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Evaluating the Effects of Renewable Energy Consumption on Carbon Emissions of China's Provinces: Based on Spatial Durbin Model

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Abstract: Renewable energy consumption is considered as the main form of energy consumption in the future. The carbon emissions produced by renewable energy can be approximately ignored, and renewable energy is essential for regional sustainable development. In this study, we used the Durbin model with panel data to explore the spatial dependence between renewable energy consumption the and carbon emissions of China's 30 provinces from 1997 to 2017. The results show that: (1) there is a negative spatial correlation between renewable energy consumption and carbon emissions, and "High-Low" areas are mainly concentrated in southern provinces in 1997–2011; (2) the center of gravity of renewable energy consumption moves southwest, which is consistent with the center of gravity of carbon emissions; (3) renewable energy consumption has a significant inhibitory effect on carbon emissions of a local region, but the spatial spillover effect is not significant. Specifically, a 1% increase in renewable energy consumption in a region will reduce carbon emissions by 0.05%. Finally, on the basis of this study, it was proposed to give full play to the advantages of renewable energy in the western region, and further accelerate the development of the renewable energy industry.

Keywords: renewable energy consumption; carbon emissions; spatial correlation; spatial Durbin model

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1. Introduction

The global warming caused by increasing carbon emissions has attracted widespread attention from the international community. Although the COVID-19 pandemic has slowed down global carbon dioxide concentration in 2020, the global temperature will still maintain an upward trend. How to reduce carbon emissions in order to achieve the goal of global temperature control is the current concern of the international community. On account of the vital status of the energy supply system, developing renewable energy has become an important way to deal with increasing energy demand and climate change. As a responsible developing country, China promised to increase its nationally determined contribution, strive to peak in its carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060[1]. To realize this goal, China proposed to build a clean, low-carbon, safe and efficient energy system. The system will control the total amount of fossil energy and improve the utilization of renewable energy to promote the reduction of carbon emissions[2]. In 2020, China's renewable energy development and utilization scale reached 680 million tons of standard coal, equivalent to replacing nearly 1 billion tons of coal [1]. Scientific analysis of the role of renewable energy in carbon emissions is of great significance for achieving carbon peaking and carbon neutrality.

In recent years, scholars have conducted much research on the influencing factors on carbon emissions at different scales by means of econometric models [2–5], structural decomposition methods [6–8], and geographic detectors [9,10]. Most viewpoints include four aspects: (1) economic development will promote the increase of carbon emissions [11],

(2) population size plays a positive role in promoting carbon emissions [12], (3) industrial structure [13,14] is the main factor leading to the growth of carbon emissions,(4) technological progress [15] and low-carbon innovation [16] can effectively reduce carbon emissions. In addition, R&D investment, population density and industrial agglomeration have also been proved to be influencing factors on carbon emissions [17–19]. Due to the short development time of renewable energy and the difficulty in availability of data, there is relatively little literature on the impact of renewable energy consumption on carbon emissions.

In terms of the relationship between renewable energy consumption and carbon emissions, scholars have found that renewable energy consumption has a negative impact on carbon emissions [20–23]. Chen [24] used the Auto-regressive Distributed Lag (ARDL) model to study the impact of renewable energy consumption on carbon emissions in China, and found that renewable energy consumption has a negative impact on carbon emissions, with a relatively significant long-term coefficient and insignificant short-term coefficient. Qiu [25] showed that renewable energy consumption has a significant impact on energy carbon emissions and there was a one-way causality between them. Some scholars believed that there was a two-way causal relationship between renewable energy consumption and carbon emissions [26–28]. Wang and Zhao [29] used the cointegration test, impulse response analysis and variance decomposition to analyze the dynamic relationship between renewable energy consumption, carbon emissions and economic growth in China from 1980 to 2009, and found that renewable energy consumption has a weak impact on carbon emissions.

In general, some researchers pay attention to the relationship between renewable energy consumption and carbon emissions, but most studies assume that each region is an island, and few or no studies have quantified the spatial effect of renewable energy consumption on carbon emissions. In fact, as the First Law of Geography states, everything is related to everything else, but near things are more related than distant things. Where China is concerned, regional carbon emissions have strong spatial and temporal attributes considering the obvious differences in regional development levels, which means that regional energy structure, urbanization level, economic development and technology spillovers all affect carbon emissions of adjacent regions. The purpose of this paper is to develop a spatial panel model to analyze the spatial spillover effect between China's 30 provinces for the period 1997–2017.

The remainder of this study proceeds as follows. Section 2 discusses the methods and data preparation. Section 3 describes spatial characteristics of renewable energy consumption and carbon emissions, and presents the results of the spatial econometric model. Section 4 provides a discussion, with Section 5 providing concluding remarks.

2. Methods and Data

2.1. Spatial Correlation Analysis

The Moran Index, 1948, is one of the most commonly used measures of spatial autocorrelation. The univariate global Moran index(I) was adopted here to measure the spatial autocorrelation of renewable energy consumption and carbon emissions. It is calculated by following formula [30,31]:

$$I = \frac{n\left[\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})\right]}{\left[\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})^2\right]} \tag{1}$$

where i and j represent the province, I represents the global Moran index, n represents the number of provinces, W_{ij} represents the spatial weight matrix, and x and $\overline{x}$ represent the variables and their mean values. Generally, the value of I ranges between -1 and 1. The value from 0 to 1 means a positive spatial correlation. Otherwise, the value from -1 to 0 means a negative spatial correlation. The value 0 means no spatial autocorrelation.

The bivariate global Moran index indicates the correlation of one variable of a spatial unit to another observed variable of an adjacent spatial unit. This paper used the bivariate global Moran index and the bivariate local Moran index to measure bivariate spatial correlation. The bivariate global spatial autocorrelation (Bivariate Moran's I, I_{kl}) is used to explore the spatial correlation characteristics of two variables, and its expression is [32]:

$$I_{kl} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_k^i - \overline{x}_l)(x_k^j - \overline{x}_l)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{2}$$

The expression for the bivariate local Moran index (I'_{kl}) is [33]:

$$I'_{kl} = \frac{x_k^i - \overline{x}_k}{S_k^2}\sum_{j=1}^{n} W_{ij}\frac{x_l^i - \overline{x}_l}{S_l^2} \tag{3}$$

where x_k^i represents the observed value of k variable on space unit i, x_l^j represent the observed value of l variable on spatial unit j, $\overline{x_k}$ and $\overline{x_l}$ represent the mean values of the observed values of the k and l variables, W_{ij} is the spatial weight matrix, and S_k^2 and S_l^2 represent the variances of the observed values of the k and l variables.

