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How does environmental regulation impact low-carbon transition? Evidence from China's iron and steel industry

Xiaoling Wang [1], Yu Chen [1], Yizhe Dong [2], Tianyue Zhang [1], Baofeng Shi [3,*]
(1. School of Economics and Management, University of Science and Technology Beijing, China;
2. Business School, University of Edinburgh, Edinburgh, UK;
3. Northwest A&F University: Northwest A&F University, Yangling, Shaanxi China)

Abstract
Comprehensive evaluation and identification of the critical regulatory determinants of carbon emission efficiency (CEE) are very important for China's low-carbon transition. Accordingly, this paper first employs an undesirable global super-hybrid measure approach to calculate the CEE of China's iron and steel industry (ISI). We then further use spatial error and threshold regression models to examine the spatial and non-linear effects of heterogeneous environmental regulations on CEE, respectively. Our empirical results show that (1) CEE varies significantly across China's regions, with the eastern region having the highest CEE score, followed by the western and central regions, with the northeast region ranking the lowest; (2) command-and-control and market-incentive regulations both promote CEE, whereas the public participation approach does not significantly contribute to performance gains; (3) all three types of environmental regulations exhibit a non-linear threshold effect on CEE; (4) openness level, technological progress, and industrial concentration enhance efficiency gains, while urbanization level exerts a negative impact on CEE. Our findings have important implications for the design of environmental regulations.

Keywords: environmental regulation; carbon emission efficiency, low-carbon transition, iron and steel industry; spatial error model; panel threshold analysis

1 Introduction

China's economy has had an impressive growth rate over the past four decades. However, this economic success has been associated with a dramatic deterioration of the environment (Bian et al., 2017). Since the issue of the 11th Five Year Plan (FYP, 2006-2010), a series of environmental policies and regulations have been implemented at both the national and provincial levels to address environmental issues and achieve sustainable development (Zhang et al., 2022). More recently, at the 75th United Nations General Assembly, Chinese President Xi Jinping pledged that China would reach peak carbon dioxide (CO_2) emissions by 2030 and become carbon neutral before 2060. As one of the largest greenhouse gas (GHG) emitters in the world, China plans to cut its CO_2 emissions per unit of gross domestic product (GDP), a measure of carbon intensity, by more than 65% by 2030, compared with 2005 levels. Improving carbon efficiency and achieving carbon neutrality are being integrated into the entire process of China's ecological modernization development (Stern & Xie, 2022). As a typical energy-intensive industry, the iron and steel industry (ISI) is characterized by high energy consumption and large emissions[①]. The coal-based energy structure also makes it one of the most carbon-intensive industries, currently accounting for about 14% of national CO_2 emissions (Ren et al., 2021a). Although the sector has made progress in low-carbon transformation over the years, the energy- and carbon-intensive features of the industry have not yet been fundamentally changed (Xu & Lin, 2016). The industry has a great deal of room to further save energy and reduce emissions by deploying innovative technologies and models (Li et al., 2019). Moving forward, the ISI has a key role to play in the low-carbon transformation of the Chinese economy. China is going through a late stage of industrialization and its economic development has entered a phase of strategic transformation and adjustment, characterized by "adjusting structure", "stabilizing growth", "reducing energy consumption" and "reducing emissions." Within this framework, the low-carbon transformation of the ISI is critical to China's achievement of its 30-60 decarbonization goal and realization of its high-quality and sustainable development.

Managing the transition to a low-carbon economy should mean not only paying attention to the amount of carbon emissions but also focusing on emission efficiency (Sun & Huang, 2020). Carbon emission efficiency (CEE) is a widely used indicator for evaluating carbon emissions, as it reflects the level of low-carbon economic development and also the environmental impact of economic expansion (Li et al., 2021a). Total factor CEE analysis draws on a multiple input-output evaluation framework that takes carbon emissions, labor, capital, energy use and value-added into consideration simultaneously. Many previous studies have used frontier efficiency methods, including data envelopment analysis (DEA) and stochastic frontier analysis (SFA), to calculate the potential reductions and efficiency of CO_2 emissions in China (e.g., Choi et al., 2012; Ma, et al., 2018; Zhou et al., 2019; Sun & Huang, 2020). As yet no consensus has been reached on CEE concepts, however evaluation methods and the driving forces of low-carbon transformation, the impact of environmental and energy policies and regulations on low-carbon transition plans and realized paths have been widely recognized (Hou et al., 2018). The "negative externalities" of

① The ISI is one of the most important elements of a nation's industrial economic infrastructure as all other industries depend on it for their machinery. In this study, the ISI refers to the sector involving the smelting and pressing of ferrous metals (Lin & Tan, 2016). In this sector, coal, coke and electricity are the main sources of energy depletion (Qi et al., 2021).

environmental problems caused by economic activities can easily lead to a certain degree of market failure, indicating that the realization of low-carbon development goals should rely on environmental regulations that restrict and guide the production behavior of enterprises (Peng et al., 2018). Some scholars examine the effects of environmental regulations on carbon emissions or on carbon intensity in industrial sectors (e.g., Chen et al., 2019; Pei et al., 2019; Zhang et al., 2020; Dong et al., 2022). However, the impact of environmental regulation heterogeneity on CEE has not yet been comprehensively studied, especially when the impacts of different types of regulations on specific industries may diverge. Understanding the influencing mechanisms of heterogeneous environmental regulations on CEE can be very helpful for accelerating GHG emission reductions and the low-carbon transformation of industrial sectors. Therefore, we first calculate the CEE of the ISI over the period from 2006 to 2017 by constructing a non-parametric efficiency model. We further analyze the influencing mechanisms of heterogeneous environmental regulations on the industrial CEE from the perspective of spatial and non-linear effects. Corresponding recommendations and implications are then provided to aid the low-carbon transformation of China's ISI.

The contribution of this paper is threefold: First, this paper is the first study to examine the efficacy of environmental regulations in China by providing a systematic study of low-carbon transition drawing on the Porter Hypothesis (PH)[②]. A scientific environmental governance system not only includes the government but also the market and the social public (Carvalho et al., 2019; Kostka & Mol, 2013), and a narrow version of the PH asserts that flexible regulatory policies represented by market-based instruments are usually more effective than non-market approaches such as conventional command-and-control regulations (Ambec et al., 2013; Jaffe & Palmer, 1997; Peng et al., 2021). Therefore, we divide the environmental regulations into command-and-control, market-incentive, and public-participation types to observe the heterogeneous impacts of environmental regulations on the CEE of the ISI. Our findings show that command-and-control and market-incentive regulation can significantly improve CEE, with the former exerting more significant effects than the latter. Our findings also show that public participation has no significant effect on CEE improvement. Second, we propose a novel method to reflect the low-carbon transition degree of the ISI, combining the undesirable hybrid model with the super-efficiency and global technique when estimating the CEE. The hybrid method avoids the bias caused by the traditional DEA and slacks-based measure (SBM) models that have difficulties balancing radial and non-radial input-output variables, while the super-efficiency method can further estimate the efficiency scores of efficient DMUs (decision-making units). The global technology set is composed of input and output data for all periods, which can effectively avoid the possibility of inward shifting of the production front. Third, we use both spatial and threshold models to simultaneously examine the spatial and non-linear impacts of environmental regulations on CEE. The spatial analysis considers the spatial correlation of economic activities and environmental impacts, including CO_2 emissions, while the threshold analysis reveals a non-linear link between variables. With this examination, we bring a comprehensive perspective to the impacts of heterogeneous environmental regulations on CEE in the ISI.

[②] The PH is an important theoretical foundation of environmental regulations. It suggests that well-designed environmental regulations can promote innovation, improve resource utilization efficiency, increase firms' competitiveness, and achieve better environmental outcomes, which, in turn, partially or completely offset the compliance costs of environmental regulation (Porter, 1991; Porter & Van der Linde, 1995).

The rest of this paper is organized as follows: Section 2 reviews the related literature, Section 3 outlines the variables, data sources, and models used, Section 4 presents the results and Section 5 discusses our conclusion, recommendations, and limitations.

