causing SARS and COVID-19, and importantly, the similar impact of SARS and COVID-19 on human activities (i.e., social distancing and business shutdown), we study and compare the economic effect of the SARS epidemic on total investment and green investment. We find SARS negatively impacts total investment but does not affect green investment, possibly due to insufficient attention to green development and low corporate green investment in China in 2003.

Our paper contributes to the extant literature in two ways. First, our study adds to the literature on the economic consequences of the pandemic (e.g., Ferguson et al., 2006; Chen et al., 2020; Hassan et al., 2020; Ru et al., 2020). However, while most prior studies focus on the impact of the pandemic on consumption, economic growth, and stock price crashes, there needs to be more evidence on how firms react to pandemic shocks. We extend the literature by showing that the COVID-19 pandemic shock impedes firms' green investment, with financial constraints playing an essential role in reducing firms' green investment.

Second, our study contributes to the literature on the determinants of firm green investment. Prior literature identifies various factors affecting firms' green investment, for example, media coverage (Chang et al., 2020), provincial green governance (Wang and Wang, 2023), and green capital (Tran et al., 2020). Ma et al. (2024) find green credit policy could stimulate firms' green investment. However, little attention has been paid to economy-wide shocks such as pandemics. Recently, with increased urbanization and globalization, high-risk infectious diseases (e.g., SARS, HINI, MERS, COVID-19) have appeared frequently around the globe, and society is facing unprecedented public health threats. Harmony between humans and the natural environment and sustainable economic development have become the focus of attention. How to make green transition decisions in the face of pandemics has important policy implications for sustainable economic growth.

2 Data

2.1 Sample selection

Our sample consists of all Chinese A-share firms listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange in 2020-2021. We measure the COVID-19 pandemic using the newly confirmed cases obtained from the China Healthcare Commission (CHC). Green investment and financial information are obtained from the China Stock Market and Accounting Research database. We obtain firm headquarters information from the Resset database. In line with common practice, we exclude observations with missing values and winsorize all continuous variables at the top and bottom 1%.

2.2 Variable definition

Green investment (*GInvest*) refers to environmentally friendly investment, which helps firms transfer to green. Following Chang et al. (2020), we construct the green investment variable based on the term of projects under construction in the financial report. We extract the construction in progress related to green investments, such as the "desulphurization project," "purification project," "eco-project," and so on. Thus, we sum up these projects to present the green investment. We construct the green investment variable (*GInvest*) as the natural log of one plus green investment, obtained from the term of projects under construction.

Our key independent variable is exposure to the COVID-19 pandemic (*COVID*), defined as the natural log of one plus the number of newly confirmed in the city of the year. We match the COVID-19 pandemic measure according to the firms' registered cities.

Following Yu et al. (2014), Shen et al. (2012), and Shen et al. (2010), we control for a series of variables that have been proven to influence firm green investment. Firm size (*Size*) is defined as the natural log of total assets. We compute firm leverage (*Leverage*) using the ratio of total debts to total assets. Tobin's Q (*TobinQ*) represents investment opportunities, calculated as the ratio of the market value of equity plus the book value of debts to total assets. We control for firm cash flow (*Cfo*) as the net operating cash flow, scaled by the year's beginning total assets. *Top* represents firm equity structure, calculated as the percentage of shares held by the largest shareholder. *Age* is defined as the years since the firm was first listed on the Shanghai or Shenzhen Stock Exchange. *Roa* is calculated as the return on assets.

2.3 Descriptive statistics

Panel A of Table 1 shows the descriptive statistics. The mean and maximum of green investment, defined as the natural log of one plus green investment, are 1.755 and 22.497, respectively. The standard deviation of the COVID-19 pandemic measure is 2.180, which suggests that different cities experienced different exposure to the COVID-19 pandemic. Panel B of Table 1 presents the correlation matrix of variables used in the main regression. The correlation coefficient of the COVID-19 pandemic and firm green investment is -0.079, and statistically significant at the 1% level, suggesting that firms in cities where the exposure to COVID-19

TABLE 1 Descriptive statistics.

Panel A: Summary statistics					
Variables	Mean	SD	Min.	Median	Max.
GInvest	1.755	5.165	0.000	0.000	22.497
Invest	0.029	0.223	-0.303	0.002	11.758
COVID	3.981	2.180	0.000	4.382	10.827
Size	22.381	1.255	20.025	22.229	26.031
Leverage	0.422	0.190	0.061	0.417	0.861
TobinQ	2.154	1.464	0.855	1.699	9.543
Top	23.776	16.683	0.150	21.519	65.752
Cfo	0.073	0.077	-0.118	0.066	0.351
Roa	0.038	0.075	-0.351	0.039	0.230
Age	11.668	7.911	0.750	9.750	27.000

Panel B: Correlation matrix									
	Invest	GInvest	COVID	Size	Leverage	TobinQ	Top	Cfo	Roa
GInvest	**0.062**								
COVID	-0.026	**-0.079**							
Size	-0.012	**0.114**	-0.032						
Leverage	-0.036	**0.062**	**0.042**	**0.500**					
TobinQ	0.011	**-0.085**	-0.002	**-0.282**	**-0.301**				
Top	-0.006	**0.071**	**-0.057**	**0.293**	**0.116**	0.022			
Cfo	**0.057**	**0.043**	**-0.056**	**0.075**	**-0.185**	**0.211**	0.006		
Roa	**0.059**	0.020	-0.025	**0.040**	**-0.314**	**0.222**	0.032	**0.455**	
Age	-0.027	**0.089**	**-0.054**	**0.455**	**0.278**	**-0.167**	**0.314**	**-0.109**	**-0.111**

This table reports the descriptive statistics of the variables used in the empirical analyses. The sample consists of 4377 observations of firms listed on either the Shanghai or the Shenzhen Stock Exchange in 2020-2021. *GInvest* is the natural log of one plus the green investment obtained from the notes on construction in progress. *Invest* is defined as the change in the net value of fixed assets, scaled by the year's beginning total assets. *COVID* is the COVID-19 pandemic measure, defined as the natural log of one plus the newly confirmed cases. Firm size, *Size*, is defined as the log of total assets. *Leverage* is calculated as the ratio of total debts to total assets. *TobinQ* is the ratio of the market value of equity plus the book value of debts to total assets. *Top* is firm equity structure, calculated as the percentage of shares held by the largest shareholder. *Cfo* is the net operating cash flow scaled by the year's beginning total assets. *Roa* is the return on assets. *Age* is defined as the years since first listed on the Shanghai or Shenzhen Stock Exchange. All continuous variables are winsorized at the 1% level at both tails of their distributions. Panel A reports the summary statistics, while Panel B presents the correlation matrix for the variables in the baseline regression. The numbers in bold indicate statistical significance at the 1% level.

pandemic invest in green less. Firm green investment is negatively related to the COVID-19 pandemic. Larger firms with greater leverage were likely to have more green investment. The following section describes the regressions conducted to explore the relationship between the COVID-19 pandemic and firm green investment.

3 Main findings

3.1 Baseline results

To investigate the relationship between the COVID-19 pandemic and firm green investment, we conduct multivariate regression analysis using the equation below:

$$GInvest_{it} = a_0 + \beta_1 COVID_{jt} + \gamma Controls_{i,t-1} + \delta industry_i + \epsilon_{it} \quad (1)$$

where *GInvest* is green investment for firm *i* at the end of 2020 and 2021, *COVID* is our city-level COVID-19 pandemic measure for firm *i* located in city *j*.*Controls* is a series of control variables: *Size*, *Lev*, *TobinQ*, *Top* , *Cfo*, *Age*, and *Roa*. Industry fixed effects (*Industry*) are included to account for the industry heterogeneity in investment. ϵ is the standard error item. The standard errors of the estimated coefficients are corrected for heteroscedasticity. Our conclusion is not affected if we allow for clustering by city or by province.

We first estimate the relation between the COVID-19 pandemic and firm green investment. The results are presented in Column (1) of Table 2. The coefficient of our COVID-19 pandemic measure is negative and significant at 1% (coefficient=−0.1151, t-statistics= −3.1253). The results suggest that firms in regions where the COVID-19 pandemic was severe have a lower willingness to make a green investment. Economically, a 1%in the number of confirmed cases in the city would result in a 0.12% decrease in green investment. The sign of coefficients of the control variables is largely consistent with prior studies. The coefficients of firm size (*Size*), equity structure (*Top*), and firm age (*Age*) are positive and significant, indicating that larger and older firms, firms with bigger stockholders, make more green investments. Cash flow (*Cfo*) is positively related to firm green investment, suggesting that green investment is limited to the firm's cash flow.

In order to verify whether the reduction in green investment is caused by a reduction in the total amount of investment in the general sense of the term. We explore the effect of the COVID-19 pandemic on firm total investment. We define firm investment (*Invest*) as the ratio of the change of net value of fixed assets, to the year's beginning total assets. The associated results are presented in Column (2) of Table 2. The coefficient of our city-level COVID-19 pandemic measure is negative, but it is not significant statistically (coefficient = −0.0018, t -statistics = −1.2654). This suggests that the COVID-19 pandemic did not have a significant negative impact on total investment.

Taken together, our baseline results in Table 2 suggest that firms in regions where the exposure to the COVID-19 pandemic was higher tended not to make green investments. Meanwhile, the effect of the COVID-19 pandemic on total investment is not significant. This suggests that under the shock of the COVID-19 pandemic, firms first reduce environmentally friendly investments such as green investment. Alessio and Simona (2024) show firm environmental performance was related to lower returns during the period of the COVID-19 pandemic. Because the higher cost of green projects makes firms more exposed to uncertainty. This may be related to the characteristics of green investment, which, in the

TABLE 2 Effect of COVID-19 pandemic on corporate investment.

	(1)	(2)
	GInvest	*Invest*
COVID	-0.1151***	-0.0018
	(-3.1253)	(-1.2654)
Size	0.2413***	-0.0012
	(2.9023)	(-0.4710)
Leverage	0.3877	-0.0096
	(0.7659)	(-0.5565)
TobinQ	-0.2615***	-0.0016
	(-5.2121)	(-0.8067)
Top	0.0146***	-0.0000
	(2.8149)	(-0.3072)
Cfo	2.9991***	0.0945**
	(2.8205)	(2.1133)
Roa	0.8683	0.1145***
	(0.8819)	(5.7779)
Age	0.0418***	-0.0004
	(3.5191)	(-1.0060)
_cons	-4.7272**	0.0946*
	(-2.5484)	(1.6847)
Industry fixed effects	Yes	Yes
N	4377	4377
R^2_adj	0.050	0.002

This table reports the regression results for the relation between the COVID-19 pandemic and corporate investment. The sample consists of 4377 firm-year observations of firms listed on either the Shanghai or the Shenzhen Stock Exchange in 2020-2021. Column (1) presents the results of the relation between COVID-19 pandemic and corporate green investment. Column (2) presents the results of the relation between COVID-19 pandemic and corporate total investment. G*Invest* is the natural log of one plus the green investment obtained from the notes on construction in progress. *Invest* is defined as the change in the net value of fixed assets, scaled by the year's beginning total assets. *COVID* is the COVID-19 pandemic measure, defined as the natural log of one plus the newly confirmed cases. Firm size, *Size*, is defined as the log of total assets. *Leverage* is calculated as the ratio of total debts to total assets. *TobinQ* is the ratio of the market value of equity plus the book value of debts to total assets. *Top* is firm equity structure, calculated as the percentage of shares held by the largest shareholder. *Cfo* is the net operating cash flow scaled by the year's beginning total assets. *Roa* is the return on assets. *Age* is defined as the years since first listed on the Shanghai or Shenzhen Stock Exchange. All continuous variables are winsorized at the 1% level at both tails of their distributions. Industry fixed effects are included. The standard errors are corrected for heteroscedasticity and t-statistics are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

short term, generates more social than economic benefits. The negative relationship between the COVID-19 pandemic and firm green investment shows that the outbreak of COVID-19 damaged sustainable economic development, causing a decrease in firm green investment.

3.2 Robustness and endogeneity tests

We conduct further analyses to ensure the negative relationship between the COVID-19 pandemic and firm green investment is robust to alternative green investment measures, COVID-19 pandemic measures, and sample constructions. We present the results in Table 3. For the sake of brevity, we only show the coefficient of the COVID-19 pandemic measure.

We start by examining whether our results are sensitive to alternative green investment measures. Following Zhang et al. (2019), we measure firm green investment using *GInvest*, defined as natural log of one plus the greening fees and sewage charges. Panel A in Table 3 presents the results, consistent with the baseline results. The coefficient of *COVID* is −0.0880, which is negative and significant at the 1% level.

In our baseline regression, we measure the COVID-19 pandemic using the city-level confirmed cases. We further adjust our COVID-19 pandemic measure using province-level confirmed cases. We name this adjusted variable *COVID*1, which then replaces *COVID* in Equation (1). We present the results in Panel B of Table 3. We find that the negative coefficient of *COVID*1 is significant, suggesting that our main findings are robust to different measures of the COVID-19 pandemic.

Last, we redefine the period of the sample to test whether our results are sensitive to subsamples. We estimate the relationship between the COVID-19 pandemic and green investment for 2020 and 2021 separately. We present the results in Panels C and D of Table 3, respectively. We find that the coefficients of the COVID-19 pandemic are negative and significant for the subsamples.

While we have shown a robust negative relationship between the COVID-19 pandemic and firm green investment, its causal interpretation could be subject to endogeneity resulting from omitted variables. The type of reverse causal maybe not an endogeneity issue in our paper because the COVID-19 pandemic was an external shock that could not be affected by firm green investment. To remove endogeneity concerns arising from omitted variable bias, our strategy is to control for several variables that could be correlated with both the COVID-19 pandemic and firm green investment.

We include year-fixed effects in the regression to account for time effects and show the results in Panel E. The negative relationship between COVID-19 and green investment remains. We further include area fixed effects (i.e., East area, Central area, and West area) in the regression to account for cross-area differences in corporate green investment and re-estimate the effects of the COVID-19 pandemic on firm green investment. The results are presented in Panel F of Table 3. The coefficient of *COVID* is negative and significant at the 1% (coefficient = −0.1109, t-statistics = −3.0058), consistent with the baseline results. Concerning the COVID-19 pandemic may affect firm operations, the controlling variables may be related to the COVID-19 pandemic. To deal with the concerns, we replace the controlling variables using the controls in 2019 and re-estimate the Equation (1). The results presented in Panel G of Table 3 show COVID-19 pandemic has negative impact on firm green investment, consistent with baseline regression.

TABLE 3 Robustness and endogeneity checks.

Panel A: Estimating Equation (1) with an alternative measure of green investment (N = 4184)		
COVID	Coefficients	*t*-statistics
	-0.0880***	(-2.9222)
Panel B: Estimating Equation (1) with an alternative measure of COVID-19 pandemic (N = 4377)		
*COVID*1	Coefficients	*t*-statistics
	-0.1332**	(-2.0830)
Panel C: Estimating Equation (1) with the subsample for the year of 2020 (N = 2346)		
COVID	Coefficients	*t*-statistics
	-0.3007***	(-3.9479)
Panel D: Estimating Equation (1) with the subsample for the year of 2021 (N = 2031)		
COVID	Coefficients	*t*-statistics
	-0.1760***	(-3.8545)
Panel E: Estimating Equation (1) controlling for year fixed effects (N = 4377)		
COVID	Coefficients	*t*-statistics
	-0.2113***	(-5.3863)
Panel F: Estimating Equation (1) controlling for area fixed effects (N = 4377)		
COVID	Coefficients	*t*-statistics
	-0.1109***	(-3.0058)
Panel G: Estimating Equation (1) with controlling variables in 2019 (N = 4263)		
COVID	Coefficients	*t*-statistics
	-0.1266***	(-3.3613)

This table presents the results of the robustness tests and endogeneity tests. The sample consists of 4377 firm-year observations of firms listed on either the Shanghai or the Shenzhen Stock Exchange in 2020-2021. Panel A presents the results based on an alternative measure of firm green investment, *GInvest*1, defined as the natural log of one plus the greening fees and sewage charges, which are obtained from the overhead items in the income form. Panel B presents the results using an alternative measure of the COVID-19 pandemic, *COVID*1, which is calculated as the newly confirmed cases in the province level. Panels C and D exhibit the results using subsamples for the years 2020 and 2021, respectively. Panel E presents the results controlling for the year fixed effects. Panel F presents the results controlling for area fixed effects. We divide the provinces into east, center and west areas. Panel G exhibits the results with the controlling variables in 2019. Industry fixed effects are included. All regressions include the control variables as listed in Table 2 and their coefficients are not tabulated. Detailed variable definitions are in the legend of Table 2. The standard errors are corrected for heteroscedasticity and t statistics are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4 Further analysis

4.1 Cross-sectional heterogeneity in results

Our baseline results imply a negative and causal relation between the COVID-19 pandemic and firm green investment. In this section, we conduct cross-sectional tests to explore the channels through which the COVID-19 pandemic impeded firm green investment. On the basis of prior literature (e.g., Kahle and Stulz, 2013; Liu et al., 2016; Tang et al., 2020), we posit that the COVID-19 pandemic negatively influenced firm green investment by increasing firm financial constraints. For the financial constraints channel, crises increase uncertainty about firm prospects and/or government policies, thereby decreasing the willingness of capital suppliers (e.g., banks) to fund corporate green investment (Shleifer and Vishny, 2010). Moreover, pandemic may cause panic in the credit market, raising the cost of debt (Easley and O'Hara, 2010). The lower availability and higher cost of loans during the COVID-19 pandemic increased firms' financial constraints, thereby impeding their green investment. Further, if the negative effect of the COVID-19 pandemic on firm green investment was felt through the financial constraints channel, the effect should be stronger for firms with higher financial constraints.

To test the financial constraints channel, in this section, we explore how the relationship between the COVID-19 pandemic and firm green investment varies according to financial constraints. Specifically, we measure financial constraints at the firm level with four variables, namely firm age, dividend, state ownership, and WW index. Older firms and firms paying dividends have lower financial constraints. State ownership of enterprises affects firms' financing ability. Chang et al. (2019) show that the top managers of SOEs in China are often high-ranking party cadres, and consequently, SOEs have the advantage of financial resources. Thus, SOEs have greater access to capital than non-SOEs. According to Whited and Wu (2006) and Liu et al. (2015) we also calculate WW index to measure firm financial constraints. The WW index equals $-0.091\times CF-0.062\times DivPos+0.021\times Lev-0.044\times Size+0.102\times ISG-0.035\times SG$, where *CF* is the cash flow to total assets ratio, *DivPos* is the dummy variable of whether the firm pays cash dividends, *Lev* is the ratio of long debt on total assets, *Size* is the natural log of total assets, *ISG* is the average industry sales growth rate, *SG* is the sales revenue growth rate. Higher WW index indicates higher financial constraints. We divide the sample into two groups according to the median level of age, whether firms paying dividends, state ownership, and median of WW index, respectively.