2.2. Standard Deviation Ellipse

The standard deviation ellipse can reflect the overall dominant distribution direction of spatial elements and the degree of dispersion in each direction [34], revealing the spatial distribution characteristics of the dispersion and direction. This study drew the standard deviation ellipse of carbon emissions and renewable energy consumption in China from 1997 to 2017, and analyzed the spatial pattern changes of these two according to their azimuth and standard deviation at the X/Y axis.

Azimuth tan ∝ can be calculated by following expression:

$$\tan\alpha = \frac{\sum_{i=1}^{n}\widetilde{m}_i^2 - \sum_{i=1}^{n}\widetilde{n}_i^2 + \sqrt{\left(\sum_{i=1}^{n}\widetilde{m}_i^2 - \sum_{i=1}^{n}\widetilde{n}_i^2\right)^2 + 4\left(\sum_{i=1}^{n}\widetilde{m}_i\widetilde{n}_i\right)^2}}{2\sum_{i=1}^{n}\widetilde{m}_i\widetilde{n}_i} \tag{4}$$

where m_i and n_i represent the horizontal and vertical coordinates of center of each province, $\widetilde{m}_i$ and $\widetilde{n}_i$ represent the deviations from the center coordinates of each province to the barycentric coordinates.

Standard deviation along the X axis (σ_x) and Y axis (σ_y) are calculated by the following expression:

$$\sigma_x = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}(\widetilde{m}_i\cos\alpha - \widetilde{n}_i\sin\alpha)^2}{n}} \tag{5}$$

$$\sigma_y = \sqrt{2}\sqrt{\frac{\sum_{i=1}^{n}(\widetilde{m}_i\sin\alpha + \widetilde{n}_i\cos\alpha)^2}{n}} \tag{6}$$

2.3. Center of Gravity Analysis

The center of gravity model is derived from the concept of center of gravity in physics; the forces in all directions around the center of gravity of the regional space are relatively balanced, which can reveal the degree of spatial equilibrium in the distribution of regional carbon emissions and renewable energy consumption. In order to detect the center of gravity and moving direction of China's carbon emissions and renewable energy consumption, the formulas are as follows [35]:

$$U = \frac{\sum_{i=1}^{n} x_i m_i}{\sum_{i=1}^{n} x_i} \tag{7}$$

$$v = \frac{\sum_{i=1}^{n} x_i n_i}{\sum_{i=1}^{n} x_i} \tag{8}$$

where U and V represent the longitude and latitude of the center of gravity of a certain attribute (per capita carbon emissions and per capita renewable energy consumption) in China, respectively; x_i represents the per capita carbon emissions and per capita renewable energy consumption of each province in China.

2.4. Spatial Econometric Model

The spatial Durbin model can test the influence of the explained variables affected by explanatory variables in local areas and neighboring areas [36,37]. Considering the spatial correlation of dependent and independent variables, this study employed spatial Durbin model to test the influence of renewable energy consumption on carbon emissions. This study takes explanatory variables in natural logarithm to solve the endogenous problem [38]. The model is described as in [39]:

$$\ln(Y_{it}) = \rho\sum_{j=1}^{n} W_{ij}\ln(Y_{it}) + \beta_1\ln(REC_{it}) + \beta_2\ln(X_{it}) + \theta_1\sum_{j=1}^{n} W_{ij}\ln(REC_{it}) + \theta_2\sum_{j=1}^{n} W_{ij}\ln(X_{it}) + \mu_i + \gamma_t + \varepsilon_{it} \quad (9)$$

where Y denotes the dependent variable, W_{ij} indicates spatial weight matrix, X_{it} refers generically to the explanatory variables in the model, $\theta_1\sum_{j=1}^{n} W_{ij}\ln(REC_{it})$ and $\theta_2\sum_{j=1}^{n} W_{ij}\ln(X_{it})$ denote the spatially lagged exogenous regressors. ρ denotes spatial autoregressive parameter representing the intensity of spatial autocorrelation. β denotes fixed unknown associated coefficients. θ_1 and θ_2 indicate the spatial impacts from explanatory variables in neighboring provinces. $\mu_i,\ \gamma_t$ *and* ϵ_{it} represent space effect, time effect and the theoretical disturbance, respectively.

To analyze the spatial correlation characteristics of renewable energy consumption and carbon emissions for a more comprehensive analysis, this paper established three spatial weight matrices based on the existing literature [40–42]:

$$Queen\ adjacency.W_1 = \begin{cases} W_{ij} = 1\ if\ province\ i\ and\ j\ are\ neighbors \\ W_{ij} = 0\ otherwise \end{cases} \quad (10)$$

$$Inverse\ distance.W_2 = \begin{cases} W_{ij} = \frac{1}{d_{ij}}\ if\ province\ i\ and\ j\ are\ neighbors \\ W_{ij} = 0\ otherwise \end{cases} \quad (11)$$

$$Economic\ distance.W_3 = \begin{cases} W_{ij} = 0\ i = j \\ W_{ij} = \frac{1}{|GDP_i - GDP_j|}\ i \neq j \end{cases} \quad (12)$$

where d_{ij} represents the distance between the centroids of provinces i and j, GDP_i represents the GDP per capital of spatial unit i in 2017.

2.5. Index Selection and Data Source

Due to the lack of data from Tibet, Hong Kong, Macao and Taiwan, 30 provinces and autonomous regions in China are adopted as the research objects. The research period is 1997–2017 due to data limitations on renewable energy consumption. Description of the variables are shown in Table 1.

Table 1. Description of variables.

Variables	Abbreviation	Unit	Mean	Min	Max
carbon emissions	*C*	ton	6.281	0.130	42.540
economic growth	*GDP*	yuan	20,006.771	2107.815	93,123.248
energy intensity	*EI*	10^4 tons of standard coal/10^4 yuan	1.382	0.253	5.147
renewable energy consumption	*REC*	tons of standard coal	2.267	0.002	3.548
technological progress	*PT*	pieces	8305.171	5	199,293

(1) **Dependent variable**. Carbon emissions per capita (C), which is calculated by total emissions and population. Provincial total carbon emissions are from the CEAD database (https://www.ceads.net/, accessed on 1 June 2022) and population from the provincial statistical yearbooks.

