



China's industrial green development and its influencing factors under the background of carbon neutrality

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Abstract

To measure and analyze the evolution characteristics and influencing factors of China's industrial green development level is of great significance in achieving carbon neutrality goal. Based on the panel data from 2000 to 2018 of 30 provinces in China, this research uses the super slack-based measuring model and the Malmquist-Luenberger index to calculate China's industrial green total factor productivity and to describe its evolution characteristics using the kernel density function and moreover uses the Spatial Durbin model and the partial differential method to explore its main influencing factors. This study finds that China's overall industrial green development level is not high but shows an upward trend year by year; carbon emissions, fiscal decentralization, and urbanization are not conducive to improving the national industrial green development level, whereas economic development, foreign direct investment, industrial structure, and technological progress are positive contributors. At the same time, the level of economic development and technological progress have significant direct and spatial spillover effect. Our findings also provide some policy implications for improving China's industrial green development.

Keywords Industrial green development · Carbon neutrality · Industrial green total factor productivity · Spatial dynamic panel model · Malmquist-Luenberger index · Technological progress

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Introduction

World economic growth for a long time has been excessively dependent on energy and resource consumption; this traditional mode of economic development has brought serious environmental problems while bringing economic prosperity (Li et al. 2022; Chen et al. 2022a). The UN has identified that industry sector as a vital enabler for most of the Sustainable Development Goals. From a global perspective, since the industrial revolution, the carbon dioxide (CO₂) concentration has increased by 47%, increasing the earth temperature by 1.9 Fahrenheit and sea level by 7 inches (IPCC 2019); fossil energy generates over 80% of global greenhouse gas (GHG) emissions, of which industry accounts for more than half (International Energy Agency 2015). More and more people realized that the current level of already stowed industrial emissions will continue to affect future generations. The 9th sustainable development goal in the 2030 Agenda for the UN Sustainable Development Goals, which is to “Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation,” points out the direction and presents arduous tasks for the future industrial development of countries. Countries are simultaneously taking

a special interest in addressing industrial economic growth and environmental challenges, especially the way to deal with the current enormous industrial carbon emission reduction pressure. In terms of China's reality, during its urbanization and the over 40 years of reform and opening up, China's industry has become an important engine of China's rapid economic development, with China's industrial gross domestic product (GDP) already accounting for over 30% of GDP by 2020. At the same time, China's industrial sector has become a major source of GHG such as the CO₂ (Zhu et al. 2021, 2020; Teng et al. 2019; Pusnik et al. 2017; Bin and Lin 2016), especially from 2001 to 2014. China's carbon emission intensity has been maintained at a growth rate of more than 8%, showing the characteristics of crude development with high input, high energy consumption, high pollution, and low efficiency (Sohail et al. 2022; Pan et al. 2021; Chen et al. 2020a; Zhang et al. 2022a, 2022b).

China pledged in September 2020 to achieve carbon peak by 2030 and carbon neutrality by 2060. The so-called carbon neutrality which means achieving net zero emissions of CO₂, which means huge challenges for China's industrial carbon reduction in achieving the goal of green development, also has strengthened China's commitment to green and low-carbon development. Promoting innovation efficiency, enhancing green productivity, and reducing CO₂ emissions are the main targets of China's industrial green development in achieving carbon neutrality goals (Liu et al. 2021; Zhao et al. 2022a, 2022b; Zou et al. 2022). In fact, the China government attaches great importance to resource and environmental pollution issues and is committed to promoting sustainable industrial development. The country has proposed five development concepts of innovation, coordination, greenness, openness, and sharing and has issued a series of relevant laws and regulations to support industrial green development. GHG reduction needs to be carried out from the energy and industry dimensions, giving full play to the support of technological innovation, supporting the improvement of energy use efficiency (Sun et al. 2021a; Sun et al. 2021b; Chien et al. 2021a; Chen et al. 2022b). All these are inseparable from the transformation of prompting the improvement of energy structure and the adjustment of industrial structure of the industrial section (Pan et al. 2021; Yang et al. 2022; Zhang et al. 2022a, b). To scientifically and rationally evaluate China's industrial green development level, it is not simply to examine its total output value or added value, but also to consider the level of industrial total factor productivity. Therefore, to assess the industrial green development level, factors such as environment and resources should be included in the framework, and the influencing factors in economy and society, such as industrial structure adjustment and technological innovation, should be considered comprehensively, so as to accurately assess the economic and social welfare brought by industrial development and provide more meaningful references for the decision-making of government and enterprises, so as to achieve the goal of coordinated economic and social

development (Yu et al. 2020; Zhao et al. 2022c). Therefore, under the constraint of carbon neutrality target, industrial green development is to achieve carbon reduction in industrial production while enhancing industrial green total factor productivity (IGTFP) with consideration of environment and resources (Cui et al. 2019; Chen and Golley 2014; Ma et al. 2020).

Since the 1980s, China has begun an attempt to reform the fiscal decentralization, aiming to give local governments certain tax management powers. In the context of Chinese-style decentralization, the environmental regulation goals of local governments and the central government are often not completely consistent. Due to the lack of incentives, compatibility, and constraints, and the performance appraisal system that advocates GDP, it is easy to breed local governments' short-sighted behavior in environmental protection work. The Prisoner's Dilemma of "race to the bottom" appears when attracting liquidity elements (Zhao et al. 2022d; Li et al. 2022; Zhang et al. 2011). However, it is not necessarily that fiscal decentralization will have a negative impact on the environment, which is closely related to the local government's awareness of environmental protection and the concept of scientific development. Under the conditions of a promising government and an efficient market, fiscal decentralization enables local governments to better formulate environmental regulatory policies that conform to the actual conditions of the region, and is more conducive to handling the dilemma between promoting growth and protecting the environment (Jiang et al. 2022; Tu et al. 2021; Liu et al. 2021). How to effectively promote China's industrial carbon emission reduction is a significant way to realize the transformation of China's industrial green development and achieve carbon neutrality, especially addressing the waste of resources and the destruction of environment generated in the process of industrial production. How to improve IGTFP clarifies its influencing factors and then explores the path to improve the level of industrial green development, which not only provides a basis for China's industrial transformation but also is of great theoretical and practical significance to accomplish China's established CO₂ reduction tasks (You et al. 2022; Tu et al. 2021; Xue 2021).

Therefore, this paper based on panel data of 30 provinces from 2000 to 2018 (Tibet, Hong Kong, Macao, and Taiwan are not included, due to serious data deficiencies) calculates the industrial green total factor productivity and its evolution characteristics in China, and more comprehensively assesses the green productivity of Chinese industry, so as to clarify the China's industrial green development level under the global GHG reduction and high-quality economic development goals. Furthermore, exploratory spatial analysis is selected to study the influencing factors of China's industrial green development level, explore the direct effects and spatial spillover effects of the factors, and on this basis, the paper proposes relevant strategies to promote China's industrial low-carbon transformation, which can provide some reference for China's transformation from a large industrial country to an industrial power (Shi et al. 2022).

The research arrangement of this paper is as follows: Sect. 2 is the literatures review, Sect. 3 is the research design, Sect. 4 is the empirical analysis, and Sect. 5 is the conclusions and recommendations.

Literature review

There are many studies on economic green development, most of which focus on the connotation, measurement, and evaluation of economic green development. There are relatively few studies on industrial green development, which mainly focuses on the basic connotation of realizing economic growth, environmental protection, and resource conservation by industrial green development. Some studies have aimed to promote the sustainable development of industry and coordinate the contradiction between industry and environment (De Alba and Todorov 2018; Hu et al. 2011). In the early process of global industrialization, the extensive production mode not only produced economic benefits, but also caused serious environmental pollution (Worrell 2000; Chen et al. 2011). Therefore, from the perspective of industrial production's characteristics, the Research Group of Institute of Industrial Economics (2011) defined industrial green development as the industrial process of "intensive utilization of energy, reduction of pollutant emissions, reduction of environmental impact, improvement of labor productivity and enhancement of sustainable development." Some scholars disassemble the goal into sub-goals, including industrial structure, technical system, energy structure, financial support, and environmental optimization, based on the direction of industrial green development (Ping et al. 2010; Bonilla et al. 2018; Zhou et al. 2020). In order to realize industrial green transformation and upgrading, it is necessary to improve industrial green development efficiency by introducing the concept of industrial green development into specific industries, especially industries with high investment and energy consumption (Wu et al. 2016; Heravi et al. 2015).

Ortiz et al. (2009) from the research of life cycle assessment pointed out that the theory of industrial green development can be used to optimize the extraction of raw materials in the construction industry, so as to realize the industrialization and sustainable development in this field. Supino et al. (2016) summarized the emission reduction experience of the cement industry in Italy and Germany, and believed that cement manufacturing, as an industrial process with the most intensive use of materials and energy, has great potential for carbon emission reduction. In short, with the increasing attention to global warming, the connotation and viewpoint of industrial green development are constantly improved and enriched when the research fields and horizons of it are constantly expanded. This is of great significance

for the research on realizing carbon neutralization through industrial low-carbon transformation.