We re-estimate the regression for these subsamples and present the results in Table 4. Consistent with the financial constraints channel, the negative effect of the COVID-19 pandemic is stronger for firms with higher financial constraints (i.e., younger firms, non-dividend, non-SOEs, or higher WW index). The coefficients of the COVID-19 pandemic for the older firms, firms with dividends, SOEs, and lower WW index, are much smaller or not significantly different from zero. Collectively, our cross-sectional analysis in Table 4 supports our argument that the COVID-19 pandemic impeded corporate green investment by increasing firms' financial constraints.

TABLE 4 Cross-sectional differences in the effects of COVID-19 pandemic on corporate green investment.

	(1)	(2)
Panel A: Dividing the sample based on firm Age_Dummy (N_{young} = 2277; N_{old} = 2100)		
	Young	Old
COVID	-0.1461***	-0.0878
	(-3.2338)	(-1.5162)
Panel B: Dividing the sample based on firm dividend ($N_{non\text{-}dividend}$ = 3225; $N_{dividend}$ = 1051)		
	No	Yes
COVID	-0.1253***	-0.0535
	(-2.7915)	(-0.8798)
Panel C: Dividing the sample based on SOE ($N_{non\text{-}SOEs}$ = 3067; N_{SOEs} = 1310)		
	Non-SOEs	SOEs
COVID	-0.1262***	-0.1217
	(-3.2811)	(-1.4870)
Panel D: Dividing the sample based on WW (N_{high} = 1524; N_{low} = 1525)		
	High	Low
COVID	-0.1208**	-0.0789
	(-2.3511)	(-1.0664)

The sample consists of 4377 firm-year observations of firms listed on either the Shanghai or the Shenzhen Stock Exchange in 2020-2021. In Table 4, the sample is split according to our financial constraints measures. In Panel A, we partition the firms into two groups according to the median firm age. In Panel B, we divide the firms into two groups according to whether or not the firms pay dividends. In Panel C, we split the subsample with state ownership into two groups based on whether or not the firms are SOEs. In Panel D, we divide the firms into two groups according to the sample median of the WW index. According to Whited and Wu (2006) and Liu et al. (2015) we calculate WW index as $-0.091\times$CF-$0.062\times$DivPos+$0.021\times$Lev-$0.044\times$Size+$0.102\times$ISG-$0.035\times$SG, where CF is the cash flow to toal assets ratio, DivPos is the dummy variable of whether the firm pays cash dividends, Lev is the ratio of long debt on total assets, Size is the natural log of total assets, ISG is the average industry sales growth rate, SG is the sales revenue growth rate. Firms with an older age, paying dividends, with lower WW index, or owned by governments have lower financial constraints. All regressions include the control variables as listed in in Table 2 and their coefficients are not tabulated. Detailed variable definitions are in the legend of Table 2. The standard errors are corrected for heteroscedasticity and t-statistics are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.2 SARS epidemic and investment

In this section, we explore the economic effect of the SARS epidemic on total investment and green investment. We measure the exposure of the SARS epidemic based on SARS-related news published by China's provincial official party newspapers. In comparison with confirmed cases or deaths variables, our media-based variable is better suited to capturing the province-level exposure to SARS. Because SARS outbreaks are concentrated in some provinces, each province implemented strict controlling policies to prevent the spread of the virus. It is difficult to capture differences in exposure to the SARS epidemic using confirmed cases almost all provinces. In line with prior literature (e.g., Baker et al., 2016; Chang et al., 2020), we measure media-based SARS epidemic

variables using the dictionary method. This method classifies documents into different categories based on a pre-specified dictionary (Stone et al., 1967). The procedure for measuring the media-based SARS epidemic is as follows. We first create a list of words used to refer to the SARS epidemic. Specifically, we use different names for SARS to identify SARS-related news. Next, we use "jieba," a popular word segmentation package used to analyze Chinese text data, to break down sentences into words. We add the eight SARS names to the "jieba" list to extract the dictionary words from the news. We remove the "stop words" (e.g., "is", "of", and "then"), from the news. We then use the standard dictionary method to classify the news published in China's provincial official newspapers between November 2002 and July 2003 into SARS-related and non-SARS-related categories. SARS-related news is that containing the dictionary words in the news. We compute the media-based SARS epidemic measure using the following ratio: *SARS_Media = the number of SARS news/the number of total news.*

We use the sample of all Chinese A-share firms listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange in 2003 and explore the relation between SARS and investment (i.e. total investment and green investment). The results presented in Table 5 show that SARS epidemic has significantly negative effects on total investment. When we control for the confirmed cases in the baseline regression, the results remain. The results are consistent with financial constraints channel. Besides the financial constraints channel, we think the demand shocks may be another channel. According to the literature (e.g., Kahle and Stulz, 2013; Liu et al., 2016; Tang et al., 2020), the outbreak of the SARS epidemic led regions to take mandatory quarantine measures, which restricted people's spending power. Chen et al. (2020) show that the COVID-19 pandemic has caused daily offline consumption to fall by 32%. The decrease in demand for firms' products can reduce investments (Kahle and Stulz, 2013; Tang et al., 2020). Liu and Zhang (2020) explore the effect of the SARS epidemic on macroeconomics and show the SARS epidemic heat economics, especially the tertiary sector. Such decreases in demand drive down corporate investment. However, the coefficient of SARS epidemic is not significant when the dependent variable is green investment. The results suggest that firms in regions where the exposure to SARS was higher tended not to invest. But SARS epidemic has not yet crowded out corporate green investment, possibly at a lower level of green development itself in 2003.

TABLE 5 Effect of media-based SARS epidemic on corporate investment.

	(1)	(2)
	Invest	*GInvest*
SARS_Media	-0.1891***	-0.5381
	(-3.0431)	(-1.0082)
Size	0.0069	0.0573
	(1.3939)	(1.4013)
Leverage	0.0484**	0.0319
	(2.1334)	(0.6190)
TobinQ	-0.0145***	0.0420
	(-2.8528)	(1.5977)
Top	0.0006	-0.0055
	(1.0105)	(-1.0719)
Cfo	0.0625	0.3112
	(1.4379)	(1.2491)
Roa	0.1249***	0.2198
	(3.1294)	(1.5538)
Age	-0.0326***	-0.0097
	(-4.0616)	(-0.2372)
_cons	-0.0306	-1.1017
	(-0.2945)	(-1.3545)
Industry fixed effects	Yes	Yes
N	976	976
R^2	0.106	0.009

This table reports the regression results for the relation between the SARS epidemic and corporate investment. The sample consists of 976 firm-year observations of firms listed on either the Shanghai or the Shenzhen Stock Exchange in 2003. Column (1) presents the results of the relation between the SARS epidemic and corporate total investment. Column (2) presents the results of the relation between the SARS epidemic and corporate green investment. *SARS_Media* is defined as the ratio of SARS-related news to all news in the province-level. Industry fixed effects are included. All regressions include the control variables as listed in Table 2 and their coefficients are not tabulated. Detailed variable definitions are in the legend of Table 2. The standard errors are corrected for heteroscedasticity and t statistics are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5 Conclusion

Corporate green investment is an environmentally friendly investment, which is a major tool for combating climate change. With the outbreak of COVID-19, scholars and policymakers are paying more attention to sustainable economic development. It is necessary to better understand the real economic impact of such large-scale health crisis shocks as the COVID-19 pandemic. While some have debated the effects of the pandemic on macroeconomics, such as consumption and economic growth, little is known about its firm-level impact. In this study, we examine the relationship between the COVID-19 pandemic and firm green investment.

Using a sample of Chinese listed firms, we show that the COVID-19 pandemic negatively affected firms' green investments. However, the COVID-19 pandemic has no significant effects on total investment. The results are robust to a variety of tests on variable measures, subsamples, and endogeneity issues. We also find that increased financial constraints account for the negative relation between the COVID-19 pandemic and firm green investment. Further analysis reveals that the SARS epidemic has no significant effects on firm green investment.

Collectively, our findings suggest that the COVID-19 pandemic had a negative effect on firm green investment and policymakers can rely on these findings to support economic recovery and sustainable development from the shock of the health crisis. Thus, our study offers new evidence about the firm-level effects of the COVID-19 pandemic, indicating that financial constraints played

an important role in accounting for the negative shock of the pandemic. In the future, it is necessary to research on how to mitigate the negative effects of the pandemic on green development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding authors.

Author contributions

YH: Methodology, Writing – original draft. LF: Writing – review & editing. TL: Conceptualization, Supervision, Writing – original draft. RW: Formal analysis, Software, Writing – original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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New industrial land use policy and firms' green technology innovation in China—an empirical study based on double machine learning model

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China is facing a serious land resource mismatch problem, which will profoundly affect the acceleration of economic growth and technological innovation. Reform of the industrial land allocation system can solve the mismatch of land resources, and that also has an important impact on the promotion of economic and technological development. This paper selects the data of Chinese A-share listed companies in Shanghai and Shenzhen from 2007 to 2020 as the research sample, constructs a double machine learning model, and empirically investigates the impact of a new industrial land use policy on firms' green innovation behavior. The study shows that: (1) the new industrial land use policy significantly promotes firms' substantive and strategic green technological innovation, and the effect on substantive green technological innovation is greater than that on strategic green technological innovation. (2) The enhancement of R&D investment sustainability and the "talent pool" effect are important mechanisms through which the new industrial land use policy influences firms' substantive and strategic green technological innovation. Meanwhile, the new industrial land use policy is conducive to firms' green co-innovation. (3) There is heterogeneity in the effect of the new industrial land use policy, which can significantly promote green technological innovation of firms in the eastern region, while it does not play a significant role in the green innovation behavior of firms in the central and western regions. The above research results enrich the research in the field of industrial land and innovation, help to understand more comprehensively the mechanism of new industrial land affecting firms' green technological innovation, and provide policy insights for strengthening the application of industrial land allocation reform in firms' green innovation.

KEYWORDS

new industrial land use policy, green innovation, China, double machine learning, R&D investment sustainability, talent pool

1 Introduction

China has achieved rapid growth for more than 4 decades by relying on an abundant land supply, large labor inputs, high energy consumption, and high capital. This pattern of economic growth has been called “unsustainable growth" (Young, 2003; Wang et al., 2023a). Rough development and trade liberalization have all contributed to China’s energy constraints and environmental pollution problems becoming more and more prominent, and has also caused ecological environmental protection and economic development to be on the verge of imbalance (Hao et al., 2006; Wang et al., 2023b). Firm innovation has always been an important part of national innovation development, and the importance of innovation for industrial manufacturing industries is far greater than that of other industries (Hsu et al., 2014). At the same time, green technology innovation is an inevitable choice to balance economic growth and ecological environmental protection. Compared with traditional innovation, green innovation is a new innovation model that deals with energy saving, pollution control, recycling waste, and designing green products (Tsai and Liao, 2017). Green innovation has both the economic characteristics of improving the productivity and competitiveness of firms and the social characteristics of energy saving, emission reduction and environmental protection (Wang et al., 2023c). Green technology innovation is an important force for China to get out of economic difficulties, cope with the environmental crisis, break the energy constraint and promote the construction of innovation-driven country (Wang et al., 2023d). Green technology innovation is also a key initiative for China to grasp the major opportunities of the new round of technological revolution and industrial change. According to Xinhua News Agency on 24 October 2021, the article “Opinions on Complete and Accurate Comprehensive Implementation of the New Development Concept to Do a Good Job of Carbon Peak and Carbon Neutrality” explicitly proposes to strengthen the major green and low-carbon technological research and popularization of its application, in order to support the establishment of a green, low-carbon and recycling development of the economic system. In recent years, China has accelerated the construction of innovative country and innovative cities, which has promoted the development of green technology innovation. According to data from the State Intellectual Property Office, China has been an important contributor to global green and low-carbon technological innovation. From 2016 to 2022, the global patent authorization for green and low-carbon technology inventions reached a cumulative total of 558,000 pieces. Chinese patentees were granted 178,000 pieces, accounting for 31.9% of the global share. The average annual growth rate of green patents in China reached 12.5%, significantly higher than the overall global level of 2.5%. At the same time, the problems of few high-quality patents and low utilization rate of results transformation are still prominent, and China’s green technology innovation is still seriously disconnected from the actual demand (Show et al., 2018).

As a necessary input factor and spatial carrier in the production or innovation process of firms, the way land is configured and the supply strategy will inevitably have a profound impact on the production and innovation of firms. Local governments in China have taken advantage of the unique arrangement of land policy to dominate economic development. On the one hand, local governments have promoted industrialization by offering industrial land at low prices to attract investment. On the other hand, they have been able to obtain funds for building urban infrastructure and promoting urbanization by offering commercial and residential land at high prices and promoting land mortgages. The rapid structural change driven by land created China’s growth miracle (Gao et al., 2021). In China’s land factor market, land resource allocation is not entirely subject to market mechanisms. China’s current land system gives local governments control over the allocation of land resources. As managers and suppliers of land, local governments are subject to both economic performance constraints and market regulation in land resource allocation. Local governments’ land grant decisions are often accompanied by a greater degree of resource mismatch and negative externalities (Lu and Xiang, 2016; Xie et al., 2023) For example, local government officials with limited tenure tend to opt for the strategy of attracting investment through the establishment of industrial parks. So they offer as much industrial land as possible at low prices during their tenure. They are more concerned with the short-term fixed-asset investment that the project will bring than with the future growth in gross industrial output that the project will bring to the city. Intense competition for investment will prompt local governments to further reduce land prices, lower entry barriers and open their doors to industries with poor prospects and overcapacity. The entry of these “low-level” firms will crowd out scarce land resources, while creating a “crowding-out effect” on technology-intensive, capital-intensive and cleaner high-value-added industries. This model may lead to a lack of public service systems and a disconnection of supporting facilities, making cities less attractive to factors such as talent and capital. Ultimately, it leads to difficulties in building an urban innovation system to support green, high-quality local development.

Literature related to this paper can be categorized into two main groups, one of which is on the impact of the land system on economic development and other aspects. This type of literature mainly carries out research in the following four aspects. In the first aspect, the impact of local government’s land transfer price strategy on government land revenue, urbanization, enterprise investment and industrial structure upgrading is studied from the perspective of government officials’ incentives (Wang and Hui, 2017). The land grant price strategy is specifically manifested in the fact that local governments pursue the maximization of local finance by granting commercial and residential land at high prices. Meanwhile, they grant industrial land at low prices in order to achieve the goal of economic growth. In addition, there is a kind of bottom-line competition for the quality of attracted capital in the government’s land concessions, which leads to the poor quality of the projects that are attracted. In the second aspect, the impact of industrial land resource mismatch on firm productivity is studied. For example, Li et al. (2016) found that the crude land grant, which is dominated by low land prices and agreement granting methods, impedes the improvement of resource allocation efficiency among industrial firms. In the third area, the impact of the allocation of urban construction land targets on the Chinese real estate market, the elasticity of China’s housing supply, and firms’ investment is investigated (Han and Lu, 2017; Shen et al., 2018; Wang et al., 2023e). For example, Han and Lu (2017) find that regions with

tighter land grants have faster rising house prices, which is less favorable to firms' real investment. On the one hand, high house prices enable firms to obtain loans and increase investment by increasing the value of collateral. On the other hand, there is a "crowding-out effect" of high house prices, which discourages firms from investing. Rising house prices attract firms to hold investment property and reduce investment in fixed assets. The fourth aspect is to study the impact of land supply on environmental pollution, energy consumption and other aspects (Zheng and Shi, 2018; Li J. et al., 2023). Another category of literature is the research on the influencing factors of green technology innovation. Scholars mainly focus on the impact of governmental factors on green technology innovation, such as environmental regulation, tax policy, government subsidies and green financial policies (Jia and Ma, 2017; Miao et al., 2019; Wu and Hu, 2020; Rao et al., 2022). Some literature has begun to focus on the relationship between land markets and innovation, such as land marketization and urban innovation (Cheng et al., 2022), land resource allocation and firm innovation (Ma et al., 2022), land resource mismatch green technological innovation (Gao et al., 2021), but the above studies are relatively macroscopic, focusing mostly on the provincial and regional levels. The literature focusing on the impact of land reform on firm-level innovation is relatively scarce. At the same time, China is implementing a new industrial land use policy, but the impact of this policy on firm innovation has not been studied by scholars. This paper focuses on the new industrial land policy and examines its impact on firms' green innovation. This will complement research on land system reform and firm innovation.

Based on this, this paper takes 3,574 listed companies in China from 2007 to 2020 as the research object, and systematically examines the impact of new industrial land use policy on green technological innovation through the construction and measurement of a double machine learning model. This paper finds that the new industrial land use policy significantly promotes substantive green innovation and strategic green innovation of firms within the pilot cities, and has a greater impact on substantive green innovation than strategic green innovation. The reason is that the implementation of the new industrial land use policy improves the scale of R&D investment and the continuity of R&D investment, and then promotes firms' green technological innovation. On the other hand, the new industrial land use system exerts the effect of "talent pool", attracts high-level talents, and increases the proportion of technical talents in firms, which in turn affects firms' green technological innovation. The heterogeneity study shows that the new industrial land use policy has a significant impact on the green technology of firms in the eastern region, but not in the central and western regions of China. Compared with non-heavily polluted industries and politically connected firms, the new industrial land use policy has a stronger promotion effect on firms in heavily polluted industries and politically connected firms.

The marginal contributions of this paper may be as follows: first, using China's new industrial land use policy as an entry point, this paper empirically tests the impact of industrial land use policy on firms' substantive and strategic green innovation, enriching the current literature on land and innovation. Second, this paper uses a double machine learning method in the empirical research process. Compared with the traditional causal inference method, the double machine learning model does not require complex and strict strong assumptions. For example, when the sample data do not satisfy the balanced trend test of the double difference method, the empirical research can be carried out by the double machine learning modle, which broadens the current research method. Third, with the help of micro-level data, this paper confirms the impact of the new industrial land use policy on firms' green technological innovation and cooperation innovation, as well as its mechanism and heterogeneity. This study provides a theoretical basis for further promoting the replication and scaling up of the new industrial land use policy in China.

The remainder of the paper is organized as follows: The second section describes the evolution of China's land system and the implementation of the new industrial land use policy. The theoretical mechanism of the new industrial land use policy affecting firms' green innovation is analyzed. The third section introduces the model and data used in this paper. The fourth section reports the basic regression results of the new industrial land use policy affecting firms' green technology innovation, as well as a series of robustness tests, heterogeneity and mechanism analysis results. The fifth section further discusses the empirical findings of the article. The sixth section summarizes the full paper.