2 Literature Review

There has been an increase in research on CEE in recent years. Various methods have been used to calculate CEE and explore the driving forces and paths to low-carbon transformation. Some have used a single-factor index (i.e., carbon intensity) to measure CEE, such as CO_2 emissions per unit of energy, fossil fuel CO_2 emissions per GDP, or carbon emissions per industrial value added (Gazheli et al., 2016; Pretis & Roser, 2017; Wang et al., 2020). Although those intensity indicators are straightforward and easy to calculate, they are imperfect proxies for CEE, as they ignore other important inputs (i.e., labor, capital, and machines) and the interaction of those factors (Tan et al., 2020). Therefore, the total-factor carbon emission performance index, estimated using frontier efficiency methods such as DEA, has recently and gradually gained popularity for CEE analysis. This type of index not only considers the relationship between emissions and outputs but also has a good balance between different input elements and expected and unexpected output factors, giving it stronger explanatory power than a single-factor emission performance indicator. For example, Choi et al. (2012) employed a non-radial slacks-based DEA model to calculate the potential reductions and efficiency of carbon emissions in China. They found that the emission efficiency of the economically well-developed east was higher than that of the other two regions. Ding et al. (2019) combined a CCR (Charnes, Cooper and Rhodes)-DEA cross-efficiency model with the Malmquist productivity index to explore the dynamic changes in the CEEs of China's 30 provinces. The eastern regions show the best performance in CEE, followed by the central and western regions. Wang et al. (2019) employed the direction distance function (DDF) to evaluate the CEE in China during 2005-2016, and found an upward trend of both efficiency gains and spatially heterogeneous CEE.

In order to control energy consumption and pollution emissions, regulatory bodies usually use regulatory measures to restrict or influence enterprises' behavior (Yu & Zhang, 2021). According to the PH, stricter environmental regulations may encourage firms to limit their polluting activities and adopt more environmentally-friendly technology to reduce carbon emissions (Bi et al., 2014). Many studies have proven that the institutional framework and environmental regulations are critical in mitigating climate change and facilitating low-carbon development. For example, Gao et al. (2019) constructed an environmental regulation stringency index (ESI) based on indicators of pollution reduction consequences and pollution reduction measures, and concluded that the ESI facilitated China's industrial carbon emission productivity gains in general, although the positive impacts varied across sectors with different polluting levels. However, another view, represented by the "green paradox", points out that the PH does not necessarily hold all the time (Sinn, 2008). For example, He et al. (2022) used the ratio of investment in environmental pollution control to GDP to represent environmental regulation, and found that environmental regulation was not conducive to reducing the agricultural carbon intensity under the influence of fiscal decentralization. In addition, several studies have suggested that the impact of environmental regulations on CEE could be non-linear and spatially correlated. For example, Yang et al. (2020) utilized the factor analysis method to measure environmental regulation intensity using indicators of wastewater emission intensity, waste gas emission intensity, sulfur dioxide (SO_2) emission intensity, and solid waste emission intensity. Empirical tests based on the data of 30 provinces in China, spanning the period 2005–2016, revealed a U-shaped relationship between environmental regulation and carbon intensity. He et al. (2022) found that environmental regulation in neighboring areas exerted a remarkable promoting effect on agricultural carbon intensity.

As demonstrated above, the existing studies mainly rely on either radial (e.g., CCR) or non-radial (e.g., SBM) models for CEE estimation. However, these models may result in biased estimations when processing input and output variables with radial and non-radial characteristics (Ai et al., 2015). Moreover, traditional DEA methods fail to discriminate distinguish efficient DMUs, nor can they make the estimations among different data points in the sample period consistent and comparable (Yu et al., 2019; Zhu et al., 2018). The existing research has mainly focused on the relationship between environmental regulation intensity and carbon intensity. Although the heterogeneous effects of diversified regulations have been noticed (e.g., Zhao et al., 2015), comprehensive research regarding the impact of heterogeneous environmental regulations on CEE in the Chinese context is very limited. That is to say, it is as yet unclear whether the PH and the narrow version of the PH are valid in the context of low-carbon transition. Furthermore, the research has usually used squared items in the equations to estimate the non-linear effects of regulations. However, such a method cannot be used to observe non-linear effects appearing in the same direction. Additionally, existing research has not taken into account the possible spatial correlations under different types of spatial matrixes of regulatory policies and CEE across regions, which may result in biased estimation outcomes (Espoir & Sunge, 2021). Last but not least, current studies that have examined the relationship between environmental regulations and CEE have mainly focused on regional or provincial levels, with little in-depth research conducted in the context of carbon-intensive industries such as the ISI. We aim to fill these research gaps by examining both the spatial and non-linear effects of different types of environmental regulations on the CEE of China's ISI.

3 Research Design

According to the research purpose, this paper first constructs an undesirable global super-hybrid model to measure the CEE of China's ISI. We then use the spatial panel model and threshold model to analyze the spatial impacts and non-linear correlation between environmental regulations and CEE.

3.1 Variables and Data Sources

(1) Carbon Emission Efficiency

Input and output variables are important factors in efficiency evaluation. Energy, labor, and capital are often considered critical inputs as they are the most essential production factors (Ding et al., 2019). Output is generally expressed by economic indicators such as gross industrial output value or industrial value added (Xiong et al., 2019; Zhou et al., 2019), while the amount of carbon emissions is considered an undesirable output for CEE measurement (Du et al., 2022; Yu & Zhang, 2021). Therefore, considering the characteristics of China's ISI as well as data availability, we have used the following input and output variables to measure CEE.

Following the studies of Lin and Tan (2016), Shen et al. (2019), and Wu et al. (2019), energy consumption, labor force, and capital stock of the ISI are selected as input variables. Energy consumption is estimated by the consumption of coal, coke, crude oil, diesel oil, gasoline, natural gas, fuel oil, kerosene, and electricity (10 thousand tons standard coal equivalent); labor force is measured by the annual average number of employees of the industry (10 thousand persons); and capital stock is proxied by the total fixed assets (100 million Chinese Yuan), estimated using the perpetual inventory method. The desirable output variable is measured by the gross industrial output value (100 million Chinese Yuan). The undesirable output of carbon emissions of the ISI (10 thousand tons) are estimated using the Guidelines for National Greenhouse Gas Inventories as proposed by the Intergovernmental Panel on Climate Change (IPCC, 2006).

(2) Environmental Regulations

A scientific environmental governance system not only includes the government but also the market and the social public (Carvalho et al., 2019; Kostka & Mol, 2013). Some scholars assert that flexible regulatory policies represented by market-based instruments are usually more effective than non-market approaches such as conventional command-and-control regulations (Ambec et al., 2013; Jaffe & Palmer, 1997; Peng et al., 2021). In order to capture such differential impacts, we classify environmental regulations into three types, namely command-and-control, market-incentive, and public-participation.

Command-and-control regulation (ER1): Command-and-control regulation is a policy instrument the government can use to correct, prevent, and control the behaviors of polluting firms, and to exert coercive pressures on such firms to force them to comply with and/or implement environmental standards, through environmental laws, regulations, and related administrative measures (Wu & Gao, 2021). Although this type of regulation is usually criticized for its lack of flexibility in implementation, it still forms the main part of the environmental regulatory system in China (Li & Ramanathan, 2018). Considering data availability, we select three indicators, namely investment in industrial pollution source treatment, urban environmental infrastructure construction, and the "three simultaneous"[3] construction projects of the year, to calculate the intensity of command-and-control regulation (ER1), referencing the studies of Li et al. (2019), Pan et al. (2019), and Yin and Wu (2021). The entropy weight method (EWM) is used to convert these three indicators into one single index and make the different types of regulatory indicators comparable (see appendix). Entropy is a concept and measure of the state of disorder, randomness, or uncertainty in information (Shannon & Weaver, 1949). When the actual importance of attributes is almost the same or the subjective preference can be neglected, the EMW based on Shannon entropy theory can be used to increase the bipartite degree of decision-making or evaluation results (Chen, 2019). Accordingly, the EMW has started to be utilized to comprehensively evaluate the intensity or stringency of environmental regulations (Gao et al., 2019; Li & Du, 2020; Song et al., 2020a).