(2) **Independent variable**. Renewable energy consumption per capita (REC); renewable energy does not emit greenhouse gases. The development of renewable energy (water, wind, light, biomass, etc.) is the main way to deal with climate change and achieve sustainable development. Renewable energy consumption data come from the Energy Economics Data Platform (http://inems2.bit.edu.cn/Home/Menu, accessed on 1 June 2022).

(3) **Control variables**. We set economic growth, quadratic economic growth, energy intensity, and technological progress as control variables. Economic growth is described by per capita *GDP* of each province. Quadratic economic growth is added to verify the EKC curve. Energy intensity is calculated by energy consumption divided by *GDP*, which means the higher the energy intensity, the more energy contained in economic activities. Since technological progress has positive effects on improving production processes and energy utilization efficiency, this study employed the number of patents as the indicator of technological progress. Previous studies found R&D investment would overestimate the actual level of technological progress [16]. Provincial *GDP* is from the statistical yearbooks and treated at a constant price of 1990. Energy consumption and patents are from the China Energy Statistical Yearbook and China Science and Technology Statistical Yearbook, respectively.

3. Result

3.1. Spatial Characteristics of Renewable Energy Consumption and Carbon Emissions

3.1.1. Univariate Spatial Autocorrelation Analysis

To test the spatial autocorrelation before constructing the spatial Durbin model, we firstly examine the spatial dependence among energy consumption and carbon emissions by global Moran'I, which are shown in Table 2.

Table 2. Global Moran'I of energy consumption and carbon emissions from 1997 to 2017.

Year	REC	C	Year	REC	C
1997	0.260 ***	0.361 ***	2008	0.094 *	0.398 ***
1998	0.229 ***	0.326 ***	2009	0.045	0.355 ***
1999	0.214 ***	0.412 ***	2010	0.054	0.393 ***
2000	0.196 ***	0.345 ***	2011	0.169 ***	0.377 ***
2001	0.332 ***	0.364 ***	2012	0.132 **	0.388 ***
2002	0.300 ***	0.348 ***	2013	0.086 **	0.327 ***
2003	0.280 ***	0.333 ***	2014	0.150 ***	0.316 ***
2004	0.085	0.389 ***	2015	0.103 *	0.324 ***
2005	0.050	0.450 ***	2016	0.072	0.327 ***
2006	0.098 *	0.396 ***	2017	0.081	0.308 ***
2007	0.090 *	0.405 ***			

Notes: ***, **, and * indicate the significance of the 1%, 5% and 10% level, respectively.

As shown in Table 2, the Moran'I of carbon emissions are all significant at the 1% level, indicating that there is a positive spatial correlation in carbon emissions, and carbon emissions show spatial agglomeration characteristics rather than randomly distribution in geographic space. Renewable energy consumption shows a random distribution in several years since the total renewable energy consumption increased to a large extent on the basis of a steady increase in a few years. However, the Moran'I of renewable energy consumption in most years is larger than 0 and passes the 10% significance test, which indicates a positive spatial correlation, i.e., renewable energy consumption presents a state of agglomeration distribution in geographic space.

3.1.2. Bivariate Spatial Correlation Analysis

Considering the spatial interaction of regional renewable energy consumption and carbon emissions in adjacent provinces, we calculated the bivariate global Moran'I of 30 provinces from 1997 to 2017 using provincial renewable energy consumption as the first variable and carbon emissions as the second variable. Results are shown in Table 3. On the whole, the Moran index ranks from −0.239 to −0.076 in the study period, and most years passed the 10% significance test, which indicates that REC has a negative spatial spillover effect on carbon emissions, and REC in one area has a negative effect on carbon emissions in adjacent areas.

Table 3. Bivariate global Moran index from 1997 to 2017.

Year	Value	Year	Value	Year	Value
1997	−0.128 *	2004	−0.220 ***	2011	−0.124 *
1998	−0.107	2005	−0.206 ***	2012	−0.121 *
1999	−0.102	2006	−0.217 ***	2013	−0.076
2000	−0.098	2007	−0.177 **	2014	−0.089
2001	−0.155 *	2008	−0.259 ***	2015	−0.128 *
2002	−0.191 **	2009	−0.183 **	2016	−0.134 *
2003	−0.239 ***	2010	−0.136 **	2017	−0.161 **

Notes: ***, **, and * indicate the significance of the 1%, 5% and 10% level, respectively.

To intuitively observe the spatial relationship and distribution between renewable energy consumption and carbon emissions in China, we drew bivariate local spatial LISA agglomeration maps of 1997, 2004, 2011, and 2017 (Figure 1). The cluster types are "High-High", "Low-Low", "High-Low" and "Low-High", while "High-Low" type indicates provinces with high renewable energy consumption surrounded by low carbon emissions provinces.

Figure 1 shows that China's renewable energy consumption-carbon emissions agglomeration type is mainly "High-Low", which fluctuated during the study period. There are three provinces (Guangdong, Hunan, Guizhou) belonging to "High-Low" in 1997 and seven provinces (Guangdong, Hunan, Guizhou, Hubei, Guangxi, Sichuan, Yunnan) in 2004, which means that the utilization rate of renewable energy in these provinces is increasing, from high energy consumption–high emission to low energy consumption–low emission. On the whole, the use of renewable energy has a certain negative effect on the carbon emissions of surrounding provinces. However, due to policies such as the development of the western region and the rise of the central region, the carbon emissions of the central and western regions increased dramatically, resulting in a downward trend in the "High-Low" regions from 2004 to 2017.

"Low-High" areas move from North China to Northeast China, and then to North China and Northwest China from the spatial perspective. The number of "Low-High" areas increases from three provinces (Inner Mongolia, Jilin and Hebei) in 1997 to six provinces (Heilongjiang, Jilin, Liaoning, Hebei, Shanxi and Ningxia) in 2011, and reduces to four (Gansu, Shanxi, Shanxi, Hebei) in 2017. As China's heavy industrial bases, three northeast provinces gradually enter the "Low-High" region from 1997 to 2011, along with small proportion of renewable energy in the energy consumption structure. During 2011–2017, the Northeast region increased the use of renewable energy and did not belong to the "Low-High" areas.

