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RESEARCH ARTICLE

Spatiotemporal changes in efficiency and influencing factors of China's industrial carbon emissions

Guangming Yang[1] · Fan Zhang[1] · Fengtai Zhang[1] · Dalai Ma[1] · Lei Gao[2] · Ye Chen[1] · Yao Luo[1] · Qing Yang[1]

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Abstract

The industrial sector is the backbone of China's national economy. The industrial carbon emission efficiency (ICEE) of China is directly related to the achievement of carbon emission reduction targets. This paper reports on the use of the minimum distance (min-SBM) method to determine the ICEE of 30 provinces in China during 1998–2015, as well as the use of a spatial econometric method to investigate the convergence and influencing factors of the regional ICEE. The results indicate significant regional differences in the ICEE. The provinces with higher average values of ICEE are located in the eastern coastal areas, whereas the provinces with lower average values of ICEE are located in the central and western inland regions. The results of the spatial autocorrelation index reveal that China's inter-provincial ICEE exhibits significant spatial autocorrelation characteristics, and its spatial distribution demonstrates a certain regularity. The local indicators of spatial association diagram further illustrate that most provinces in China have high and low agglomeration values. With the introduction of the spatial effect, the absolute and conditional convergence rates increase. In addition to the non-significant industrial structure effect, the level of economic development, foreign direct investment, technological progress, and government intervention demonstrate a positive impact on the ICEE convergence, whereas the energy consumption structure has a negative impact. This work investigates the cause for the regional gap in China's current ICEE. Suggestions for improving the efficiency of China's industrial carbon emissions and narrowing the regional gap are provided, which serve as a reference value for China to achieve the peak of carbon dioxide emissions before 2030.

Keywords Spatial effect · Industrial carbon emission efficiency (ICEE) · Convergence · Minimum distance method to the efficient frontier

Introduction

Since the reform and opening up, along with the rapid economic growth, problems such as energy depletion and environmental pollution in China have become increasingly serious (Bryan et al. 2018). In particular, the greenhouse effect caused by carbon dioxide emissions has affected the daily life of Chinese residents owing to the frequent occurrence of abnormal climatic events. Consequently, there is a higher demand for air purification than before. Moreover, carbon emissions have also had negative impacts on economic development. Therefore, it is of utmost importance to strengthen the research on carbon dioxide emission reduction. However, to promote the reduction of carbon dioxide, it is necessary to first determine the source of the emission. For example, coal has always been the main energy source driving China's economic growth, accounting for approximately 70% of the total energy consumption between 1985 and 2016, and produces up

Highlights

- Apply min-SBM method to measure industrial carbon emissions efficiency of China
- Apply spatial effect to improve absolute convergence rate of carbon emission efficiency
- The ICEE has significant regional difference.
- Important factors that affect industrial carbon emissions efficiency are analyzed.

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✉ Fengtai Zhang
zhfthero45@cqut.edu.cn

[1] School of Management, Chongqing University of Technology, Chongqing 400054, China

[2] CSIRO, Waite Campus, Urrbrae, SA 5064, Australia

to twice as much carbon dioxide as other fossil energy sources (Wang and Yang 2015). Therefore, the enhancement of the emission reduction of industrial sectors has become a top priority. However, owing to the differences in China's economic development level and resource endowment, the industrial carbon emission efficiency (ICEE) between regions is considerably different. The existing literature suggests that the eastern coastal area is leading the work on carbon emission reduction; in contrast, the central and western hinterland is relatively backward (Ma 2017). The resulting provincial industrial carbon efficiency has significant differences between energy conservation and emissions, thereby necessitating further regulations. Therefore, it is of great significance to study the behavior of the level of industrial carbon efficiency between provinces, tendency of the gap in ICEE between different provinces to diverge or converge with time, and influencing factors, to effectively promote industrial energy conservation and emission reduction in China. To this end, in this study, the ICEEs of different regions were accurately measured and analyzed, providing a basis for strengthening the pertinence of formulating energy-conservation and emission-reduction policies. We applied the minimum distance (min-SBM) method for the assessment of the ICEE of China, and the spatial effect to improve the absolute convergence rate of carbon emission efficiency. Furthermore, important factors that affect ICEE were analyzed.

Literature review

At present, China vigorously advocates the transformation of economic development through energy-saving and emission-reduction approaches in the industrial sector. To this end, scholars have explored the relationship between economic growth and carbon emissions, for example, decoupling carbon emissions from the economy, (Wang et al. 2019a; Wang and Zhang 2020), the effects of trade openness on decoupling carbon emissions (Wang and Zhang 2021), and ICEE (Yi 2017; Zhou and Nie 2012). Current approaches include the data envelope (DEA) method (Wu et al. 2020; Zaim and Taskin 2000; Zhou et al. 2010; Zhu et al. 2020; Zofío and Prieto 2001) and stochastic frontier (SFA) method (Herrala and Goel 2012; Sun et al. 2019; Wang et al. 2012), a parametric and non-parametric measure of the ICEE, respectively. Both the DEA and SFA methods are used as efficiency measurements, each having its own advantages and disadvantages. However, overall, SFA is less efficient in comparison with DEA in terms of model flexibility and practicality. This is because the SFA method uses a fixed efficiency model as support, whereas the DEA method does not require a model support. In addition, in terms of data collection, the data used by SFA requires a unified unit (Zhou and Nie 2012), whereas DEA can use multiple data units; external environmental factors can also be incorporated into DEA. Therefore, in comparison with the SFA method, the DEA method has a greater advantage in processing flexibility. Therefore, DEA has been widely used to measure ICEE (Yi 2017).

With increasing research on industrial carbon emission reduction, regional emphasis lies on industrial emission efficiency, with a particular focus on exploring whether the ICEE has a tendency to converge. However, in comparison with the overall carbon emission efficiency convergence problem, not only is the research on ICEE convergence relatively lacking, but also the influence on spatial factors has not been investigated. A comprehensive performance model was proposed to measure the ICEE of 30 provinces in China from 1998 to 2009 using SBM containing undesired outputs to study its convergence based on the efficiency model (Zhou and Nie 2012). The study confirmed that the ICEE in the east had significant convergence characteristics in comparison with that in the central and northeast regions. China's ICEE was determined using an ultra-efficient DEA model (Lu and Wang 2015). On this basis, the industrial characteristics and its dynamic evolution were studied. The results revealed that the overall ICEE level in China was poor. The carbon emission efficiency of the industrial and other sectors not only exhibited the characteristics of absolute convergence, but also a catch-up effect. Based on the improved SBM method, an empirical study was conducted to evaluate China's carbon emission efficiency and its spatial effect (Zhang and Yu 2015). The results indicated that the ICEE of each province was significantly different. The emission efficiency level was the highest, while the ICEEs of the eastern, northeastern, and western provinces were relatively low; however, the gap between provinces was narrow.

Many scholars have explored the factors influencing carbon emissions in China. Zheng et al. (2020) analyzed the effects of an industrial structure adjustment on carbon emissions. Feng et al. (2019) demonstrated that the value of the economic output was the main driving factor of carbon emissions. However, existing research has focused on measuring the factors influencing carbon emissions from an industrial perspective, without considering the spatial effects.

