Spatial econometric analysis of China’s province-level industrial carbon productivity and its influencing factors

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HIGHLIGHTS
• We evaluate the industrial carbon productivity of China’s provinces.
• The regional disparity and clustering features exist simultaneously.
• There is evident spatial dependence in regional industrial carbon productivity.
• We employ spatial panel data models to examine the impact factors.
• Spatial effects are found to be important in understanding industrial CO2 emissions.

ABSTRACT
This study measured the industrial carbon productivity of 30 provinces in China from 2005 to 2012 and examined the space–time characteristics and the main factors of China’s industrial carbon productivity using Moran’s I index and spatial panel data models. The empirical results indicate that there is significant positive spatial dependence and clustering characteristics in China’s province-level industrial carbon productivity. The spatial dependence may create biased estimated parameters in an ordinary least squares framework; according to the analysis of our spatial panel models, industrial energy efficiency, the opening degree, technological progress, and the industrial scale structure have significantly positive effects on industrial carbon productivity whereas per-capita GDP, the industrial energy consumption structure, and the industrial ownership structure exert a negative effect on industrial carbon productivity.

1. Introduction

The industrial sector has become a major source of global carbon dioxide (CO2) emissions [1]. It has been gradually recognized that the key to dealing with climate change is to reduce fossil fuel use and CO2 emissions. With the development of both urbanization and industrialization, China has surpassed the United States to become the largest energy consumer and CO2 emitter. During this time CO2 emissions from the industrial sector in China experienced rapid growth and accounted for a large proportion. Since the reform and opening up of China in 1978 the industrial added value has accounted for only about 40% of GDP on average but it has led to more than 70% of the total CO2 emissions [2]. Clearly, the reduction of CO2 emissions in the industrial sector is the keystone of the energy-saving and emissions–reduction work, which plays an important role in the final realization of the emissions-reduction target. Carbon productivity is a concept of efficiency in the field of CO2 emissions that refers to the ratio of the GDP and CO2 emissions in a certain period [3]. It represents the efficiency of CO2 emissions during a period of economic growth. Increasing the industrial carbon productivity may be an effective way to realize the reduction of CO2 emissions in the industrial sector.

From an international perspective (see Fig. 1), the industrial carbon productivity of most developing countries is far lower than that of developed countries, which is closely related to the stage of rapid urbanization and industrialization. China is the biggest developing country in the world. The average industrial carbon productivity of China for 2000–2011 is only one third of the world average. There is still a long way to go for China to increase the industrial carbon productivity to reach a world-class level, which also implies great potential in addressing global climate change. The question of how to promote China’s industrial carbon productivity is an important subject where research is urgent.

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The realization of CO₂ emissions reduction depends on the action taken and the share of energy saving and emissions reduction achieved at the provincial level. It is well known that due to its vast territory there is remarkable regional disparity among the industrial economic development and CO₂ emissions in China. The issue of spatial dependence cannot be neglected in policy making. The spatial effect indicates that industrial carbon-reduction policies adopted in one province may generate spillovers onto neighboring provinces. The spatial dependence in regional industrial carbon productivity is the main focus of this study. Important to note, the estimate of CO₂ emissions in this study is based on provincial-level energy consumption and not actual CO₂ emissions.

The energy-related CO₂ emissions just reflect the energy consumption activities and do not take the atmospheric motion into account. For this reason, the spatial dependence in regional industrial carbon productivity is essentially the spatial effect among the energy consumption and economic activities related to industrial carbon productivity. To identify the spatial dependence, we use provincial panel data from 2005 to 2012 to examine the spatial distribution characteristics of China’s industrial carbon productivity. In addition, we analyze this spatial dependence as well as the dominating factors by specifying spatial panel data models. We hope that such a study can provide a scientific basis for policy makers to implement a regional oriented industrial carbon-reduction strategy.

This study mainly makes three contributions to the literature. Firstly, it extends the research on carbon productivity to the industrial level. By definition, our study measures the industrial carbon productivity of China’s 30 provinces to reveal the regional disparity and spatiotemporal characteristics. Secondly, this study employs the developed spatial econometric approaches to make in-depth analysis on the spatial dependence and the main drivers of industrial carbon productivity. Thirdly, we extend the data to examine China’s 30 provinces from 2005 to 2012 in order to better reflect the recent characteristics of industrial carbon productivity.

The rest of this paper is arranged as follows. Section 2 reviews the related study literature in this field. Section 3 introduces the data description and the methodology used. Section 4 presents the empirical results and analyses. Finally, in Section 5 we summarize the study and offer policy suggestions.

