



# How do different types of energy technological progress affect regional carbon intensity? A spatial panel approach

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## Abstract

This paper investigated the spatial effects of two types of technological progress, namely renewable energy technology patents (RET patents) and energy conservation and emission reduction technology patents (ECERT patents), on carbon intensity of 30 provinces in China. Based on the 2005–2017 provincial panel dataset of China, this paper used the spatial Durbin model to analyze the spatial dependence and the spillover effects of surrounding provinces. The results first proved the existence of the spatial correlation in the carbon intensity across different provinces in China. Second, we found that the energy conservation and emission reduction technological progress can effectively reduce the province's own carbon intensity; however, this role is not significantly reflected by the progress in renewable energy technologies. Nonetheless, both types of technological progress have negative indirect and total effects on carbon intensity, thereby indicating that, geographically, they have technology diffusion effects. At the same time, the results demonstrated that technology patents play a negative role in carbon intensity. Third, by taking the interaction item between energy consumption and renewable energy technology patents into consideration, it was observed that the progress in renewable energy technologies can reduce the carbon intensity, owing to its role in optimizing the energy consumption structure of the province, but increase the carbon intensity of the surrounding provinces. Finally, based on the abovementioned findings, this paper put forward corresponding policy proposals.

**Keywords** Carbon intensity · Renewable energy technology patents · Energy conservation and emission reduction technology patents · Spatial Durbin model

## Introduction

There are series of ecological and environmental damages led by greenhouse gas emissions. The excessive emissions of carbon dioxide (CO<sub>2</sub>) directly led to climatic oscillation, which has a profound impact on many natural ecosystems, such as climate anomalies, sea level rise, and glacier retreat. According to BP Energy Outlook (2019), due to the rapid economic expansion and the soaring energy consumption, China's carbon emissions have surpassed all other countries. Although China's economic strength is very competitive in the world, it is still a developing country, which means that

there are still many aspects to be explored in its development. Based on this understanding, the BP Energy Outlook (2019) concluded that there is much to be done towards green and sustainable development. Therefore, in 2009, at the UN climate change conference in Copenhagen, China undertook to reduce its carbon intensity to 40–45% of 2005 level by 2020. Accordingly, there are also discussions in the existing literatures on whether and how China can reduce carbon emissions so as to fulfill its commitment (Yi et al. 2016; Andersson 2018; Andersson et al. 2018). The 18th National Congress of the Communist Party of China proposed a series of new ideas, including ideas on the building of an ecological civilization and protection of the ecology. According to the annual report, i.e., *China's Policies and Actions for Addressing Climate Change* (2019), issued by the Ministry of Ecological Environment, the national carbon intensity in 2018 decreased by 45.8% compared with 2005, thereby maintaining a continuous downward trend. This number means that China has fulfilled its emission reduction commitments well in advance of the 2020 target. As a great power with a strong

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sense of responsibility, China has not stopped the construction of an ecological civilization. There will be more measures to promote the domestic and even international low-carbon cause after the previous commitments to the world are fulfilled.

Hereafter, further reduction of China's carbon intensity and achieving the 2030 carbon reduction target will be significant challenges. Energy technological progress is considered to be one of the effective ways to save energy and decline carbon emissions (Feng et al. 2009; Lantz and Feng 2006). Wang et al. (2012) divided the technology patents into different types, such as fossil fuel technology patents and carbon-free energy technology patents, to discuss the influence of technological progress on CO<sub>2</sub> emissions. According to BP Energy Outlook (2019), renewable energy is the most rapidly growing energy in the world. It is estimated that by 2040, it can provide at least 15% of the global energy structure. For example, recent trends indicate that, by 2040, solar power will constitute 12% of the global total. This quota could increase to 21% following the Paris Agreement climate target. Wang and Wang (2018) concluded that the innovation and application of renewable energy technology patents in China have developed rapidly, along with household energy conservation and emission reduction technology patents. Various energy technology patents have corresponding varying effects on carbon intensity. Therefore, considering that China is a country with considerable territory and resources, it is essentially meaningful to further explore the influence mechanisms of different types of energy technological progress on carbon intensity. The development and resource allocation of each province are unbalanced, as is the distribution of carbon intensity levels.

Meanwhile, several studies have considered spatial dependence when studying the relationship between technological progress (or other independent variables) and carbon intensity. Spatial correlation refers to the potential interdependence of some variables in the same distribution area. For example, the rapid economic development in one province may influence a similar development pattern in the neighboring province. Similarly, the carbon intensity of one province will, to a certain extent, also affect the carbon intensity of neighboring provinces. Therefore, it is essential and necessary, in the research of carbon intensity, to consider specific spatial correlations in order to achieve accurate results and recommendations. Energy consumption is one of the primary factors that cause a rise in emissions of carbon (Alam et al. 2016). At the same time, due to the rebound effect, technological progress will have an impact on carbon intensity in two ways. First, it will increase energy consumption efficiency, thus resulting in reduced carbon intensity. Second, the economic growth brought by technological progress can result in a rise in total energy consumption, thus resulting in increased carbon intensity (Berkhout et al. 2000). Therefore, this paper also discussed whether technological progress can affect carbon

intensity through other factors. The fundamental purpose of this paper was to discuss the effect of different kinds of technological progress, as represented by two types of patents, on carbon intensity. The study contributed to determining the corresponding emission reduction methods and China's low-carbon cause. Particularly, renewable energy technology patents and energy conservation and emission reduction technology patents were used to represent technological progress and we discussed the relation between the above patents and carbon intensity. Concurrently, the spatial aggregation effect of carbon intensity was used to ensure the accuracy of the conclusions. After considering all the above concerns, this study suggested and discussed three key problems:

- (I). Is there a significant spatial correlation of carbon intensity?
- (II). Considering the spatial spillover effect, how will the two different types of energy technological progress, namely renewable energy technology patents and energy conservation and emission reduction technology patents, individually impact carbon intensity?
- (III). How will the interaction item between energy technological progress and other factors affect carbon intensity?

In the context of China's efforts to pursue carbon emission reduction goals, it is particularly important to solve these problems. Using the spatial econometric model, we discussed the relations between different types of energy technology patents and carbon intensity in China to determine whether progress of energy technology can effectively decline carbon intensity. Furthermore, we put forward more constructive and practical proposals to decline the carbon intensity in China.

The rest of this paper is as follows: the "Literature review" section is the literature review. The "Variables and data" section is to introduce the definition of data and their sources and variables. Introduction of the model is in the "Methodology" section. The "Results" section is the estimation results of the model. The robustness check of the results is in the "Robustness check" section. The "Conclusions and policy proposal" section is to draw the conclusion and policy proposals.

## Literature review

### The impact of technological progress on carbon intensity or carbon emissions

Currently, some literature discussed the influence of technological progress on the carbon intensity or carbon emissions, but the results are still ambiguous. Similar to the intuition, some studies, such as Dong et al. (2018), Feng et al. (2009),

and Jin et al. (2017), concluded that the technological progress in the field of energy could reduce the CO<sub>2</sub> emissions. However, some literatures have the opposite conclusion. For example, Brännlund et al. (2007) and Yang and Li (2017) found technological progress might result in the rise of CO<sub>2</sub> emissions owing to the rebound effect. In addition, some studies (Wu et al. 2018; Yang and Li 2017) concluded that technological progress had limited or no impact on carbon emissions. Therefore, it is necessary to further discuss the specific influence degree and mechanism of technological progress on carbon emissions. Since China's two major international commitments for carbon reduction, which were made in Copenhagen and Paris respectively, are both based on carbon intensity, it is very meaningful to explore the influencing factors of carbon intensity in China's provinces.