Market-incentive regulation (ER2): Market-incentive regulation is another approach widely used by governments to regulate pollution. This policy instrument uses economic signals to

[3] The “three simultaneous” system (sometimes also translated as the ‘‘three simultaneities’’ or “three synchronous’’) requires explicit anticipation of the likely pollution associated with a project and for environmental protection measures to be designed, constructed, and operated simultaneously with the project’s main components to prevent or control pollution (Wang et al., 2003).

indirectly influence enterprises' production activities and reduce or eliminate negative externalities based on the “polluter pays principle” (Wu & Gao, 2021). The pollution charging system and emissions trading have been the two dominant market-based policies in China. However, the nationwide CO_2 emissions trading system was not established until the year 2021 and the ISI has not yet been included in the system, resulting in insufficient data being available for analysis. The pollutant discharge fee has therefore become the most commonly used indicator for denoting the level of market-incentive regulation (Ren et al., 2018). Accordingly, in this study we use the pollutant discharge fees per unit of industrial value added to reflect the intensity of ER2, and we standardize the data in order to ensure comparability of the regression coefficients.

Public-participation regulation (ER3): Public participation refers to the public expressing their environmental interests and concerns by urging enterprises or individuals to exhibit self-restraint in their pollution behavior through voluntary environmental agreements and other non-mandatory measures, such as sending petition letters and reports regarding pollution issues to the government (Li & Ramanathan, 2018; Wu & Gao, 2021). This type of participation has become a democratic “fix” for the governance of environmental issues, solving the problem of information and power asymmetry between governments and enterprises (Carvalho et al., 2019). In China, public participation has become an emerging topic in environmental governance, especially since the promulgation of *Measures on Public Participation in Environmental Protection* in 2015. Generally speaking, environmental hearings, environmental complaint letters and visits, and environmental education are the main forms of citizen participation. Considering the issue of data availability, and referencing the studies of Li and Ramanathan (2018) and Li (2022), we use two indicators, the number of complaint letters and the number of office visits regarding pollution and environmental-related issues received by environmental departments, to proxy for public participation. These indicators are converted into a single index using the EWM to make ER3 comparable with ER1 and ER2.

(3) Control Variables

The development of the ISI is affected by the macroeconomic and social environment, thus some factors other than environmental regulations may also exert non-trivial impacts on the CEE. Therefore, following the studies of Lin and Wang (2014) and Wu and Lin (2022), this study uses the ratio of the urban population to the total population (%) to measure the level of urbanization (*urb*), the ratio of the value added of secondary industry to GDP (%) to reflect industrial structure (*ind*), the ratio of the total imports and exports of goods to GDP (%) to reflect the openness level (*open*), the total energy consumption per output value of the ISI (tons of standard coal equivalent/10,000 CNY) to measure technology progress (*tech*), and the ratio of the gross industrial output value of the ISI to the number of enterprises (100 million CNY) to measure the industrial concentration ratio (*cr*).

The industrial steel industry is the most important element of a nation's industrial economic infrastructure. In this paper, the ISI is defined as including the smelting and pressing of ferrous metals, referencing the study of Lin and Tan (2016), and the study comprises a panel dataset of 29 provinces/cities and autonomous regions (hereafter provinces) over the period 2006–2017. Tibet, Hainan, Taiwan, Hong Kong, and Macau are not included due to data unavailability. **Table A1** provides a list of the variables used in the analysis, their abbreviations, definitions, and the data sources. In addition, value-type indicators are converted to real values using the base year of 2000 to eliminate price fluctuation.

3.2 Undesirable Global Super-Hybrid Measure (UGSHM)

The DEA technique has been widely used to measure CEE with multiple inputs and outputs (Zhu et al., 2021). However, both radial and non-radial techniques applied in conventional DEA models have certain drawbacks that may lead to biased outcomes. Against this background, Tone (2004) proposed a hybrid measure that deals with both radial and non-radial variables within a unified framework, to improve the credibility of efficiency evaluation. Drawing on this approach, we further consider the undesired output characteristics of CO_2 emissions and combine them with super-efficiency and global DEA technology.

Suppose we have *i* DMUs and each DMU uses *l* inputs to generate *s* desirable outputs and *h* undesirable outputs within *T* years. The input matrix can then be decomposed into the radial part $X_i^R \in R_+^{l_1}$ and the non-radial part $X_i^{NR} \in R_+^{l_2}$, respectively. Correspondingly, the expected output matrix can be separated into a radial output matrix $Y_i^R \in R_+^{s_1}$ and a non-radial one $Y_i^{NR} \in R_+^{s_2}$, respectively. Similarly, the undesirable output matrix can be divided into a radial output matrix $E_i^R \in R_+^{h_1}$ and a non-radial output matrix $E_i^{NR} \in R_+^{h_2}$.

Therefore, for any decision-making unit $DMU(x_o, y_o, e_o) = (x_o^R, x_o^{NR}, y_o^R, y_o^{NR}, e_o^R, e_o^{NR}) \in P^t$

(i.e., *P* is a production set), an undesirable hybrid measure is constructed as follows:

$$\beta^* = min \frac{1-\frac{l_1}{l}(1-\theta)-\frac{1}{l}\sum_{i=1}^{l_2} s_i^{NR-}/s_{io}^{NRt}}{1+\frac{s_1}{s+h}(1-\varphi)+\frac{1}{s+h}\sum_{i=1}^{s_2} s_i^{NR+}/y_{io}^{NRt}+\frac{h_1}{s+h}(1-\gamma)+\frac{1}{s+h}\sum_{i=1}^{h_2} s_i^{NR-}/e_{io}^{NRt}} \tag{1}$$

$$\begin{gathered} s.t.\, \theta x_o^{Rt} \geq \lambda X^R \\ x_o^{NRt} = \lambda X^{NR} + S_1^{NR-} \\ \varphi y_o^{Rt} \leq \lambda Y^R \\ y_o^{NRt} = \lambda Y^{NR} - s^{NR+} \\ \gamma e_o^{Rt} \geq \lambda E^R \\ e_o^{NRt} = \lambda E^{NR} + s_2^{NR-} \\ \lambda \geq 0,\ , s^{R-} \geq 0, s^{NR-} \geq 0, s^{R+} \geq 0, s^{NR+} \geq 0 \\ l = l_1 + l_2; s = s_1 + s_2; \mathrm{h} = \mathrm{h}_1 + \mathrm{h}_2 \end{gathered}$$

DMUs with an efficiency score estimated as 1 are further estimated referencing the super efficiency technique proposed by Andersen and Petersen (1993). Meanwhile, the production technology set of the undesirable global super-hybrid DEA (i.e.,$P^G = P^1 \cup P^2 \cup P^3 \cup \ldots P^T$) consists of the production technology sets in all observation years.

3.3 Spatial Panel Model

A certain attribute or a given economic phenomenon of a spatial unit is always correlated with that same attribute or phenomenon of the neighboring areas, and such characteristics need to be reflected through spatial measurement models. In addition, whether a model has spatial autocorrelation is the prerequisite for judging whether the spatial panel model can be used (Zhou & Zhang, 2021). In order to reveal the spatial characteristics of a dataset, exploratory spatial data analysis (ESDA) is utilized to test spatial autocorrelation by identifying the existence of spatial dependence. Spatial autocorrelation is usually tested based on the global Moran's I model presented below (Liu et al., 2018):

$$I = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} wij} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} wij(xi-\bar{x})(xj-\bar{x})}{\sum_{i=1}^{n}(xi-\bar{x})^2/n} \tag{2}$$

where x_i and x_j denote the standardization of the observed values of regions *i* and *j*, respectively; w_{ij} is the spatial weight matrix.

