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Assessing the impacts of industrial digitization on synergistic effects of pollution and carbon reduction

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Synergistic effects of pollution and carbon reduction forms the core of ecological civilization construction in the “14th Five-Year Plan” period. Based on the panel data of prefecture-level cities in China from 2012 to 2023, first, the baseline regression model and the spatial panel Durbin model are used to discuss the direct and spatial effects of industrial digitization on synergistic effects of pollution and carbon reduction. Second, based on whole-process management, through the construction of a multiple intermediary effects model, the indirect impact of industrial digitization on synergistic effects of pollution and carbon reduction was explored. Third, heterogeneity tests from multiple perspectives are conducted. It is found that: (1) industrial digitalization has a remarkable positive impact on synergistic effects of pollution and carbon reduction, and there is a positive spillover effect. (2) Industrial digitization can indirectly promote synergistic effects of pollution and carbon reduction by strengthening “Source prevention” through renewable energy substitution, enhancing “process control” through green process innovation, and strengthening “end-of-pipe treatment” through environmental regulations. (3) Industrial digitization has a more remarkable promoting effect on synergistic effects of pollution and carbon reduction in energy basins, higher-level cities, large cities, and urban agglomerations. The research conclusions promote traditional industries to use the “digital cloud” to help the combined development of pollution and carbon reduction and offer a scientific foundation and theoretical reference for promoting industrial digitization to empower synergistic effects of pollution and carbon reduction.

KEYWORDS

industrial digitization, synergistic effects of pollution and carbon reduction, whole-process management, spatial spillover effect, indirect effect

1 Introduction

The report of the 20th National Congress, the 14th Five-Year Plan, and the Central Economic Work Conference was proposed to boost the synergistic effects of pollution and carbon reduction (SPC). The essence of SPC lies in the construction of a closed governance chain that links the whole process of “source–process–end-of-pipe”, and the “Pareto optimality” of pollution goals and carbon goals is achieved, which is the “Imperial sword” for building a “Beautiful China.” However, at this stage, China’s SPC is still in the exploratory period, and there are governance difficulties, such as cracking of pollution and carbon policies, and governance models of “pollution first and then treatment”; the governance mode is “heavy Andover source” and fragmented (Yi et al., 2022). In addition,

as a large developing industrialized country, China has long-term contradictions between economic development and environmental protection, and facing multiple pressures such as economic recovery, air quality standards, and the “dual carbon” goal, it needs to rearrange the joint reduction work of pollution and carbon, break through the governance dilemma, and promote higher-quality development of SPC as soon as possible.

The scale of industrial digitization (*INDIG*) is 4.5 times that of digital industrialization, and due to its effects, *INDIG* plays a more vital role in SPC. The proportion of *INDIG* in the digital economy has risen steadily, becoming an essential starting point for the digital economy to empower SPC (Lyu et al., 2023). On 30 August 2023, General Secretary Xi Jinping highlighted at the National Environment Protection Conference: “Deepen the application of digital technologies, build a beautiful digital governance system in China, and build a green and intelligent digital ecological civilization.” At present, China’s traditional industries urgently need to grasp the occasion of *INDIG*; rely on abundant human and capital resources; give full play to the advantages of “integration”; quickly cover all links such as economic input, production, and sales; and inject a steady stream of impetus into the “joint governance” of regional pollution and carbon. So, what is the impact of *INDIG* on SPC, and is there a spatial spillover effect? Which transmission mechanism of SPC is affected by *INDIG*? Under different transmission mechanisms, how does *INDIG* influence SPC? How to validly employ the indirect transmission mechanisms to improve SPC? These deserve to be explored. Based on the whole-process management and heterogeneity, the mechanism of *INDIG* on SPC is deeply researched, offering empirical basis for governments to bridge the “digital divide” and improve SPC in all aspects.

The potential marginal contributions are as follows: first, based on whole-process governance, it introduces renewable energy substitution (*RES*), green process innovation (*GPI*), and environmental regulations (*ER*) and employs a multiple mediating model to deeply probe the mechanism of how *INDIG* affects SPC. This provides theoretical support for deepening the understanding of how the digital economy can enhance SPC. Second, it depicts the spatial distribution of *INDIG* and SPC and employs the spatial panel Durbin model (*SPDM*) to test the spatial spillover effect of *INDIG* on SPC to provide empirical support for local governments to coordinate the policies for the transformation of *INDIG*. Third, the study explored the multiple heterogeneous impacts of *INDIG* on SPC, offering a reference for the government to enact and modify policies in a targeted manner.

2 Literature review

2.1 Research on *INDIG*

At present, the research on *INDIG* can be conducted from two dimensions: connotation and measurement methods. First, from the connotation of *INDIG*, Tapscott (1996) first put forward the term “digital economy.” The China Academy of Information and Communications Technology classified the digital economy into two major systems: digital industrialization (basic digital economy) and *INDIG* (integrated digital economy). This division has been widely accepted, and subsequent studies have further developed it on

this basis. Some scholars have found that in regions with increased *INDIG* compared to digital industrialization, the “substitution effect” generated by the digital economy exceeds the “carbon-friendly effect,” which effectively reduces carbon (Yang et al., 2023). Other scholars have deemed that *INDIG* refers to the process in which new-generation digital technologies empower traditional industries, enabling the digital upgrading, transformation, and reconstruction of all factors of the industrial chain and promoting the whole-round and whole-chain transformation of *INDIG* (Lu et al., 2025; Wang et al., 2022). Second, regarding the macro-level measurement of *INDIG*, some scholars have constructed an evaluation system that includes indicators such as industry output value and capital factors, focusing on reflecting the depth of digital penetration from the industrial level (Lu et al., 2025). At the micro level, some scholars have adopted text analysis methods. Using Python technology, they extracted keywords from corporate annual reports within a digital thesaurus to construct an enterprise-level *INDIG*, which makes up for the deficiency that macro data cannot easily capture the behaviors of micro subjects (Lyu et al., 2023; Liu and Hong, 2022). It is worth noting that studies have mostly centered on the digital economy and its two subsystems: *INDIG* and digital industrialization, exploring the contribution of the digital economy to social and economic development. However, specialized measurements targeting *INDIG* remain scarce (Han D. R. et al., 2023; Zhang et al., 2025).

2.2 Research on the environmental governance effect of the digital economy

At present, the study on the effect of *INDIG* on SPC still has no direct theoretical support, but the research on pollution and carbon control in the digital economy provides a reference. While the environmental consequences of the digital economy remain ambiguous (Ma et al., 2022), a growing number of studies affirm its positive role in environmental governance, especially its unique value in addressing the fragmented predicament of traditional environmental governance (Jiang et al., 2022). From the government, the issue of regulatory fragmentation in traditional environmental governance caused by departmental division and regional barriers can be effectively alleviated through use of digital technologies. The government has built a unified monitoring network using technologies to realize real-time sharing and dynamic tracking of cross-departmental and cross-regional pollution emission data, breaking down “data silos.” Meanwhile, supplemented by informal environmental regulatory methods such as online public participation (Liang and Li, 2023), it has constructed a collaborative governance pattern of “government-led and public-supervised.” By mitigating the efficiency losses arising from fragmented governance actors, the model markedly enhances the coherence and synergy of environmental governance. From the enterprise, digital technologies provide tool support for breaking the fragmentation of environmental governance in the industrial chain. Relying on digital technologies, enterprises have built a global database using “grid-based” and “three-dimensional” approaches (Yang et al., 2023), bridging the information gap between production links and environmental governance links. Furthermore, by establishing digital trading platforms, they accurately connect the demand for ecological products from the consumer side, promoting cross-regional

and cross-subject supply–demand matching of regulatory service ecological products such as water rights and emission rights (Wang et al., 2025), thus effectively resolving the fragmentation problems in traditional governance, such as poor factor mobility and insufficient market synergy.

2.3 Research on SPC

IPCC first proposed the co-benefits of ecological and environmental governance (“co-benefits”), and its Fifth Assessment Report defined it as “positive side effects of policies or measures.” Academic research on the externality of pollution and carbon mainly focuses on four aspects: first, unilateral management of pollution and carbon, including the generation mechanism, hazards, and emission reduction measures of pollutants such as SO₂ (Nazari et al., 2012), as well as CO₂ emission reduction, carbon emission rebound, and carbon peak prediction (Jia et al., 2022). Second, theoretical research on SPC focuses on the connotation, mechanism, and feasibility of collaborative governance. Some scholars have pointed out that pollution and carbon emissions in China share the same root cause due to fossil fuel combustion, and they evaluated SPC, the synergistic pollution reduction effect of greenhouse gas governance, and the synergy degree between the two (Zhang Y et al., 2022; Qian et al., 2025). Third, the evaluation of the policies of SPC. Scholars have taken China’s urban agglomerations or industrial parks as samples; constructed indicator systems from the aspects of pollutant emissions, environmental protection investment, and resource utilization efficiency (Liu and Hong, 2022; Li et al., 2025); and used methods such as the composite system synergy degree model and entropy-weighted TOPSIS (Behzadian et al., 2012) to assess synergistic benefits. However, conclusions are divergent due to differences in methods and indicators. Fourth, research on the driving paths of SPC, focusing on “source prevention” (Sun and Deng, 2022), “end-of-pipe treatment” (Nam et al., 2013), etc. For example, Yi et al. (2022) proposed that “process control,” such as energy structure transformation, can promote synergistic efficiency.

In summary, the current research progress still has room: first, regarding research on SPC, few studies have incorporated whole-process management on account of its essential requirements and constructed a multiple mediating effect model for empirical research. Second, among the existing limited research on the mechanism of influence between the digital economy and pollution, there are relatively few studies on *INDIG*. Few scholars have focused on the characteristics of *INDIG* or explored its spatial spillover effects. Third, existing studies have not fully incorporated multiple heterogeneous perspectives, such as regional and urban characteristics, making it hard to accurately identify the differential impacts of *INDIG* on SPC.

3 Theoretical analysis and research hypotheses

3.1 Direct effect

As a subsystem of the digital economy, *INDIG* increases the output and improves efficiency of traditional industries employing

digital technology and resources. Based on the concept of “integration,” the development of *INDIG* with “Dingxin” pulling “revolution” promotes the integrated development of smart agriculture, digital finance, and digital government (Tapscott, 1996), which not only improves regulatory transparency but also helps reduce resource loss caused by information asymmetry. From the perspective of externality theory, pollution emissions are a typical form of negative externality. *INDIG* improves regulatory transparency and reduces information asymmetry, which is essentially a process of internalizing negative externalities. It becomes more difficult for enterprises to hide pollution activities, and the government or society can hold them accountable at a lower cost, forcing enterprises to bear environmental costs. Meanwhile, this is also in line with the Coase theorem. *INDIG* reduces the transaction costs of defining environmental property rights (such as the division of pollution liabilities) through technical means, creating conditions for solving externality problems. “Metcalfe’s Law” believes that when enterprises add the investment in digital factors, it will decrease the marginal cost of products, achieve economies of scale, and increase benefits, and *INDIG* makes digital factors fully penetrate the industrial chain of traditional industries, adopt an intelligent production mode to improve the production efficiency, provide conditions suitable for clean production of enterprises, and exert environmental welfare effects (Ma et al., 2022). In terms of the market, *INDIG* has broken the business model of traditional industries, created a disruptive innovation model, spawned new business formats, and opened up many market segments. Based on the theories of economies of scale and by leveraging the advantages of digital platforms, the “scale effect” in resource allocation can be achieved through measures such as reducing transportation, thereby reducing pollution emissions (Liu and Hong, 2022). In terms of green production, due to the abundant capital and resources of traditional industries, *INDIG* can more quickly and extensively open up the upstream and downstream industrial chain, quickly integrate digital technology, improve production efficiency and cleanliness overall, and achieve sustainable development of green production, compared with the green influence of digital industrialization, while improving economic benefits and promoting the sustainable development of enterprises through green production (Zhao and Meng, 2022).