For exploring the impact of technological progress on carbon intensity or emissions, the first key step is to quantify technological progress. In fact, the methods for measuring technological progress have been discussed in many studies. For example, some literatures divided technological progress into two, i.e., technological efficiency and technological change (Kim and Kim 2012). Specially, Song et al. (2018) calculated above two variables by using the super-efficiency slack-based model-data envelopment analysis on the basis of total factor productivity (TFP). The treatments of technological progress are not limited to the above categories, and have more intuitive approaches. For instance, Wang et al. (2012) replaced technological progress with the number of mineral fuel technology patents and carbon-free energy technology patents, while Li et al. (2017) used the introduction of foreign technology and technological innovation to measure technological progress, so as to discuss the learning effect of technological progress on regional CO<sub>2</sub> emissions.

### The application of spatial econometric model in the study of carbon intensity or carbon emissions

In recent years, the spillover effect of carbon emissions or carbon intensity between provinces has attracted extensive attention of scholars. Considering the spatial spillover effects of various factors, their impacts on carbon emissions or carbon intensity have gradually become important research issues. So far, spatial econometric model has been widely utilized. In the early days, Anselin and Bera (1998) and Bockstael (1996) respectively used spatial econometric model to solve the related problems in the field of real estate economy and environmental economy. Up until now, a large number of literatures have applied it to the field of energy. For example, Li et al. (2019) studied the impact of economic development and high-tech industry on carbon emissions on the basis of considering the spatial spillover effects of economic development and high-tech industries. Zhang et al. (2018a) used spatial panel regression model to explore the impact of

energy structure on industrial carbon emissions. At the same time, the impact of energy investment on carbon emissions is also fully discussed through the spatial Durbin model (Li and Li 2020). Moreover, spatial econometric models were used in various scopes. For example, You and Lv (2018) conducted a research on carbon dioxide emissions at the national level, while Song et al. (2018) focused on the provincial panel data of China, and Zhang et al. (2018b) discussed the panel dataset of China's 109 county-level cities. Apergis et al. (2013) studied the influence of R&D expenditure on CO<sub>2</sub> emissions at the enterprise level in three European countries.

### The contribution of this paper

In general, this paper contributed to the current research from the following two aspects. First, previous research often used the number of energy technology patents to measure the technological progress in the field of energy. However, the energy technology patents can be divided into different types, which may have different impacts on carbon intensity. Few studies have paid attention to this issue. To fill this gap, this paper divided energy technology patents into RET patents and ECERT patents, and discussed their impacts on carbon intensity on the basis of spatial Durbin model. Second, although some papers (e.g., Gu et al. 2019) have discussed the interaction item between energy consumption and RET patents, the spatial spillover effect of the interaction has not been considered in such researches. Therefore, by considering the spillover effect, this paper added the interaction item between energy technology patents and energy consumption into the spatial Durbin model and explored the impact of energy technology patents on the optimization of energy consumption structure on the carbon intensity of local and surrounding provinces.

### Variables and data

#### Dependent variable

As mentioned before, carbon intensity is the main object of China's commitments in various international conferences. Therefore, carbon intensity was used as a dependent variable in this paper, including panel dataset of 30 provinces from 2005 to 2017. Dividing CO<sub>2</sub> discharge amount by gross domestic product is the value of carbon intensity.

The data on GDP were obtained from the Chinese Statistical Yearbook 2006–2018. However, official reports do not contain provincial data on CO<sub>2</sub>. Therefore, the CO<sub>2</sub> discharge amount data, in this study, were calculated by the methods of the Intergovernmental Panel on Climate Change (Eq. 1) (Eggleston et al. 2006).

$$CO_2 \text{ emission} = \sum_{i=1}^8 (CO_2)_i = \sum_{i=1}^8 E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \quad (1)$$

where  $i$ ,  $E$ ,  $CEF$ ,  $ECV$ , and  $COF$  denote the type of fossil energy consumption, consumption of fossil energy, carbon content, low calorific value, and the oxidation rate of carbon respectively. The accurate values of  $E$ ,  $ECV$ ,  $CEF$ , and  $COF$  were gathered from the Chinese Energy Statistical Yearbook 2006–2018. Finally, the provincial carbon intensity panel data of 2005–2017 were obtained.

### Explanatory variables influencing carbon intensity

According to Copeland and Taylor (2004) and Grossman and Krueger (1995), the impact on environmental quality had been recognized by many researchers by considering the scale effect, structural effect, and technical effect (Balsalobre et al. 2015). In this study, carbon intensity was obtained using Eq. 2 (Cheng et al. 2018).

$$\text{Carbon intensity} = f(\text{Structural effect, Scale effect, Technical effect, Variables}) \quad (2)$$

In Eq. (2), structure effect, scale effect, and technical effect refer to the variables influencing carbon intensity from the above three effects, respectively, while variables refer to other relevant factors that affect carbon intensity. At the same time, the control variables included urbanization level (UL), energy consumption (EC), and foreign direct investment (FDI), which will be explained later.

*Scale effect* denotes the influence of the economy scale activities on carbon intensity. According to Kaika and Zervas (2013) and the EKC theory, economic scale and economic development level can have an essential and far-reaching impact on the environment. When the level and speed of economic expansion are low and the economic scale is small, excessive pursuit of rapid economic growth will result in the rise of CO<sub>2</sub> emissions. With the continuous growth of economic scale and level of economic development, people and the government pursue a better living environment, thus strengthening the regulations to reduce CO<sub>2</sub> emissions (Cheng et al. 2018). Simultaneously, changes in technological progress and industrial structure will also have negative impacts on CO<sub>2</sub> discharge (Apergis 2016). We used per capita income as the measurement of *scale effect*.

*Structural effect* refers to the effect of industrial structure changes on carbon intensity. In China, change in the industrial structure mainly denotes the transformation from industry to service. For example, when the industrial structure changes from agriculture and industry to the

service industry, the energy elements will flow from the previous industry to the service industry. Compared with other industrial structures, the energy efficiency of the service industry is relatively high. Therefore, industrial structure factors will lead to changes in energy efficiency, which will bring about a plus or minus in CO<sub>2</sub> emissions (Chang 2015). The influence of industrial structure on carbon intensity will be discussed later. In this study, the structure effect was quantified using Eq. 3 (Song et al. 2018).

$$\begin{aligned} \text{Industrial Structure (IS)} = & (\text{Proportion of provincial primary industry} \\ & \times 1 + \text{Proportion of provincial secondary industry} \\ & \times 2 + \text{provincial proportion of tertiary industry}) \times 3 \end{aligned} \quad (3)$$

where the primary, secondary, and the tertiary industry refer to the agriculture, industry, and service industry, respectively, as discussed above (Gu et al. 2019).

*Technical effect* denotes the influence of technical factors on carbon intensity. The *technical effect* in this paper refers to technological progress. In the existing literature, there are many ways to quantify technological progress, but most researchers use the number of patents to reflect technological progress (Gu et al. 2019; Wang et al. 2018). Some research further divided patents into different types to reflect different technological progress. For example, Wang et al. (2018) divided energy technology patents into three types of technology groups, i.e., emission reduction and household energy saving, energy saving, and renewable energy. In this paper, in order to further explore the role of different types of technological progress in carbon reduction from a spatial econometric perspective, this paper divided energy technology patents into RET patents and ECERT patents. The patent dataset was from the supplemental material of Wang and Wang (2018).

