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Spatiotemporal Characteristics and Driving Factors of China's Provincial Energy Carbon Intensity

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Abstract

By controlling the decline of energy intensity, we can achieve economic growth and reduce energy consumption at the same time, but the reduction of total energy consumption can not guarantee the decline of total carbon emissions, and we need to see the change of energy carbon intensity. With the rapid development of China's economy, the total coal consumption continues to rise, and the environmental problems caused by coal consumption are becoming increasingly serious. The sustainable development of economy, energy and environment is facing great challenges, and the low-carbon transformation of energy consumption is imperative. Therefore, on the basis of exploring the historical evolution of energy consumption structure, this paper analyzes the temporal and spatial characteristics of energy carbon intensity, and constructs a spatial Durbin panel model to study the driving factors of reducing carbon emissions by promoting the reduction of energy carbon intensity. The research shows that China's energy carbon intensity has a positive spatial correlation. The upgrading of industrial structure, the degree of government intervention and energy consumption can significantly promote the decline of energy carbon intensity. Provinces with higher environmental regulation, energy consumption structure and energy endowment also have higher energy carbon intensity. Regions with higher energy technical efficiency, scientific and technological level and economic openness have lower energy carbon intensity. However, this result fails to pass the test, that is, these factors are not the main factors for the change of energy carbon intensity during the study period. The government should increase the financial support for the development and utilization of clean energy, speed up the optimization and upgrading of industrial structure, low-carbon transformation of energy system, and promote the reduction of energy carbon intensity, so as to achieve the national emission reduction goal.

Keywords

Energy Carbon Intensity; Spatiotemporal Characteristics; Spatial Dubin Model (SDM); Technical Efficiency of Energy.

1. Introduction

The essence of the reduction of energy intensity is the reduction of the dependence of economic growth on energy consumption, that is, when the economic output is fixed, the energy consumption is relatively reduced. However, the reduction of total comprehensive energy consumption does not necessarily promote the reduction of carbon emissions. The reason is that the carbon emission coefficients of various energies are quite different. If the expansion of coal consumption share with high carbon emission coefficient leads to the increase of energy carbon intensity more than the decrease of energy intensity, it will lead to energy saving but not emission reduction. Therefore, to achieve carbon emission reduction, we should reduce energy intensity to save energy, and promote low-carbon optimization of energy structure to reduce energy carbon intensity (Lin Boqiang et al., 2010). The adjustment of energy structure is mainly reflected in the choice of different energy consumption, which is generally determined by the resource endowment and industrial structure of each region. Therefore, the energy consumption elasticity and substitution elasticity in different regions are not the same (CHO et al., 2004). Pindyck (1979) analyzed the energy substitution of 10 developed countries from 1959 to 1973 based on the super logarithmic cost function. The results showed that the coal price elasticity of these countries was large, followed by the natural gas price elasticity, and the electricity price elasticity was the smallest. Urga and Walters (2003) used the 1960-1992 U.S. industrial energy demand data to study the substitution relationship between coal and oil, and found that there was a significant substitution relationship between oil and coal energy in the United States. Ma et al. (2008) used the two-stage superlog cost function to analyze the energy substitution effect in China from 1995 to 2004. The results showed that there was a significant substitution relationship between coal and electricity, and a significant complementary relationship between coal and diesel, while there was a substitution relationship between gasoline and electricity and diesel. Zhu Qing and Luo Zhihong (2015) analyzed China's energy production structure and consumption structure from 2000 to 2011 based on the grey correlation model. The results show that China's energy production and consumption are still dominated by fossil energy, and the proportion of clean energy is growing rapidly in both production and consumption.

The adjustment of the energy consumption structure is affected by the internal driving factors of the energy structure itself, as well as external factors such as macroeconomic and institutional factors (Song Hui and Wei Xiaoping, 2013). Therefore, the academic community not only studies the energy structure adjustment itself, but also analyzes its external influencing factors. At present, the main external factors affecting the adjustment of energy structure are: economic growth, industrial structure, environmental regulation, resource endowment, etc. The improvement of social and economic development level can accelerate the process of energy structure optimization. Shao Qinglong (2017) empirically analyzed the long-term equilibrium and dynamic relationship between economic growth and energy utilization in the three industries. The results showed that economic growth was the main driving force to promote the adjustment of energy consumption structure, and the growth of the tertiary industry was the main driving force for future economic development. It was necessary to maintain the growth of energy consumption in the tertiary industry to achieve energy structure optimization. Burke et al. (2015) believe that economic growth will not only have an impact on the optimization of energy structure in that year, but also in the next few years. In the research on the impact mechanism of industrial structure on energy consumption structure, the impact of the upgrading level of industrial structure, that is, the rationalization and upgrading of industrial structure, on the optimization and transformation of energy consumption structure is generally positive, that is, with the improvement of industrial structure, the optimization degree of energy consumption structure will also increase, but there may be regional differences and spatial spillover effects in different regions. The upgrading of industrial structure can reduce the "negative lock-in" of energy endowment to energy consumption structure in various regions (Zou Xuan, 2019).

The optimization of energy structure needs to take environmental factors into account. Lin Boqiang et al. (2015) believe that only the optimization of energy structure considering environmental factors can be sustainable. Ge Hong et al. (2017) measured the optimization of energy structure from the perspective of environment. Xu Shan et al. (2016) believed that the coordination of economic development and environmental protection was one of the evaluation criteria for the optimization of energy structure. With the continuous deterioration of environmental conditions, governments at all levels have issued various environmental regulations to prevent further deterioration of the environment. Environmental regulations can effectively reduce energy consumption with high pollution and high emissions, that is, environmental regulations can promote the optimization of energy consumption structure (Shi et al., 2009; Lin Boqiang and Li Jianglong, 2015). It is due to the increase of high emission and high pollution energy consumption by enterprises in pursuit of short-term profits. Due to the large share of coal consumption in China's energy consumption structure, the impact of environmental regulation on energy consumption structure focuses on the impact of environmental regulation on coal consumption. Most scholars have found that China's regional environmental regulation can promote the optimization of energy structure by limiting some coal consumption (Tao Changqi et al., 2018). China's carbon emission constraints will limit the consumption of high-carbon coal and oil, and encourage the use of low-carbon natural gas and renewable energy, so as to reduce the share of coal consumption in the total energy consumption. However, Liu Yaqin and Zhao Guohao (2015) found that carbon emission constraints reduced energy prices and indirectly stimulated the rise of coal consumption share. Traditional economic theory believes that when the price of fossil energy rises, the premium of new energy to traditional energy will shrink, which has a good role in promoting the investment and production of new energy, that is, the rise of fossil energy price can promote the increase of the share of new energy consumption, and the share of coal and other fossil energy consumption will decline. The consumption of fossil energy will release a large number of harmful gases and greenhouse gas carbon dioxide into the air at the same time. Although the price of fossil energy is low because it does not consider the negative externality of consumption, on the contrary, new energy has a positive externality in consumption due to its high price. The government should increase the cost of using fossil energy through carbon tax and reduce the cost of using new energy through subsidies and tax exemptions, Reduce the premium of new energy to fossil energy to promote the optimization of energy consumption structure (Fang Debin et al., 2016).