Most studies have evaluated industrial green development by IGTFP, and most traditional of IGTFP is calculated by parameterization analysis methods, such as the Solow residual method, CD production function, and stochastic frontier analysis (SFA). However, they only considered expected output and input factors such as labor and capital, thus distorting the impact of factors such as the environment and resources on industrial sustainable development. In fact, China's industrial development comes largely at the cost of excessive consumption of resources and continuous deterioration of the environment. If environmental factors are not considered, then the evaluation results will be distorted. Therefore, based on the traditional literature, some scholars adopt the non-parametric method without any preset model, regard environmental pollutants and energy consumption as unexpected outputs, and choose the directional distance function (DDF) that comprehensively considers various inputs and outputs, in order to estimate IGTFP (Su et al. 2013; Chen and Golley 2014; Boyd et al. 2002; Zhang et al. 2011). In addition, some scholars have introduced DDF into the Malmquist model, decomposed IGTFP through the Malmquist-Luenberger (ML) index, and highlighted the importance of technological progress (Watanabe and Tanaka 2007; Zhang et al. 2011; Ning et al. 2015). However, with some defects in the traditional DDF and ML index, some scholars have calculated IGTFP by adopting Super slack-based measuring model (Super-SBM model), which comprehensively considers radial and non-radial indicators (Zhou et al. 2020; Shi et al. 2022), and the global ML (GML) index, which avoids spurious regression and the infeasibility of linear regression (Yan et al. 2013; Fan et al. 2015), so as to improve the accuracy and reliability of their results.

Interests of various aspects need to be considered for industrial green transformation. In combination with industrial structure adjustment measurement and panel regression model, Zhu et al. (2019) proposed that industrial structure adjustment improves the green development of the whole industry by reducing the share of high energy-consuming and high-polluting enterprises on the one hand, and by supporting green industries with low energy consumption, high technological content, and high innovation on the other. However, Pan et al. (2019) pointed out that the impact of China's industrial structure on the green transformation of the industrial economy is transient, and industrial green development should rely more on scientific and technological progress. Scientific and technological progress interacts with labor productivity and the organic composition of capital to promote the transformation and upgrading of industrial structure and build green production and consumption methods, thus improving the green development of industry. Some scholars have reached similar conclusions

when exploring the influencing factors of industrial green development level—that is, scientific and technological innovation is the most critical factor for improving the industrial green level (Norberg-Bohm 1999; Cheng et al. 2018; Garetti and Taisch 2012; Yang et al. 2016). Li et al. (2022) further studied the impact of environmental regulation on green technology innovation. There are many kinds of environmental regulation, including mandatory environmental regulation, market-incentive environmental regulation, and voluntary environmental regulation, of which regional heterogeneity is obvious, and their impacts on IGTFP are different.

From the perspective of fiscal decentralization, many researchers agree that the role of local governments can affect the technological progress of enterprises to a certain extent, so as to realize the upgrading of energy consumption structure and the reduction of energy consumption; on the production side, because technological progress is the core part of realizing green industrial development, and the effect of environmental regulation is closely related to enterprises (Chen et al. 2022a; Zhao et al. 2022c). The research and development of green technology is closely related to its use, so the superposition of environmental regulation and technological progress will better improve industrial total factor productivity. Huang (2017) points out that the Chinese-style of fiscal decentralization has closely linked the promotion of local officials to the state of economic development, causing damage to the local and surrounding environment through environmental “Race to the bottom” and environmental “free-riding,” which in turn is detrimental to the improvement of industrial green development. In addition, some scholars have comprehensively considered internal and external factors and regarded factors such as foreign direct investment, urbanization level, and economic development level as indicators affecting the level of industrial green development, pointing out that the increase of urbanization level has brought about the expansion of urban development zone and the concentration of people, resulting in the agglomeration of industries and the transformation and expansion of infrastructure, thus creating a huge load on resources, energy, and the environment, which is disadvantageous to the promotion of industrial green growth efficiency. The actual impact of foreign investment confirms the “pollution paradise” hypothesis. The preference of foreign capital providers to invest in high energy consumption, high emission, and high pollution industries has exerted tremendous pressure to the environment, while the improvement of the economic development level has prompted the adoption of more complete environmental protection technologies and pollution control systems, and improve the corresponding infrastructure, promote and accelerate the formation of green industrial structure, thus improving the level of industrial green development (Qiu et al. 2021; Ayamba et al. 2019; Zhong et al. 2022).

Since achieving the goals of carbon peak and carbon neutrality has become China’s national strategy, industrial green development should be transformed according to a national unified arrangement. It is necessary to correctly measure the green development and influencing factors of China’s industry and to consider the impact of CO₂ on IGTFP. In addition, when measuring the level of industrial green development, most studies used the non-radial SBM model to deal with the relaxation of input and output, ignored frontier efficiency ranking, did not involve comprehensive provinces, and did not use enough of a time span, making it difficult to reasonably classify the influencing factors when studying industrial green development level and thus affecting the accuracy of the evaluation framework. In the previous literature, the measurement framework of industrial green total factor productivity, the non-desired output generally includes only the industrial “three wastes.” Through the collection of latest literature, it is found that a few authors have expanded the range of the non-desired output to take into account the indicator of the CO₂ emissions (Ma et al. 2021). To sum up, based on the above research, this study offers the following innovations. First, fully considering the principles of scientific, comprehensiveness, and data availability, this paper selects panel data of 30 provinces from 2000 to 2018 and uses the super-efficiency SBM model and ML index to calculate China’s IGTFP and evaluate China’s green development level more comprehensively. Second, the impact of CO₂ is fully considered in this research on the influencing factors of IGTFP, and so the impact of carbon emissions on China’s industrial green development can be clearly displayed. Third, by considering spatial factors, this research analyzes the influencing factors of China’s industrial green development level by using the spatial econometric model and fully discusses the direct effect and spatial spillover effect of these influencing factors.

Research design

Research methods

Super-efficiency SBM model containing undesirable outputs

Data envelopment analysis (DEA) is the main method to measure energy efficiency. Tone (2001) proposed the non-radial and non-angular SBM (Slacks-Based Measure) model in 2001 and the SBM model containing undesirable outputs in 2003. In order to solve the problem that the existing SBM model cannot rank multiple decision-making units on the frontier, thus preventing a comparison among efficiency values, Tone (2002) proposed the super-efficiency SBM model. Our study considers environmental pollution when

calculating the green development level of China’s regional industry, and therefore the super-efficiency SBM model containing undesirable outputs can calculate the industrial green development level better. The specific model runs as follows (the assumption here is constant returns to scale; if the returns to scale are variable, then constraints of $\sum_{j=1}^n \lambda_j = 1$ need to be added):

$$\rho^* = \min \frac{\frac{1}{m} \sum_{i=1}^m \bar{x}_i}{\frac{1}{s_1+s_2} (\sum_{r=1}^{s_1} \bar{y}_r + \sum_{q=1}^{s_2} \bar{z}_q)} \tag{1}$$

$$s.t. \left\{ \begin{array}{l} \bar{x} \geq \sum_{j \neq 1 \neq 0}^n \lambda_j x_{ij} \\ \bar{y} = \sum_{j \neq 1 \neq 0}^n \lambda_j y_{ij} \\ \bar{z} = \sum_{j \neq 1 \neq 0}^n \lambda_j z_{ij} \\ \lambda > 0, j = 1, 2, \dots, n, \text{ and } j \neq 0 \\ \bar{x} \geq x_{i0} \\ \bar{y} \geq y_{r0} \\ \bar{z} \geq z_{q0} \\ i = 1, 2, \dots, m; r = 1, 2, \dots, s; q = 1, 2, \dots, k \end{array} \right.$$

This study uses m to represent the efficiency value, which can be greater than 1. When m is greater than 1, the decision-making unit is efficient; the greater the value is, the higher is the efficiency. When m is greater than 0 and less than 1, the decision-making unit is inefficient. Here, \bar{x} , \bar{y} , and \bar{z} represent the slack variables of input, desirable output, and undesirable output, respectively; x_{ij} , y_{ij} , and z_{ij} represent input variables, desirable output variables, and undesirable output variables of the evaluated units, respectively; and m , s_1 , s_2 , and n represent the number of input indicators, desirable output indicators, undesirable output indicators, and decision-making units, respectively.

Malmquist-Luenberger index and its decomposition

This paper calculates and decomposes change in the industrial green development level by the Malmquist-Luenberger index. According to Chung et al. (1997), the output-oriented Malmquist-Luenberger index from period t to period $t + 1$ goes as follows.

$$ML_t^{t+1} = \left[\frac{1 + D_0^t(x^t, y^t, b^t; g^t)}{1 + D_0^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})} \times \frac{1 + D_0^{t+1}(x^t, y^t, b^t; g^t)}{1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})} \right]^{1/2} \tag{2}$$

Here, $D_0^t(x^t, y^t, b^t; g^t)$ and $D_0^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})$ respectively are the SBM directional distance functions of period t and period $t + 1$ with period t as the reference; and $D_0^{t+1}(x^t, y^t, b^t; g^t)$, $D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})$ respectively represent the SBM directional distance functions of period t and period $t + 1$ with period $t + 1$ as the reference. The ML index represents the total factor productivity change considering undesirable outputs; when it is greater than 1, the total factor productivity has increased; when it is equal to 1, the total factor productivity remains the same; when it is less than 1, the total factor productivity has decreased.