The number of provinces belonging to "High-High" area is the smallest. Inner Mongolia has been in the "High-High" area since 2011, owing to substantial fossil energy and an energy-intensive development pattern. The "Low-Low" area has a small change range, and is situated in the southern provinces during the study period.

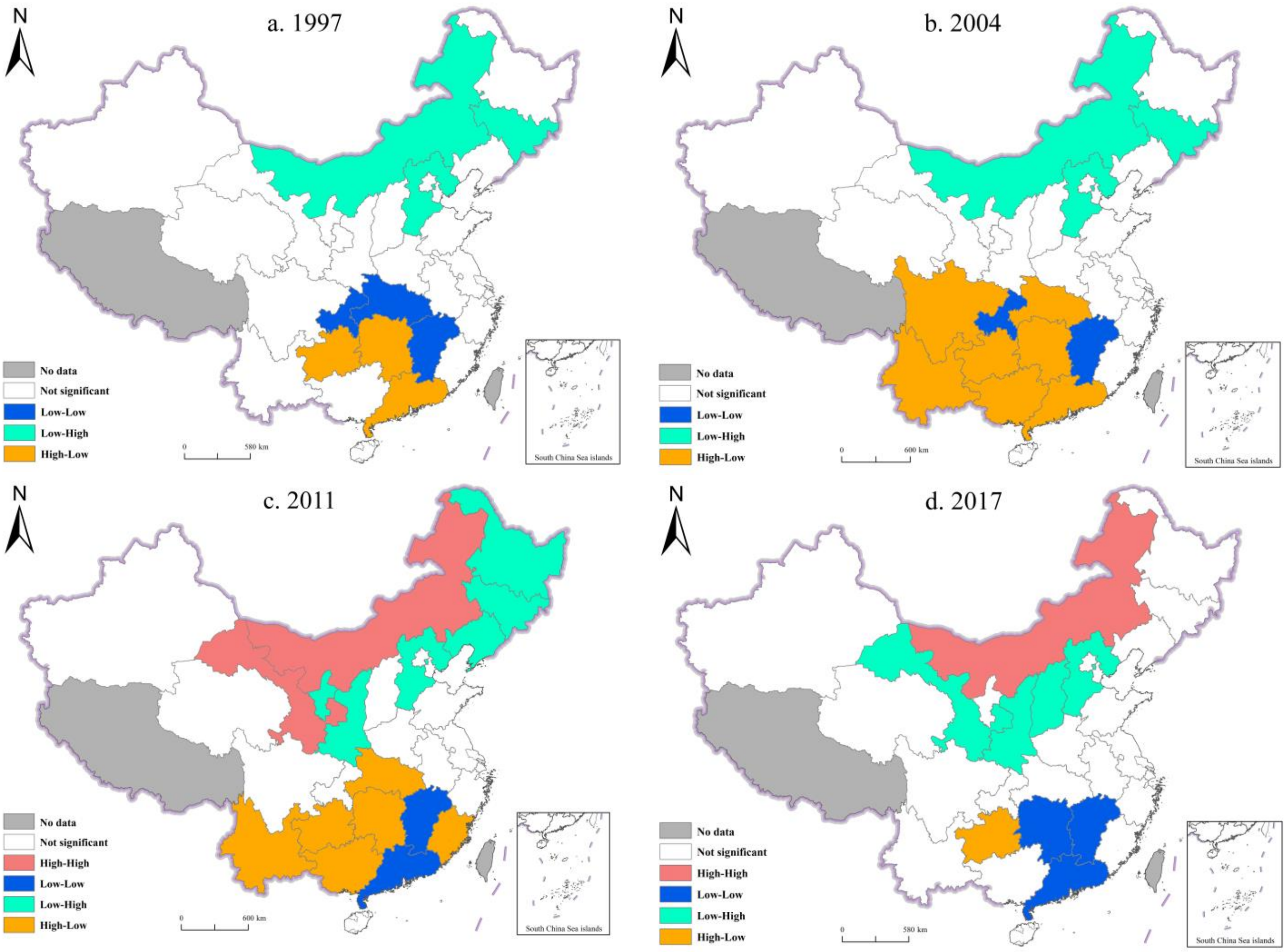

Figure 1. Spatiotemporal agglomeration of renewable energy consumption-carbon emissions (Notes: This map is based on the standard map with the approval number of GS (2020)4632).

3.1.3. Standard Deviation Ellipse and Center of Gravity Evolution

As shown in Figure 2, the standard deviation ellipses of carbon emissions are characterized by developing along the east-west (X) axis and spreading along the north-south (Y) axis. Their spatial distributions show a "northeast-southwest" trend on the whole. During the study period, the coverage area of the carbon emissions standard deviation ellipse gradually decreased, from 3,721,807 km^2 (in 1997) to 3,619,345 km^2 (in 2017), indicating that the growth rate of carbon emissions inside the standard deviation ellipse is greater than that outside. Compared with the eastern provinces, carbon emissions in the western provinces grew faster, mainly due to the abounding natural resources, and high proportion of heavy industry in the industry in western regions (except for Yunnan, Guangxi). The standard deviation along the Y-axis decreased during 1997–2017, while it fluctuated in the X-axis direction, indicating that the spatial distribution of carbon emissions tends to be concentrated in the north-south direction. The main reason may be that the growth rate of carbon emissions of provinces such as Sichuan, Guizhou and Hunan decreased through replacing fossil energy gradually by clean energy.

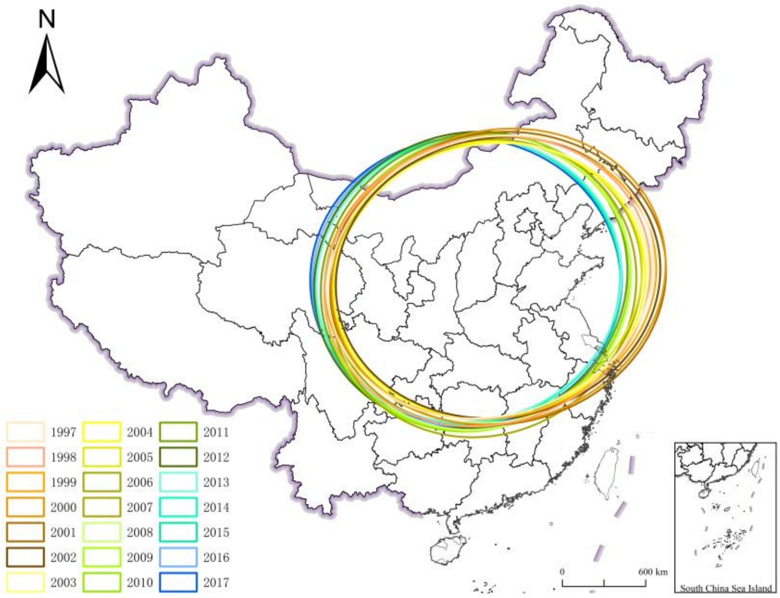

Figure 2. Standard deviation ellipse of per capita carbon emissions.