Based on previous research, this study uses the minimum distance (min-SBM) method to measure ICEE as a new approach. Because traditional estimation methods have not considered the spatial effects, regional differences or spatial agglomeration in the regional ICEE cannot be estimated; thus, research in this area may have important impacts on energy-saving and emission-reduction work. To this end, by introducing the relevant knowledge of spatial econometrics, this study aims to examine the spatial effect of ICEE and its convergence characteristics by establishing a panel data model containing spatial effects, which is conducive to improving the overall depth of the research.

Methodology

min-SBM efficiency evaluation method

In this study, the ICEEs of 30 provinces in China during 1998–2015 were quantified using the min-SBM technique, and the convergence and influencing factors of regional emission efficiencies were explored using a spatial econometric approach. The traditional SBM model is also known as the maximum distance method; however, this method is not intensive enough to deal with the input and output of the improvement process. Thus, the min-SBM model was constructed, which is also known as the minimum distance method of the Xeon effective frontier (Aparicio et al. 2007; Jahanshahloo et al. 2012). The most significant feature of this model is that it can determine the projection point on the production front by minimizing the L1 distance, and can calculate the efficiency of the entire model. Based on the above principles, we constructed a min-SBM model including undesired outputs.

Consider a complete production set composed of n decision-making units. In each decision-making unit, m production factors need to be inputted into the input-output process, where s1 and s2 represent the quantities of the expected and undesired outputs, respectively. Suppose the factor input, expected output, and undesired output are respectively determined by $X=(x_1\ ,x_2,\ldots,x_n)\in R_+^{m\times n}$ $_,X=(x_1,x_2,\ldots,x_n)\in R_+^{m\times n}$ and other vectors. Assume that the final decision system is $DMU_0=\left(x_0,y_0^g,y_0^b\right)$. The set of production possibilities is represented by the formula $P^t(x)=\{(x,y):x$- can product $y\}$, where $F\ ^s(P)$represents all output units of the Xeon effective frontier on the production set.

In the process of inputting the elements of the production system into production, by minimizing the L1 distance, the calculation for the minimum distance method of the Xeon effective frontier can be expressed as follows:

$$(mSBM)\quad \min\left(\sum_{i=1}^{m}s_{i0}^{-}+\sum_{r=1}^{s_1}s_{r0}^{+}+\sum_{l=1}^{s_2}s_{l0}^{-}\right)+M\left(\sum_{i=1}^{m}\overline{s}_{i0}^{-}+\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}+\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}\right) \tag{1}$$
$$s_{i0}^{-}\geq 0, i=1,\ldots,m$$
$$s_{r0}^{+}\geq 0, r=1,\ldots,s_1$$
$$s_{l0}^{-}\geq 0, l=1,\ldots,s_2$$

$$\max\left(\sum_{i=1}^{m}\overline{s}_{i0}^{-}+\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}+\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}\right) \tag{2}$$
$$s.t.\quad \sum_{j\in E_c}\lambda_j x_{ij}+\overline{s}_{i0}^{-}=x_{i0}-s_{i0}^{-}$$
$$\sum_{j\in E_c}\lambda_j y_{ij}^{g}-\overline{s}_{r0}^{+}=y_{i0}^{g}+s_{r0}^{+}$$
$$\sum_{j\in E_c}\lambda_j y_{ij}^{b}+\overline{s}_{l0}^{-}=y_{i0}^{b}-s_{l0}^{-}$$
$$\lambda_j\geq 0,\overline{s}_{i0}^{-}\geq 0,\overline{s}_{r0}^{+}\geq 0,\overline{s}_{l0}^{-}\geq 0$$

In formula (1), $s_{i0}^{-},s_{ro}^{+},s_{l0}^{-},s_{i0}^{-},s_{r0}^{-},s_{l0}^{-}$ represent different relaxation variables, and M is a constant with a positive value. If the two formulas (1) and (2) are combined, the resulting formula represents a typical two-level linear programming with constraints, that is, the minimum distance method of the strongest effective frontier proposed. This two-level linear programming is known as the min-SBM model because the model further optimizes the traditional SBM model. Then formula (2) can be rewritten as follows:

$$\min\left(\frac{1-\frac{1}{m}\sum_{i=1}^{m}\overline{s}_{i0}^{-}/x_{i0}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}/y_{r0}+\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}/b_{l0}\right)}\right) \tag{3}$$

If the two formulas (1) and (3) are combined, the resulting relationship represents another two-level linear programming, that is, the common SBM model. To rationalize the construction of the SBM model, the final values are maximized, such as $\sum_{i=1}^{m}\overline{s}_{i0}^{-}/x_{i0}$, $\sum_{r=1}^{s_1}\overline{s}_{r0}^{+}/y_{r0}$, $\sum_{l=1}^{s_2}\overline{s}_{l0}^{-}/b_{l0}$. These three formulas are generally composed of constant values. This implies that these three relaxation variables, $\overline{s}_{i0}^{-},\overline{s}_{r0}^{+},\overline{s}_{l0}^{-}$ must be maximized to meet the constraint condition (3) of the SBM model to minimize the result.

Spatial autocorrelation coefficient and LISA diagram

Regardless of whether the ICEE between regions demonstrates an obvious spatial effect, the main aim is to examine the spatial agglomeration characteristics. Spatial agglomeration implies that the ICEE between neighboring provinces does not exist independently, but exhibits typical characteristics of space spillover and space diffusion. The closer the performance, the more prominent the characteristic, resulting in the neighboring provinces having a high spatial homogeneity. The most important indicator is the spatial autocorrelation coefficient, which is denoted by Moran′s I. According to the research by Moran (Moran 1948), the formula is expressed as

$$\text{Moran's I}=\frac{n}{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\left(x_i-\overline{x}\right)\left(x_j-\overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \tag{4}$$

In formula (4), W_{ij} is the spatial weight matrix (adjacency distance matrix) used by the model, n is the specific number of space units to be investigated, x_i represents the value of area i, x_j represents the value of area j, $\overline{x}=\left(\sum_i x_i\right)/n$ is the average value of Moran′s I in the area under investigation. The value of global Moran′s I exists in a certain range; the upper limit of the value is 1, and the lower limit is − 1. A calculated value of − 1 implies that the area under investigation exhibits negative spatial outliers and a completely negative spatial characteristic; when the value calculated by Moran′s I is 1, it implies that it is under investigation. Objects have positive spatial agglomeration characteristics. In addition, to further verify the true level of the Moran′s I index, the Z statistical test is typically used.

$$Z = \frac{[I - E(I)]}{\sqrt{VAR(I)}} \tag{5}$$

The global spatial autocorrelation index Global Moran′s I only verifies whether there exists a spatial effect problem from the overall perspective of the investigated object; however, it cannot be determined from the internal specific spatial characteristics. To this end, we use the local scatter plot (LISA), which is the local spatial autocorrelation index, to characterize the local spatial correlation problem of the object under investigation. Intuitively, the LISA graph represents the distribution of the investigated objects in the four quadrants (H-H, L-H, L-L, H-L) of the spatial coordinate graph. In addition, according to the research by Moran (Moran 1950), the following formula of Local Moran′s I can be expressed as

$$\text{Moran's I} = \frac{n^2}{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2} \frac{\left(x_i - \overline{x}\right)\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{6}$$