2 Policy background and theoretical mechanisms

2.1 Policy background

China's State Council promulgated the "Interim Regulations on the Granting and Transfer of State-owned Land Use Rights in Urban Areas" in 1990, which gave local governments monopoly development rights in the primary market for state-owned construction land. At the same time, the "Regulations on the Implementation of the Land Administration Law of the People's Republic of China" was introduced in 1998, which further signaled that local governments had the right to franchise and trade in land resources. In the early 21st century, motivated by the dual incentives of local fiscal revenue and regional competitive objectives, local governments in China have used industrial land concessions at low prices as a key focus for investment attraction and economic development (Chen and Kung, 2016). Since then, the competition for land attraction has been increasingly characterized by bottom-line competition, with local governments arbitrarily suppressing the real price of industrial land. This not only reduces the quality of investment attraction, but also further leads to a very serious waste of land resources and a mismatch of resource within cities. In response to the above problems, China has introduced a series of policies to curb the trend of illegal land transfers. In 2002, the former Ministry of Land and Resources promulgated the "Regulations on the Tendering, Auctioning and Listing of State-owned Land Use Rights", which for the first time stipulated that operational land, including land for commerce, tourism, entertainment and commercial residential land, had to be transferred through tendering, auctioning and listing. In 2006, the "State Council's Circular on Relevant Issues on Strengthening Land Regulation and Control" further explicitly required that industrial land must also be sold by tender, auction and listing. To a certain

extent, this system avoids the inefficiency problems caused by government monopoly, improves the transparency of the decision-making process, and facilitates supervision by higher levels of government and the public. In 2007, China's former Ministry of Land and Resources promulgated the "National Minimum Pricing Standard for Industrial Land Sale", which for the first time set out clear regulations on industrial land transfer prices at the national level. This has led to land supply constraints and higher land costs in eastern China, and the large stock of inefficiently utilized industrial land prevalent in all regions has become an important constraint on high-quality economic development.

With industrial development and firm production innovation, the traditional management of industrial land has been unable to meet the innovation needs of industries. Innovation-led development objectively requires that innovation factors continue to cluster towards industrial entities. In 2006, Beijing issued the "Detailed Control Plan for Beijing Central City", taking the lead in exploring the use of industrial land for R&D. In 2015, the Ministry of Land and Resources issued the "Guidelines for Implementation of Industrial Land Use Policy". On the basis of this policy, local governments may make land use proposals to the urban and rural planning departments at the same level and to higher-level industry authorities for new industries and new business forms that are not specified in the current national standard classifications. Local governments can prioritize the supply of land for new industries and implement flexible supply of industrial land in various ways. By transforming land use to guide the development of innovative industry clusters, local economies can adapt to the new normal of economic development. Against this background, some Chinese cities have successively introduced land use policies applicable to new types of industries in accordance with the direction of regional industrial development from the perspective of land use standards, planning layout, industrial land reserves, land supply, and project construction. They explore a new industrial land management model, which mainly focuses on the policies of land spatial planning, land use control, land use planning arrangement, land supply, land utilization, and real estate registration involved in specific industries (Mi, 2022). As of December 2020, a total of 28 cities in China have implemented the reform of the new industrial land use policy, adding innovative industrial land to existing industrial land, commercial service facility land, or R&D headquarters land. The main features of new industrial land use include: first, the upper limit of plot ratio has been raised. Most cities have adjusted the plot ratio for new industrial land use to 5.0–6.0, and some cities have even abolished the upper limit. This work has led to an increase in the intensity of land development. Second, industrial supporting construction is improved. The new industrial land use policy grants a certain proportion of supporting services to the land parcel, which is not entirely industrial or commercial land. The subject of land use and development can plan supporting facilities and space according to the requirements of industrial support and development trends. This allows new industrial land projects to aggregate a variety of industrial forms. Third, land prices have become more favorable. The new industrial land use policy has set high standards for the resident firms, and only those firms that meet the standards can enjoy the preferential land use policy. For example, whether the main business of the firm belongs to the scope of policy encouragement, and whether the firm is a listed company or unicorn enterprise will all affect the admission of the firm.

2.2 Theoretical mechanisms

As one of the important factors of production indispensable to the operation and development of industrial firms, land provides the basic factors of production for the debugging of equipment and R&D innovation. It also increases the initial investment in research and development innovation of firms. China's new industrial land policy has increased the plot ratio of buildings and the development intensity of land, thereby facilitating industrial firms' access to industrial land. This provides production factors and test sites for firm production and R&D, and fulfills the function of land as a production factor. It improves the economies of scale of land and facilitates the enhancement of firms' green technology innovation capacity. On the other hand, China's local governments once used low-priced land supply as an important means of investment attraction behavior while showing obvious characteristics of bottom-line competition (Chen et al., 2018). A large number of low-end manufacturing firms with weak R&D capabilities were able to invest in industrial parks due to lower land costs. This low-priced and wide-supply industrial land strategy attracted a large number of inefficient, high-consumption, and high-pollution low-end manufacturing industries to cluster (Tang et al., 2018; Zheng and Shi, 2018). Following that, a huge scale of low-end manufacturing capacity with backward technology and low technological content has been formed on the scarce industrial land. It squeezes out investment in high-end manufacturing and emerging industries with strong innovation capacity (Zhou et al., 2021). This mismatch of land resources has driven the rapid development of high-emission and high-pollution firms, but it has also inhibited the incentives of firms to strengthen green technological innovation and greening development (Huang and Du, 2017; Luo et al., 2018; Gao et al., 2021; Du et al., 2023; Li R. et al., 2023). Meanwhile, under the new industrial land use policy, the government requires firms to have high innovation ability as well as low pollution emission. Otherwise, industrial firms will face the risk of being retired and the land they use will be taken back as inefficient industrial land. Local governments revitalize that land again. Thus, the new industrial land use policy will push firms to accelerate their green technological innovations in order to meet the appropriate standards.

Hypothesis 1 (H1). The new industrial land use policy promotes green technological innovation in firms.

New industrial land policy can promote the growth of R&D investment. As one of the long-term fixed assets of a firm, land can be used as a collateral asset for firm financing. It alleviates the agency cost, adverse selection and incomplete contract problem under information asymmetry in the debt financing process of firms (Berger et al., 2011). The traditional industrial land use policy has restrictions on the development and use of the subject of the functional limitations and sale, resulting in a contradictory situation of idle real estate resources and enterprise financing constraints. The new industrial land policy enables industrial firms to enjoy more favorable land prices. At the same time, each development zone in

order to increase investment will also give relevant supporting preferential policies. So that the cost of firm land is lower, will reduce the occupation of internal funds, and enhance the internal financing ability of firms. Split sales of the new policy is also conducive to reducing the pressure on firm funds, reduce the squeeze on innovation funds. Under the new industrial land use policy, local governments have promoted the increased availability of land resources to firms by setting higher plot ratios for industrial land. Firms can more easily acquire industrial land as collateral for firms' external financing, which will substantially increase firms' credit capacity (Chaney et al., 2016; Cheng et al., 2022). In the context of China's imperfect financial market and predominantly bank credit, the increased availability of land resources will provide an important source of credit for firms' R&D innovation. Firms' innovation is highly sensitive to internal capital endowment due to the long cycle and uncertainty of R&D investment (Brown et al., 2013) Therefore, loose financial conditions will stimulate R&D activities, which is conducive to the acceleration of technological innovation and the improvement of green innovation performance (Du and Li, 2019; Du et al., 2019; Li J. et al., 2023; Wang et al., 2023f). In the meantime, firms' R&D is not only the main way for them to gain a competitive advantage, but also an important driver of the country's economic development (Slow, 1957). Once a firm's R&D activity stops or lacks continuity, that competitive advantage quickly disappears (Tavassoli and Karlsson, 2015). R&D persistence reflects a firm's long-term knowledge accumulation and technological progress in terms of R&D investment, product development or process improvement, and it is closely related to the durability of a firm's competitive advantage (Clausen et al., 2012). The continuity and stability of R&D investment is sometimes more important to firms than the scale and intensity of R&D (Schroth and Szalay, 2010). The new industrial land use policy requires a high level of innovation. Industrial firms will not be removed from new industrial land use only if they continue to invest in innovation and vigorously promote technological innovation. Therefore, under the hard constraint of "innovate or be retired", firms will continue to increase their R&D investment to promote green technological innovation.

Hypothesis 2 (H2). Promoting the increase and sustainability of R&D funding is an important channel through which new industrial land use policy can contribute to firms' green technological innovations.

New industrial land use policy can cluster human capital. The innovative requirements of the new industrial land use policy for firms have stimulated the demand for high-quality human capital. At the same time, compared with the traditional industrial land use of a single function of the relevant provisions of the new industrial land use policy to give a certain proportion of the plot of land supporting services part. For example, Shanghai stipulates that the ancillary area should not exceed 15% of the project ceiling. Shenzhen and Ningbo set a cap of 30%. The liberalization of the policy on the supporting area of industrial land will help innovative entities to create good conditions for business services and a livable external environment in the region. For example, providing a better working and living environment for high-quality green technology innovators will help attract an influx of highly skilled personnel. Wang et al. (2022) also found that higher plot ratios are conducive to labor aggregation. Human capital is an intangible resource of firms, and highly skilled personnel are also an important force in promoting green technology innovation (Kianto et al., 2017). Baumol (1996) suggests that human resource differences are an important factor contributing to differences in innovation efficiency. On the one hand, highly skilled human capital can learn and imitate advanced technologies, as well as use them to improve production processes and create new products. Non-knowledge production unrelated to R&D is particularly important for firms in developing countries, and technology imitation activities rely heavily on engineers, technicians (Rammer et al., 2009). On the other hand, highly skilled people can enhance the development, modification, and adaptation of existing knowledge, which in turn drives the creation of new technologies (Greiner et al., 2004; Arundel et al., 2007; Goedhuys et al., 2013). Overall, this learning-by-doing model facilitates incremental innovation in firms (Grimpe and Sofka, 2009). Not only do highly educated R&D personnel hired from universities and research institutions have a significant contribution to technological breakthrough innovation in firms (Herstad et al., 2015; Arvanitis et al., 2016; Sun et al., 2020), but also experienced managerial human capital and HR can organize firm resources well and thus play a positive role in firm innovation (Capozza et al., 2018). In their study, Stuart et al. (2007) found that innovators within firms play the role of "gatekeepers", which facilitates the interaction between firms' internal and external knowledge. Good business support services can also effectively enhance the work experience of highly skilled personnel, which in turn significantly improves innovation efficiency. Highly skilled personnel not only provide manpower and knowledge support for firms' green technological innovation, but also promote the research and development and diffusion of green and low-carbon technologies, which is also conducive to the iterative development of firms' green products.

Hypothesis 3 (H3). The industrial land use policy promotes green technological innovation in firms by utilizing the "talent pool" effect.

3 Data and methods

3.1 Model design

The double machine learning (DML) approach proposed by Chernozhukov (2018) relies on a classical semiparametric theoretical framework. In contrast to traditional causal inference methods, DML does not require complex and rigorous strong assumptions, allowing it to handle a wider range of data forms and model structures. More importantly, unlike traditional machine learning methods used for causal inference, DML uses Neyman orthogonalization to overcome regularization bias. Moreover, DML uses sample partitioning to correct for overfitting bias to obtain de-biased and efficient estimation. Following Chernozhukov et al. (2018), We innovatively applies the DML model to test the causal relationship between new industrial land use policies and firms' green innovation by establishing the following regression model:

$$Y_{it} = \theta_0 \,\text{Event}_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$E(U_{it} \mid \text{Event}_{it}, X_{it}) = 0 \tag{2}$$

where i and t represent firm and year respectively. Y_{it} is the dependent variable, representing firm i in t year's green technology innovation. Event_{it} is a dummy variable for the pilot of new industrial land use policy where the firm is located. If coefficient θ_0 is significantly positive, indicating that the new industrial land use policy has a promoting effect on firms' green innovation. X_{it} is a series of multidimensional control variable. We need to use machine learning algorithms to estimate the specific form $\hat{g}(X_{it})$. U_{it} is the error term, and its conditional mean is 0. We have directly estimated Eqs 1, 2, then we obtain the coefficient estimates as follows:

$$\hat{\theta}_0 = \left(\frac{1}{n}\sum\nolimits_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1}\frac{1}{n}\sum\nolimits_{i\in I,t\in T}\text{Event}_{it}\,(Y_{it} - \hat{g}(X_{it})) \tag{3}$$

where n is the sample capacity.

Based on the above estimators, the estimation bias can be further examined:

$$\sqrt{n}\left(\hat{\theta}_0 - \theta_0\right) = \left(\frac{1}{n}\sum\nolimits_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T}\text{Event}_{it}U_{it} + \left(\frac{1}{n}\sum\nolimits_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1}\frac{1}{\sqrt{n}}\sum\nolimits_{i\in I,t\in T}\text{Event}_{it}\left[g(X_{it}) - \hat{g}(X_{it})\right] \tag{4}$$

$$a = \left(\frac{1}{n}\sum\nolimits_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T}\text{Event}_{it}U_{it} \tag{5}$$

$$b = \left(\frac{1}{n}\sum\nolimits_{i\in I,t\in T} \text{Event}_{it}^2\right)^{-1}\frac{1}{\sqrt{n}}\sum\nolimits_{i\in I,t\in T}\text{Event}_{it}\left[g(X_{it}) - \hat{g}(X_{it})\right] \tag{6}$$

where a obeys a normal distribution with mean 0. It should be noted that dual machine learning uses machine learning and its regularization algorithm to estimate a specific functional form $\hat{g}(X_{it})$, which inevitably introduces a "regularity bias" that prevents the estimator from having too much variance, but also makes it unbiased. This is shown by the slower convergence of $\hat{g}(X_{it})$ to $g(X_{it})$, with $n^{-\varphi_g} > n^{-1/2}$. Thus, as n and b tend to infinity, $\hat{\theta}_0$ has difficulty converging to θ_0.

To speed up convergence, the disposal coefficient estimates are made to satisfy unbiasedness with small samples. We construct the auxiliary regression as follows:

$$\text{Event}_{it} = m(X_{it}) + V_{it} \tag{7}$$

$$E(V_{it} \mid X_{it}) = 0 \tag{8}$$

where $m(X_{it})$ is the regression function of the disposition variable on the control variable, which again needs to be estimated using a machine learning algorithm in the specific form $\hat{m}(X_{it})$. V_{it} is the error term with a conditional mean of 0.

The procedure is as follows:First, a machine learning algorithm is used to estimate the auxiliary regression $\hat{m}(X_{it})$. We can get its residual. $\hat{V}_{it} = \text{Event}_{it} - \hat{m}(X_{it})$. Second, the same machine learning algorithm is used to estimate $\hat{g}(X_{it})$. We change the main regression form to $Y_{it} - \hat{g}(X_{it}) = \theta_0 \,\text{Event}_{it} + U_{it}$. Finally, $\hat{V}_{it}$ is regressed as an instrumental variable for Event_{it}, and then unbiased coefficient estimates can be obtained as follows:

$$\check{\theta}_0 = \left(\frac{1}{n}\sum\nolimits_{i\in I,t\in T} \hat{V}_{it}\text{Event}_{it}\right)^{-1}\frac{1}{n}\sum\nolimits_{i\in I,t\in T}\hat{V}_{it}\left(Y_{it} - \hat{g}(X_{it})\right) \tag{9}$$

$$\sqrt{n}\left(\check{\theta}_0 - \theta_0\right) = \left[E\left(V_{it}^2\right)\right]^{-1}\frac{1}{\sqrt{n}}\sum\nolimits_{i\in I,t\in T} V_{it}U_{it} + \left[E\left(V_{it}^2\right)\right]^{-1}\frac{1}{\sqrt{n}}\sum\nolimits_{i\in I,t\in T}\left[m(X_{it}) - \hat{m}(X_{it})\right]\left[g(X_{it}) - \hat{g}(X_{it})\right] \tag{10}$$

where $\left[E\left(V_{it}^2\right)\right]^{-1}\frac{1}{\sqrt{n}}\sum\limits_{i\in I,t\in T} V_{it}U_{it}$ obeying a normal distribution with mean 0. Since two machine learning estimates are used, the overall rate of convergence of $\left[E\left(V_{it}^2\right)\right]^{-1}\frac{1}{\sqrt{n}}\sum_{i\in I,t\in T}\left[m(X_{it}) - \hat{m}(X_{it})\right]\left[g(X_{it}) - \hat{g}(X_{it})\right]$ depends on the rate of convergence of $\hat{m}(X_{it})$ to $m(X_{it})$ and $\hat{g}(X_{it})$ to $g(X_{it})$, i.e., $n^{-(\varphi_g+\varphi_m)}$. Compared to Eq. 4, $\sqrt{n}(\check{\theta}_0 - \theta_0)$ converges to 0 faster. Therefore, we can obtain unbiased estimates of the disposition coefficients.

3.2 Variable settings

3.2.1 Dependent variable

Green Innovation. Drawing on the methods of Gao et al. (2021), this paper measures green innovation based on green patent data. The Green List of the International Patent Classification (GLIPC), launched by the World Intellectual Property Organization (WIPO) in 2010, is an online tool for searching information on patents related to environmentally friendly technologies. The search classifies green patents into seven categories according to the United Nations Framework Convention on Climate Change (UNFCCC), including alternative energy, transportation, waste management, energy conservation, etc., and covers about 200 topics directly related to environmentally friendly technologies. In this paper, the green patent applications of A-share listed firms were obtained from China Research Data Service Platform (CNRDS) and compared with the database search of State Intellectual Property Office (SIPO) to finally form a green patent database of listed companies with high confidence. The advantages of adopting patent data are as follows. Data availability and accuracy are guaranteed. Green patents can intuitively reflect the output of firms' green technological innovation activities, which can be categorized according to different technological attributes, and can reflect the different value connotations and contributions of innovation. The above two features make it possible for patents to measure green innovation activities with different motivations. Among them, invention patents have a high-level of technology, difficulty and innovation. Utility model patents have relatively low-level of technology, difficulty and innovation. Therefore, this paper regards the number of green invention patents as substantive green innovation and the number of green utility model patents as strategic green innovation. We take these two indicators as the dependent variables of concern in this paper.

3.2.2 Independent variable

The core explanatory variable is whether the city where the firm is located implements the new industrial land use policy. The

independent variable is assigned a value of one when the city where the firm is located implements the new industrial land use policy in the sample period, and 0 otherwise.

3.2.3 Control variables

In order to accurately estimate the promotion effect of the new industrial land use policy on firms' green innovation, the following control variables are selected. Firm size (Size), measured by the natural logarithm of total assets at the end of the year; gearing ratio (Lev), measured by the ratio of total liabilities at the end of the year and total assets at the end of the year; cash flow ratio (Cashflow), measured by the ratio of net cash flow generated from the operating activities of the firm to the total assets; growth rate of operating income (Growth), measured by the ratio of operating income of the firm in the current year and operating income of the previous year minus 1; number of directors (Board), measured by the number of board of directors taking the natural logarithm of the number of directors; the proportion of independent directors (Indep), expressed as a share of the number of directors who are independent directors; the age of the firm (Age), the sample year minus the year of the firm's establishment, plus one to take the natural logarithm of the year of the establishment of the firm; the proportion of management shareholding (Mshare), measured by the number of shares held by management of the firm as a percentage of the total equity share; institutional investor shareholding (INST), measured by the total number of shares held by institutional investors as a share of the outstanding share capital; and firm ownership (SOE), which takes the value of one when the firm is a state-controlled firm, and 0 otherwise.