Energy consumption (EC), urbanization level (UL), and foreign direct investment (FDI) were selected as the control variables of the model. Many studies (Wang et al. 2011; Zaman et al. 2017) explained that energy consumption plays an essential role in carbon intensity, but it is uncertain whether the role is positive or not. Therefore, this variable is added to the model to determine, from a spatial perspective, the impact of energy consumption on carbon intensity. Liu et al. (2018) applied the panel dataset of 285 Chinese cities from 2003 to 2014 to investigate, from the geospatial perspective, the influence of FDI on pollution and the spatial aggregation effect of pollution. The FDI on carbon intensity is also discussed in this study.

China is facing increasing difficulty in attaining high urbanization levels and reducing CO<sub>2</sub> emissions. The influence of urbanization index on CO<sub>2</sub> emissions has been studied (Wang et al. 2019; Bai et al. 2019; Liu and Liu 2019). Therefore, this study used population urbanization as another control variable and discussed it in the follow-up study. In addition, because of the different order of magnitude of some



statistical variables, we transformed some of them to the logarithmic scale. In particular, the three variables of carbon intensity, i.e., urbanization, industrial structure, and energy consumption, were logarithmically treated. All processed variables’ statistical descriptions are presented in Table 1.

All data were gathered from Chinese Statistical Yearbook 2006–2018 (i.e., GDP, per capita income, urban population, total population, proportion of various industries, total foreign investment), Chinese Energy Statistical Yearbook (i.e., energy consumption and carbon emissions), and from literature (i.e., RET patents and ECERT patents).

It is well-known that China is a vast country; thus, the economic development and resource distribution among the provinces are imbalanced. Therefore, it is yet unknown whether the differences in carbon intensity and the spatial characteristics per province are significant. This study is premised on Tobler’s first law, which indicates that spatial data (i.e., locations) can interplay with each other depending on their proximity within the geographical space (Wang et al. 2018). Based on the above assumptions, the quartile map is used to investigate the spatial aggregation effect or diffusion effect of carbon intensity. As the following years can reflect the spatial aggregation effect of carbon intensity apparently, this section presents the carbon intensity quartiles maps in 2005, 2009, 2011, and 2014 (Figs. 1, 2, 3, and 4). The carbon intensity levels of every province in China were divided into four levels (excluding the provinces with no data). The first level represents the provinces with the highest carbon intensity, while the fourth level represents the provinces with the lowest carbon intensity. Based on the quartile maps of all the years, it can be seen that carbon intensities in neighboring provinces show similar trend. For example, the carbon intensities of Qinghai, Gansu, Shaanxi, Yunnan, Hebei, Liaoning, Heilongjiang, and Jilin always belong to the second level. That is to say, carbon intensity shows a strong spatial accumulation. This phenomenon may be caused by government policies. On the one hand, regional-coordinated development has become an important strategy of China. Many economic circles are built by neighboring provinces such as Beijing Tianjin Hebei capital

economic circle, Yangtze River Delta urban agglomeration, and Pearl River Delta urban agglomeration. Such strategy can break the geographical limitation and make resource sharing and optimization in a larger scope, which can help the provinces in the economic circle achieve coordinated development. At the same time, the flows of economic factors between provinces cause corresponding spillover effects of energy consumption and carbon emissions. On the other hand, there may be policy imitation between governments. If the policies of a region make the local economy develop rapidly, it will make the neighboring provinces imitate these policies, so that the carbon intensity of each province has a strong spatial correlation in the geographical space.

According to the quartile maps, we can only preliminarily judge that the carbon intensity has a certain aggregation effect on the geographical distribution. However, we need more scientific and accurate methods to explore whether carbon intensity really has a certain spatial correlation.

For further investigating the spatial agglomeration effect of carbon intensity, the global Moran’s I (Eq. 4) and the local Moran’s scatter diagrams were used to describe the correlation degree of all spatial units with the surrounding areas. Only when the spatial correlation of China’s provincial carbon intensity is verified by global Moran’s I and the local Moran’s scatter diagrams, the spatial econometric model can be used to explore the influencing factors of carbon intensity.

The formula for calculating the global Moran’s I is as follows:

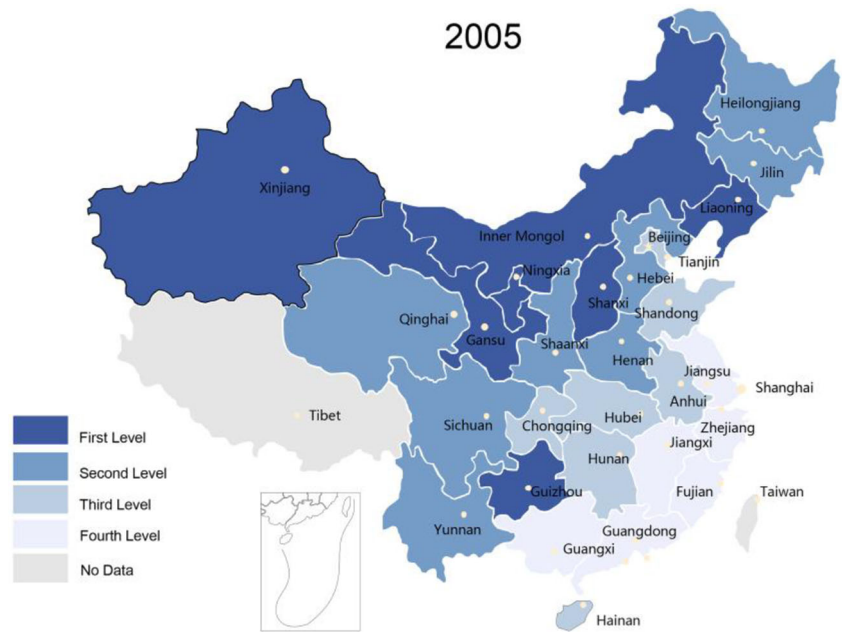
$$\text{Moran's I} = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (4)$$

where  $w_{ij}$  represents the corresponding spatial weight matrix’s elements.  $X_i$  represents the observation value of

**Table 1** Statistical descriptions of variables

Variables	Mean	Std. dev	Min	Max	Skewness	Kurtosis
lnCI	1.2921	0.5068	0.3721	2.5704	0.0001	0.0038
PCI	1.2481	0.6699	0.3563	4.2926	0.0000	0.0000
lnUR	− 0.6710	0.2483	− 1.3154	− 0.1097	0.0761	0.7339
lnIS	5.4423	0.0531	5.3337	5.6355	0.0000	0.0000
lnEC	5.6862	0.4501	4.5981	6.8580	0.3685	0.1540
FDI	7.3164	12.0514	0.0473	118.9802	0.0000	0.0000
RET	40.2651	44.0880	1.5876	184.9057	0.0000	0.0008
ECERT	50.0701	56.4083	1.4688	235.8317	0.0000	0.0000
LnEC*RET	226.4777	250.8651	7.9470	979.8145	0.0000	0.0022