Convergence model

Traditional convergence model

The traditional convergence model was first adopted in the study of the income gap between residents. The model was used to determine whether the dynamic evolution of the income gap between different countries (regions) exhibited convergent or divergent characteristics over time. Later, the application scope of the model was further expanded and introduced in a large number of fields, such as national trade, residential consumption, and ecological environment. The general manifestation of the convergence model is β convergence. The necessary condition for the establishment of the theory is the assumption that the marginal return on the capital has a diminishing effect, leading to the economic growth of areas with lagging or high initial income levels. Moreover, the proportion of the former is significantly higher than that of the latter, and a catch-up effect is observed. Consequently, the gap between the income level of backward and developed areas is gradually narrowed. Two types of convergence exist: absolute β and conditional β convergence. Absolute β convergence is the study of the convergence of different regions, without the consideration of external factors, whereas conditional β convergence considers the influence of external factors. Then, there is convergence among different regions. According to the general convergence theory, the formula for defining the absolute β convergence is

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta\ln\left(y_{i,t}\right) + \varepsilon_{i,t} \quad \varepsilon N\left(0, \sigma^2\right) \tag{8}$$

In formula (8), $y_{i,\ t+T}$ represents the output capacity of region i at time $t + T$; $y_{i,\ t}$ represents the output capacity of region i at time t, and the value of α is constant, $\beta = -(1 - e^{-\theta T})$, θ is the inspection speed during the inspection period. If $\beta < 0$ appears in the calculation, it implies that the object under investigation exhibits β convergence within the time period T, and the development speed of the advanced economic income regions is significantly lower than that of the backward economic income regions.

The conditional β convergence model is further linked with the absolute β convergence model. The most significant feature of this model is that it considers the control variables; thus, the basic equation can be expressed as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta_1\ln\left(y_{i,t}\right) + \beta_2 \mathrm{X}_{i,t} + \varepsilon_{i,t} \quad \varepsilon \sim N\left(0, \sigma^2\right) \tag{9}$$

Convergence model considering spatial effects

The β convergence model constructed above is based on the common measurement method, and fails to consider the spatial effects between possible areas; thus, there may be a large deviation from the reality in calculating the convergence rate. Based on the theory of spatial economy, this study combines the spatial measurement method and the convergence model to establish the spatial autoregressive (SAR) model and spatial error model (SEM).

(1) Spatial autoregressive model

This model is established by introducing the spatial autoregression concept into the general convergence model. The formulas of the absolute β and conditional β convergence models based on the SAR model are as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta\ln\left(y_{i,t}\right) + \rho W\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) + \varepsilon_{i,t} \quad \varepsilon \sim N\left(0, \sigma^2\right) \tag{10}$$

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta_1\ln\left(y_{i,t}\right) + \beta_2 \mathrm{X}_{i,t}\ \rho W\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) + \varepsilon_{i,t} \quad \varepsilon \sim N\left(0, \sigma^2\right) \tag{11}$$

In formulas (10) and (11), ρ represents the spatial autoregressive coefficient to measure the spatial effect; W is the spatial weight matrix coefficient to be introduced in the model calculation, and ε is the random error.

(2) Spatial error model

This model is established by introducing the spatial error concept into the general convergence model. The formulas of the absolute β and conditional β convergence models based on the SEM are as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta_1 \ln\left(y_{i,t}\right) + \varepsilon_{i,t}\ \varepsilon_{i,t} = \lambda \mathrm{W} + u, u \sim N\left(0, \sigma^2 I\right) \tag{12}$$

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta_1 \ln\left(y_{i,t}\right) + \beta_2 \mathrm{X}_{i,t} + \varepsilon_{i,t}\ \varepsilon_{i,t} = \lambda \mathrm{W} + u, u \sim N\left(0, \sigma^2 I\right) \tag{13}$$

where λ represents the spatial correlation parameters between different regression residuals, and u represents random perturbation terms, which are spatially uncorrelated with each other.

Spatial econometric model construction and variable description

A previous study demonstrated that China's regional ICEE not only exhibits regional differences, but also important characteristics of spatial correlation. To determine whether its regional gap tends to expand or shrink over time, it is necessary to investigate its convergence. The tendency of the ICEE of different provinces to exhibit convergence characteristics over time is mainly determined using the following two methods: absolute β and conditional β convergence. The absolute β convergence method is simple and clear, and does not need to include possible external factors; however, the actual application value reflected is low. Therefore, to improve the actual operating value, it is necessary to analyze the external influencing factors that cause regional convergence, which requires the use of the conditional β convergence method. In recent years, research has been conducted on the convergence of regional carbon emission efficiencies, yielding many valuable results. Drawing on the existing research conclusions, this study believes that the regional ICEE convergence and external macro factors include industrial scale and structure, foreign investment, energy consumption structure, and technological progress. On this basis, the following research hypotheses were proposed:

Assumption 1 The improvement in the economic development level has a significant positive effect on the convergence of ICEE. On the one hand, the country currently advocates a large number of transformations in the economic development and industry as an important part of the national economy, and pays particular attention to the realization of industrial green development transformation by enhancing the level of economic development. On the other hand, with the advancement in the national economic development, there is an increase in per capita income, increasing the demand for regional environmental quality, which is undoubtedly conducive to improving the efficiency of regional industrial carbon emissions.

Assumption 2 Changes in the industrial structure due to the proportion of heavy industries have suppressed the convergence of ICEE. At present, China as a whole is still in a period of rapid industrialization, and the heavy industry sector is responsible for high-carbon emissions from the production of cement, steel, and automobiles. These industries consume a considerable amount of fossil energy in the production process (Wang et al. 2012; Yao et al. 2015; Zaim and Taskin 2000). Furthermore, the current industrial development in China is characterized by significant regional disparities, which are highlighted by the larger proportion of heavy industries in the central and western regions in comparison with that in the eastern region; and with the eastern region moving to the Midwest, the differences in the industrial structure have been further strengthened, thereby leading to an adverse effect on the convergence of regional ICEE.

Assumption 3 Increasing the degree of opening up to the outside world has contributed to the convergence of regional carbon emission efficiency. With the improvement in the level of foreign direct investment (FDI), not only an advanced enterprise management experience but also low-carbon technology has been introduced, which have played a positive role in improving the energy utilization efficiency of the host country's industrial sector (Cheng et al. 2018; Meng et al. 2016; Wang et al. 2016). In contrast, the introduction of foreign-funded enterprises has yielded good environmental standards, not only demonstrating the improvement in the host country's overall environmental standards, but also producing good "overflow" between different regions. The "effect" plays an important role in narrowing the environmental protection standards between different regions.

Assumption 4 The energy consumption structure characterized by the use of coal has a restraining effect on the convergence of regional ICEE. In comparison with zero-emission or low-emission energy, such as wind energy, water energy, and renewable energy, fossil energy consumption is accompanied by a large amount of carbon dioxide (Wang et al. 2019b; Zhang et al. 2016). On the whole, a large amount of fossil energy is required to support China's industrial production process, and coal accounts for a large proportion of the overall energy consumption. In addition, owing to the impact of economic and technological levels and differences in regional energy endowments, there exists a large gap in coal consumption between regions, and this gap continues to expand over time, which is obvious for narrowing regional industrial carbon. The discharge efficiency gap clearly has a negative impact.

