frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 05 February 2026
DOI 10.3389/fenvs.2025.1638765

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OPEN ACCESS

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RECEIVED 31 May 2025
REVISED 17 November 2025
ACCEPTED 03 December 2025
PUBLISHED 05 February 2026

CITATION
Fu Y, Yao W, Zhang X, Zeng T, Huang J, Han G, Zeng B and Li Y (2026) The U-shaped relationship between environmental regulation and carbon emission efficiency: evidence from China's provincial panel data.
Front. Environ. Sci. 13:1638765.
doi: 10.3389/fenvs.2025.1638765

The U-shaped relationship between environmental regulation and carbon emission efficiency: evidence from China's provincial panel data

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Under the global imperative for energy conservation and emission reduction, a critical yet underexplored question is how environmental regulation (ER) specifically affects carbon emission efficiency (CEE). In this paper, the Super-Slacks-Based Measure (SBM) model with undesirable outputs is used to measure the CEE of 30 Chinese provinces from 2010 to 2022. Based on the results, the Tobit model is used to study the impact of ER on CEE empirically. The results show that (1) China's CEE is low, and the eastern region has the highest CEE, followed by the central and northeastern regions, and the lowest is the western region. (2) There is a U-shaped curve relationship between ER and CEE, namely, the impacts of ER on CEE are first inhibitory and then promotive; Currently, ER is having a negative effect on CEE, and the inflection point has yet to emerge. (3) Opening up level and population density have positive influences on CEE, while industrial structure exerts a negative impact. This research provides a reference for improving the CEEs of China and other developing countries. Policy implications include the need to strengthen and optimise the regulations to promote the high-quality development of the Chinese economy. The results offer a reference for policymakers.

KEYWORDS

environmental regulation, carbon emission efficiency, impact mechanism, super-SBM model with undesirable outputs, tobit model

1 Introduction

Global warming has become increasingly intense in recent decades, which results from human survival and development (Zhai et al., 2021; Yaman 2024; Zou et al., 2025; Wu et al., 2023; Phiri et al., 2021; Zhao et al., 2023; Cao et al., 2023; Cao et al., 2022; Hansen 1999; Li et al., 2024). As one of the key greenhouse gases, Carbon dioxide (CO_2) is the major factor driving global climate change (Zhao et al., 2022; Wu et al., 2022; Wu et al., 2023; Phiri et al., 2021; IPCC, 2021; IEA, 2025). As the largest consumer of energy in the world, China faces great pressure to reduce its CO_2 emissions. The CO_2 emissions from fossil energy in mainland China have soared from 3,387 million tons in 2000 to 11,314 million tons in 2021, and China has taken over from the United States as the largest producer of CO_2 in the world (6). At the 75th UN General Assembly in 2020, China made a commitment to achieve carbon neutrality by 2060 (Shi et al., 2023; Chi et al., 2021; Chen et al., 2023; Li et al., 2022; Wang et al., 2024). However, China is striving to shift its economic development mode, and it has pushed its economy towards high-quality development (Hu et al., 2024). The traditional mode of economic growth characterized by high energy consumption, high emissions and low efficiency cannot meet the requirements of high-quality development. Therefore, improvements in carbon emission efficiency (CEE) are undoubtedly of great significance to enhance the economic development quality for China.

CEE can be distinguished into two categories: the single-factor and the total-factor efficiencies (Wang et al., 2023; Xu et al., 2024). The measurement of the single-factor efficiency only focuses on an indicator that can reflect the relationship between energy carbon emissions and economic output; for example, carbon emission intensity is a typical single-factor indicator, which is the proportion of energy-based carbon emissions to GDP (Kaya and Yokobori, 1993; Alqaness et al., 2023). However, the single factor efficiency only considers the relationship between carbon emissions and economic output, and it neglects the contribution of other factors to production (Zhang et al., 2022). The total factor efficiency integrates labour, capital, energy, and other input factors into the production function, comprehensively reflecting the impact of various production factors on economic output, so it is widely recognized (Cao et al., 2023; Zhao et al., 2023).

The calculation methods of total factor efficiency include stochastic frontier analysis (SFA) and data envelopment analysis (DEA). SFA clarifies the production function's specific form and sets the error term's probability distribution (Zhao et al., 2020; Qu et al., 2022; Li et al., 2023). SFA is primarily applied for single-output and multi-input efficiency measurements and many studies have applied the SFA method to calculate the CEE (Lv et al., 2021; Wang et al., 2019; Zhang and Chen, 2021; Wang et al., 2021; Wang et al., 2023). However, the SFA model needs to make strict assumptions about the production function. If the assumptions are improper, this will lead to a difference between the estimated results and the actual situation (Zeng et al., 2022). DEA uses linear programming in mathematics to estimate the objective function and then evaluate the efficiency of decision-making units with multiple inputs and outputs, which does not need to set a strict production function (Zhao et al., 2022). Therefore, researchers use it widely to measure CEE (Yang et al., 2023; Ren et al., 2023; Zhang et al., 2023; Jiang et al., 2022; Ning et al., 2021; Zhang and Xu, 2023; Liu et al., 2021; Gao et al., 2021; Gao et al., 2022).

How can CEE be improved? Conventional wisdom has it that environmental regulation has a crucial influence on improving CEE (Sun et al., 2019; Zhu et al., 2020). ER is an integral means of social regulation through which government authorities regulate the operation and production activities of producers through tax collection for pollution emissions, administrative penalties, emission permits, and administrative orders to protect the ecological environment (Zhang et al., 2022). Many scholars have deeply studied the impact of ERs on carbon emissions over the last 10 years. Many scholars have deeply studied the impact of ERs on carbon emissions over the last 10 years. Existing research has covered carbon emission measurement, efficiency drivers, and policy effects from global and regional perspectives (Cao et al., 2023; Gao et al., 2021; Gao et al., 2022; IEA, 2025; IPCC, 2021; Phiri et al., 2021; Yuan et al., 2023; Zhao et al., 2023; Zhao et al., 2023). Some studies have confirmed that ER can inhibit carbon emissions by encouraging technological progress (Mehmood et al., 2024; Yin et al., 2025; Radulescu et al., 2024; Khodaparasti et al., 2025). Some scholars have agreed that ER may increase the production cost of enterprises, which may not be offset completely by the compensating effect of technological progress, leading to a decline in production efficiency and the production of more carbon emissions. A third opinion is that ER has a nonlinear impact on carbon emissions, and this influence may be different in different regions or periods (Su and Gao, 2023). In addition, most of the prior studies focused on carbon emissions, and the impacts of ER on regional CEE were rarely explored.