**Fig. 1** The quartile maps of China’s carbon intensity in 2005

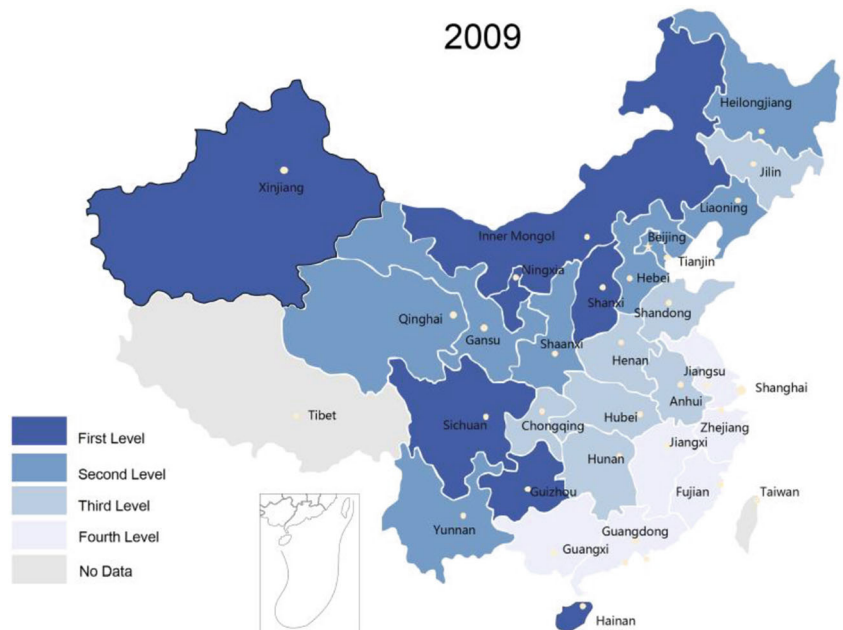


the province  $i$ , and  $\bar{X}$  represents the average value of carbon intensity. The positive Moran’s  $I$  imply that there is a positive spatial aggregation effect in the carbon intensity, while the negative means the opposite. The global Moran’s  $I$  values for carbon intensity are not significant at 10% confidence level except for 2017, 2016, and 2015 (Table 2). In other years, the global Moran’s  $I$  values are significant at 10% confidence level. It is apparent that China’s carbon intensity has positive agglomeration, indicating that the provinces with high-carbon intensity (HCI) are enclosed by HCI provinces. Similarly, the provinces with low-

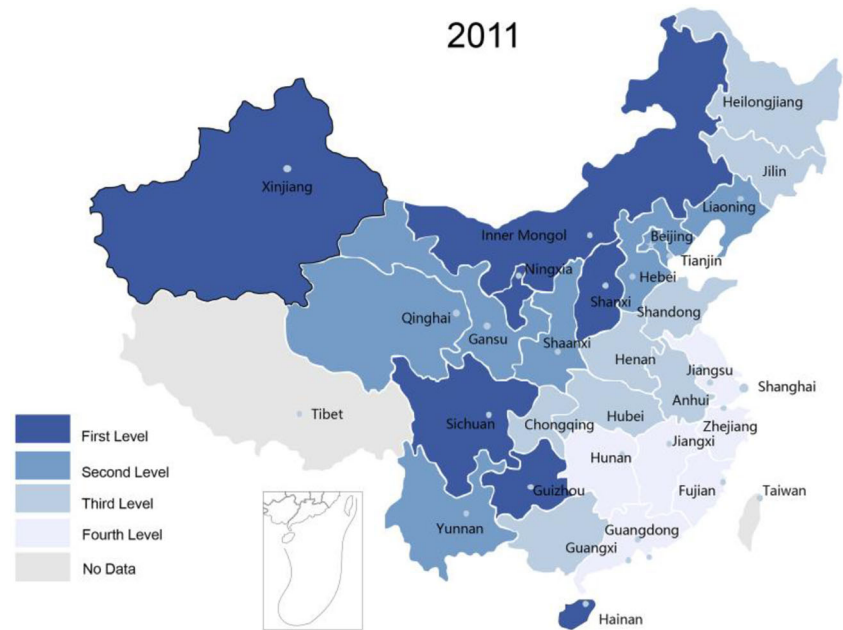
carbon intensity (LCI) are enclosed by LCI provinces. However, global Moran’s  $I$  test has limitations in determining the spatial correlation of carbon intensity at a provincial level. One of the limitations is that it is not specific to each province, i.e., it seeks the average spatial correlation. For example, considering two provinces, i.e., one with a negative global Moran’s  $I$  value and another with a positive value, will result in a zero global Moran’s  $I$  value. This may consequently lead to biased conclusions.

The local Moran’s  $I$  test was performed to test and verify further the correctness of global Moran’s  $I$  results and

**Fig. 2** The quartile maps of China’s carbon intensity in 2009



**Fig. 3** The quartile maps of China's carbon intensity in 2011



subsequent deductions for the years 2005, 2009, 2011, and 2014, respectively. The results are presented using local Moran's I scatter diagrams (Fig. 5)<sup>1</sup>. The results in the alpha and gamma quadrants (Fig. 5) indicate the clustering of high-high and low-low, respectively. Thus, these results imply that the HCI (LCI) provinces are enclosed by corresponding HCI (LCI) provinces. Contrarily, the beta and delta quadrants indicate clustering of low-high and high-low, respectively, therefore, implying that the LCI (HCI) provinces are enclosed by HCI (LCI) provinces, respectively (Wang et al. 2018). A stable spatial aggregation of the carbon intensity in provinces can be deduced from the unchanging number in all the quadrants (Fig. 5). In comparison, the local Moran's I scatter diagrams (Fig. 5) are better in representing the spatial aggregation features of carbon intensity than the quartered maps (Figs. 1, 2, 3, and 4).

## Methodology

### Spatial econometric model

“First law of geography” (Tobler 1970) suggested that everything is correlative to other things, but things that are close are more closely interrelated. With the development of Information System of Geographic (GIS), there is also increasing spatially referenced data. In academic research,

<sup>1</sup> Numbers 1–30 in Fig. 5 respectively represent Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

people effect, neighborhood effect, spillover effect, and network effect need to consider the space effect (Krugman 1991). Increasingly, a number of researchers begin to focus on the spatial correlation of the data (i.e., spatial effect) in recent years, which is limited in mining the geographic information in the data, and cannot guarantee unbiased estimation results. Therefore, we adopted the spatial econometric model in this study to determine the impacts of two types of energy technology patent on carbon intensity.

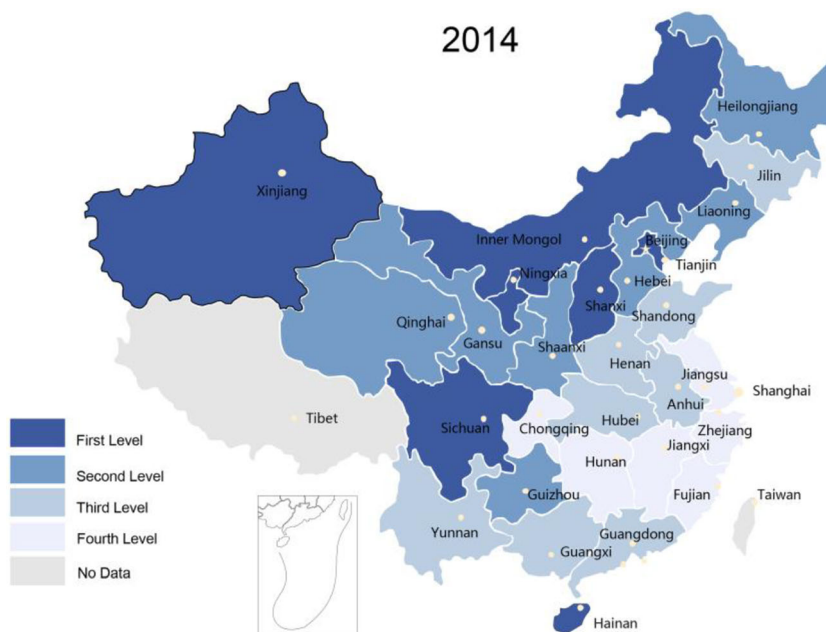
The spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM) are the most widely used spatial econometric models (Elhorst 2012). The main distinction between SLM and SEM is the way in which the spatial correlation is adopted in the regression function. The function of SLM is the following:

$$y_{it} = \rho \sum_{j=1}^N w_{ij} y_{jt} + X_{it} \beta + \mu_i + \varepsilon_{it} \quad (5)$$

where  $y_{it}$  denotes the carbon intensity of province  $i$  at time  $t$ .  $\rho$  represents the spatial regression coefficient, which signifies the effect of the carbon intensity of neighboring provinces on the local province.  $X_{it}$  is a weight matrix of the explanatory variables, including per capita income, urbanization level, industrial structure, energy consumption, foreign direct investment, RET patents, ECERT patents, and the interaction item between energy consumption and RET patents.  $w_{ij}$  denotes a fundamental element in the spatial weight matrix.  $\varepsilon_{it}$  is the error term; we assumed that it is identically distributed and independent with a mean of 0 and a variance of  $\sigma^2$ .

Contrarily, the SEM (Eq. 6) considers the interaction effect between error terms.

**Fig. 4** The quartile map of China’s carbon intensity in 2014



$$y_{it} = X_{it}\beta + \mu_i + \varphi_{it}$$

$$\varphi_{it} = \lambda \sum_{j=1}^N w_{ij}\varphi_{jt} + \varepsilon_{it} \tag{6}$$

$\varphi$  denotes the spatial autocorrelation error term, while  $\lambda$  is the error term’s spatial autocorrelation coefficient. Other terms have already been defined in Eq. 5. The cardinal distinction between  $\lambda$  and  $\rho$  is the way that spatial correlation is adopted in the regression function. LeSage and Pace (2009) advised that SEM and SLM models can be combined into a more comprehensive spatial Durbin model (SDM) (Eq. 7) to overcome limitations in SEM and SLM.

$$y_{it} = \rho \sum_{j=1}^N w_{ij}y_{jt} + X_{it}\beta + \mu_i + \sum_{j=1}^N w_{ij}X_{jt}\gamma + \varepsilon_{it} \tag{7}$$

$\gamma$  is the vector of spatial autocorrelation coefficient, and other terms have already been defined in Eqs. 5 and 6 above.

Later, in the “Results” section, LR test and Wald test will be adopted to determine the most suitable method (SDM) for our study.

**Spatial weight matrix**

It is necessary to construct an appropriate spatial weight matrix for the spatial econometric model to measure the spatial relationship of studied units. Therefore, following Anselin (2013), there are three kinds of spatial weight matrix, i.e., spatial distance, economic distance, and spatial adjacency weight matrices were applied in this study.

The spatial adjacency weight matrix is the spatial weight matrix that is most widely used. The value of  $w_{ij}$  in the matrix

is either 1 or 0. If region  $i$  and region  $j$  are contiguous on map, that is, the same boundary, then  $w_{ij} = 1$ ; otherwise,  $w_{ij} = 0$ . The adjacent relationships may take one of three kinds, i.e., (1) Rook contiguity occurs when two adjacent areas have the same edge. (2) Bishop contiguity occurs when two adjacent regions have the same vertex, but no common edge. (3) Queen contiguity occurs when two adjacent areas have the same vertex or edge. This study used the queen continuity to calculate the geographic accessibility matrix.

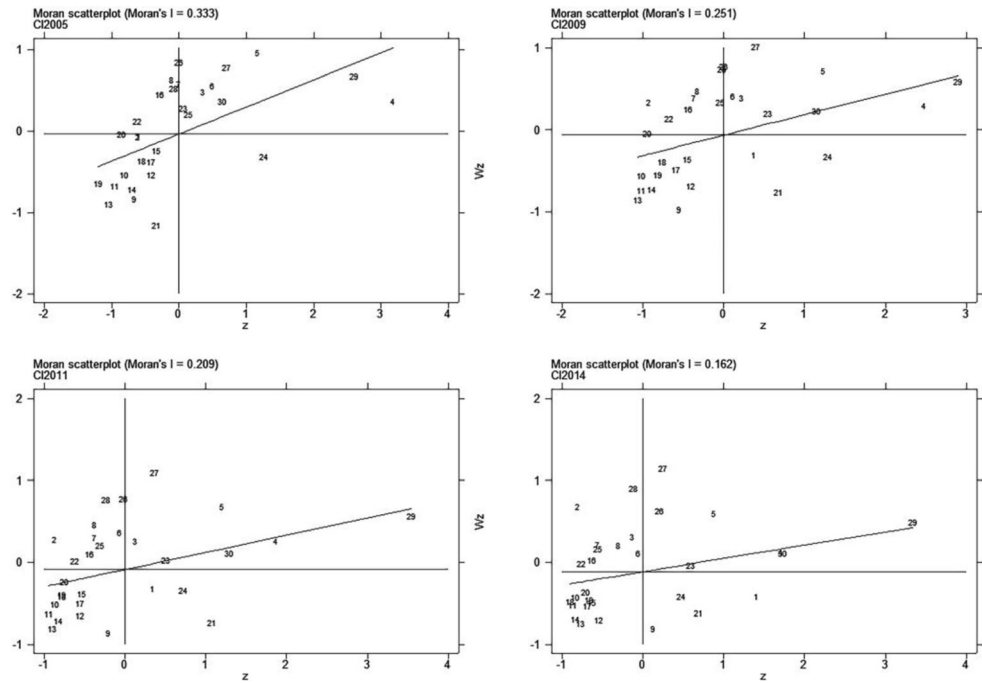
The spatial distance weight matrix is obtained by considering the distance in geographical space. Specifically, if the linear distance from the capital of the province  $i$  to the capital of the province  $j$  is greater than the set threshold value in this

**Table 2** Global Moran’s I test and significance test

Year	Moran’s I	Z value	p value
2017	0.038	0.612	0.270
2016	0.047	0.689	0.246
2015	0.08	0.968	0.167
2014	0.162	1.693	0.045
2013	0.201	2.06	0.020
2012	0.199	2.048	0.020
2011	0.209	2.144	0.016
2010	0.227	2.222	0.013
2009	0.251	2.399	0.008
2008	0.293	2.749	0.003
2007	0.295	2.795	0.003
2006	0.375	3.478	0.000
2005	0.333	3.181	0.001



**Fig. 5** Local Moran’s I scatter diagrams of China’s carbon intensity



study, then  $w_{ij} = 1$ , and otherwise  $w_{ij} = 0$  (Maddison 2006). In order to ensure that each province has at least one neighboring province in the matrix, we chose a threshold of 1439 km, i.e., the distance between Urumqi and Xining (Hao et al. 2016).