2. Literature review

Carbon productivity was proposed by Kaya & Yokobori in 1993. The McKinsey Global Institute made a further annotation to it in their 2008 report entitled “The Carbon Productivity Challenge: Curbing Climate Change and Sustaining Economic Growth." The report also points out that in order to achieve the 2050 goal proposed by the IPCC of controlling greenhouse gas emissions (keeping concentrations below 500 ppm CO₂-eq in 2050), humans need to increase carbon productivity tenfold over the next 40 years [4]. People like He et al. [5] have said that the growth rate of carbon productivity may measure the extent of a country’s efforts to address climate change. They argued that although China’s carbon productivity is relatively much lower, its average annual growth rate of carbon productivity is higher than the world average level. Other scholars have discussed carbon productivity from the perspective of its main influencing factors, such as technological progress, the industrial structure, and the energy structure [6,7].

The factors influencing CO₂ emissions have always been a topic of great interest to researchers. Numerous past studies have shown that the main factors driving China’s CO₂ emissions are the population size, urbanization, industrialization, the economic output, the industrial structure, and energy consumption [8–13]. Based on the STIRPAT model, Fan et al. [12] and Li et al. [13] found that China’s CO₂ emissions are determined by economic growth, the industrial structure, the population size, and the urbanization and technical levels. Using an index decomposition analysis, Xu et al. [9] found that China’s CO₂ emissions are mostly produced by industry, and the major factors of CO₂ emissions are the economic output and energy intensity effects. As for the industrial sector, Zha et al. [14] made an empirical analysis on the factors affecting China’s industrial carbon emissions performance with dynamic panel data models. They found that some factors have strong and complicated impacts on China’s industrial carbon emissions performance; these include the economic development level, the structure and energy factors, and environmental regulation. Yang et al. [15] analyzed the effects of different technological factors on industrial CO₂ intensity, including R&D activity, spillovers through increasing openness, and inter-regional R&D spillovers.

A possible shortcoming of the above studies is that all are based on the independence assumption and ignore the significant spatial interaction effects. As Anselin [16] and LeSage et al. [17] pointed out, a local region would be more or less influenced by neighboring regions. According to Tobler’s first law of geography [18], all attribute values on a geographic surface are related to each other and closer values are more strongly related than those more distant ones. It breaks the assumption of the classical econometric model that the variables are independent and that ignoring spatial dependence may lead to model misspecification and estimation bias.

Geography is important as well in the study of CO₂ emissions. Technical progress is considered to be an important factor in improving the issue of CO₂ emissions, and the diffusion of technology may help to improve the surrounding CO₂ emissions conditions [15]. Based on the “pollution haven” effect, under the different strengths of environmental regulation for regions, the location of carbon-intensive industries may transfer from the provinces with high intensity levels of environmental regulation to the weak ones [19]. This means that undeveloped provinces that are adjacent to the developed ones might have lower carbon productivity. In addition, geographical location is important to policy factors as an effective environmental policy in one region might cause neighboring regions to follow and for the policy to eventually spread to the surrounding area [20]. Thus, it is necessary to take the spatial effects into account when we study the issue of CO₂ emissions. Burnett et al. [21] and Zhao et al. [22] studied the factors affecting CO₂ emissions with spatial panel data models and found that there is significant spatial dependence in CO₂ emissions and that the spatial economical models that have incorporated the spatial effects significantly improve the estimation. For this reason
this study tends to discuss the industrial carbon productivity from the spatial effect perspective.

3. Variables and methodology

3.1. Variables and data sources

3.1.1. Calculations for industrial carbon productivity

This study takes the industrial carbon productivity (CP) as the dependent variable. As the government has attached importance to environmental issues and has set a lot of carbon-reduction policies since 2005, we focus on the industrial carbon productivity of China’s 30 provinces and municipalities from 2005 to 2012 (Hong Kong, Macao, Taiwan, and Tibet are not included due to lack of data). According to Kaya & Yokobori’s definition of carbon productivity, we argue that it is more in line with the definition of carbon productivity to take the industrial added value as the output variable instead of the industrial output value. The industrial carbon productivity can be defined as Eq. (1):

\[ CP = \frac{IAV}{CO_2} \]  

(1)

In this formula, CP refers to the industrial carbon productivity, IAV represents the industrial added value, and \( CO_2 \) stands for the industrial carbon dioxide emissions. The provincial industrial added values are collected from the provincial Statistical Yearbooks and adjusted to the constant price of the year 2012.