In the research on the path of low-carbon optimization of energy structure, there is a lack of characterization indicators for low-carbon optimization of energy structure. Energy carbon intensity can accurately characterize the degree of low-carbon optimization of energy structure. In the research on the influencing factors of energy carbon intensity, most of the existing studies are to establish ordinary panel econometric regression models to identify the direction and size of influencing factors, but energy carbon intensity has significant spatial correlation, the spatial panel econometric model can more accurately identify the direction and size of the influencing factors. Therefore, in this paper, the energy carbon intensity is used as the characterization index of low-carbon energy structure, and the spatial panel Durbin model is constructed to study the driving factors of reducing carbon emissions by promoting the reduction of energy carbon intensity.

2. Temporal and Spatial Characteristics of China's Energy Carbon Intensity

According to the calculation formula of energy carbon intensity (see formula 8), the energy carbon emission intensity of 30 provinces and cities in China from 2001 to 2020 is calculated. In this section, the values of energy carbon intensity and its change rate of 30 provinces and cities in China in 2005, 2010, 2015 and 2020 are selected for comparative analysis (see Table 1).

At the end of the "Tenth Five Year Plan" in 2005, the provinces with the highest energy carbon intensity in China were Shanxi, Inner Mongolia and Henan, with 3.36 tons of carbon dioxide per ton of standard coal, 3.49 tons of carbon dioxide per ton of standard coal and 2.87 tons of carbon dioxide per ton of standard coal, respectively. The provinces with the lowest energy carbon intensity are Qinghai, Guangdong and Beijing, which are 1.16 tons of carbon dioxide per ton of standard coal, 1.56 tons of carbon dioxide per ton of standard coal and 1.60 tons of carbon dioxide per ton of standard coal, respectively. At the end of the 11th Five Year Plan in 2010, the provinces with the highest energy carbon intensity in China were Inner Mongolia, Shanxi and Anhui, with 3.67 tons of carbon dioxide per ton of standard coal, 3.41 tons of carbon dioxide per ton of standard coal and 3.20 tons of carbon dioxide per ton of standard coal, respectively. The provinces with the lowest energy carbon intensity are Qinghai, Beijing and Sichuan, which are 1.02 tons of carbon dioxide per ton of standard coal, 1.48 tons of carbon dioxide per ton of standard coal and 1.66 tons of carbon dioxide per ton of standard coal, respectively. At the end of the 12th Five Year Plan in 2015, the provinces with the highest energy carbon intensity in China were Inner Mongolia, Ningxia and Shanxi, with 3.61 tons of carbon dioxide per ton of standard coal, 3.21 tons of carbon dioxide per ton of standard coal and 3.17 tons of carbon dioxide per ton of standard coal, respectively. The provinces with the lowest energy carbon intensity are Qinghai, Yunnan and Sichuan, which are 1.10 tons of carbon dioxide per ton of standard coal, 1.11 tons of carbon dioxide per ton of standard coal and 1.20 tons of carbon dioxide per ton of standard coal, respectively. At the end of the 13th Five Year Plan in 2020, the provinces with the highest energy carbon intensity in China are Inner Mongolia, Ningxia and Shanxi, which are 3.43 tons of carbon dioxide per ton of standard coal, 3.25 tons of carbon dioxide per ton of standard coal and 3.18 tons of carbon dioxide per ton of standard coal, respectively. The provinces with the lowest energy carbon intensity are Qinghai, Beijing and Sichuan, respectively 0.84 tons of carbon dioxide/ton of standard coal, 0.96 tons of carbon dioxide/ton of standard coal and 1.00 tons of carbon dioxide/ton of standard coal.

Due to the significant differences in economic basis, energy endowment, industrial structure, energy consumption structure and environmental regulation among provinces and cities, China's energy carbon intensity has obvious regional heterogeneity. Provinces and cities with high energy carbon intensity are mainly distributed in the main coal producing areas, while provinces and cities with low energy carbon intensity are mainly divided into regions with rich clean energy resources. According to the change rate of energy carbon intensity of 30 provinces and cities in China during the Tenth Five Year Plan period, only seven provinces and cities such as Beijing, Shanghai and Guangdong have decreased energy carbon intensity, while other provinces and cities have increased energy carbon intensity. During the "11th Five Year Plan" and "12th Five Year Plan" period, the energy carbon intensity decreased in 18 provinces and cities and 22 provinces, respectively. During the "13th Five Year Plan" period, only Jilin, Heilongjiang and Hubei provinces and cities' energy carbon intensity increased slightly, while other provinces and cities' energy carbon intensity decreased, which also shows that the overall energy carbon intensity of China's provinces and cities is increasingly obvious. By the end of the 13th Five Year Plan period, the energy carbon intensity had increased compared with the end of the 10th Five Year Plan period in Inner Mongolia, Anhui, Ningxia and Xinjiang, four provinces and cities rich in coal resources. The energy carbon intensity of other provinces and cities had decreased during the study period, and the provinces and cities with the largest decline were Beijing, Qinghai and Sichuan provinces and cities with low energy carbon intensity at the beginning of the period.