Hypothesis 1: *INDIG* can promote SPC.

3.2 Spatial effect

Compared with pollution types with clear boundaries such as soil and water, pollutants and carbon emissions have the characteristics of mobility and spillover, and atmospheric pollutants and greenhouse gases generated in a certain area are easily diffused and spilled over to adjacent areas due to the presence of atmospheric circulation so that atmospheric pollution carbon presents regional characteristics (Zhang Y. H. et al., 2022). Digitalization has the characteristics of permeability and sharing. Based on knowledge spillover theory, in the digital network, knowledge, technology, information, and other key elements can break space and industry barriers; achieve cross-regional flow, form

“mobile space” and “mobile industry”; and radiate to drive the development of adjacent regions. Based on the spatial interconnectedness of regional and social development, digitally transformed industries have a spatial effect on regional green development through technology and information spillover across spatial constraints (Jia et al., 2022), such as digital government. The “trickle-down effect” theory holds that any development is driven by local outward radiation to drive overall development; *INDIG* fully penetrates all fields of the society, strengthens regional cooperation, promotes multi-subject joint participation, realizes cross-regional collaborative governance, reduces negative environmental externalities, and exert a decisive influence on the greening of social production (Huang et al., 2022). On the one hand, information elements can boost the digital and intelligent transformation of environmental management, establish a database for rapid and accurate monitoring, and adopt a differentiated management method of “one source and one file” to achieve the integration of “sky, ground and sea.” On the other hand, the flow of technical elements promotes exchanges and learning flow between neighboring regions and other industries, improves the overall green innovation ability, and technologies such as big data help collect accurate information on regional green innovation capabilities, help identify substantive and strategic green innovation, and effectively improve green progress in neighboring regions (Han et al., 2022), thereby promoting *SPC*.

Hypothesis 2: *INDIG* has a positive spatial spillover impact on *SPC* in neighboring regions.

3.3 Indirect effect

The whole-process governance system is built based on the cleaner production theory. The vital requirement of *SPC* is to boost the transformation of the end governance model of “pollution first, treatment later” to the whole-process governance model. To break the dilemma of “pollution first, then treatment” and “emphasis on the end over the source,” this paper probes the path of *SPC* from the three links of whole-process governance. First, coal combustion releases large amounts of greenhouse gases and atmospheric pollutants. By replacing high-carbon and high-pollution energy sources (such as coal), *RES* can prevent the source of pollution and carbon emissions at the energy input end, which serves as the core means of “source prevention” (Liu et al., 2021). Second, under the realistic constraints of production costs, although *GPI* requires more resource input in the short term, it can effectively curb the disorderly consumption of energy and reduce unit energy consumption through the iterative upgrading of production equipment and systematic reconstruction of processes, thereby improving production efficiency and output scale. From a long-term perspective, such innovation can not only gradually offset various costs required for environmental governance but also directly reduce pollution generation during manufacturing, thus achieving “process control” over atmospheric pollutants and carbon emissions (Wang et al., 2016). Finally, the “Porter Hypothesis” proposes that there is a close correlation between *ER* and corporate innovation. Its core “innovation compensation” effect not only promotes enterprises to reduce pollution and carbon

during manufacturing through technological improvement but also urges enterprises to improve their secondary treatment capacity for the generated pollution and carbon. As the last guarantee for environmental governance, this post-processing mechanism belongs to the “end-of-pipe treatment” link (Fare et al., 2016). In addition, *GPI* can improve the efficiency of *RES*, while *RES* can reduce the pressure of end-of-pipe treatment and make *ER* more likely to be implemented. These three factors form a governance closed loop through the dynamic coordination of “source prevention—process control—end-of-pipe treatment.” Therefore, research centers on analyzing the mediating roles of *RES*, *GPI*, and *ER* in the path of *INDIG*’s impact on *SPC*.

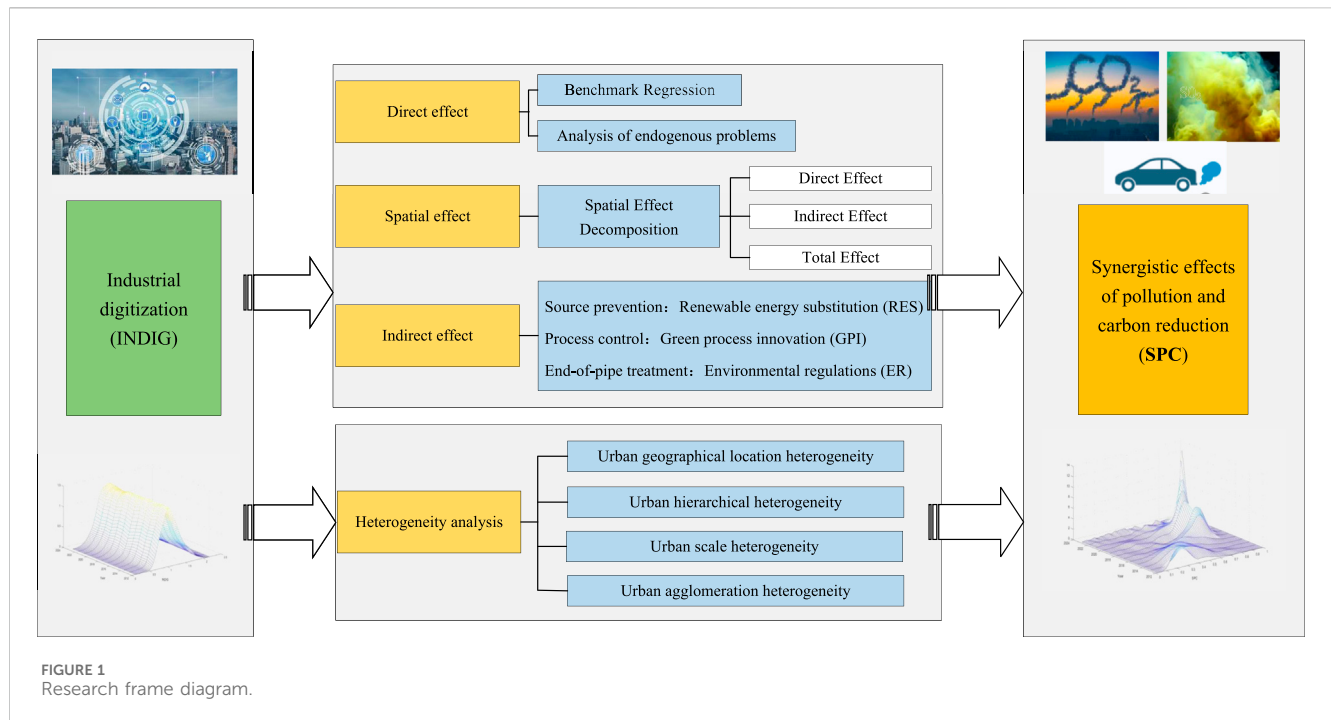
3.3.1 Analysis on the mediating role of *RES*

From enterprise production, *INDIG* promotes innovation of traditional industrial structures and models. According to the energy substitution theory (core logic: when the cost-benefit ratio of clean energy improves, it will replace high-carbon energy as the dominant energy for production), the in-depth digital integration of the industrial chain has promoted *RES*: in traditional industrial production, the demand for traditional industrial raw materials has decreased, while the demand for clean energy such as electricity has increased. Existing studies have shown that the digital economy can promote *RES* by curbing the total energy consumption (Zhang S et al., 2022). Meanwhile, services such as intelligent decision-making and analysis on digital platforms have reduced information and R&D costs, facilitating the precise development and application of new clean energy. Although the short-term investment is relatively high, the long-term green benefits are more remarkable (Shahbaz et al., 2022a). From the public perspective, digital platforms reduce the difficulty of resource acquisition, and competition among suppliers lowers energy prices, which may stimulate consumption and produce a “rebound effect”; However, *INDIG* creates diverse job opportunities to increase *per capita* income, and the increase in income makes it easier for the public to choose clean energy (Wang and Cao, 2019). To sum up, *INDIG* promotes *RES* by reducing the demand for traditional energy and developing clean energy and ultimately contributes to *SPC*.

Hypothesis 3a: *INDIG* promotes *SPC* by advancing *RES*.

3.3.2 Analysis on the mediating role of *GPI*

GPI focuses on technical optimization during manufacturing, which can validly alleviate the contradiction between economy and ecology and offer technical support for the synergy between the digital and green economy during manufacturing. The theory of technological innovation and the theory of endogenous economic growth propose that technological innovation is a valid element for high-quality economic progress (Zhao and Meng, 2022). On the one side, *INDIG* accelerates the cross-regional flow of innovation factors by opening up the innovation system, forcing policy innovation to create an open innovation environment, helping break the “resource curse” and improving the level of *GPI*; the intelligent transformation of enterprise production equipment and processes through green technologies can promote the clean transformation of energy (Cao et al., 2021), thereby promoting *SPC*. On the other side, *GPI* can boost factor collaboration and production efficiency, increase output and reduce energy consumption under the same input, and promote



resource recycling and pollution and carbon emission reduction; meanwhile, with the help of pollution data collection and the construction of dynamic monitoring and early warning platforms, production strategies can be supervised and adjusted on time (Feng et al., 2022), stimulating “smart potential” for emission reduction and having a positive impact on SPC.

Hypothesis 3b: *INDIG* promotes *SPC* by improving *GPI*.

3.3.3 Analysis on the mediating role of ER

INDIG relies on digital technologies to strengthen the effectiveness of *ER* through information sharing and real-time monitoring, providing institutional guarantees for *SPC*. This process can be explained by the Porter Hypothesis: appropriate *ER* can incentivize corporate innovation, and *INDIG* makes regulation more precise and effective through technological empowerment, amplifying the “innovation compensation” effect (Fare et al., 2016). At this stage, China mainly adopts incentive-based and public-participation *ER* (Liang and Li, 2023), and both have enhanced effectiveness due to the in-depth integration of *INDIG*. In incentive-based regulation, digital technologies improve the measurement accuracy and market transparency of carbon emission rights and energy use rights trading, dynamically adjust quotas through intelligent algorithms, make corporate emission costs measurable and controllable, and force enterprises that have not achieved green transformation to withdraw from the market through a “survival of the fittest” mechanism (Sun and Deng, 2022). In public-participation regulation, digital platforms break down information barriers, enabling the public to easily access enterprise pollution discharge data and participate in supervision, which prompts enterprises to accelerate green transformation through digital means and take the initiative to invest in end-of-pipe treatment (Han X. F. et al., 2023).

Hypothesis 3c: *INDIG* promotes *SPC* by strengthening *ER*.

The research frame diagram of this paper is constructed, see Figure 1.

4 Measurement methods and data sources

4.1 Model building

First, the benchmark regression model is used to explore the direct effect of *INDIG* on *SPC*, see Equation 1.

$$SPC_{it} = \alpha_{it} + \theta_1 INDIG_{it} + \theta_n \ln Z_{it} + u_i + v_t + \varepsilon_{it}, \quad (1)$$

where: i means the city, t means the year, Z_{it} represents the control variables, including green finance level (*GH*), opening up to the outside world (*OPEN*), human capital accumulation (*HCA*), informationization level (*INFO*), and population density (*PD*). α is a constant term; θ represents regression coefficients; u_i and v_t , respectively, represent individual-fixed and time-fixed effects; and ε is a random perturbation term.

Second, referring to Elhorst (2010), the research employs *SPDM* to probe the spatial spillover impact of *INDIG* on *SPC* in neighboring regions, see Equation 2.

$$SPC_{it} = \alpha_{it} + \rho W_{ij} SPC_{it} + \beta_1 INDIG_{it} + \beta_n \ln Z_{it} + \varphi_1 W_{ij} INDIG_{it} + \varphi_n W_{ij} \ln Z_{it} + u_i + v_t + \varepsilon_{it}, \quad (2)$$

where α is the constant, i and j represent the city, W is the spatial weight matrix of order 264×264 , β_1 is the spatial autoregressive coefficient, β_2 and β_3 represent the regression coefficients of each

variable, and β_4 and β_5 represent the regression coefficients of the spatial lag term of each variable.