Industrial \( CO_2 \) emissions mainly derive from the burning of fossil fuels and the process of industrial production, the former of which is the major source of \( CO_2 \) emissions. Due to data limitations, we calculate industrial \( CO_2 \) emissions related to fossil fuel combustion only on the basis of the calculation method provided by the IPCC, which is defined as Eq. (2):

\[ CO_2 = \sum_{i=1}^{E} CO_2i = \sum_{i=1}^{E} Ei \times NCVi \times CEFi \times COFi \times 44/12 \]  

(2)

where \( CO_2i \) represents the total amount of industrial \( CO_2 \) emissions, \( i \) is the category of energy, \( E \) denotes the amount of energy consumption, \( NCV \) is the net calorific value, \( CEF \) is the carbon emissions factor, \( COF \) is the carbon oxidation factor, and the figure 44/12 is the molecular weight ratio of carbon dioxide over carbon. To avoid the simple division of primary energy, this study divides the final energy consumption into the categories of coal, coke, crude oil, gasoline, diesel, kerosene, fuel oil, natural gas, and electricity. The calculation is based on the final energy consumption in the energy balance tables in the China Energy Statistical Yearbook. Except for electricity, the \( CO_2 \) emissions coefficients of each fuel type are provided by The Guidelines to Make Provincial Lists of Greenhouse Gas Inventory.

For the calculation of the total \( CO_2 \) emissions, some scholars have argued that as a secondary energy the use of electricity in terminals would not produce \( CO_2 \) directly and so electricity is excluded. Given that the \( CO_2 \) emissions from electricity are mainly produced by coal-fired power, some other scholars have calculated the \( CO_2 \) emissions from electricity by calculating the \( CO_2 \) emissions from the fossil fuel combusted by the local coal-fired power; this follows the principle “whoever generates the electricity should take the charge.” In this study, we argue that whether considering the indirect \( CO_2 \) emissions embodied in inter-provincial electric power transmission depends on your research targets. In view of the large amount of final electricity consumption in industry, we follow the principle of “whoever consumes the electricity should take the charge” and calculate the regional industrial \( CO_2 \) emissions based on the final energy consumption including electricity, which is more reflective of the true \( CO_2 \) emissions levels. The estimation of the \( CO_2 \) emissions coefficient of electricity follows the methodology set out in The Guidelines to Make Provincial Lists of

Greenhouse Gas Inventory, which divides China into the Northeast China, North China, East China, Central China, Northwest China, and Southern China power grids, as given in Table 1.

We were able to obtain the annual provincial coefficients by dividing the \( CO_2 \) emissions from coal-fired power in each region by all electricity produced in the power grid of each region (see Table 2).

3.1.2. Explanatory variables

Based on the literature review, the explanatory variables selected to explain the spatial interaction mechanism of China’s industrial carbon productivity are: per-capita GDP, industrial energy efficiency, the industrial energy consumption structure, the opening degree, technological progress, the industrial ownership structure and the industrial scale structure. The variables are explained as follows.

Per-capita GDP (PGDP) is the gross domestic product divided by the population. The environmental Kuznets curve (EKC) indicates that the relationship between economic growth and \( CO_2 \) emissions is nonlinear [23]. For industrializing nations the rapid economic growth may lead to a steep increase in \( CO_2 \) emissions, thus reducing the industrial carbon productivity. However, the economic development process is often accompanied by the technological progress and the optimization of the industrial structure. The data for the variable is obtained from the China Statistical Yearbook.

Industrial energy efficiency (IEE) refers to the ratio of total energy consumption and industrial added value. Industrial energy efficiency is one of the main drivers of energy-related \( CO_2 \) emissions reduction. The empirical results of Fan et al. indicated that the overwhelming contributor to the decline of energy-related carbon intensity was the reduction in real energy intensity [24]. So we predict that the coefficient is positive. The data for the variable is obtained from the China Energy Statistical Yearbook and the Local Statistical Yearbook.

The industrial energy consumption structure (ECS) denotes the proportion of coal consumption to overall energy consumption in
industry. As a high-carbon energy source, coal accounts for an overwhelming majority of the energy consumption in China [25]. So it is assumed that the lower the percentage of coal consumption, the higher the carbon productivity will be in each province. We predict that the coefficient is negative. The data for the variable is obtained from the China Energy Statistical Yearbook.

The opening degree (OPEN) refers to the proportion of the total import–export volume to the GDP. There are two opposite hypotheses about the environmental externalities of the opening degree. According to “pollution haven hypothesis”, some researchers indicated that the opening up of developing countries attracts polluting industries and contributes to pollution [26]. In contrast, proponents of the “pollution halo hypothesis” believe that the opening up of developing countries boosts the inflow of advanced techniques and managerial experience, which may exert a positive influence on regional environment [27]. The data for the value is obtained from the China Statistical Yearbook.

