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Research Article

CO_2 Emissions, Energy Consumption, and Economic Growth Nexus: Evidence from 30 Provinces in China

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Under the situation of global low-carbon development, the contradiction among energy consumption, economic growth, and CO_2 emissions is increasingly prominent. Considering the possible two-way feedback among the three, based on the panel data of 30 regions in China from 2000 to 2017, this paper establishes a spatial Durbin model including economic growth, energy consumption equation, and CO_2 emissions and studies the dynamic relationship and spatial spillover among economic growth, energy consumption, and CO_2 emissions effects. The results show that the economic growth can significantly improve carbon dioxide emissions, and China's economic growth level has become a positive driving force for carbon dioxide emissions. However, economic growth will not be significantly affected by the reduction of carbon dioxide emissions. There is a two-way relationship between energy consumption (ENC) and carbon dioxide emissions (CO_2). Energy consumption and carbon emissions are interrelated, which has a negative spatial spillover effect on the carbon dioxide emissions of the surrounding provinces and cities.

1. Introduction

The process of global industrialization has brought about the rapid economic growth of all countries. With the continuous improvement of energy consumption, the rapid economic growth leads to the rise of carbon dioxide emissions. The problem of global climate change caused by the aggravation of greenhouse gas emissions is threatening the survival and development of human beings, which become a worldwide concern. Since the 1960s, environmental problems have erupted all over the world, prompting governments to pay more and more attention to environmental problems. The world has successively held "Rio Conference," "Kyoto Conference," and "Copenhagen Conference" and signed the Kyoto Protocol. At present, with the high energy consumption mode of economic growth, China has become the largest fossil energy consumption country in the world and China's per capita carbon emissions are also increasing. Facing such problems, our government makes great efforts to take measures to reduce carbon emissions and advocate the development concept of "Green GDP." In the 13th five-year plan, China proposes the object of reducing CO_2 emissions by 40%–45% in 2020 and 60%–65% in 2030 compared with 2005. Therefore, it is very important to develop low-carbon economy and study the nexus among energy, environment, and economy. In the past 30 years, China's economy has maintained a sustained growth, with an average annual GDP growth rate of 7%. With economic growing, energy consumption and CO_2 emissions are also increasing. Under the existing technical conditions, whether reducing emissions and energy consumption will affect economic development, whether economic development will react on energy consumption and carbon dioxide emissions, and what kind of relationship and mechanism exist among the three, all of which involve the causal relationship among economic development, energy consumption, and carbon emissions. Therefore, in this trend, the research on social and economic development, energy consumption, and carbon emissions has become the focus of global climate change research.

Our contributions are threefold. First, this paper aims to look at the long-run relationship between CO_2 emissions, energy consumption, and economic growth using the spatial Durbin model. Second, we estimated CO_2 emissions based on the amount of fuel burned and the default emission factors. Third, our empirical results, to some extent, indicate that there is a two-way relationship between energy consumption (ENC) and carbon dioxide emissions (CO_2).

2. A Brief Literature Review

The literature on economic growth, energy consumption, and carbon dioxide emissions can be divided into three categories: the first category studies the relationship between economic growth and energy consumption; the second category studies the relationship between economic growth and carbon dioxide emissions; there are abundant literatures about the relationship between the two kinds of research, while the third kind is a new trend, that is to study the relationship among economic growth, energy consumption, and carbon dioxide emission in a unified framework.

The research on the relationship between economic growth and carbon dioxide emission mainly focuses on testing the existence of "Environmental Kuznets hypothesis (EKC)." Many scholars, such as Schmalensee, Thomas, and Saboori, have verified the inverted U-shaped relationship between economic growth and carbon dioxide emissions, but in the existing literature, "EKC hypothesis" is often regarded as a phenomenon to be tested [1, 2]. Apergis tested for the validity of the Environmental Kuznets Curve (EKC) using both panel-based and time-series-based methodological approaches of cointegration and used data from fifteen countries, spanning the period 1960–2013 [3]. Salahuddin et al. applied the autoregressive distributed lag (ARDL) bounds testing approach and found that cointegration exists among the series. Findings indicate that economic growth, electricity consumption, and FDI stimulate CO_2 emissions in both the short and long run [4]. Coondoo et al. adopted the Environmental Kuznets Curve (EKC) to examine the presence or otherwise of an inverted U-shaped relationship between the level of pollution and the level of income. Customarily, in the diagram of EKC, the level of income is shown on the horizontal axis and that of pollution is shown on the vertical axis [5].