The spatial weights matrix: W_{ij} . A geographical distance spatial weight matrix is used, and explanatory power is not impacted by the sample size (Feng et al., 2021). d_{ij} calculates the Euclidean distance between the centroid of i city and j city according to the latitude and longitude, see Equation 3.

$$W_{ij} = \begin{cases} 0 & d_{ij} < d \\ 1/d_{ij} & d_{ij} \geq d. \end{cases} \quad (3)$$

Finally, this paper introduces three types of mediating variables: RES_{it} , GPI_{it} , and ER_{it} , and the multiple mediating effect model is used to research the indirect influence mechanism of *INDIG* on *SPC*, see Equations 4, 5.

$$mediation_{it} = \gamma_0 + \gamma_1 INDIG_{it} + \gamma_n \ln Z_{it} + u_i + v_t + \varepsilon_{it}, \quad (4)$$

$$SPC_{it} = \varphi_0 + \varphi_1 INDIG_{it} + \varphi_2 mediation_{it} + \varphi_n \ln Z_{it} + u_i + v_t + \varepsilon_{it}, \quad (5)$$

where, γ_0 and φ_0 are constant terms and γ_n and φ_n represent the regression coefficient ($i = 1, 2, 3, \dots$).

4.2 Variable measurement and description

4.2.1 Variable measures

1. Explained variable: *SPC*. The issues with reduction of air pollution and greenhouse gas are key to China's current environmental governance, and the two generation processes have the same origin, course, and influence on each other (Zhang J et al., 2022; Sun and Deng, 2022), and *SPC* is feasible. We selected the emission of sulfur dioxide, soot, and wastewater to measure pollution reduction. CO₂ emissions are selected to represent carbon reduction. Drawing on the practice of Hu (2023), the coupling coordination model is used. The range standardization method is used to process the index dimensionless, and the model is modified by referring Wang et al. (2021), see Equations 6–8.

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2}, \quad (6)$$

$$T = aU_1 + bU_2, \quad (7)$$

$$SPC = \sqrt{C \times T}. \quad (8)$$

Among them, U_1 is pollutant emissions, U_2 is carbon emissions, and a and b represent the proportion of gravity, taking $a = b = 0.5$. *SPC* is measured as a coupling-coordination index bounded between 0 and 1; the larger the value, the better the coupling state between the two, and vice versa, the weaker.

2. Explanatory variable: *INDIG*. Referring to Zhang S et al. (2022), from the three dimensions of primary industry, secondary industry, and tertiary industry, the Indicator of *INDIG* is measured using the projection pursuit method based on the real-coded accelerated genetic algorithm. Specifically, the indicators for the primary industry include the number of internet broadband access users and the added

value of the primary industry; the indicator for the secondary industry includes the added value of the secondary industry; the indicators for the tertiary industry include e-commerce transaction volume, digital inclusive finance index, and the added value of the tertiary industry.

3. Mediating variables: Different from the traditional model of governance in a certain link, research explores the transmission path of *SPC* in the affected areas of *INDIG* based on the whole-process management of “source--process--end-of-pipe.”

Source prevention is a preventive environmental management strategy (Liu et al., 2021). China's environmental governance has focused on end-of-pipe and over-the-source, which, to a certain extent, has led to slow *ESA* and industry structure adjustment in high-carbon and high-energy-consuming industries, slowing down the governance process. Promoting the clean transformation of energy and minimizing pollution at the source, we refer to Shahbaz et al. (2022b) to denote *RES*.

Process control is based on the source prevention that has not been fully realized. Further treatment of pollutant sources that raise resource utilization and production efficiency effectively reduces pollutant generation, creating a subtractive effect on emissions and reinforcing pollution control. *GPI* reduces pollution through methods such as production process reengineering and equipment renewal. We refer to Feng et al. (2022) to denote *GPI*.

End-of-pipe treatment is a complement to the association between process and source, which refers to taking advantage of high and new technology to clean the air pollutants and greenhouse gases that have been produced at the end of product production to meet emission standards, which is a “first pollution and then treatment” model of emission reduction, which is hard to remove pollutants and is a “palliative” behavior. Due to the “competitive tournament” system, government officials are limited by the tenure rule and prefer to adopt investment methods to deal with air pollution at the end of the treatment and to quickly achieve the constraint goal of pollution carbon emission reduction; we refer to Chen and Chen (2018) to denote *ER*.

4. Control variables: *SPC* will be affected by internal and external factors in addition to *INDIG*. Drawing on existing studies, the control variables are selected: (1) *GH*. Green finance is an essential part of the economic system and promotes *SPC*, referring to Cao et al. (2021) to denote *GH*. (2) *OPEN*. Openness determines the flow of factors, thereby affecting resource consumption and green technology innovation, which is an important factor affecting *SPC*, referring to Wang et al. (2019) to measure *OPEN*. (3) *HCA*. Human capital is the main body of technological innovation and a vital factor affecting sustainable development, referring to Lin et al. (2021) to measure *HCA*. (4) *INFO*. The informatization process promotes technological progress, optimal allocation of resources, industrial structure optimization, etc., forming the “energy factor substitution effect”, which is an important way to reduce energy consumption and improve *SPC*, referring to Wu and Deng (2023) and Rao (2025) to measure *INFO*. (5) *PD*. *PD* is strongly correlated with energy consumption and green development, and it is an important focus in the research on *SPC*. It is denoted concerning Ribeiro et al. (2019).

TABLE 1 Qualitative description of the variables.

Classify	Variable	Calculation method
Explained variable	<i>SPC</i>	Model calculations are coordinated by coupling
Explanatory variable	<i>INDIG</i>	Measured by the evaluation index system
Mediating variables	<i>RES</i>	Total supply of artificial/natural gas
	<i>GPI</i>	Total investment in tech transformation and internal R&D expenditure
	<i>ER</i>	Proportion of environmental-related word frequency in government work reports
Control variables	<i>GH</i>	Measured from four dimensions: green credit, securities, insurance, and investment
	<i>OPEN</i>	Proportion of total import–export volume to regional GDP
	<i>HCA</i>	Proportion of regular higher education enrollments to year-end total population
	<i>INFO</i>	Derived from mobile phone and internet penetration rates
	<i>PD</i>	Proportion of the registered population to the administrative land area

TABLE 2 Correlation analysis and multicollinearity analysis.

Variable	<i>SPC</i>	<i>INDIG</i>	<i>GH</i>	<i>OPEN</i>	<i>HCA</i>	<i>INFO</i>	<i>PD</i>
<i>SPC</i>	1.000***						
<i>INDIG</i>	0.374***	1.000***					
<i>GH</i>	0.243***	0.380***	1.000***				
<i>OPEN</i>	0.019	0.394***	0.296***	1.000***			
<i>HCA</i>	0.069***	0.419***	0.048***	0.276***	1.000***		
<i>INFO</i>	0.423***	0.592***	0.308***	0.546***	0.474***	1.000***	
<i>PD</i>	−0.014	0.530***	0.232***	0.405***	0.219***	0.323***	1.000***
VIF	—	2.12	1.25	1.59	1.38	2.07	1.50
1/VIF	—	0.472690	0.801980	0.630855	0.722257	0.482500	0.665965

***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

4.2.2 Data sources and descriptions

Considering the availability of data and avoiding the estimation bias caused by data omission, the panel data of 264 cities in China from 2012 to 2023 were selected as the research object, and the data were derived from *China City Statistical Yearbook*, the website of the National Bureau of Statistics, and the statistical yearbooks of various provinces and public information. The linear interpolation and logarithmic methods are used. Tables 1, 2 show that there are no outliers in all variables, and the mean VIF is 1.65, showing that the possibility of multilinearity between the explanatory variables is not serious. To further enhance the visibility of the results, additional figures, Figures 2, 3, have been added.

5 Empirical results and analysis

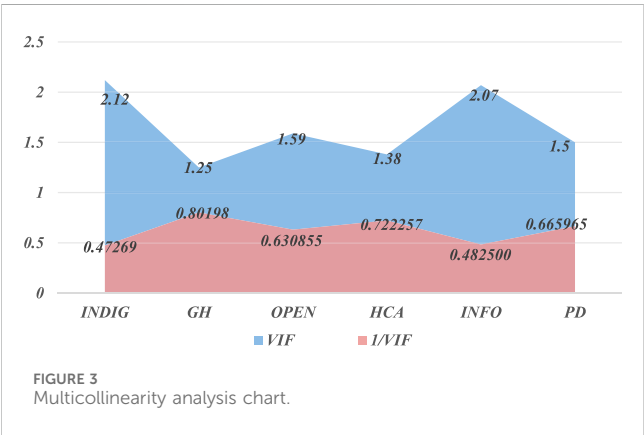
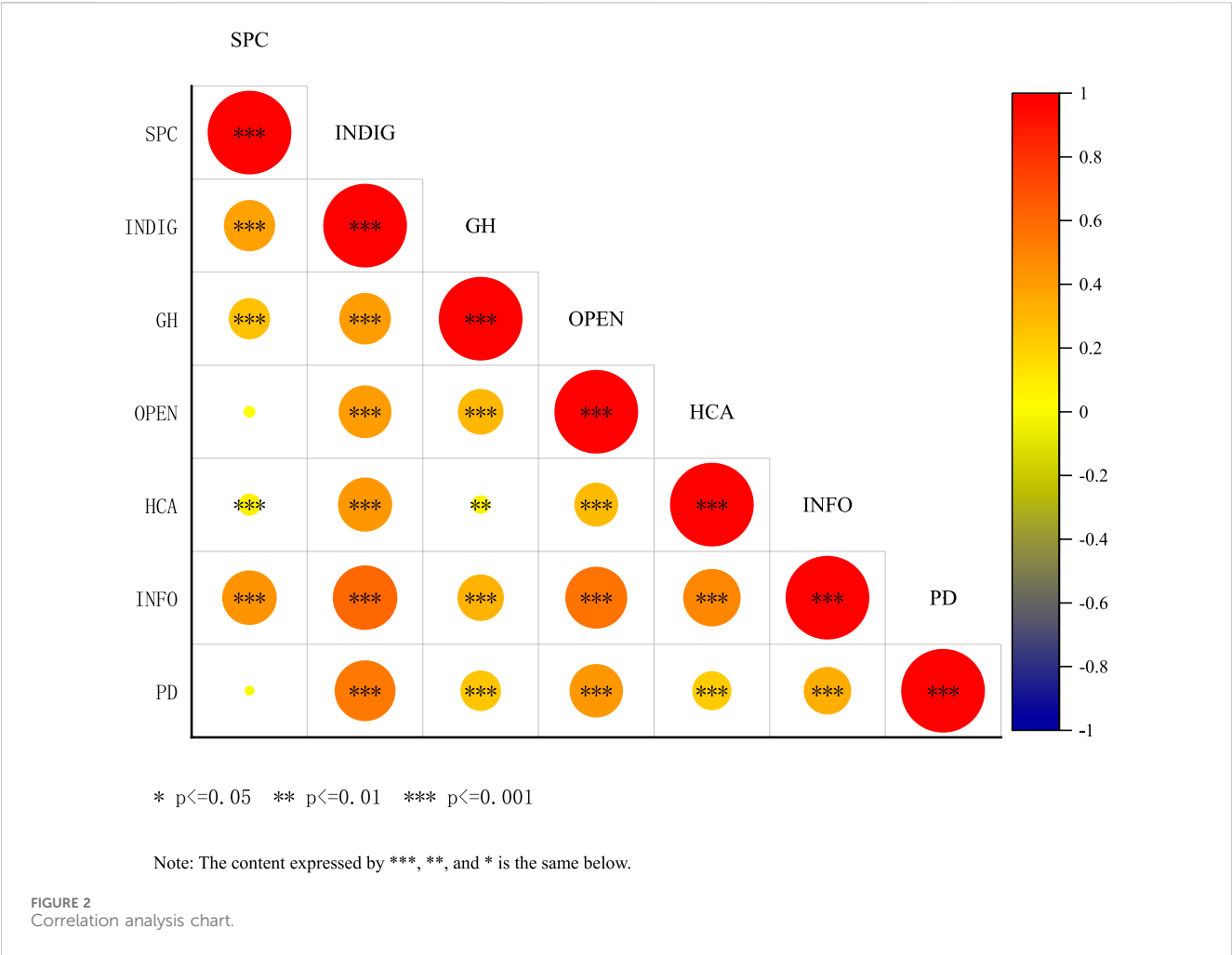
5.1 Benchmark regression

After the Hausman test, a fixed-effects model is selected (see Table 3). The effect coefficient of *INDIG* on *SPC* is remarkably optimistic, showing that *INDIG* can help boost *SPC* and test H1,

referring to Yang et al. (2023). From a control variable perspective, *GH* promotes *SPC* at the 1% significance level. By guiding social capital to tilt toward fields, clean energy, and R&D of carbon emission reduction technologies, green finance provides financial support for enterprises' green production transformation and regional ecological governance projects, thereby promoting *SPC* (Lin et al., 2021). The effect coefficient of *INFO* on *SPC* is very optimistic at the 1% level. With the help of technologies, real-time tracking of enterprise pollution discharge and energy consumption data can be realized, timely early warning of excessive behaviors and rapid traceability can be carried out, and dynamic control and management of pollution and carbon emissions can be strengthened, which is conducive to the implementation of work of *SPC* (Ribeiro et al., 2019).