This study further decomposes the ML index into technical efficiency change index (EC) and technological progress index (TC) as follows.

$$ML_t^{t+1} = EC_t^{t+1} \times TC_t^{t+1} \tag{3}$$

$$EC_t^{t+1} = \frac{1 + D_0^t(x^t, y^t, b^t; g^t)}{1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})} \tag{4}$$

$$TC_t^{t+1} = \left[\frac{1 + D_0^{t+1}(x^t, y^t, b^t; g^t)}{1 + D_0^t(x^t, y^t, b^t; g^t)} \times \frac{1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}{1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})} \right]^{1/2} \tag{5}$$

Here, EC and TC represent the change in economic growth caused by the change in internal efficiency and technological progress, respectively. When $EC(TC)$ is greater than 1, technical efficiency (technological progress) has improved; when $EC(TC)$ is equal to 1, technical efficiency (technological progress) remains the same; when $EC(TC)$ is less than 1, technical efficiency (technological progress) has decreased.

Spatial Durbin model (SDM)

It is inevitable that spatial factors influence the study of an economy. Therefore, this study examines the inter-regional spatial effect by establishing the spatial econometric model. Spatial econometric models mainly include spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). The SAR model reflects the spatial spillover effect of explained variables in adjacent areas; the SEM model reflects the spatial dependence of random disturbance items and emphasizes that the spatial correlation between explained variables is caused by the random disturbance items between regions; the SDM model considers that the observed value of the explained variable is affected by both the explained variables and

the explanatory variables of the adjacent area, to a greater extent, which can avoid the spatial spillover effects of omitted variables and neglected influencing factors while using panel data for regression, while taking into account the spillover effects of the “neighboring” regions, and it is set as follows.

$$y_{it} = \rho \sum_{j=1}^N w_{ij} y_{jt} + x'_{it} \beta + \sum_{j=1}^N w_{ij} x'_{jt} \delta + \mu_{it} + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma^2) \tag{6}$$

Here, y_{it} and x_{it} represent the explained variable and the explanatory variable, respectively; $\sum_{j=1}^N w_{ij} x_{jt} \delta$ represents the spatial lagged explanatory variable of adjacent areas; N represents the number of regions; ρ represents the spatial autoregressive coefficient; β and δ represent the unknown regression coefficient; w_{ij} represents the elements in the spatial weight matrix; μ_{it} represents the spatial individual effect; and ε_{it} represents the random disturbance item.

The SDM model is transformed into matrix form as follows.

$$Y = \rho WY + X\beta + WX\delta + \varepsilon^* \tag{7}$$

This study shifts items to get the following form.

$$Y = (I - \rho W)^{-1}(X\beta + WX\delta) + (I - \rho W)^{-1}\varepsilon^* \tag{8}$$

The partial differential matrix of the explained variable to the explanatory variable of number k in different regions at a certain time can be expressed as follows.

$$\begin{aligned} \left[\frac{\partial Y}{\partial X_{1k}} \dots \frac{\partial Y}{\partial X_{Nk}} \right]_t &= \begin{bmatrix} \frac{\partial y_1}{\partial X_{1k}} & \dots & \frac{\partial y_1}{\partial X_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial X_{1k}} & \dots & \frac{\partial y_N}{\partial X_{Nk}} \end{bmatrix}_t \\ &= (I - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\delta_k & \dots & w_{1N}\delta_k \\ w_{21}\delta_k & \beta_k & \dots & w_{2N}\delta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\delta_k & w_{N2}\delta_k & \dots & \beta_k \end{bmatrix} \end{aligned} \tag{9}$$

The mean value of diagonal elements in the matrix represents the direct effect, while the mean value of the sum of row or column corresponding to off-diagonal elements in the matrix represents the indirect effect.

Variable selection and data description

Input and output of industrial green development level

Considering the principle of availability and comparability and based on industrial input–output panel data of 30 provinces in China from 2000 to 2018, some of the data are standardized by means of price deflators in order to increase the authenticity of the results. This paper measures the green development level of various regions in the country by the following indicators.

- (1) Labor input: the number of industrial enterprises employment at the end of the year in each province is selected as a proxy variable.
- (2) Capital input: capital stock is selected. Since there are no direct accounting data of capital stock, this study uses industrial fixed asset investment as a proxy variable for capital stock, estimates capital stock by the perpetual inventory method, and calculates it at constant prices with 2000 as the base period.
- (3) Energy input: the industrial energy consumption of each region is selected as the proxy variable. Energy input is not included in the traditional TFP measurement as an intermediate input. However, energy consumption is also the key input factor to undesirable outputs such as pollutant emissions, and thus this paper utilizes an input index. The energy input, which is 100 million tons of equivalent coal (TEC), is calculated by the standard coal coefficient from various energy consumption values. The standard coal coefficients of various energy are shown in Table 1.
- (4) Desirable output: considering the influence of price factors, this study converts the added value of the secondary industry by the producer price index for industrial products (PPI) to obtain the constant price gross industrial output value with 2000 as the base period.
- (5) Undesirable output: industrial “three wastes,” including industrial solid waste discharge, industrial wastewater discharge, and industrial sulfur dioxide discharge, are selected as undesirable output.

Table 1 Standard coal coefficients of various energy

Energy type	Raw coal (kg)	Kerosene (kg)	Coke (kg)	Diesel (kg)	Crude oil (kg)	Petrol (kg)	Fuel oil (kg)	Natural gas (m ³)
Standard coal coefficient	0.7143	1.4714	0.9714	1.4571	1.4286	1.4714	1.4286	1.3300

Variable selection of the spatial Durbin model

This study refers to the research results of some scholars (Ma et al. 2021; Cheng et al. 2018; Qiu et al. 2021; Zhou et al. 2020) and constructs the following explanatory and explanatory variables:

(1) Explained variable

Industrial green development level (*IGTFP*). In this paper, the super-efficiency SBM model containing the undesirable outputs is used to calculate *IGTFP* of the 30 provinces.

(2) Explanatory variables

Carbon emissions (*CE*) are taken as an explanatory variable. Carbon dioxide (CO_2) emissions are taken as the proxy variable of carbon emissions. This study works out provincial CO_2 emissions based on Chen et al. (2020c, a, b)'s estimation of CO_2 emissions for 2735 counties from 1997 to 2017 and then predict the CO_2 emissions in 2018 by the ARIMA model. Areas with high carbon emissions tend to develop extensively and have large energy consumption with low utilization efficiency, which inevitably have a negative impact on the environment. Therefore, this study speculates that high carbon emissions inhibit improvement of the industrial green development level.

Fiscal decentralization (*FD*) is taken as an explanatory variable. Referring to the practice of Huang (2017), this study chooses the ratio of local fiscal expenditure per capita to central government fiscal expenditure per capita to represent fiscal decentralization. Fiscal decentralization reflects the degree of local fiscal autonomy, as local government officials tend to pursue economic development and ignore the environment. Therefore, this study speculates that fiscal decentralization has a negative effect on the level of regional green industrial development.

Economic development level (*EDL*) is taken as an explanatory variable and reflected by regional GDP. The higher the regional economic development level is, the more social capital the region has, which may promote the improvement of environmental quality and production technology. Therefore, this study speculates that the economic development level has a positive effect on the industrial green development level.

Urbanization level (*UR*) is taken as an explanatory variable and represented by the ratio of urban population to total population. Urbanization promotes population movement,

thus leading to an increase of urban population. On the one hand, the living needs of the urban population promote the development of high energy-consuming industries, which may have an adverse impact on the industrial green development level. On the other hand, an increase of urban labor input promotes the expansion of enterprises' production scale, which may be conducive to the improvement of industrial green development level. Therefore, the impact of urbanization level on industrial green development level is uncertain.

Foreign direct investment (*FDI*) is taken as an explanatory variable and measured by the total amount of actual utilized foreign capital. Foreign direct investment is conducive to the improvement of regional technical level and enterprise productivity by promoting the introduction of foreign advanced technology. However, with the introduction of foreign direct investment, some high-polluting enterprises may also arise, thus aggravating environmental pollution. Therefore, the impact of foreign direct investment on the industrial green development level needs to be further tested.

Industrial structure (*IS*) is taken as an explanatory variable. As China is still in the industrialization stage, it is reasonable to measure industrial structure by the ratio of the added value of the secondary industry to regional GDP. The rationality behind industrial structure determines the prospect of economic development. This study speculates that industrial structure has a positive impact on the industrial green development level.

Technological progress (*TI*) is taken as an explanatory variable and measured by the regional patent application quantities. Patent application quantities directly reflect the output level of regional R&D investment and the level of technological progress (Xin et al. 2020; You et al. 2022). Since technological progress will bring more efficient and advanced technologies, this study speculates that it is conducive to improving industrial green development level.

Population density (*PD*) is taken as an explanatory variable and measured by the ratio of the regional total population at the end of the year to regional land area. To a certain extent, population density can represent the degree of agglomeration of population, resources, and social activities in a certain area. High population density will promote the agglomeration of resource elements, which are theoretically conducive to improving the utilization efficiency of water resources. However, the agglomeration of human social activities may be unfriendly to the environment. Therefore, the impact of population density on the industrial green development level is uncertain.

Data description

(1) Data source

This study selects panel data of 30 provinces from 2000 to 2018 as the research object. The original data of the above indicators come from China Statistical Yearbook, China Industrial Economic Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, various provincial statistical yearbooks, and EPS database.