There are some researches on the relationship between energy consumption and output. This relationship shows that economic growth and energy consumption may be jointly determined, because economic growth is closely related to energy consumption, and higher economic growth requires more energy consumption. Since Hussain [6], many scholars have used Granger's causality test and cointegration model to evaluate the relationship between economic growth and energy consumption, such as Narayan, Stamler, and Zeng [7–9]. Based on the data of France from 1960 to 2000, Ang used cointegration analysis and error correction model (ECM) to test the relationship between economic growth, energy consumption, and carbon dioxide emissions. It was found that in the long run, the relationship between economic growth and carbon dioxide emissions was inverted U-shaped, and economic growth promoted the increase of energy consumption, while the increase of energy consumption led to the increase of carbon dioxide emissions [10]. Apergis and Payne used VECM to study the relationship between economic growth, energy consumption, and carbon dioxide emissions in six Central American countries from 1971 to 2004 [11, 12]. Combining ECM and ARDL model, Halicioglu studied Turkey's per capita income, energy consumption, carbon dioxide emissions, and foreign trade from 1960 to 2005 and found that there was a causal relationship between income and emissions in both the short and long term [13]. Saboori et al. studied the relationship between electricity consumption, economic growth, and carbon dioxide emissions of BRICS countries in 1990–2010 under the framework of panel causal analysis [14]. Feng et al. revealed that the air pollution is affected by not only local environmental regulations, but also regulations implemented in the surrounding cities [15]. Song et al. studied the decoupling relationship between CO_2 emissions and economic development based on two-dimensional decoupling theory; they get some important implications [16–19].

On the whole, scholars at home and abroad have studied the relationship between economic growth and energy consumption, economic growth, and carbon dioxide emissions, which provides a good foundation for this study. As a developing country, China is in a period of high-speed development. It is the second largest energy producer and consumer in the world, and the second largest CO_2 emitter in the world. It is faced with various pressure from the international energy conservation and emission reduction. In this case, this paper chooses the relationship among China's economic growth, energy consumption, and carbon emissions as the research topic, with a view to energy policy and the formulation of energy conservation and emission reduction policies can improve the reference to achieve a positive interaction among economic growth and energy conservation and emission reduction.

3. Methodology

3.1. Spatial Correlation Test. Spatial correlation, also known as spatial dependence, refers to the spatial interdependence, mutual restriction, mutual influence, and interaction between things and phenomena in different regions. It is the inherent spatial economic attribute of things and phenomena and the essential attribute of geospatial phenomena and spatial processes. Based on the complexity of spatial econometric model, before empirical analysis using spatial econometric model, it is necessary to test the spatial correlation of research variables to determine whether they have spatial correlation or not. The commonly used methods of spatial correlation test are Moran's index test, Guillain's index test, cetis index, etc. Among them, Moran's index is a more practical way to measure the spatial correlation of variables. Global Moran's I statistic is a common measure of global spatial autocorrelation. Moran's I index comes from Pearson's correlation coefficient in statistics. The correlation coefficient is extended to autocorrelation coefficient; the autocorrelation coefficient of time series is extended to autocorrelation coefficient of space series. Finally, the weighted function is used to replace the lag function, and the one-dimensional autocorrelation coefficient is extended to the two-dimensional autocorrelation coefficient to obtain Moran's I index. Moran's I index is actually a standardized spatial autocorrelation [20, 21].

Assuming a vector $x = [x_1, x_2, \ldots, x_n]'$, Moran's I index is expressed in vector form as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i}^{n}(x_i - \overline{x})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \quad (1)$$

where n is the total number of regions in the study area and w_{ij} is the spatial weight (set w_{ij} by whether area i and area j are adjacent: when i region is adjacent to region j, $w_{ij} = 1$; when i region is not adjacent to region j, $w_{ij} = 0$);x_i and x_j are attributes of region i and region j, respectively; $\overline{x} = 1/n\sum_{i=1}^{n} x_i$ is the average value of all attributes; and $S^2 = 1/n\sum_{i=1}^{n}(x_i - \overline{x})^2$ is the variance of the attribute. Moran's I index can be regarded as the correlation coefficient between the observation value and its spatial lag. The spatial lag of variable x_i is the average value of x_i in neighborhood j, defined as $x_{i,-1} = \sum_{j=1}^{n} w_{ij}x_{ij}/\sum_{j=1}^{n} w_{ij}$.

Therefore, the value of Moran's I is generally between −1 and 1. If it is greater than 0, it means positive correlation. The closer the value is to 1, it means similar attributes are clustered together (high value is adjacent to high value; low value is adjacent to low value). If it equals 1, it means complete positive correlation. If it is less than 0, it means negative correlation. If it is closer to −1, it means different attributes are clustered together (high value is adjacent to low value. If the Moran I index is close to 0, it indicates that the attribute is randomly distributed, or there is no spatial autocorrelation.

3.2. Setting of Spatial Weight Matrix. The spatial weight matrix reflects the interdependence degree of each variable in different regional space, which is the basis and precondition for spatial correlation analysis. Everything is related to other things to some extent, but according to the law of geography, things with closer space distance are more closely related to each other than things with longer space distance. In view of this, in order to objectively analyze the relationship between energy consumption, carbon dioxide emissions, and economic growth, this paper constructs a 0, 1 adjacency weight matrix w_{ij} for empirical analysis. The spatial weight matrix formula is as follows:

$$w_{ij} = \begin{cases} 1 \\ 0 \end{cases} \quad (2)$$

The 0, 1 adjacency weight matrix w is constructed according to whether provinces and cities are adjacent in geographical location. If provinces and cities i are adjacent to provinces and cities j, w is assigned as 1. If provinces and cities i are adjacent to provinces and cities j, w is assigned as 0.