Assumption 5 The improvement in the regional technological level has a positive effect on promoting the convergence of ICEE. On the one hand, the continuous advancement of the regional industrial technology can not only digest relatively surplus industrial capacity, but also update existing industrial production equipment, thereby reducing energy consumption and improving industrial production efficiency. On the other hand, the improvement in the regional technical level plays an "overflow" role. Through continuous technology diffusion channels, the improvement in the technical level of the surrounding areas has been achieved, which plays an important role in reducing the technical gap between regions.

Assumption 6 The increase in government intervention has played a positive role in improving regional ICEE and achieving convergence. With continuous intervention, government expenditure has gradually increased, and environmental protection investment for improving the environment has also increased. Government intervention has also played an important role in the construction of energy-saving and emission-reduction mechanisms in the region, and is conducive to achieving strong control of carbon emissions. In addition, local governments have a demonstrative role in achieving effective control of environmental pollution through the "diffusion" effect.

The regional ICEE mentioned above has significant spatial autocorrelation characteristics. Therefore, empirical research on the convergence of ICEE, without the consideration of the spatial effects of the model, may provide incorrect regression results. To this end, it is necessary to incorporate the spatial effects while establishing the measurement model. Because the object of this study is the panel data of 30 provinces, it is difficult to select between spatial and random effects during model construction. The difference between these two effects is based on the degree of connection between the model's individual effects and variables. If there exists a strong relationship between the model's individual effects and variables, the model exhibits fixed effects; otherwise, it exhibits random effects. As this study aims to examine the problem of individual effects, there exists an inherent relationship with the model variables; thus, the selection of fixed effects is the best approach. According to formulas (10) and (13), this paper establishes an absolute β convergence model including spatial effects and a conditional β convergence model; the absolute β convergence model is defined as follows:

$$\begin{aligned} &g\mathrm{INCTE}_{i,t} = \alpha_i + \phi_t + \beta Ln\left(\mathrm{INCTE}_{i,t-1}\right) + \delta \textstyle\sum_j W_{ij}\left(g\mathrm{INCTE}_{i,t}\right) + \mu_{i,t} \\ &\mu_{i,t} = \lambda \textstyle\sum_j W_{ij} {*} u_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{14}$$

The conditional β convergence model with control variables is defined as follows:

$$\begin{aligned} &g\mathrm{INCTE}_{i,t} = \alpha_i + \phi_t + \beta_1 \mathrm{Ln}\left(\mathrm{INCTE}_{i,t}\right) + \beta_2 X_{i,t} + \delta \textstyle\sum_j W_{ij}\left(g\mathrm{INCTE}_{i,t}\right) + \mu_{i,t} \\ &\mu_{i,t} = \lambda \textstyle\sum_j W_{ij} {*} u_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

The general manifestation of the model is the ordinary spatial-fixed effect model, where δ and λ are two different spatial effects, namely the spatial autoregressive and spatial error coefficients. If δ is equal to 0, it implies that the representation of the model is an SEM, whereas if λ is equal to 0, it implies that the representation of the model is an SAR model; αi and ϕ_t are fixed effects in space and time, respectively.

$g\mathrm{INCTE}_{i,\ t}$: The growth rate index of regional ICEE is expressed by the natural logarithm of ICEE in the *t*-th year of province *i* minus the natural logarithm of ICEE in the *t*-1th year of province *i* , namely $g\mathrm{INCTE}_{i,\ t} = \Delta Ln(\mathrm{INCTE}_{i,\ t}) = Ln(\mathrm{INCTE}_{i,\ t}) - Ln(\mathrm{INCTE}_{i,\ t-1})$.

$Ln(\mathrm{INCTE}_{i,\ t-1})$: It is the initial ICEE of the region, which is characterized by taking the natural logarithm of the ICEE in the *t*-1th year of province *i*. The positive and negative coefficients indicate whether there is a convergence of regional ICEE. If the coefficient is negative and passes the significance level test, it proves that the regional ICEE has a clear β convergence.

The control variables examined in this article include the following:

The gross domestic product (GDP) is an indicator of the economic development level, expressed by the natural logarithm of the GDP per capita of each province; $STR_{i,\ t}$ is an indicator of industrial structure, characterized by the proportion of heavy to total industrial output; $FDI_{i,\ t}$ represents the index of FDI, based on foreign investment and GDP. In this study, the foreign investment amount expressed in US dollars is converted into RMB according to the exchange rate; the actual use of FDI is expressed as the proportion of GDP; $ECS_{i,\ t}$ is used as an energy consumption structure indicator, including coal and energy consumption, and is expressed as the ratio of the total amount; TEG represents the technical progress indicator, expressed by the natural logarithm of the number of patent applications granted in each province; $GOV_{i,\ t}$represents the government intervention indicator, characterized by the ratio of the provincial fiscal expenditure to GDP.

To meet the research requirements and usability standards of available data, in this study, 30 provinces and regions in China were selected for the investigation from 1998 to 2015.

Because the data for several years from Tibetan provinces were blank and could not be calculated, they were excluded. The data used in this article were obtained from the "China Statistical Yearbook," "China Energy Statistical Yearbook," and local statistical yearbook.

Variable description and data source

This study investigated the industrial departments of various provinces to measure the ICEE. In view of the availability of input-output data of the industrial sectors in China's provinces and the actual development status, this paper presents the industrial input factors from the perspectives of capital, labor, and energy. The industrial output value and carbon dioxide emissions are used as the expected output results, respectively. The meaning of each input-output variable is summarized in Table 1.

Empirical results and discussion

Evaluation results of regional ICEE

Based on formulas (1) and (2) and the input-output variables presented above, the DEA software was used to calculate the ICEE of 30 provinces and cities in China from 1998 to 2015. It can be observed from Table 1 that in the sample period, only the ICEE of Shanghai and Guangdong, which are the two largest industrial centers, reach the maximum value of 1, whereas the ICEE of the remaining provinces are all less than 1, failing to satisfy the production preamble. From the perspective of the specific ICEE of each province, Shanghai, Guangdong, Zhejiang, Heilongjiang, and Tianjin are the five provinces with the highest average ICEE, exceeding 0.8. Except for Heilongjiang, which is located in the middle, the other provinces are located in the economically developed eastern coastal area, and are also the most developed provinces and cities in the country. Owing to the relatively high level of opening up, these eastern provinces not only have more developed industrial production technology, but also have more efficient industrial emission-reduction equipment. Their industrial output capacity and drainage reduction are on average in the forefront of the country. In recent years, the eastern region has vigorously advocated the development and transformation of the industrial structure, gradually phasing out high-energy consumption and emission industrial sectors. The heavy pollution industry has gradually moved to the Midwest, with a higher ICEE. The ICEE of Heilongjiang is also at the forefront of the country, which is closely related to