As a major energy consumer, China has the energy endowment characteristics of "rich in coal, poor in oil and less gas", and the proportion of coal in the energy consumption structure has been high. However, with the economic development, the total coal consumption continues to rise, the environmental problems caused by coal consumption are becoming increasingly serious, and the sustainable development of economy, energy and environment is facing great challenges. Therefore, it is imperative to reduce the energy carbon intensity, which is the low-carbon transformation of energy consumption. It can be seen that the optimization of energy structure is not easy and cannot be completed overnight.

Table 1. Energy Carbon Intensity and Change Rate of Provinces and Cities in 2005, 2010, 2015 and 2020

Unit: ton carbon dioxide/standard coal,%

Area	2005		2010		2015		2020	
	Numerical value	Rate of change	Numerical value	Rate of change	Numerical value	Rate of change	Numerical value	Rate of change
Beijing	1.60	10.29	1.48	7.18	1.21	18.72	0.96	-20.38
Tianjin	2.38	13.22	2.21	7.15	1.88	15.02	1.84	-1.98
Hebei	2.78	4.77	2.64	4.97	2.49	-5.68	2.29	-8.05
Shanxi	3.36	10.25	3.41	1.52	3.17	-7.08	3.25	2.48
Inner Mongolia	3.49	0.29	3.67	5.11	3.61	-1.76	3.43	-5.05
Liaoning	2.27	-1.15	2.29	0.56	2.08	-9.00	1.89	-9.20
Jilin	2.61	20.47	2.46	-5.79	2.58	4.54	2.56	-0.55
Heilongjiang	2.51	12.87	2.53	0.54	2.39	-5.30	2.45	2.53
Shanghai	1.97	-6.84	1.82	-7.67	1.65	-9.28	1.57	-4.59
Jiangsu	2.60	3.38	2.41	-7.19	2.32	-3.66	2.04	-12.32
Zhejiang	1.94	-2.90	2.04	5.39	1.77	13.41	1.44	-18.79
Anhui	2.71	5.11	3.20	17.86	2.89	-9.64	2.69	-6.79
Fujian	1.90	13.36	1.84	-3.02	1.63	11.36	1.63	0.04
Jiangxi	2.47	12.23	2.48	0.54	2.20	11.34	2.11	-4.03
Shandong	2.58	31.93	2.48	-3.81	2.48	0.18	2.17	-12.47
Henan	2.87	8.39	2.65	-7.46	2.51	-5.19	2.21	-12.28
Hubei	1.78	-9.17	1.78	-0.22	1.64	-8.03	1.52	-6.77
Hunan	2.06	22.68	2.00	-3.36	1.82	-8.59	1.72	-5.54
Guangdong	1.56	-9.15	1.74	11.06	1.56	10.10	1.42	-9.28
Guangxi	1.94	11.17	1.87	-3.54	1.57	16.36	1.73	10.28
Hainan	1.88	3.65	1.83	-2.50	1.90	3.85	1.54	-19.01
Chongqing	2.16	11.57	2.12	-1.90	1.93	-9.07	1.72	-10.89
Sichuan	1.88	4.88	1.66	11.96	1.20	27.85	1.00	-16.60
Guizhou	2.75	19.10	2.72	-1.18	2.28	16.33	2.25	-1.07
Yunnan	2.20	24.62	2.03	-7.98	1.11	45.15	1.05	-5.25
Shaanxi	2.51	14.07	2.79	11.16	2.65	-5.01	2.48	-6.46
Gansu	1.98	35.74	2.10	6.09	1.90	-9.66	1.84	-2.91
Qinghai	1.16	-2.65	1.02	11.94	1.10	8.12	0.84	-23.97
Ningxia	2.80	7.52	3.11	11.05	3.21	3.30	3.18	-1.10
Xinjiang	2.02	18.36	2.26	11.76	2.55	12.81	2.71	6.14

3. Empirical Design and Data Sources

3.1. Spatial Correlation Analysis Model

3.1.1. Global $Moran's\ I$ Index

The global $Moran's\ I$ index is the most common method used in global clustering testing and one of the indicators used to measure global spatial correlation. It reflects the similarity of attribute values of adjacent or adjacent regional units in space, describing the overall distribution of a phenomenon and determining whether it has clustering characteristics in space. The calculation formula is shown in equation (1):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(E_i - \bar{E}\right)\left(E_j - \bar{E}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(E_i - \bar{E}\right)^2} \tag{1}$$

In equation (1), I is the global $Moran's\ I$ index,$S^2 = \frac{1}{n}\sum_{i=1}^{n}(E_i - \bar{E})^2$,n is the sample size,E_i, E_j is the attribute value of the region.i and region j ,$\bar{E} = \frac{1}{n}\sum_{i=1}^{n} E_i$, W_{ij} is the spatial weight of region i and region j . I usually takes a value between -1 and 1, If it is greater than 0, it indicates a positive correlation in the attribute value space, and if it is less than 0, it indicates a negative correlation in the attribute value space; The closer it is to -1, the more dispersed the spatial distribution of attribute values is. On the contrary, the closer it is to 1, the more concentrated the spatial distribution of attribute values is.The standardized global $Moran's\ I$ statistic is shown in equation (2):

$$Z(I) = \frac{I - E(I)}{\sqrt{var(I)}} \tag{2}$$

In equation (2), I is the global $Moran's\ I$ index,$E(I) = -\frac{1}{n-1}$ is the mathematical expectation for the global $Moran's\ I$ index,$VAR(I) = E[I^2] - E[I]^2$, is the variance of the global $Moran's\ I$ index.$Z(I)$ can be used to test the significance of the global $Moran's\ I$ index. If the absolute value of $Z(I)$ is greater than 2.58, the global $Moran's\ I$ index is significant at the 0.01 level; If the absolute value of $Z(I)$ is greater than 1.96, the global $Moran's\ I$ index is significant at the 0.05 level; If the absolute value of $Z(I)$ is greater than 1.65, the global $Moran's\ I$ index is significant at the 0.1 level.