3.3. Spatial Econometric Model. The Spatial Durbin Model (SDM) is chosen to analyze the relationship among energy consumption, carbon dioxide emission, and economic growth, because the carbon dioxide emission of a province is easily affected by the energy consumption level of neighboring provinces. Spatial Durbin Model (SDM) considers not only the spatial lag term of energy consumption, but also the spatial lag term of carbon dioxide emissions. Considering the spatial correlation of carbon dioxide emissions, it also considers the spatial correlation of energy consumption; that is, the carbon dioxide emissions of the province are not only affected by the energy consumption of the province, but also by the energy consumption of the neighboring provinces. In view of the above content, this paper constructs the following basic form of Spatial Durbin Model (SDM) based on the existing research:

$$Y = \rho WY + X\beta + \theta WX + \alpha I_n + \varepsilon. \quad (3)$$

Among them, Y stands for the explained variable, X stands for the explained variable, ρ stands for the spatial autocorrelation coefficient, W stands for the constructed spatial weight matrix, WX and WY stand for the explained variable energy consumption and the spatial lag term of carbon dioxide emission of the explained variable, and β and θ stand for the regression coefficient of the model, α for the constant term, I_n for the unit matrix, and ε for the error term.

3.4. Decomposition of Spatial Effect. The spatial lag of energy consumption, carbon dioxide emission, and economic growth is considered in the regression analysis of SDM. Based on the research of Lesage [22], this paper uses the partial differential method to decompose the spatial spillover effect of Spatial Durbin Model into three parts: direct effect, indirect effect, and total effect, so as to reduce or even avoid the biases of the Spatial Durbin Model in testing the spatial spillover effect. Among them, the direct effect refers to the impact of energy consumption and economic growth on carbon dioxide emissions of the province; the indirect effect refers to the impact of energy consumption and economic growth on carbon dioxide emissions of surrounding provinces. The specific calculation formula is as follows:

$$Y = (1 - \rho W)^{-1}\alpha I_n + (1 - \rho W)^{-1}(X_t\beta + WX_t\theta) + (1 - \rho W)^{-1}\varepsilon,$$
$$Y = \sum_{r=1}^{k} S_r(W)X_r + V(W)I_n\alpha + V(W)\varepsilon. \quad (4)$$

In which, $S_r(W) = V(W)\ (I_n\beta + W\theta_r)$, $V(W) = (I_n - \rho W)^{-1}$, I_n is the nth-order unit matrix, by transforming the above formula into matrix form, we can get

$$\begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{bmatrix} = \sum_{r=1}^{k} \left[\begin{bmatrix} S_r(W)_{11} \ldots S_r(W)_{1n} \\ \cdots \\ \cdots \\ S_r(W)_{n1} \ldots S_r(W)_{nn} \end{bmatrix} \right] \begin{bmatrix} x_{1r} \\ x_{2r} \\ \cdots \\ x_{nr} \end{bmatrix} + V(W)\varepsilon. \tag{5}$$

The total effect ATI is equal to the sum of direct effect ADI and indirect effect AII, and the specific formula is as follows:

$$\begin{aligned} \mathrm{ATI} &= n^{-1} I_n S_r(W)_{I_n}, \\ \mathrm{ADI} &= n^{-1} t_r(S_r(W)), \\ \mathrm{AII} &= \mathrm{ATI} - \mathrm{ADI}. \end{aligned} \tag{6}$$

4. Variables and Data Sources

This paper studies the relationship among carbon dioxide emissions, energy consumption, and economic growth in 30 provinces of China by using the Spatial Durbin Model. The data are from China Statistical Yearbook and China Energy Statistical Yearbook. According to the availability of data, the sample interval of this paper is 2000–2017. Each variable is an annual variable, which adopts the form of logarithmic transformation.

At present, most of these studies use per capita GDP to express the level of economic development. This paper also uses per capita GDP as the representative variable of economic growth. We use energy consumption per capita (kg oil equivalent/person) to represent energy consumption. For carbon dioxide emissions, per capita carbon dioxide emissions (metric tons/person) are selected as the research variable. These three variables are expressed by GDP_{in}, ENC_{in}, and CO_2, respectively, and are shown in Table 1.

Table 1: Variable description.

Variables	Description
GDP	Level of economic development
ENC	Energy consumption per capita
CO_2	Per capita carbon dioxide emissions

5. Estimation of Carbon Dioxide Emissions

In 2006 IPCC guidelines for national green gas inventories, the international panel on climate change of the United Nations Intergovernmental Panel on climate change introduced three methods for estimating the CO_2 emissions from fossil fuel combustion in fixed and mobile sources in detail. Method 1 estimates CO_2 emissions based on the amount of fuel burned and the default emission factors. Although the calculation results of this method are relatively rough, it is relatively simple and easy to operate, and the data requirements are not high (Wang et al.) [23]. In this paper, "method 1" in IPCC (2006) is used to estimate the data of 30 provinces and municipalities (excluding Tibet) in mainland China from 2000 to 2017.