5.2 Endogenous problem analysis

Starting from the research theme, it is very likely that there may be a certain causal endogenous relationship between *INDIG* and *SPC*. Although *GH*, *OPEN*, *HCA*, *INFO*, and *PD* have been



included as control variables to solve the endogenous problem of missing variables, there are many factors affecting *SPC*, and use of a regression model makes it hard to contain all factors, and the problem of missing variables is produced.

The DWH test method of heteroscedasticity is used, which solves the problem that the Hausman test cannot solve the heteroscedasticity, and obtains a statistic of 5.398 and a P-value of 0.020, showing that the *INDIG* index in the model has endogenous problems. To reduce the existing endogenous problem, the instrumental variable method is used

to alleviate the endogenous problem, drawing on the methods of [Chen et al. \(2022\)](#) and [Huang et al. \(2019\)](#), taking the topographic undulation (*iv1*) and Interaction term between 1984 provincial post offices per hundred people and prior-year national internet users (*iv2*) as the tool variables of *INDIG*, see [Table 4](#).

The p-value of the LM statistic is 0.002, indicating that there is no under-identification. Instrumental variables are remarkably relevant to *INDIG*, thus verifying their validation. The coefficients of *INDIG* are remarkably positive, showing that the conclusion of the research still holds after alleviating the endogenous problem. From the system GMM model's results, the feasibility of the system GMM model is verified by AR, Hansen, and other tests, and compared with the traditional model; this model underestimates the promotion impact of *INDIG* on *SPC*. Both models show that *INDIG* has a remarkably positive impact on *SPC*, which further confirms H1.

5.3 Spatial effect test

5.3.1 Initial exploration

The three-dimensional nuclear density map of *INDIG* and *SPC* from 2012 to 2023 is drawn, and its temporal evolution trend and spatial distribution are observed, as shown in [Figure 4](#). From (a), the graph presents the characteristics of “single peak dominance, peak

TABLE 3 Baseline regression results.

Variable	Coefficient	Standard error	T-value	P-value	[95% Confidence interval]	
<i>INDIG</i>	1.022***	0.039	25.89	0.000	0.945	1.099
<i>GH</i>	0.931***	0.123	7.54	0.000	0.689	1.173
<i>OPEN</i>	−0.031	0.042	−0.73	0.468	−0.113	0.052
<i>HCA</i>	0.492	0.425	1.16	0.247	−0.342	1.326
<i>INFO</i>	0.054***	0.008	6.85	0.000	0.038	0.069
<i>PD</i>	−0.000	0.000	−0.46	0.643	−0.000	0.000
_cons	−1.041***	0.040	−25.89	0.000	−1.120	−0.962
Sigma_u	0.342		N	3168	F	752.40
Sigma_e	0.177		R ²	0.609		
rho			0.788			

F test that $u_i = 0$: F (263, 2898) = 8.20; Prob > F = 0.000.

elevation, and distribution convergence.” The single peak stems from policy inclusiveness and low technology reuse costs, which promote synchronous digital transformation in all regions and avoid regional polarization. The peak growth reflects the advancement of *INDIG* from a production auxiliary to a core link. The distribution convergence indicates that the gap in *INDIG* between regions has narrowed. From (b), the phenomenon of “coexistence of multiple peaks and right shift of the main peak” appears. Multiple peaks indicate that *SPC* is not very stable, being in a state of constant fluctuation with regional differences. The right shift of the main peak shows that, despite large intra-regional differences, *SPC* has gradually strengthened over time.

5.3.2 Exploratory spatial data analysis

The spatial correlation test of the research objects is conducted using global Moran’s *I*, as shown in Table 5; Figure 5. Both *INDIG* and *SPC* exhibit a remarkable positive spatial correlation, with stable changes in their spatial correlation characteristics. This indicates a positive connection between local and adjacent regions, meaning that the improvement of *SPC* and *INDIG* in one region helps drive up the corresponding indicator levels in neighboring regions. Moreover, over time, the connections between various regions remain relatively stable, and their spatial agglomeration and dependence degree will not weaken accordingly.

5.3.3 Spatial spillover effect

The above model verifies the remarkable positive impact of *INDIG* on *SPC*, but it does not consider the mutual influence between regions. Therefore, *SPDM* is adopted for further research. After LM, Wald, LR, and Hausman tests, this paper finally selects the *SPDM* of space-time dual fixed spatial panel to analyze the spatial spillover effects of *INDIG* on *SPC*, see Tables 6, 7. Column (1) of Table 6 shows that the impact coefficient of the interaction term W^*INDIG on *SPC* is remarkably positive.

To fully verify the rationality of the selection of spatial weight matrices, economic distance matrices and economic–geographical nested matrices are further used for empirical tests; see columns (2)–(3) of Table 6. The results show that the impact coefficient of *INDIG* on *SPC* is not remarkable. This may be because the spatial logic

of *SPC* is more dependent on the governance convenience and pollution diffusion characteristics brought about by geographical proximity, while economic distance matrices and economic–geographical nested matrices have a weak correlation with this logic, which ultimately leads to the insignificant impact coefficient.

Robustness test. According to column (4) of Tables 6, 7, to mitigate endogeneity issues, this paper further adopts the dynamic of *SPDM* for testing. The results show that the spatial lag term of *SPC* is remarkable. The intra-regional spillover effect of *INDIG* on *SPC* is not remarkable, but there exists a strong inter-regional spillover effect, and the long-term spillover impact of *INDIG* is significantly greater than the short-term one. Its economic logic can be further elaborated by combining the characteristics of regional factor flows and the research by Ren et al. (2023): regarding the insignificant intra-regional spillover, on the one hand, it stems from the “polarization effect” in the core regions of *INDIG*: factors of technology and capital agglomerate in regions with marked digitalization, making it difficult to effectively diffuse to surrounding areas within the same region in the short term. In contrast, the high energy-consuming nature of the digital industry itself leads to an increase in local pollution and carbon, while measures of emission reduction, such as energy structure optimization and green innovation, have a time lag in taking effect. The reallocation of factors within the region has not yet formed sufficient compensation for green benefits, so no remarkable intra-regional spillover has been observed. In terms of the long-term and short-term differences in inter-regional spillover, the short-term effect mainly arises from the rapid cross-regional diffusion of digital technologies and the real-time flow of information factors. *INDIG* forms a demonstration effect through technology promotion and model innovation, forcing enterprises in the surrounding regions to participate in *SPC* by introducing technologies or conducting independent innovation. This process quickly manifests itself, relying on the high mobility of digital factors. The strengthening of the long-term effect is closely related to the continuous cross-regional allocation of factors such as capital and talent. With the

TABLE 4 2sls and system GMM regression of *INDIG* to *SPC*.

Variable	(1)	(2)	(3)
	One-stage	Two-stage	Dynamic GMM
<i>L SPC</i>			0.260*** (0.002)
<i>INDIG</i>		1.192** (0.493)	0.172*** (0.005)
<i>iv1</i>	−0.018** (0.007)		
<i>iv2</i>	−0.000** (0.000)		
<i>GH</i>	0.536*** (0.045)	1.192** (0.493)	0.009 (0.015)
<i>OPEN</i>	−0.073*** (0.025)	1.192** (0.493)	0.002 (0.010)
<i>HCA</i>	2.161*** (0.206)	1.192** (0.493)	−0.560*** (0.054)
<i>INFO</i>	0.101*** (0.007)	1.192** (0.493)	0.006** (0.002)
<i>PD</i>	0.000*** (0.000)	1.192** (0.493)	−0.000*** (0.000)
cons	0.678*** (0.019)	1.192** (0.493)	0.447*** (0.008)
DWH		0.020	
Kleibergen-Paap rk LM statistic		12.279[0.002]	
Hansen			0.996
AR(1)			0.000
AR(2)			0.113

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

increase in *INDIG*, the optimal reorganization of factors across regions becomes more adequate, promoting the gradual formation of a long-term mechanism for collaborative emission reduction, thus producing remarkable long-term spillover effects. Compared with the results of the static of *SPDM*, the dynamic of *SPDM* is not an obvious change in regression, showing that the model is robust and verifying H2.

5.4 Mechanism analysis

Based on the above results, the mediating mechanism of how *INDIG* affects *SPC* is further tested, see Table 8. From whole-process management, under the impacts of *RES*, *GPI*, and *ER*,

INDIG has an indirect impact on *SPC* in China to a certain extent, and H3a, H3b, and H3c have been confirmed.

Columns (1) and (2) present the test results with *RES* as the mediating variable. Under the influence of *RES*, *INDIG* has a partial mediating effect on *SPC*. For every 1-unit change in *INDIG*, *RES* will increase by 2.255 units, which in turn exerts an indirect effect of 0.092 (2.255*0.041) on *SPC*. This result is supported by Lin et al. (2021) and Ren et al. (2023), demonstrating that *INDIG* can reduce the technical threshold and cost of *RES* through smart grid dispatching and digital twin simulation, enhance *RES*, and reduce pollutants and carbon emissions from fossil energy combustion at the energy input stage.

Columns (3) and (4) present the test results with *GPI* as the mediating variable. *INDIG* has a remarkable optimistic effect on *GPI*, with an impact coefficient of 2.187, while *GPI* significantly promotes *SPC*, with an impact coefficient of 0.029. The product of the two regression coefficients is significantly positive, indicating that *INDIG* exerts an optimistic impact on *SPC* by promoting *GPI*, with an impact coefficient of 0.960. This conclusion is supported by Feng et al. (2022), which states that *INDIG* effectively improves *GPI*, thereby indirectly promoting *SPC*.

Columns (5) and (6) report the test results with *ER* as the mediating variable. When other factors remain unchanged, every 1-unit change in *INDIG* will promote an increase of 0.006 units in *ER*; every 1-unit increase in *ER* will significantly drive up *SPC* by 4.444 units. That is, *INDIG* indirectly promotes *SPC* through the mediating role of enhancing *ER*, with a total impact coefficient of 0.994. This result is evidence in Han X. F. et al. (2023), which indicates that *ER* is a mediating mechanism through which *INDIG* affects *SPC*.