3.1.2. Local Spatial Autocorrelation Model

The global $Moran's\ I$ index describes the overall distribution of an attribute value. It can judge whether this phenomenon has aggregation characteristics in space, but it can not point out which regions it is clustered in. When it is necessary to further consider whether the attribute value has local spatial aggregation characteristics, it is necessary to build an index for local spatial autocorrelation analysis. Local indicators of Spatial Association (LISA) is used to measure the spatial correlation between a region and its adjacent regions, that is, to test whether there are similar or different observed values in local regions. The local index is one of the most commonly used local autocorrelation indicators, and its calculation formula is shown in formula (3):

$$I_i = \frac{\left(E_i - \bar{E}\right)}{\sum_{i=1}^{N}\left(E_i - \bar{E}\right)^2} \sum_{j=1}^{N} w_{ij}\left(E_j - \bar{E}\right) \tag{3}$$

In equation (3), E_i, E_j is the attribute value of the region i and the region j, $\bar{E} = \frac{1}{n}\sum_{i=1}^{n} E_i$, w_{ij} is the spatial weight of region i and region j. When $I_i > 0$, it means that regions with similar attributes have agglomeration ("high-high" agglomeration or "low-low" agglomeration); When $I_i < 0$, it indicates that regions with different attributes have agglomeration (high-low agglomeration or low-high agglomeration).

3.2. Spatial Metrology Model Setting

By analyzing the spatio-temporal characteristics of China's energy carbon intensity, it is found that China's energy carbon intensity has a significant positive correlation in space. Therefore, this chapter uses the spatial panel Durbin model to analyze the driving factors of energy carbon intensity.

3.2.1. Spatial Weight Matrix

In this paper, 0-1 adjacency matrix is used.

0-1 adjacency matrix:

$$w_{ij} = \begin{cases} 1 & \text{When region i and region j are adjacent} \\ 0 & \text{else} \end{cases} \tag{4}$$

In this paper, adjacency is defined as having a common edge or vertex, that is, if the region i and the region j have a common vertex or boundary, it is set w_{ij} to 1; If the region i and the region j have no common vertices or boundaries, it is set w_{ij} to 0, and the weight matrix is standardized.

3.2.2. Spatial Panel Model

From the above analysis, it is concluded that China's energy carbon intensity has spatial correlation, so this chapter uses spatial panel data model.

General space panel model, as shown in equation (6-8):

$$\begin{cases} y_{it} = \tau y_{i,t-1} + \rho w_i' y_t + x_{it}'\beta + w_i' X_t \delta + \gamma_t + u_i + \varepsilon_{it} \\ \varepsilon_{it} = \lambda m_i' \varepsilon_t + v_{it} \end{cases} \tag{5}$$

In equation (6-8), i represents the province, t represents the year, y_{it} is the explained variable of the i-th Province in the t-th year, $w_i' y_t = \sum_{j=1}^{n} w_{ij} y_{jt}$ is the spatial lag of the explained variable, w_{ij} is the (i, j) element of the spatial weight matrix W, $y_{i,t-1}$ is the first-order lag term of the explained variable y_{it};x_{it} is the explanatory variable (including the control variable) of the i-th Province in the t-th year, $w_i' X_t$ is the spatial lag of the explanatory variable, u_i is the individual correspondence of the province i,γ_t is the time effect of the year t, m_i' is the i-th row of the spatial weight matrix of the disturbance term.

If λ= 0, it is spatial Doberman model (SDM); If $\lambda = 0$ and $\delta = 0$, it is the spatial autoregressive model (SAR); If $\tau = 0$ and $\delta = 0$, it is the spatial autocorrelation model (SAC); If $\tau = \rho = 0$ and $\delta = 0$, it is the spatial error model (SEM). This paper adopts the static spatial panel model, namely $\tau = 0$.

For the selection of models, the LM statistic test is used to judge the selection of SAR and SEM models; Wald test statistics and LR test were used to determine whether SDM model can degenerate into SAR and SEM models; Hausman test selects random effect or fixed effect estimation.

Therefore, the benchmark econometric regression model set in this paper is shown in equation (6):

$$ECI_{it} = X_{it}^{'}\alpha_1 + \delta_1 u_i + \delta_2 \lambda_t + \varepsilon_{it} \tag{6}$$

In equation (9), i represents the province, t represents the year, and the explained variable ECI_{it} is energy carbon intensity; X_{it}' is the main explanatory variable, including energy structure, industrial structure upgrading, scientific and technological level, environmental regulation, the degree of government intervention, economic openness, energy consumption, energy efficiency, energy endowment and economic development level; u_i is the individual effect of province i, λ_t is the time effect of year t.

Further, according to the previous discussion, it is found that energy carbon intensity has spatial correlation. According to the practice of Chen Qiang (2015), the spatial lag terms of all variables are selected for regression, and it is found that the spatial lag terms of AIS, PWS and EEF in the dependent variables are significant. Therefore, in this paper, the spatial lag terms of the dependent variables in the impact of energy carbon intensity are only selected for AIS, PWS and EEF. Therefore, the spatial panel Dobbin model 1 is constructed as shown in equation (7):

$$ECI_{it} = X_{it}^{'}\alpha_1 + \beta_1 w_i^{'} ECI_{it} + w_i^{'} X_{it}^{'} \beta_2 + \delta_1 u_i + \delta_2 \lambda_t + \varepsilon_{it} \tag{7}$$

In equation (7), $w_i' ECI_{it}$ is the explained variable ECI_{it} Spatial lag term of it, $w_i' X_{it}'$ is the explanatory variable x_X_{it}' The meaning of other variables is the same as above.

3.3. Variable Selection and Data Source

The explained variable is energy carbon intensity (ECI), which is measured by carbon emissions per unit of energy consumption. Here, various energy consumption is converted into standard coal equivalent, and the carbon emissions of various energy consumption are aggregated to obtain the total energy consumption and carbon emissions in the region. Energy carbon intensity is the ratio of total carbon emissions to total energy consumption. The specific calculation formula is shown in formula (8):

$$ECI_i = \frac{\sum_j C_{ij}}{\sum_j E_{ij} \times \eta_j} \tag{8}$$

In equation (8), ECI_i represents the carbon intensity of energy in Province i, C_{ij} represents the carbon emissions of j kinds of energy in Province i, E_{ij} represents the consumption of j kinds of energy in Province i, and η_j represents the conversion coefficient of j kinds of energy into standard coal.