All kinds of energy data consumed by 30 provinces and regions in 2000–2017 are from China Energy Statistical Yearbook in 2000–2017. In order to avoid double calculation, 654 energy balance tables of 30 provinces and regions in 2000–2017 are selected in this paper. Among them, 11 kinds of energy are obtained in 2000–2009: coal, coke, coke oven gas, other gas, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, and natural gas. In 2010–2017, according to the balance sheet, 14 kinds of energy sources were added, including blast furnace gas, converter gas and liquefied natural gas. The input and loss in the process of energy processing and conversion as well as the part used as raw materials and materials in industrial production are eliminated from various energy sources consumed in each province year by year, so as to obtain the (net) consumption of 30 provinces and regions in 2000–2017. IPCC (2006) not only provides the calculation method of carbon dioxide, but also provides the carbon content and effective carbon dioxide emission factors of various types of fuels. The specific estimation method is as follows:

$$CO_2 = \sum_{i=1}^{14} CO_{2,i} = \sum_{i=1}^{14} E_i \cdot \mathrm{NCV}_i \cdot \mathrm{CEF}_i. \tag{7}$$

In the formula, CO_2 represents the carbon dioxide emission to be estimated; i represents various energy fuels, including coal, coke, coke oven gas, blast furnace gas, converter gas, other gas, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, natural gas, and liquefied natural gas; E_i represents the combustion consumption of various energy sources; NCV_i is the average low calorific value of various energy sources, which is used to convert various energy consumption into energy units (TJ); and CEF_i represents the carbon dioxide emission factors of various energy sources. The formula is as follows:

$$\mathrm{CEF}_i = \mathrm{CC}_i \cdot \mathrm{COF}_i \cdot \left(\frac{44}{12}\right). \tag{8}$$

In the formula, CC_i is the carbon content of all kinds of energy; COF_i is the carbon oxidation factor of all kinds of energy, usually the value is 1, indicating that the energy is completely oxidized. In this paper, coal and coke are set as 0.99 and the rest as 1 [24]. (44/12) is the molecular weight ratio of carbon dioxide to carbon. The specific values are shown in Table 2.

Source of data: (1) NCV comes from China Energy Statistical Yearbook 2018, in which the average low calorific value of raw coal is selected;CEF is from IPCC (2006).

6. Empirical Results

6.1. Spatial Autocorrelation Test. Firstly, the spatial autocorrelation test of data is used to verify whether there is spatial correlation. The global Moran's I values of carbon dioxide emissions of 30 provinces and cities in China were calculated by Stata software, as shown in Table 3. It can be seen from Table 3 that Moran's I of carbon dioxide emission under the 0, 1 spatial weight is significantly positive, and

Table 2: Various indexes and coefficients involved in the calculation of carbon dioxide.

Energy types	NCV (kj/kg)	CEF (kg/TJ)
Coal	20908.0	95977.0
Coke	28435.0	105996.0
Coke oven gas	17981.0	44367.0
Blast furnace gas	3855.0	259600.0
Converter gas	8585.0	181867.0
Other gas	18273.6	44367.0
Crude oil	41816.0	73333.0
Gasoline	43070.0	70033.0
Kerosene	43070.0	71500.0
Diesel oil	42652.0	74067.0
Fuel oil	41816.0	77367.0
Liquefied petroleum gas	50179.0	63067.0
Natural gas	38931.0	56100.0
Liquified natural gas	44200.0	64167.0

Table 3: Global Moran's I of carbon dioxide emission in China.

Year	Moran's I	p value*
2000	0.055	0.0052
2001	0.106	0.0023
2002	0.099	0.0536
2003	0.135	0.0061
2004	0.022	0.0911
2005	0.064	0.0793
2006	0.068	0.0761
2007	−0.036	0.0992
2008	0.007	0.0794
2009	0.025	0.0923
2010	0.011	0.0657
2011	0.054	0.0847
2012	0.056	0.0828
2013	0.06	0.0808
2014	0.068	0.0746
2015	0.079	0.0067
2016	0.085	0.0628
2017	0.097	0.0054

both can pass the test under 10% significance level. This shows that there is a significant correlation effect between the provincial carbon dioxide emissions, and the spatial agglomeration characteristics are more obvious. Therefore, in the study of carbon dioxide emissions, we should fully consider the impact of spatial factors and select the spatial econometric model to reduce or even avoid the shortcomings of the general econometric model.

Based on the overall autocorrelation test of the data, the local Moran I of carbon dioxide emission in each province is further obtained. Here, the local Moran scatter plots of 2000, 2005, 2010, 2015, and 2017 are selected for research and analysis, as shown in Figures 1–5.

From the Moran scatter plots of 2000, 2005, 2010, 2015, and 2017, it can be seen that the overall carbon dioxide emissions of provinces in China still present the trend of agglomeration. Most of the provinces and cities in the Moran scatter plots of carbon dioxide emissions are located in the second and third quadrants, showing the characteristics of "high-high" and "low-low" spatial clusters as a whole.