Table 1 Meaning of input-output variables

Type	Variables	Meaning	Source
Input	Industrial capital stock	The industrial capital stock is calculated using the formula $K_{i,t}=I_{i,t}+(1-\delta)K_{i,t-1}$ where $K_{i,t}$, $I_{i,t}$, and δ represent the capital stock, industrial investment, and capital depreciation rate of province i in the first period. In addition, to ensure the authenticity of the data, this study adopts the deflation method to convert the nominal industrial stock into the real industrial capital stock with 1978 as the base period.	(Jefferson et al. 1992)
	Industrial labor	We use industrial employees at the end of each year to represent the input of industrial labor.	(Ma 2017) Dalai M., 2017
	Industrial energy consumption	Industrial energy consumption with different terminal types is summed according to the unified energy standard of 10,000 t of standard coal.	Dalai M., 2017
Output	Industrial output value	The actual industrial output value of each province each year eliminates the distortion caused by price inflation. We use the deflator index method to convert the nominal industrial output value into the actual industrial output value based on the price in 1978.	Dalai M., 2017
	Industrial carbon dioxide emissions	$CO_2=\sum_{i=1}^{3} E_i\times nNCV_i\times CEF_i\times COF_i\times(44/12)$ where CO_2 is the estimated industrial carbon dioxide emissions after inputting the relevant data into the formula, and the industrial carbon dioxide emissions are calculated using the formula, and i is composed of the following primary energy sources: coal, oil, and natural gas. E represents the energy consumption. For the calculation, the energy conversion coefficient of 10,000 t of standard coal is considered. NCV is the net calorific value of energy; $CEF$is the carbon emission coefficient, and COF is the carbon oxidation factor; 44 is the molecular weight of carbon dioxide, and 12 is the molecular weight of carbon.	IPCC (2006); (Ma 2017) Dalai M., 2017

the eastern industrial revitalization strategy promoted by the state. The average ICEE of Hunan, Inner Mongolia, Xinjiang, Guizhou, and Qinghai are the bottom five in the country, which can be attributed to the relatively backward industrial development level of these provinces and the imperfect emission-reduction facilities. In short, China's ICEE exhibits significant inter-provincial differences. Most eastern provinces have higher ICEE average levels, in comparison with the central and western provinces.

The ICEE demonstrates a strong spatial dependence (Table 2), consistent with the findings of Zhonghua et al. (2018). Therefore, improving the ICEE of inland provinces and narrowing the inter-provincial gap would improve the overall ICEE.

Spatial correlation of regional ICEE

Based on the basic spatial adjacency matrix consisting of 0 and 1, and running the surveyed data with Geoda software, we calculated the specific $GlobalMoran's I$ values of China's ICEE. According to the results in Table 3, all the values of $GlobalMoran's I$are positive, and the performance is significant at the 5% or 10% level. China's inter-provincial ICEE exhibits a strong positive spatial correlation on the whole; thus, spatial correlation affects the development and changes of ICEE. In addition, this also confirms that ICEE demonstrates a strong spatial clustering and distribution law in space, which implies that it does not simply exhibit a random dispersion phenomenon. The ICEE of neighboring provinces has a strong spatial imitation effect, that is, it exhibits the spatial clustering phenomenon of high- and low-value aggregation. Ignoring the spatial correlation yields a large deviation in the results.

Figure 1 a–d depict the spatial autocorrelation LISA cluster map of the ICEE of 30 provinces between 1998 and 2015 in four quadrants. The first quadrant (HH) represents a high-value agglomeration, indicating a province's own high ICEE level; the neighboring provinces also exhibit high ICEE characteristics; the third quadrant (LL) represents a low-value agglomeration, corresponding to a province's own low ICEE level, and the neighboring provinces also exhibit low ICEE characteristics; the second (LH) and fourth quadrants (HL) are both atypical regions, of which the second represents low ICEE values and with high ICEE values in neighboring provinces. The fourth quadrant represents high ICEE values with low ICEE values in neighboring provinces. In addition, the first and second quadrants reflect a typical spatial agglomeration, demonstrating a positive local correlation; while the second and third quadrants represent a typical spatial outlier, reflecting a negative local correlation.

In 1998, the spatial LISA map of China's ICEE showed that Shanghai, Zhejiang, Jiangsu, Fujian, and Hainan were located in the first quadrant, representing a typical spatial cluster of positive local correlations (HH). The provinces located in the second quadrant were the three provinces of Jiangxi, Anhui, and Guangxi, representing spatial outliers (HL) with negative correlation. The provinces in the third quadrant were Henan, Hubei, Hunan, Yunnan, Hebei, Inner Mongolia, Ningxia, Sichuan, Chongqing, Shanxi, Guizhou, and Gansu Provinces, such as Qinghai and Xinjiang, all of which reflected typical low agglomerated spatial clusters (LL). Liaoning, Tianjin, Shaanxi, Guangdong, and Heilongjiang were located in the fourth quadrant, reflecting negative spatial correlation (HL). The provinces of Shandong, Jilin, and Beijing spanned two quadrants and were considered relatively special provinces.

Table 2 Average ICEE of 30 provinces in China from 1998 to 2015

Province	Average value	Rank	Province	Average value	Rank
Shanghai	1.000	1	Anhui	0.618	16
Guangdong	1.000	2	Henan	0.611	17
Zhejiang	0.868	3	Sichuan	0.595	18
Heilongjiang	0.867	4	Hebei	0.593	19
Tianjin	0.807	5	Guangxi	0.589	20
Jiangsu	0.781	6	Jiangxi	0.567	21
Fujian	0.762	7	Gansu	0.556	22
Shaanxi	0.753	8	Shanxi	0.524	23
Liaoning	0.710	9	Ningxia	0.511	24
Beijing	0.693	10	Yunnan	0.491	25
Shandong	0.678	11	Hunan	0.478	26
Hainan	0.655	12	Inner Mongolia	0.465	27
Chongqing	0.654	13	Xinjiang	0.458	28
Hubei	0.640	14	Guizhou	0.457	29
Jilin	0.639	15	Qinghai	0.401	30

Table 3 Inter-provincial ICEE *Moran ' s I* index from 1998 to 2015

Year	*Moran's I*	*E* (I)	Mean	sd (I)	"*Z*" value
1998	0.264	– 0.035	– 0.033	0.118	2.528
1999	0.216	– 0.035	– 0.031	0.118	2.128
2000	0.300	– 0.035	– 0.031	0.121	2.762
2001	0.263	– 0.035	– 0.038	0.121	2.457
2002	0.245	– 0.035	– 0.039	0.119	2.343
2003	0.123	– 0.035	– 0.041	0.117	1.351
2004	0.143	– 0.035	– 0.046	0.119	1.486
2005	0.178	– 0.035	– 0.039	0.120	1.762
2006	0.244	– 0.035	– 0.040	0.120	2.318
2007	0.255	– 0.035	– 0.046	0.119	2.434
2008	0.227	– 0.035	– 0.037	0.116	2.247
2009	0.277	– 0.034	– 0.037	0.117	2.662
2010	0.247	– 0.035	– 0.037	0.118	2.386
2011	0.245	– 0.035	– 0.036	0.119	2.358
2012	0.224	– 0.035	– 0.038	0.122	2.139
2013	0.221	– 0.035	– 0.042	0.121	2.106
2014	0.287	– 0.035	– 0.038	0.132	2.778
2015	0.319	– 0.0345	– 0.031	0.129	2.922

In 2004, China's ICEE spatial LISA map indicated that six provinces in the first quadrant, including Shanghai, Jiangsu, Fujian, Zhejiang, Beijing, and Shandong, were typical spatial clusters with positive local correlations (HH). The provinces in the second quadrant were Hainan, Jiangxi, Jilin, Anhui, and Hunan, representing negative spatial correlation (HL). The provinces in the third quadrant were Henan, Hubei, Guangxi, Inner Mongolia, Shanxi, Ningxia, Sichuan, Guizhou, Gansu, Yunnan, Xinjiang, and Qinghai, which were typical low-value agglomerated spatial clusters (LL). Guangdong, Heilongjiang, Tianjin, Shaanxi, Liaoning, and Chongqing were located in the fourth quadrant, representing negative spatial correlation (HL).