This paper selects the main factors affecting energy carbon intensity, including:

(1) Energy structure (ESC). Referring to the measurement method of Yu Zhuangxiong (2020), the proportion of coal energy consumption in the total energy consumption is adopted, and the data is from the China energy statistical yearbook over the years.

(2) Industrial structure upgrading (AIS). Referring to the practice of Wang Guixin and Li Gang (2020), the ratio of the added value of the tertiary industry to the added value of the secondary industry is used to measure the upgrading of the industrial structure. The data is from the China Bureau of statistics.

(3) Energy consumption (VEC). It is measured by logarithm of per capita energy consumption.

(4) Environmental regulation (pws). Referring to the treatment method of Ren yayun et al. (2019), the environmental regulation is measured by selecting the proportion of waste gas treatment investment in GDP in the completion of industrial pollution control investment in various regions. The data is from the China Environmental Statistics Yearbook over the years.

(5) Economic Openness (eo). Referring to the practice of Chenqianli et al. (2019), the ratio of regional total foreign direct investment to regional gross domestic product is used to measure. The regional total foreign direct investment is converted at the annual average exchange rate of RMB against the US dollar, and the data is from the statistical yearbook of provinces and municipalities directly under the central government over the years.

(6) Economic development level ($vGDP$). The per capita GDP is adopted, adjusted based on the year 2000, and the logarithm is taken as the proxy variable. The data is from the China Bureau of statistics.

(7) Energy efficiency (eef). Referring to the method of (Wang Ke, 2021), this paper first measures the energy efficiency index of the five sectors of agriculture, industry, construction, transportation and services in various provinces and cities. The energy efficiency index of each sector uses the reciprocal of energy intensity, that is, the sector added value per unit of terminal energy consumption, as its energy efficiency index, and then aggregates the sector efficiency index into the energy efficiency of each province and city by using the proportion of the added value of the five sectors after standardization. The calculation formula is shown in formula (9):

$$eef_i = \sum_{j}^{5} \omega_{ij} \times eef_{ij} \tag{9}$$

In equation (9), eef_i is the energy efficiency index of i province; eef_{ij} is the energy efficiency index of j sectors of i province; ω_{ij} is the proportion of added value of j sectors in standardized i province. The calculation formula of sector energy efficiency index eef_{ij} is shown in equation (10):

$$eef_{ij} = \frac{G_{ij,2000}}{E_{ij}} \tag{10}$$

In equation (10), $G_{ij,2000}$ is the output of j sector in Province i at the constant price of gas gathering in 2000, and E_{ij} is the final energy consumption of j sector in province i. the final energy consumption here is the sum of various energy consumption converted into standard coal. When calculating the sectoral energy efficiency index, due to the differences in resource endowment, economic development stage and other factors between provinces and cities, as well as the large differences in the energy consumption structure of each sector, the gap in the sectoral energy efficiency index is too large. In order to avoid the influence of extreme values and maintain the relative stability of the energy efficiency index, this paper adopts the logarithmic efficacy function method to standardize the relevant data.

(8) Scientific and technological level (STL). Referring to the practice of Huang Xianglan et al. (2018), the investment intensity of technology level research and experimental development funds is used to measure the level of science and technology. The China Science and Technology Statistical Yearbook in 2006 and later directly provides the data of the investment intensity of technology level research and experimental development, but the previous data is missing. Therefore, this paper uses the calculation formula of the investment intensity of technology level research and experimental development, that is, the investment intensity of technology level research and experimental development=the ratio of the investment intensity of technology level research and experimental development to GDP. The data comes from the statistical bulletin of national science and technology investment over the years.

(9) Energy endowment (eed). Referring to the practice of Luochaoyang and LiXueSong (2019), the per capita energy output is used as the expression, and the data is from the China energy statistical yearbook.

(10) The degree of government intervention (gov). Referring to the measurement method of Yubinbin (2017), the proportion of local general budget expenditure and local general budget revenue in each region is adopted, and the data is from the National Bureau of statistics.

The descriptive statistical results of main variables are shown in Table 2.

Table 2. Statistical description of main variables

variable	variable	sample size	mean value	standard deviation	minimum value	Maximum value
Energy carbon intensity	ECI	600	2.2039	0.5836	0.9132	4.0409
energy-resource structure	ESC	600	73.2055	12.9969	33.4201	94.6198
Upgrading of industrial structure	AIS	600	1.1440	0.5944	0.5182	5.2340
Scientific and technological level	STL	600	1.3939	1.0589	0.1381	6.3016
Environmental regulation	pws	600	51.7387	21.9143	0.0025	99.1042
Degree of government intervention	gov	600	2.2589	0.9415	1.0517	6.7447
Economic Openness	eo	600	0.4609	0.5395	0.0484	5.9537
Energy consumption	VEC	600	0.8485	0.5552	-0.6191	2.3570
energy efficiency	eef	600	0.5586	0.1553	0.1424	0.8502
Energy endowment	eed	600	2.9440	6.3929	0.0000	42.9402
Economic development level	$vGDP$	600	9.8907	0.7909	7.9226	12.0318

4. Analysis of Empirical Results

4.1. Global Spatial Correlation Analysis

In this paper, $Moran's\ I$ index is selected to test the global spatial correlation of China's energy carbon intensity from 2001 to 2020. The test results are shown in Table 3.