Technological progress (TECH) is represented as the R&D expenditure input intensity by region, which denotes the ratio of R&D expenditure and GDP. Certainly the technological progress plays an important role in combating climate change [28]. The coefficient is assumed to be positive. The data for the value is derived from the China Statistical Yearbook on Science and Technology.

The industrial ownership structure (IOS) is measured as the proportion of the output of state-owned and state-holding industrial enterprises to the gross industrial output. Different systems of property rights have different incentives for enterprises [29], and may influence their allocative and productive efficiency. Thus it is important to note how the changes in the industrial ownership structure affect the carbon productivity. The data for the value is obtained from the China Industry Economy Statistical Yearbook.

The industrial scale structure (ISS) is measured as the proportion of the output of large- and medium-sized industrial enterprises to the gross industrial output. Trianni et al. [30] argued that smaller enterprises show a greater perception of the barriers expenditure input intensity by region, which denotes the ratio of R&D expenditure and GDP. Certainly the technological progress plays an important role in combating climate change [28]. The coefficient is assumed to be positive. The data for the value is derived from the China Statistical Yearbook on Science and Technology.

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The three models are specified as Eqs. (5)–(7):

\[ y = \rho Wy + X\beta + \varepsilon \quad \text{(SAR)} \]
\[ \begin{align*}
\{ y & = X\beta + \mu \\
\mu & = \lambda W\mu + \varepsilon \end{align*} \quad \text{(SEM)} \]
\[ \begin{align*}
\{ y & = \rho Wy + X\beta + \mu \\
\mu & = \lambda W\mu + \varepsilon \end{align*} \quad \text{(SAC)} \]

where y denotes an \( n \times 1 \) vector of one observation on the dependent variable (industrial carbon productivity); \( X \) denotes an \( n \times k \) matrix of observations on the explanatory variables (per-capita GDP, industrial energy efficiency, the industrial energy consumption structure, the opening degree, technological progress, the industrial ownership structure, and the industrial scale structure); \( \beta \) is an associated \( k \times 1 \) vector with unknown parameters to be estimated, which reflects the influence of the explanatory variables on the dependent variable; \( W \) is the spatial weight matrix; \( Wy \) denotes the endogenous interaction effects among the dependent variable; \( \mu \) and \( W\mu \) denote a vector of error terms and the interaction effects among the error terms; \( \varepsilon \) is a vector of disturbance terms that are independent and identically distributed normal random variables; \( \rho \) is the spatial autoregressive coefficient; and \( \iota \) denotes the spatial

3.2. Spatial analysis methods

For general research spatial econometric analysis is usually divided into two steps. The first step is to undertake a spatial autocorrelation analysis of the dependent variable to test whether there is spatial autocorrelation (dependence). If there is spatial dependence, we should establish a spatial econometric model, which is the second step; otherwise, the classic econometric model could be effective.

3.2.1. Global spatial autocorrelation

To test the spatial dependence of regional industrial carbon productivity, we adopt the global Moran’s I index. The formula for calculating the global Moran’s I index can be expressed as Eq. (4):

\[ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i - \overline{y})(y_j - \overline{y})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij})\sum_{i=1}^{n}(y_i - \overline{y})^2} \quad \text{(4)} \]

In this formula, \( y_i \) and \( y_j \) represent the industrial carbon productivity of province \( i \) and \( j \), respectively; \( n \) is the number of regions; and \( W_{ij} \) stands for the spatial weight matrix, which describes the spatial adjacent relations between each geographical unit. In this study we adopt the binary contiguity matrix with the rook criterion. If province \( i \) is adjacent to province \( j \), then the matrix elements \( W_{ij} = 1 \) and \( W_{ij} = 0 \) otherwise. In general, the spatial weight matrix should be normalized by line, which means the sum of elements \( W_{ij} \) in each line equals 1. The value range of Moran’s I index is \([-1, 1]\). The closer that this value is to 1, the greater the clustering in the pattern; the closer to −1, the greater the dispersion in the pattern; if the value equals 0, there is no spatial dependence and the carbon productivity exhibits a random spatial distribution.