In the field of provincial-level carbon emission reduction efficiency research in China, existing literature has completed the measurement of provincial Carbon Emission Efficiency (CEE), but fails to integrate regional differences with the regional implementation heterogeneity of environmental regulations and lacks discussions on the regional heterogeneous policy adaptability between Environmental Regulations (ER) and CEE, which makes it difficult for the conclusions to guide local governments in formulating precise policies; based on measuring the CEE and regional differences of 30 provinces from 2010 to 2022, this paper proposes regionalized ER policy recommendations, fills the gap in existing literature regarding the correlation analysis between regional heterogeneity and policy adaptability, and provides targeted support for local governments to formulate differentiated carbon emission reduction policies.

The main contributions of this paper are: (1) proposing a theoretical framework for the impacts of ER on CEE; (2) exploring the possible non-linear relationship between ER and CEE with an empirical economic model, which is conducive to the in-depth study of the policy effects of ERs in China; (3) This paper analyses the temporal and spatial characteristics of CEE; a better understanding of CEE can assist policymakers in formulating more reasonable reduction policies.

2 Methodology

2.1 Research area and data

We collected data from 2010 to 2022. Due to the unavailability of sufficient data and consistency and to minimise data-curation errors, we removed Tibet, Hong Kong, Macao, and Taiwan from this study's analysis. We therefore compiled the data for the remaining 30 provinces of China from China Statistical Yearbooks (2010–2023), Author Anonymous (2023a), National Bureau of Statistics of China (NBSC, 2026), and CEAD (2025). According to NBSC, the researched 30 provinces are in four regions: the eastern, the central, the western, and the northeastern (Figure 1).

China has been selected as the research area due to its prominent global position in carbon emissions and unique policy context (Hu et al., 2025a). Furthermore, China's commitment to achieving carbon neutrality by 2060, announced at the 2020 UN General Assembly, is driving a transition towards high-quality development.

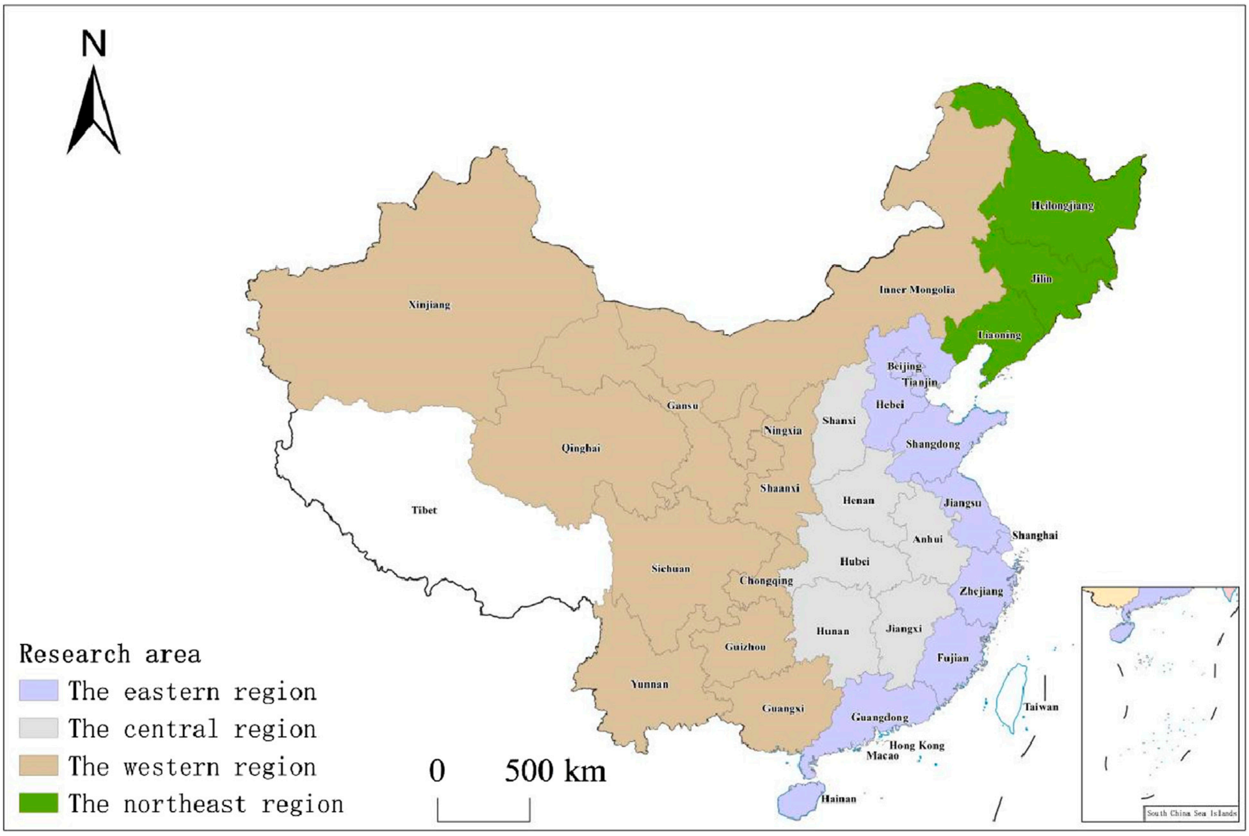

FIGURE 1
The research areas.

This makes improving carbon efficiency crucial, thereby enhancing the research's representativeness and practical significance.

2.2 Theoretical mechanism

There are three perspectives on the impacts of ER on carbon emissions. Some researchers agree that ERs have a negative effect on carbon emissions. Firstly, the implementation of ERs has raised the entry threshold for the environmental protection requirements for manufacturing industry, which restricts the expansion of traditional energy-intensive industries (Shen et al., 2020). Secondly, the government has established ERs to impose taxes on pollutant discharge enterprises, which will increase the costs of fossil fuels. For survival and development, enterprises need to research cleaner technology to increase their energy efficiency and reduce emissions. Furthermore, the Porter hypothesis states that the cost pressure imposed on enterprises could potentially arouse their enthusiasm for innovative activities, thereby promoting productivity and offsetting the cost of ER (Porter and Linder, 1995). Specifically, the government uses administrative means to ensure that enterprises meet emission standards, and to eliminate factories that are equipped with outdated industrial capacity and that cause heavy environmental pollution. This will promote the upgrading of production equipment and further reduce carbon emissions (Lin et al., 2023).