The calculation of the economic distance weight matrix (Eq. 8) is constructed according to the economic development gap between provinces and it is normalized (Wang et al. 2018).

$$w_{ij} = \frac{1/|\overline{\text{GDP}}_i - \overline{\text{GDP}}_j|}{\sum_{j=1}^N 1/|\overline{\text{GDP}}_i - \overline{\text{GDP}}_j|} \quad (8)$$

where  $\overline{\text{GDP}}_i$  refers to the average actual gross domestic product of province  $i$  from 2005 to 2017.

We adopted the geographical adjacency matrix as the spatial weight matrix in result estimation part of this study. Moreover, the robustness test used economic distance weight matrix and spatial distance weight matrix.

### Results

The Wald test was for selecting the appropriate spatial measurement model. The results of the test rejected the null hypothesis that SDM could be simplified as SEM (Wald test: 107.21,  $p = 0.0000$ ). Then, the results of LR test also rejected the null hypothesis that SDM could be simplified as SLM (LR test: 69.46,  $p = 0.0000$ ). Therefore, SDM was considered the final estimation model. The specific form of SDM in this study is indicated in Eq. 9.

$$\ln \text{CI}_{it} = \alpha + \rho \sum_{j=1}^N w_{ij} \ln \text{CI}_{jt} + [\text{PCI}_{it}, \ln \text{UR}_{it}, \ln \text{IS}_{it}, \ln \text{EC}_{it}, \text{FDI}_{it}, \text{RET}_{it}, \text{ECERT}_{it}, \ln \text{EC} * \text{RET}_{it}] \beta + \mu_i + \sum_{j=1}^{30} w_{ij} [\text{PCI}_{it}, \ln \text{UR}_{it}, \ln \text{IS}_{it}, \ln \text{EC}_{it}, \text{FDI}_{it}, \text{RET}_{it}, \text{ECERT}_{it}, \ln \text{EC} * \text{RET}_{it}] \gamma + \theta_t + \varepsilon_{it} \quad (9)$$

Finally, the fixed effect and random effect of the SDM were estimated. The results (Table 3) of the random effect and fixed effect models are mostly similar. We used the Hausman test to determine whether this study should accept the results of the models of the above two effects. The results mean that the random effect model could be acceptable.

Table 3 describes the estimation results of SDM under two effects in each province of China. It is notable that  $\rho$  is significant at 5% and 10%, respectively. This implies that there is a spatial correlation in the panel data. The results demonstrate that the carbon intensity of a province will rise with the rising carbon intensity of its neighboring province. The coefficients of  $W * \text{PCI}$ ,  $W * \ln \text{EC}$ ,  $W * \text{RET}$ ,  $W * \text{ECERT}$ , and  $W * \ln \text{EC} * \text{RET}$  are significant, thus indicating that the per capita income, energy consumption, RET patents, ECERT patents, and the interaction item of energy consumption and RET patents in local provinces can certainly influence the carbon intensity of neighboring provinces.

Notably, the estimation coefficients of the explanatory variables could not be directly explained. This is due to the existence of the feedback effect which is transmitted back to the province itself through the neighboring provinces. The feedback effect includes not only the influence of the spatial lag dependent variable but also the influence of the spatial lag value from the explanatory variable (Zhao et al. 2014). For

**Table 3** Results of random effect and fixed effect models

	Spatial fixed effect model		Spatial random effect model	
	Coefficients	<i>t</i> values	Coefficients	<i>t</i> values
$\rho$	0.1690**	2.74	0.2090*	3.73
PCI (per capital income)	0.596***	9.00	0.612***	9.90
lnUR (urbanization level)	-0.869***	-4.02	-0.964***	-4.92
lnIS (industrial structure)	-0.0143	-0.03	0.129	0.24
lnEC (energy consumption)	0.353***	3.97	0.359***	4.17
FDI (foreign direct investment)	0.00383*	2.37	0.00453**	2.84
RET (RET patent)	0.0185*	2.05	-0.0174**	3.78
ECERT (ECERT patent)	-0.0174**	-3.16	-0.00576***	-4.12
LnEC*RET	-0.00504***	-4.42	-0.00465***	-3.93
W*PCI	-0.604***	-6.94	-0.648***	-7.88
W*lnUR	0.277	0.80	0.228	0.71
W*lnIS	-1.325	-1.60	-1.152	-1.36
W*lnEC	-0.302*	-2.25	-0.228	-1.68
W*FDI	0.000452	0.26	0.00252	1.55
W*RET	-0.0509***	-4.28	-0.0301**	-3.16
W*ECERT	-0.0207*	-2.02	0.00336*	2.03
W*lnEC*RET	0.00420**	2.74	0.00463**	3.00
R-sq	0.5883		0.3222	
Hausman test	6.89 ( $p = 0.5528$ )			

\*\*\*, \*\*, and \* imply 1%, 5%, and 10% level of significance, respectively

instance, if the direct effect of PCI is 0.577 and coefficient of it is 0.596, then -0.019 is the feedback effect of PCI. To analyze and discuss the impact of each influencing variable further, we explored the three effects of each of the variables according to LeSage and Pace (2010).

The direct, indirect, and total effects are presented in Table 4. The direct effects of PCI, lnEC, and FDI are significant, with coefficients of 0.577, 0.344, and 0.00387, respectively. The results indicate that per capita income has the

strongest positive direct effect on carbon intensity, followed by foreign direct investment and energy consumption. This finding is in accordance with the fact that high income, high energy consumption, and high investment will bring about a rise of carbon intensity. And the direct effect of lnUR is significant, with a coefficient of -0.871, thus implying that urbanization decreases the carbon intensity. This finding is inconsistent with the popular belief that the level of urbanization is higher, the faster the economic development, and thus the

**Table 4** Three effects of spatial fixed effect model

	Direct effects		Indirect effects		Total effects	
	Coefficients	<i>t</i> value	Coefficients	<i>t</i> value	Coefficients	<i>t</i> value
PCI (per capital income)	0.577***	8.79	-0.582***	-6.40	-0.00477	-0.07
lnUR (urbanization level)	-0.871***	-4.35	0.151	0.41	-0.719*	-2.39
lnIS (industrial structure)	-0.0170	-0.03	-1.658	-1.84	-1.675	-1.71
lnEC (energy consumption)	0.344***	4.04	-0.278	-1.89	0.0658	0.50
FDI (foreign direct investment)	0.00387*	2.43	0.00123	0.56	0.00511	1.75
RET (RET patent)	0.0168	1.91	-0.0545***	-3.75	-0.0377*	-2.07
ECERT (ECERT patent)	-0.0184**	-3.20	-0.0276*	-2.23	-0.0460**	-2.81
LnEC*RET	-0.00496***	-4.16	0.00372*	2.06	-0.00124	-0.60

\*\*\*, \*\*, and \* imply 1%, 5%, and 10% level of significance, respectively

higher the carbon intensity. As suggested by Liu and Liu (2019), this could have been because the traditional energy consumption in the rural districts is being upgraded with new energy technology and energy use efficiency in basic facilities. Particularly, the direct effect of ECERT is significantly negative, with a coefficient of  $-0.0184$ , indicating that the technological progress, brought by the increase in ECERT patents, will bring about the decline of the local province's carbon intensity. In addition, by comparing the direct effects of ECERT patents in three spatial weight matrices, we found that the direct effect of ECERT patents in spatial adjacency weight matrix is the largest and significantly negative. That is to say, it is among neighboring provinces where ECERT patents have the most significant spillover effect, which can provide inspirations for Chinese government. By accelerating the propagation and application of technical patents among neighboring provinces, regional integration policy can not only promote the coordinated economic development but also help to achieve coordinated energy conservation and emission reduction. Notably, the direct effect of the interaction item between  $\ln EC$  and  $RET$  is  $-0.00496$ , possibly due to the rise of the number of  $RET$  patents bring about the rise of the consumption of renewable energy. Hence, the consumption of fossil energy may relatively decrease, resulting in the reduction in carbon intensity in local provinces. In other words, the  $RET$  patents can restrain carbon intensity by optimizing the energy consumption structure.