3.2.2. Spatial econometric models

There are two main types of spatial econometric models, which correspond with different setting modes of spatial interaction. The first model, namely the spatial autoregressive model (SAR) or the spatial lag model (SLM), contains endogenous interaction effects among the dependent variable. This model is applied to a situation where the economic activity of a local region is affected by the economic activities of neighboring regions because of the spillover effects. The second model, namely the spatial error model (SEM), contains interaction effects among the error terms. This model is applied to a situation where the regional interaction effects are caused by the omitted variables that affect both the local and neighboring regions. In addition, there is a combination of the former two models that includes both endogenous interaction effects among the dependent variable and interaction effects among the error terms. This model was named “SAC” by LeSage and Pace [17] but they did not point out what this acronym stands for. The three models are specified as Eqs. (5)–(7):

SAR:
\[ y = \rho Wy + X\beta + \varepsilon \]

SEM:
\[ \begin{align*}
\{ y & = X\beta + \mu \\
\mu & = \lambda W\mu + \varepsilon \end{align*} \]

SAC:
\[ \begin{align*}
\{ y & = \rho Wy + X\beta + \mu \\
\mu & = \lambda W\mu + \varepsilon \end{align*} \]
autocorrelation coefficient on the error terms. If the coefficient $\rho$ is statistically significant then it can be implied that the spatial spillover effects of the dependent variable are obvious. If the coefficient $\lambda$ is statistically significant it indicates that there are some explanatory factors other than the explanatory variables contributing to the autocorrelation among the error terms.

The spatial econometric panel models cannot be estimated by ordinary least squares (OLS) due to the simultaneity of the model, as there are endogenous variables on the right-hand-side of the equations. The OLS estimation may lead to estimation bias or invalidity in the regression results. For this reason we use maximum likelihood (ML) to estimate the parameters of the spatial econometric models.

4. Empirical research

4.1. The spatial distribution characteristics

Fig. 2 summarizes China’s province-level industrial carbon productivity for the years 2005, 2008, and 2012. Since the Eleventh Five-Year Plan, along with the improvement of energy efficiency and the optimization of the industrial structure, the industrial carbon productivity of most provinces has been rising each year. However, China’s industrial carbon productivity has obvious differences at the provincial level. For example, in 2012 the three provinces with the highest industrial carbon productivity were Guangdong (9510 yuan/tonne), Beijing (9280 yuan/tonne), and Shanghai (7780 yuan/tonne) while the three provinces with the lowest industrial carbon productivity were Ningxia (1100 yuan/tonne), Qinghai (1530 yuan/tonne), and Xinjiang (1530 yuan/tonne). The results show that the industrial carbon productivity of Guangdong province was 8.62 times the level of Ningxia Province.

This disparity in industrial carbon productivity may also exhibit spatial dependence. Due to space limitations, we only list the quartile graphs of China’s province-level industrial carbon productivity at the beginning (2005) and the end (2012) of the period. As Fig. 3 shows, the two graphs display both spatial disparity and clustering. In 2005 the eight provinces with the highest industrial carbon productivity were, in order, Guangdong, Shanghai, Zhejiang, Beijing, Jiangsu, Jiangxi, Shanxi, and Tianjin while Ningxia, Guizhou, Shanxi, Yunnan, Gansu, Qinghai, and Inner Mongolia had the lowest industrial carbon productivity. In 2012 the top eight provinces were Guangdong, Beijing, Shanghai, Tianjin, Zhejiang, Chongqing, Jiangsu, and Jiangxi while Ningxia, Qinghai, Xinjiang, Guizhou, Gansu, Shanxi, and Hebei were on the bottom of the list. Overall, the industrial carbon productivity of the southeast coastal provinces is higher than that of the northwest inland provinces.

4.2. Global spatial autocorrelation and its dynamics

As shown in Table 3, the global Moran’s I index of China’s province-level industrial carbon productivity ranges from 0.234 to 0.351. The annual Moran’s I from 2005 to 2011 passed the significance test at the 1% level while in 2012 it was significant at the 5% level. This indicates that there is significant spatial autocorrelation of China’s province-level industrial carbon productivity. The geographic distribution of industrial carbon productivity tends to cluster together.

It is important to note that the global Moran’s I test has a certain limitation. The test can only be applied to describing the average degree of correlation overall. If there is a positive spatial autocorrelation in some provinces and a negative spatial autocorrelation in others then the effects will offset each other, in which case the Moran’s I index may tend to 0 and reveal non-spatial autocorrelation. For this reason, in order to further test the spatial dependence, we deploy a Moran’s I scatter plot analysis. We choose four points in time (2005, 2008, 2010, and 2012) to display the Moran’s I scatter plots of China’s province-level industrial carbon productivity, which are summarized in Fig. 4. The horizontal axis of the scatter plot represents the provincial industrial carbon productivity while the vertical axis represents the corresponding spatial lag. The scatter plot is divided into four quadrants. The first quadrant is High-High clustering (HH), which means provinces with high industrial carbon productivity (above the average) are surrounded by neighboring provinces with high industrial carbon productivity. The second quadrant is Low-High clustering (LH), which means provinces with low values are surrounded by neighboring provinces with high values. The third quadrant is Low-Low clustering (LL), which means provinces with low values are surrounded by neighboring provinces with low values. The fourth quadrant is High-Low clustering (HL), which means provinces with high values are surrounded by neighboring provinces with low values. The first and third quadrants reveal positive spatial autocorrelation characteristics whereas the second and fourth quadrants reveal negative characteristics.