Other scholars believe that ER has a positive effect on carbon emissions; Firstly, the transfer of manufacturing capital can usually bring in higher technology for local industries. If the ERs in a locality are much stricter than that in other regions, the situation will not be conducive to the technology spillover effect or the transfer of manufacturing capital, as well as the absorption of advanced technology and experience. Secondly, the compliance cost hypothesis posits that ER increases the cost of operating industries, and this may inhibit technological research and development capability, which is not conducive to the improvement of emission reduction capacity (Barbera and McConnell, 1990; Hu et al., 2019; Liu J. et al., 2022). In addition, intensified ER may cause enterprises to increase their output for offsetting rising costs, potentially resulting in further pollution emissions (Fünfgelt and Schulze, 2016).

A third group thinks that the effects of ER on carbon emissions are nonlinear; the effects of ER on carbon emissions depend on the accumulation of knowledge and technology, economic development level (Li and Liu, 2018; Hamamoto, 2006) and the implementation intensity of ERs (Lin et al., 2023). Therefore, the effects of ER on carbon emissions have had different features in different periods. At this stage, stringent ERs in China have not had a clear positive impact on carbon emissions. Some methods of environmental governance still need to be improved, and many industrial enterprises may not yet have adapted to the new regulatory environment. As regulatory measures become more robust and

TABLE 1 Index system of CEE.

Primary indicator	Secondary indicator	Unit
Input	Capital stock	100 million renminbi (RMB)
	Energy	10,000 tons
	Labor	10,000 people
Desired output	Gross domestic product	100 million RMB
Undesired output	Carbon dioxide emissions	10,000 tons

comprehensive, industrial enterprises must adapt through technological innovations and improved practices, leading to a positive impact on CEE in the future (Hong et al., 2023). Therefore, there is potential for positive outcomes once the turning point is reached.

Based on this theoretical analysis, we raise the following two hypotheses:

Hypothesis 1: ER has a significant impact on CEE in China.

Hypothesis 2: ER has a nonlinear impact on CEE in China.

2.3 Variable description

2.3.1 Explained variable

CEE is the explained variable in this paper. According to the literature (Zeng et al., 2025; Qu et al., 2022; Liu et al., 2022; Wang and Zhang, 2022), we have constructed a measurement index system for CEE. The input indicators include capital stock, energy, and labour, the desirable output indicator is GDP, and the undesirable output indicators include CO_2 (Table 1).

2.3.1.1 Input indicators

Labour is the number of employees in each province. These data come from China Statistical Yearbook (2010–2023). The calculation formula of the capital stock is: $K_{it} = (1 - \delta)K_{it-1} + I_{it}$, where K and I indicate the stock of social fixed-asset investment and new social fixed-asset investment, respectively; δ denotes the depreciation rate of fixed assets, with a value of 9.6% (Zhang et al., 2004; Li et al., 2025). These data also come from China Statistical Yearbooks (2010–2023). Energy is defined as the total energy consumption in each province. These data come from China Energy Statistical Yearbooks (2010–2023).

2.3.1.2 Desirable output

We selected GDP as the desirable output, which we converted into 2010 constant prices based on the GDP deflator. These data come from NBSC.

2.3.1.3 Undesirable output

The CO_2 emission data come directly from the Carbon Emission Accounts and Datasets database.

2.3.2 Explanatory variable and control variables

From the perspective of the implementation cost of environmental regulation intensity (ER), ER is measured as the proportion of the total operation and investment in industrial waste gas treatment to local GDP to measure ER indicators (Nie et al., 2023). The unit is a percentage.

The research on factors affecting CEE in China has gradually increased in recent years. To analyse the impact of ER on CEE more comprehensively and accurately, after sorting out and referring to relevant literature, we selected the three indicators as the control variables shown in Table 2. These three control variables include industrial structure (IS) (Cao et al., 2023; Cao et al., 2022), opening up level (OUL) (Yuan et al., 2023; Liu et al., 2023; Jiang et al., 2022) and Population density (PD) (Zeng et al., 2022c; Bozatli et al., 2025; Timmons et al., 2016; Matsuhashi and Ariga, 2016; Yıldız and Kahveci, 2025).

2.3.2.1 Industrial structure (IS)

Transformation and improvement of the industrial structure directly influence energy consumption, which causes a change in carbon emissions (Chen et al., 2021). The secondary industry has relatively high energy demands and significantly impacts carbon emission efficiency. Therefore, we use the proportion of the secondary industry in GDP to depict the industrial structure. The unit of measurement is a percentage.

2.3.2.2 Opening up level (OUL)

By opening up to international trade, China has been able to import advanced machinery and cleaner technologies that are more energy efficient, thereby reducing the carbon intensity of its industrial processes. Increasing OUL can promote the introduction of advanced technology. Therefore, OUL is also an essential aspect in analysing the factors affecting CEE. This article selects the proportion of foreign trade in GDP to measure OUL.

2.3.2.3 Population density (PD)

Concentration of residents and economic activities can promote energy efficiency by reducing *per capita* infrastructure costs, encouraging public transportation use, and enabling centralized energy management. Population density, measured as the number of people per square kilometer (persons/km^2).

TABLE 2 Explanatory variable and control variables.

Variable	Definition
Environmental regulation (ER)	Proportion of the total operation and investment in industrial waste gas treatment to local GDP (%)
Industrial structure (IS)	Proportion of secondary industry to GDP (%)
Opening up level (OUL)	Proportion of foreign trade to GDP (%)
Population density (PD)	Proportion of the resident population to the regional area (persons/km^2)

2.4 Methodology

2.4.1 The Super-slacks-based measure (SBM) model with undesirable outputs

DEA is an important method for calculating CEE, as it uses linear programming to estimate the relative efficiency of decision-making units (DMU) in a multi-input, multi-output system (Xia et al., 2023). The traditional DEA models neglected the slack variable problem, which leads to inaccurate measurement results (Zhu et al., 2024). Therefore, Tone (2001) proposed the slacks-based measure (SBM) to solve this problem. Tone and Sahoo (2003) developed an SBM model that can consider undesirable outputs. We combined the super-efficiency model and SBM model with undesirable outputs to calculate the CEE, which can calculate and rank the efficient DMUs with undesirable outputs, which is as follows:

There is the production system that has N DMUs, and each DMU has M kinds of inputs, S_1 kinds of desirable outputs, and S_2 kinds of undesirable outputs. Assuming $x_o = X_\eta + S^-$, $y^g{}_0 = Y_\eta - S^g$, $y^b{}_0 = Y^b{}_\eta + S^b$ to accurately depict the production process incorporating multiple inputs, desirable outputs, and undesirable outputs, we define the production possibility set for decision-making units (DMUs) as follows (Equation 1):

$$P\left(\left(x_0, y_0^g, y_0^b\right)\right) = \left\{\left(\bar{x}, \bar{y}^g, \bar{y}^b\right) \middle| \bar{x} \geq \sum_{j=1, j\neq 0}^{N} X_j \eta_j + S^-, \bar{y}^g \leq \sum_{j=1, j\neq 0}^{N} Y_j^g \eta_j - S^g, \bar{y}^b \geq \sum_{j=1, j\neq 0}^{N} Y_j^b \eta_j + S^b, \eta_j \geq 0\right\} \quad (1)$$