3.3 Data sources

This paper selects the data of 3574 A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2007 to 2020 as the research sample. The data of firm characteristics and financial data come from CSMAR database. The green patent data of firms are from CNRDS. The sample data are processed as follows. We do not focus on financial firms and have excluded the financial sector sample because the format of financial firms' statements and the structure of their assets and liabilities differ significantly from those of other firms. ST and delisted companies are no longer normal listed companies, so they are not our concern. In order to weaken the influence of sample outliers, all continuous variables are shrink-tailed at the 1% and 99% quantile. The data of urban industrial land use policy in this paper comes from the official website of each city government, which is manually collected and organized by us.

4 Results

4.1 Baseline regression results

In this paper, a dual machine learning model is used to estimate the policy effect of new industrial land policy on firms' green innovation. We set the sample split ratio to 1:4, then we solved the main and auxiliary regressions for the prediction. Table 1 shows the results of the linear regression of the impact of the new industrial land use policy on firms' green technological innovation. Columns (1) and (2) of Table 1 show the results of the dual machine learning model without and with control variables respectively, and the estimated coefficients of the independent variable are both significantly positive at the 1% statistical level. This suggests that the new industrial land use policy significantly promotes firms' substantial green technological innovation. Columns (3) and (4) show the impact of new industrial land use policies on firms' strategic green technological innovations without and with control variables respectively. The estimated coefficients on the independent variables are both significantly positive at the 1% statistical level, and smaller than those in columns (1) and (2). This suggests that the new industrial land use policy can also significantly promote firms' strategic green technology innovation. This is consistent with the conclusion of hypothesis 1. However, the effect of the new industrial land use policy on firms' strategic green innovation is smaller than that on substantive green technological innovation. This may be due to the fact that new industrial land use policies in Chinese cities explicitly require firms to meet pollution emission standards and technological innovation targets. Firms will step up their green technology efforts in order to adapt to the current industrial land use requirements. Meanwhile, although strategic green technological innovation can also enable firms to achieve the goal of reducing emissions or accomplishing innovations to a certain extent, in contrast, substantive green technological innovation is the high-quality technological innovation targeted by the new industrial land use policy. Therefore, in order to maintain competitiveness, firms will pay more attention to substantive green technological innovation.

4.2 Robustness tests

4.2.1 Changing the regression model

This paper further chooses different models to analyze and test the impact of new industrial land use policies on firms' green technology innovation. First, this paper adopts the PSM method to deal with the sample self-selection problem, and takes firms' substantive green technology innovation and strategic green technology innovation as PSM treatment variables respectively. We select firm size, gearing ratio, cash flow ratio, revenue growth ratio, number of directors, proportion of independent directors, age of the firm, proportion of management ownership, proportion of institutional investor ownership, and ownership of the firm as PSM matching covariates. Propensity scoring is performed through Logit modeling. Then the nearest neighbor matching is performed in the ratio of 1:1 to find cities in the control group that have the same or similar tendency score value as the sample tendency score of the treatment group as the matching object. We end up with a new data sample. Columns (1) and (2) of Table 2 report the regression results of the dual machine learning model by the PSM method, and the estimated coefficients of the independent variables are significant at the 1% statistical level, reflecting the positive effect of the new industrial land use policy on firms' green technological innovation. Second, the double machine learning model may have setting bias. To avoid its influence on the conclusion, this paper changes the sample split ratio of the double machine learning model from the previous 1:4 to 1:9. This helps to avoid the possible

TABLE 1 Baseline regression.

	Substantive green technology innovation		Strategic green technology innovation	
	(1)	(2)	(3)	(4)
Event	4.513***	3.224***	2.546***	1.681***
	(0.47)	(0.39)	(0.28)	(0.22)
Control variables	NO	YES	NO	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	31238	31238	31238	31238

Notes:*, **, and *** indicate significant at the 10%, 5%, and 1% levels respectively. Robust standard errors are in parentheses. The following table is the same.

TABLE 2 Changing the regression model.

	PSM-DML		Resetting Double Machine learning Models		Interactive Model	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)	(5)	(6)
Event	3.247***	1.677***	3.152***	1.657***	2.063***	1.169***
	(0.40)	(0.22)	(0.39)	(0.22)	(0.37)	(0.21)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
Observations	31064	31064	31238	31238	31076	31075

influence of the sample split ratio on the conclusion. Columns (3) and (4) of Table 2 show the regression results after changing the sample split ratio. We can see that the estimated coefficients on the independent variables remain positive. Finally, a partial linear model based on double machine learning is constructed for analysis in the benchmark regression, and there is some subjectivity in the model form setting. In this paper, double machine learning is used to construct a more general interactive model to explore the effect of model setting on the conclusions of this paper. Columns (5) and (6) show the results of the interactive model regression with significantly positive estimated coefficients on the independent variables. This again demonstrates the reliability of hypothesis one of this paper.

4.2.2 Excluding other policy effects

Another challenge to the regression results of this paper is that in verifying the policy effect of the new industrial land use policy on firms' green technology innovation, it is inevitably disturbed by other policies in the same period. In order to ensure the accuracy of the estimation of the policy effect, this paper controls for other policies in the same period. On the one hand, during the sample period of this paper, China implemented a number of low-carbon pilot cities in 2010, 2012, and 2017 respectively, and this policy has an important impact on green innovation (He et al., 2023). To control the impact of low-carbon pilot city policies, this paper sets the policy dummy variable Low_carbon.It is assigned a value of one when the city where the sample is located has implemented a low-carbon city policy in the observation period, and 0 otherwise. The Low_carbon variable is added as a control variable to the baseline model regression of this paper, and the results in columns (1) and (2) of Table 3 are obtained. It can be seen that the estimated coefficients of the independent variables are still significantly positive when controlling for the impact of the low-carbon pilot city policy. On the other hand, the "Green Credit Guidelines" issued by China in 2012 promoted the development of green credit, which can play an important role in firms' green technology innovation (Su et al., 2022). In order to control the disturbance of green credit policy, this paper sets a dummy variable Green_credits. It is assigned a value of one when the sample of heavy polluting industries suffered from green credit policy in the observation period, and 0 otherwise. Adding the Green-credits variable as a control variable to the regression model of this paper, we get the results in columns (3) and (4) of Table 3. It can be found that the new industrial land use policy can still significantly promote firms' substantive and strategic green technology innovation.

TABLE 3 Exclusion of other policy effects and using balanced panel data.

	Excluding the impact of low-carbon pilot city policies		Excluding the impact of green credit policies		Balance panel	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)	(5)	(6)
Event	3.177***	1.381***	3.221***	1.645***	6.377***	1.914***
	(0.42)	(0.22)	(0.39)	(0.22)	(1.09)	(0.42)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
Observations	31238	31238	31238	31238	9,520	9,520

4.2.3 Using balanced panel data

Because of the unbalanced panel used in the baseline regression of this paper, the entry and exit of firms may affect the assessment of the role of new industrial land use policies on green innovation. In this context, this paper further obtains the balanced panel data of 680 A-share listed companies in China between 2007 and 2020. Based on the balanced panel data, the double machine learning model regression is applied to obtain the results in columns (5) and (6) of Table 3. As shown by the estimated coefficients of the independent variables are still significantly positive at the 1% statistical level, the conclusion that the new industrial land use policy has a positive impact on firms' substantive and strategic green technological innovations remains robustly established.

4.3 Endogeneity tests

In this paper, the PSM-DML method avoids the problem of bidirectional causality and takes into account the factors affecting firms' green technology innovation as much as possible. However, the regression analysis faces the endogeneity problem due to the inevitable omitted variables. Therefore, instrumental variable method regression is used to alleviate the endogeneity problem. In this context, this paper refers to Nathan and Nancy (2014) and uses as instrumental variables the interaction term between urban terrain relief and exchange rate, and the interaction term between urban terrain relief and interest rate respectively, which satisfy the exogeneity and correlation assumptions of instrumental variables. Meanwhile, this paper builds a partial linear instrumental variable model for double machine learning based on Chernozhukov et al. (2018), and the regression results are shown in Table 4. From columns (1) and (3) of Table 4, the estimated coefficients of the independent variables are significantly positive, and the role of the new industrial land use policy on firms' substantial green technology innovation remains significant. From the results in columns (2) and (4), it can be seen that the new industrial land use policy can significantly promote firms' strategic green technological innovations, but the effect is smaller than the effect on substantive green technological innovations. Accordingly, Hypothesis one of this paper is confirmed again.

4.4 Mechanism tests

In the theoretical analysis section, we explore that the new industrial land use policy can promote firms' green technological innovations by facilitating the sustainable improvement of innovation inputs and the increase of skilled personnel. This paper further validates these two channels of action. On the one hand, this paper uses the two indicators of innovation investment intensity and innovation investment sustainability to proxy for the R&D investment channel. The amount of firms' R&D investment as a share of operating revenue is used to measure innovation investment intensity, and innovation investment sustainability is measured based on the methodology of Triguero and Córcoles (2013). Innovation investment intensity and innovation investment persistence are put into the benchmark regression model as dependent variables respectively, and the regression results are shown in columns (1) and (2) of Table 5. As can be seen from the regression results, the estimated coefficients of the independent variables are all significantly positive at the 1% statistical level, which indicates that the new industrial land use policy can significantly contribute to the innovation input intensity and innovation input continuity enhancement of firms. In firms' innovation activities, innovation input intensity and innovation input sustainability enhancement are the key for firms to actively engage in green technological innovation, which can enable firms to maintain green competitiveness (Tavassoli and Karlsson, 2015). It can be seen that the new industrial land use policy promotes green technological innovation by enhancing the intensity and sustainability of R&D investment. Thus, Hypothesis two of this paper is proved. On the other hand, this paper uses the number of R&D personnel and the share of R&D personnel as proxies for firms' skilled human capital, where the share of R&D personnel is the number of R&D personnel as a proportion of the total number

TABLE 4 Endogeneity tests.

	IV1		IV2	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	3.809***	1.973***	3.318***	1.895***
	(0.60)	(0.40)	(0.61)	(0.41)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	31192	31192	31192	31192

TABLE 5 Mechanism results.

	Intensity of innovation inputs	Sustainability of innovation inputs	Number of R&D staff	Share of R&D staff	Talent investment continuity
	(1)	(2)	(3)	(4)	(5)
Event	0.643***	0.127***	0.0710***	1.847***	0.478***
	(0.09)	(0.02)	(0.01)	(0.19)	(0.09)
Control variables	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES
Observations	21480	20454	15515	15373	8,675

of employees in the firm. The number of R&D personnel and the share of R&D personnel are put into the benchmark regression model as dependent variables respectively, and the regression obtains columns (3) to (5) in Table 5. From the regression results, it can be seen that the estimated coefficients of the independent variables are all significantly positive, reflecting that the new industrial land use policy plays the effect of "talent pool", which can significantly promote the growth of firms' skilled human capital. Skilled human capital can promote the dissemination of knowledge and accelerate technological innovation, which plays a crucial role in the green technological innovation process of firms (Sun et al., 2020). Based on this, hypothesis three of this paper is confirmed. Besides, China's new industrial land use policy can facilitate the agglomeration of various types of actors and factors because of its high floor area ratio and diversified land uses. In this context of more intensive economic and innovation activities, how the new industrial land use policy affects green co-innovation needs to be investigated. In order to promote co-innovation, China has developed a series of supportive policies. This has contributed to the fact that co-innovation has become a new way for firms to carry out technological innovation activities. However, the failure rate of R&D alliances in China is still as high as 50% and the alliance partnerships are unstable (Fan et al., 2015). Against this background, this paper further investigates the role of new industrial land use policy on co-innovation of firms' green technologies. In this paper, we obtain the data of joint applications for green invention patents of A-share listed companies from CNRDS database. The number of joint applications for green invention patents of firms is used to represent green co-innovation, as well as the share of co-innovation is proxied by the proportion of joint applications for green invention patents to the total number of green invention patent applications of firms. The co-innovations of substantive and strategic green technology are put into the baseline regression model as dependent variables respectively, and the regression obtains columns (1) and (2) in Table 6. As can be seen from the results, the estimated coefficients of the independent variables are all significantly positive at the 1% statistical level, and the estimated coefficients of substantive green technology innovation are larger. This reflects that the new industrial land use policy can significantly promote the co-innovations of firms' substantive and strategic green technology. On the other hand, the share of co-innovation as the dependent variable is put into the baseline regression model, and the regression obtains columns (3) and (4). It can be seen that the estimated coefficients of the independent variables are still significantly positive, indicating that the new industrial land use policy significantly promotes the share of co-innovations in firms' green innovation in substantive and strategic green technology.

TABLE 6 The impact of new industrial land use policies on green innovation cooperation.

	Collaborative innovative		Share of collaborative innovative	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	1.406***	0.541***	0.017***	0.013***
	(0.25)	(0.08)	(0.002)	(0.001)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	31238	31238	31238	31238

TABLE 7 Regional heterogeneity tests.

	Eastern region		Central region		Western region	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)	(5)	(6)
Event	2.394***	1.122***	0.359	0.924	−0.683	−0.699
	(0.39)	(0.21)	(1.04)	(0.60)	(1.03)	(0.45)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES	YES	YES
Observations	20914	20914	5,175	5,175	4,233	4,233

4.5 Heterogeneity tests

4.5.1 Regional heterogeneity

Due to differences in resource endowments and development stages, there are regional differences in the impact of new industrial land use policies on firms' green technology innovation. In this paper, based on the distinction between east, center and west made by the National Bureau of Statistics of China, the sample is divided into east sample, center sample and west sample depending on the province where the enterprise is located. Double machine learning regression using the sub-regional samples obtained the results in Table 7. Among them, the estimated coefficients of the independent variables in columns (1) and (2) are both significantly positive at the 1% statistical level, reflecting the fact that the new industrial land use policy can significantly promote firms' substantive and strategic green technological innovation in the eastern region. From the results in columns (3) to (6), the estimated coefficients of the independent variables are all insignificant, indicating that the new industrial land use policy has no significant effect on both firms' substantive and strategic green technology innovation in the central and western regions. The possible explanations are the competition for land between high value-added and low value-added industries, which pushes up the price of industrial land in the eastern region. Industrial land resources are also relatively scarce here. While in the central and western regions, land resources and labor supply are relatively abundant. And in the process of further developing the manufacturing industry, there are more new industrial land resources in the central and western regions (Chen et al., 2018). This results in the new industrial land use pattern in the central and western regions does not occur the innovation effect.

4.5.2 Industry heterogeneity

There may be differences in the motivation for green technology innovation among firms belonging to industries with different levels of environmental threats. This paper determines the scope of heavy pollution industries according to the "Green Credit Guidelines issued" by China in 2012, and divides the full sample of this paper into heavy pollution industry samples and non-heavy pollution industry samples. On this basis, the sub-sample regression obtains the results in Table 8. The estimated coefficients of the independent variables in columns (1) and (2)

TABLE 8 Heavily and non-heavily industry heterogeneity tests.

	Heavily polluting industries		Non-heavily polluting industries	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	6.111***	2.392***	2.069***	1.434***
	(0.99)	(0.28)	(0.39)	(0.27)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	8,841	8,841	22397	22397

are both significantly positive, indicating that the new industrial land use policy can significantly promote substantive and strategic green technology innovation of firms in heavy polluting industries. The estimated coefficients of the independent variables in columns (3) and (4) are both significantly positive at the 1% statistical level, reflecting that the new industrial land use policy also significantly promotes green technological innovations of firms in non-polluting industries. Comparing the regression results in columns (1) and (3), it can be obtained that the estimated coefficients of the independent variables are larger for the heavily polluted industries than for the non-heavily polluted industries. This reflects the fact that the green innovation effect of the new industrial land use policy is greater for heavy polluting industries than for non-heavy polluting industries. Possible explanations are as follows. According to the relevant requirements of the new industrial land use policy, heavy polluting industries face stronger constraints and their pressure to reduce emissions is greater, which also leads to the fact that firms in the heavy polluting industries are more motivated to green innovation.

4.5.3 Firm heterogeneity

Green innovation is product, technology or process innovation on an environmentally friendly basis. Its process mainly consists of three aspects: resource acquisition, resource input and resource output. In this process, the main subjects of resource acquisition and resource investment in the early stage are firms, which need to pay a lot of time, manpower, material resources and land and other resources. Political affiliation is an important factor that affects the business development of Chinese firms. For example, firms with political affiliation have more advantages in obtaining resource subsidies (Conyon et al., 2015; Li R. et al., 2023). Specifically, if a firm' executives or actual controllers serve as deputies to the National People's Congress or members of the Chinese People's Political Consultative Conference at all levels, it means that the firm is politically affiliation. Based on this, this paper distinguishes between politically affiliated samples and non-politically affiliated samples, and obtains the results in Table 9 after sub-sample regression. The estimated coefficients of the independent variables in columns (1) through (4) are all significant at the 1% statistical level for. This shows that the new industrial land use policy can not only influence the green innovation of politically affiliated firms, but also significantly promotes the innovation of non-politically affiliated firms. Meanwhile, according to the estimated coefficients of the independent variables in columns (3) and (4) are larger than those in columns (1) and (2) respectively, the green innovation effect of the new industrial land policy on non-politically affiliated firms is larger than that on politically affiliated firms. Possible reasons for these results are as follows. The new industrial land policy makes land resources more abundant, which facilitates the access of non-politically affiliated firms to land resources and helps them to carry out innovative activities. On the other hand, in the context of the high threshold of the new industrial land policy, the risk of non-politically affiliated firms being retrenched is stronger. However, politically affiliated firms have a lower risk of being retired, thanks to their links with the government. As a result, non-politically affiliated firms will take a more cautious approach to the new industrial land use policy and endeavor to carry out green technological innovations to meet the relevant requirements of the policy.

5 Discussion

This paper examines the impact of China's new industrial land use policy on firms' green technological innovation using data from China's A-share listed firms from 2007 to 2020. The article examines the role of R&D investment sustainability and the "talent pool" in the process of new industrial land use policy affecting firms' green innovation. Although this study focuses on prefecture-level cities in China, the methodology can also be used to explore the role of industrial land policy on firms' innovation in other developing countries. In addition, this study discusses the heterogeneous effects of new industrial land policy on firms' green innovation. The specific contributions of this paper are as follows.

First of all, by reviewing relevant information and literature, this paper has sorted out the evolution of China's industrial land use system. China's industrial land system has been reforming towards marketization. Due to the mismatch between the supply and demand of industrial land and the demand for industrial innovation, various regions in China are actively exploring the new industrial land system. For example, enterprises can set up R&D organizations and build human resources housing facilities on new types of industrial land. The article sorts out the timing of the implementation of new industrial land policy in various regions of

TABLE 9 Political affiliated and non-political affiliated firm heterogeneity tests.