The 2010 LISA map of China's ICEE demonstrated that Shanghai, Zhejiang, Tianjin, Fujian, Hainan, Jiangsu, Shandong, and Beijing were typical spatial clusters with positive local correlations (HH). Provinces, such as Henan, Anhui, Jiangxi, Hunan, and Inner Mongolia, were in the second quadrant, representing negatively correlated spatial outliers (HL). The provinces in the third quadrant were Jilin, Shanxi, Ningxia, Guangxi, Qinghai, Yunnan, Guizhou, and Xinjiang, reflecting the typical low-value agglomerated spatial clusters (LL). Gansu, Sichuan, Chongqing, Hebei, Liaoning, Shaanxi, Hubei, Heilongjiang, Guangdong, and nine other provinces were located in the fourth quadrant, representing negative spatial autocorrelation (HL).

The 2015 LISA map of China's ICEE showed that Shanghai, Zhejiang, Fujian, Hainan, Beijing, Tianjin, Jiangsu, and Shandong, located in the first quadrant, demonstrated a positive spatial autocorrelation (HH). Only Inner Mongolia, Jiangxi, and Anhui, located in the second quadrant, exhibited a typical negative local correlation of spatial outliers (LH). The third quadrant included Shaanxi, Guangxi, Sichuan, Ningxia, Hubei, Yunnan, and provinces, such as Shanxi, Gansu, Guizhou, Qinghai, and Xinjiang, as spatial clusters (HH) of typical positive local correlations; The fourth quadrant included Guangdong, Heilongjiang, Jilin, Liaoning, and Chongqing (HL). In addition, Henan and Hunan spanned the second and third quadrants and were considered relatively special provinces. The ICEEs of most provinces were in the first and third quadrants, exhibiting spatial clustering. Thus, we can infer that the ICEE of most provinces exhibits the H-H and L-L differentiation of local spatial clusters, reflecting the important characteristics of spatial dependence and spatial heterogeneity in geographical spatial distribution.

Analysis of ICEE convergence with space effect

Measurement results and spatial correlation of ordinary panel data model

First, the ordinary measurement method was used to perform regression analysis on the models (14) and (15), and then the residuals of the models were verified and analyzed. The results are presented in Table 3. The fixed effect models were classified into multiple models; however, distinguishing between the better and poorer models among them was difficult. Table 4 presents the comparison of four models with no fixed effect, a spatial-fixed effect, a time-fixed effect, and a bidirectional-fixed effect. This indicates that the fixed effect of model control plays an important role in improving the effectiveness of the overall model.

It can be seen from the regression results of the absolute β convergence model in Table 4 that the determination coefficients of the goodness of fit for the no fixed, spatial-fixed, time-fixed, and bidirectional-fixed effect models are 0.043, 0.075, 0.049, and 0.122, respectively. The bidirectional-fixed effect model exhibits the best fit; similarly, based on the regression results of the conditional β convergence model, the fits of the no fixed, spatial-fixed, time-fixed, and bidirectional-fixed effect models are optimal. The determination coefficients of the goodness of fit are 0.077, 0.197, 0.069, and 0.433, respectively, which also implies that after the introduction of the space- and time-fixed effects, the bidirectional-fixed effect model exhibits the best fit. The determination coefficient of the goodness of fit of the bidirectional-fixed model is the largest, as it has the highest overall model quality. Based on the comparison of the log-likelihood function values of the four econometric models, in the absolute β and conditional β convergence models of the bidirectional-fixed effect model, the former is 679.057 and the

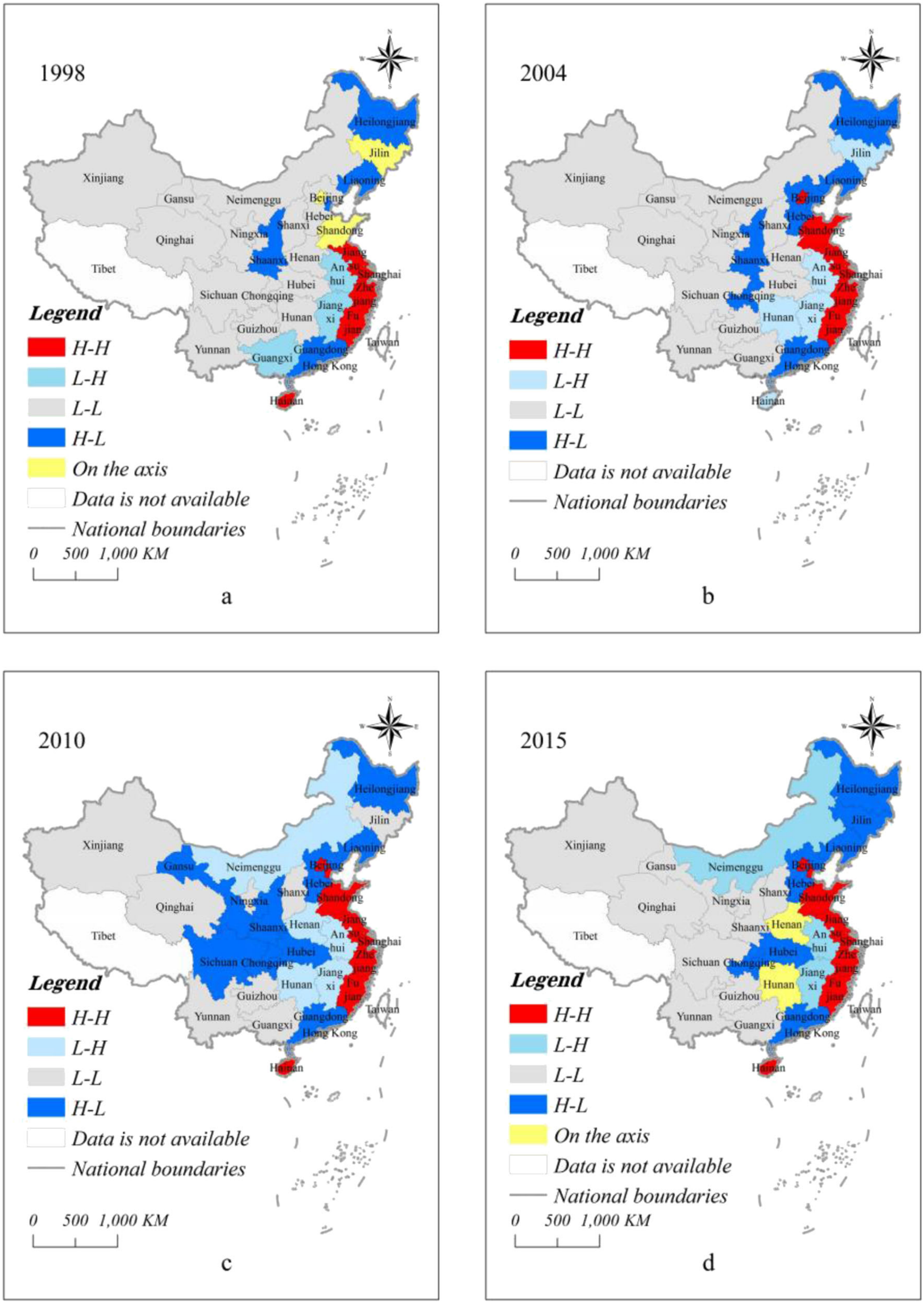

Fig. 1 **a**–**d** Local scatterplot of ICEE in Chinese provinces

latter is 688.508, which also indicates that the bidirectional-fixed effect model has the highest log-likelihood function value among the four models. As mentioned above, in the four econometric models, the bidirectional-fixed effect model performs better in terms of multiple indicators than the no fixed, space-fixed and time-fixed effect models; thus, this study adopts the regression results of the bidirectional-fixed effect model to better explain China's ICEE.