Equation 1 clarifies the feasible combination of inputs and outputs, laying the foundation for subsequent efficiency measurement by constraining the linear combination of DMUs. In Equation 1 η denotes the non-negative intensity vector. Based on the production possibility set defined in Equation 1, we further construct the super-SBM efficiency measurement formula to calculate the CEE value of DMU (x_0 $y^g{}_0$,$y^b{}_0$), which is expressed as Equation 2:

$$\gamma^* = \min \left[\frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{S_r^g}{y_{ro}^g} + \sum_{p=1}^{s_2} \frac{S_p^b}{y_{po}^b} \right)} \right]$$
$$s.t. \begin{cases} x_{i0} = \sum_{j=1, j\neq 0}^{N} x_{ij} \eta_j + S_i^- & (i = 1, 2, \ldots, m) \\ y_{r0}^g = \sum_{j=1, j\neq 0}^{N} y_r^g \eta_j - S_r^g & (r = 1, 2, \ldots, s_1) \\ y_{p0}^b = \sum_{j=1, j\neq 0}^{N} y_{pj}^b \eta_j + S_p^b & (p = 1, 2, \ldots, s_2) \\ \eta_j \geq 0, S_i^- \geq 0, S_r^g \geq 0, S_P^b \geq 0 \end{cases} \quad (2)$$

In Equation 2, the slack variables (S^-, S^g, S^b) are integrated to address the inefficiency of inputs and outputs, ensuring the accuracy of CEE measurement. γ* is the CEE value, where γ*> 1 indicates the DMU is on the production frontier with optimal efficiency. S^-, S^g, S^b indicate the slack in inputs, desirable outputs, and undesirable outputs, respectively.

2.4.2 Tobit

Considering that the model setting, the CEE values are a truncated segment value or cut value, the application of the traditional OLS regression method for testing the impact of ER on CEE may result in a seriously biased answer as the CEE values are discrete distributed data with lower bounds. Tobit regression is a famous variable-limited model, which can solve this problem by using a maximum likelihood estimation (MLE) (Zeng et al., 2022a). Since CEE values are truncated data with a lower bound of 0, the traditional OLS regression may lead to biased results. Thus, we adopt the Tobit model with the following basic form (Equation 3):

$$Y^* = \beta X_i + u_i$$
$$Y_i = \begin{cases} Y_i^* & \text{if } Y_i^* > 0 \\ 0 & \text{if } Y_i^* \leq 0 \end{cases} \quad (3)$$

Equation 3 specifies the latent variable and observed variable relationship of the Tobit model, effectively addressing the estimation bias caused by truncated data.In Equation 3, i denotes the ith DMU. Y^* indicates the latent variable, and Y_i refers to the actually observed dependent variable. β stands for the regression coefficient vector. X is the independent variable. u is a random error term.

3 Calculation results of CEE

The calculation results of CEE are shown in Table 3 and Figure 2. The average value of the CEE among all provinces from 2010 to 2022 was 0.357. This indicates that the overall level of CEE in China has not reached an effective state and remains relatively low, suggesting substantial room for improvement.

Analysis of the provincial data reveals two distinct patterns. Firstly, Beijing and Shanghai stand out, with mean CEE values significantly greater than 1 throughout the entire study period. This places them consistently on the production frontier, representing benchmarks of high efficiency within the national context. Beijing and Shanghai exhibit high CEE due to their advanced energy utilization technologies, abundant talent, and sufficient funding in the eastern region. These factors enable superior innovation and resource management, positioning them as benchmarks nationally. In contrast, the vast majority of the other 28 provinces exhibit CEE levels below 0.5. Among these, the performances of Guangdong, Jiangsu and Zhejiang were relatively stronger, with mean CEE values above 0.5 from 2010 to 2019. This indicates a better balance between economic and environmental objectives, though there is still room for improvement. The CEE levels of the remaining provinces are all below 0.5, highlighting greater challenges in their transition to cleaner energy and more efficient production systems. Consequently, more than two-thirds of the provinces fall below the national average, underscoring a widespread need to accelerate

TABLE 3 The values of CEE for 30 provinces in China (2010–2022).