	Political affiliation		Non-political affiliation	
	Substantive innovation	Strategic innovation	Substantive innovation	Strategic innovation
	(1)	(2)	(3)	(4)
Event	2.872***	1.606***	3.433***	1.727***
	(0.80)	(0.42)	(0.48)	(0.26)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Industry fixed effects	YES	YES	YES	YES
Observations	10112	10112	20052	20052

China. This work helps us to empirically study the impact of new industrial land policy on firms' green innovation.

Second, this paper adopts a dual machine learning approach to analyze the causal relationship between new industrial land policy and firms' green innovation. Compared with the traditional causal inference method, the dual machine learning method does not require complex strong assumptions. Therefore, the dual machine learning method has more application scenarios than the traditional causal model. Based on the regression estimation results, we find that the new industrial land policy has a significant positive impact on both substantive and strategic green innovation of firms. The estimated coefficients of their core explanatory variables are 3.224 and 1.681, respectively. This result is consistent with the findings of Xie et al. (2023) and Li R. et al. (2023). We continue with robustness tests such as resetting the dual machine learning model, using the PSM-DML model, and excluding the effects of low-carbon cities and green credit policies. We also use the instrumental variables approach to endogeneity. We find that the article's benchmark regression results still hold.

Furthermore, this paper examines the role of R&D investment sustainability and "talent pool" in the impact of new industrial land policy on firms' green innovation. We find that the implementation of new industrial land policy can significantly promote the intensity of innovation investment and its sustainability. The estimated coefficients of their core explanatory variables are 0.643 and 0.127, respectively.

This result is basically consistent with the findings of Ma et al. (2022) and Cheng et al. (2022). Meanwhile, the new industrial land policy significantly contributes to the increase in the number and share of R&D personnel. In conclusion, the implementation of the new industrial land policy helps to stimulate firms' demand for talent and enhances their human capital. The new industrial land policy allows firms to build housing for talent security, which increases the plot ratio of the land. This policy facilitates firms to attract talents. This is consistent with the findings of Wang et al. (2022). In addition, the government supports firms to utilize the new industrial land to build public science and technology R&D platforms. Therefore, the new industrial land policy would promote joint innovation among firms. This paper tests this potential mechanism and finds that the new industrial land policy significantly promotes firms' joint innovation and increases the share of jointly filed patents in their total patents.

Finally, this paper further investigates the heterogeneous effects of new industrial land policy on firms' green innovation. The findings show that the new industrial land policy has a significant impact on firms' green innovation only in the eastern region. This is because eastern China faces a serious land resource mismatch. This hinders the development of high-end industries, as well as constrains firm innovation. When firms are provided with sufficient land supply, their innovative energies are released (Gao et al., 2021). However, the policy does not have a significant impact on the green innovation of firms in central and western China. This is due to the fact that the central and western regions of China are relatively rich in available industrial land resources. In terms of industry heterogeneity, the new industrial land policy has a greater impact on heavily polluted industries than on non-heavily polluted industries. New industrial land has higher emission requirements for firms. Heavily polluting firms will be more active in green technology innovation in order to meet the environmental requirements of that land. In addition, some scholars believe that political affiliation has a negative effect on firm innovation (Chung et al., 2016), but there is also literature that suggests that political affiliation has a positive effect on firm innovation (Jiang et al., 2023). Our results suggest that the new industrial land policy has a facilitating effect on green innovation for both politically connected firms and non-politically connected firms. However, compared to politically connected firms, the new industrial land policy has a stronger role in promoting green innovation in non-politically connected firms. Non-politically connected firms have poorer access to resources. The new industrial land policy can improve the availability of land resources, which makes it easier for non-politically connected firms to obtain industrial land. Non-politically connected firms will be more motivated to develop new green technologies.

There are some limitations in this study. First, for the identification of firms affected by the new industrial land policy, this paper is based on whether the city where the firm is located has implemented the new industrial land policy. This does not directly assess the impact of a firm's ownership of emerging industrial land on its own development. Therefore, the identification strategy used in this study may need further refinement. Second, the proxy variable used for green innovation, firms' green patent data, may not fully reflect firms' green innovation behavior. For example, although a firm's patents may not fall into the category of green

patents, the firm may have cited green patents in the process of inventing patents. At this point, the firm's patent may also be green. This limitation needs to be further studied to develop more comprehensive and accurate indicators of firms' green innovation.

6 Conclusion and policy implication

6.1 Conclusion

Based on the panel data of Chinese A-share listed firms, we find that the new industrial land use policy significantly promotes firms' substantive and strategic green technology innovation. And it has a greater effect on substantive green technology innovation than on strategic green technology innovation. The sustainability of R&D investment and the "talent pool" effect are important mechanisms through which the new industrial land use policy influences firms' green technological innovation. At the same time, the new industrial land use policy can promote firms' green co-innovation. In the context of China's land resource mismatch, the new industrial land use policy significantly promotes green technological innovation among firms in the eastern region, although it has no significant impact on this Green innovation behavior among firms in the central and western regions. New industrial land use policies have a stronger impact on the green innovation behavior of firms in heavily polluting industries and non-politically affiliated firms than non-polluting firms and politically affiliated firms.

6.2 Policy implications

First of all, the implementation of the new industrial land use policy should be tailored to local conditions. The new industrial land use policy can effectively promote firms' green technological innovation in order to balance economic growth and environmental protection. This policy can also alleviate the problem of land resource mismatch. Local governments in China urgently need to further clarify the allocation of new industrial land, continuously improve the new industrial land use model, and actively promote this model in eastern China. For example, they need to rationalize floor area ratios, dynamically update the thresholds for enterprises, and scientifically identify areas for new industrial land use. Eastern provinces can learn from the digital reform of new industrial land that has already been carried out in some places, and use digital technology to fully utilize the functions of new industrial land. However, in the central and western regions of China, the new industrial land use system has not significantly affected firms' green technology innovation. On the one hand, we suggest that the central and western regions raise the target requirements for indicators of energy consumption, carbon emissions and innovation in setting up the new industrial land use policy, thereby promoting green technological innovation in firms. On the other hand, the central and western regions should be wary of the abuse of the new industrial land use policy, and should focus their efforts on fully utilizing the existing industrial land.

Second, Secondly, the new industrial land use policy should be actively utilized to gather talents and alleviate financial pressure. New industrial land generally has a higher floor plot ratio, making it possible to host more fixed facilities and economic activities on the same area of land. Meanwhile, the provision of land for R&D and staff accommodation facilities is an important advantage of the new industrial land use policy. Government departments should focus on the residential living and working needs of highly skilled and high-quality talents, and strive to strengthen the accumulation of urban and industrial human capital. This requires a comprehensive assessment of land allocation imbalances within cities. There is a need to mitigate the negative impact of the imbalance between residential and industrial land use structures on the innovative participation of talent and the accumulation of industrial innovation, and to emphasize the crowding-out effect of land use mismatches on industrial innovation talent. In addition, we have responded positively to the reasonable requests of firms and vigorously promoted the new modes of flexible and divided land grants. The allocation of industrial land needs to be more scientific. The availability of land resources for firms needs to be enhanced to ensure that firms have comparable land use and mortgages.

Third, we should explore ways to amplify the promotional effect of the new industrial land use policy on green innovation and cooperation among firms. Relying on higher plot ratios and diversified land use patterns, new industrial land can cluster market and innovation players in different production segments, as well as various economic factor resources. This new agglomeration force contributes to the dissemination of knowledge and the acceleration of technological innovation. Government departments can consider actively developing and supplying supporting land for different purposes, such as land for laboratories in universities and incubators for innovation and entrepreneurship, centering on innovation cooperation among firms or innovation cooperation among industries, universities and research institutes. At the same time, government departments can also actively explore the construction of public service technology platforms, shared laboratories, or promote the sharing of key experimental instruments and equipment on new industrial land. They should actively incorporate technological innovation cooperation into the new industrial land use policy. Local governments must strengthen the positive impact of new industrial land use policies in green knowledge dissemination and technological innovation cooperation. Efforts should be made to promote the formation of closer green technology innovation platforms and networks among various subjects.

6.3 Limitations and future recommendations

Our results suggest that the implementation of new land use policy in areas with scarce industrial land resources is favorable to firms' green innovation. This study is important for a better understanding of China's development model. However, our study focuses on the impact of new land policy pilot cities on firms. We did not get data on firms' access to land for new uses. Therefore, our study still has some shortcomings. In the future, we believe that the impact of the new land policy on firms' innovative behavior can be further explored in the data on firms' access to land for new uses. The Chinese government already publishes detailed information on each land transaction in the land market. We are collecting information on these land transactions. It is possible to

put together information that identifies land purchased by firms and match each piece of land to a firm. In this way, future work can utilize more detailed land information to study the impact of the land market on various decisions made by firms. It will also be possible to explore the impact of firms acquiring land on neighboring firms. Land belongs to a resource of a fixed space. Firms operate on it, which is likely to produce space effects. Therefore, identifying the spillover effect of land resources is particularly important for the role of research on land reform. In addition, the spillover impact on suppliers and customers of firms that acquire new use land is also worth being explored. At present, scholars are increasingly concerned about the mutual influence of up and downstream firms in the supply chain. Various regions in China are actively building specialised industrial chains. They have built numerous industrial clusters and want upstream and downstream firms to cluster inside the same industrial parks. This brings about a very realistic problem that firms purchasing new use land will affect the operation of upstream and downstream firms. Therefore, we suggest using more detailed data of land transactions in future studies. At the same time, future studies should consider the spillover effects of land market reforms.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

ZG: Conceptualization, Formal Analysis, Methodology, Writing–original draft, Writing–review and editing. LC: Conceptualization, Methodology, Supervision, Writing–original draft, Writing–review and editing. XZ: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Investigating the nonlinear carbon reduction effect of AI: empirical insights from China's provincial level

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In the context of rapid advancement in automation and increasing global warming, understanding the impact of artificial intelligence (AI) on carbon emissions (CES) is a cutting-edge research topic. However, there is limited focus in existing research on the nonlinear carbon reduction effect (CRE) of AI. This paper first theoretically elaborates the dual impact mechanisms of AI on CES and illuminates the nonlinear carbon reduction mechanisms of AI. Then, this study employs panel data encompassing 30 Chinese provinces between 1997 and 2019 to empirically test the net effect of AI on CES and the nonlinear carbon reduction effect of AI through econometric models. The results are as follows: first, although AI can both reduce and increase CES, AI primarily helps decrease CES. This conclusion holds true even after considering robustness, endogeneity, and spatial heterogeneity. Secondly, relative to the central and western regions, AI has significant achievement in reducing carbon intensity and *per capita* CES in the eastern region. However, there is still room for improvement in terms of reducing the total CES in the eastern region. Thirdly, improving the AI development level (AIDL) can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Lastly, even if the AIDL remains constant, improving the level of marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. To fully harness the potential of AI for green development, concerted efforts should be directed towards enhancing the innovation and application of AI technologies with carbon reduction potential.

KEYWORDS

artificial intelligence, carbon emissions, carbon reduction effect, nonlinear characteristic, China

1 Introduction

Climate change, primarily attributed to carbon emissions (CES) resulting from human activities, has exerted a significant and detrimental impact on human survival and development (Zhang W. et al., 2022; Li et al., 2022; Wang et al., 2023b). The global community has consequently made decarbonization a key priority (Vorozheykina, 2022). Additionally, artificial intelligence (AI) has emerged as one of the most eagerly anticipated technologies. In this context, the impact of AI on CES has become a focal point of scholarly inquiry. Extensive research has highlighted the dual nature of AI's impact on CES,

encompassing both reduction and increase (Chen P. et al., 2022; Kaack et al., 2022; Cowls et al., 2023). Hence, the questions arise: Will the development of AI ultimately result in a carbon reduction effect (CRE)? Does the CRE of AI exhibit a nonlinear characteristic? Resolving these inquiries holds substantial theoretical and practical significance. Regrettably, existing studies have not fully addressed the aforementioned questions.

To address these gaps, firstly, this paper will theoretically analyze the carbon reduction mechanisms and carbon increase mechanisms of AI, and will point out that AI will ultimately reduce CES. Secondly, from a theoretical perspective, the paper will illustrate that the improvement of AI development, marketization, human capital, digital infrastructure, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Finally, this paper will empirically test the aforementioned theoretical perspectives using provincial panel data from China spanning from 1997 to 2019 and econometric models.

This paper makes significant contributions in three key points. Firstly, this paper will provide a unified framework for understanding of the impact of AI on CES. Existing research has primarily focused on analyzing the carbon reduction mechanisms and CRE of AI. While some studies also consider the carbon increase mechanisms and carbon increase effect of AI, there is limited research that systematically analyzes both the carbon reduction and increase mechanisms within a unified framework. Moreover, there is relatively little discussion in existing research regarding the crucial question of whether the CRE or the carbon increase effect of AI is greater. This paper, at the theoretical level, systematically analyzes both the carbon reduction and increase mechanisms of AI and empirically confirms the viewpoint that the CRE of AI is greater than the carbon increase effect. Secondly, this paper will contribute to a deeper understanding of the CRE of AI. Although existing research indicates that AI can reduce CES, there is limited analysis of the nonlinear characteristic of the CRE of AI. This paper, both theoretically and empirically, confirms that the improvement of AI development, marketization, human capital, digital infrastructure, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Thirdly, our research employs more refined methodologies to gauge the AI development level (AIDL). Measuring the AIDL represents a contemporary research Frontier. Current research primarily relies on industrial robot data and AI patent data to assess AIDL. However, industrial robot data predominantly reflects the extent of intelligent manufacturing rather than offering a holistic evaluation of AIDL. Although AI patent data can offer a holistic evaluation of AIDL, previous studies have employed a limited set of keywords in their searches for AI patents. In contrast, our paper measures AIDL using a broader array of AI-related keywords.

The rest of our study is outlined as follows: Section 2 provides a systematic literature review. Section 3 introduces the theoretical framework and research hypotheses. Section 4 introduces the empirical models and details the sources of data. Section 5 provides the empirical results and discussion. Section 6 provides the conclusions, implications, and limitations.

2 Literature review

The literature pertinent to our research can be categorized into three key domains: the measurement of carbon emission level (CEL) and the influencing factors of CES, the measurement of AIDL, and the impact of AI on CES.

2.1 The measurement of CEL and the influencing factors of CES

Currently, there are four proxy variables employed to characterize CEL. The initial proxy variable is the total CES (Wang et al., 2023b; Ding et al., 2023; Tang and Yang, 2023). Some scholars have developed carbon emission databases containing total CES data (Shan et al., 2020). Furthermore, a positive correlation exists between satellite light data and total CES, prompting some scholars to derive total CES based on satellite light data (Meng et al., 2023). The second proxy variable pertains to carbon density, quantified as the ratio of total CES to GDP (Chen P. et al., 2022; Li et al., 2022; Tang and Yang, 2023), the ratio of total CES to the value added by the secondary industry (Yi et al., 2022), or the ratio of industry energy-related CES to industry sales value (Liu et al., 2022). The third proxy variable relates to *per capita* CES, determined by dividing total CES by the year-end population (Wang et al., 2023b; Tang and Yang, 2023). The fourth proxy variable is carbon emission performance, a measure that considers both economic development and total CES. Typically, it is assessed using a Data Envelopment Analysis (DEA) model featuring multiple input and output indicators (Zhang W. et al., 2022).

Existing research indicates that numerous factors can influence CES. For example, economic development, *per capita* income, population size, technological advancement, green technology innovation, openness, urbanization, industrial concentration, industrial upgrading, energy regulations, energy demand, energy consumption, energy intensity, energy prices, energy structure, energy efficiency, energy innovations, human capital, carbon taxation, financial development, transportation infrastructure, environmental regulation, marketization, green total factor productivity (GTFP), working hours, digital economy, and AI can influence CES (Chen Y. et al., 2022; Zhang X. et al., 2022; Li et al., 2022; Yi et al., 2022; Wang et al., 2023b; Ding et al., 2023; Meng et al., 2023; Tang and Yang, 2023; Yanzhe and Ullah, 2023).

2.2 The measurement of AIDL

Given the rapid development, extensive application, and the challenge of defining precise boundary and composition for AI, an ongoing debate persists regarding the measurement of AIDL (Damioli et al., 2021; Bianchini et al., 2023). Consequently, a consensus on the measurement of AIDL remains elusive. Presently, there are five proxy variables utilized to gauge AIDL. The first proxy variable is the frequency of AI-related terms appearing in the reports of publicly listed companies (Zhang W. et al., 2022) or in the annual government work reports (Tang and Yang, 2023). The second proxy variable is the industrial robot data

sourced from the International Federation of Robotics (IFR). This encompasses metrics such as the increment of industrial robots (Li and Tian, 2023), the increment of industrial robots per worker (Chen Y. et al., 2022), the stock of industrial robots (Zhang X. et al., 2022; Liu et al., 2022; Wang et al., 2023b; Li and Tian, 2023), the stock of industrial robots per unit of GDP (Li et al., 2022), the stock of industrial robots per worker (Chen P. et al., 2022; Chen et al., 2022 Y.; Li et al., 2022; Lv et al., 2022; Vorozheykina, 2022; Yang and Shen, 2023), and the adjusted penetration of industrial robots (Acemoglu and Restrepo, 2020; Chen Y. et al., 2022). The third proxy variable relates to the number of AI patents (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). The fourth proxy variable involves AI-related research paper counts (Li et al., 2022). The fifth proxy variable employs an AI Index (Ding et al., 2023; Maslej et al., 2023), typically exemplified by Stanford University's AI Index (Maslej et al., 2023).

2.3 The impact of AI on CES

Extensive research has highlighted the dual nature of AI's impact on CES, encompassing both reduction and increase (Chen P. et al., 2022; Kaack et al., 2022; Cowls et al., 2023). On the one hand, AI has the potential to reduce CES through various pathways. AI can reduce CES by fostering green technology innovation, improving energy efficiency, and driving industrial upgrading (Elnour et al., 2022b; Himeur et al., 2022; 2023; Ding et al., 2023). The deployment of industrial robots can diminish CES by promoting green technology innovation, optimizing the industry structure, enhancing digital infrastructure, improving GTFP, lowering energy intensity, driving technological innovation, promoting research and development investment, encouraging manual labour substitution, saving work time, and promoting green employment (Chen P. et al., 2022; Chen et al., 2022 Y.; Elnour et al., 2022a; Li et al., 2022; Meng et al., 2022; Wang et al., 2023b; 2024; Li and Tian, 2023).

On the other hand, AI can also contribute to a surge in CES through various channels. First, the operation of computationally intensive industrial robots will consume substantial energy and will generate CES (Wang et al., 2023b). Training and deploying large AI models, such as ChatGPT, can generate substantial CES (An et al., 2023). Second, in addition to being responsible for the CES generated during the operational phase, AI devices should also share responsibility for the embodied emissions resulting from other stages of its life cycle, including the raw material extraction phase, manufacturing phase, transportation phase, and hardware disposal phase (Kaack et al., 2022; Wu et al., 2022; Cowls et al., 2023). Third, the digital infrastructures supporting AI development have significantly contributed to increased CES by increasing energy consumption (Tang and Yang, 2023). Last, AI's capacity to enhance production and consumption efficiency can result in a rebound effect, leading to increased production and consumption level and consequently, elevated CES (Kaack et al., 2022).