Considering the existence of spatial fluidity, pollutant emissions can spill over from one area to adjacent areas, and the stringency of environmental protection policies in an area may also affect the environmental protection policies in surrounding areas (Zhou & Zhang, 2021). For energy-intensive industries that have serious environmental impacts, such as the ISI, the influence of policy regulations is usually significant (Ouyang et al., 2020). The implementation of regulations often affects the activities of production enterprises in both the areas in question and regions related to them through the flow of energy, labor, and capital. Accordingly, it is of practical significance to observe the spatial correlations of CEE across regions and the relationships between environmental regulations and CEE.

According to differences in spatial dependence, spatial panel models can be divided into the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM) (Elhorst, 2012). The SLM considers dependent variables in an area along with other areas associated with it, and the SEM takes into account the dependency of the error values of an area on the errors in other areas associated with it. The SDM includes both the spatial error term and the spatial lag term and can simultaneously observe endogenous spatial effects and spatial spillover effects (Wu et al., 2020). The specifications of the SEM, SLM, and SDM are as follows:

$$CEE_{\mathrm{it}} = \alpha_1 ER1_{it} + \alpha_2 ER2_{it} + \alpha_3 ER3_{it} + \alpha_4 X_{it} + \mu_{it} + \delta_{it} + \varepsilon_{it} \tag{3}$$
$$\varepsilon_{it} = \lambda W \varepsilon_{it} + \varphi_{it}, \varphi_{it} \sim N(0, \sigma_{it}^2 I_n)$$
$$CEE_{\mathrm{it}} = \phi W \times CEE_{it} + \alpha_1 ER1_{it} + \alpha_2 ER2_{it} + \alpha_3 ER3_{it} + \alpha_4 X_{it} + \mu_{it} + \delta_{it} + \varepsilon_{it} \tag{4}$$
$$\varepsilon_{it} \sim N(0, \sigma_{it}^2 I_n)$$
$$CEE_{\mathrm{it}} = \phi W \times CEE_{it} + \alpha_1 ER1_{it} + \alpha_2 ER2_{it} + \alpha_3 ER3_{it} + \alpha_4 X_{it} + \alpha W \times ER1_{it} + \beta W \times ER2_{it} + \theta W \times ER3_{it} + \mu_{it} + \delta_{it} + \varepsilon_{it} \tag{5}$$
$$\varepsilon_{it} \sim N(0, \sigma_{it}^2 I_n)$$

where, CEE_{it} indicates the CEE value of the ISI in region *i* and year *t*, $ER1_{it}$, $ER2_{it}$, and $ER3_{it}$ are the measures of the intensities of command-and-control, market-incentive and public-participation regulations, respectively, X_{it} represents a series of control variables, including openness (*open*), industry structure (*ind*), urbanization level (*urb*), technology progress (*tech*), and industrial concentration (*cr*), α, β, θ, and ρ represent the corresponding coefficients matrix, μ and δ are the region and time fixed effects, respectively and ε_{it} are the random error terms. When α, β, θ, and ρ are zero, the SDM will degenerate into the SAR; when ϕ is 0, the SDM will degenerate into the SEM; when all the above parameters are zero, the model becomes a standard least squares regression model, that is, a linear regression model. W is a spatial weight matrix. This study first uses the geographic distance matrix ($W1_{ij}$) to analyze the impacts of environmental regulations and other factors on CEE:

$$W1_{ij} = \begin{cases} 1/d_{ij}, i \neq j \\ 0, i = j \end{cases}$$

Provinces with similar economic development levels usually show similarities in population quality, industrial foundation, and social development. They may also have similar governance patterns and development strategies (Millimet & Roy, 2016). Moreover, the radiation effect of economic development is one of the influencing factors that cannot be ignored when analyzing spatial spillover effects. Therefore, an economic geographic distance matrix that incorporates geographic factors and economic influences can make up for the shortcomings of a singular geographic distance matrix (Wu et al., 2020). Thus, we further construct an economic geographic matrix ($W2_{ij}$) to estimate the spatial impacts of environmental regulations on CEE:

$$W2_{ij} = \begin{cases} E/d_{ij}^2, i \neq j \\ 0, i = j \end{cases}$$

where, d_{ij} is the geographic distance between the capital cities of each pair of provinces, $E = 1/\left|\bar{Y}_i - \bar{Y}_j\right|$, and $\bar{Y}i$ represents the average *GDP* per capita of province *i.*

The selection of the spatial panel model is based on the Lagrange multiplier (LM) test. If the results reject the original hypothesis of no spatial lag effect and/or no spatial error effect, it will indicate that the spatial panel model instead of an ordinary panel model should be used (Zhou & Zhang, 2021). In addition, if the SAR or SEM passes the test, the corresponding panel model can be used. If both of them pass the test, the SDM should be used for the empirical analysis.

3.4 Panel Threshold Model

Non-linear effects of environmental regulation on carbon emissions have been found in the existing research. However, whether environmental regulations, especially different types of regulatory approaches, exert significant and heterogeneous impacts on CEE is still in question (Chen et al., 2019). Specifically, observing the optimal intensity range of different regulatory approaches in the ISI can provide useful implications for decision-making in policy design and implementation. Therefore, this study further constructs panel threshold models to observe the non-linear effects of different regulations on CEE.

The general form of the single threshold model is presented below:

$$CEE_{it} = \lambda_1 ER_{it} I(ER \leq \gamma) + \lambda_2 ER_{it} I(ER > \gamma) + \sigma X_{it} + \varepsilon_{it} \tag{6}$$

Meanwhile, double or even triple thresholds may also exist. These models are presented in equations (7) and (8).

$$CEE_{it} = \lambda_1 ER_{it} I(ER \leq \gamma_1) + \lambda_2 ER_{it} I(\gamma_1 < ER \leq \gamma_2) + \lambda_3 ER_{it} I(ER > \gamma_2) + \sigma X_{it} + \varepsilon_{it} \tag{7}$$

$$CEE_{it} = \lambda_1 ER_{it} I(ER \leq \gamma_1) + \lambda_2 ER_{it} I(\gamma_1 < ER \leq \gamma_2) + \lambda_3 ER_{it} I(\gamma_2 < ER \leq \gamma_3) + \lambda_4 ER_{it} I(ER > \gamma_3) + \sigma X_{it} + \varepsilon_{it} \tag{8}$$

where ER represents environmental regulation and is also a threshold variable, $I(\bullet)$ is an indicative function, X represents the control variables, γ is the threshold value of environmental regulation, and λ and σ are the corresponding coefficients and random error terms, respectively.

4 Empirical Results

4.1 Carbon Emission Efficiency

Based on the calculation of the CEE scores in different provinces according to equation (1), the annual average values for different regions④ during 2006-2017 are obtained so that the temporal and spatial differences in the CEE of the ISI can be observed, as shown in Figure 1.

④ See Appendix A2 for details.

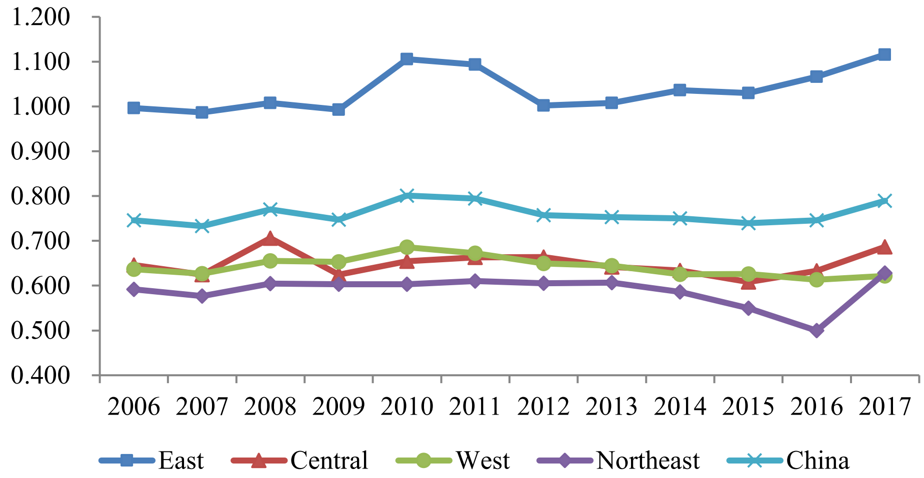


Fig. 1 Annual average CEE of ISI in different regions

Figure 1 shows the CEE of China's ISI during the observation period follows a fluctuating upward trend. Specifically, the CEE increased from 0.746 in 2006 to 0.789 in 2017. In addition, from a spatial perspective, the CEE of the eastern region has always been ahead, followed by the central and western regions, with the northeastern region ranking last.