Province	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean
Beijing	1.178	1.279	1.254	1.265	1.270	1.269	1.289	1.314	1.287	1.294	1.385	1.410	1.355	1.296
Tianjin	0.425	0.394	0.403	0.407	0.403	0.403	0.408	0.406	0.391	0.389	0.357	0.353	0.350	0.391
Hebei	0.247	0.245	0.245	0.240	0.237	0.232	0.228	0.225	0.220	0.219	0.216	0.212	0.206	0.229
Shanxi	0.260	0.250	0.244	0.251	0.239	0.228	0.216	0.216	0.216	0.219	0.225	0.229	0.240	0.233
Inner Mongolia	0.236	0.230	0.228	0.237	0.229	0.234	0.233	0.229	0.223	0.220	0.218	0.217	0.224	0.227
Liaoning	0.282	0.243	0.244	0.243	0.238	0.241	0.241	0.242	0.242	0.246	0.230	0.231	0.236	0.243
Jilin	0.305	0.231	0.235	0.238	0.236	0.252	0.253	0.251	0.245	0.238	0.232	0.230	0.226	0.244
Heilongjiang	0.333	0.257	0.254	0.252	0.245	0.252	0.245	0.242	0.236	0.237	0.234	0.227	0.229	0.250
Shanghai	1.243	1.105	1.109	1.092	1.092	1.102	1.105	1.107	1.099	1.093	1.073	1.059	1.047	1.102
Jiangsu	0.567	0.516	0.528	0.517	0.517	0.520	0.516	0.512	0.507	0.498	0.455	0.446	0.432	0.502
Zhejiang	0.563	0.533	0.539	0.517	0.512	0.505	0.497	0.486	0.478	0.472	0.417	0.397	0.378	0.484
Anhui	0.338	0.314	0.315	0.303	0.302	0.300	0.298	0.297	0.294	0.289	0.284	0.277	0.268	0.298
Fujian	0.527	0.461	0.472	0.469	0.453	0.456	0.457	0.442	0.429	0.420	0.411	0.394	0.384	0.444
Jiangxi	0.357	0.334	0.344	0.324	0.321	0.317	0.315	0.312	0.310	0.306	0.287	0.287	0.279	0.315
Shandong	0.381	0.325	0.328	0.338	0.334	0.324	0.320	0.322	0.321	0.319	0.305	0.300	0.297	0.324
Henan	0.316	0.296	0.304	0.308	0.300	0.303	0.302	0.302	0.300	0.304	0.294	0.282	0.268	0.298
Hubei	0.374	0.341	0.348	0.366	0.364	0.370	0.366	0.362	0.358	0.350	0.313	0.308	0.300	0.348
Hunan	0.356	0.337	0.347	0.358	0.356	0.360	0.353	0.348	0.346	0.343	0.324	0.313	0.308	0.342
Guangdong	0.765	0.685	0.688	0.684	0.643	0.627	0.609	0.586	0.565	0.547	0.493	0.466	0.475	0.603
Guangxi	0.295	0.278	0.282	0.277	0.272	0.268	0.260	0.253	0.245	0.236	0.218	0.207	0.203	0.253
Hainan	0.425	0.382	0.376	0.356	0.343	0.328	0.323	0.308	0.297	0.293	0.278	0.276	0.274	0.328
Chongqing	0.328	0.325	0.340	0.368	0.366	0.391	0.400	0.399	0.388	0.383	0.352	0.344	0.355	0.365
Sichuan	0.319	0.303	0.310	0.314	0.312	0.324	0.322	0.319	0.319	0.311	0.289	0.280	0.277	0.307
Guizhou	0.215	0.224	0.221	0.230	0.226	0.223	0.220	0.217	0.212	0.208	0.199	0.192	0.190	0.213
Yunnan	0.285	0.271	0.274	0.279	0.274	0.276	0.269	0.263	0.256	0.255	0.229	0.222	0.217	0.259
Shaanxi	0.015	0.015	0.015	0.015	0.015	0.016	0.016	0.016	0.016	0.016	0.016	0.015	0.015	0.015
Gansu	0.230	0.223	0.224	0.218	0.212	0.208	0.205	0.199	0.195	0.196	0.194	0.189	0.190	0.206
Qinghai	0.200	0.199	0.190	0.193	0.187	0.181	0.177	0.174	0.169	0.168	0.169	0.159	0.165	0.179
Ningxia	0.193	0.196	0.197	0.207	0.200	0.191	0.185	0.175	0.169	0.168	0.178	0.178	0.180	0.186
Xinjiang	0.309	0.284	0.263	0.261	0.248	0.233	0.221	0.210	0.207	0.203	0.198	0.191	0.193	0.232
Eastern region	0.632	0.593	0.594	0.589	0.580	0.577	0.575	0.571	0.559	0.554	0.539	0.531	0.520	0.570
Central region	0.333	0.312	0.317	0.318	0.314	0.313	0.308	0.306	0.304	0.302	0.288	0.283	0.277	0.306
Western region	0.239	0.231	0.231	0.237	0.231	0.231	0.228	0.223	0.218	0.215	0.205	0.199	0.201	0.222
Northeast region	0.306	0.243	0.244	0.244	0.240	0.248	0.246	0.245	0.241	0.240	0.232	0.229	0.230	0.245
Mean	0.395	0.369	0.371	0.371	0.365	0.364	0.362	0.358	0.351	0.348	0.336	0.330	0.325	0.357

efforts in energy conservation, emission reduction, and enhanced environmental governance.

From a regional perspective, the mean CEE values in eastern, central, northeastern, and western China during the study period were 0.570, 0.306, 0.245, and 0.222, respectively, revealing significant regional disparities. The eastern region benefits from advanced energy utilization technologies, talent, and funding, allowing it to apply advanced methods to improve resource efficiency and reduce carbon emissions. The central region, a key base for heavy industry in China, serves as a geographical link between the east and the west

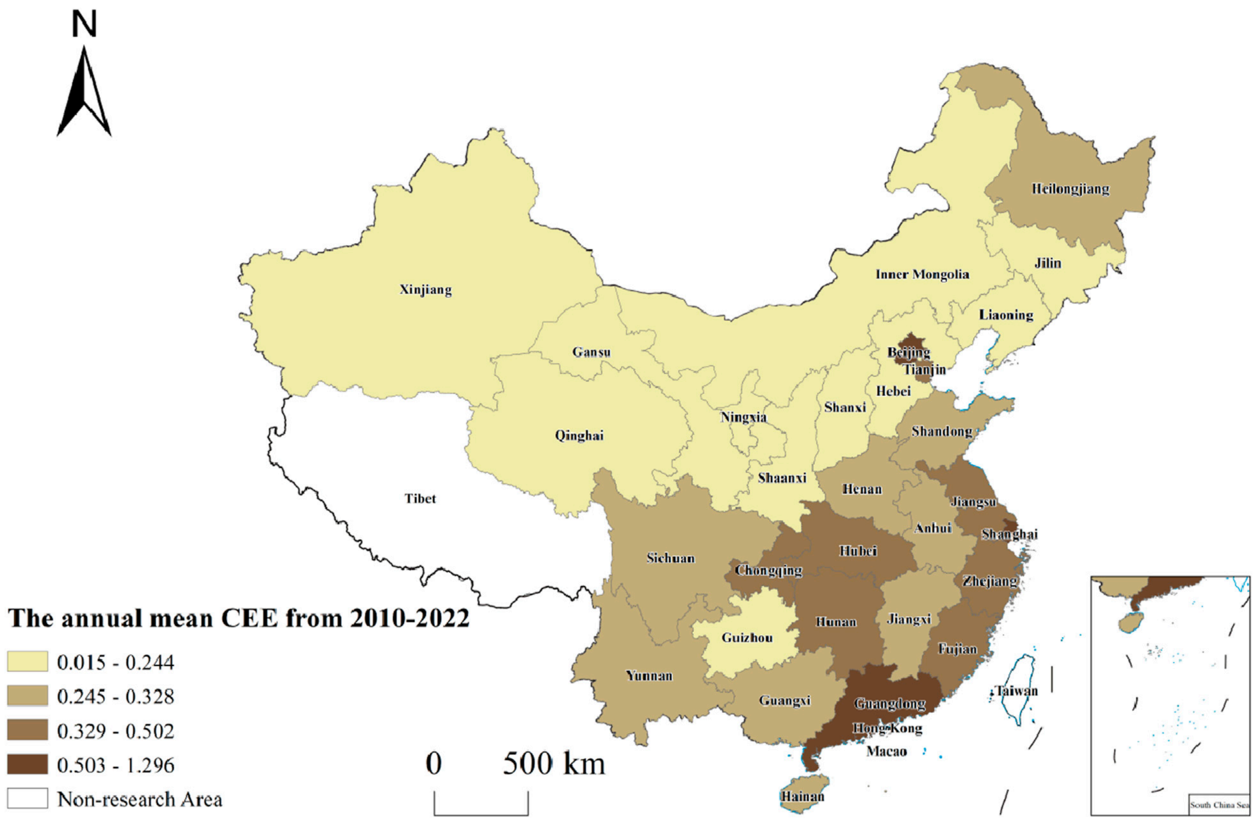

FIGURE 2
The annual mean values of CEE for 30 provinces in China (2010–2022).