As shown in Fig. 4, most of the provinces exhibit HH and LL clustering and show positive spatial autocorrelation. In 2005, 2008, 2010, and 2012, there are 22 provinces (73.33%), 22 provinces (73.33%), 20 provinces (66.67%), and 19 provinces (63.33%) located in the first and third quadrants, respectively. Table 4 reports the results of the Moran’s I scatter plots in 2005, 2008, 2010, and 2012. As shown in Table 4, the provinces with HH clustering are centralized mainly in the coastal areas of Southeast China whereas the provinces with LL clustering are distributed mainly in the inland areas of Midwest China, which provides further evidence of the clustering characteristics. However, some provinces show negative spatial autocorrelation. For example, in 2012 Hebei, Hubei, Guangxi, Hainan, and Guizhou belonged to the LH clustering group and Beijing, Heilongjiang, Shaanxi, Sichuan, Chongqing, and Henan belonged to the HL group. Compared to 2005, in 2012 the number of provinces belonging to the HH clustering decreased by 5 and the number belonging to the HL clustering increased by 2 while the number of provinces belonging to the LH and LL clustering groups increased by 1 and 2, respectively. This indicates that the degree of spatial clustering of the industrial car-

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A measure of the spatial stability could be Eq. (8):

$$S_i = F_{0i}/n$$  \hspace{1cm} (8)$$

where $F_{0i}$ denotes the number of observations that experience a transition of Type 0 in the period $t \rightarrow t+1$ and $n$ is the sum of the number of all transitions in the period $t \rightarrow t+1$. As $0 \leq S_i \leq 1$, the closer that number is to 1, the stronger is the spatial stability of China’s industrial carbon productivity, while the closer that number is to 0, the stronger is the spatial flux.

Table 5 reports the transitions of the Moran’s I scatter plots of China’s industrial carbon productivity in three time periods. From 2005 to 2012, Guangxi, Hebei, and Guizhou transitioned from the LL quadrant to the LH quadrant while Sichuan, Chongqing, and Henan transitioned from the LL quadrant to the HL quadrant, which indicated the regional differentiation tendency of the six provinces. Xinjiang transitioned from the HL quadrant to the LL quadrant while Anhui and Hunan transitioned from the LH quadrant to the HH quadrant, which indicated the regional clustering tendency of the three provinces. Based on the calculation results, the transitions were inactive for the period of observation. The values of spatial stability in 2005–2008, 2008–2010, and 2010–2012 were 0.933, 0.800, and 0.967, respectively, which indicated that the distribution of China’s industrial carbon productivity was characterized by path dependence or the spatial lock-in effect to some extent.

4.3. Estimation results of spatial panel data models

The results of the Moran’s I analysis imply that there is significant spatial dependence of China’s province-level industrial carbon productivity during the observation period. However, the Moran’s I analysis on its own does not make clear how the various factors influence the industrial carbon productivity and in any event, the certification of spatial dependence makes the classical assumption of independence invalid. Due to the spatial dependence of industrial carbon productivity, the non-spatial panel models may lead to estimation bias in the regression results to some extent. For this reason we adopt the spatial panel econometric models to illustrate the driving mechanism of these selected factors of China’s industrial carbon productivity.

Based on the R package splm, this study attempts to analyze the spatial dependence of the selected factors by specifying three spatial panel data models, namely SAR, SEM, and SAC, which are estimated by maximum likelihood estimation. The estimation results are reported along with those of the non-spatial panel data models in Table 6. As we focus more on the significance and comparison of the regression coefficients than the comparison of each model, some statistic indicators such as the fitting degree ($R^2$) are omitted for the sake of simplicity (the results would not be affected). Based on the Hausman test results ($\chi^2 = 51.96$, $p < 0.01$), and considering that the research objects
of this thesis are certain provinces in mainland China, it is more appropriate to use the fixed effect model (FE). Accordingly, for additional assurance, the estimation of the random effect model (RE) is listed also for reference purposes. As reported in Table 6, by comparing the results of various spatial panel data models it can be seen that the spatial autoregressive coefficients $q$ and $k$ are significantly positive. This implies that there is obvious spatial dependence in regional industrial carbon productivity, which means the industrial carbon productivity of one province is affected by both the local economic activity and the neighboring provinces due to spatial spillovers.