Overall, the positive indirect impact of *INDIG* on *SPC* runs through the entire governance chain of “source–process–end-of-pipe”: through *RES*, it reduces reliance on fossil energy and the generation of pollutants from the source of energy consumption; relying on *GPI*, it strengthens energy efficiency improvement and pollution control during manufacturing; and through the transmission of *ER*, it forces technological upgrading and collaborative emission reduction at the end of governance. These three paths confirm that *INDIG* not only affects *SPC* through direct spillover effects but also constructs a collaborative mechanism of “prevention-control-treatment” through the whole-process transmission of “source - process - end.” This transition facilitates *SPC* evolution from isolated process improvements to holistic system upgrades, while simultaneously enhancing the systematic coordination of regional eco-environmental governance through digital enablement.

5.5 Robustness test

The robustness of the results is further verified, see Table 9: addressing endogeneity issues, adjusting research samples, and modifying control variables: first, addressing endogeneity issues. This paper employs a dynamic panel regression model, selecting the t-1 lagged term of *SPC* as the explained variable. The results in column (1) are like the above results, indicating model robustness; second, adjusting research samples. ① To resolve the problem of right-censored samples, this paper excludes relevant data for 2023. The results of Column (2) show no remarkable differences from the previous test results, demonstrating the robustness of the empirical

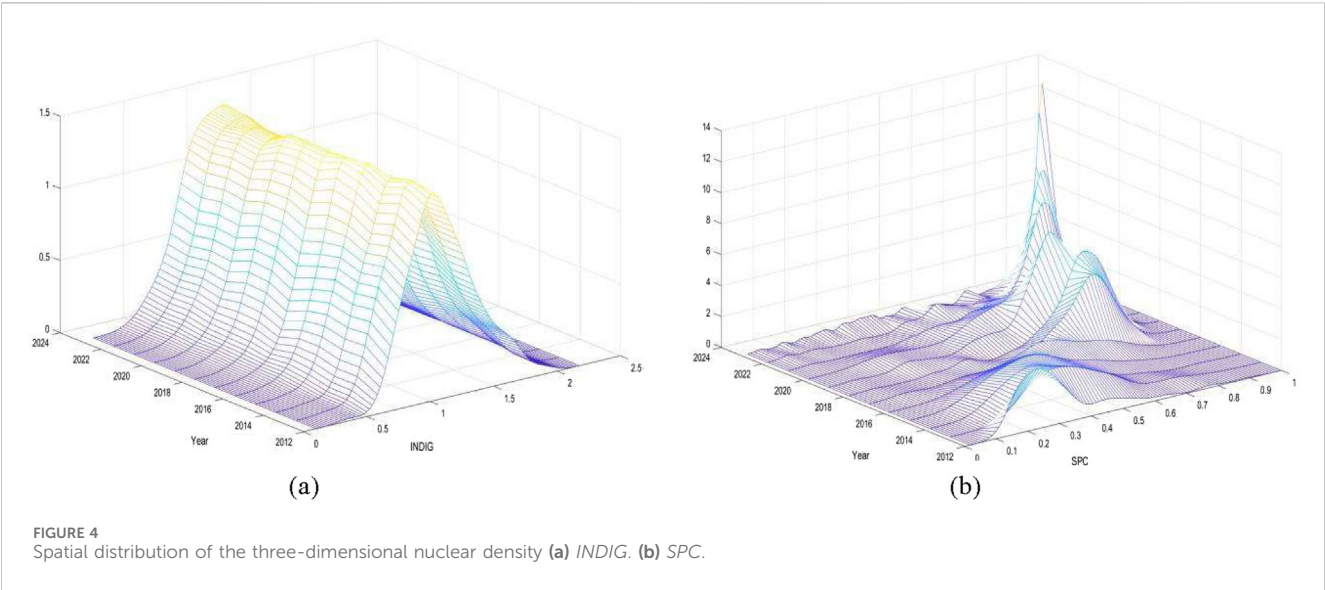


TABLE 5 Spatial correlation test.

Year	<i>INDIG</i>			<i>SPC</i>		
	Moran value	Z-value	P-value	Moran value	Z-value	P-value
2012	0.026***	5.427	0.000	0.018***	3.985	0.000
2013	0.025***	5.263	0.000	0.026***	5.434	0.000
2014	0.024***	5.171	0.000	0.007**	1.977	0.024
2015	0.019***	4.232	0.000	0.022***	4.778	0.000
2016	0.016***	3.748	0.000	0.015***	3.473	0.000
2017	0.024***	5.156	0.000	−0.005	−0.213	0.416
2018	0.025***	5.364	0.000	−0.002	0.357	0.361
2019	0.026***	5.490	0.000	0.009***	2.461	0.007
2020	0.031***	6.367	0.000	0.079***	15.369	0.000
2021	0.031***	6.461	0.000	0.022***	4.753	0.000
2022	0.031***	6.403	0.000	0.018***	4.028	0.000
2023	0.030***	6.170	0.000	0.019***	4.220	0.000

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

findings. ② Samples from regions with the largest and smallest 1%, 5%, and 10% of *SPC* are sequentially removed, and benchmark regression tests are conducted on 258, 236, and 210 cities, respectively. The results of *INDIG* in column (3) are similar to the previous results with no obvious differences (due to space constraints, only the empirical results for 236 cities are presented in this paper). Third, modifying control variables. ① Adding control variables. Urbanization level (*UR*) in China is highly correlated with *SPC*, and it is also a factor influencing *SPC*. Therefore, *UR* is increased as a control variable, measured by the proportion of non-agricultural population in the registered population (Nam et al., 2013), as shown in column (4). ② Reducing control variables by excluding *PD*, see column (5). The results obtained by adding or

reducing control variables are similar to the above results, showing the robustness of the findings in this paper.

Figure 6 is provided to more clearly present the robustness test results and their differences from the benchmark regression results.

6 Heterogeneity analysis

6.1 Urban geographical location heterogeneity

To further explore the heterogeneous impact of *INDIG* on *SPC*, the sample is divided into two regions, energy basin and non-energy basin, as

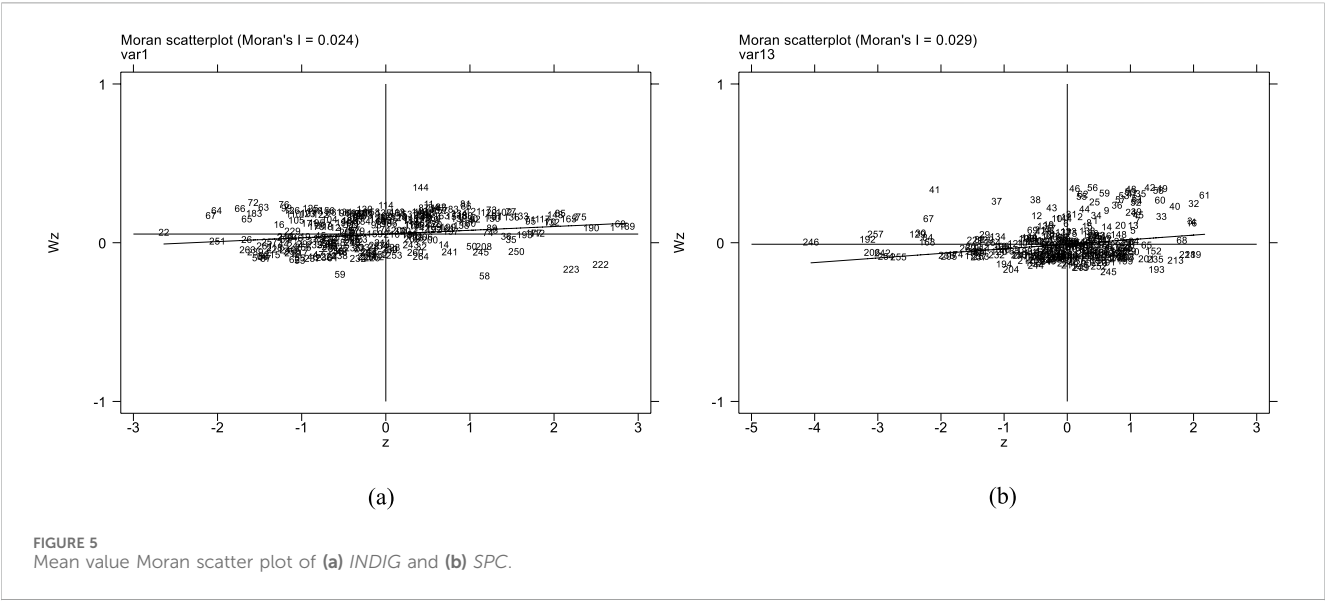


TABLE 6 Results of SPDM.

Variable	(1)	(2)	(3)	(4)
	SPDM (W1)	SPDM (W2)	SPDM (W3)	The dynamic of SPDM (W1)
L.W* SPC				−0.693*** (0.035)
INDIG	−0.176** (0.079)	−0.091 (0.061)	−0.103 (0.070)	−0.051 (0.068)
W* INDIG	0.754* (0.397)	−0.059 (0.152)	0.103 (0.151)	0.432** (0.199)
ρ	0.758*** (0.062)	0.047 (0.034)	0.164*** (0.033)	0.912*** (0.019)
σ^2	0.019*** (0.000)	0.020*** (0.000)	0.019*** (0.000)	0.015*** (0.000)
Controls	YES	YES	YES	YES
R-sq	0.473	0.415	0.000	0.686
Log-L	1797.08	1737.84	1747.74	2076.83
N	3168	3168	3168	2904

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

TABLE 7 Results of the dynamics of SPDM.

变量	Short-term			Long-term		
	Direct	Indirect	Total	Direct	Indirect	Total
INDIG	−0.028 (0.063)	4.493** (1.943)	4.466** (1.932)	−0.133 (0.221)	5.563** (2.576)	5.430** (2.527)

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

shown in columns (1)–(2) of Table 10. INDIG has significantly promoted SPC in energy basins, and the impact coefficient and significance are higher than those of non-energy basins. The rationale stems from the energy basin’s dual role as both a critical ecological barrier and a key economic zone in China. As government recognition of the basin’s strategic importance has grown, so has policy attention. This enhanced focus manifests in two ways: on the one hand, enterprises are more likely to grasp the chance of digitization to carry out the clean

transformation, and on the other hand, the government and individuals rely on digital platforms to dynamically monitor environmental pollution and governance and implement stricter ER than other regions; the “pollution shelter” hypothesis considers that polluting corporations are easier to be transferred to other regions. In contrast, non-energy basins experience weaker governmental oversight and support. These regions additionally suffer from negative environmental externalities resulting from the transfer of polluting industries from energy basins.

TABLE 8 Test of the mechanism of *INDIG* affecting *SPC*.