(Liu et al., 2022). Compared to the east, the central, western, and northeastern regions are relatively less developed economically and often have weaker environmental awareness (Zhang et al., 2022). Therefore, provinces in these regions need to enhance production technologies, adjust industrial and energy structures, and improve overall efficiency to reach an effective state.

4 Regression analysis

4.1 Unit root tests

The stationarity of the data was examined to avoid the spurious regression phenomenon (Zeng et al., 2022b). We employed the unit root tests. The test results presented in Table 4 indicate that all variables become stationary after first differencing at the 5% significance level, rejecting the null hypothesis of unit root tests.

4.2 Tobit test

To empirically examine the U-shaped relationship between environmental regulation (ER) and CEE, as well as the impacts of control variables, we establish the specific regression equation of the Tobit model as Equation 4:

$$CEE_{i,t} = \beta_1 ER_{i,t} + \beta_2 (ER)^2_{i,t} + \beta_3 IS_{i,t} + \beta_4 OUL_{i,t} + \beta_5 PD_{i,t} + \varepsilon_{i,t} \tag{4}$$

Equation 4 includes the core explanatory variable (ER and its quadratic term), control variables (IS, OUL, PD), and error term, providing a comprehensive framework for the empirical analysis. $CEE_{i,t}$ is a censored dependent variable (range [0,1]) and the Tobit model is used to account for its censoring nature. In addition, we performed a multicollinearity test for each variable before performing an empirical study. It can be seen from Table 5 that the VIF of environmental regulation (ER) is relatively high (6.26), but it remains below 10, so there is no multicollinearity among the variables. The results of Tobit model are shown in Table 6.

As shown in Columns (1) to (4) of Table 6, the coefficient on the primary term of ER is significantly negative at the 1% level, while the coefficient on its quadratic term is positive and significant at the 1% level. This U-shaped relationship remains robust with or without the inclusion of control variables. Before the U-shaped turning point, the system of ER in China is still imperfect, and the investment level of environmental pollution control was low, and the effect of ER on CEE may be limited. In addition, an increase in the investment in governance crowds out investment in environmental R&D; therefore, the strengthening of ERs led to a decline in CEE. After the U-shaped turning point, the equipment and technology used for environmental pollution treatment had been greatly improved due to financial support. Along with the rapid development of

TABLE 4 Results of the unit root test.

Variable	Levin, Lin, and Chu	Im, Pesaran, and Shin	Augmented dickey−fuller−fisher	Phillips and perron−fisher
CEE	−5.73392***	−1.55519***	121.737***	134.202***
ER	−17.7123***	−5.28866***	96.5106***	71.9839
ER^2	−92.9141***	−21.0814***	119.220***	94.1160***
IS	−3.57997***	2.31475	40.6934	51.0528
OUL	−5.21707***	0.92630	72.0187	71.4856
PD	−8.15653***	−2.99416***	125.552***	191.260***
ΔCEE	−21.1057***	−14.3097***	253.159***	340.978***
ΔER	−22.3843***	−15.6145***	289.603***	358.240***
ΔER^2	−24.6250***	−16.8536***	308.493***	390.369***
ΔIS	−11.2190***	−8.02249***	164.981***	179.438***
ΔOUL	−11.1439***	−7.30228***	155.224***	152.885***
ΔPD	−3.33576***	−0.28497***	74.3651*	81.2488**

* $p < 0.1$ indicates marginal statistical significance, meaning the probability that the test result is randomly generated is less than 10%.
** $p < 0.05$ indicates statistical significance, meaning the probability that the test result is randomly generated is less than 5%.
*** $p < 0.01$ indicates high statistical significance, meaning the probability that the test result is randomly generated is less than 1%.

TABLE 5 VIF test.

Variable	ER	ER^2	IS	OUL	PD	Mean VIF
VIF	6.26	5.46	2.02	2.63	3.33	4.04
1/VIF	0.160	0.183	0.495	0.380	0.300	

investment in environmental pollution control and the gradual perfection of related systems of ER, the positive effect of ER on CEE began to appear, and ER began to promote the improvement of CEE.

Regarding the control variables, the coefficient for the proportion of the industrial structure (IS) is significantly negative, indicating that an increase in the share of the secondary industry exerts an inhibitory effect on the dependent variable. This may reflect challenges faced by traditional industrial sectors in aspects such as efficiency or green transformation within the industrial structure. The coefficient for the level of openness to trade (OUL) is significantly positive, suggesting that the expansion of foreign trade has a positive promoting effect on the dependent variable. This may be attributed to technology spillovers, competition effects, or the introduction of higher environmental standards. The coefficient for population density (PD) in column (4) is significantly positive, implying that population agglomeration may positively influence the dependent variable through mechanisms such as knowledge spillovers and economies of scale.

4.3 Robustness test model

4.3.1 Excluding special regions

Building on baseline regression, samples from the four municipalities (Beijing, Tianjin, Shanghai, Chongqing) are excluded to test for potential bias from their unique economic and policy status. Results in Column 6 of Table 7 show the core variable's significance and direction remain consistent with baseline estimates, confirming the findings are not driven by these special

TABLE 6 Regression results of the Tobit model.

Variable	Column (1)	Column (2)	Column (3)	Column (4)
ER	−0.324***	−0.26***	−0.101***	−0.108***
$(ER)^2$	0.04***	0.033***	0.011***	0.012***
IS		−0.01***	−0.006***	−0.005***
OUL			0.007***	0.005***
PD				0.976***
Cons	0.483	0.841	0.467	0.432

* $p < 0.1$ indicates marginal statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 10%.
** $p < 0.05$ indicates statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 5%.
*** $p < 0.01$ indicates high statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 1%.

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TABLE 7 The results of Robustness Test 1.