China's renewable energy consumption showed a "northwest-southeast" spatial distribution pattern during 1991–2007 (Figure 3). The azimuths of the standard deviation ellipses were large and fluctuated with time, indicating that the spatial pattern of renewable energy consumption was in an unstable state. In 2009, the standard deviation ellipse increased significantly along the *Y*-axis, indicating that the spatial distribution of renewable energy along the *Y*-axis tends to be scattered. The main reason is that the national renewable energy consumption level in 2009 had risen to a certain extent, which also echoes the aforementioned—that the spatial autocorrelation of renewable energy did not pass the significance test in 2009. From 1999 to 2003, the standard deviation ellipse gradually shortened in the direction of the *X*-axis, indicating a shrinking trend of renewable energy in the east-west direction; while from 2004 to 2014, the fluctuation of the standard deviation of the *Y*-axis was small, which means there was no obvious contraction or expansion in the north-south direction.

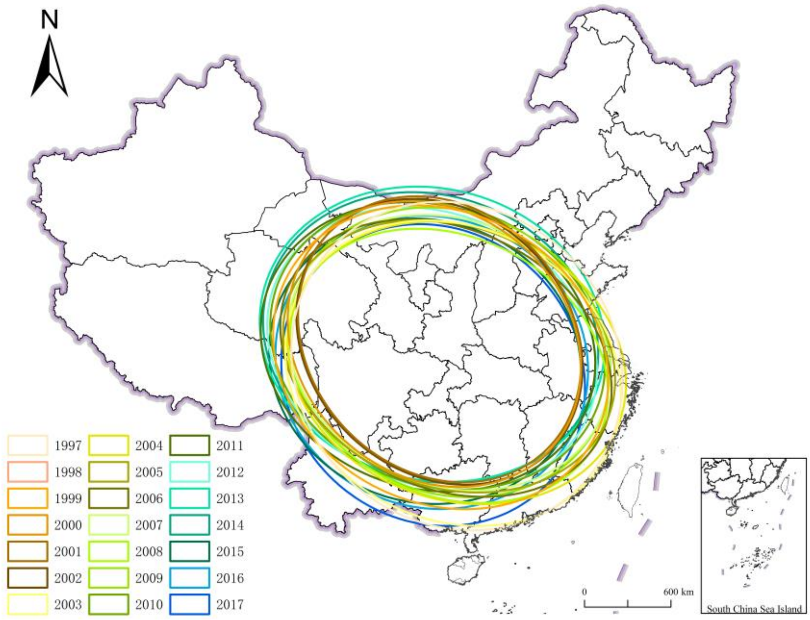

Figure 3. Standard deviation ellipse of per capita renewable energy consumption.

It can be seen from Figure 4 that the center of gravity of China's per capita carbon emissions is mainly distributed longitudinally between 111.28 and 114.06° E and latitudinally between 35.73 and 36.41° N during 1997–2017. From 1997 to 2005, the center of gravity of China's per capita carbon emissions generally shifted to the southwest, from 1998 (113.43° E, 36.41° N) to 2005 (113.15° E, 36.22° N). After 2005, the center of per capita carbon emissions showed a trend of moving to the southwest firstly and then to the northwest. Changes of carbon emissions at latitude is more obvious than that at longitude, indicating that China's carbon emissions show large changes in the east-west direction. This is directly related to the adjustment of the national strategy, which is consistent with the industrial gradient transfer effect caused by China's eastern, central and western development strategies, indicating that structural adjustment will directly lead to changes in carbon emissions.

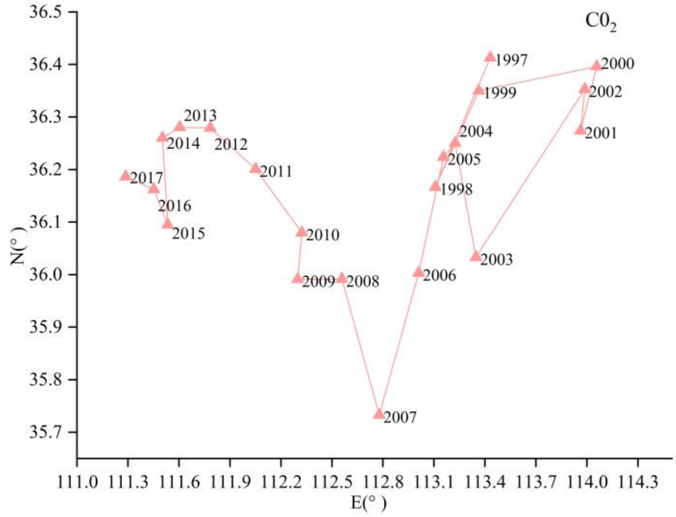

Figure 4. The evolution of the center of gravity of per capita carbon emissions.

During the research period, the center of gravity of China's per capita renewable energy consumption was between 106.71–109.06° E, 31.02–33.47° N, and showed a relatively large offset in most years (Figure 5). The moving trend of this center of gravity is mainly divided into two stages: the center of gravity of per capita renewable energy consumption fluctuated and moved to the northwest from 1997 to 2013; and moved to the south from 2013 to 2017. The moving tendency to the south is mainly due to the increased utilization of hydro, wind and biomass energy in the southern regions (Guangdong, Guangxi, Yunnan, Guizhou).