Table 3. Global spatial correlation test results of China's energy carbon intensity

Year	$Moran's\ I$ statistic	Z statistic	P value	Year	$Moran's\ I$ statistic	Z statistic	P value
2001	0.4109	3.7501	0.002	2011	0.3304	3.0024	0.002
2002	0.3868	3.4758	0.002	2012	0.3114	2.8369	0.006
2003	0.4597	4.0324	0.001	2013	0.3278	2.94	0.003
2004	0.4485	4.0824	0.001	2014	0.2995	2.8246	0.008
2005	0.403	3.5249	0.003	2015	0.3634	3.0694	0.004
2006	0.3793	3.3817	0.001	2016	0.3726	3.3977	0.003
2007	0.3718	3.3878	0.002	2017	0.356	3.1249	0.003
2008	0.3832	3.3373	0.001	2018	0.3332	2.9823	0.006
2009	0.3948	3.5992	0.001	2019	0.3276	2.9632	0.002
2010	0.3291	3.0274	0.002	2020	0.3508	3.177	0.005

According to the global spatial correlation test results in Table 3, the $Moran's\ I$ index of China's provincial energy carbon intensity ECI fluctuated between 0.2995-0.4597 from 2001 to 2020, and passed the significance test of 1% in all years, indicating that China's energy carbon intensity had a significant positive correlation in space from 2001 to 2020, that is, the higher the energy carbon intensity of China's provinces in spatial distribution, the higher the energy carbon intensity of the surrounding provinces, While cities with low energy carbon intensity have low risk in surrounding provinces. In addition, the $Moran's\ I$ index of energy carbon intensity shows a downward trend, that is, the aggregation of energy carbon intensity is decreasing.

4.2. Local Spatial Correlation Analysis

According to the results of the global spatial correlation test, the energy carbon intensity has a positive spatial correlation at the significance level of 1%. In order to determine the spatial agglomeration status of the energy carbon intensity of each province, this paper further analyzes the local spatial correlation of each province through the Lisa agglomeration table, including the spatial agglomeration characteristics and the evolution process of the agglomeration region. The results are shown in Table 4.

China's energy carbon intensity has a strong spatial correlation. From the perspective of spatial distribution, at the 10% significance level, the "high-high" agglomeration of energy carbon intensity is mainly distributed in the Northeast comprehensive economic zone and the comprehensive economic zone in the middle reaches of the Yellow River, and the "low-low" agglomeration is mainly distributed in the southwest comprehensive economic zone.

China's energy carbon intensity has obvious local aggregation, and changes with time. The economic zone in the middle reaches of the Yellow River is rich in coal resources. As the main coal producing area in China, the coal share in the energy consumption structure is high, and the change is small. It has always been a "high-high" gathering area. Ningxia and Xinjiang in the northwest comprehensive economic zone are also the "high-high" agglomeration formed by the high share of coal production and consumption. Since the northern coastal comprehensive economic zone entered the 12th Five Year Plan period, the production capacity of high energy consuming industries has been limited, and the share of coal in the energy consumption structure has decreased. The "high-high" agglomeration has disappeared since the 13th Five Year Plan period. Thanks to the abundant hydropower resources and the use of other non-fossil energy, the southwest comprehensive economic zone has gradually formed a "low-low" agglomeration area.

Table 4. China's energy carbon intensity Lisa agglomeration table

region	province	2005	2010	2015	2020
Northern coastal Comprehensive Economic Zone	Beijing	-	-	-	-
	Tianjin	-	-	-	-
	Hebei	H-H	H-H	H-H	-
	Shandong	H-H	H-H	H-H	-
Northwest Comprehensive Economic Zone	Gansu	-	-	-	-
	Qinghai	L-L	-	-	-
	Ningxia	H-H	H-H	H-H	H-H
	Xinjiang	L-L	L-L	H-L	H-L
Southwest Comprehensive Economic Zone	Guangxi	-	-	-	L-L
	Chongqing	-	-	-	-
	Sichuan	-	-	-	L-L
	Guizhou	-	H-L	H-L	L-L
	Yunnan	-	-	L-L	L-L
Northeast Comprehensive Economic Zone	Liaoning	L-H	L-H	L-H	L-H
	Jilin	H-H	H-H	H-H	H-H
	Heilongjiang	H-H	H-H	H-H	H-H
Eastern coastal Comprehensive Economic Zone	Shanghai	-	-	-	-
	Jiangsu	-	-	-	-
	Zhejiang	-	-	-	-
Comprehensive economic zone in the middle reaches of the Yellow River	Shanxi	H-H	H-H	H-H	H-H
	Inner Mongolia	H-H	H-H	H-H	H-H
	Henan	H-H	H-H	H-H	H-H
	Shaanxi	H-H	H-H	H-H	H-H
Southern coastal economic zone	Fujian	-	-	-	-
	Guangdong	-	-	L-L	-
	Hainan	L-L	-	-	-
Comprehensive economic zone in the middle reaches of the Yangtze River	Anhui	-	-	-	-
	Jiangxi	H-L	-	-	-
	Hubei	-	-	-	-
	Hunan	-	-	L-L	-

Note: "-" is not significant at the significance level of 10%.

4.3. Empirical Analysis on Driving Factors of Energy Carbon Intensity

The above study found that China's energy carbon intensity has significant spatial agglomeration, and the $Moran's\ I$ index passed the significance test of 1% in all years (see Table 3). Therefore, this chapter uses the spatial panel model as the basic model for analysis.

As for the choice of specific model form, this paper carries out LM Test, Hausman test, LR test and Wald test in turn. As shown in table 6-7, first of all, compare the SAR model with the SEM model. Using LM Test, LM-LAG test was not significant, LM-ERR test was significant under 1% significance, and Robust LM-LAG test and Robust LM-ERR test were significant under 1% significance, so SEM model was selected; Secondly, the fixed effect model was compared with the random effect model, and the Hausman test was used. The test results showed that the Hausman test was 92.56, which was significant under 1% significance. Therefore, the fixed effect model was selected; Then, the SDM model is compared with SAR model and SEM model. Using likelihood ratio LR test, Robust LM-ERR test and LR-SD-ERR test are significantly positive under 1% significance, SDM model is selected. Finally, Wald test. Wald-lag and Wald-error were significantly positive under the significance of 1%. SDM model was further selected by AIC and BIC criteria. To sum up, the fixed effect spatial panel Dobbin model is selected, and the time and spatial effects are controlled at the same time.

Table 5. Test results of spatial panel model selection

Inspect	**Result**
LM-LAG test	1.0937
LM-ERR test	183.4186***
Robust LM-LAG test	87.0314***
Robust LM-ERR test	269.3563***
LR-SD-LAG test	44.72***
LR-SD-ERR test	45.96***
Hausman test	92.56***
Wald-lag	27.94***
Wald-error	29.19***

Note: ***, **, * respectively mean significant at the significant level of 1%, 5% and 10%.