(2) Data descriptive statistics

In order to eliminate possible heteroscedasticity between variables, all variables involved in exploratory spatial data analysis are processed with a logarithm, as shown in Table 2.

Empirical analysis

Measurement and decomposition of China’s industrial green development level

Analysis of China’s regional industrial green development level

This study uses MaxDEA to calculate the regional industrial green development level of 30 provinces in China from 2000 to 2018. The results are in Table 3.

(1) Overall analysis of change

Figure 1 illustrates the dynamic change in the mean value of China’s regional industrial green development level from 2000 to 2018. In terms of the temporal evolution from 2000 to 2018, China’s industrial green development level has been increasing year by year and has more than doubled, while

not high on the whole. The average value of it for 2000–2018 is only 0.52. Although China’s industrial green development level has improved, it is at a low level on the whole, thus still having great room for improvement. Therefore, the government should pay attention to not only economic development, but also the coordinated development of the economy and environment, so as to further improve the industrial green development level.

(2) Specific analysis of regions

In order to analyze the industrial green development level of different regions in China, this study calculates the eastern region and the central and western regions, respectively, as shown in Fig. 1. The industrial green development level of different regions in China varies greatly; that of the eastern region is the highest, with its mean value for 2000–2018 reaching 0.61; that of the central and western regions is lower than the national average, with a mean value for 2000–2018 lower than 0.50. In the initial stage the industrial green development levels of the eastern region and the central and western regions are almost the same. In later years, the industrial green development level of the eastern region had been increasing significantly with a slight decline in 2008; thus, the industrial green development level hit 0.83 in 2018; the industrial green development level of the central and western regions had been increasing slightly; thus, the gap between the eastern region and the central and western regions has further widened.

It can be seen from the above analysis that thanks to the high industrial green development level of the eastern region, the mean value of China’s industrial green development level remains above 0.5. In the future, the improvement space of industrial green development level of the eastern region is limited, but there is great potential for its improvement in the central and western regions, offering a direction for further enhancing China’s industrial green development level.

In order to further compare the industrial green development level among different provinces in China, this study calculates the average IGTFP for 2000–2018 of the

Table 2 Descriptive statistics

Variable	Meaning	N	Mean	Std dev	Min	Max
<i>lnIGTFP</i>	Industrial green development level	570	-0.7321	0.3965	-1.4623	0.1395
<i>lnCE</i>	Carbon emissions	570	5.1667	0.8304	2.7306	6.7118
<i>lnFD</i>	Fiscal decentralization	570	0.0887	0.4134	-0.6593	1.5594
<i>lnEDL</i>	Economic development level	570	10.0775	0.8462	7.9226	11.8509
<i>lnUR</i>	Urbanization level	570	3.8813	0.2968	3.1485	4.4954
<i>lnFDI</i>	Foreign direct investment	570	4.9219	1.7150	-1.2203	7.7219
<i>lnIS</i>	Industrial structure	570	3.8090	0.2062	2.9248	4.1190
<i>lnTI</i>	Technological progress	570	9.4478	1.7201	4.8203	13.5846
<i>lnPD</i>	Population density	570	5.4569	1.2841	2.0083	8.3158

Table 3 Provincial IGDL from 2000 to 2018

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Mean
Beijing	0.359	0.443	0.434	0.467	0.501	0.426	0.451	0.515	0.658	0.587	0.669	0.718	0.708	0.749	0.771	0.798	0.841	1.001	1.095	0.642
Tianjin	0.567	0.563	0.552	0.577	0.637	0.678	0.721	0.737	1.023	0.683	0.688	0.785	0.876	1.001	1.006	1.025	0.976	1.004	1.008	0.795
Hebei	0.318	0.318	0.323	0.329	0.343	0.326	0.333	0.348	0.376	0.349	0.381	0.411	0.417	0.428	0.423	0.415	0.424	0.444	0.446	0.376
Shanxi	0.313	0.344	0.347	0.362	0.391	0.363	0.353	0.384	0.501	0.342	0.388	0.450	0.427	0.404	0.367	0.309	0.298	0.460	1.044	0.413
Inner Mongolia	0.390	0.415	0.356	0.319	0.322	0.291	0.313	0.350	0.437	0.406	0.433	0.481	0.491	0.455	0.453	0.440	0.427	0.349	0.412	0.397
Liaoning	0.424	0.405	0.390	0.354	0.319	0.310	0.326	0.367	0.443	0.426	0.480	0.529	0.557	0.584	0.563	0.598	0.428	0.450	0.487	0.444
Jilin	0.381	0.401	0.399	0.406	0.409	0.362	0.347	0.366	0.387	0.415	0.463	0.532	0.669	0.846	1.009	0.882	0.860	0.679	0.540	0.545
Heilongjiang	1.011	0.555	0.546	0.612	1.013	0.624	0.580	0.516	0.555	0.452	0.528	0.615	0.490	0.443	0.421	0.361	0.338	0.308	0.299	0.540
Shanghai	0.445	0.484	0.483	0.544	0.585	0.582	0.608	0.642	0.734	0.601	0.830	1.003	1.002	0.860	0.881	0.767	0.780	0.915	1.028	0.725
Jiangsu	0.370	0.368	0.375	0.376	0.406	0.418	0.436	0.476	0.556	0.532	0.567	0.623	0.658	0.710	0.766	0.790	0.817	0.945	1.016	0.590
Zhejiang	0.407	0.391	0.380	0.384	0.417	0.421	0.445	0.485	0.583	0.511	0.571	0.717	0.740	0.778	0.778	0.723	0.724	0.764	1.005	0.591
Anhui	0.359	0.355	0.352	0.349	0.344	0.308	0.315	0.334	0.372	0.389	0.457	0.535	0.563	0.579	0.583	0.543	0.544	0.586	0.616	0.446
Fujian	0.417	0.406	0.415	0.402	0.403	0.381	0.379	0.395	0.418	0.421	0.479	0.527	0.552	0.577	0.632	0.643	0.667	0.693	0.788	0.505
Jiangxi	0.343	0.343	0.327	0.319	0.344	0.353	0.369	0.398	0.450	0.429	0.512	0.641	0.723	0.837	1.014	0.706	0.564	0.621	0.647	0.523
Shandong	0.339	0.330	0.330	0.358	0.397	0.417	0.434	0.457	0.523	0.500	0.507	0.536	0.559	0.580	0.585	0.545	0.560	0.594	0.582	0.481
Henan	0.327	0.321	0.312	0.326	0.350	0.348	0.345	0.357	0.403	0.375	0.405	0.430	0.440	0.445	0.430	0.429	0.450	0.496	0.507	0.394
Hubei	0.372	0.317	0.320	0.322	0.331	0.307	0.309	0.322	0.369	0.400	0.452	0.509	0.566	0.577	0.584	0.653	0.770	0.829	1.009	0.490
Hunan	0.336	0.315	0.312	0.296	0.314	0.318	0.329	0.344	0.403	0.394	0.443	0.513	0.566	0.615	0.708	0.786	0.840	1.013	1.002	0.518
Guangdong	0.412	0.505	0.481	0.536	0.652	0.530	1.000	0.720	1.026	0.672	0.789	1.011	0.926	0.931	0.944	1.003	1.009	0.934	1.034	0.795
Guangxi	0.290	0.288	0.280	0.275	0.287	0.257	0.268	0.276	0.290	0.258	0.281	0.326	0.344	0.390	0.398	0.409	0.424	0.442	1.015	0.358
Hainan	1.060	1.097	0.879	0.866	0.877	0.763	0.767	1.036	1.021	0.788	0.893	0.699	0.631	0.659	0.533	0.591	0.609	0.600	0.635	0.790
Chongqing	0.295	0.324	0.311	0.304	0.312	0.312	0.322	0.362	0.428	0.477	0.540	0.658	1.001	0.733	0.635	0.675	0.777	1.010	0.746	0.538
Sichuan	0.291	0.264	0.262	0.259	0.270	0.275	0.287	0.306	0.362	0.372	0.430	0.516	0.562	1.005	0.616	0.545	0.517	0.540	0.555	0.433
Sichuan	0.264	0.235	0.232	0.240	0.258	0.258	0.264	0.279	0.313	0.273	0.285	0.283	0.286	0.303	0.317	0.322	0.329	0.353	0.352	0.287
Guizhou	0.331	0.325	0.314	0.304	0.308	0.283	0.293	0.313	0.349	0.282	0.276	0.256	0.272	0.279	0.273	0.272	0.273	0.280	0.296	0.294
Yunnan	0.286	0.312	0.312	0.311	0.333	0.344	0.376	0.375	0.431	0.407	0.450	0.533	0.589	0.673	0.664	0.590	0.574	0.701	1.019	0.488
Shaanxi	0.336	0.326	0.312	0.305	0.324	0.308	0.332	0.351	0.354	0.330	0.368	0.363	0.364	0.359	0.344	0.284	0.275	0.330	1.029	0.368
Gansu	1.150	1.003	1.102	1.009	1.017	0.584	0.582	0.583	1.010	1.000	1.009	1.024	1.002	1.011	1.007	0.826	0.806	0.670	0.662	0.898
Qinghai	1.011	1.003	0.787	0.574	0.535	0.453	0.436	0.496	1.005	0.439	0.550	0.577	0.604	0.604	0.552	0.515	0.526	0.521	0.507	0.615
Ningxia	0.435	0.423	0.396	0.392	0.419	0.413	0.440	0.430	0.473	0.400	0.437	0.448	0.373	0.327	0.302	0.264	0.256	0.275	0.281	0.378
Xinjiang																				