Interesting results emerged from the indirect effects. The spillover effect of  $PCI$  is  $-0.582$ . An interpretation of this coefficient is that the growth of per capita income in other provinces will bring about the descent of carbon intensity. The possible reason is that provinces with rapid economic development will attract more investment or population, thus resulting in more energy consumption. Therefore, for provinces with low per capita income, the intensity of carbon emissions will be reduced due to the spillover effect of the economic factors. A similar result was found with the  $RET$  patents and  $ECERT$  patents. The spillover effects of  $RET$  and  $ECERT$  are  $-0.0545$  and  $-0.0276$ . This discovery shows the rise of  $RET$  patents and  $ECERT$  patents in the neighboring provinces will result in the declining carbon intensity for the local province. The deductions could be made from the results, i.e., two types of technological progress can contain the carbon intensity from increasing. At the same time, by observing the spillover effects of  $RET$  patent and  $ECERT$  patent in the three spatial weight matrices, it could be clearly observed that the spillover effects of  $RET$  and  $ECERT$  are all significantly negative. This verifies the robustness of conclusion that  $RET$  patents and  $ECERT$  patents can reduce the carbon intensity of surrounding provinces. Meanwhile, it can be seen that the above two kinds of technology patents can spread among provinces on the basis of transcending the spatial adjacency weight matrix. It is not difficult to find that the

spillover effects and total effects of  $RET$  patents and  $ECERT$  patents in the spatial adjacency weight matrix are strongest and significantly negative. This implies that compared with the geographical distance and economic distance between provinces, only in the spatial adjacency weight matrix,  $RET$  patents and  $ECERT$  patents can exert the strongest inhibition on carbon intensity. Therefore, when using  $RET$  patents and  $ECERT$  patents to reduce provincial or regional carbon intensity, we should consider the adjacency of each province. It is noteworthy that the spillover effect of  $\ln EC * RET$  is  $0.00372$ , which is statistically significant. The potential reason for this finding is that the rise of  $RET$  patents' number in local provinces results in the demand and consumption of the renewable energy increase rapidly, thus leading to the price of renewable energy ascent. As a result, other provinces will be more inclined to consume fossil energy, eventually leading to the rise of the carbon intensity of such (neighboring) provinces. Therefore, the fluidity of energy technology patents among provinces should be strengthened to avoid the above situation. As shown in Table 4, the spillover effect and direct effect of  $PCI$  are very close, and the negative spillover effect is slightly higher than the positive direct effect. So, we can conclude that  $PCI$  has a small negative effect on the carbon intensity of such a region in the local province and its neighboring provinces. This conclusion follows the fact that the decrease of carbon intensity is not only unrelated the economic expansion scale of the local provinces, but also has a relation with the economic expansion scale of the surrounding provinces.

Similarly, in both the local and neighboring regions, the level of urbanization has a strong negative effect on the carbon intensity. At the same time, the results in Table 4 subtly indicate that the total effects of  $RET$  patents and  $ECERT$  patents are mainly owing to their spillover effects. Table 4 also indicates that the spillover effect of technology has an essential role in the mechanism of the influence of technological progress on carbon intensity. Compared with the coefficient of direct effects, the indirect effects of all variables (except for the interaction item of energy consumption and  $RET$  patents) are relatively large.

The results above show that the increases of carbon intensity in China are fundamentally owing to the rise in energy consumption and per capita income. The main factors explaining the decrease in carbon intensity are the increase in urbanization level and the development of technological progress measured by  $RET$  patents and  $ECERT$  patents.

## Robustness check

Instead of geographical adjacency matrix, we adopted economic distance weight matrix and spatial distance weight matrix, to examine the robustness of the estimation results. The model estimation results on the basis of two kinds of spatial

weight matrices mentioned above are presented in Table 5. Tables 6 and 7 show the direct, indirect, and total effects based on the above two spatial weight matrices, respectively. Due to space limitation, Table 5, Table 6, and Table 7 are included in the Appendix.

The results in the Appendix indicate that the three key core explanatory variables, i.e.,  $W*RET$ ,  $W*ECERT$ , and  $W*\ln EC*RET$ , have significant coefficients and consistent signs. Furthermore, on the basis of the spatial distance weight matrix, regression results (Tables 6 and 7) demonstrate that the other three types of effects are significant, except the direct effect of ECERT. Some differences in the signs of some of the variables are also due to the rebound effect. In the estimation results based on the economic distance weight matrix,  $\rho$  is not significant, but its core explanatory variables are significant. This phenomenon is not difficult to understand; with the popularity of the Internet and economic development, energy technology-related patents not only are rapidly transferred from the local to neighboring provinces but also are easy to transfer within provinces that have similar economic distances. Generally, the robustness check did not affect the analysis of the “Results” section and the subsequent conclusions and recommendations. Therefore, our analyses of the “Results” section on the influence of various variables on carbon intensity are robust.

## Conclusions and policy proposal

This study investigated the influence of energy technological progress represented by energy conservation and emission reduction technology patents and renewable energy technology patents on carbon intensity using the panel dataset, from 2005 to 2017, of China’s provinces. The SDM model was used to make the estimation results of the spatial aggregation effect and technology diffusion effect of carbon intensity more precise and unbiased. Finally, through the robustness test, we verified whether the main conclusions of this study were robust. The main conclusions are the following:

- (1). From the quartile maps of carbon intensity at the provincial level, we can conclude that the provincial carbon intensity has a stable spatial aggregation effect, which is similar to Wang et al. (2018). However, the above literature mainly studies the spatial spillover effect of total carbon emissions rather than carbon intensity.
- (2). The total effect and spillover effect of renewable energy technology patents are negative at a significance level of 1%, and the results are robust. This finding means that the publication and application of renewable energy technology patents can be an economical and effective

way for China to realize the emission reduction targets that it committed to before the international community and enable the implementation of its low-carbon development strategy.

- (3). The three effects of energy conservation and emission reduction technology patents are significantly negative. In the spatial adjacency weight matrix, the technological progress, represented by the energy conservation and emission reduction technology patents, has a strongly confined impact on the carbon intensity of relevant regions. Similar results were found using the spatial distance weight matrix and economic distance weight matrix. Moreover, the total effect of energy conservation and emission reduction technology patents is stronger than that of renewable energy technology patents.
- (4). The positive indirect effect and negative direct effect of the interaction item between energy consumption and renewable energy technology patents reflect that the renewable energy technology patents can optimize the energy consumption structure of China. Although it can promote the carbon intensity of the surrounding provinces, it can restrain local province’s carbon intensity. Gu et al. (2019) added the interaction item of energy technology progress and energy consumption in their research to study the rebound effect of energy technology progress. However, the optimization effect of technology patents on energy consumption structure was not discussed in Gu et al. (2019). In contrast, this paper makes more optimization in the conclusion.
- (5). It is worth mentioning that the direct effect and spillover effect of PCI are significantly obvious, which shows that the level of economic development plays a very important and even decisive role in the carbon intensity of a province. Just from the positive and negative of its direct effect and spillover effect value, we could know that higher income may cause more consumption from residents, leading to a higher carbon intensity. This conclusion is contrary to the conclusion of Liu et al. (2019) which believed that the higher the per capita income is, the stronger the environmental awareness of residents will be so it can effectively inhibit the emission of pollutants. Obviously, different research entry points will lead to inconsistent conclusions, but all of them are reasonable.