Firstly, the spatial effect is not considered. The estimation results are shown in column 2 of table 5. There is a significant spatial effect in China's energy carbon intensity. Ignoring the spatial effect may affect the unbiased, consistent and effective estimation results (Zhaoyanyun et al., 2017). The estimated results under the spatial panel Durbin model are shown in column 3 of table 6. The coefficient of the spatial lag term $W \times ECI$ of energy carbon intensity is significantly positive at the significance level of 1%, indicating that China's energy carbon intensity has a positive spatial correlation, which is consistent with the above analysis results. The regression results of various influencing factors of energy carbon intensity are analyzed as follows:

(1) The regression coefficients of industrial structure upgrading (AIS), government intervention (gov) and energy consumption (VEC) were significantly negative at the significance level of 1%. The upgrading of industrial structure can significantly promote the decline of energy carbon intensity, and the upgrading of industrial structure can promote the low-carbon optimization of energy structure. The main reason is that the tertiary industry has a higher proportion of low-carbon clean energy consumption, which is conducive to the low-

carbon development of energy structure; The degree of government intervention can promote the decline of energy carbon intensity. Increasing government financial expenditure to support the development of enterprises can accelerate the transformation of energy structure. At the initial stage of energy transformation, more government support is needed to accelerate the development and use of clean energy; During the study period, the energy carbon intensity decreased with the increase of per capita energy consumption, that is, the optimization of energy structure was carried out with the increase of per capita energy consumption, mainly because the proportion of relatively clean natural gas and clean electricity consumption in the new energy consumption increased year by year. Therefore, with the increase of per capita energy consumption and the synchronous optimization of energy structure, the government should encourage the supply and investment of clean energy to make the new energy consumption come from clean energy as much as possible.

(2) The regression coefficients of environmental regulation (pws), energy consumption structure (ESC) and energy endowment (eed) were significantly positive at the significance level of 5%. The provinces with higher intensity of environmental regulation also have higher energy carbon intensity. This index is measured by the proportion of waste gas treatment investment in GDP in the completion of industrial pollution control investment. When the environmental pollution in a region is serious, the government will increase the investment in environmental treatment. Therefore, the government needs to coordinate the relationship between economic development and environmental treatment. It needs to grasp the degree of pollution first and then treatment, Reduce energy carbon intensity through continuous energy structure optimization. The optimization of energy consumption structure can effectively reduce the energy carbon intensity. The energy consumption structure is measured by the proportion of coal consumption in energy consumption. When the proportion of coal consumption increases, it will obviously promote the increase of energy carbon intensity. Therefore, it is necessary to reduce the proportion of coal in the energy consumption structure as much as possible, promote the clean and optimized energy structure, and promote the reduction of energy carbon intensity. The higher the energy endowment, the higher the regional energy carbon intensity. China is relatively abundant in coal resources. In areas rich in coal resources, the price of coal is relatively cheap, leading to energy consumption dominated by coal. Therefore, regions with high resource endowment should strengthen the development of clean coal use to weaken the impact of the high proportion of coal consumption in the energy consumption structure on energy carbon intensity.

(3) The regression coefficients of energy efficiency (eef), scientific and technological level (STL) and economic openness (eo) are negative, but not significant. The regression coefficient of economic development level ($vGDP$) is positive, but not significant. That is, during the research period, the level of science and technology, economic openness and economic development are not the main influencing factors of energy carbon intensity.

(4) The regression coefficients of spatial lag terms $W \times AIS$, $W \times pws$ and $W \times eef$ of industrial structure upgrading (AIS), environmental regulation (pws) and energy efficiency (eef) are significantly negative. It shows that the level of industrial structure, the intensity of environmental regulation and energy efficiency of a geographically adjacent province can affect the energy carbon intensity of the province, and is consistent with the impact direction of the level of industrial structure, the intensity of environmental regulation and energy efficiency of the province on the energy carbon intensity of the Province. It further shows that there is a spatial spillover effect of energy carbon intensity.

Table 6. Regression estimation results

variable	Common panel	Spatial panel Dobbin model
ESC	0.0167^{***} (11.55)	0.0141^{***} (10.07)
AIS	-0.1899^{***} (-5.28)	-0.171^{***} (-5.13)
STL	-0.0583^{**} (-2.22)	-0.0127 (-0.49)
pws	0.0008^{**} (2.05)	0.0009^{**} (2.43)
gov	-0.0943^{***} (-2.86)	-0.0917^{***} (-3)
eo	-0.022 (-1.07)	-0.0373^{*} (-1.93)
VEC	-0.4385^{***} (-5.56)	-0.3956^{***} (-5.35)
eef	-0.2844 (-1.41)	-0.1267 (-0.66)
eed	0.0147^{***} (5.97)	0.0139^{***} (5.93)
$vGDP$	-0.0117 (-0.08)	0.0682 (0.5)
$W \times AIS$	-	-0.1599^{**} (-2.46)
$W \times pws$	-	-0.0027^{***} (-3.45)
$W \times eef$	-	-1.0946^{***} (-3.75)
$W \times ECI$	-	0.1227^{**} (2.03)
sample size	600	600
Individual effect	yes	yes
Year effect	yes	yes
Log-likelihood	-	345.2698
R^2	0.3054	0.332

Note: ***, **, * are significant at the significance level of 1%, 5% and 10%, respectively. The Z-test value in brackets.

It is biased to directly test whether the explanatory variable has spillover effect through the spatial lag term of the explanatory variable. This problem can be solved through the test of direct effect and indirect effect (Le sage and Pace, 2009). The influencing factors of China's energy carbon intensity can be divided into intra regional direct effect and inter regional spillover effect, which exist simultaneously and complement each other. Table 6-9 shows the test results of the direct and indirect effects of the influencing factors of China's energy carbon intensity, so the conclusion is robust. The direct effects of ESC, pws and eed are significantly positive, that is to say, the energy structure, environmental regulation and energy endowment of the region are not conducive to the decline of energy carbon intensity of the region. However, when this effect is transmitted to the adjacent regions, it will react on the region, and their indirect effects are significantly negative, indicating that the energy structure, environmental regulation and energy endowment of the region have an inhibitory effect on the energy carbon intensity of the adjacent regions. The direct effect of AIS and eef is significantly negative, and their indirect effect is also significantly negative, indicating that the upgrading of industrial structure and energy efficiency can not only reduce the local energy carbon intensity, but also reduce the energy carbon intensity of adjacent regions. The direct effect of gov is significantly negative, while the indirect effect is significantly positive, indicating that government intervention will reduce the local energy carbon intensity, but increase the energy carbon intensity of adjacent areas.