6.2. Estimation of Spatial Econometric Model

6.2.1. LM, Hausman, and LR Tests. Through the spatial autocorrelation test, it can be determined that the spatial autocorrelation factors should be fully considered in the empirical analysis of carbon dioxide emissions to avoid large differences in research results. On this basis, the paper first determines the spatial error model, spatial lag model, and spatial Durbin model which are more suitable for the spatial measurement model of this study through LM test and then further confirms the specific spatial measurement model according to Hausman test and LR test. The LM, Hausman, and LR tests' results of panel data are shown in Table 4.

It can be seen from Table 4 that in the regression LM Test, the test values of LM error and LM lag reject the original hypothesis at the significance level of 1%; it shows that not only the variables have spatial lag effect, but also the error items have spatial correlation. Therefore, the spatial Durbin model is used as the model of spatial econometric analysis for empirical research. Then, the Hausman test results of panel data show that the test results under 0, 1 adjacency weight matrix are significantly positive, so the fixed effect space Durbin model is selected. The LR test results of this paper show that the LR test value of the spatial fixed effect model is 24.34, which is significant at the level of 1%, indicating that there are significant differences in time and space for each variable. Therefore, the spatial Durbin model is selected as the best model for panel data in our research.

6.2.2. Spatial Econometric Model Test. In order to further confirm the applicability of the selected model, this paper uses LR statistics test to confirm whether the spatial Durbin model (SDM) will degenerate into the other two spatial econometric models. The test results are shown in Table 5.

It can be seen from Table 5 that the LR statistics test results reject the original hypothesis that the spatial Durbin model (SDM) will degenerate into the spatial lag model (SAR) and the spatial error model (SEM) at the significance level of 1%. Therefore, the LR test results still support the use of the spatial Durbin model as the empirical model of this study.

6.2.3. SDM Estimation. In this paper, Stata 13.0 is selected to study the spatial effect between carbon dioxide emissions, energy consumption, and economic growth. The estimation results of spatial Durbin model (SDM) is as shown in Table 6.

It can be seen from the table that the explanatory variable GDP (economic growth) under the 0, 1 adjacency weight matrix is significantly positive at the level of 10%. It can be seen that economic growth can significantly improve carbon dioxide emissions, and China's economic growth level has become a positive driving force for carbon dioxide emissions. The result of Equation Estimation with GDP as the

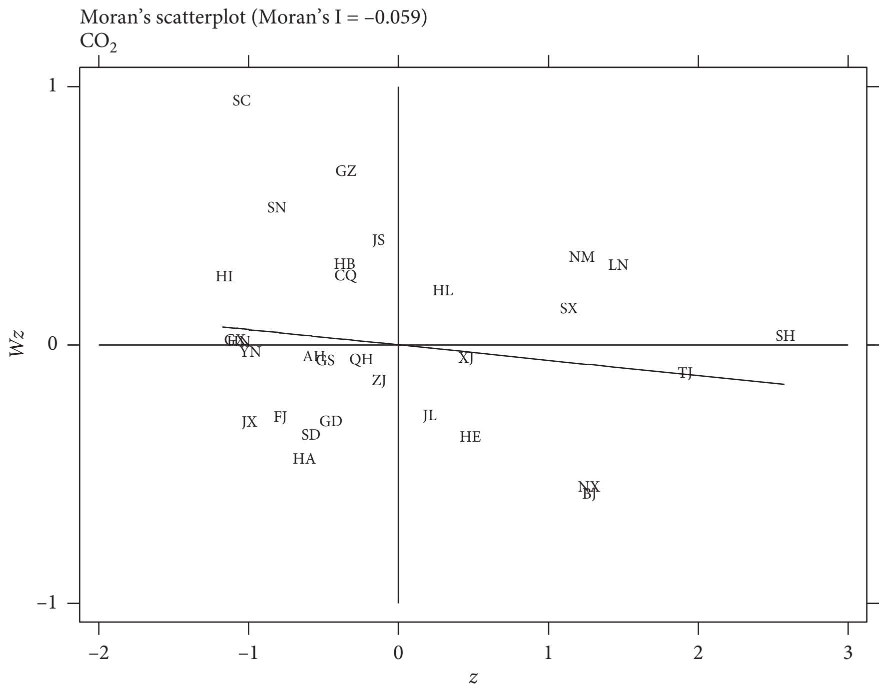

Figure 1: Moran's scatter plot in 2000.