Variable	(1) <i>RES</i>	(2) <i>SPC</i>	(3) <i>GPI</i>	(4) <i>SPC</i>	(5) <i>ER</i>	(6) <i>SPC</i>
<i>INDIG</i>	2.255***	0.930***	2.187***	0.960***	0.006***	0.994***
	(0.127)	(0.041)	(0.233)	(0.039)	(0.001)	(0.040)
<i>RES</i>		0.041***				
		(0.006)				
<i>GPI</i>				0.029***		
				(0.003)		
<i>ER</i>						4.444***
						(1.446)
<i>GH</i>	2.759***	0.819***	0.401	0.919***	−0.004***	0.949***
	(0.399)	(0.123)	(0.729)	(0.122)	(0.002)	(0.123)
<i>OPEN</i>	0.676***	−0.058	−0.944***	−0.004	0.000	−0.031
	(0.136)	(0.042)	(0.249)	(0.042)	(0.001)	(0.042)
<i>HCA</i>	2.853**	0.376	4.282*	0.370	0.015***	0.427
	(1.374)	(0.422)	(2.511)	(0.420)	(0.005)	(0.425)
<i>INFO</i>	0.043*	0.052***	0.035	0.053***	−0.000***	0.056***
	(0.025)	(0.008)	(0.046)	(0.008)	(0.000)	(0.008)
<i>PD</i>	0.000	−0.000	−0.000	−0.000	−0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
cons	5.425***	−1.262***	9.542***	−1.314***	0.005***	−1.062***
	(0.130)	(0.050)	(0.237)	(0.049)	(0.001)	(0.041)
Bootstrap test	Z = 6.080, P = 0.000		Z = 6.260, P = 0.000		Z = 2.990, P = 0.003	
Sobel test	Z = 6.619, P = 0.000		Z = 6.573, P = 0.000		Z = 2.986, P = 0.003	
N	3168	3168	3168	3168	3168	3168
F	330.47	663.31	63.89	675.69	42.05	648.14
R ²	0.406	0.616	0.117	0.620	0.080	0.610

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

6.2 Urban hierarchical heterogeneity

Further analysis is conducted on the effect of urban hierarchy on *INDIG*. Referring to [Yu et al. \(2021\)](#), the samples are divided into three categories: first-tier cities, second/third-tier cities, and fourth/fifth-tier cities for research, see columns (3)–(5) of [Table 10](#). *INDIG* remarkably promotes *SPC*, but the impact coefficients follow the order: first/second/third-tier cities > fourth/fifth-tier cities. The reason may be that first-/second-/third-tier cities have more complete digital infrastructure, with stronger support from 5G, industrial internet, etc., enabling real-time monitoring and regulation of pollution discharge. In addition, these cities have more high-end industries, providing a sound foundation and greater space for digital transformation. In contrast, fourth-/fifth-tier cities are dominated by traditional industries, which face higher costs and greater difficulties in transformation.

6.3 Urban scale heterogeneity

Further investigation is made into the impact of urban scale on the effect of *INDIG*. For samples of different urban scales, we examine whether there are differences in the impact of *INDIG* on *SPC*. By the *Notice on Adjusting the Standards for Classifying Urban Scales* published by the State Council, cities are classified as follows: large cities (with a permanent population of more than 1 million) and small and medium-sized cities (less than 1 million), see columns (1)–(2) of [Table 11](#). The results show that *INDIG* significantly promotes *SPC* in large cities, with a higher impact coefficient compared to small cities. The reason lies in that large cities have greater superiority in terms of resource endowment, industrial foundation, technical support, and policy coordination, which form a more efficient match with the technical characteristics of *INDIG* and the implementation conditions for *SPC*. Conversely, small and medium-sized cities have a lag in digital infrastructure,

TABLE 9 Robustness test.

Variable	(1)	(2)	(3)	(4)	(5)
	<i>L SPC</i>	Adjust study sample 1	Adjust study sample 2	Increase control variables	Reduce control variables
<i>INDIG</i>	1.186*** (0.047)	1.051*** (0.039)	1.069*** (0.042)	1.017*** (0.039)	1.017*** (0.038)
<i>GH</i>	1.072*** (0.125)	0.937*** (0.127)	0.939*** (0.132)	0.881*** (0.125)	0.922*** (0.122)
<i>OPEN</i>	−0.011 (0.045)	−0.009 (0.043)	−0.037 (0.044)	−0.026 (0.042)	−0.031 (0.042)
<i>HCA</i>	−0.003 (0.416)	−1.809*** (0.655)	0.716 (0.469)	0.462 (0.425)	0.504 (0.424)
<i>INFO</i>	0.060*** (0.008)	0.077*** (0.008)	0.055*** (0.008)	0.051*** (0.008)	0.055*** (0.007)
<i>PD</i>	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	
<i>UR</i>				0.166** (0.067)	
<i>_cons</i>	−1.326*** (0.046)	1.051*** (0.039)	−1.109*** (0.042)	−1.080*** (0.043)	−1.049*** (0.036)
<i>N</i>	2904	2904	2832	3168	3168
<i>F</i>	746.9	766.47	737.3	646.9	903.08
<i>R²</i>	0.630	0.636	0.631	0.610	0.609

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

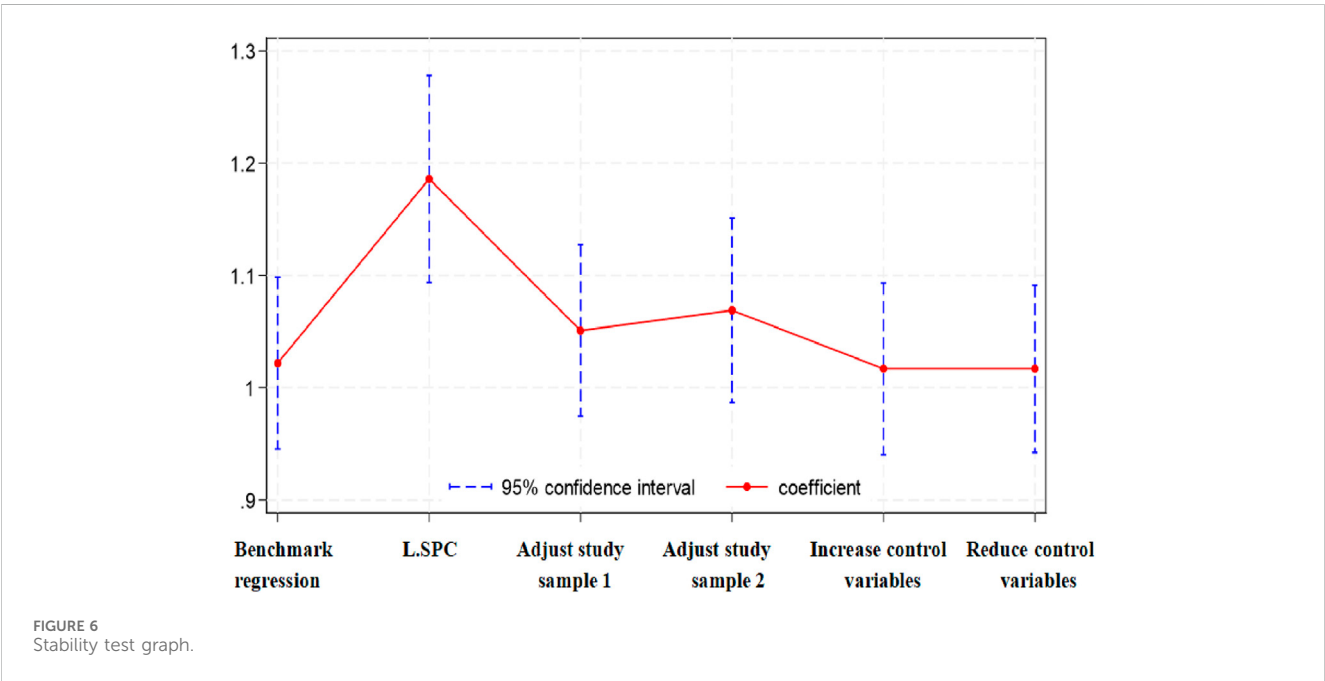


TABLE 10 Heterogeneity analysis 1.

Variable	(1)	(2)	(3)	(4)	(5)
	Energy basin	Non-energy basin	First-tier cities	Second-/third-tier cities	Third-/fourth-tier cities
<i>INDIG</i>	1.264***	0.921***	1.261***	1.063***	0.991***
	(0.077)	(0.046)	(0.172)	(0.065)	(0.053)
<i>GH</i>	0.699***	1.009***	0.265	1.114***	0.745***
	(0.269)	(0.139)	(0.470)	(0.193)	(0.172)
<i>OPEN</i>	0.128	−0.059	−0.065	−0.093	0.044
	(0.115)	(0.045)	(0.115)	(0.068)	(0.064)
<i>HCA</i>	0.567	0.545	−2.127**	0.800	1.587**
	(0.843)	(0.493)	(0.860)	(0.603)	(0.792)
<i>INFO</i>	0.007	0.070***	0.076***	0.057***	0.049***
	(0.015)	(0.009)	(0.020)	(0.014)	(0.011)
<i>PD</i>	0.001***	−0.000	0.000	−0.000**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
<i>_cons</i>	−1.662***	−0.994***	−1.946***	−1.072***	−0.563***
	(0.154)	(0.044)	(0.177)	(0.090)	(0.120)
<i>N</i>	804	2364	216	1308	1644
<i>F</i>	194.94	571.46	72.01	352.40	349.30
<i>R</i> ²	0.615	0.613	0.692	0.639	0.583

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.

and some traditional industries have not even completed the intelligent transformation of basic equipment, making it difficult for *INDIG* to be implemented, and thus *SPC* is naturally limited.

6.4 Urban agglomeration heterogeneity

Further examination is conducted on the impact of urban agglomerations on the effect of *INDIG*. The influences of *INDIG* on *SPC* in the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta urban agglomerations are tested, respectively, see columns (3)–(4) of Table 11. The impact coefficients of *INDIG* on *SPC* in these three urban agglomerations are larger than those of the full sample. The reason may be that industrial connections within urban agglomerations are close, enabling digital technologies to spread rapidly along the industrial chain and realize cross-regional collaborative governance of energy consumption and pollution. In addition, these areas are rich in innovative resources, facilitating faster R&D and application of digital technologies, and are supported by national collaborative policies, which reduce coordination costs.

To present the heterogeneity analysis results of *INDIG* concerning *SPC* more clearly and to highlight the differences between these results and the previous results, the effect coefficients of *INDIG* on *SPC* are summarized (see in Figure 7).