4.2 Spatial Effect Estimation

As discussed in Section 3.3, this paper first analyzes the spatial autocorrelation of CEE over the years, based on the global Moran's I index (Table 1).

Table 1 Results of global Moran's I index

Year	Geographic distance matrix		Economic geographic matrix	
	MI	Z	MI	Z
2006	0.117	4.043***	0.385	4.399***
2007	0.125	4.248***	0.424	4.815***
2008	0.127	4.263***	0.425	4.777***
2009	0.104	3.684***	0.378	4.331***
2010	0.059	2.439**	0.215	2.550**
2011	0.091	3.302***	0.334	3.809***
2012	0.121	4.201***	0.408	4.703***
2013	0.107	3.857***	0.375	4.381***
2014	0.100	3.614***	0.327	3.821***
2015	0.081	3.087***	0.266	3.160***
2016	0.107	3.735***	0.332	3.800***
2017	0.115	3.845***	0.347	3.879***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results show that the spatial relevance is significant under both the geographic distance matrix and the economic geographic matrix, indicating that the CEE is spatially correlated in general. This outcome also proves that the choice of spatial econometric model in our study is correct and necessary.

In addition, the existence of spatial effects among the variables should be verified using LM tests (LM-lag and LM-error) and robustness tests (robust LM-lag and robust LM-error) before the spatial econometric analysis can be conducted. The null hypothesis of the LM-lag test and robust LM-lag test is that there is no spatial lag effect between the variables, and the null hypothesis of the LM-error test and the robust LM-error test is that there is no spatial error effect between the variables. Accordingly, the results of the LM test can not only be used to decide whether a spatial panel model is suitable, but also to distinguish the specific type of spatial panel model to use. The results of the LM tests are reported in Table 2.

Table 2 Results of LM tests

Test	LM error	LM error (robust)	LM lag	LM lag (robust)
Geographic distance matrix	38.182***	50.285***	1.199	13.302***
Economic geographic matrix	35.713***	33.274***	4.319*	1.881

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As can be seen from Table 2, the LM error and robust LM error tests reject the null hypothesis at the significance level of 1% under both distance matrixes (i.e., geographic and economic geographic), whereas the LM lag and robust LM lag tests fail to reject the null hypothesis, indicating that the SEM should be constructed for the spatial analysis in this case. In addition, we further conduct the Hausman test for the SEM. The untabulated results show that the statistical values of the test under the geographic and economic geographic matrixes are 27.79 and 17.49, respectively, suggesting that the fixed effect model should be selected for our analysis.

The spatial effects of heterogeneous environmental regulations and other important control variables on CEE are estimated using equation (3) and the results are presented in **Table 3**⑤. The results in columns (1) and (5) of **Table 3** show that the effect of command-and-control (*ER1*) and market-incentive (*ER2*) regulations on CEE are positive and significant, whereas the impact of public participation (*ER3*) is not significant. For the control variables, openness level (*open*), technological progress (*tech*), and industrial concentration (*cr*) all contribute to the efficiency gains at a significance level of 1%. The increase of urbanization (*urb*) exerts an inhibitory effect on efficiency improvement, while the effect of industry structure (*ind*) is not significant when using the geographic distance matrix. In addition, using either spatial weight matrix, the coefficient results for the spatial error term are all significant, indicating that the determinants of CEE omitted from the model are spatially related. When a single environmental regulation is studied regarding the impacts of regulations on CEE, the results also show good consistency.

⑤ We have also added the regression results for each type of environmental regulation and using each of the two distance matrixes as a comparison (see columns (2), (3), (4), (6), (7), and (8)).

Table 3 Regression results of spatial panel model

Matrix	Geographic distance matrix				Economic geographic matrix			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnER1	0.082***	0.076***			0.031*	0.044**		
	(0.021)	(0.018)			(0.019)	(0.019)		
lnER2	0.033**		0.033**		0.052***		0.022*	
	(0.016)		(0.015)		(0.016)		(0.015)	
lnER3	0.002			0.012	-0.014			0.002
	(0.111)			(0.010)	(0.017)			(0.011)
lnopen	0.128***	0.115***	0.141***	0.129***	0.109***	0.111***	0.125***	0.119***
	(0.150)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
lntech	-0.25***	-0.242***	-0.256***	-0.243***	-0.236***	-0.222***	-0.228***	-0.221***
	(0.016)	(0.015)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
lnind	0.077	0.088	0.130**	0.120*	0.016	0.083	0.082	0.091
	(0.065)	(0.063)	(0.063)	(0.064)	(0.066)	(0.059)	(0.058)	(0.058)
lnurb	-0.301***	-0.334***	-0.323***	-0.335***	-0.317***	-0.296***	-0.288***	-0.300***
	(0.065)	(0.058)	(0.061)	(0.061)	(0.057)	(0.065)	(0.065)	(0.065)
lncr	0.095***	0.094***	0.127***	0.122***	0.096***	0.108***	0.125***	0.121***
	(0.197)	(0.02)	(0.019)	(0.019)	(0.019)	(0.02)	(0.019)	(0.019)
lambda	-1.201***	-0.963***	-0.568***	-0.503*	-0.988***	0.068	0.161	0.177*
	(0.310)	(0.292)	(0.276)	(0.261)	(0.283)	(0.117)	(0.099)	(0.100)
sigma2	0.006***	0.032***	0.034***	0.034***	0.031***	0.034***	0.034***	0.034***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Non-linear Effects Estimation

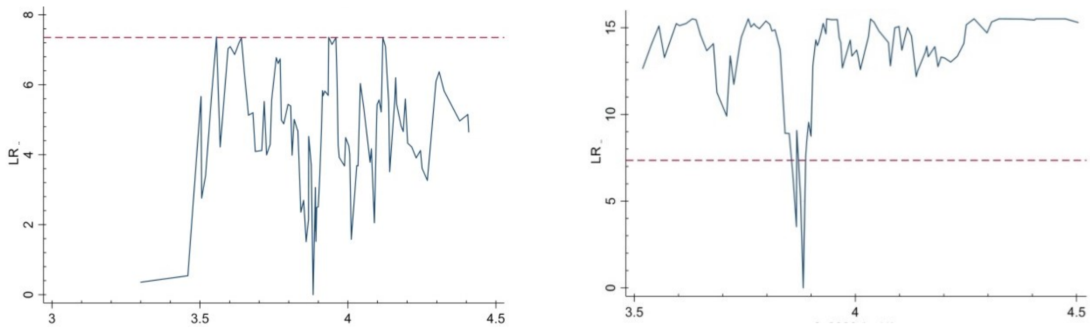
The threshold effects of heterogeneous environmental regulations are estimated using equations (5)-(7) to determine the optimal regulation intensity for effectively promoting efficiency gains. The outcomes are presented in Table 4.

As shown in Table 4, the effects of different regulations on CEE all have dual thresholds, and the confidence intervals of the thresholds are obtained using likelihood ratio (LR) statistics. In addition, Figures 2a-b, 3a-b, and 4a-b graphically show the LR functions of the two thresholds of the three types of regulations, respectively. Table 5 further presents the detailed regression results within each threshold for the variables.