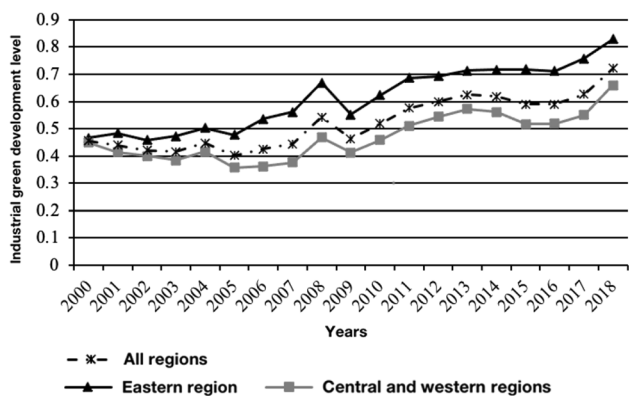


Fig. 1 Trends of IGTFP from 2000 to 2018

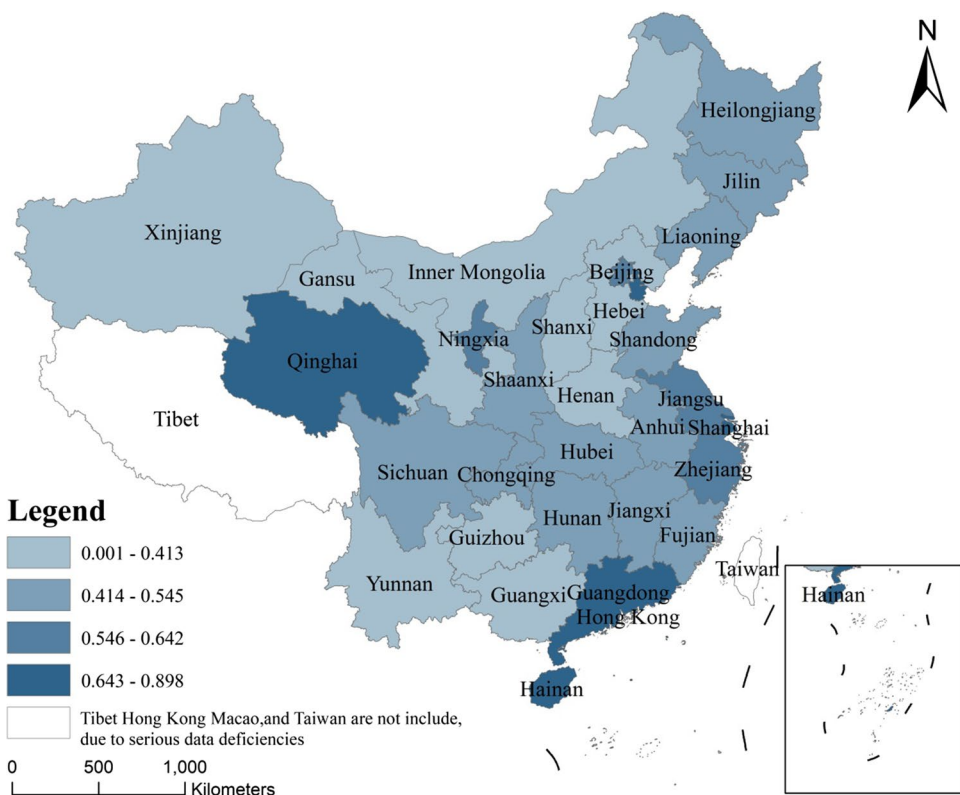
30 provinces, and the results are in Fig. 2. It can be seen that IGTFP of most provinces in China is low: the average IGTFP for 2000–2018 of Hebei, Henan, Shanxi, Anhui, Hubei, and most western regions are less than 0.5. However, IGTFP of the eastern region such as for Tianjin, Guangdong, Hainan, and Shanghai is generally high. Although Hebei is in the eastern region with a relatively developed economy, its IGTFP is low due to serious industrial pollution. IGTFP of the central region in China is about 0.5, while IGTFP of Henan is relatively low and below 0.4. IGTFP of the western region in China is low and between 0.2 and 0.5, except

for Qinghai, Ningxia, and Chongqing whose IGTFP values are higher than 0.5. Although the economic development of Qinghai, Ningxia, and Chongqing is not high, these areas have less industrial pollution, thus having relatively high IGTFP.

From Table 3, the main trends of IGTFP change can be divided into four kinds: gradual upward trend, fluctuating upward trend, stability trend, and fluctuating downward trend. The fluctuating upward trend is the most and accounts for 40%, represented by Tianjin, Shanghai, Zhejiang, Guangdong, and Jilin; followed by gradual upward trend and stability trend, which account for 23.33% each. Only IGTFP of Hainan, Heilongjiang, Qinghai, and Ningxia shows a fluctuating downward trend. Comparing IGTFP of 2000 with that of 2018, IGTFP of Shaanxi, Guangxi, Shanxi, Gansu, and Beijing increased more than twice, while IGTFP of Heilongjiang, Ningxia, and Qinghai deteriorated to varying degrees, with IGTFP of Heilongjiang decreasing more than 70%.

The difference between the IGTFP change trend of different provinces is mainly caused by the following reasons. First, most provinces with improved IGTFP did not have high IGTFP in the initial stage; these areas have been gradually improving their economic development conditions, making innovations in technology and controlling the emission of pollutants, thus improving their industrial green development level. Second, provinces

Fig. 2 Average IGTFP of China's 30 provinces for 2000–2018



with decreasing IGTFP tended to have high IGTFP in the initial stage: IGTFP of Ningxia, Qinghai, and Hainan exceeded 1 in 2000, but in the process of economic development later, they might have introduced production technologies that did not match their economy and ignored the impact of the environment; on the other hand, their own development may be insufficient: for example, in Yunnan and Xinjiang the level of human capital is not high, and their own economic development is relatively weak, thus lagging behind in the process of industrial green development.

ML index analysis of China’s regional industrial green development

Table 4 lists the ML indices and their decomposition of China’s industrial green development level over the years.

The mean value of the TFP index of its industrial green development level for 2000–2018 is 1.040, which indicates that this development level shows an upward trend on the whole. The TFP index is relatively stable during the sample period. The TFP index of a few years is less than 1, which indicates that the industrial green development level has decreased, and green technology innovation may have problems such as insufficient motivation. From the perspective of the source of growth, the changes in technical efficiency and technological progress fluctuated from 2001 to 2018, with an average of 1.054 and 1.045, respectively, indicating that the improvement of the industrial green development level is caused by both technical efficiency and technological progress. Therefore, increasing investment in technological innovation and improving technical efficiency are important ways to improve industrial green development level.

Table 4 ML index and its decomposition of China’s industrial green development level

Period	TFP	EC	TC	Period	TFP	EC	TC
2000–2001	0.991	0.955	1.144	2009–2010	1.118	1.052	1.104
2001–2002	0.971	1.134	0.920	2010–2011	1.110	1.497	1.034
2002–2003	0.998	0.927	1.144	2011–2012	1.044	1.149	0.957
2003–2004	1.067	0.969	1.103	2012–2013	1.050	0.959	1.122
2004–2005	0.932	1.001	0.948	2013–2014	0.991	0.962	1.041
2005–2006	1.056	0.985	1.097	2014–2015	0.959	0.957	1.022
2006–2007	1.056	1.039	1.018	2015–2016	0.997	0.979	1.031
2007–2008	1.204	1.021	1.203	2016–2017	1.071	1.142	1.000
2008–2009	0.895	1.170	0.812	2017–2018	1.206	1.079	1.119
/	/	/	/	Mean	1.040	1.054	1.045

TFP refers to the change trend of China’s industrial green development level between 2 years: if its value is greater than 0, then the industrial green development level has improved compared with the previous year, and otherwise it decreases

Table 5 ML index and its decomposition of industrial green development level of China’s different regions

Region	ML	EC	TC	Region	ML	EC	TC	Region	ML	EC	TC
Beijing	1.132	1.121	1.075	Jilin	1.089	1.113	1.063	Inner Mongolia	1.068	1.120	1.121
Tianjin	1.103	1.061	1.100	Heilongjiang	1.017	1.017	1.098	Guangxi	1.163	1.150	1.070
Hebei	1.080	1.050	1.091	Shanxi	1.172	1.235	1.160	Chongqing	1.132	1.147	1.083
Shanghai	1.118	1.056	1.120	Anhui	1.094	1.090	1.080	Sichuan	1.119	1.098	1.104
Jiangsu	1.121	1.064	1.123	Jiangxi	1.107	1.134	1.072	Guizhou	1.078	1.073	1.065
Zhejiang	1.119	1.065	1.123	Henan	1.086	1.059	1.087	Yunnan	1.055	1.039	1.076
Fujian	1.098	1.070	1.107	Hubei	1.123	1.102	1.099	Shaanxi	1.143	1.135	1.093
Shandong	1.092	1.053	1.151	Hunan	1.128	1.112	1.084	Gansu	1.185	1.209	1.141
Guangdong	1.147	1.058	1.147					Qinghai	1.048	1.056	1.045
Hainan	1.040	1.831	1.417					Ningxia	1.061	1.083	1.045
Liaoning	1.073	1.072	1.087					Xinjiang	1.037	1.016	1.082
Eastern region	1.102	1.136	1.140	Central and western regions	1.100	1.105	1.088				

EC technical efficiency, TC technical progress

From the regional perspective (Table 5), the TFP indices of the eastern region and the central and western regions are 1.102 and 1.100, respectively. The levels of technical efficiency and technological progress of the eastern region are also higher than that of the central and western regions. Compared with the central and western regions, the eastern region has higher levels of industrialization, human capital, and economic development, which provide a basis for its high technical efficiency. From the provincial perspective (Table 5), the TFP index, technical efficiency, and technological progress of all provinces are greater than 1, indicating that the industrial green development level has improved. In addition, the TFP growth of the eastern provinces mainly comes from industrial technological progress, while the TFP growth of the central and western regions mainly comes from industrial technical efficiency.