7 Main conclusions and implications

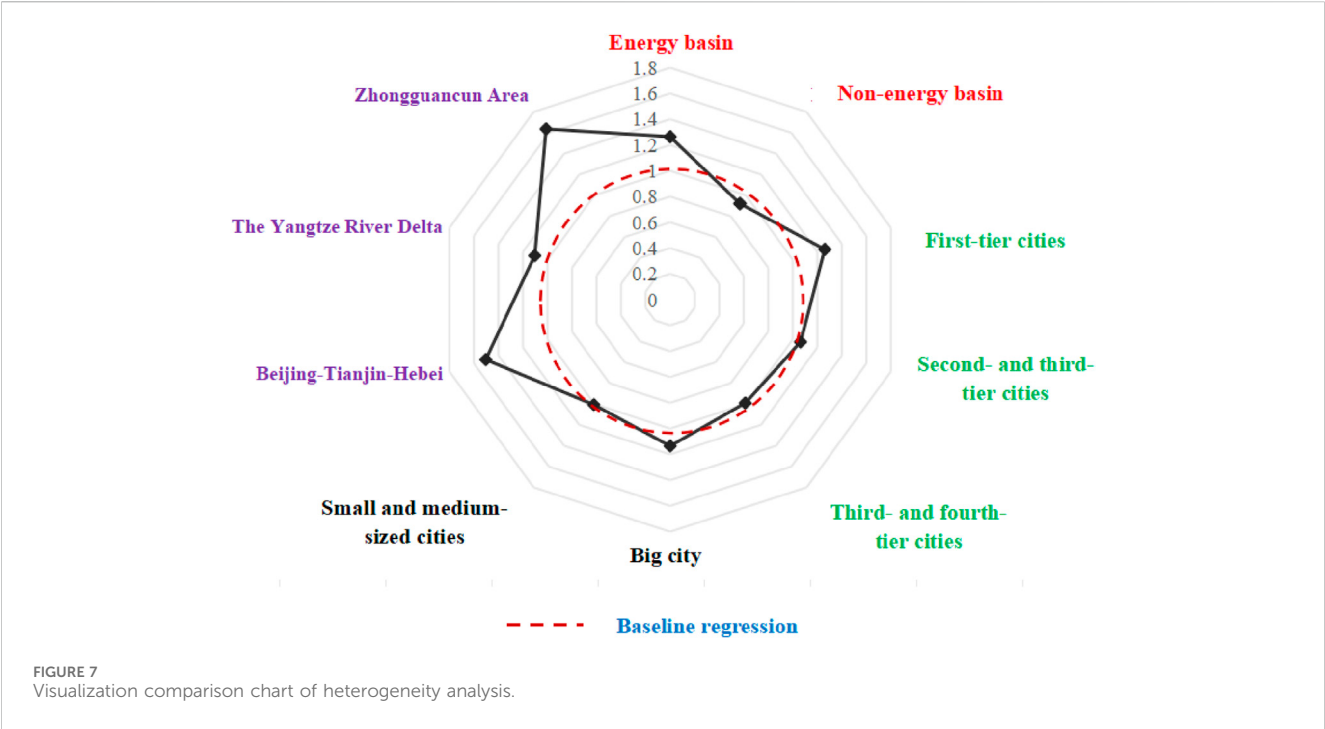
7.1 Main conclusions

1. *INDIG* has exerted a remarkable positive effect on *SPC*. The instrumental variables are introduced, and the robustness tests are conducted. The conclusion is still robust.
2. Through exploratory spatial data analysis, the spatial correlation between *INDIG* and *SPC* is remarkably optimistic. *INDIG* has obvious spatial spillover characteristics for *SPC*, and the inter-regional spillover effect is strong, and the long-term spillover effect of *INDIG* is significantly greater than that of the short term.
3. Based on whole-process governance, explore the mechanism of *INDIG* on *SPC*. It can be found that *INDIG* has different degrees of indirect impact on *SPC*, which is manifested in indirectly promoting *SPC* by improving *RES* of “source prevention,” *GPI* by improving “process control,” and strengthening *ER* of “end-of-pipe treatment.”
4. In terms of the heterogeneity of urban geographical locations, it is found that compared with non-energy basins, *INDIG* has a greater impact on *SPC* in energy basins. In terms of urban hierarchy heterogeneity, *INDIG* plays a more vital role in boosting *SPC* in first-, second-, and third-tier cities. In terms of urban scale heterogeneity, *INDIG* has a more remarkable promoting impact on *SPC* in large cities. Regarding urban agglomeration heterogeneity, *INDIG* exerts a more remarkable promoting effect on *SPC* in urban agglomerations.

TABLE 11 Heterogeneity analysis 2.

Variable	(1)	(2)	(3)	(4)	(5)
	Big city	Small and medium-sized cities	Beijing–Tianjin–Hebei	The Yangtze River Delta	Zhongguancun Area
INDIG	1.135***	1.007***	1.503***	1.104***	1.637***
	(0.083)	(0.045)	(0.259)	(0.101)	(0.480)
GH	0.814***	0.954***	1.035*	0.969***	0.688
	(0.224)	(0.148)	(0.537)	(0.315)	(0.962)
OPEN	0.001	−0.0147	−0.091	−0.119	0.276*
	(0.079)	(0.051)	(0.161)	(0.075)	(0.163)
HCA	0.261	0.883	0.908	−1.432	−2.308
	(0.549)	(0.679)	(1.844)	(1.102)	(1.838)
INFO	0.066***	0.0434***	0.146***	0.075***	0.0487
	(0.014)	(0.010)	(0.049)	(0.020)	(0.037)
PD	−0.000	0.000	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
_cons	−1.513***	−0.929***	−2.280***	−1.639***	−2.385***
	(0.082)	(0.091)	(0.370)	(0.231)	(0.541)
N	924	2244	120	312	84
F	237.39	520.36	97.36	199.14	11.70
R ²	0.629	0.604	0.849	0.810	0.497

*, **, *** indicate significance at the 1%, 5%, and 10% levels respectively. The values within parentheses represent robust standard errors.



7.2 Practical enlightenment

1. Strengthen the spatial spillover effect of *INDIG*. On the one side, establish a cross-administrative regional digital joint platform to promote the sharing of digital technologies, interconnection of green data, and coordination of emission reduction standards among adjacent cities. For example, through the joint construction of regional-level industrial internet platforms, the diffusion of environmental protection technologies and energy-saving solutions is accelerated in adjacent regions and the spatial cost of technology spillover is reduced. On the other side, in response to the geographical attenuation characteristics of spillover effects, they give play to the leading role of core cities and the undertaking role of surrounding cities. Encourage cities with a higher level of *INDIG* to transfer green digital technologies and low-carbon industrial resources to adjacent regions, and meanwhile, incentivize adjacent cities to actively undertake spillover dividends through tax incentives, subsidy policies, and other measures. In addition, it is needed to boost the inter-regional ecological compensation and benefit-sharing mechanism, provide reasonable compensation to the exporting regions that have made emission reduction contributions due to spillover effects, avoid the “free-rider” phenomenon from weakening the collaborative motivation, and ensure that the spatial spillover effect is continuously transformed into the green development momentum of the regional whole.
2. Attach importance to heterogeneity and promote coordinated development. Previous studies have found that the impact of *INDIG* on *SPC* varies. In the process of advancing *INDIG* to empower *SPC*, the government needs to fully respect the development differences of different spatial units and implement differentiated and precision-oriented policy strategies. At the geographical location level, emphasis should be placed on strengthening the layout of *INDIG* in cities in energy basins. Relying on their resource endowments and industrial foundations, digital technologies should be used to optimize energy development and utilization efficiency. Meanwhile, increase investment in digital infrastructure in cities in non-energy basins to narrow the gap in green transformation capabilities between regions. Regarding differences in urban hierarchy and scale, both gradient advancement and key breakthroughs should be considered. On one side, support first-/second-/third-tier cities and large cities to leverage their first-mover advantages in digitalization and form a benchmarking effect for green development through the digital transformation of industrial clusters. Take Baoshan District in Shanghai as an example: the green low-carbon supply chain platform integrates enterprises, and the digitalization of Baosteel and Ouyee Cloud has formed a cross-field demonstration. Linfen has promoted technological emission reduction in enterprises while building 5G smart coal mines, providing a model for the transformation of resource-based cities. On the other side, improve the digital application level of fourth-/fifth-tier cities and small cities through policy guidance and technology deployment so as to avoid the imbalance of emission reduction capabilities exacerbated by the digital divide.
3. Enshi Prefecture can rely on policies to strengthen infrastructure and introduce technologies to support the green development of agriculture and hydropower. Gaoyang County has promoted the digitalization of textile enterprises through special plans to achieve “zero discharge” in printing and dyeing, providing a path for the transformation of small cities. For urban agglomerations, efforts should be made to further strengthen the collaborative linkage of internal *INDIG*. By the convenience of factor mobility and the advantages of functional complementarity within urban agglomerations, promote cross-city sharing of digital technologies and radiation of green achievements, amplify the scale effect of *INDIG* and the synergy of emission reduction, and provide sustainable green momentum for coordinated regional development.
3. Emphasize the effective integration of environmental governance across the entire process and multiple links. Previous studies have found that *INDIG* can exert an indirect impact on *SPC* by empowering the whole-process management, which demands the government to focus on building an integrated pollution control and prevention system to achieve closed-loop management of *SPC*. First, adjust *RES* for “source prevention.” The government can establish a digital monitoring system for *RES*, relying on the blockchain technology to record data such as enterprises’ clean energy usage ratios and carbon emission reduction. These data should be linked to tax incentives and green credit eligibility to encourage enterprises to expand the scale of *RES* through digital means. Meanwhile, through inter-regional data sharing, the achievements of *RES* should be incorporated into the cross-regional collaborative assessment of *SPC*. Second, enhance *GPI* for “process control.” The government should support enterprises to join forces with universities and research institutions to establish digital process R&D centers, focusing on tackling key issues such as clean production technologies based on the industrial internet and optimization algorithms for low-carbon manufacturing processes. For example, promote the “digital twin factory” model in high-energy-consuming industries, where virtual simulation is used to test the emission reduction effects of different process parameters, accelerating the transformation of green processes from laboratories to production lines. Third, strengthen *ER* for “end-of-pipe treatment.” The government should make full use of digital platforms for precise monitoring, strengthen both formal *ER* and informal *ER* involving public participation, formulate appropriate policies of *ER*, increase investment in pollution control, and ensure rational allocation of funds, with particular emphasis on controlling industrial pollutant discharge. It should use a combination of tools of *ER* to jointly address the drawbacks of externality in pollution governance and the “green paradox.” In summary, the government should formulate digital collaborative linkage policies for whole-process environmental governance. Local governments are required to build a management platform with data integration across “source-process-end,” where policies should clarify data docking standards for each link (e.g., real-time association between clean energy usage data and production process parameters), cross-departmental collaboration procedures (e.g., tax authorities verifying incentives based on emission reduction data, environmental protection departments optimizing supervision frequency based

on process data), and take the effectiveness of integrated governance (e.g., the proportion of emission reduction across the entire chain) as a core indicator in the ecological assessment of local governments, thus forming an institutional guarantee for closed-loop management.

7.3 Shortcomings and outlook

The impact of *SPC* on *INDIG* has been measured and analyzed, and it proposes applicable differentiated development strategies for regional actual scenarios. There are still certain shortcomings: first, this research uses prefecture-level city panel data, and the applicability of the research results to smaller scales (such as within urban agglomerations) has not been verified. Future studies can use micro-level data of enterprises for specific research and explore the impact mechanism of *INDIG* on *SPC* according to the characteristics of various sub-sectors. This will help put forward more applicable guiding suggestions for effectively exerting the spatial spillover effect of *INDIG* and improving *SPC*. Second, although this paper mitigates endogeneity through methods such as *SPDM*, instrumental variable approach, and dynamic GMM, the two-way causal relationship between *INDIG* and *SPC* may exist, which can be further explored in subsequent studies. Third, this research probes the indirect effect of *INDIG* on *SPC* based on whole-process governance. Future research can try to incorporate threshold or moderating variables to further probe the “black box” of the mechanism through which *INDIG* affects *SPC*. Fourth, this research uses some variables as control variables to explore the relationship between *INDIG* and *SPC* with reference to previous studies. However, in real scenarios, there must be many factors affecting the relationship between the two. In the future, a synthetic analysis of the various factors that impact *SPC* can be conducted, and these factors can be added to the model to make the research more rigorous.

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

LZ: Writing – review and editing, Supervision, Visualization, Funding acquisition, Resources. YD: Writing – original draft, Funding acquisition, Project administration, Software. YC: Methodology, Supervision, Investigation, Resources,

Writing – review and editing. TM: Supervision, Project administration, Investigation, Writing – review and editing, Validation.

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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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References

- Behzadian, M., Otaghsara, S. K., Yazdani, M., and Ignatius, J. (2012). A state-of-the-art survey of TOPSIS applications. *Expert Syst. Appl.* 39 (17), 13051–13069. doi:10.1016/j.eswa.2012.05.056
- Cao, S., Nie, L., Sun, H., Sun, W., and Taghizadeh-Hesary, F. (2021). Digital finance, green technological innovation and energy-environmental performance: evidence from China's regional economies. *J. Clean. Prod.* 327, 129458. doi:10.1016/j.jclepro.2021.129458
- Chen, S. Y., and Chen, D. K. (2018). Air pollution, government regulations and high-quality economic development. *Econ. Res. J.* 53 (2), 20–34.
- Chen, G. F., Han, J., and Han, K. M. (2022). Urban digital economy development, skill-biased technological change and underemployment. *China Ind. Econ.* (8), 118–136. doi:10.19581/j.cnki.ciejournal.2022.08.007
- Elhorst, J. P. (2010). Applied spatial econometrics: raising the bar. *Spat. Econ. Anal.* 5 (1), 9–28. doi:10.1080/17421770903541772
- Fare, R., Grosskopf, S., and Pasurka, C. (2016). Technical change and pollution abatement costs. *Eur. J. Operational Res.* 248 (2), 715–724. doi:10.1016/j.ejor.2015.07.040