By comparison it can be seen that the estimated coefficients of the non-spatial panel data models and the spatial panel data models are not consistent. According to the results of the non-spatial panel data models, the coefficient of per-capita GDP is positive and not significant both in the fixed effect model and the random effect model, which is inconsistent with the theoretical expectations. Furthermore, the coefficients of energy efficiency and technical progress in the spatial panel data models are smaller than those of the non-spatial panel data models, from which it can be seen that the non-spatial panel models would overestimate the marginal effects of these factors without considering the spatial effects. The reason for this might be that both energy efficiency and technical progress have strong spatial spillover effects, as the transfer and diffusion of energy-saving technology across provinces will affect the neighboring industrial carbon productivity. Therefore, it is only with the ability of the spatial econometric model to eliminate the spatial spillover effects of independent variables that the coefficients can reflect the unbiased marginal effects on industrial carbon productivity. From the above analysis it is shown that the estimation results of spatial panel data analysis are more precise than those of non-spatial panel data analysis. In the spatial panel data models most coefficients of the explanatory variables are statistically significant and consistent with our expectations. As shown in Table 6 all the coefficients in Model (3) pass the significance test, which is superior to the other models. Based on this we take the estimation results of Model (3) (the fixed effect SAR model) as the main interpretative object to illustrate the factors of industrial carbon productivity (as discussed below), and the others just for reference.
Based on the current economic mode per-capita GDP has a negative impact on regional industrial carbon productivity. As shown in Table 6 a 10% increase in per-capita GDP leads to a 0.335% decrease in the industrial carbon productivity (with other conditions unchanged), which is consistent with the literature [33,34]. On the basis of the carbon Kuznets curve hypothesis, the relationship between economic development and CO₂ emissions varies in different stages. During the observation period as China was at a critical state of accelerated industrialization the economy had yet to get rid of the “high energy consumption, high carbonization” label. Therefore, Chinese industry as a whole is still under the rising phase in the inverted U-shape curve (EKC) [35] and economic development and industrial CO₂ emissions have not become decoupled.

The improvement in energy efficiency and the optimization of the industrial structure are important drivers for promoting regional industrial carbon productivity. The coefficients of IEE and ECS are both significant at the 1% level. The coefficients imply that a 10% increase in energy efficiency leads to an 11.02% increase in the industrial carbon productivity while a 10% increase in the ratio of coal consumption to overall energy consumption leads to a 0.576% decrease in the industrial carbon productivity, which is consistent with our expectations. As has been proved by many studies, energy factors, including the energy efficiency and the energy consumption structure, are the most direct factors influencing CO₂ emissions. With the overall progress in energy saving and emissions reduction, industrial energy efficiency has improved significantly, which should be an important measure for promoting industrial carbon productivity. In terms of the energy consumption structure, reducing coal consumption as a percentage of total final energy consumption is conducive to increasing industrial carbon productivity. Hence, avoiding the direct burning of coal in the terminal and using natural gas and electricity as an industrial energy as much as possible is one of the effective ways to reduce the amount of coal used.

The opening degree is positively associated with regional industrial carbon productivity. The coefficient of OPEN is significant at the 1% level and indicates that a 10% increase in the opening degree leads to a 0.167% increase in the industrial carbon productivity. Increasing the opening degree is conducive to expanding international cooperation in the sustainable development area, introducing advanced techniques and managerial experience, and attracting low-carbon foreign direct investment, which then exerts a positive influence on industrial carbon productivity.

Technological progress is also conducive to regional carbon productivity. The coefficient of TECH is significant at the 1% level and indicates that a 10% increase in the R&D expenditure input intensity leads to a 0.240% increase in the industrial carbon productivity, which is consistent with our expectation. R&D expenditure is an important approach to technological progress. Achieving progress in energy technology is beneficial to improving energy efficiency and economic efficiency, which then promotes industrial carbon productivity.

The industrial ownership structure has a negative impact on regional industrial carbon productivity. The coefficient of IOS is −0.0364 and is significant at the 1% level. The coefficient indicates that a 10% increase in the industrial ownership structure leads to a 0.364% decrease in the industrial carbon productivity. Other studies have shown that non-state-owned enterprises have higher levels of technical efficiency and energy efficiency than the state-owned enterprises [36] so it may be necessary to take industrial ownership structure factors into account when promoting industrial energy saving and carbon reduction.

The industrial scale structure has a positive impact on regional industrial carbon productivity. The coefficient of ISS is 0.0470 and is significant at the 1% level and indicates that a 10% increase in the industrial scale structure leads to a 0.470% decrease in the industrial carbon productivity. This result suggests that an increase in the proportion of large- and medium-sized industrial enterprises leads to an increase in industrial carbon productivity. Large- and medium-sized industrial enterprises have distinct advantages in respect of the capital, technology, human resources, management, and other aspects, which may result in higher carbon productivity. Thus,
it can be seen that large- and medium-sized enterprises are the main force in industrial carbon reduction. In small enterprises, carbon reduction measures are rarely implemented. We suggest providing small industrial enterprises with more support in terms of system, funds, policy and technology.