Dynamic evolution in the distribution of China's regional industrial green development level

In order to further explore the dynamic distribution characteristics and evolution law of China's regional industrial green development level, this study employs the Epanechnikov Kernel function and the optimal bandwidth to work out the Kernel density estimation, as shown in Figs. 3 (a), (b), (c).

As shown in Fig. 3, the Kernel density curve of industrial green development level shows a unimodal distribution, and the peak position falls year by year and shows a right shift trend, indicating that the overall industrial green development level is increasing. There are multiple peaks in the initial stage, but less peaks later, which means that the distribution of industrial green development level tends to be more concentrated, the gap of industrial green development level among provinces is gradually narrowing, and the overall distribution tends to be balanced.

Analysis on the influencing factors of China's provincial industrial green development level

Spatial autocorrelation test

Based on the adjacent spatial weight, this study conducts global and local spatial autocorrelation tests on the industrial green development level of the 30 provinces from 2000 to 2018. The global *Moran's I* is shown in Table 6. According to the results, this study concludes that the industrial green development level has positive spatial autocorrelation.

In order to further study the spatial agglomeration characteristics of industrial green development level among regions, this study selects 2003, 2007, 2011, and 2015 as the time nodes of spatial agglomeration analysis for local autocorrelation analysis. The industrial green development level in most regions shows positive spatial autocorrelation—that is, high-value spatial clustering (H–H) and low-value spatial clustering (L–L); this verifies the above conclusions, as shown in Table 7.

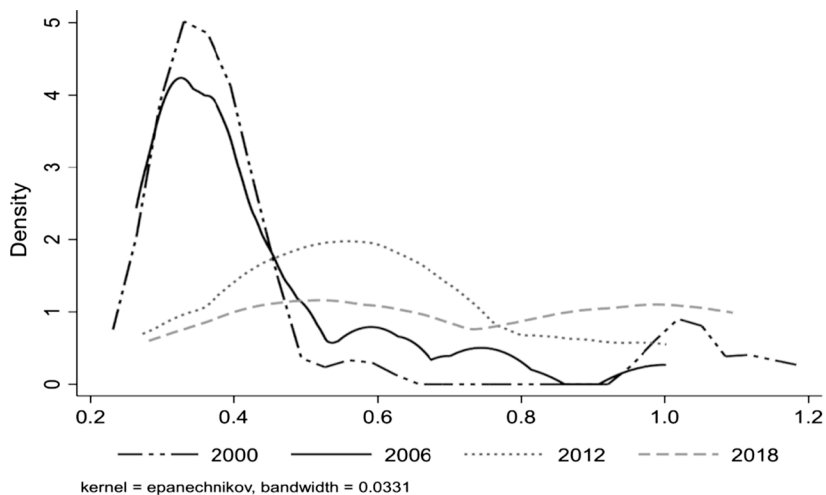
Spatial panel regression

According to the above results of the spatial autocorrelation test, there is spatial correlation in China's industrial green development level. The traditional OLS will cause estimation deviation, and therefore this study should consider spatial factors and estimate them by the spatial econometric model. According to the result of the Hausman test (-29.63), the original hypothesis of the random effect cannot be rejected. Compared with the spatial lag model and spatial error model, the spatial Durbin model has the greatest goodness of fit R^2 and relatively small Akaike information criterion (*AIC*) and Bayesian information criterion (*BIC*), thus being the most suitable choice. Analysis of the results of the spatial Durbin model (Table 8) is shown as follows.

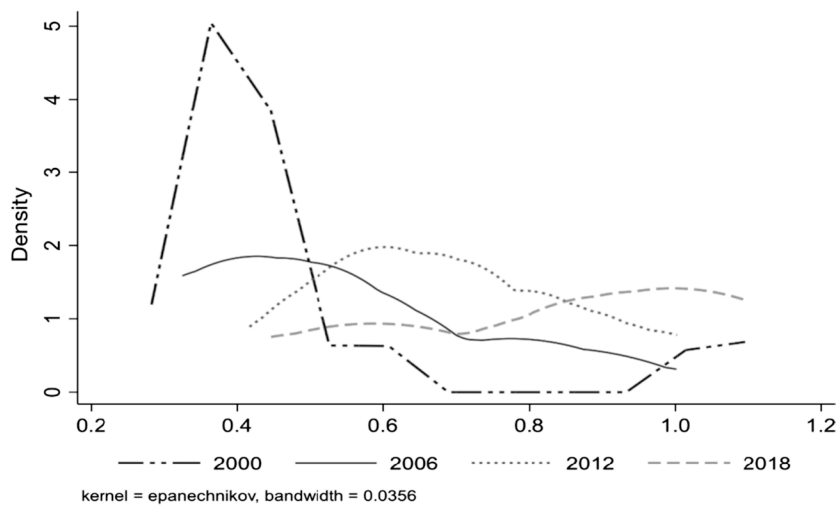
The influence coefficient of carbon emissions on industrial green development level is -0.5809 , which passes the significance test of 1%, indicating that carbon emissions have a negative effect on industrial green development level; when carbon emissions increase by 1 unit, industrial green development level decreases by 0.5809 units. The increase of CO_2 emissions means that energy consumption is increasing, which will lead to more environmental pollution, thus having an adverse impact on the industrial green development level. With the continuous increase of carbon emissions, the relevant industrial departments will spend more to deal with the environmental problems under the pressure of the national policy of energy conservation and emission reduction, which will then inhibit the improvement of industrial total factor productivity. In addition, the increase of CO_2 emissions also means that energy efficiency is low, which will further limit the expansion of industrial production scale and thus restrain industrial total factor productivity, too.

The elasticity coefficient by the regression estimation of fiscal decentralization is -0.5637 , which passes the significance test of 1%, indicating that when fiscal decentralization increases by 1 unit, industrial green development level decreases by 0.5637 units. An increase in the fiscal autonomy of local governments causes a large number of resources and capital to be used to develop the economy. Thus, the source of environmental pollution increases, and so the increase of fiscal decentralization has a negative effect on the industrial green development level.

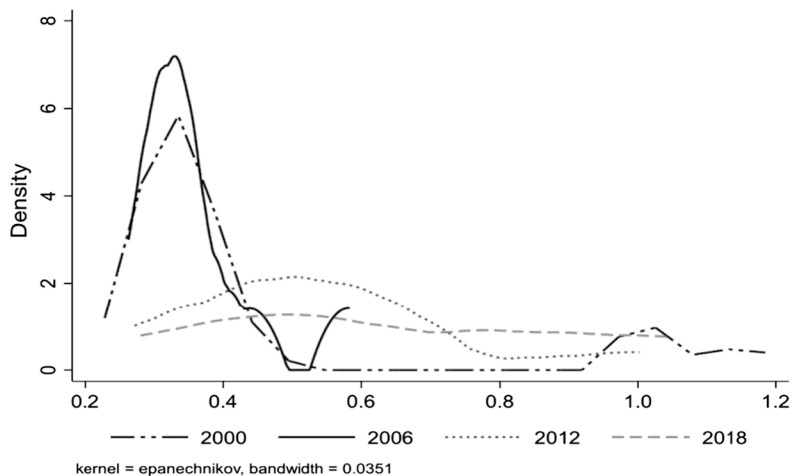
Fig. 3 Dynamic evolution of China’s industrial green development level for 2000–2018



(a) Dynamic evolution of national industrial green development level for 2000-2018.



(b) Dynamic evolution of industrial green development level of the eastern region for 2000-2018.



(c) Dynamic evolution of industrial green development level of the central and western regions for 2000-2018.