- Feng, Y. C., Wang, X. H., and Hu, S. L. (2021). Effects of fdl and ofdi on green total factor productivity in China: an analysis based on spatial econometric models. *Chin. J. Manag. Sci.* 29 (12), 81–91. doi:10.16381/j.cnki.issn1003-207x.2018.0346
- Feng, S., Zhang, R., and Li, G. (2022). Environmental decentralization, digital finance and green technology innovation. *Struct. Change Econ. Dyn.* 61, 70–83. doi:10.1016/j.strueco.2022.02.008
- Gao, D., Li, G., and Yu, J. Y. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247, 123395. doi:10.1016/j.energy.2022.123395
- Han, J., Chen, X., and Feng, X. H. (2022). The real challenge and path of enabling green development of digital economy. *Reform* (9), 11–23.
- Han, D. R., Shi, Z. Y., and Ding, Y. Y. (2023). Research on the impact of digital economy development and its internal coupling and coordinated development on regional economic resilience. *Reform Econ. Syst.* (3), 72–79. doi:10.06012X/j.cnki.tjyj.2023.03.0072(08)
- Han, X. F., Zheng, Z. J., Song, W. F., and Li, B. X. (2023). Research on the dynamic influence of digital finance on green technology innovation under environmental regulation. *Chin. J. Manag.* 20 (8), 1180–1188. doi:10.3969/j.issn.1672-884x.2023.08.008
- Hu, J. (2023). Synergistic effect of pollution reduction and carbon emission mitigation in the digital economy. *J. Environ. Manag.* 337, 117755. doi:10.1016/j.jenvman.2023.117755
- Huang, Q. H., Yu, Y. Z., and Zhang, S. L. (2019). Internet development and productivity growth in manufacturing industry: internal mechanism and China experiences. *China Ind. Econ.* (8), 5–23. doi:10.19581/j.cnki.ciejournal.2019.08.001
- Huang, Y. M., Chen, C., Lei, L. J., and Zhang, Y. (2022). Impacts of green finance on green innovation: a spatial and nonlinear perspective. *J. Clean. Prod.* 365, 132548. doi:10.1016/j.jclepro.2022.132548
- Jia, R. N., Shao, S., Du, K. R., and Yu, Y. T. (2022). Spatial-temporal pattern, dynamic evolution, and driving factors of carbon rebound effect in China: based on improved stochastic frontier model of carbon emission. *China Soft Sci.* 384 (12), 23–34. doi:10.3969/j.issn.1002-9753.2022.12.003
- Jiang, H. D., Purohit, P., Liang, Q. M., Liu, L. J., and Zhang, Y. F. (2022). Improving the regional deployment of carbon mitigation efforts by incorporating air-quality co-benefits: a multi-provincial analysis of China. *Ecol. Econ.* 204, 107675. doi:10.1016/j.ecolecon.2022.107675
- Li, J. M., Hu, Y. X., Du, W. J., Li, J. Q., Li, Z. R., and Pei, N. I. (2025). Nonlinear effects and spatial differentiation of synergy in pollution reduction and carbon emission reduction driven by science and technology under the background of new quality productive forces. *Econ. Geogr.* 45 (4), 109–122. doi:10.15957/j.cnki.jdl.2025.04.011
- Liang, L., and Li, Y. (2023). How does government support promote digital economy development in China? The mediating role of regional innovation ecosystem resilience. *Technol. Forecast. Soc. Change* 188, 122328. doi:10.1016/j.techfore.2023.122328
- Lin, X., Zhao, Y., Ahmad, M., Ahmed, Z., Rjoub, H., and Adebayo, T. S. (2021). Linking innovative human capital, economic growth, and CO₂ emissions: an empirical study based on Chinese provincial panel data. *Int. J. Environ. Res. Public Health* 18 (16), 8503. doi:10.3390/ijerph18168503
- Liu, B., and Hong, X. J. (2022). Measurement and analysis of the degree of industrial digitalization in China. *Stat. Res.* 39 (10), 3–18. doi:10.19343/j.cnki.11-1302/c.2022.10.001
- Liu, J. Y., Hu, Y., and Li, B. (2021). Environmental regulation at source, entrepreneurship and sustainable development of export. *China Popul. Resour. Environ.* 31 (8), 43–53. doi:10.12062/cpre.20210413
- Lu, X. X., Long, Z. M., and Luo, X. F. (2025). Can industrial digitization enhance the resilience of industrial and supply chain? —based on the perspective of forward linkage and backward industry linkage. *Econ. Problems* (7), 1–12. doi:10.16011/j.cnki.jjw.2025.07.007
- Lyu, Y. W., Wang, W. Q., Wu, Y., and Zhang, J. (2023). How does digital economy affect green total factor productivity? Evidence from China. *Sci. Total Environ.* 857 (2), 159428. doi:10.1016/j.scitotenv.2022.159428
- Ma, Q., Tariq, M., Mahmood, H., and Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: the moderating role of investments in research and development. *Technol. Soc.* 68 (4), 101910. doi:10.1016/j.techsoc.2022.101910
- Nam, K. M., Waugh, C. J., Paltsev, S., Reilly, J. M., and Karplus, V. J. (2013). Carbon co-benefits of tighter SO₂ and NO_x regulations in China. *Glob. Environ. Change* 23 (6), 1648–1661. doi:10.1016/j.gloenvcha.2013.09.003
- Nazari, S., Shahhoseini, O., Sohrabi-Kashani, A., Davari, S., Sahabi, H., and Rezaeian, A. (2012). SO₂ pollution of heavy oil-fired steam power plants in Iran. *Energy Policy* 43, 456–465. doi:10.1016/j.enpol.2012.01.040
- Qian, X. Y., Yu, Y. Y., Yan, S. Y., and Jiang, H. D. (2025). Environmental and economy-wide impacts of green fiscal policies on digital economy development: a CGE-Based analysis. *Econ. Analysis Policy* 86, 65–75. doi:10.1016/j.eap.2025.03.019
- Rao, B. (2025). Does digital infrastructure construction serve as a new engine for green sustainable innovation? A quasi-natural experiment based on the “Broadband China” pilot policy. *Pol. J. Environ. Stud.* 34 (4), 4363–4376. doi:10.15244/pjoes/195700
- Ren, X. H., Zeng, G. D., and Gozgor, G. (2023). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *J. Environ. Manag.* 330, 117125. doi:10.1016/j.jenvman.2022.117125
- Ribeiro, H. V., Rybski, D., and Kropp, J. P. (2019). Effects of changing population or density on urban carbon dioxide emissions. *Mature Commun.* 10, 3204. doi:10.1038/s41467-019-11184-y
- Shahbaz, M., Wang, J., Dong, K. Y., and Zhao, J. (2022a). The impact of digital economy on energy transition across the globe: the mediating role of government governance. *Renew. & Sustain. Energy Rev.* 166, 112620. doi:10.1016/j.rser.2022.112620
- Shahbaz, M., Li, J., Dong, X., and Dong, K. (2022b). How financial inclusion affects the collaborative reduction of pollutant and carbon emissions: the case of China. *Energy Econ.* 107, 105847. doi:10.1016/j.eneco.2022.105847
- Sun, H., and Deng, Y. Y. (2022). The effect of “Reducing pollution and carbon emissions” in environmental policy: a study based on the perspective of pollution fee collection. *China Econ. Stud.* (3), 115–129. doi:10.19365/j.issn1000-4181.2022.03.07
- Tapscott, D. (1996). *The digital economy: promise and peril in the age of networked intelligence[M]*. New York: McGraw-Hill.
- Wang, D. F., and Cao, J. H. (2019). The impact of internet development on China’s total factor energy efficiency and its network effects. *China Popul. Resour. Environ.* 29 (1), 86–95. doi:10.12062/cpre.20180926
- Wang, Q. W., Wang, Y. Z., Zhou, P., and Wei, H. (2016). Whole process decomposition of energy-related SO₂ in Jiangsu Province, China. *Appl. Energy* 194 (15), 679–687. doi:10.1016/j.apenergy.2016.05.073
- Wang, R., Zameer, H., Feng, Y., Jiao, Z., Xu, L., and Gedikli, A. (2019). Revisiting Chinese resource curse hypothesis based on spatial spillover effect: a fresh evidence. *Resour. Policy* 64, 101521. doi:10.1016/j.resourpol.2019.101521
- Wang, S. J., Kong, W., Ren, L., Zhi, D. d., and Dai, B. t. (2021). Research on misuses and modification of coupling coordination degree model in China. *J. Nat. Resour.* 36 (3), 793–810. doi:10.31497/zrzyxb.20210319
- Wang, G. J., Li, C. M., and Zhang, H. (2022). The technological innovation effect of industrial digitalization. *J. Finance Econ.* 48 (9), 139–153. doi:10.16538/j.cnki.jfe.20220715.301
- Wang, S. H., Liu, S. Z., and Li, X. M. (2025). Research on the impact mechanism of the digital economy spatial correlation network on pollution reduction and carbon reduction. *J. China Univ. Geosciences Social Sci. Ed.* 25 (2), 105–119. doi:10.16493/j.cnki.42-1627/c.20250228.003
- Wu, C. Q., and Deng, M. L. (2023). Study on the path of informationization level promoting the growth of total factor carbon productivity in China. *China Soft Sci.* (4), 177–188.
- Yang, G. Q., Wang, H. S., Fan, H. S., and Yue, Z. Y. (2023). Carbon reduction effect of digital economy: theoretical analysis and empirical evidence. *China Ind. Econ.* (5), 80–98. doi:10.3969/j.issn.1006-480X.2023.05.005
- Yi, L., Yang, T. T., Du, X., Yang, L., and Deng, W. (2022). Collaborative pathways of pollution reduction and carbon abatement: typical countries’ driving mechanisms and their implications for China. *China Popul. Resour. Environ.* 32 (9), 53–65. doi:10.12062/cpre.20220605
- Yu, W., Zhang, P., and Ji, Z. H. (2021). Study on regional difference, distribution dynamics and convergence of eco-efficiency of urban clusters in China. *J. Quantitative & Technol. Econ.* 38 (1), 23–42. doi:10.13653/j.cnki.jqte.2021.01.002
- Zhang, Y., Sun, Q., Xue, J. J., and Yang, C. H. (2022). Synergistic effects of pollution control and carbon reduction and their pathways. *China Popul. Resour. Environ.* 32 (5), 1–13. doi:10.12062/cpre.20220202
- Zhang, Y. H., Wang, M. F., and Liu, T. T. (2022). Spatial effect of digital economy on high-quality economic development in China and its influence path. *Geogr. Res.* 41 (7), 1826–1844. doi:10.11821/dlyj020210644
- Zhang, S. S., Cui, Q., and Ma, X. Y. (2022). Energy saving and emission reduction effect of biased technological progress under digital factor empowerment. *China Popul. Resour. Environ.* 32 (7), 22–36. doi:10.12062/cpre.20220428
- Zhang, J. N., Lyu, Y. W., Li, Y. T., and Geng, Y. (2022). Digital economy: an innovation driving factor for low-carbon development. *Environ. Impact Assess. Rev.* 96, 106821. doi:10.1016/j.eiar.2022.106821
- Zhang, L., Nie, R., and Zhang, Y. (2025). The impact of the digital economy on carbon emissions and its spatial spillover effects. *Statistics & Decis.* 41 (12), 113–117. doi:10.13546/j.cnki.tjyj.2025.12.019
- Zhao, H. X., and Meng, Y. J. (2022). Measurement and evaluation of the coupling coordination of urban digital economy and green technology innovation in China. *China Soft Science.* (9), 97–107.

Appendix

To clearly present the correspondence between the abbreviations and full names of the variables in this article, a table is constructed, as shown in [Table A1](#).

TABLE A1 Correspondence table of abbreviations and full names.

Variable	Abbreviation
Synergistic effects of pollution and carbon reduction	<i>SPC</i>
Industrial digitization	<i>INDIG</i>
Renewable energy substitution	<i>RES</i>
Green process innovation	<i>GPI</i>
Environmental regulations	<i>ER</i>
Green finance level	<i>GH</i>
Opening up to the outside world	<i>OPEN</i>
Human capital accumulation	<i>HCA</i>
Informationization level	<i>INFO</i>
Population density	<i>PD</i>
Urbanization level	<i>UR</i>
Spatial panel Durbin model	<i>SPDM</i>