5. Conclusions and implications

The spatial dependence is an important issue that cannot be ignored in energy, and environmental researches. However, few literatures have paid attention to the spatial spillover effects on CO2 abatement. In order to fill such a research gap, we evaluated the province-level industrial carbon productivity in China, and applied spatial econometric approaches to focus on the spatial dependence and the main driving factors of industrial carbon productivity.

The empirical results show that the distribution of China’s industrial carbon productivity can be depicted as “high in the east and lower in the west; high in the south and lower in the north.” The issue associated with the regional disparity of industrial carbon productivity remains serious. As pointed out by Dong et al. [37], challenges of emissions-reduction policy not only comes from the technical constraints, but also from the fact that China has a large regional disparity. This finding suggests that it is rather important to address such regional disparity and balance the regional development in policy making toward industrial CO2 abatement.

Moreover, the results imply that there is steady spatial dependence in regional industrial carbon productivity. The Moran’s I analysis highlights a clustering pattern of regional industrial carbon productivity. The provinces with HH clustering are centralized mainly in the coastal areas of Southeast China whereas the provinces with LL clustering are distributed mainly in the inland areas of Midwest China. Compared to related studies [22,37,38], we can find that the industrial carbon productivity (Table 1) exhibit more statistically significant spatial dependence than overall CO2 emission and its intensity. Since industry is relatively less dependent on natural conditions, industrial activities are easier to agglomerate so that the regional industrial carbon productivity has a stronger spillover effect, which is crucial for future policy making.

Due to the spatial dependence the estimation results of the spatial panel data analysis are more precise than those of the non-spatial panel data models to some extent. Our regression results suggest that industrial energy efficiency, the opening degree, technological progress, and the industrial scale structure have significantly positive effects on industrial carbon productivity whereas the per-capita GDP, the industrial energy consumption structure, and the industrial ownership structure exert a negative effect on industrial carbon productivity. From these findings, policy makers can further clarify the complex effects of various factors on industrial carbon productivity.

The increase in industrial carbon productivity is not only a local problem, but also a global problem. As the biggest developing country and the largest CO2 emitter in the world, China is experiencing a transition period from mid-industrialization to late-industrialization. The industrial economy is embracing an important opportunity to realize low carbonization. On the basis of the above discussions and conclusions, this study puts forward some feasible measures as follows:

- The importance of spatial spillovers should be taken into account when formulating emissions reduction policies. Our results identified the spatial spillover effects of industrial carbon productivity. The spatial spillover effects indicate that improving the industrial carbon productivity in a region has
positive externalities. Accordingly, the government should encourage the exchange and sharing of information, technology, talents, and other resources across provinces to boost inter-provincial cooperation on energy conservation and emissions reduction. For China’s local governments, the southeast coastal provinces with high industrial carbon productivity should take advantage of technology and policy to play a demonstration role in realizing the virtuous circle of the low-carbon coordinated development; the midpoint inland provinces with low industrial carbon productivity should strengthen cooperation with the southeast coastal provinces and actively learn from the latest technology and the mature experience to help improve environmental quality gradually.

- Industry should abandon the traditional high-speed growth mode. The government need to weaken its goals for GDP growth and set some obligatory targets for CO2 emissions and energy consumptions to promote the transition of the existing industrial economic mode to a “green, recycling, and low-carbon” mode. Important to note, the southeast coastal provinces of China should take on more responsibilities for industrial CO2 emissions reduction to ensure that the midpoint inland provinces realize economic transition smoothly.

- Industrial CO2 abatement basically depends on technology updates, including the alternative energy, energy saving, and carbon-sequestration technologies. As the main low-carbon technology used in China is still in a lower level, the government should increase investment in science and technology, strengthen independent R&D capacity and introduce advanced foreign low-carbon technology and managerial practices. It is also essential to establish a sound system of intellectual property protection to promote the diffusion of low-carbon technology.

- Given the remarkable regional disparity in China, the role of industrial transfer can be better managed. The government could encourage some sustainable industries in the southeast coastal provinces to transfer to the midpoint inland provinces. Meanwhile, the local governments should set up environmental protection rules and regulations to raise the market entry threshold for high energy consuming industries. During the transfer process it would be a good time to upgrade the industrial and energy structures, which would alleviate the regional imbalance and enhance the development of industrial low carbonization.

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