Table 6 Moran's *I* of industrial green development level of the 30 provinces from 2000 to 2018

Year	Moran's <i>I</i>	<i>E</i> (<i>I</i>)	Std (<i>I</i>)	Z statistic	<i>P</i> value
2000	0.041	-0.034	0.119	0.630	0.264
2001	0.141	-0.034	0.119	1.481	0.069
2002	0.113	-0.034	0.118	1.243	0.107
2003	0.166	-0.034	0.120	1.673	0.047
2004	0.171	-0.034	0.121	1.698	0.045
2005	0.250	-0.034	0.123	2.314	0.010
2006	0.320	-0.034	0.121	2.934	0.002
2007	0.361	-0.034	0.120	3.288	0.001
2008	0.181	-0.034	0.123	1.749	0.040
2009	0.222	-0.034	0.121	2.125	0.017
2010	0.272	-0.034	0.122	2.512	0.006
2011	0.238	-0.034	0.122	2.232	0.013
2012	0.150	-0.034	0.123	1.499	0.067
2013	0.088	-0.034	0.124	0.983	0.163
2014	0.133	-0.034	0.124	1.348	0.089
2015	0.189	-0.034	0.124	1.803	0.036
2016	0.183	-0.034	0.125	1.750	0.040
2017	0.310	-0.034	0.125	2.766	0.003
2018	0.132	-0.034	0.124	1.340	0.090

The economic development level has a significantly positive impact on the national industrial green development level, and the elasticity coefficient is 0.6878. With improvement of the regional economic development level, the capital owned by the region will gradually increase. After accumulation of capital, the investment in R&D and green sustainable development will increase, making this conducive to improvement of the industrial green development level.

The influence coefficient of urbanization level on industrial green development level is -0.3269, which passes the significance test of 5%. This indicates that urbanization level has a negative effect on industrial green development level; when urbanization level increases by 1 unit, industrial green development level decreases by 0.3269 units. An improvement in urbanization level increases the urban population, which drives the large-scale expansion of resource-intensive industries such as coal and steel. The aggravation of industrial pollution causes great external pressure on the environment, which is not conducive to improvement of the industrial green development level.

The impact of industrial structure on the national industrial green development level is significantly positive at the 1% level, and the elasticity coefficient is 0.8929, indicating when the industrial structure increases by 1 unit that the industrial green development level increases by 0.8929 units. The main reason is that while China is in the stage of industrial development, the industrial structure is reasonably adjusted according to national demand and resource

Table 7 Agglomeration of China's industrial green development level in 2003, 2007, 2011, and 2015

Agglomeration type	2003	2007	2011	2015
H-H	Beijing, Tianjin, Shanghai, Jilin, Fujian, Guangdong, Hainan, Heilongjiang, Xinjiang	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong, Hainan, Xinjiang	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Jiangxi, Guangdong, Hainan	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Jiangxi, Guangdong, Hunan, Hubei, Fujian, Hainan, Liaoning, Chongqing
L-H	Jiangsu, Zhejiang, Gansu, Inner Mongolia, Hebei, Jiangxi, Sichuan	Hebei, Anhui, Gansu, Jilin, Jiangxi, Fujian, Inner Mongolia	Jilin, Fujian, Hebei, Anhui, Hubei, Gansu, Xinjiang	Heilongjiang, Hebei, Anhui
L-L	Anhui, Shandong, Henan, Shanxi, Shaanxi, Hunan, Hubei, Guangxi and Chongqing, Yunnan, Guizhou, Liaoning	Liaoning, Henan, Shanxi, Shaanxi, Hunan, Hubei, Chongqing, Guangxi, Sichuan, Guizhou, Yunnan	Liaoning, Hunan, Shaanxi, Shaanxi, Shandong, Sichuan, Inner Mongolia, Guangxi, Guizhou, Yunnan	Shandong, Sichuan, Ningxia, Guangxi, Henan, Inner Mongolia, Guizhou, Shanxi, Yunnan, Gansu, Xinjiang
H-L	Ningxia, Qinghai	Heilongjiang, Shandong, Ningxia, Qinghai	Heilongjiang, Chongqing, Ningxia, Qinghai	Shaanxi, Jilin, Qinghai

Table 8 Results of spatial panel model regression

Variable	Spatial lag model	Spatial error model	Spatial Durbin model
<i>lnCE</i>	−0.6601*** [−12.98]	−0.6781*** [−12.83]	−0.5809*** [−10.66]
<i>lnFD</i>	−0.3652*** [−4.66]	−0.3950*** [−5.02]	−0.5637*** [−5.69]
<i>lnEDL</i>	0.3671*** [7.70]	0.4084*** [8.79]	0.6878*** [6.15]
<i>lnUR</i>	−0.1422 [−0.96]	−0.1302 [−0.86]	−0.3269** [−2.02]
<i>lnFDI</i>	0.013 [0.91]	0.0139 [0.94]	0.014 [0.96]
<i>lnIS</i>	0.8959*** [9.89]	0.8932*** [9.58]	0.8929*** [9.01]
<i>lnTI</i>	0.1530*** [6.12]	0.1560*** [5.79]	0.1039*** [3.83]
<i>lnPD</i>	−0.003 [−0.09]	−0.006 [−0.18]	−0.0236 [−0.55]
Constant	−5.2299*** [−9.24]	−5.7153*** [−10.37]	−4.8078*** [−4.37]
<i>WlnCE</i>	—	—	−0.2921*** [−2.65]
<i>WlnFD</i>	—	—	0.3747** [2.46]
<i>WlnEDL</i>	—	—	−0.3453*** [−2.59]
<i>WlnUR</i>	—	—	−0.0073 [−0.03]
<i>WlnFDI</i>	—	—	0.0570** [2.06]
<i>WlnIS</i>	—	—	0.1626 [0.90]
<i>WlnTI</i>	—	—	0.1418*** [3.35]
ρ/λ	0.1492*** [2.85]	0.0792 [1.21]	0.1004* [1.72]
σ_2_e	0.0365*** [16.27]	0.0370*** [16.29]	0.0333*** [16.23]
<i>N</i>	570	570	570
<i>R</i> ²	0.5526	0.5449	0.5906
<i>AIC</i>	−149.4800	−143.0041	−176.3159
<i>BIC</i>	−97.33239	−90.8565	−93.74877

The values in brackets are *z* statistics

conditions, promotes the optimal allocation of resource elements among various industrial departments, and improves the utilization efficiency of resources, thus helping to lift the industrial green development level.

The elasticity coefficient of technological progress is 0.1039, which is significant at the 1% level, indicating that when technological progress increases by 1 unit,

Table 9 Decomposition of the spatial spillover effect

Variable	Direct effect	Indirect effect	Total effect
<i>lnCE</i>	−0.5875*** [−10.67]	−0.3751*** [−3.38]	−0.9626*** [−8.66]
<i>lnFD</i>	−0.5585*** [−5.90]	0.3569** [2.24]	−0.2017 [−1.25]
<i>lnEDL</i>	0.6915*** [6.49]	−0.3098** [−2.42]	0.3817*** [3.83]
<i>lnUR</i>	−0.3319** [−2.17]	−0.0728 [−0.25]	−0.4047 [−1.33]
<i>lnFDI</i>	0.0156 [1.09]	0.0653** [2.08]	0.0809** [2.21]
<i>lnIS</i>	0.8977*** [9.33]	0.2643 [1.42]	1.1620*** [6.01]
<i>lnTI</i>	0.1062*** [3.84]	0.1675*** [3.83]	0.2738*** [5.89]
<i>lnPD</i>	−0.025 [−0.60]	−0.0031 [−0.53]	−0.028 [−0.60]

industrial green development level increases by 0.1039 units. Technological progress is the fundamental driving force of industrial green development. Improvement of the technological level greatly raises resource utilization efficiency and promotes the development of green production technology, so as to achieve the goal of energy conservation and emission reduction and maintain the coordinated development of the economy, resources, and environment. Therefore, technological progress obviously promotes the improvement of industrial green development level.

The impact of foreign investment on industrial green development level is positive, and the impact of population density on industrial green development level is negative, but neither of them passes the significance test of 10%. Therefore, foreign investment and population density have no significant impact on industrial green development level.

According to the effect decomposition method of the spatial panel model described above, the effects of explanatory variables on the explained variables are decomposed into direct effects and indirect effects. The decomposition results are shown in Table 9.

It can be seen from the table that the direct and indirect effects of carbon emissions on the national industrial green development level pass the significance test of 1%, indicating that the increase of carbon emissions in a certain region not only significantly inhibits the improvement of industrial green development level in this region, but also has a significantly negative impact on industrial green development level in adjacent regions. The direct effect of fiscal decentralization on the national industrial green development level is significantly negative at the 1% level, while the indirect effect is positive at the 5% significance level, meaning that

an increase of local fiscal autonomy significantly reduces a region’s industrial green development level, but promotes adjacent regions’ industrial green development level, partly because the competitive behavior between regions causes the adjacent regions to pay more attention to the environment. The direct effect of economic development level on industrial green development level is positive and the indirect effect is negative, which pass the significance levels of 1% and 5% respectively, indicating that economic development level has a positive impact on industrial green development level in a region, but has a negative impact on its adjacent regions.

The improvement of a certain region’s economic development level attracts resources, capital, and labor from adjacent regions, thus reducing their available resources and inhibiting improvement of the industrial green development level of these adjacent regions. The direct effect of urbanization level on national industrial green development level is significantly negative at the 5% level, but the indirect effect is not significant, indicating that although a higher urbanization rate inhibits the progress of industrial green development level in a region, it has no impact on its adjacent regions. The indirect effect of foreign investment on industrial green development level is significantly positive, but the direct effect is not significant, indicating that foreign investment greatly promotes the improvement of industrial green development level of adjacent areas.