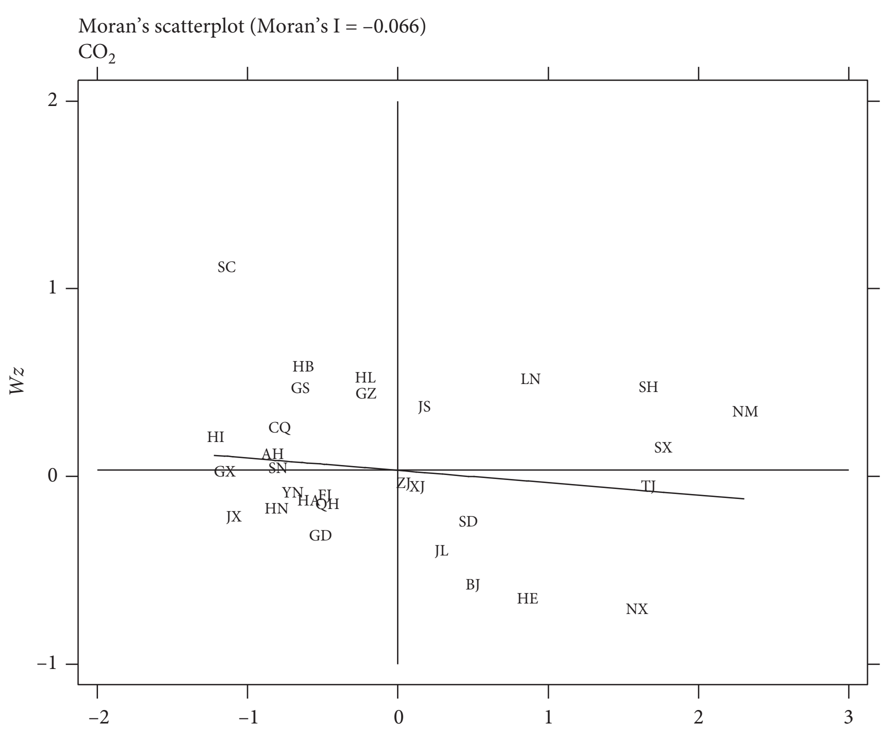

Figure 2: Moran's scatter plot in 2005.

explanatory variable shows that at the level of 10% significance, economic growth will not be significantly affected by the reduction of carbon dioxide emissions. However, if there is a causal relationship between carbon dioxide emissions and economic growth, it means that carbon dioxide emissions contain relevant information of future economic growth, and economic growth will be significantly impacted by "energy conservation and emission reduction" measures.

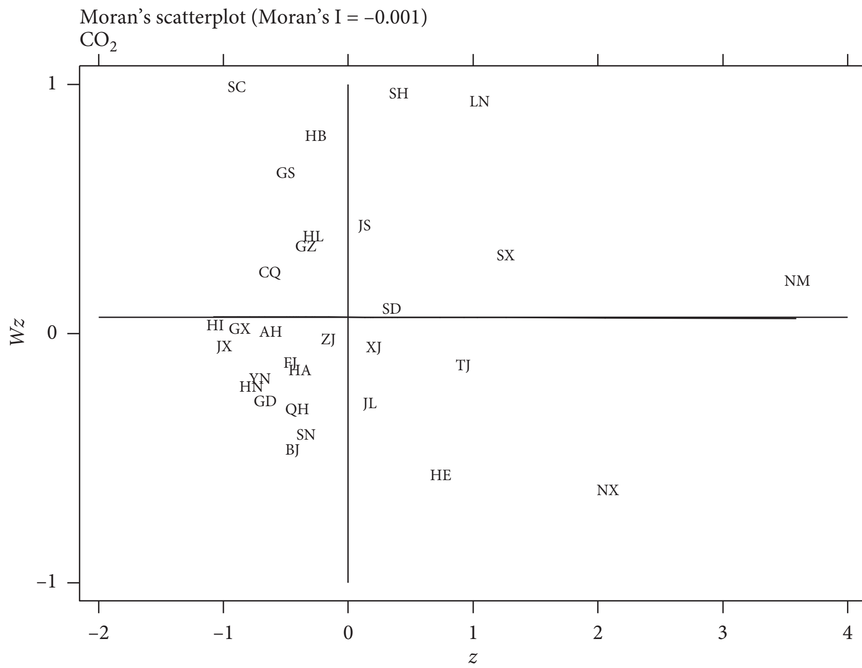

Figure 3: Moran's scatter plot in 2010.