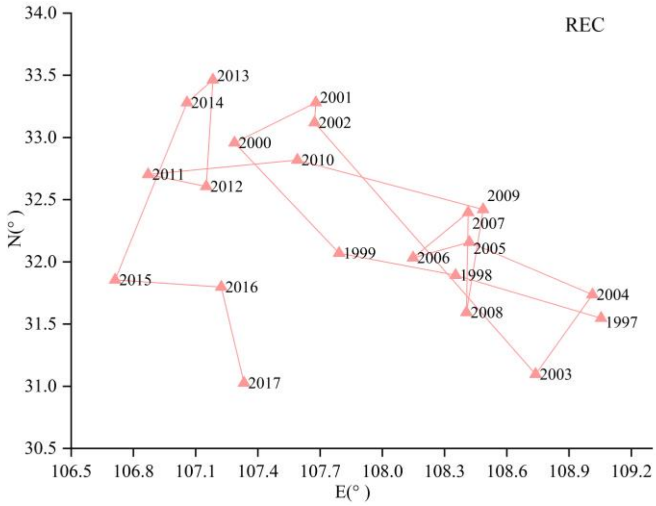

Figure 5. The evolution of the center of gravity of per capita renewable energy consumption.

Form the analysis above, we confirm that there is an obvious spatial agglomeration between renewable energy consumption and carbon emissions, and their distribution within regions is not balanced. The characteristics of "High-Low" and "Low-High" agglomeration indicate that renewable energy consumption has a spatial spillover effect on carbon emissions. The center of gravity of these two variables generally shows the same direction shifting, indicating that renewable energy has a significant impact on carbon emissions. In order to fully understand the impact of renewable energy consumption on carbon emissions, the spatial econometric model is employed for further analysis.

3.2. Result of Spatial Econometric Estimation

Considering the spatial incorporation of renewable energy consumption and carbon emissions, three classical specifications with panel data are tested: spatial autoregressive model (SAR), spatial error model (SEM) and spatial Durbin model (SDM). The specification of the Queen adjacency (W1) was adopted as spatial weight matrix when carrying out these tests. First, Lagrange multiplier (LM) tests were adopted to determine which model is appropriate [43]. LM tests consist of the error dependence test (LM-error) and the test for endogenous spatially lagged dependent variables (LM-lag). Results showed that both the LM-error (LM = 18.17, p = 0.000) and the LM-lag (LM = 81.11, p = 0.000) test passed the 1% significance level, indicating the necessary need for spatial auto-correlation of disturbances [44]. The robust LM-error and robust LM-lag test were used since both tests above are significant. The robust LM-error (LM = 11.05, p = 0.000) and robust LM-lag (73.99, p = 0.000) test are both significant, indicating that using SAR or SEM singly would have deviations, and therefore SDM is appropriate [38]. Additionally, we also employed the LR-test to testify whether the SDM would not be simplified to the SAR and SEM [45]. Results of the LR-test (in Table 4) indicate that SDM is appropriate here. Second, several tests are employed to decide the form of SDM. The Hausman test is used to make sure the fixed effects or the random effects are suitable [46]. The results (chi-square = 46.35, p-value = 0.000) show that the optimal model is a panel with fixed effects. Generally, we see the spatial fixed effect, the temporal fixed effect and spatial-temporal-fixed effect in SDM. Bayesian information criterion (BIC) and Akaike information criterion (AIC) are employed to determine which effect is appropriate [47]. The lowest AIC and BIC indicators indicate that spatial-temporal-fixed effect is preferred in this study.

Table 4. SDM model analysis results.

Variable	Spatial Fixed Effect	Temporal Fixed Effect	Spatial-Temporal-Fixed Effect
LnGDP	5.621 ***	2.438 ***	5.450 ***
LnGDP^2	−0.191 ***	−0.088 ***	−0.183 ***
LnEI	0.479 ***	0.897 ***	0.508 ***
LnREC	−0.050 ***	−0.075 ***	−0.051 ***
LnPT	−0.170 ***	0.025	−0.154 ***
W * LnGDP	−4.766 ***	1.419	−2.862 ***
W * LnGDP^2	0.214 ***	−0.056	0.136 ***
W * LnEI	0.487 ***	0.449 ***	0.980 ***
W * LnREC	−0.030	−0.018	−0.074
W * LnPT	0.163 **	−0.046	0.147 **
LR test-spatial lag	52.43 ***	33.59 ***	40.05 ***
LR test-spatial error	38.34 ***	41.40 ***	41.50 ***
AIC	307.948	537.501	227.350
BIC	361.296	590.850	280.698

Notes: ***, **, and * indicate significance of the 1%, 5% and 10% level, respectively.

Analysis in Section 3.1 shows that the renewable energy consumption and carbon emissions of China's 30 provinces fluctuated with time, and the unit root test is necessary to verify the stationarity of variables. The panel unit root test has advantages of cross-sectional correlations, rather than unit root tests based on univariate time series or cross-sectional data [38]. Three unit-root tests were used in this paper, including the Levin-Lin-Chu (LLC) test, the Im-Pesaran-Shin (IPS) test, and the Breitung test. It can be seen from the test results in Table 5 that all variables show a stable trend at the 1% significance level after the first-order difference.

Table 5. Panel unit root test.

Variable		LLC	IPS	Breitung
Ln	level	−7.351 ***	−5.866 ***	−4.098 ***
	First difference level	−6.410 ***	−12.686 ***	−13.061 ***
LnGDP	level	−1.991 **	4.267	7.025
	First difference level	−3.462 ***	−6.156 ***	−3.389 ***
LnGDP^2	level	−1.718 **	5.351	7.634
	First difference level	−3.446 ***	−5.961 ***	−3.080 ***
LnEI	level	−2.408 ***	−1.197	1.203
	First difference level	−7.321 ***	−11.843 ***	−10.933 ***
LnREC	level	−2.857 ***	−4.518 ***	−1.411 *
	First difference level	−8.345 ***	−13.302 ***	−11.720 ***
LnPT	level	0.128	−0.451	3.599
	First difference level	−5.398 ***	−11.506 ***	−7.992 ***

Notes: ***, **, and * indicate the significance of the 1%, 5% and 10% level, respectively.

Based on the stationarity test, it is found that the variables after the logarithmic first-order difference are single integral of the same order. The cointegration test is adopted to examine the long-term equilibrium relationship between variables [38,39]. Passing the cointegration test means there is a long-term stable equilibrium relationship between variables, and the variance regression residuals are stable. The Pedroni test and Kao test are used to verify whether the regression result is accurate. Results of both tests (Table 6) reject the null hypothesis at the 1% significance level, indicating that there is a co-integration relationship between panel data and a long-term stable relationship between variables.

Table 6. Panel cointegration test.