From the enterprise perspective, foreign-funded enterprises in a certain region bring advanced technologies and experiences. Enterprises in adjacent areas then apply these technologies and experiences to their own enterprises and improve them after study, exchange, and cooperation, making them conducive to the improvement of industrial green development levels. The direct effect of industrial structure on industrial green development level is significantly positive at the 1% level, while the indirect effect is not significant, indicating that a reasonable adjustment of industrial structure can promote this region’s industrial green development level. The direct and indirect effects of technological progress on industrial green development level are significantly positive at the 1% level, indicating that the progress of science and technology promotes this region’s industrial green development level and the adjacent regions’. Population density has no significant impact on the industrial green development level of this region and adjacent regions.

Stability test

In view of the purpose of this paper, this study only tests robustness on national samples. Two methods are used to verify the robustness of the empirical results: the first method replaces the adjacent spatial weight matrix with the economic spatial weight matrix and also uses the spatial

Table 10 Results of robustness test

Variable	Replace spatial weight matrix	Eliminate the sample data of 2000
<i>lnCE</i>	− 0.6200*** [− 12.77]	− 0.5869*** [− 10.85]
<i>lnFD</i>	− 0.3944*** [− 4.42]	− 0.5262*** [− 5.25]
<i>lnEDL</i>	0.5390*** [5.28]	0.6539*** [5.85]
<i>lnUR</i>	0.175 [1.17]	− 0.2901 [− 1.63]
<i>lnFDI</i>	0.0074 [0.53]	0.0085 [0.58]
<i>lnIS</i>	0.9688*** [9.61]	0.9556*** [9.56]
<i>lnTI</i>	0.1307*** [5.17]	0.0869*** [3.22]
<i>lnPD</i>	− 0.007 [− 0.21]	− 0.006 [− 0.14]
<i>Constant</i>	− 2.6115*** [− 2.59]	− 5.2581*** [− 4.40]
<i>WlnCE</i>	− 0.1024 [− 1.11]	− 0.2656** [− 2.46]
<i>WlnFD</i>	0.0897 [0.67]	0.3216** [2.01]
<i>WlnEDL</i>	− 0.0361 [− 0.28]	− 0.2603* [− 1.93]
<i>WlnUR</i>	− 1.7422*** [− 5.74]	0.0005 [0.00]
<i>WlnFDI</i>	− 0.1198*** [− 3.41]	0.0594** [2.17]
<i>WlnIS</i>	0.1365 [0.98]	0.0907 [0.50]
<i>WlnTI</i>	0.2164*** [4.24]	0.1181*** [2.75]
ρ/λ	0.1947*** [3.46]	0.1150* [1.92]
σ^2_e	0.0314*** [16.22]	0.0308*** [15.76]
<i>N</i>	570	540
<i>R</i> ²	0.6036	0.6085
<i>AIC</i>	− 217.6098	− 203.2268
<i>BIC</i>	− 135.0427	− 121.687

Durbin model for regression fitting; the second method eliminates the sample data of 2000 and also uses the spatial Durbin model for modeling analysis on the remaining sample data of 2001–2018. After the Hausman test is conducted with stata15.0 software, this study finds that the two robustness test methods still choose random effects, and the

regression results are shown in Table 10. From the table, it has been seen that except for urbanization level, which has no significant impact on industrial green development level, the regression results of other variables are completely consistent with the results in Tables 5, 6, 7, and 8. Compared with the regression results of the spatial Durbin model in Table 8, the goodness of fit of the regression models of the two robustness test methods is higher, and the Akaike information criterion and Bayesian information criterion are relatively lower. Therefore, the results of robustness test are very good and also indicate that the previous empirical results are accurate.

Conclusions and suggestions

Conclusions

In previous studies, scholars have mostly used China's industrial green total factor productivity to measure the level of China's industrial green development, which includes the industrial "three wastes" as non-desired outputs in the measurement framework, providing a quantitative indicator for assessing the level of China's industrial green development and effectively evaluating the real level of China's industrial development. At the same time, the influencing factors of China's industrial development level are explored from the economic and social and other macro levels. However, most scholars mostly adopt the static efficiency evaluation system, ignore the CO₂ emissions, and pay attention to the influencing factors of China's industrial development level from a single perspective. Therefore, based on panel data of 30 provinces in China from 2000 to 2018, this research uses the super-efficiency SBM model containing undesirable outputs to calculate the industrial green development level, decomposes technical efficiency and technological progress by the ML index, and dynamically analyzes the changes of industrial green development level with the Kernel density function. This study explores the impact of variables such as carbon emissions on the industrial green development level through the spatial Durbin model and partial differential equations and decomposes them into direct effect and spatial spillover effect. Our study draws the following conclusions.

- (1) China's industrial green development level has been increasing year by year and is not high on the whole, but the level of the eastern region is generally higher than that of the central and western regions. The differences in industrial green development level between different provinces are great, but have gradually decreased. The technical efficiency and technological progress of the eastern region are higher than those of the central and western regions. The TFP growth of the
- industrial green development level of the eastern region mainly comes from industrial technological progress, while that of the central and western regions mainly comes from industrial technical efficiency.
- (2) There is a positive spatial autocorrelation in ITFP of the 30 provinces. Carbon emissions, fiscal decentralization, and urbanization are not conducive to improvement of the national industrial green development level. Economic development, foreign direct investment, industrial structure, and technological progress can significantly promote industrial green development level, while population has no significant impact on it.
- (3) The increase of regional carbon emissions not only significantly inhibits improvement of a region's industrial green development level, but also has a significantly negative impact on adjacent areas' industrial green development level. Economic development level has a positive impact on a region's industrial green development level, but a negative impact on that in adjacent areas. Technological progress often plays a good role in promoting a region's industrial green development level and that of adjacent areas. Greater local fiscal autonomy significantly reduces a region's industrial green development level, but positively promotes that in adjacent areas. Urbanization level and industrial structure have direct effects on industrial green development level, but their spatial spillover effects are not significant. Foreign direct investment has a contrary effect, while population density's effect is not significant.

Suggestions

- (1) From a dynamic perspective, to construct a more comprehensive measurement framework of green total factor productivity, and to explore the factors influencing the level of green total factor development of China's industry from multiple perspectives and levels. On the one hand, future research should include the CO₂ emissions in the non-expected output in order to more realistically assess the level of green development of China's industry, and on the other hand, this paper builds a multi-faceted model of the factors influencing industrial green total factor productivity from three levels: macro, medium, and micro, and sinks the attention angle into industries to the industry to provide countermeasure suggestions for the green transformation of each specific industry.
- (2) Maintain the goal of high-quality economic development and lay the foundation for the synergistic effects of industrial green transformation and high-quality ecological civilization: Contemporary China must change the industrial development pattern, promote the estab-

lishment of an efficient, safe, clean, low-carbon, and green industrial energy structure, and promote industrial green transformation for high-quality economic development.

- (3) Promote the upgrading of industrial structure and build a green industrial development system: On the one hand, controlling traditional high pollution industries and promoting power transition and cleaner production are meaningful. On the other hand, cultivating high-end manufacturing with low energy consumption and high added value and comprehensively breaking through the technical barriers in clean energy and renewable energy are also conducive to reducing industrial carbon emissions, thus achieving carbon peak and carbon neutralization.
- (4) Deepen fiscal decentralization reform, and establish a fiscal system suitable for China's green industrial development level: To promote China's industrial green development level, reduce regional differences, and arrange fiscal decentralization levels according to local conditions, the central government should also improve environmental regulation policies and the importance of green development in local assessment, thus guiding local industrial green transformation at the strategic level.
- (5) Promote the level of green technological innovation and build regional technological innovation networks: The government can use environmental regulation policies to guide enterprises' green technological innovation and create a strong innovation environment for green technology. Strengthen policies and financial support for industrial green technology innovation, encourage leading enterprises in industry to form joint technology R&D centers with universities and research institutes, and build joint innovation platforms. Construct an advanced green manufacturing technology support system, and promote the joint construction of high-tech parks between regions. In addition, the government should encourage the free flow of technological innovation elements, promote the optimal allocation of resources, actively carry out technological innovation activities, and promote the spillover of green technology diffusion.
- (6) Promote the construction of new-type urbanization, improve the quality of China's urbanization, and realize the mutually beneficial development of urbanization and industry. Delineate the boundaries of urban development, transform the development model of closed towns to intensive and compact ones, improve land use efficiency, establish multi-functional urban development land, establish industrial parks, and reasonably avoid environmental pollution and resource waste caused by disorderly competition and overcapac-

ity. Promote the transition from rural to urban population in an orderly manner, enhance the comprehensive carrying capacity of cities and towns for population and factors, and promote the upgrading of consumption structure.

Limitation and future research directions

Although we have expanded the related research from both theoretical and practical aspects, there are still the following shortcomings. First, our research focuses on provincial administrative units and fails to cover data on prefecture-level cities and enterprises. Subsequent research should further analyze the data of prefecture-level cities or enterprises, and conduct detailed research according to the industrial layout of urban agglomerations and the nature of enterprises. Second, this study lacks an examination of different types of industries. Future research should divide specific industries and further investigate the role of factor allocation ratios between different industries in the impact of environmental regulation on industrial green development. Third, we only test the influence of CO₂ emission, technological progress, and fiscal decentralization, while the green development effect of environmental regulation may also be affected by other factors, especially the role of government behavior and its results. Subsequent research should be expanded from other perspectives such as government competition, market segmentation, and factor distortion.

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Declarations

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