Table 4 Estimated results and test of environmental regulation threshold

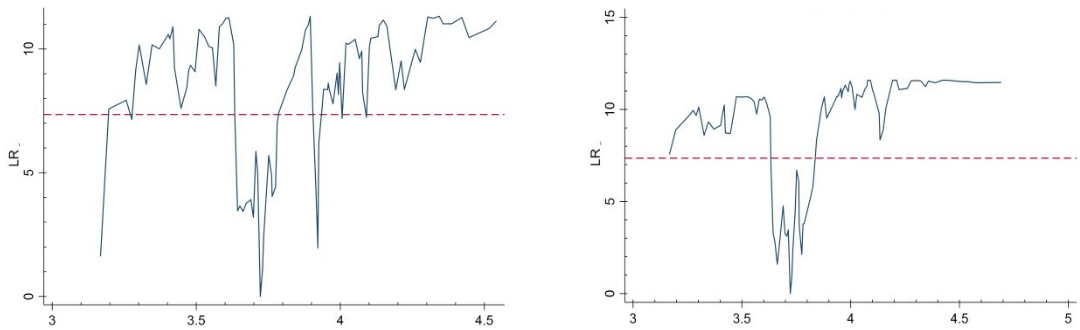
Threshold variable	Model	F value	Threshold value	95% confidence interval
ER1	Single threshold	7.362***	3.882	[3.300,4.408]
	Double threshold	16.871**	3.459	[3.300,3.568]
			3.882	[3.859,3.882]
ER2	Single threshold	12.989***	3.722	[3.168,4.091]
	Double threshold	8.368***	3.722	[3.633,3.827]
			3.916	[3.168,4.278]
ER3	Single threshold	4.934***	4.032	[2.811,4.420]
	Double threshold	13.214***	3.794	[3.565,4.032]
			3.981	[3.116,4.235]

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



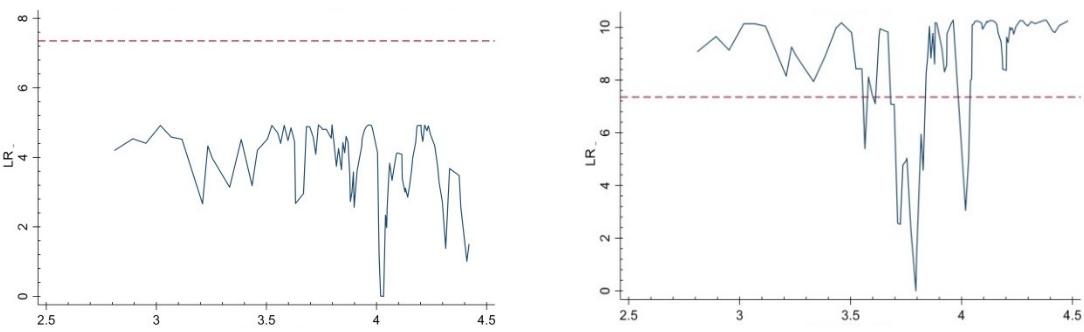
(a) (b)

Fig. 2 Confidence intervals of the first and second thresholds of ER1



(a) (b)

Fig. 3 Confidence intervals of the first and second thresholds of ER2



(a) (b)

Fig. 4 Confidence intervals of the first and second thresholds of ER3

Table 5 Regression results of panel threshold model

Variable	ER1 threshold regression	ER2 threshold regression	ER3 threshold regression
lnER＜γ1	0.224*** (0.037)	0.088*** (0.020)	0.015(0.012)
γ1≤lnER＜γ2	0.192*** (0.032)	0.080*** (0.019)	0.024** (0.011)
lnER≥γ2	0.181*** (0.030)	0.073*** (0.018)	0.019* (0.010)
lnopen	0.060*** (0.012)	0.038*** (0.014)	0.017*** (0.013)
lntech	-0.141*** (0.019)	-0.098*** (0.012)	-0.084*** (0.014)
lnind	-0.513*** (0.066)	-0.092(0.061)	-0.031(0.043)
lnurb	-0.096(0.056)	-0.088(0.054)	-0.245*** (0.052)
lncr	0.121*** (0.020)	0.051*** (0.013)	0.050*** (0.019)
cons	-0.979*** (0.123)	-0.434*** (0.067)	-0.250*** (0.050)

Note: Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As presented in **Tables 4** and **5**, the optimal range for the intensity of *ER1* lies within the first threshold, implying that the intensity of command-and-control regulations should not be too strict. The impact of market-incentive regulation (*ER2*) is more significant when the intensity is lower than 45.49. Its positive impact will decrease significantly once the intensity goes above its first threshold. Moreover, the incentive effect of ER2 will turn into an inhibiting effect when its intensity passes the second threshold. Meanwhile, the most ideal intensity range for public-participation regulation (*ER3*) falls between its first and second thresholds. Finally, we note that ER1 has the most significant effect of the three types of environmental regulations, indicating that the narrow version of the PH does not hold in this case.

5 Conclusion

5.1 Conclusion and Discussion

As an energy-intensive and carbon-intensive industry, the ISI is facing great pressure to accomplish a low-carbon transformation through CEE gains. This paper comprehensively analyzes the CEE of the ISI by constructing an undesirable global super-hybrid measure. On this basis, a spatial error model and panel threshold model are constructed to investigate the spatial and non-linear impacts of heterogeneous regulations on the CEE of China's ISI.

(1) Features of the CEE of China's ISI

The CEE of the ISI presents regional heterogeneity and shows a fluctuating upward trend during the observation period. We also see that the spatial distribution of CEE in China is unbalanced, as the eastern region has the highest efficiency score, followed by the central and western regions, with the northeastern region exhibiting the lowest values.

Driven by a growth in market demand, the ISI experienced fast expansion during the period of the 11^{th} FYP (i.e., 2006-2010). Such expansion not only supported economic prosperity and social development, but also introduced serious environmental pressure. Fortunately, corporations in the industry were actively adopting and developing energy-efficient, low-carbon, and clean-production technologies to cope with increased environmental regulations and to gain more financial support from the government (Hasanbeigi et al., 2014; Zhang et al., 2014). After the start of the 12th FYP (i.e., 2011-2015), the CEEs of the central, western, and northeastern regions all declined, leaving the eastern region as the exception. During this period, the market for iron and steel products contracted due to the decline in downstream demand from the building industry (Zhang et al., 2014). Meanwhile, the industrial concentration was still low and the pressure to eliminate outdated production capacity was high, especially in western and central China (He et al., 2021; Lin & Wang, 2014).

Since the beginning of the 13th FYP (i.e., 2016-2017), the CEE of the ISI has seen significant improvement. The overcapacity reduction policy has resulted in significant achievements in the ISI, and breakthroughs have been made in key technologies for low-carbon transformation, which effectively promote the reduction of energy consumption and pollution emissions (MIIT, 2020). Since the implementation of the overcapacity reduction policy in 2013, the eastern region has responded based on its own economic development and industrial adjustment advantages, leading to significant improvements in its CEE since 2015. During 2015-2017, the CEE of the western region remained relatively stable and its downward trend was curbed. As a traditional industrial base, the northeast has a solid production foundation and a complete industrial system. However, low energy efficiency, strong resource dependence, and weak innovation and technological transformation capabilities still exist and inhibit the low-carbon transformation of the sector there (Miao et al., 2021).

(2) Impacts of Environmental Regulations on CEE Considering Spatial Influences

As can be seen from the empirical results, spatial autocorrelation is significant for CEE according to both the geographic distance matrix and the economic geographic matrix, indicating that CEE has a positive effect on adjacent regions and areas with similar economic development levels. Therefore, more attention needs to be paid to promoting such spillover effects of the ISI's CEE across regions. In addition, command-and-control and market-incentive regulations significantly improve the CEE of the ISI, demonstrating that the constraints introduced by administrative instruments and the incentives of the market mechanism can both contribute to efficiency gains in the industry. Therefore, the PH is generally supported in this study as environmental regulations indeed facilitate the low-carbon transition of the ISI. In addition, compared to the traditional command-and-control approach, no marked advantages of a flexible market-incentive policy, as represented by pollutant discharge fees, have yet been found, indicating that the narrow version of the PH does not hold based on our findings. This outcome can largely be explained by certain drawbacks of the pollutant discharge fee system itself. If the pollutant discharge fee levy standard is lower than the marginal emissions reduction cost, or effective market competition is lacking, an enterprise's pollution control motivation will be lowered (Ren et al., 2018). Moreover, the charge standards differ between regions, which may also fail to restrain enterprises' pollution behaviors (Paras, 1997). Therefore, China has replaced the pollutant discharge fee system with a new environmental protection tax, and has been developing national-level carbon trading since 2021 to let the market play a stronger role in environmental governance (Shi et al., 2019). Finally, there is seemingly no positive impact of ER3 on CEE. This may be because a complete system of public engagement in environmental governance has not yet been formed, as the public-government communication channels are quite limited and environmental information disclosure is not yet at an adequate level (Li et al., 2021b; Wu & Gao, 2021). Moreover, information asymmetry in environmental governance may distort facts and fail to effectively urge enterprises to reduce emissions (Zhu & Zhang, 2012).