Test		Statistic
Pedroni	Modified Phillips-Perron t	5.485 *
	Phillips-Perron t	−8.404 *
	Augmented Dickey-Fuller t	−9.157 *
Kao	Modified Dickey-Fuller t	−5.977 *
	Dickey-Fuller t	−5.269 *
	Augmented Dickey-Fuller t	−5.897 *
	Unadjusted modified Dickey-Fuller t	−8.121 *
	Unadjusted Dickey-Fuller t	−5.993 *

Notes: * indicates the significance of the 1% level.

The Spatial Durbin model contains the total effects of independent variables on dependent variables, both the direct and indirect effects. The direct effect is the influence of the explanatory variable on the carbon emissions of the local province; the indirect effect is the influence of the explanatory variable of other neighboring provinces on carbon emissions in a local province, and the total effects are the sum of direct effects and indirect effects. Results of SDM based on three weight matrices are shown in Tables 7–9.

According to the estimated results in Table 7, the direct effect of REC is −0.050, which means REC is significantly negative for local carbon emissions. This is verified by other studies [20,24,29]. Renewable energy consumption will restrain the growth of local carbon emissions to a certain extent, which means that, with the increase of wind, hydro, solar, nuclear and other renewable energy increase, local carbon emissions will gradually decrease. The indirect effect of REC is −0.064, while not passing the significance test. REC of neighboring regions may have negative effect on local carbon emission while the spillover effect of renewable energy consumption is not obvious. One possible reason may be the administrative barriers in forms of energy consumption such as electricity [48]. It is worth mentioning that the effect of REC is smaller than other explanatory variables, which is consistent with previous studies [49,50]. One possible reason is that renewable energy accounts for a small proportion in China's energy structure, which is still dominated by fossil energy [51], and the impact of renewable energy policies on carbon emissions has a lagging effect [52]. Another possible reason may be insufficient renewable energy storage technology, since there is abundant wind-generated electricity in China [53]. The total effect of REC is −0.114 with 5% significance, indicating the increase in renewable energy consumption has an inhibitory effect on the growth of carbon emissions. From the specific path of the impact of renewable energy on carbon emissions, the most obvious effect on carbon emission reduction is the proportion of renewable energy consumption, and renewable energy can inhibit carbon emissions through energy efficiency [54]. To realize the reduction goal of carbon emissions, it is necessary to effectively increase the proportion of clean renewable energy in the energy consumption side through incentive policies and economic means, such as the tiered electricity price and the peak-valley time-of-use electricity price system, and take multiple measures to promote the consumption of renewable energy. On this basis, carbon emission reduction can be achieved.

Table 7. Effects of variables on carbon emissions based on W1.

Variable	Excluding REC Variables (M1)			Including REC Variables (M2)		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
$\mathrm{Ln}(GDP)$	5.669 ***	−3.115 ***	2.554 ***	5.516 ***	−3.051 ***	2.465 ***
$\mathrm{Ln}(GDP^2)$	−0.197 ***	0.132 ***	−0.065 **	−0.186 ***	0.141 ***	−0.045
$\mathrm{Ln}(EI)$	0.497 ***	1.030 ***	1.527 ***	0.507 ***	0.901 ***	1.408 ***
$\mathrm{Ln}(PT)$	−0.166 ***	0.131 *	−0.035	−0.154 ***	0.151 **	−0.004
$\mathrm{Ln}(REC)$	–	–	–	−0.050 ***	−0.064	−0.114 **

Notes: ***, **, and * indicate the significance of the 1%, 5% and 10% level, respectively.

Table 8. Effects of variables on carbon emissions based on W2.

Variable	M1			M2		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
$\mathrm{Ln}(GDP)$	3.502 ***	1.223	4.725 ***	3.582 ***	0.755	4.338 ***
$\mathrm{Ln}(GDP^2)$	−0.091 ***	−0.088 *	−0.179 ***	−0.092 ***	−0.066	−0.158 ***
$\mathrm{Ln}(EI)$	0.437 ***	0.725 ***	1.162 ***	0.476 ***	0.627 **	1.103 ***
$\mathrm{Ln}(PT)$	−0.163 ***	0.091	−0.073	−0.150 ***	0.102	−0.048
$\mathrm{Ln}(REC)$	–	–	–	−0.057 ***	−0.019	−0.076

Notes: ***, **, and * indicate the significance of the 1%, 5% and 10% level, respectively.

Table 9. Effects of variables on carbon emissions based on W3.

Variable	M1			M2		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
$\mathrm{Ln}(GDP)$	3.470 ***	−0.272	3.197 ***	3.693 ***	−0.531	3.162 ***
$\mathrm{Ln}(GDP^2)$	−0.092 ***	0.027	−0.065 *	−0.101 ***	0.034	−0.067 *
$\mathrm{Ln}(EI)$	0.580 ***	0.830 ***	1.411 ***	0.600 ***	0.721 ***	1.322 ***
$\mathrm{Ln}(PT)$	−0.202 ***	0.068	−0.134 **	−0.196 ***	0.095	−0.101
$\mathrm{Ln}(REC)$	–	–	–	−0.053 ***	−0.010	−0.062

Notes: ***, **, and * indicate the significance of the 1%, 5% and 10% level, respectively.

As shown in Table 7, the direct effect of *GDP* is positive significantly, indicating that *GDP* has a promoting effect on local carbon emissions, while the indirect effect of *GDP* is negative significantly, indicating that *GDP* has an inhibitory effect on carbon emissions of adjacent regions. As for quadratic economic growth, the relationship between GDP^2 and carbon emissions shows an inverted U-shaped relationship [55,56], indicating that when *GDP* reaches a certain level, carbon emissions will decline with economic growth. The effects of EI are significantly positive, with high energy intensity economic growth during 1997–2017, which is consistent with previous studies [57,58]. The direct effect of PT is −0.154 indicating that technological progress has an obvious inhibitory effect on local carbon emissions. In other words, China's technological innovation is still in the commercialization stage on the whole, and its role is still mainly limited to local regions, while the spatial spillover effect of PT is positive at the 5% significance level, indicating that increase on the number of patents in local region may lead to an increase in carbon emissions of adjacent areas. This means that technological benefits are more likely to happen in local regions, a situation also found in a previous study [59]. One possible reason is that when technological innovation promotes the reduction of local carbon emissions, low-tech industries would be transferred to adjacent areas with low environmental regulations, resulting in increased carbon emissions in other regions.