Overall, strengthening the development of renewable energy technology patents and ECERT patents can contribute to achieving Chinese low-carbon development strategy and the realization of international emission reduction commitments. Some relevant specific policy proposals are as follows:



- (1). Strengthening regional cooperation. Because the carbon intensity has a strong aggregation effect in the geographical space, each province should strengthen the cooperation of regional carbon emission reduction to effectively reduce the level of carbon intensity in China. There are many ways of regional cooperation among provinces; for example, sharing technology patents is a very typical and effective way. For example, Beijing has moved a large number of enterprises and factories that consume too much energy to Hebei Province, which will undoubtedly increase the burden of carbon emission reduction in Hebei Province. However, as an area with developed technology, Beijing can share the patented technology with Hebei Province, which can accelerate the economic restructuring of Hebei Province, and at the same time promote the carbon emission reduction in Hebei Province.
- (2). Encourage public innovation and the publication of energy technology patents. For improving the environment for mass innovation, corresponding laws and regulations could be designed and issued. Universities and research institutes should try to speed up the construction of public innovation support platform and innovative education system. The state could increase the awards for patent application and simplify the patent application process.
- (3). Pay more attention to the coordinated development of urban and rural urbanization. For relatively developed urban areas, green and low-carbon development is regarded as an important driving force for economic transformation and upgrading under the new normal. The government should lead the industrial structure to the middle and high end, cultivate and develop new economic power, and take cultural tourism, new energy vehicles, artificial intelligence, and other emerging industries as the main development direction. In rural areas where the levels of economic development and fundamental facilities are relatively backward, while speeding up the process of urbanization, we need to uphold the idea of sustainable development, vigorously develop ecological agriculture, and effectively control greenhouse gas emissions from rural life and agriculture.
- (4). Focus on the application of renewable energy technology patents. The energy conservation and emission reduction technology patents have many applications at the micro and macro level, while at present, renewable energy technology patents may not be as good as energy conservation and emission reduction technology patents. Because fossil energy is still the main component of the Chinese energy structure, the improvement of energy saving and emission reduction technology will contribute to reduce carbon intensity in the short run. Nevertheless, in the long run, considering the low-carbon development mode and energy security issues, renewable energy is a crucial energy structure in China, and the indirect effect of renewable energy technology patents on carbon intensity is higher than that of energy conservation and emission reduction technology patents. Therefore, in terms of the patent application, the government should give priority to the renewable energy technology patent applications in terms of actual effect and expected effect. Increasing investment in technological patent innovation will be beneficial to China's carbon emission reduction cause.
- (5). Accelerate the transformation of national economy and promote the upgrading of residents' consumption. China's economy is changing from a high-speed development stage to a high-quality development stage. This strategy means that China's economy has ushered in a critical period of development relying on high energy consumption. In such a critical period, the transformation of national economy is imminent, and the consumption of residents accounts for a large proportion. At present, housing and transportation have become the main areas of residents' life style changes, and the change of life style is rigid, which leads to the rigid dependence of construction and transportation on energy. Therefore, reducing the price of cars and houses, lower transportation costs, and other measures can effectively promote the consumption upgrading of residents to achieve carbon emission reduction.

In fact, different provinces in China should adopt different policies according to the development laws of different provinces, ensuring that the development of technological progress is coordinated with the rise of the economy and energy consumption. This study discussed the impacts of different kinds of energy technology progress on carbon intensity; however, some aspects need further study owing to the missing data that may have impacted the estimation results. For example, with all the data of Macao, Hong Kong, Tibet, and Taiwan, further improvement in the data could improve the estimated results.

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### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

## Appendix

**Table 5** Results of spatial Durbin models using different matrices

	Geographic		Economic	
	Coefficients	t values	Coefficients	t values
$\rho$	-0.264*	-1.84	0.0708	0.73
PCI	0.427***	7.36	0.597***	9.18
lnUR	-0.692***	-4.36	-0.846***	-5.02
lnIS	0.0584	0.12	0.651	1.26
lnEC	0.553***	7.02	0.695***	8.43
FDI	0.00339*	2.19	0.00428**	2.75
RET	0.00961***	3.74	0.0104***	4.08
ECERT	0.00214	1.22	0.00452*	2.32
LnEC*RET	-0.00324***	-5.72	-0.00364***	-6.13
W*PCI	-0.0536	-0.31	-0.349**	-2.70
W*lnUR	-0.764	-1.09	-0.651	-1.33
W*lnIS	-3.205*	-2.45	-1.894	-1.88
W*lnEC	-0.607***	-3.51	-0.555**	-3.26
W*FDI	-0.00320	-0.69	0.00122	0.18
W*RET	-0.0268***	-4.93	-0.0310***	-5.22
W*ECERT	-0.0100**	-2.62	-0.0116**	-2.81
W*lnEC*RET	0.00546***	5.39	0.00729***	6.51
R-sq	0.6073		0.6018	

\*\*\*, \*\*, and \* imply 1%, 5%, and 10% level of significance, respectively

**Table 6** Three effects based on the spatial distance weight matrix

	Direct effects		Indirect effects		Total effects	
	Coefficients	t value	Coefficients	t value	Coefficients	t value
PCI	0.432***	7.22	-0.125	-0.94	0.307*	2.24
lnUR	-0.686***	-4.35	-0.500	0.91	-1.186*	-2.38
lnIS	0.171	-0.35	-2.706**	-2.61	-2.536**	-2.59
lnEC	0.568***	7.31	-0.613***	-4.45	-0.0442	-0.38
FDI	0.00345*	2.30	-0.00310	-0.81	0.000349	0.09
RET	0.0102***	3.86	-0.0238***	-5.31	-0.0136***	-3.72
ECERT	0.00232	1.31	-0.00846**	-2.58	-0.00614*	-2.34
LnEC*RET	-0.00337***	-6.16	0.00516***	5.91	0.00179**	-2.64

\*\*\*, \*\*, and \* imply 1%, 5%, and 10% level of significance, respectively

**Table 7** Three effects based on the economic distance weight matrix

	Direct effects		Indirect effects		Total effects	
	Coefficients	t value	Coefficients	t value	Coefficients	t value
PCI	0.598***	8.98	-0.329*	-2.21	0.269*	2.19
lnUR	-0.859***	-5.31	-0.731	-1.42	-1.591**	-3.17
lnIS	0.691	1.41	-2.066*	-2.01	-1.375	-1.29
lnEC	0.692***	8.57	-0.553**	-3.24	0.139	0.81
FDI	0.00429**	2.84	0.00166	0.23	0.00595	0.78
RET	0.0102***	4.05	-0.0325***	-5.24	-0.0223***	-3.81
ECERT	0.00440*	2.26	-0.0119**	-2.71	-0.00754*	-2.12
LnEC*RET	-0.00359***	-6.42	0.00759***	6.58	0.00400***	3.93

\*\*\*, \*\*, and \* imply 1%, 5%, and 10% level of significance, respectively

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