The dual nature of AI's impact on CES sparks ongoing debate regarding the net effect of AI on CES. Presently, there exist three main perspectives regarding this point. The first perspective contends that the net effect of AI on CES is negative. This perspective has been substantiated by research conducted at various levels, including the city (Chen P. et al., 2022; Zhang W. et al., 2022; Wang et al., 2023b), provincial (Wang et al., 2023a; Ding et al., 2023), manufacturing industry (Liu et al., 2022; Li and Tian, 2023), and national (Chen Y. et al., 2022; Li et al., 2022) levels. Furthermore, the CRE of AI demonstrates spatial heterogeneity (Chen P. et al., 2022; Chen et al., 2022 Y.; Zhang W. et al., 2022; Li et al., 2022; Meng et al., 2022; Wang et al., 2023b; 2024; Ding et al., 2023), time heterogeneity (Liu et al., 2022), industry heterogeneity (Li et al., 2022; Liu et al., 2022; Li and Tian, 2023; Wang et al., 2024), and spatial spillover (Zhang W. et al., 2022; Ding et al., 2023) characteristics. Some scholars have also pointed out that the intensity of the CRE of AI is closely related to the scale of high-skilled labor, digital endowment, and the intensity of environmental regulation (Wang et al., 2024). The second viewpoint holds that the net effect of AI on CES is positive. This perspective has been substantiated by certain studies (Bianchini et al., 2023; Tang and Yang, 2023). For example, some scholars have suggested that the carbon increment effect of AI is weaker in regions with large green technology endowments (Bianchini et al., 2023). The third perspective considers the net effect of AI on CES to be uncertain. Some scholars have proposed that estimating the overall immediate impact of AI on CES is exceedingly challenging due to the absence of data on the deployment rate of AI, the diversity of application areas, and the lack of precise procedures to attribute emissions effect to AI usage (Kaack et al., 2022). Some scholars have proposed that the development of AI does not necessarily lead to an immediate carbon emission effect, and AI can only reduce carbon emissions in the industrial sector when the level of intelligence reaches a certain threshold (Wang et al., 2024). Some scholars have also proposed that the impact of industrial robots on CES exhibits an inverted U-shaped relationship (Liu et al., 2024).

In summary, existing research has not systematically analyzed the impact mechanisms and effects of AI on CES. There is a shortfall in revealing the nonlinear CRE of AI and precisely measuring the AIDL. The main purpose of this paper is to address these gaps by utilizing provincial panel data from China.

3 Theoretical analysis and hypotheses development

3.1 The net effect of AI on CES

AI can both reduce and increase CES. On the one hand, AI can reduce CES. Firstly, AI can play a pivotal role in guiding scientists, governments, and individuals to mitigate CES (Yi et al., 2022; Al-Nefaie and Aldhyani, 2023; Hu and Man, 2023; Nassef et al., 2023; Zadmirzaei et al., 2023; Zhao et al., 2023). Secondly, AI assumes a crucial role in promoting the innovation, dissemination, and adoption of green technologies (Chen P. et al., 2022; Li et al., 2022), thereby reducing CES. Thirdly, AI, which plays a crucial role in accelerating the shift of energy supply structure and energy consumption structure from a high CES scenario to a low CES scenario, is effective in mitigating CES (Chen Y. et al., 2022; Yi et al., 2022). Fourthly, AI contributes to CES reduction by facilitating the industrial structure with high CES transfer to the industrial structure with low CES (Chen P. et al., 2022; Ding et al., 2023). Fifthly, AI can enhance energy efficiency and GTFP (Paryanto et al., 2015), thereby

mitigating energy consumption and CES. Sixthly, AI contributes to CES reduction by reducing trade-related costs and enhancing openness, because enhanced openness can attract foreign enterprises with advanced green technologies and management practices. Lastly, AI plays a vital role in carbon reduction by enhancing the efficiency of carbon capture (Priya et al., 2023).

On the other hand, AI can also increase CES. Firstly, AI system, including AI models and AI devices, is carbon-intensive due to its heavy energy reliance, continuous upgrading, and widespread utilization (Strubell et al., 2019; Kaack et al., 2022; Bianchini et al., 2023; Bieser et al., 2023; Cowls et al., 2023; Jean-Quartier et al., 2023). Secondly, AI has the potential to impede the transition to a more sustainable energy structure, consequently contributing to increased CES. For instance, oil companies can utilize AI to extract and sell oil and gas more efficiently, which could hinder the energy structure transformation. Thirdly, AI may lead to a rebound effect in production and consumption, consequently resulting in increased CES (Huang et al., 2022; Kaack et al., 2022). Lastly, AI can potentially contribute to increased CES by enhancing openness and expanding the scale of trade. Drawing upon the above, this paper proposes the following hypothesis:

Hypothesis 1: Although AI can exert both positive and negative impact on CES, but the CRE of AI is greater, and the net effect is a reduction in CES.

3.2 The nonlinear CRE of AI

The nonlinear CRE of AI primarily stems from two aspects. On the one hand, change in the AIDL can affect the marginal CRE of AI, thereby leading to a nonlinear CRE of AI. Data, computational infrastructure, and algorithms constitute the pivotal elements of the AI system. Unlike other inputs, data often yields increasing marginal return, thereby leading to an increasing marginal CRE of AI and a nonlinear CRE of AI. For example, as the scale of data grows, AI models trained on data can become more precise in predicting CES and can offer more possibilities to promote carbon reduction. Some scholars have observed an increasing positive marginal effect of intelligent manufacturing on industrial GTFP (Yang and Shen, 2023). Therefore, this paper proposes the following hypothesis:

Hypothesis 2: The enhancement of AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI.

On the other hand, variations in other factors that facilitate the innovation and implementation of AI technologies can also impact the marginal CRE of AI, thereby leading to a nonlinear CRE of AI. Firstly, change in the level of marketization can impact the marginal CRE of AI and lead to a nonlinear CRE of AI. Increased marketization can enhance the ability to optimize resource allocation and provide more opportunities in the market to unlock the business potential of technologies (Yi et al., 2022). Consequently, a higher degree of marketization encourages the innovation and application of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Secondly, change in the level of human capital can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. AI comprises a complex technological ecosystem. Undoubtedly, the innovation and application of AI technologies pose substantial challenges. Thus, a higher level of human capital enables a more effective identification, innovation, absorption, and application of AI technologies, drawing upon prior relevant knowledge, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Thirdly, change in the level of digital infrastructures can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. Data is pivotal in both the development and application of AI technologies. A higher level of digital infrastructures can enhance the generation, collection, storage, transmission, and analysis of valuable data. Consequently, improved digital infrastructures foster the advancement and utilization of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Fourthly, change in the level of economic development can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. Greater economic development will amplify the capacity and demand for AI products and services. This, in turn, promotes the innovation and application of AI technologies, further magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Fifthly, change in the level of openness can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. A higher level of openness translates to more opportunities for acquiring new knowledge. Consequently, greater openness facilitates the identification, innovation, absorption, and application of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Lastly, change in the level of government intervention can influence the marginal CRE of AI and lead to a nonlinear CRE of AI. AI is recognized as a strategic technology, prompting many countries to implement policies aimed at fostering its innovation and application. Therefore, a higher level of government intervention accelerates the pace of innovation and application of AI technologies, thereby magnifying the marginal CRE of AI and leading to a nonlinear CRE of AI. Drawing upon the above, this paper proposes the following hypothesis:

Hypothesis 3: The improvement of marketization, human capital, digital infrastructures, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI.

4 Models and data

4.1 Models

This paper will employ the following model to test whether the net effect of AI on CES is negative (Li et al., 2022):

$$\begin{aligned} CEL_{it} = {} & \alpha_0 + \alpha_1 AIDL_{it} + \alpha_2 lnpgdp_{it} + \alpha_3 gover_{it} + \alpha_4 lnfdi_{it} \\ & + \alpha_5 lnindus_{it} + \alpha_6 lndroad_{it} + \alpha_7 urban_{it} + \alpha_8 lngreen_{it} \\ & + \alpha_9 estruc_{it} + \alpha_{10} higher_{it} + \alpha_{11} gtfp_{it} + \alpha_{12} lnenergy_{it} \\ & + \omega_i + \omega_t + \omega_{it} \end{aligned} \quad (1)$$

where, i represents the province, and t denotes the year. CEL_{it} represents the carbon emission level. $AIDL_{it}$ denotes the AI development level. $lnpgdp_{it}$, $gover_{it}$, $lnfdi_{it}$, $lnindus_{it}$, $lndroad_{it}$, $urban_{it}$, $lngreen_{it}$, $estruc_{it}$, $higher_{it}$, $gtfp_{it}$, and $lnenergy_{it}$ are the control variables, and these variables represent economic development level, government intervention level, openness level,

TABLE 1 The variable symbols and measurement methods.

Variables	Symbols	Measurement methods
CEL	*lncb*	Natural logarithm of total CES (tons) (Tang and Yang, 2023)
	lndcb	Natural logarithm of the ratio of total CES to real GDP (tons/100 million CNY) (Tang and Yang, 2023)
	lnpcb	Natural logarithm of the ratio of total CES to the year-end population (tons/10,000 people) (Tang and Yang, 2023)
AIDL	*lnAI*	Natural logarithm of the quantity of AI patents (count) (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023)
	lnstock	The operational stock of industrial robots (Chen et al., 2022b; Li et al., 2022; Yang and Shen, 2023)
	lninstall	The increment of industrial robots (Chen et al., 2022b; Li et al., 2022; Yang and Shen, 2023)
Economic development level	*lnpgdp*	Natural logarithm of real *per capita* GDP (CNY *per capita*) (Tang and Yang, 2023)
Government intervention level	*gover*	The proportion of government expenditure in GDP (%) (Zhang et al., 2022a)
Openness level	*lnfdi*	Natural logarithm of FDI (100,000 CNY) (Wang et al., 2023b)
Industrial scale	*lnindus*	Natural logarithm of the quantity of employees in the secondary industry (10,000 employees) (Liu et al., 2022)
Transportation development level	*lndroad*	Natural logarithm of the density of roads and railways (miles per square kilometre) (Chen et al., 2023)
Urbanization level	*urban*	Proportion of construction land area to the total area (%) (Li et al., 2022)
Green technological innovation level	*lngreen*	Natural logarithm of the quantity of granted green patents (count) (Zhang et al., 2022a; Yi et al., 2022)
Energy structure	*estruc*	The ratio of coal consumption to total energy consumption (%) (Yi et al., 2022)
Industrial structure upgrading	*higher*	The ratio of value-added in the tertiary industry to that in the secondary industry (%) (Meng et al., 2023)
Green total factor productivity	*gtfp*	Measured using a global super-efficiency SBM model (Li et al., 2022)
Energy consumption level	*lnenergy*	Natural logarithm of total energy consumption (tons of standard coal) (Wang et al., 2023b)
Marketization level	*lnmarket*	Natural logarithm of the marketization index (Yi et al., 2022)
Human capital level	*hcapital*	Average number of college students per 10,000 population
Digital infrastructure level	*digital*	Mobile phone exchange capacity per 10,000 people

industrial scale, transportation development level, urbanization level, green technological innovation level, energy structure, industrial structure upgrading, green total factor productivity, and energy consumption level, respectively. The literature basis for selecting these control variables and the measurement methods for the CEL, the AIDL, and the control variables are presented in Table 1. α_0 is the intercept term. ω_i, ω_t and ω_{it} are the province fixed effect, the time fixed effect, and the random error term, respectively. The coefficient of AI is negative, indicating that the net effect of AI on CES is negative.

As depicted in Table 1. To demonstrate the robustness of the empirical results, this article will adopt three methods to measure the CEL in the empirical analysis.

As shown in Table 1. To demonstrate the robustness of the empirical results, this paper will also adopt three methods to measure the AIDL in the empirical analysis. First, this study will use the number of AI patents to characterize the AIDL. Several studies have chosen the quantity of AI patents (lnAI) to characterize the AIDL (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). However, identifying AI patents is not a straightforward task, as there is no unified criterion for their identification, unlike green patents. To address this challenge, most studies begin by selecting keywords related to AI and then extract the quantity of AI patents from the patent database using a keyword-matching approach (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). In this paper, we will also extract the quantity of AI patents from the patent database based on a keyword-matching approach. Table 2 shows the keywords related to AI, drawing from existing studies and the AI category (Damioli et al., 2021; Yang, 2022; Bianchini et al., 2023). In comparison with previous research, this paper adopts a more extensive list of AI-related keywords and further categorizes them into hardware, software, and application layers.

TABLE 2 AI-related keywords for extracting the number of AI patents.

AI	AI-related keywords
Hardware layer	intelligent processing unit, intelligent processor, inference chip, intelligent chip, AI chip, neural network chip, brain-like chip, accelerator, acceleration processor, acceleration chip, hard acceleration, acceleration core, acceleration unit, smart sensor, application-specific integrated circuit, field programmable gate array, graphics processor, image signal processor, neural processing unit, tensor processor, tensor processing unit, data processor, data processing unit, integrated processing unit, collaborative processing unit, mass processor, deep learning processor, edge computing
Software layer	natural language, computer vision, machine vision, augmented reality, AR, image recognition, speech recognition, voiceprint recognition, object tracking, speech processing, sentiment analysis, speaker recognition, scene understanding, machine translation, speech synthesis, information extraction, biometrics, face recognition, iris recognition, video recognition, pattern recognition, predictive analytics, semantic, speech-to-speech, text-to-speech, character recognition, text recognition, machine learning, supervised learning, support vector machines, biological heuristic methods, genetic algorithms, swarm intelligence, classification and regression trees, decision trees, learning algorithms, deep learning, instance learning, multitasking learning, reinforcement learning, rule learning, transfer learning, fuzzy logic, expert system, logic programming, neural network, CNN, latent representation, probabilistic graphical model, probabilistic reasoning, descriptive logic, generative adversarial network, multilayer perception, MLP, hidden Markov model, HMM, clustering, random forest, stochastic method, probabilistic method, feature selection, Bayesian network, gradient lift, gradient descent, GBDT, data mining, learning model, self-learning, objective function, logistic regression, latent Dirichlet distribution, cognitive computing, artificial intelligence, AI, artificial reality, automatic classification, Bayesian model, big data, computational neuroscience, data science, evolutionary computing, gesture recognition, holographic display, knowledge representation, machine intelligence, machine-to-machine, mixed reality, neuro-linguistic programming, object detection, predictive model, probabilistic model, statistical learning, voice recognition, virtual reality, VR, unsupervised learning, path planning, knowledge graph, swarm intelligence, intelligent cloud, intelligent speech, quantum computing, cloud computing, image recognition, federated learning
Application layer	smart industry, smart factory, smart manufacturing, smart energy, smart water affairs, smart detection, smart inspection, smart monitoring, smart city, smart transportation, smart network, smart traffic management, smart bus, intelligent parking, unmanned driving, autonomous driving, intelligent medical, clinical decision support system, intelligent medical case, intelligent finance, intelligent marketing, smart logistics, smart education, smart agriculture, smart farming, smart greenhouses, smart irrigation, smart weather, smart house, smart life, smart security, human-computer interaction, smart robot, smart search, intelligent recommendation, virtual assistant, intelligent assistant, chat machine, self-driving car, humanoid robot, internet of things, robot, smart glasses, unmanned aerial vehicle, unmanned aerial system

Second, we will use both the cumulative inventory of operational industrial robots and the growth in the quantity of industrial robots to measure the AIDL. Following the methodology of related studies (Chen Y. et al., 2022; Li et al., 2022; Yang and Shen, 2023), we can obtain the cumulative inventory of operational industrial robots (*lnstock*) and the growth in the quantity of industrial robots (*lninstall*) at the provincial level, which can be measured as follows:

$$robot_{pt} = \sum_{j}\left(\frac{labour_{pjt}}{labour_{jt}} \times robot_{jt}\right) \tag{2}$$

where, p represents the province. t denotes the year. j is the type of industry. $robot_{pt}$ denotes the cumulative inventory of operational industrial robots or the growth in the quantity of industrial robots. $labour_{pjt}$ and $labour_{jt}$ represent the labour force quantity. $robot_{jt}$ is the operational stock of industrial robots or the increment of industrial robots.

This paper will employ the following model to test whether the improvement of AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI (Li et al., 2022):

$$\begin{aligned} CEL_{it} = {} & \lambda_0 + \lambda_1 AIDL_{it} + \lambda_2 AIDL_{it}^{\ 2} + \lambda_3 lnpgdp_{it} + \lambda_4 gover_{it} \\ & + \lambda_5 lnfdi_{it} + \lambda_6 lnindus_{it} + \lambda_7 lndroad_{it} + \lambda_8 urban_{it} \\ & + \lambda_9 lngreen_{it} + \lambda_{10} estruc_{it} + \lambda_{11} higher_{it} + \lambda_{12} gtfp_{it} \\ & + \lambda_{13} lnenergy_{it} + \xi_i + \xi_t + \xi_{it} \end{aligned} \tag{3}$$

where, $AIDL_{it}^{\ 2}$ is the quadratic term of AIDL. The meanings of other variables are similar to that in Formula (1).