4. Discussion

4.1. Results Based SDM without REC

A previous study [22] found that, when adding renewable energy consumption in the ARDL model, the inversed U-shaped EKC hypothesis is supported in the long run, while this did not happen without renewable energy consumption. Thus, we constructed a spatial Durbin model (SDM) without renewable energy consumption (M1) to verify whether REC affected other variables. Our results show the inversed U-shaped EKC hypothesis is both supported under these two types of SDM, which is contrary to Chen et al. [22]. A possible reason may be due to the fact that the variables and data selected in the empirical analysis are different. This result is similar to previous studies that verified an EKC curve in China [60,61].

Comparing the effects of other variables in M1 and M2, under the W1 weight matrix, the elasticity coefficient of economic growth on local carbon emissions in M2 is lower than that in M1, weakening the promotion effect of economic growth on local carbon emissions and the inhibition effect on carbon emissions of adjacent provinces and regions. The negative effects of PT on local carbon emissions slightly increased, while the positive effects on adjacent regions' carbon emissions slightly decreased in M1 compared with that in M2. As for EI, the direct and indirect effects on carbon emissions decreased less in M1 compared with that in M2.

In general, in the case of three spatial weight matrices, results in M1 are slightly changed, indicating that the results in Section 3.2 are reliable.

4.2. Robustness Test

Since the spatial weight matrix is a substantial part of the spatial Durbin model, different spatial weight matrices need to be employed for verifying the stability of our empirical results. We examined the spatial weight matrix based on inverse distance and economic distance, which are described in Section 2.4. The results of robustness tests are listed in Tables 7–9. The estimations of renewable energy consumption, *GDP*, GDP^2, EI and PT of both M1 and M2 are similar in coefficients and significance under three spatial weight matrices. The estimated results of all variables are not significantly changed by the spatial weight matrix. In a word, the estimations are robust.

4.3. Policy Recommendations

Renewable energy consumption will become the main energy consumption in future considering increasingly serious climate change [62], and China need to increase the proportion of renewable energy in its energy structure. On the one hand, this energy structure should be improved gradually by establishing an energy price system with fossil energy tax and renewable energy subsidies. On the other hand, energy transformation should be promoted through diverse ways, such as taking advantage of the abundant reserves of renewable energy such as hydropower, wind energy and biomass energy in the western region to build a large-scale renewable energy base, or accelerating the construction of large-scale wind power photovoltaic base projects focusing on desert areas.

Regional cooperation in energy transition should be promoted, due to the diverse development levels of different provinces in China. Since the center of gravity of renewable energy consumption and carbon emissions is moving southwest, western provinces with advantages in substantial renewable energy resources and a developing economy need establish a long-term and stable partnership of cooperation with provinces in coastal regions which have leading technologies and a developed economy, to realize advantages of complementarity and to promote common development. An effective compensation mechanism based on a market-oriented economy, such as a carbon emission trading market, will realize this common development.

Investment and subsidies in technological innovation for renewable energy consumption should be increased. The level of key technology development in China lags behind developed countries on the whole [63]. As for provinces with abundant natural reserves, such as Yunnan and Guizhou, it is necessary to increase research on energy alternative technologies [18]. As for provinces with renewable energy consumption, such as Qinghai and Xizang, it is necessary to improve renewable energy utilization by developing new energy storage technology.

4.4. Research Deficiencies and Prospects

The limitation of this study is that it mainly focuses on the impact of renewable energy consumption on carbon emissions, with less attention to other factors and the role of co-occurring factors that would influence aggregate emissions. Some socio-economic factors, such as environmental regulation and industrial structure, are neglected. In fact, the environmental regulations formulated by government or the market could promote energy efficiency [64], and industrial structure optimization is essential to carbon performance [65]. Future research can focus on the effects of renewable energy consumption on these socio-economic factors and the role of co-occurring factors on carbon emissions. Besides, when using the number of patents to represent technological progress, this may overestimate the actual level of technological progress, and further research can focus on the representation of technological progress. In addition, this study constructed a research framework from a spatial perspective to clarify the relationship between carbon emissions, renewable energy consumption and other influencing factors. Due to the limitation on renewable energy consumption data, the research was analyzed at provincial scale. In fact, the prefecture-level city is considered as the core of low-carbon development [66]. Furthermore, adjacent cites will have more impact on space through the liquidity of elements, such as capital and labor [67]. Future research can focus on the effects of renewable energy consumption on carbon emissions at the prefecture level or the country level.

5. Conclusions

From the provincial perspective, this study analyzes the spatial correlation and spatial distribution pattern of renewable energy consumption and carbon emissions of China's 30 provinces from 1997 to 2017, and explores the impact of renewable energy consumption on carbon emissions based on the spatial-temporal-fixed SDM. Conclusions are as follows.

First, carbon emissions and renewable energy consumption presented statistically significant spatial autocorrelations at the provincial level from 1997 to 2017. Bivariate global Moran'I values confirmed the spatial negative correlation between renewable energy consumption and carbon emissions in most years. According to bivariate local spatial LISA agglomeration maps, negative spatial correlation was the main spatial association among provinces exhibiting spatial clustering. "High-Low" areas are mainly concentrated in southern provinces, while "Low-High" areas are mainly concentrated in northeastern provinces. Second, the center of gravity of carbon emissions was located in Shanxi province and presented a "northeast-southwest" trend on the whole. The center of gravity of renewable energy consumption was unstable, and showed a northwest trend during

1997–2013, and a southerly trend during 2013–2017. The center of gravity for renewable energy consumption moved southwest in the same direction as carbon emissions.

Third, results of the spatial Durbin model indicate that renewable energy consumption has a significant inhibitory effect on the growth of carbon emissions of a local region. Specifically, a 1% increase in renewable energy consumption in a region will reduce carbon emissions by 0.05% in that region. Renewable energy consumption has not played a significant role in reducing carbon emissions as seen by the statistically smaller effect, along its small proportion of the total energy structure of China. Form the spatial perspective, renewable energy consumption also has negative effect on carbon emissions of neighboring provinces, but this negative effect is not significant statistically.

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Notes

[1] Chinese Government Network. Xi Jinping delivers an important speech at the general debate of the 75th UN General Assembly. (2020-09-22) [2020-11-20].

[2] Grasp the key period and window period of carbon peak in the 14th five-year plan. China Electric Power News, 2021-03-23(1).

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