The lower part of Table 4 indicates the test part of the overall model, that is, to verify whether the models exhibit significant spatial autocorrelation. Based on the regression results of the absolute β convergence model, the $LM-lag$ and $LM-err$values are 3.635 and 4.665, respectively, and both of them perform significantly at the 1% level. Similarly, in the β convergence model, the $LM-lag$ value of the bidirectional-fixed effect model is 3.764, whereas the $LM-err$ value is 4.971, and both pass the 1% significance level test. This validates that there is obvious spatial autocorrelation between the residual terms of the two common econometric models. In addition, in the bidirectional-fixed effect model of the two convergence models, the statistic of $LM-err$ is greater than $LM-lag$. After comparing the two, SEM is found to be the best manifestation of the spatial measurement model.

Estimation results of spatial panel data model

The above test on the residuals of the ordinary panel model demonstrates that there is a significant spatial autocorrelation in the ordinary model. Thus, this study adopts the spatial measurement method to perform re-regression based on the common model, and obtains two basic forms of the spatial measurement model, namely*SAR*and*SEM*. The measurement results are presented in Table 4. It can be seen from Table 5 that after introducing the spatial lag term $W*dep.\mathrm{var}$. and the spatial error term $W*dep.\mathrm{var}$. in the spatial measurement model, in comparison with the ordinary panel data model, in terms of the determination coefficient of the goodness of fit and the log-likelihood function value $Log-L$, the spatial measurement of the model improves. In addition, based on the regression results of the spatial econometric model, regardless of the coefficient of the variable or the T test value, the positive and negative values are consistent with those of the ordinary data model; however, the values of both models are improved, indicating that the spatial econometric model is in the ordinary. Based on the data model, optimization and improvement are achieved. In the absolute β and conditional β convergence models, by comparing the $Log-L$ values of the *SEM* and *SAR* models, we found that the former is greater than the latter, indicating that the *SEM* model has a better interpretation force than that of the *SAR* model; thus, this study mainly focuses on spatial errors. The measurement results of each explanatory variable in the model (*SEM*) are interpreted and analyzed.

The data in parenthesis represent the T test value, and *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively

Based on the regression results of the absolute β convergence model, the estimated coefficient of $Ln(INCTE_{i,\ t-1})$ is significantly negative at the level of 1%, which verifies that China's inter-provincial ICEE shows significant absolute β convergence characteristics during the sample period. According to the calculation method of the neoclassical economic growth model β^2 and convergence theory, the absolute convergence rate of China's regional ICEE is calculated to be 2.734%, while the convergence rate of 2.922% in the ordinary panel model is improved. This confirms that after incorporating the spatial effect into the ordinary convergence model, the convergence rate of industrial carbon emissions in different regions increased. This can be attributed to the spillover and diffusion effects of the industrial carbon emissions in neighboring areas. After incorporating the spatial effect, the convergence rate of ICEE also becomes faster.

In comparison with the regression results of the absolute β convergence model, after the control variables are included in the conditional β convergence model, the overall interpretation of the model is further enhanced. According to the estimation result of the conditional β convergence *SEM* model, the estimation coefficient of $Ln(INCTE_{i,\ t-1})$ is significantly negative at the 1% level. Similarly, based on the calculation method of β convergence above, the conditional convergence rate of ICEE is finally calculated to be 3.677%. As various influencing factors, in addition to the insignificant influence of the industrial structure, the level of economic development, FDI, energy consumption structure, technological progress, and government intervention exert an important influence on the convergence of regional ICEE from different perspectives.

Economic development level GDP The impact on the convergence of carbon emission efficiency at a 10% significance level is positive, verifying assumption 1. At present, the transformation of China's economic development has achieved the initial results. In particular, the current level of China's economic development is constantly improving, which provides the necessary economic conditions for the green transformation of regional industrial development. According to statistics, China's per capita GDP has increased from 6835 yuan in 1998 to 49,992 yuan in 2015, an increase of 7.31 times in 18 years. In addition, with the improvement in living standards, environmental protection awareness has increased. Furthermore, it has not only raised higher demands for a high-quality environment, but also vigorously participated in environmental protection actions, which are undoubtedly important for strengthening regional environmental protection work.

The estimated coefficient of the industrial structure (STR) is negative, but fails the significance level test. This may be because although the current output value of China's heavy industry still accounts for more than 70% of the total industrial

Table 4 General panel data model estimation and test results

Variables	Absolute β convergence				Conditional β convergence			
	No fixed effect	Spatial-fixed effect	Time-fixed effect	Bidirectional-fixed effect	No fixed effect	Spatial-fixed effect	Time-fixed effect	Bidirectional-fixed effect
$Ln(INCTE_{i,\ t-1})$	– 0.089*** (– 4.607)	– 0.248** (– 6.213)	– 0.086*** (– 4.978)	– 0.353*** (– 8.172)	– 0.168*** (– 5.470)	– 0.514*** (– 8.162)	– 0.139*** (–5.218)	–0.439*** (–9.123)
GDP – gross domestic product					0.016** (2.107)	0.036*** (2.554)	0.015 1.282	0.0421* (1.666)
STR – industrial structure					0.013 (0.530)	0.035 (1.1153)	0.0104 (0.477)	0.032 (1.149)
FDI – foreign direct investment					0.006* (0.482)	0.073** (2.3793)	0.007 (0.448)	0.017* (1.540)
ECS – energy consumption structure					– 0.026* (– 1.520)	– 0.057* (– 1.769)	– 0.017 (– 1.211)	– 0.046* (– 1.648)
TEG – technological progress					0.002* (0.607)	0.011** (2.109)	0.0010 (0.283)	0.023** (2.161)
GOV – government intervention					0.004* (0.082)	0.398*** (4.382)	0.003*** (0.054)	0.230*** (2.792)
R−squared	0.043	0.075	0.049	0.122	0.077	0.197	0.069	0.433
Log−L	563.496	577.373	651.623	679.057	572.384	611.473	656.798	688.508
DW	1.367	1.3076	1.966	1.952	1.401	1.502	1.972	1.964
LM−lag	69.767***	68.949***	2.880*	3.635***	66.863***	60.135***	3.415**	3.764***
Robust LM−lag	0.559	4.162**	1.746	0.534	1.778	50.667***	0.353	0.859
LM−err	74.108***	81.699***	2.152	4.665***	65.139***	38.148***	3.124**	4.971***
Robust LM−err	4.900**	16.914***	1.017	1.564	0.055	28.679***	0.062	2.067*