This paper will employ the following models to test whether the improvement of marketization, human capital, digital infrastructures, economic development, openness, and government intervention level can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI (Li et al., 2022), respectively:

$$\begin{aligned} CEL_{it} = {} & \gamma_0 + \gamma_1 AIDL_{it} + \gamma_2 lnpgdp_{it} + \gamma_3 gover_{it} + \gamma_4 lnfdi_{it} \\ & + \gamma_5 lnindus_{it} + \gamma_6 lndroad_{it} + \gamma_7 urban_{it} + \gamma_8 lngreen_{it} \\ & + \gamma_9 estruc_{it} + \gamma_{10} higher_{it} + \gamma_{11} gtfp_{it} + \gamma_{12} lnenergy_{it} \\ & + \gamma_{13} lnmarket_{it} + \gamma_{14} lnmarket_{it} \times AIDL_{it} + \tau_i + \tau_t + \tau_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} CEL_{it} = {} & \beta_0 + \beta_1 AIDL_{it} + \beta_2 lnpgdp_{it} + \beta_3 gover_{it} + \beta_4 lnfdi_{it} \\ & + \beta_5 lnindus_{it} + \beta_6 lndroad_{it} + \beta_7 urban_{it} + \beta_8 lngreen_{it} \\ & + \beta_9 estruc_{it} + \beta_{10} higher_{it} + \beta_{11} gtfp_{it} + \beta_{12} lnenergy_{it} \\ & + \beta_{13} hcapital_{it} + \beta_{14} hcapital_{it} \times AIDL_{it} + \delta_i + \delta_t + \delta_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} CEL_{it} = {} & \zeta_0 + \zeta_1 AIDL_{it} + \zeta_2 lnpgdp_{it} + \zeta_3 gover_{it} + \zeta_4 lnfdi_{it} \\ & + \zeta_5 lnindus_{it} + \zeta_6 lndroad_{it} + \zeta_7 urban_{it} + \zeta_8 lngreen_{it} \\ & + \zeta_9 estruc_{it} + \zeta_{10} higher_{it} + \zeta_{11} gtfp_{it} + \zeta_{12} lnenergy_{it} \\ & + \zeta_{13} digital_{it} + \zeta_{14} digital_{it} \times AIDL_{it} + \varepsilon_i + \varepsilon_t + \varepsilon_{it} \end{aligned} \tag{6}$$

$$\begin{aligned} CEL_{it} = {} & \eta_0 + \eta_1 AIDL_{it} + \eta_2 lnpgdp_{it} + \eta_3 gover_{it} + \eta_4 lnfdi_{it} \\ & + \eta_5 lnindus_{it} + \eta_6 lndroad_{it} + \eta_7 urban_{it} + \eta_8 lngreen_{it} \\ & + \eta_9 estruc_{it} + \eta_{10} higher_{it} + \eta_{11} gtfp_{it} + \eta_{12} lnenergy_{it} \\ & + \eta_{13} lnpgdp_{it} \times AIDL_{it} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} CEL_{it} = {} & \theta_0 + \theta_1 AIDL_{it} + \theta_2 lnpgdp_{it} + \theta_3 gover_{it} + \theta_4 lnfdi_{it} \\ & + \theta_5 lnindus_{it} + \theta_6 lndroad_{it} + \theta_7 urban_{it} + \theta_8 lngreen_{it} \\ & + \theta_9 estruc_{it} + \theta_{10} higher_{it} + \theta_{11} gtfp_{it} + \theta_{12} lnenergy_{it} \\ & + \theta_{13} lnfdi_{it} \times AIDL_{it} + \vartheta_i + \vartheta_t + \vartheta_{it} \end{aligned} \tag{8}$$

TABLE 3 The results of descriptive statistics and the data sources of variables.

Variables	Observations	Mean	Standard deviation	Min	Max	Data source
lncb	690	18.9381	1.0096	13.6048	21.2539	China Carbon Accounting Database (https://www.ceads.net.cn/data/)
lndcb	690	10.3258	0.7453	7.3874	12.3145	China Carbon Accounting Database (https://www.ceads.net.cn/data/)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnpcb	690	10.7881	0.7981	7.1371	13.0943	China Carbon Accounting Database (https://www.ceads.net.cn/data/)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnAI	690	4.0295	2.5475	0.0000	10.3975	PatentHub (https://www.patenthub.cn/search/advanced.html)
lnstock	420	7.3783	1.7594	2.6567	11.8745	International Federation of Robotics (https://ifr.org/)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						China Research Data Service Platform (https://www.cnrds.com/Home/Login)
lninstall	420	6.1720	1.6419	1.7267	10.2445	International Federation of Robotics (https://ifr.org/)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						China Research Data Service Platform (https://www.cnrds.com/Home/Login)
lnpgdp	690	9.6777	0.7764	7.7003	11.5619	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnindus	690	7.7405	1.1881	4.1225	10.2340	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lndroad	690	8.5143	0.9232	5.3192	9.9881	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
gover	690	0.2012	0.1048	0.0530	0.7583	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
urban	690	0.0157	0.0280	0.0001	0.1952	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lngreen	690	5.8767	1.9457	0.0000	10.4248	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
estruc	690	0.9629	0.3790	0.0248	2.4609	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
hihger	690	1.1230	0.5707	0.4346	5.2340	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
gtfp	690	0.3732	0.3023	0.1124	4.6188	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnfdi	690	11.1415	2.5600	0.4828	17.7481	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
lnenergy	690	18.1827	0.8339	15.1765	19.8411	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)

(Continued on following page)

TABLE 3 (*Continued*) The results of descriptive statistics and the data sources of variables.

Variables	Observations	Mean	Standard deviation	Min	Max	Data source
hcapital	690	0.0139	0.0080	0.0011	0.0389	State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
digital	570	1.0946	0.7146	0.0803	3.7877	China Research Data Service Platform (https://www.cnrds.com/Home/Login)
						EPS database (https://www.epsnet.com.cn/index.html#/Index)
						State Statistics Bureau (https://data.stats.gov.cn/easyquery.htm?cn=C01)
lnmarket	690	1.8155	0.3685	0.3097	2.4418	China Provincial Marketization Index Database (https://cmi.ssap.com.cn/)

$$CEL_{it} = \mu_0 + \mu_1 AIDL_{it} + \mu_2 lnpgdp_{it} + \mu_3 gover_{it} + \mu_4 lnfdi_{it} + \mu_5 lnindus_{it} + \mu_6 lndroad_{it} + \mu_7 urban_{it} + \mu_8 lngreen_{it} + \mu_9 estruc_{it} + \mu_{10} higher_{it} + \mu_{11} gtfp_{it} + \mu_{12} lnenergy_{it} + \mu_{13} gover_{it} \times AIDL_{it} + \nu_i + \nu_t + \nu_{it} \quad (9)$$

where, $lnmarket_{it}$, $hcapital_{it}$, and $digital_{it}$ denote marketization level, human capital level, and digital infrastructure level. The literature basis for selecting above three variables and the measurement methods for above three variables are presented in Table 1. The meanings of other variables are similar to those in Formula (1). The coefficient of AI and the interaction term are both significant and share the same sign, indicating that the moderating variable can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI.

4.2 Data sources

A balanced panel dataset comprising 30 Chinese provinces for the period spanning 1997–2019 has been used in this study. Tibet, Hong Kong, Macao, and Taiwan are excluded from the analysis because of data unavailability. Missing data has been imputed using the interpolation method. For all currency-measured variables, the influence of inflation has been removed by using the GDP index of each province, with the base period price level set at 1998. The natural logarithm has been applied to some variables to ensure data stability and address heteroscedasticity issues. Table 3 shows the results of descriptive statistics and the data sources of variables.

5 Results and discussion

5.1 The spatial and temporal characteristics of the development of AI in China

Figure 1 demonstrates the chronological evolution of the number of AI patents in China from 1997 to 2019. In Figure 1, we characterize the temporal evolution of AI patent counts in China during the study period using two indicators: the total number of AI patents per year and the average number of AI patents per province per year. Two significant observations can be made from Figure 1. First, both indicators show a growth trend, indicating that the number of AI patents in China has been increasing consistently. Second, the values of both indicators have shown an accelerated growth trend since 2012, especially after 2014, with a significantly faster growth rate. This is attributed to the breakthrough advancements made in AI technologies such as deep learning, image recognition, natural language processing, and intelligent chips during this period. For instance, in 2012, Google's deep learning algorithm achieved a breakthrough performance in the ImageNet image recognition competition. This demonstrates that the AI patent data used in this study can effectively capture the evolution of AI technology development. It further reinforces the scientific validity of the AI patent data employed in this research.

Table 4 presents the spatial distribution of the number of AI patents across China's provinces in certain years. From Table 4, it can be observed that the provinces with a high level of economic development and technological innovation capability, such as Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Guangdong, Henan, Hubei, Hunan, Shaanxi, Sichuan, and Chongqing, possess a larger number of AI patents. This indicates that AI technological innovation is closely related to the level of economic development and technological innovation capability.

5.2 Results of the AI's CRE test

5.2.1 Results of baseline regression

Table 5 shows the results based on Formula 1. Three findings can be obtained. First, it can be found from the model 5A-5C that when adopting different dependent variables, the AI coefficients are highly significant and exhibit negative values. The results imply that although AI can exert both positive and negative impacts on CES, the CRE of AI is more substantial. In other words, the net effect of AI on CES is negative, and the Hypothesis 1 can be supported. This finding aligns with the conclusion in existing research (Ding et al., 2023). Second, when replacing the core explanatory variable, related coefficients in model 5D-5I also exhibit negative values although some coefficients are insignificant. The results can provide support for Hypothesis 1 again. Third, the CRE of AI in model 5A-5C is greater than that in model 5D-5I. The results indicate that measuring the AIDL based on Formula 2 would underestimate the CRE of AI. Instead, employing the quantity of AI patents to gauge the AIDL can provide a more scientifically accurate

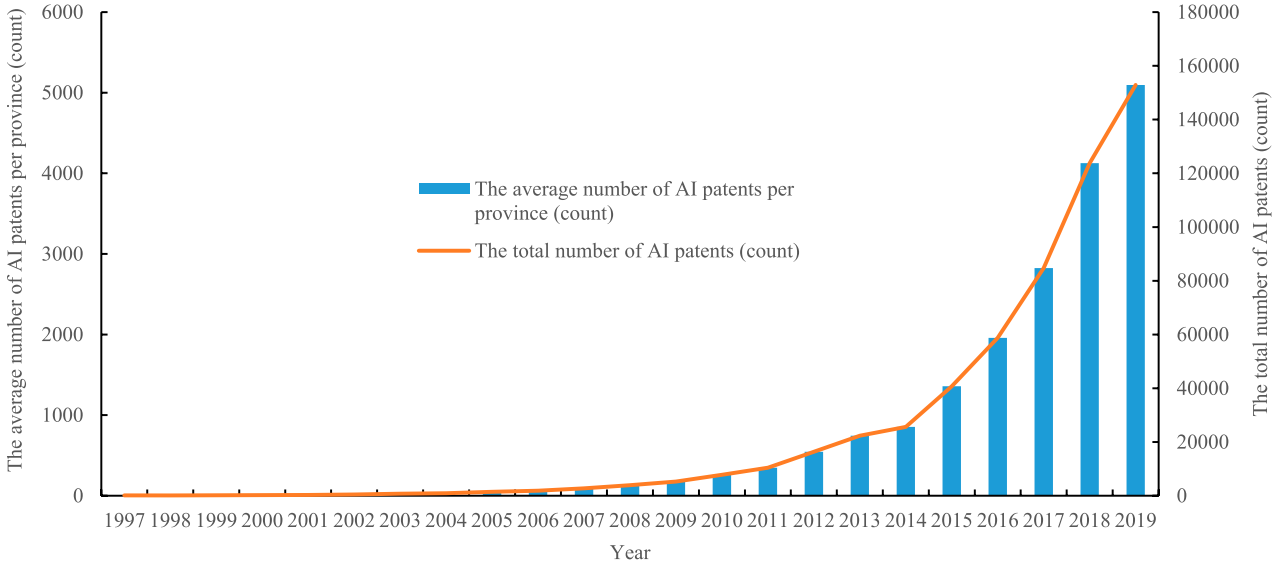


FIGURE 1
The chronological evolution of the number of AI patents in China from 1997 to 2019.

measurement of the AI's CRE. Therefore, in the following sections, we will continue our analysis by using AI patent data.

5.2.2 Results of endogenous processing

Endogeneity issue may be present in this study for several reasons. Firstly, there could be a reverse causality relationship between AI and CES. For instance, AI can reduce CES, and regions with higher CES may have a stronger incentive to adopt AI for carbon reduction. Secondly, errors may arise due to missing variables. Although the current model incorporates some control variables, certain factors influencing CES may not have been included. Lastly, measurement errors may exist in the model because some variables used in this study may not have been precisely measured due to data availability. Consequently, this paper aims to address the endogeneity problem using the instrumental variable (IV) method.

The IV chosen must exhibit a strong association with AI while being unrelated to the error term. In this research, we utilize a lagged phase of AI as the IV for endogeneity testing (Liu et al., 2022; Wang et al., 2023b). Table 6 presents the results of the endogeneity treatment. Model 6A details the first-stage empirical outcomes of the 2SLS method, and the second-stage empirical results provided in model 6B. Firstly, the null hypothesis regarding the IV's identifiability can be rejected because the Anderson canon. corr. LM statistic is significant. The null hypothesis of weak IV can also be rejected since the Cragg-Donald Wald F statistic is significant. Because the model 6A passes the Anderson-Rubin Wald test, the null hypothesis that the sum of endogenous regression coefficients equals zero can be rejected. The above tests indicate that the IV we selected is appropriate. Secondly, in model 6B, the AI coefficient is significantly negative, reaffirming AI's capacity to decrease CES. This outcome aligns with the results in Table 5. Thirdly, the results in model 6C and 6D are similar to the results in model 6B. The results imply that when adopting different dependent variables, the results of the endogeneity treatment are robust.

5.2.3 Results of spatial heterogeneity analysis

Variations in AIDL and CEL exist among different regions in China due to disparities in resource endowments, developmental phases, and national policies (Ding et al., 2023). To investigate whether there is spatial heterogeneity in the CRE of AI, this research classifies the 30 provinces into eastern, central, and western regions. Table 7 shows related results. Two findings can be obtained. Firstly, it is evident that when adopting different dependent variables, most of the coefficients of AI are highly significant and exhibit negative values although some of the coefficients of AI in the western region are insignificant. The results imply that the net effect of AI on CES is negative in three regions, reaffirming the validity of Hypothesis 1. This finding aligns with the conclusion of existing research (Ding et al., 2023). Secondly, the absolute value of the AI coefficient in model 7A is less than that in model 7B and 7C, the absolute value of the AI coefficient in model 7D is greater than that in model 7E and 7F, and the absolute value of the AI coefficient in model 7G is greater than that in model 7H, and 7I. The results indicate that, relative to the central and western regions, AI has significant achievement in reducing carbon intensity and *per capita* CES in the eastern region. However, there is still room for improvement in terms of reducing the total CES in the eastern region. The eastern region has been the most active in technological innovation in China, with a significant advantage in the innovation and application of AI technologies. Therefore, AI can effectively reduce carbon intensity and *per capita* CES in the eastern region. The eastern region has also experienced the fastest economic and population growth in China, leading to continuous growth in CES. Thus, AI has limited impact on reducing the total CES in the eastern region.

5.2.4 Results of time heterogeneity analysis

Figure 1 indicates that China has experienced rapid growth in AI patent counts since 2012. Given this, we hypothesize that there may be temporal heterogeneity in the impact of AI on CES in China. Therefore, we will use 2012 as a temporal dividing point to investigate the temporal heterogeneity of AI's influence on CES.

TABLE 4 The spatial distribution of the number of AI patents in China's provinces in some years.

Year provinces	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2006	1997
Beijing	21,756	15,462	11,662	8,372	5,946	4,510	3,564	2,893	2054	1,608	410	27
Tianjin	3,321	2,922	2,306	2018	1,257	737	600	479	285	223	61	2
Hebei	1811	1,659	1,054	906	490	306	260	187	86	94	13	2
Shanxi	738	538	342	245	171	133	118	84	46	26	7	1
Inner Mongolia	334	247	236	122	151	40	25	22	15	19	3	0
Liaoning	3,090	2,401	1862	1,422	1,241	768	659	425	392	283	105	5
Jilin	1,253	904	664	468	291	230	191	143	113	66	15	0
Heilongjiang	1803	1,479	1,396	1,017	855	546	540	371	258	217	57	8
Shanghai	9,980	7,021	5,612	3,763	2,579	1889	1,662	1,472	1,047	866	302	5
Jiangsu	18,029	15,027	9,949	7,450	5,531	3,817	3,612	2,566	1,364	872	130	2
Zhejiang	11,257	9,511	5,821	3,899	2,940	1712	1,591	1,210	751	580	110	8
Anhui	5,428	6,610	3,769	2,686	1,656	727	581	316	177	100	44	3
Fujian	3,703	3,440	2043	1,166	805	423	349	274	153	94	21	5
Jiangxi	1,228	938	607	438	255	120	111	70	44	48	6	0
Shandong	6,598	5,209	4,117	3,113	2,362	1,193	1,153	798	439	350	58	7
Henan	3,203	2,896	1833	1,041	803	362	328	259	141	87	16	5
Hubei	5,386	3,809	2,737	1,699	1,167	717	625	444	320	246	38	6
Hunan	2,988	2,622	1754	1,099	763	368	405	285	182	178	28	5
Guangdong	32,776	25,743	15,920	9,877	5,590	3,559	3,038	2,286	1,482	1,067	257	15
Guangxi	1,344	1,266	1,281	849	587	322	165	117	51	24	5	2
Hainan	217	175	110	68	61	21	12	12	8	3	0	0
Chongqing	2,935	2,289	1,689	1,329	823	500	401	258	174	131	33	1
Sichuan	6,054	6,218	4,008	3,011	2,278	1,083	908	523	319	211	39	3
Guizhou	743	603	384	281	265	88	60	35	22	12	3	1
Yunnan	1,034	800	498	334	231	122	110	65	51	45	11	2
Shaanxi	4,834	3,067	2,372	1,626	1,373	1,160	1,106	666	394	274	65	7
Gansu	494	350	236	156	140	84	111	64	27	23	6	0
Qinhai	99	65	91	84	6	10	5	2	1	3	0	0
Ningxia	189	250	180	109	47	19	16	8	8	1	0	0
Xinjiang	261	246	177	95	94	44	47	20	18	15	5	2

Table 8 presents the results of our model estimations. Two key findings emerge from Table 8. First, the coefficients for AI in models 8A-8F are all negative, indicating the consistent existence of a CRE attributed to AI development. Second, compared to the AI coefficients in models 8B, 8D, and 8F, the coefficients in models 8A, 8C, and 8E are not only highly significant but also have absolute values much larger than those in models 8B, 8D, and 8F. This suggests that the CRE of AI was greater during the period from 1997 to 2011 than during the period from 2012 to 2019. We can interpret this phenomenon from two perspectives. First, while AI development does lead to a CRE, this effect may require a longer period to be observable. Second, the rapid growth of AI may lead to carbon emission increases through increased electricity consumption, consumer rebound effect, and other channels, thereby reducing the CRE attributed to AI development.

5.3 Results of the nonlinear CRE test of AI

5.3.1 The nonlinear CRE of AI development

We can analyze the nonlinear impact of AI on CES based on the marginal effect of AI on CES, and the marginal effect of AI on CES can be estimated through the econometric model. Figure 2 shows related results based on Formula 3. Two findings can be obtained.

TABLE 5 The results of baseline regression.

Models variables	5A	5B	5C	5D	5E	5F	5G	5H	5I
	lncb	*lndcb*	*lnpcb*	*lncb*	*lndcb*	*lnpcb*	*lncb*	*lndcb*	*lnpcb*
lnAI	−0.0975***	−0.0896***	−0.0888***						
	(0.0256)	(0.0257)	(0.0257)						
lnstock				−0.0222	−0.0460*	−0.0459*			
				(0.0260)	(0.0269)	(0.0269)			
lninstall							−0.0249	−0.0421*	−0.0418
							(0.0246)	(0.0255)	(0.0255)
Observations	690	690	690	420	420	420	420	420	420
R^2	0.8459	0.6215	0.8255	0.8405	0.8278	0.8049	0.8407	0.8277	0.8047

*, **, *** represent the significance of parameter values at the 10%, 5%, and 1% levels, respectively. The same applies to the following tables. The values in parentheses represent t-values, and the same applies to the following tables. The econometric models include all the control variables listed in Equation (1), as well as provincial fixed effect and time fixed effect. The same applies to the following.