Variable	Column (5)	Column (6)	Column (7)
ER	−0.11***	−0.105***	−0.1***
$(ER)^2$	0.009***	0.011***	0.01***
IS	0.003***	−0.006***	−0.006***
OUL	0.004***	0.005***	0.005***
PD	0.771**	0.815***	0.918***
Cons	0.129	0.451	0.445

* p < 0.1 indicates marginal statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 10%.
** p < 0.05 indicates statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 5%.
*** p < 0.01 indicates high statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 1%.

regions. This supports the general applicability of conclusions and reduces sample-specific estimation bias.

4.3.2 Excluding special years

To examine the impact of the COVID-19 pandemic as an external shock, observations from 2020 to 2022 are excluded. The regression results in Column 6 of Table 7 demonstrate that the estimated coefficient of the core explanatory variable remains significant and consistent with the baseline results. This robustness test shows that the main findings of the study are not dominated by extreme outliers or unique economic patterns during the pandemic period.

4.3.3 Lagging the core explanatory variable by one period

To mitigate potential reverse causality or simultaneity bias, the core explanatory variable is lagged by one period before being incorporated into the regression model. As shown in Column 7 of Table 7, the lagged core explanatory variable remains significant, and its coefficient characteristics align with the baseline results. The results suggest that even after accounting for time-lag effects, the expected impact of the core explanatory variable on the dependent variable holds, providing stronger evidence for a causal relationship between the variables and further reinforcing the reliability of the research conclusions.

4.3.4 Modify the research model

To further enhance the robustness of the findings, this study employs the panel threshold regression model by Hansen (1999), which endogenously determines nonlinear relationships without pre-specified breakpoints, thus reducing subjective bias. The results in Figure 3 and Table 8 confirm a single threshold effect ($p = 0.043$), indicating that once environmental regulation passes a certain threshold, its effect on carbon emission efficiency (CEE)changes structurally, while double and triple thresholds are insignificant ($p = 0.223$ and $p = 0.293$, respectively).

The regression results in Table 9 further reveal a non-linear relationship between environmental regulation and carbon emission efficiency. When the level of environmental regulation is below the threshold value, its regression coefficient on carbon emission efficiency is significantly negative (−0.025). This suggests that environmental regulation may initially inhibit efficiency improvement due to increased compliance costs for enterprises. After exceeding the threshold, the coefficient becomes significantly

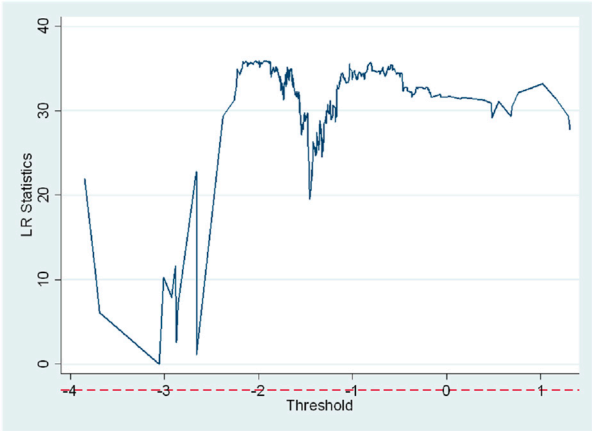

FIGURE 3
Single threshold test plot.

TABLE 8 The results of Robustness Test 2.

Threshold	RSS	Fstat	Prob
Single	1.087	26.410	0.043**
Double	1.045	15.210	0.223
Triple	1.012	12.150	0.293

* p < 0.1 indicates marginal statistical significance,meaning the probability that the estimated coefficient is randomly generated is less than 10%.
** p < 0.05 indicates statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 5%.
*** p < 0.01 indicates high statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 1%.

TABLE 9 The results of the threshold regression model.

Variable	Coef	Std. err	t	Prob
Threshold value-1	−3.0549			
InER(InER < −3.055)	−0.025**	0.011	−2.200	0.028
InER (−3.055≤ InER)	0.018*	0.010	1.810	0.070
InIS	0.233***	0.036	6.570	0.000
InOUL	0.031***	0.011	2.710	0.007
InPD	−0.521***	0.098	−5.320	0.000
Cons	−4.162	0.392	−10.620	0.000

* p < 0.1 indicates marginal statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 10%.
** p < 0.05 indicates statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 5%.
*** p < 0.01 indicates high statistical significance, meaning the probability that the estimated coefficient is randomly generated is less than 1%.

positive (0.018), indicating that stricter regulatory policies can force technological innovation and industrial upgrading, ultimately promoting carbon emission efficiency. This "U-shaped" relationship—first inhibiting and then promoting—verifies the dual-phase characteristic of environmental regulation, comprising a "pain period" and a "benefit period", thereby supporting Hypothesis 1 and Hypothesis 2.

Threshold value-1 (−3.0549) refers to the logarithmic value of environmental regulation intensity. The negative coefficient of InPD, the logarithmic form of population density, is related to the non-linear relationship arising from the variable transformation, and is essentially consistent with the positive impact of PD in the baseline regression. This reflects the complex mechanism through which population agglomeration influences carbon emission reduction efficiency.

5 Conclusion

This article empirically examines the influence mechanism of ER on the CEE. The findings provide several critical insights: (1) The overall CEE level of China is not high. The CEE shows obvious spatial heterogeneity. By regions, the CEE of the eastern region is larger than that of other regions, followed by the central, northeastern and western regions. This geographic disparity underscores the uneven progress in CEE across the country. (2) By empirically researching the relationship between ER and CEE, we found that the impacts of ER on CEE are first inhibitory and then promotive, which shows a U-shaped curve relationship between ER and CEE. Initially, stringent ERs appear to suppress CEE, likely due to increased compliance costs and operational constraints. However, as regulations continue to tighten and pass a certain threshold, they begin to incentivise technological innovations and sustainable practices, thereby enhancing CEE. This finding is in line with Li et al., (2024), Yang et al. (2025) and Shen et al. (2023). (3) The impacts of ER on CEE are negative in the early stages, indicating that the turning point, at which ER begins to have a positive impact on CEE, is yet to be reached. This turning point is contingent upon several key developments. Reaching the turning point will require concerted efforts from both the government and the private sector, implementing more stringent and effective ERs, promoting technological innovation and ensuring the equitable distribution of resources and technologies. There needs to be a significant shift in the industrial structure towards more sustainable and less polluting industries. Additionally, a more sustainable model of urbanisation that incorporates green energy solutions and efficient infrastructure is essential (Hu et al., 2025b). Enhanced openness to international trade can facilitate the transfer of energy-efficient technologies and practices (Yuan et al., 2023; Cao et al., 2023; Zhao et al., 2023). Furthermore, the study indicates that higher population density significantly contributes to CEE improvement, primarily through agglomeration effects that enhance energy efficiency.