(3) Non-linear Effects of the Regulations on CEE

As demonstrated in the results, the three types of regulations all have double thresholds. However, their optimal intensity ranges are different.

For the command-and-control regulation, its promoting impacts on CEE decrease as its intensity increases. Thus, the stringency of such mandatory measures should not be too high. Taking environmental pollution control investment as an example, although part of the funds comes from government expenditure, enterprises still rely on self-financing to some extent. Excessive increases in investment expenditure on environmental pollution control will squeeze out the funds needed for technological innovation and production improvement (Ji et al., 2022). That is, the "cost effect" is greater than the "innovation compensation effect", in the same way that the promotion effect of command-and-control environmental regulations will be greatly reduced (Liu et al., 2021). Improper command-and-control regulation may increase intervention costs, hinder innovation and resource utilization, and produce undesired results (Tang et al., 2020). Similarly, the optimal range of market-incentive regulation also lies within the first threshold. This outcome shows that, when the pollutant discharge fee rises to a certain level, the long-run production costs of the enterprise will further increase, which may in turn reduce enterprises' enthusiasm for technological innovation, cleaner production, and emissions reduction (Hu et al., 2020; Shen et al., 2019). In addition, for enterprises with low emission/output ratios, the marginal cost may still be lower than the output price when the discharge fee rises. Thus, enterprises will tend to further expand production in order to make more profits, resulting in higher gross energy consumption as well as emissions (Endres, 1983).

The optimal range of public-participation regulation lies between the first and second thresholds. When the intensity of public participation is too low, the public cannot supervise and restrain economic activities, thus the public cannot promote the low-carbon transition of the industry. With greater intensity, public participation can be an effective approach for addressing the issues of government and market failures. Public engagement becomes a more flexible and effective means of encouraging ISI enterprises to carry out cleaner production and take responsibility for environmental protection and governance. However, after the intensity passes a certain level, the positive effects may reach saturation and the marginal utility may start to diminish (Zhang et al., 2020). Excessive information disclosure may also increase the processing costs of relevant government departments (Huang & Gao, 2016).

These results also confirm that environmental regulation is a double-edged sword, and only well-designed regulatory approaches with appropriate stringency/intensity will facilitate the low-carbon transition.

(4) Impacts of Other Influencing Factors

In assessing the results for the other control variables we see that the openness level has effectively promoted the low-carbon development of China's ISI, which may be attributable to technology demonstration and spillover effects of foreign capital. Therefore, we conclude that the "pollution haven" hypothesis[⑥] is not valid in China's ISI. Technological demonstration and spillover effects of foreign capital may promote the improvement of technological innovation and R&D capabilities, which could in turn benefit the industry and promote the improvement of CEE (Wang & Yuan, 2018). At the same time, foreign trade has enhanced market demand for ISI products and improved energy efficiency (Wu et al., 2019). This has contributed to the improvement of product structure and the capacity utilization rate to a certain extent, thereby improving CEE. In addition, technological progress has contributed greatly to the low-carbon transition of the ISI. However, energy efficiency enhancement caused by technological improvement may encourage enterprises to blindly expand production, in turn leading to a "rebound effect"[⑦]. Therefore, green and low-carbon technological innovation and applications should specifically be advocated in the industry. In the ISI a scale effect exists when an increase in industrial concentration is conducive to enhancing the utilization rate of production capacity as well as innovation capabilities. Last but not least, the inhibitory effect of the urbanization rate on CEE indicates that urbanization has stimulated a high demand for iron and steel products, which may easily lead to blind investment and extensive expansion of the industry, resulting in low-end overcapacity and carbon-intensive development.

The results for the key variables (i.e., different types of environmental regulations) presented in Table 3 under the different distance matrices are inconsistent with each other while the results for the impacts of the heterogeneous regulations on CEE in the spatial and non-linear analyses in Tables 3 and 5 are in line with each other. The regression results for the control variables in the threshold regression and the spatial panel models maintain a high consistency, which also reflects the robustness of this study.

5.2 Recommendations

(1) Multiple measures should be adopted to improve CEE, with special attention paid to regional gaps.

China is the world's largest steel producer, and the low-carbon development of China's ISI will have a significant impact on the world economy and environment. Since the start of the 13th

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[⑥] The pollution haven hypothesis posits that foreign direct investment (FDI) introduces environmental impacts due to pollution-intensive industries tending to move from developed countries to developing countries or regions with less regulatory stringency (Al-Mulali & Tang, 2013).

[⑦] The rebound effect occurs when greater energy efficiency leads to an increase in industrial energy use (Jevons, 1865).

FYP, with the implementation and advancement of overcapacity reduction policies, outdated technologies and facilities have gradually been eliminated, transformed, or transferred. The production structure has been upgraded while CEE has continued to rise. However, the energy-intensive and carbon-intensive features of the ISI have not yet been essentially changed. Therefore firstly, attention should be paid to prohibiting additional production capacity, consolidating the de-capacity achievements, and speeding up the implementation of capacity replacement. According to the empirical results of our study, the openness level, technological progress, and industrial concentration all contribute to the low-carbon transition of the ISI. Therefore, the formulation and implementation of environmental protection-related regulations and industrial development policies should be accelerated to give full play to the positive effects of expanding the opening up of China. In addition, the *Catalogue for the Guidance of Industries for Foreign Investment* should be further optimized to attract "clean foreign investment" and prevent the emergence of a "pollution haven effect". Second, the current low concentration ratio of China's ISI is restricting the industry's development (He et al., 2021). Accordingly, it is necessary to further increase the industrial concentration ratio to benefit from scale effects in the sector. Third, appropriate funding and policy supports are needed to facilitate the innovation and application of low-carbon technology, especially carbon emission reduction, capture, storage, and utilization technologies, in the ISI. For example, the *Guiding Opinions on Promoting Investment and Financing of Climate Change* should be promoted actively in the industry, and the government should assist enterprises that face difficulties in investing in and financing low-carbon technologies. Last but not least, the impact of urbanization on CEE is negative. Therefore, the new type of urbanization that aims to connect the four major plans of ecological progress, urbanization quality, expanding domestic demand, and rural-urban coordination should be further enhanced to create a greener and low-carbon market demand for the ISI. Developing countries should draw on China's experience and avoid blind and extensive development. It is also important for the ISIs in developing countries to achieve green and low-carbon development through opening up, making technological progress, increasing industrial concentration, and promoting new urbanization appropriate to their own national conditions.

In addition, regional differences in CEE can be observed in the empirical results, implying a need to focus on narrowing the efficiency gaps across regions. Based on the empirical results, we believe the eastern provinces need to play an active, leading, and exemplary role to accelerate the narrowing of the efficiency gap in the ISI between regions through spillover effects. They can do so based on their advantages in production technology, complete industry systems, relatively high industrial concentration, high knowledge levels among the population, and environmental protection awareness (Xie et al., 2021). In the eastern region, the low-carbon development of the ISI has stayed ahead of the other regions' development, and technological advantages have been created. Provinces in other regions should learn from the eastern provinces and introduce advanced technologies, including clean production, energy-saving, and carbon emission reduction technologies, to promote the low-carbon development of the ISI. In addition, provinces in the eastern region have formed a relatively large industrial scale, and these provinces should cultivate an advanced productivity capacity based on their technical advantages (Ren et al., 2021b). In the meanwhile, provinces in the central, western, and northeastern regions need to optimize their production structure and rationally develop ISI production when advancing their infrastructure construction and industrial development, in order to reduce the negative effects of urbanization on low-carbon development.