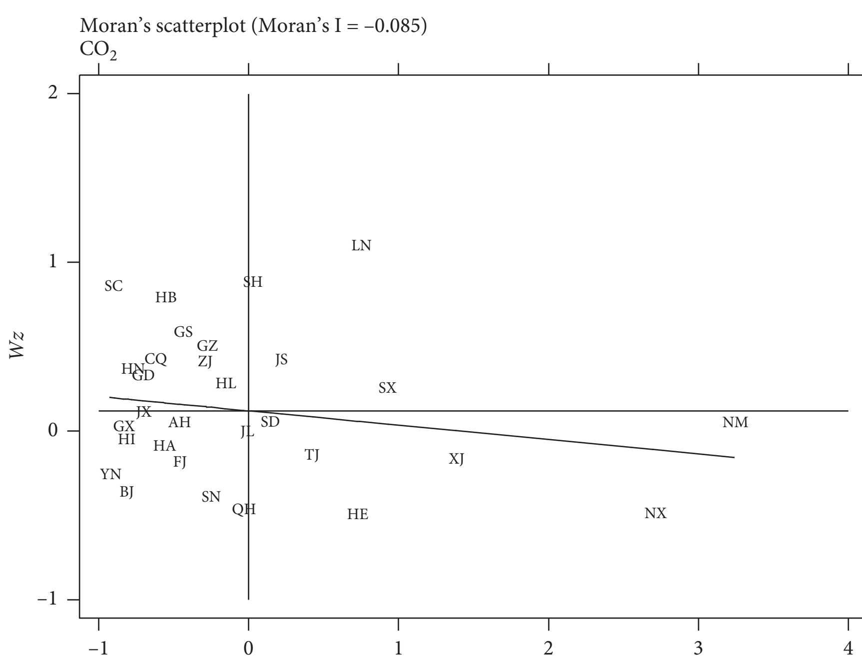

Figure 4: Moran's scatter plot in 2015.

In addition, it can be seen from the table that coefficient of WGDP is significantly positive, indicating that the positive spatial spillover effect of economic growth on carbon dioxide emissions is obvious.

There is a two-way relationship between energy consumption (ENC) and carbon dioxide emissions (CO_2). The increase of energy consumption will significantly promote the increase of carbon dioxide emissions, leading to the continuous deterioration of the environment. At the same time, the increase of carbon dioxide emissions will continue to increase energy consumption. For energy-dependent countries such as China, the constraint target of carbon dioxide emission will restrict the continuous growth of energy consumption and form the energy bottleneck constraint of economic development.

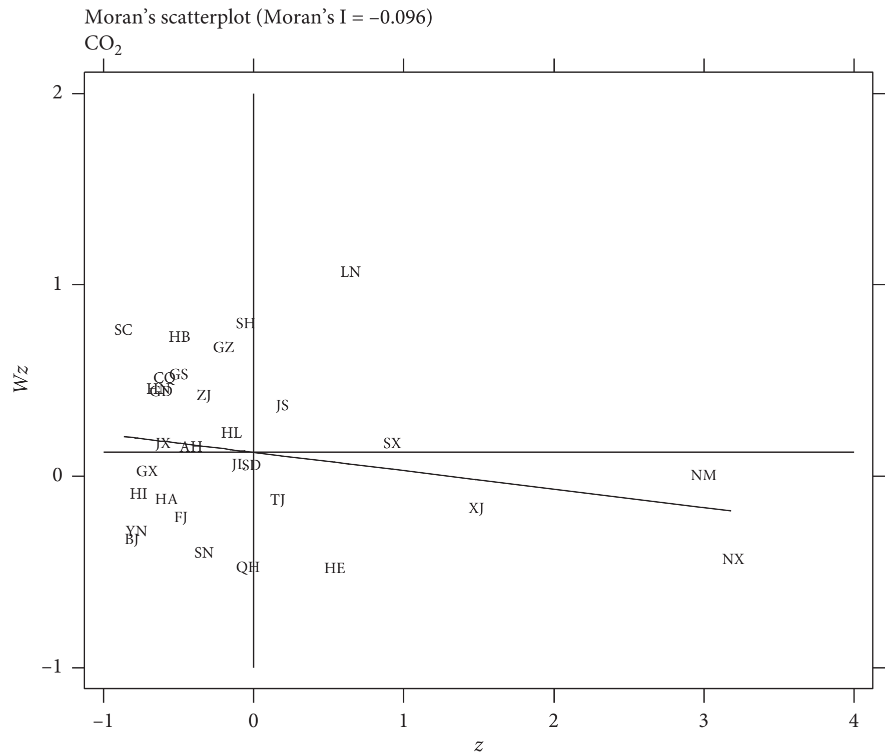

Figure 5: Moran's scatter plot in 2017.

Table 4: LM, Hausman, and LR tests.

Test type		St	p
LM test	LM (error)	4.508438	0.00
	LM (lag)	8.65328	0.00
Hausman test		0.24	0.06262
LR test		24.34	0.00

Table 5: Spatial econometric model test.

Hypothesis	SDM will degenerate into SAR	SDM will degenerate into SEM
LR test value	27.15	32.42
p value	0.0032	0.0014

Table 6: Estimation results of SDM.

Variables	CO_2		GDP		ENC	
	Coef.	p value	Coef.	p value	Coef.	p value
CO_2	—	—	0.680361	0.000	0.17246	0.000
GDP	0.197398	0.0353	—	—	0.20499	0.000
ENC	0.41966	0.000	0.845657	0.000	—	—
WCO_2	—	—	0.1235264	0.000	0.5094	0.000
WGDP	0.155793	0.393	—	—	0.19691	0.000
WENC	0.1576883	0.023	0.1436614	0.003	—	—
sigma2_e	0.0110605		0.0004057		0.001725	
Log-likelihood	389.9832		81.5463		528.7699	
R-sq	0.936		0.9103		0.9553	

6.2.4. Direct Effect, Indirect Effect, and Total Effect of Spatial Durbin Model. The coefficient of carbon dioxide emission cannot be used to directly explain its impact on economic growth and energy consumption, which is mainly due to the spatial spillover effect of the spatial Durbin model. For this reason, it is necessary to decompose the total effect of space deeply. According to the direct effect, indirect effect, and total effect of space Durbin model, we can better explain the effect of carbon dioxide emission on carbon dioxide emission in this region and other regions and the spillover effect between regions. The results are shown in Table 7.