Accordingly, we propose the following specific suggestions:

1. Local governments should comprehensively utilise ERs to promote CEE, and implement effective environmental policies based on local actual development situations in a timely manner. For high-efficiency regions like Beijing and Shanghai, the focus should be on pioneering advanced regulatory mechanisms such as carbon trading and green finance. For medium-efficiency provinces like Guangdong and Zhejiang, policies should aim to accelerate crossing the U-curve inflection point by optimizing incentives for green technology. For most central, western, and northeastern provinces where CEE is low, policies should combine financial support for pollution control with the enforcement of basic environmental standards, focusing on capacity building.
2. Continuing to improve the industrial structure, governments need to formulate a catalogue of green and cleaner industries, guide enterprises to undergo green transformation and raise investment in high-tech industries with less resource consumption and higher value added, and increase investment in the upgrading and treatment of traditional industries with the characteristics of high energy consumption, high emissions and high pollution. The eastern region should lead in developing high-end services and advanced manufacturing. The central and northeastern regions must focus on the green transformation of heavy industries. The western region should develop clean energy and characteristic low-carbon industries while cautiously undertaking industrial transfers. Economically underdeveloped areas should actively encourage the transfer of green innovative industries and services from developed areas.
3. Developing an export-oriented economy is a successful way to improve CEE. Increasing the proportion of modern service industries and high-tech industries can improve the import and export trade. It can improve the quality of foreign capital investment, especially high-tech industries such as advanced manufacturing, new materials, and biopharmaceuticals, and it can restrict foreign capital investment in industries with low technological content, high energy consumption, and severe pollution. Promoting international cooperation and learning from best practices globally can provide valuable insights into effective energy efficiency strategies. Engaging in international agreements and sharing technology and knowledge with other nations can foster collaborative efforts to combat climate change and improve energy efficiency.
4. Vigorously encouraging technological innovation and promoting technological progress; establishing innovation hubs and providing subsidies or tax breaks for companies investing in energy-saving technologies can accelerate the adoption of advanced technologies, thus improving energy efficiency and promoting the manufacturing capacities of environmentally friendly equipment. The eastern region should focus on breakthrough low-carbon technology R&D. The central, western, and northeastern regions should prioritize the application and diffusion of mature energy-saving and emission-reduction technologies.
5. Vigorously advance the education cause by establishing a lifelong learning system accessible to all, with a focus on enhancing knowledge popularization and skill training in energy conservation, environmental protection, green technology, and other related fields to raise the whole society's awareness of ecological protection and literacy in green development; optimize the talent cultivation structure by increasing investment to nurture professionals engaged in

low-carbon technology, environmental management, and other carbon emission reduction-related sectors to provide intellectual support for improving carbon emission efficiency. Meanwhile, guide the rational agglomeration of the population: leverage the scale effect generated by increased population density to optimize the layout of public transportation networks, promote the application of energy-saving facilities such as centralized heating systems and green buildings, and thereby reduce *per capita* energy consumption and carbon emissions; further improve population mobility policies to encourage the flow of high-quality talents to the central, western, and northeastern regions, which in turn drives the adoption of green technologies and the upgrading of management capabilities in underdeveloped areas, helping to narrow the regional gap in carbon emission efficiency.

6. Government policy formulation must be precisely tailored to regions based on their respective positions on the U-shaped curve. For provinces in the west, northeast, and some central regions that lie on the left side of the U-curve with relatively low Carbon Emission Efficiency (CEE), measures such as establishing special funds, building an "east-west" technological support mechanism, and formulating minimum environmental protection standards should be adopted to reduce transformation costs and develop foundational capabilities; for central provinces and certain eastern provinces like Tianjin that are in the transition phase of the U-curve, initiatives including "regional carbon trading" pilots and R&D tax credits are needed to accelerate technological breakthroughs and drive the crossing of the inflection point; for provinces with high CEE values such as Beijing and Shanghai that are on the right side of the U-curve, actions like piloting "carbon tariffs", setting up low-carbon technology innovation centers, and formulating higher local environmental protection standards can be implemented to strengthen their exemplary and leading role. This hierarchical policy design can help each region enhance its CEE according to its own endowments, and synergistically advance the national goals of carbon emission reduction and high-quality economic development.

While this study is focused on China, the findings offer significant implications for other developing and emerging economies. The identified U-shaped relationship suggests that for countries at a similar industrialization stage, such as India or Vietnam, prematurely imposing stringent, uniform environmental regulations without adequate technological and financial support may initially hinder carbon efficiency. Instead, a phased approach, beginning with capacity building, targeted incentives, and differentiated standards in key regions, could more effectively harness the positive effects of regulation in the long run. Furthermore, the critical role of technological progress and industrial upgrading highlighted in this study underscores a universal pathway toward low-carbon development, suggesting that international cooperation in technology transfer and green finance is crucial for global carbon mitigation efforts.

Despite its valuable insights, this research is subject to certain limitations that merit consideration for enhancing academic rigor. Primarily, data accessibility constraints restricted the analysis to provincial-level data in China, potentially overlooking sector-specific dynamics; future investigations could broaden the scope to examine the impact of environmental regulation (ER) on diverse economic sectors, such as manufacturing, agriculture, and transport, for more nuanced findings. Moreover, the empirical identification of a U-shaped relationship between ER and carbon emission efficiency (CEE) indicates an unrealized turning point, warranting detailed longitudinal or scenario-based analyses to elucidate the conditions facilitating the shift from inhibitory to promotive effects. Additionally, while control variables like industrial structure, openness to trade, and population density were incorporated, their interrelated nature and potential confounding influences across varying contexts and temporal scales may not have been fully controlled, suggesting the need for advanced techniques, such as structural equation modeling or machine learning, to disentangle complex interactions and causal mechanisms in future studies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YF: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft, Writing – review and editing. WY: Conceptualization, Data curation, Formal Analysis, Methodology, Funding acquisition, Software, Writing – original draft, Writing – review and editing. XZ: Funding acquisition, Supervision, Writing – original draft, Writing – review and editing. TZ: Data curation, Visualization, Software, Writing – original draft. JH: Data curation, Methodology, Validation, Writing – original draft, Writing – review and editing. GH: Conceptualization, Funding acquisition, Writing – original draft, Writing – review and editing. BZ: Data curation, Funding acquisition, Investigation, Writing – original draft. YL: Data curation, Visualization, Writing – original draft, Writing – review and editing.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Conflict of interest

The author(s) declared that this work 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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The author(s) declared that generative AI was not used in the creation of this manuscript.

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