(2) Attention should be paid to the heterogeneous and non-linear effects of the regulations.

First, the effects of heterogeneous environmental regulations vary in China. The positive impacts of command-and-control regulations on ISI's CEE are remarkable and stable, and their promoting role is the most significant among the three types of regulations, proving that the Chinese government has been playing a critical role in the low-carbon transition of the ISI. However, this promoting effect decreases as the stringency of the regulation increases. Therefore, the government should evaluate the actual situation of the ISI over time, formulate environmental protection and investment policies of a reasonable intensity, and implement effective measures based on the development characteristics of the ISI in different regions. It is also necessary to reduce the intensity of direct administrative intervention in production activities. That is to say, the government should focus its role on guiding reasonable investment, preventing the rebound of backward production capacity, and balancing supply and demand by adjusting the product structure of production, while handing over the power for regulation and control to the market. The effect of market-incentive environmental regulations is significant, but its positive impact diminishes as the intensity of such regulations increases. Therefore, more effective market-incentive measures such as the emissions trading market should be fully implemented and developed. Public participation has not yet become an important supplement to the other environmental protection approaches. Therefore, the mechanism for public participation in environmental governance should be further enhanced, and the public's environmental rights should be further clarified. Publicity should be fully utilized to enhance public awareness of environmental protection concerns. To meet the needs of the regulation and practice of pollution reduction, full play should be given to the supervisory advantages of the market, environmental protection organizations, and the public, and the protection of rights and interests should be improved through environmental protection laws. Feedback platforms and handling mechanisms for environmental issues need to be perfected, while channels and forms of public participation in environmental governance should be further expanded and enriched, so as to avoid information asymmetry in informal environmental regulation (Xiong & Wang, 2020).

Second, the positive and significant spatial correlation feature of CEE indicates that provinces and regions should work together, especially when dealing with emission reduction-related issues. Although there are differences between the ISI's emission levels and regulatory intensity in various regions, promoting regional cooperation is necessary to enhance the positive effects of regulations on the low-carbon transition. Local governments should actively negotiate and cooperate with neighboring areas or regions at a similar economic development stage, and reach consensus on coordinated regulation when formulating their own regional industrial development and environmental regulatory policies. Local governments should cooperate to advance improvement in energy efficiency, establish a synergy mechanism for industrial development and regional environmental regulations, and share governance experiences, in order to learn from each other's strengths (Zhang et al., 2021). In so doing, an industrial governance pattern can be formed with joint prevention and control of regional carbon emissions. Internationally, collaborative development mechanisms for environmental co-governance should be constructed between different countries, especially neighboring countries and those with similar income levels. They should effectively enhance communication and the exchange of environmental governance actions, strengthen their coordination regarding relevant issues, and ensure the organized promotion of environmental co-governance (Li et al., 2021c).

Third, the three types of environmental regulations all have double threshold effects. The positive effects of command-and-control and market-incentive environmental regulations on CEE will decrease as intensity increases, while the impact of public-participation environmental regulation on CEE will only happen when it reaches a certain intensity. Therefore, in the process of policy formulation and implementation, relevant departments should fully understand the development characteristics of the local ISI, correctly assess production levels and environmental carrying capacities, and maintain the strength of mandatory regulations at a reasonable level. At the same time, the government should set up dynamic monitoring and adjustment mechanisms to prevent policy rigidity (Sun et al., 2021). Due to the limitations of the pollutant discharge fee, new market-incentive regulations that are suitable for long-term development, such as an environmental tax and a carbon emissions trading system, should be developed, implemented, and perfected. As for public-participation environmental regulations, their most suitable range is between the first and second thresholds, indicating that the intensity of such a regulatory approach should be maintained at a reasonable level. Accordingly, various measures need to be taken to improve both the quantity and quality of public engagement in environmental regulation, such as formulating handling mechanisms to ensure the efficiency of responses to environmental petitions, setting up additional types of channels for public participation in environmental governance, and enhancing environmental information transparency through information disclosure.

Furthermore, it is necessary that the environmental regulations and diversified instruments are appropriately adjusted according to the actual conditions in each country, rather than adopting the same standard policy everywhere (Song et al., 2020b). The government and relevant departments should pay attention to the applicability of environmental regulations to industries and enterprises when setting up or improving them (Jiang et al., 2021). In other words, a dynamic adjustment mechanism should be set up to ensure that the regulatory intensity is suitable for the low-carbon transition of the ISI.

5.3 Limitations and Future Studies

First, in this study we considered the production process of iron and steel as a whole when estimating the CEE. The efficiency levels of different stages of iron and steel production (i.e., pre-iron stage and post-iron stage) could be further discussed to open the "black box" of carbon management. Second, this paper focuses on the spatial and non-linear effects of heterogeneous environmental regulations on the low-carbon transition of the ISI. The interaction effects between different types of regulations could be further discussed to analyze the synergistic influence of different types of regulatory tools. Third, the environmental laws and regulations promulgated by the government and relative departments also exert impacts on carbon emissions. Future research could discuss the impacts of specific policies or regulations on the low-carbon transition, using quasi-natural experiments. In addition, along with the advocacy of cleaner production and environmental protection, more and more heavy-polluting enterprises have begun to carry out spontaneous pollution-control investment and innovation activities by setting up and certifying their own environmental management systems. Voluntary regulatory measures such as ISO 14001 that reflect firms' intentions and determination to participate in environmental protection and low-carbon production development have drawn increasing attention in recent years. Therefore, the impacts of voluntary conscious environmental regulations on the low-carbon transition could be incorporated into the analysis framework in future studies.

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Declaration of interests

The authors declare that they have no competing interests.

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Appendix

Table A1 Variable definition and description

Variable type	Variable	Symbol	Definition	Data source
Inputs	energy	E	Total energy consumption of ISI	China Energy Statistical Yearbook, provincial statistical yearbooks
	labor	L	Annual average number of employees of ISI	China Industry Statistical Yearbook, provincial statistical yearbooks
	capital	C	Capital stock of ISI	China Industry Statistical Yearbook, provincial statistical yearbooks
Outputs	output value	O	gross industrial output value of ISI	provincial statistical yearbooks
	CO_2	CO_2	carbon dioxide emissions of ISI	China Energy Statistical Yearbook, provincial statistical yearbooks
Environmental Regulations	command-and-control regulation	ER1	industrial pollution source treatment investment; urban environmental infrastructure construction investment; "three simultaneous" construction projects investment	China Statistical Yearbook on Environment
	market-incentive regulation	ER2	pollutant discharge fees per unit industrial value added	China Statistical Yearbook on Environment, China Environment Yearbook
	public participation regulation	ER3	number of complaint letters on pollution; number of environment-related visits received by environmental departments	China Statistical Yearbook on Environment
Control variable	openness level	open	ratio of total import and export volume to GDP	China Statistical Yearbook
	technology progress	tech	total energy consumption per output value of ISI	China Energy Statistical Yearbook, provincial statistical yearbooks
	industrial structure	ind	ratio of value added of secondary industry to GDP	China Statistical Yearbook
	urbanization	urb	ratio of urban population to total population	China Statistical Yearbook
	industrial concentration ratio	cr	ratio of total industrial output value of ISI to	China Industry Statistical Yearbook, provincial statistical yearbooks

	number of enterprises

Table A2 Provinces in eastern, central, western, and northeastern China

Region	Provinces/cities/autonomous
Eastern	Beijing, Tianjin, Hebei, Guangdong, Fujian, Jiangsu, Zhejiang, Shanghai, Shandong
Central	Anhui, Henan, Shanxi, Jiangxi, Hubei, Hunan
Western	Sichuan, Guangxi, Shaanxi, Guizhou, Yunnan, Inner Mongolia, Gansu, Qinghai, Ningxia, Xinjiang, Chongqing
Northeastern	Heilongjiang, Jilin, Liaoning