The data in parenthesis represent the *T* test value, and *, **, and *** represent the significance level of 10%, 5%, and 1%, respectively

Table 5 Estimation and test results of the bidirectional-fixed effect spatial econometric model

Variables	Absolute β convergence		Conditional β convergence	
	SAR	SEM	SAR	SEM
$Ln(INCTE_{i,\ t-1})$	– 0.376*** (– 8.2695)	– 0.379*** (– 8.3749)	– 0.440*** (– 9.260)	– 0.445*** (– 9.379)
GDP			0.042* (1.685)	0.043* (1.745)
STR			0.030 (1.095)	0.036 (1.306)
FDI			0.017** (1.991)	0.009** (2.195)
ECS			– 0.046* (– 1.537)	– 0.048* (– 1.688)
TEG			0.025** (2.323)	0.025** (2.406)
GOV			0.227*** (2.742)	0.227*** (2.824)
$W*dep.\text{var}.$	– 0.120** (– 1.932)		– 0.119** (1.934)	
spat. aut.		– 0.142** (– 2.193)		– 0.145** (– 2.238)
$R-squared$	0.405	0.408	0.438	0.441
$Log-L$	680.888	681.464	690.367	691.143

output value, the state actively promotes the green transformation of industrial development by advocating a new industrialization path. Particularly in recent years, China's high-tech industry has been growing rapidly, and with the upgradation of heavy industry equipment, the energy-conservation and emission-reduction work has improved. The impact of industrial structure on the convergence of regional ICEE is not significant.

The estimated FDI coefficient is positive at a significance level of 5%, which indicates that increasing the level of foreign investment has a positive effect on promoting the convergence of ICEE. At present, the country vigorously advocates the region to improve the level of opening up to the outside world, and gradually increases the introduction of foreign capital to fully improve China's industrial development. In 1998, China's FDI was only 45.463 billion US dollars. By 2015, it had increased to 126.27 billion US dollars, a 2.78 increase during the 18-year period. The massive influx of FDI into China has played a positive role in accelerating the transformation of China's industrial development. On the one hand, the management level of industrial enterprises has improved, and the advanced low-carbon technologies abroad have been gradually digested. On the other hand, the FDI not only yields benefits to the economic development and environmental protection of the host country, but also has a positive effect on the income per capita (Birdsall 1993).

The energy consumption structure (ECS) at a significance level of 10% is negative for ICEE, which indicates that as the amount of coal consumption in the industrial production process increases, the extent of improvement in the local environmental quality decreases. At present, some countries have established the agenda for achieving sustainable development. Their important means are to actively conduct the "green energy revolution" and gradually realize the replacement of traditional fossil energy with clean and renewable energy, particularly in developing countries. However, owing to the influence of economic, technological, and energy levels, China still consumes a large amount of fossil energy in the industrial production process, particularly coal. In 2015, China's coal consumption accounted for more than 70% of the total energy consumption, while energy and renewable energy accounted for less than 7%. Because coal belongs to the ranks of typical high-carbon energy, the large consumption of coal has a significant negative impact on energy conservation and emission reduction in the region.

Technological progress (TEG) at a 5% significance level has a positive effect on the convergence of ICEE, which confirms that promoting regional technological progress is an effective means to narrow the gap in ICEE. The continuous enhancement in technological innovation capability has played an important role in gradually reducing the intensity of energy consumption in China's economic development. Statistics show that China's energy consumption intensity has dropped from 1.61 in 1998 to 0.64 in 2015, a decrease of 97% in 18 years. The continuous improvement of technological development has effectively driven the continuous reduction of the intensity of energy consumption in our region. In addition to effectively improving the efficiency of regional energy use, technological progress has also played an important role in improving local environmental pollution control capabilities. These two mechanisms have jointly improved the efficiency of regional industrial carbon emissions.

The estimated coefficient of government intervention (GOV) is positive and passes the 1% significance level test, which implies that strengthening government fiscal expenditure has a positive effect on narrowing the ICEE gap between regions. Thus, hypothesis 6 is verified. At present, most of China's industrial carbon emission reduction work still represents a top-down government intervention; therefore, the government has played a leading role in energy conservation and emission reduction. According to authoritative data released by the environmental protection department, China's total investment in environmental pollution control has increased from 256.6 billion yuan in 2006 to 880.63 billion yuan in 2015, and its share of GDP has also increased from 1.20 to 1.30%. The clear majority of investment in environmental pollution control is made up of government fiscal expenditure, which plays an important role in improving local environmental quality.

Conclusions and policy implications

Conclusions

This study adopted the min-SBM method to measure the ICEE and then selected a spatial econometric method to investigate the convergence and influencing factors of regional ICEE in China. The following conclusions can be drawn:

(i) Except for Shanghai and Guangdong, the ICEE of other provinces failed to reach an effective frontier, and the average ICEE values of most of the eastern coastal provinces were relatively high, whereas the average ICEE values of the inland provinces in the central and western regions were relatively low.
(ii) We found that the ICEE $Moran's I$ was positive and passed the significance level test, and combined with the spatial autocorrelation LISA chart, the ICEE exhibited a significant space heterogeneity and global spatial autocorrelation; thus, the spatial geographic effect is an important factor that cannot be ignored while investigating the convergence of ICEE.
(iii) After the introduction of the spatial effect, the absolute convergence rate of ICEE was improved in comparison with that of the ordinary convergence model, and the condition convergence rate was further improved. In addition to the insignificant impact of the industrial structure, the level of economic development, FDI, and energy consumption were evaluated. Structure, technological progress, and government intervention are all important factors that affect the convergence of ICEE.

Policy implications

Based on the above conclusions, the focus of China's future work to improve ICEE and narrow the regional gaps should include the following points:

(i) Continue to implement the national economic sustainable development strategy advocated by the country, and vigorously implement regional industrial green development transformation, through strengthening. The upgradation of industrial technology equipment is expected to gradually phase out high-pollution and high-emission industries, thereby promoting energy conservation and emission reduction in the industrial sector.
(ii) Increase the level of regional foreign investment and gradually increase the environmental protection threshold for foreign investors. Foreign-funded enterprises with backward technology should upgrade their review to ensure that foreign capital can yield environmental protection benefits.
(iii) Accelerate the transformation of regional energy consumption and vigorously advocate the consumption of clean energy, such as wind, water, nuclear energy, and bioenergy. In addition, implement clean energy subsidy policies for regions with slow transition.
(iv) Increase the intensity of industrial technology research and development through technological innovation to achieve the replacement of backward technology, while enhancing technical exchanges between regions. Furthermore, through exportation, promote backward areas toward advanced areas, and jointly improve the overall technical level of the area.
(v) The government should further increase the investment of environmental pollution control (Sun et al. 2018), and implement key controls on areas and industries with serious emissions. Enterprises must strictly rectify, thereby reducing the carbon emissions of the entire industrial sector.

Therefore, this study provides a new perspective on the efficiency of industrial carbon emissions. In the future, we will expand this research to examine the effect from multiple perspectives. More importantly, the results can provide scientific reference value for China to achieve the peak of carbon dioxide emissions before 2030.

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Data availability The data used to support the findings of this study are available from the corresponding author upon request (e-mail: zhfthero45@cqut.edu.cn).

Declarations

Ethics approval and consent to participate Not applicable

Consent for publication Not applicable

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