TABLE 6 The results of endogenous processing.

Models variables	6A	6B	6C	6D
	lnAI	*lncb*	*lndcb*	*lnpcb*
lnAI		−0.2965***	−0.2796***	−0.2746***
		(0.0646)	(0.0645)	(0.0646)
L.lnAI	0.3965***			
	(0.0347)			
Observations	660	660	660	660
R^2	0.9741	0.8305	0.5884	0.8116
Anderson canon. corr. LM statistic		112.92***	112.93***	112.92***
Cragg-Donald Wald F statistic		130.38***	130.38***	130.38***
Anderson-Rubin Wald test		23.00***	20.34***	19.50***

TABLE 7 The results of spatial heterogeneity analysis.

Models variables	Eastern region	Central region	Western region	Eastern region	Central region	Western region	Eastern region	Central region	Western region
	7A	7B	7C	7D	7E	7F	7G	7H	7I
	lncb	*lncb*	*lncb*	*lndcb*	*lndcb*	*lndcb*	*lnpcb*	*lnpcb*	*lnpcb*
lnAI	−0.0911***	−0.0972***	−0.0963*	−0.1074***	−0.0990***	−0.0886	−0.1131***	−0.1008***	−0.0803
	(0.0284)	(0.0364)	(0.0539)	(0.0284)	(0.0367)	(0.0542)	(0.0287)	(0.0367)	(0.0543)
Observations	253	184	253	253	184	253	253	184	253
R^2	0.9517	0.9380	0.8302	0.8966	0.8380	0.5555	0.9369	0.9353	0.8128

Firstly, As illustrated in Figure 2, the marginal effect of AI on CES consistently remains below zero and passes the significance test in each subplot. The results mean that the net effect of AI on CES is negative, and Hypothesis 1 can be supported again. Secondly, it can also be observed that with increasing AIDL, the absolute value of the marginal effect in each subplot grows. The results mean that the CRE of AI follows a nonlinear trend, and a higher AIDL correspond to a more significant CRE. In other words, improving the AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Thus, Hypothesis 2 can be supported.

TABLE 8 The results of time heterogeneity analysis.

Models variables	1997–2011	2012–2019	1997–2011	2012–2019	1997–2011	2012–2019
	8A	8B	8C	8D	8E	8F
	lncb	*lncb*	*lndcb*	*lndcb*	*lnpcb*	*lnpcb*
lnAI	−0.1270***	−0.0126	−0.1220***	−0.0215	−0.1211***	−0.0226
	(0.0334)	(0.0227)	(0.0334)	(0.0228)	(0.0335)	(0.0228)
Observations	450	240	450	240	450	240
R^2	0.7625	0.6035	0.4306	0.9010	0.7414	0.5616

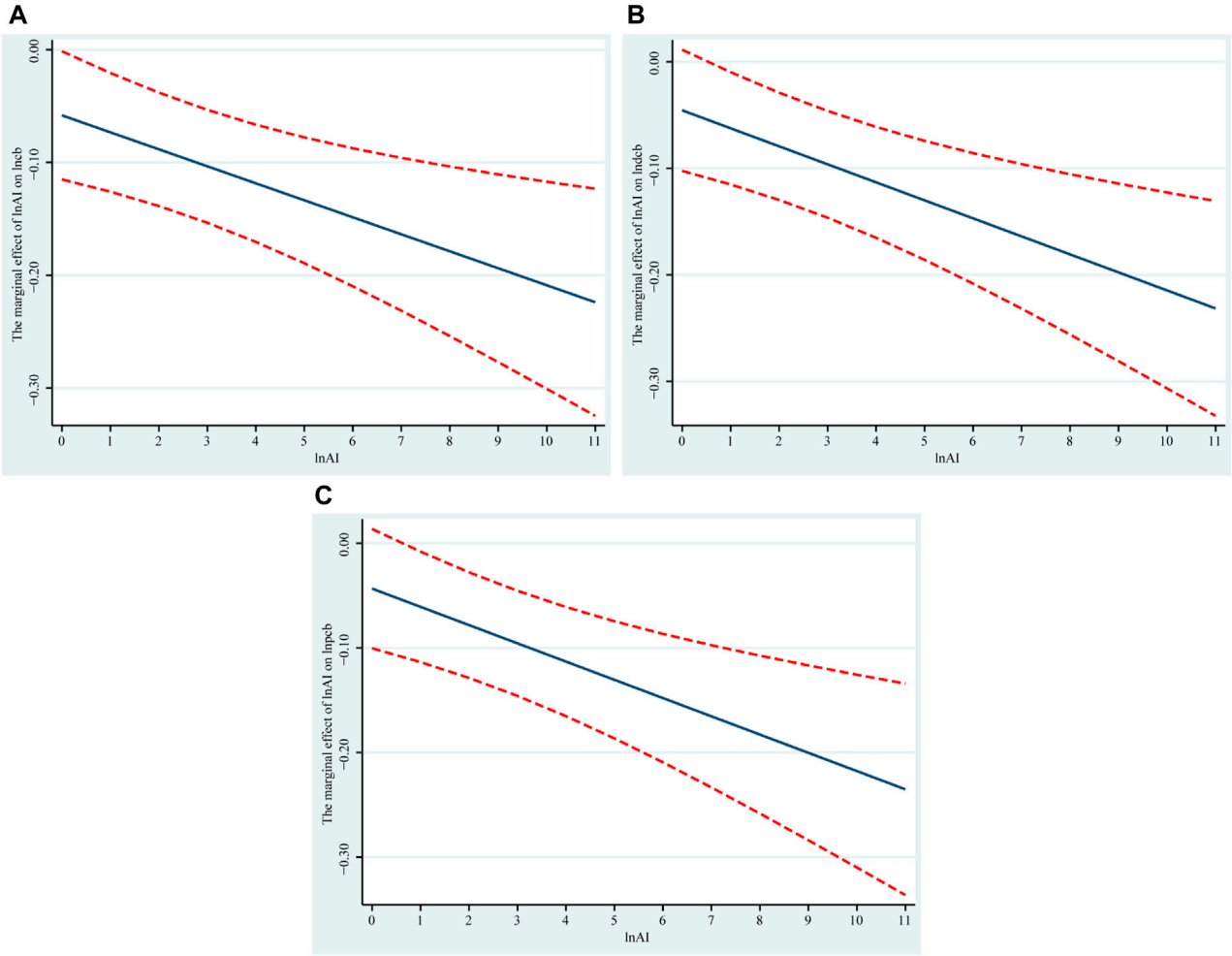


FIGURE 2
(A–C) respectively show the marginal effect of AI on the total CES, carbon intensity, and per capita CES. The blue line in each picture describes the trend of the marginal effect of AI on CES, and the red curve in each picture represents a 95% confidence interval.

5.3.2 The nonlinear CRE of AI due to changes in other factors

Even if the AIDL remains constant, improving the level of marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. Figure 3 presents related results based on Formula 4–9. Three valuable discoveries can be gleaned. Firstly, as illustrated in Figure 3, within the range of distributions for other factors, the marginal effect of AI on CES is significantly negative in each subplot. The results mean that the net effect of AI on CES is negative, and Hypothesis 1 can be supported again. Secondly, it can also be observed from

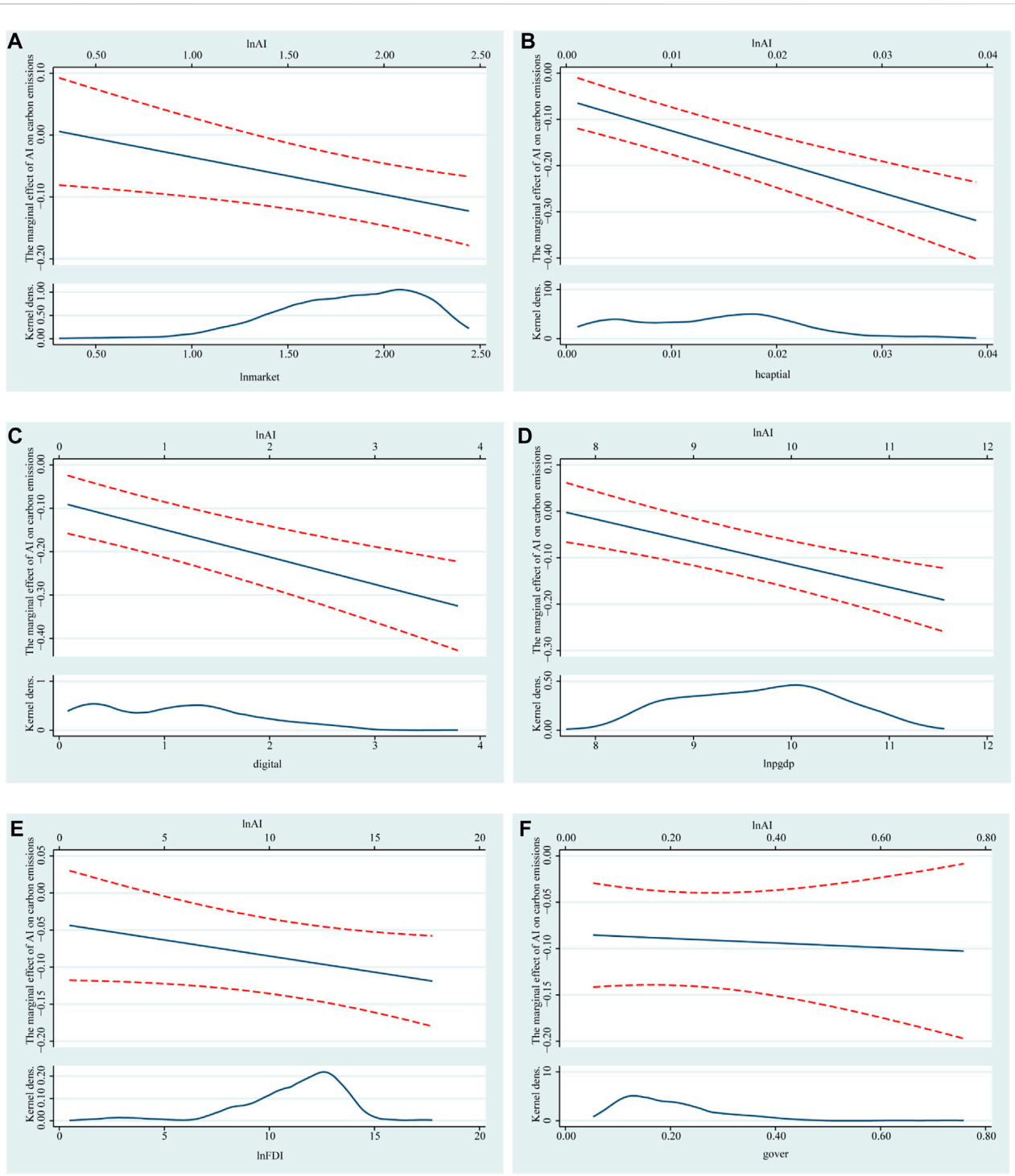


FIGURE 3
(A–F) respectively show the marginal effect of AI on carbon intensity when improving the level of marketization, human capital, digital infrastructure, economic development, openness, and government intervention. The blue line in each picture describes the trend of the marginal effect of AI on CES, and the red curve in each picture represents a 95% confidence interval. The bell-shaped curve in each picture depicts the distribution density of each variable.

Figure 3 that with the improvement in the level of these factors, the absolute values of the marginal effect of AI on CES demonstrate a rising pattern. The results imply that these factors can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Thus, Hypothesis 3 can be supported. Thirdly, it is important to highlight that the absolute values of the marginal effect of AI on CES in Figures 3B, C escalate more rapidly in comparison to Figure 3A, D–F. The outcomes imply that, among these factors under examination, human capital and digital infrastructure exert a more pronounced influence on magnifying the marginal CRE of AI. One possible reason is that innovation capability and data can play crucial roles in the innovation and application of AI

technologies. Compared to other factors, human capital serves as a significant support for technological innovation, and digital infrastructure is a critical foundation for data collection and processing.

5.4 Discussion

The above results can be discussed from two perspectives. The first perspective is the CRE of AI. The findings in this study indicate that AI can reduce CES, further confirming existing research viewpoints (Li et al., 2022). However, in contrast to existing research, this study also reveals that using the quantity of industrial robots to measure AIDL might underestimate the CRE of AI. The second perspective is the nonlinear CRE of AI. There has been limited focus in existing research on the nonlinear CRE of AI, whereas this paper places particular emphasis on this aspect. The results in this study suggest that increasing AIDL can amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. However, some scholars have proposed that the impact of industrial robots on CES exhibits an inverted U-shaped relationship (Liu et al., 2024). This result indicates that increasing AIDL will first raise the CES before eventually reducing CES. This result differs somewhat from the findings of this paper. The discrepancy may be due to the different methods used to measure AIDL in the two studies. Additionally, the results in this study suggest that even if the AIDL remains constant, changes in other factors can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. While existing research has indicated that enhancing technological absorption capacity can strengthen the CRE of AI (Li et al., 2022), this study suggests that there are additional factors, including marketization, human capital, digital infrastructure, economic development, openness, and government intervention, can amplify the marginal CRE of AI and lead to a nonlinear CRE of AI. Another novel finding relative to existing research is human capital and digital infrastructure can play the most significant role in amplifying the CRE of AI.

6 Conclusion and implications

6.1 Conclusion

The principal findings are as follows. Firstly, during the study period, the number of AI patents in China has shown a continuous growth trend. Since 2012, the growth of AI patents in China has accelerated, especially after 2014, when the number of AI patents in China entered a stage of rapid growth. Secondly, the provinces with a high level of economic development and technological innovation capability, such as Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Guangdong, Henan, Hubei, Hunan, Shaanxi, Sichuan, and Chongqing, possess a larger number of AI patents. Thirdly, although AI can exert both positive and negative impacts on CES, the CRE of AI is more substantial. This conclusion holds true even after considering robustness, endogeneity, and spatial heterogeneity. It is worth noting that employing the quantity of AI patents to gauge the AIDL can provide a more scientifically accurate measurement of the AI's CRE. Fourthly, relative to the central and western regions, AI has significant achievement in reducing carbon intensity and *per capita* CES in the eastern region. However, there is still room for improvement in terms of reducing the total CES in the eastern region. Fifthly, the CRE of AI was greater during the period from 1997 to 2011 than during the period from 2012 to 2019. Sixthly, improving the AIDL can magnify the marginal CRE of AI and lead to a nonlinear CRE of AI. Lastly, even if the AIDL remains constant, changes in other factors such as marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the marginal CRE of AI and lead to a nonlinear CRE of AI.

6.2 Implications

Based on the aforementioned conclusions, the following policy recommendations can be formulated. Firstly, facilitating AI technology innovation and leveraging AI for carbon reduction. AI can reduce CES, and improving the AIDL can magnify the marginal CRE of AI. Thus, the government should prioritize the development and utilization of AI. The enterprises should expedite the application of AI in various activities, including green energy production, the production of environmentally friendly products and services, carbon emission monitoring, carbon market trading, carbon sink management, and carbon capture technology innovation. Secondly, when assessing the CRE of AI, it is essential to utilize AI patent data and take into account the nonlinear CRE of AI. Employing the quantity of AI patents to gauge the AIDL can provide a more scientifically accurate measurement of the AI's CRE, and the CRE of AI exhibits a nonlinear characteristic. Thus, government and research institutions should take these influences into account when assessing the CRE of AI. Lastly, optimizing the economic and social environment is crucial to fully unleash the carbon reduction potential of AI. Even if the AIDL remains constant, changes in other factors such as marketization, human capital, digital infrastructure, economic development, openness, and government intervention can also amplify the CRE of AI. Thus, the government, in the process of utilizing AI for carbon reduction, should not confine its focus solely to the development of AI but also consider the impact of other factors. For example, the government and other relevant stakeholders should refine the marketization, human capital, digital infrastructure, economic development, openness, and government intervention to amplify the CRE of AI.

The main potential challenges and practical considerations in implementing the recommended policies are follows: first, promoting AI development requires ensuring data security. However, managing and protecting data securely is a challenge. The government can introduce strict data privacy and security laws to ensure the protection of data. Second, as AI technology becomes more advanced, ethical and moral questions arise, such as the use of AI in decision-making processes that affect human lives. The government should establish ethical frameworks and guidelines for AI use. This can ensure that AI is used responsibly and does not harm human interests.

6.3 Limitations

The limitations in this study are as follows. Firstly, the research conclusions are drawn based on Chinese data, and the processes of CES

and AI development in China may differ from other countries. Therefore, some research findings may not be applicable in other nations. Secondly, this paper only considers the roles of some factors, including marketization, human capital, digital infrastructure, economic development, openness, and government intervention, in amplifying the CRE of AI. There may be additional factors that can amplify the CRE of AI. Lastly, this article analyzes the impact of AI on CES using traditional panel econometric models. However, the impact of AI on CES may exhibit a spatial spillover effect, which suggests that the models used in this article still requires further improvement. In the future, a spatial panel econometric model will be employed to analyze the spatial spillover effect of AI on CES.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XW: Conceptualization, Data curation, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. TX: Data curation, Investigation, Software, Supervision, Validation, Visualization, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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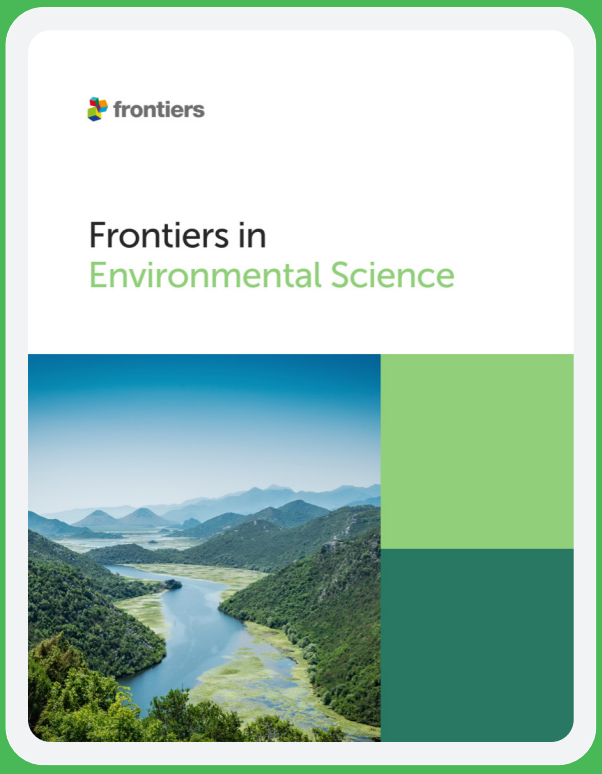
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