The direct effect of spatial Durbin model: under the 0, 1 adjacency weight matrix, the influence coefficient of economic growth (GDP) on carbon dioxide emissions in this

Table 7: Direct, indirect, and total effects of SDM.

	Direct effect		Indirect effect		Total effect	
	Coef.	Z-value	Coef.	Z-value	Coef.	Z-value
GDP	0.021308*	0.53	0.152586**	0.71	0.036566*	0.65
ENC	1.035705**	10.55	−0.76671*	−0.95	0.959034**	8.67

region is 0.21308, and it has passed the significance test of 10%, which shows that economic growth can significantly promote carbon dioxide emissions in this region. Economic growth can stimulate people's consumption demand and improve people's consumption capacity. Demand-driven production has become an important driving force for the increase of carbon dioxide emissions. The coefficient of influence of the explanatory variable energy consumption (ENC) on carbon dioxide emissions in this region is 1.035705, and it has passed the 5% significance level test, indicating that energy consumption plays a role in promoting carbon dioxide emissions.

The indirect effect of spatial Durbin model: under the 0, 1 adjacency weight matrix, the influence coefficient of economic growth (GDP) on carbon dioxide emissions of surrounding provinces and cities is 0.152586, which has passed the 5% significance test. The coefficient of influence of the explanatory variable energy consumption (ENC) on the surrounding provinces and cities is −0.76671, which has passed the significance level test of 10%, indicating that the energy consumption has a negative spatial spillover effect on the carbon dioxide emissions of the surrounding provinces and cities.

7. Conclusion

Based on the test of data and the selection of appropriate spatial econometric model, this paper selects the provincial panel data of China from 2000 to 2017, first estimates the carbon dioxide emissions of 30 provinces and cities in China, and then takes the spatial Durbin model (SDM) to conduct in-depth research and discusses on the nexus among carbon dioxide emissions, energy consumption, and economic growth in China. The empirical analysis results show the following:

(1) From the results of the global Moran test, we can see that there is a significant positive spatial correlation effect on China's carbon dioxide emissions, while the local Moran test shows that China's carbon dioxide emissions show the characteristics of "high-high" and "low-low" spatial clusters.

(2) From the SDM test results, we can see that energy consumption has a significant positive effect on carbon dioxide emissions in the region and a significant negative spatial spillover effect on carbon dioxide emissions in the surrounding provinces and cities.

Energy consumption has a decisive impact on carbon dioxide emissions. The energy consumption elasticity of carbon dioxide emissions is stable at 15%–50%. Energy consumption and carbon emissions are interrelated. Therefore, energy consumption is a crucial factor in carbon dioxide emissions. According to the IPCC Research Report and the world bank's calculation of carbon dioxide emissions, the energy consumption of fossil fuels is the main source of carbon dioxide emissions, among which coal is the fossil energy with the largest emission coefficient. Particularly for China, in the short term, it is difficult to fundamentally change the structure of coal-based high-carbon energy consumption, and the constraint goal of carbon dioxide emissions is difficult to achieve. However, in the long run, the establishment of a positive constraint target on carbon dioxide emissions can serve as a target to control fossil energy consumption and promote the development of new and renewable energy resources, forming a "forced" mechanism."

Energy is an important input factor for economic development. At present, China is still a traditional high-carbon energy system dominated by oil and coal. Therefore, the rigid demand of economic growth for energy consumption leads to the continuous increase of carbon dioxide emissions, forming the relationship chain of "economic growth⟶energy consumption⟶carbon dioxide emission," which makes the global climate change face an increasingly urgent situation. China must change the mode of economic growth and optimize industrial structure and energy structure. The government can release relevant policies to reduce the proportion of fossil energy and improve the efficiency of energy use [13].

Data Availability

This paper studies the relationship among carbon dioxide emissions, energy consumption, and economic growth in 30 provinces of China by using the Spatial Durbin Model. The data are from China Statistical Yearbook and China Energy Statistical Yearbook. According to the availability of data, the sample interval of this paper is 2000–2017. Each variable is an annual variable, which adopts the form of logarithmic transformation. At present, most of these studies use per capita GDP to express the level of economic development. This paper also uses per capita GDP as the representative variable of economic growth. The authors use energy consumption per capita (kg oil equivalent/person) to represent energy consumption. For carbon dioxide emissions, per capita carbon dioxide emissions (metric tons/person) are selected as the research variable. These three variables are expressed by GDP_{in}, ENC_{in}, and CO_2 respectively.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Authors' Contributions

All authors contributed equally to this work. All authors read and approved the final manuscript.

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