Table 7. Test results of direct and indirect effects

variable	Direct effects	Indirect effects
ESC	0.0142^{***} (9.85)	0.002 (1.57)
AIS	-0.1774^{***} (-5.56)	-0.2047^{***} (-3.07)
STL	-0.0102 (-0.41)	-0.0013 (-0.31)
pws	0.0008^{**} (2.23)	-0.0028^{***} (-2.99)
gov	-0.0917^{***} (-3.04)	-0.0128 (-1.53)
eo	-0.0365^{*} (-1.89)	-0.0051 (-1.2)
VEC	-0.3965^{***} (-5.12)	-0.0487 (-1.49)
eef	-0.1609 (-0.81)	-1.2517^{***} (-3.73)
eed	0.0141^{***} (6.28)	0.002 (1.57)
$vGDP$	0.0678 (0.48)	0.0087 (0.39)

Note: ***, **, * are significant at the significance level of 1%, 5% and 10%, respectively. The Z-test value in brackets.

5. Conclusion

This paper first analyzes the temporal and spatial characteristics of China's overall and regional energy consumption and energy consumption structure; Secondly, the energy carbon intensity of China's provinces and cities from 2001 to 2020 is calculated, and the time deductive characteristics of energy carbon intensity are analyzed; Thirdly, $Moran's\ I$ index and LISA index are used to analyze the spatial correlation of energy carbon emission intensity; Finally, based on the panel data of 30 provinces and cities from 2001 to 2020, a spatial panel Durbin model is constructed to explore the driving factors of energy carbon intensity. The research conclusions mainly include:

(1) The optimization and upgrading of China's industrial structure and the continuous improvement of energy efficiency have made the growth rate of total energy consumption continue to decline. In high emission energy, the growth rate of coal consumption decreased more than that of total energy consumption; Among low-carbon energy, natural gas and non-fossil energy have maintained a high growth rate. The share of traditional fossil energy in China's energy consumption structure has declined year by year, while the proportion of clean energy such as natural gas and primary electric energy in China's energy consumption structure has increased year by year, showing the trend of continuous optimization of China's energy structure. From the perspective of the overall change of energy consumption structure, the share of coal consumption has declined in an all-round way, the share of oil consumption has increased steadily, and the share of natural gas and non-fossil energy consumption has increased significantly.

(2) During the study period (2001-2020), the $Moran's\ I$ index of China's provincial energy carbon intensity has a significant positive correlation in space, and the $Moran's\ I$ index of energy carbon intensity shows a downward trend as a whole, that is, the aggregation of energy carbon intensity is decreasing. China's energy carbon intensity has a strong spatial correlation. From the perspective of spatial distribution, at the 10% significance level, the "high-high" agglomeration of energy carbon intensity is mainly distributed in the Northeast comprehensive economic zone and the comprehensive economic zone in the middle reaches of the Yellow River, and the "low-low" agglomeration is mainly distributed in the southwest comprehensive economic zone.

(3) The empirical study of spatial panel Durbin model shows that China's energy carbon intensity has a positive spatial correlation. The upgrading of industrial structure, the degree of government intervention and energy consumption can significantly promote the decline of energy carbon intensity. Provinces with higher environmental regulation, energy consumption structure and energy endowment also have higher energy carbon intensity. Regions with higher energy efficiency, scientific and technological level and economic openness have lower energy carbon intensity, but this result failed to pass the test, that is, these factors are not the main factors for the change of energy carbon intensity during the study period. Therefore, the government should increase financial support for the development and utilization of clean energy, speed up the optimization and upgrading of industrial structure, low-carbon transformation of energy system, and promote the reduction of energy carbon intensity, so as to achieve the national emission reduction goal. Regions with high coal resource endowment should strengthen the clean use and development of coal, control the scale of high energy consuming industries that are highly dependent on coal, change the idea of development before governance, and make economic development and environmental protection develop coordinately, so as to weaken the obstacles of environmental regulation, energy consumption structure and energy endowment to the decline of energy carbon intensity.

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References

[1] Lin Boqiang, Yao Xin, Liu Xiying. China’s Energy Strategy Adjustment under Energy Conservation and Carbon Emission Constraints [J]. Social Sciences in China, 2010 (01):58-71.

[2] Cho, W.G., Nam, K., Pagan, J.A. Economic growth and interfactor/interfuel substitution in Korea[J]. Energy Economics, 2004, 26(1): 31-50.

[3] Pindyck, R.S. Interfuel substitution and the industrial demand for energy: an international comparison[J]. The Review of Economics and Statistics, 1979: 169-179.

[4] Urga, G., Walters, C. Dynamic translog and linear logit models: a factor demand analysis of interfuel substitution in US industrial energy demand[J]. Energy Economics, 2003, 25(1): 1-21.

[5] Ma, L., Chong, C., Zhang, X., et al. LMDI Decomposition of Energy-related CO2 Emissions Based on Energy and CO2 Allocation Sankey Diagrams: the Method and an Application to China[J]. Sustainability, 2018, 10(2): 344.

[6] Zhu, Q., Peng, X., Wu, K. Calculation and decomposition of indirect carbon emissions from residential consumption in China based on the input–output model[J]. Energy Policy, 2012, 48(none):618-626.

[7] Song Hui, Wei Xiaoping. Research on the statistical characteristics of energy consumption structure [J]. Statistics & Information Forum, 2013,28 (10): 30-36.

[8] Shao Qinglong. China's economic growth and structural adjustment of energy consumption of three industries [J]. scientific research management, 2017,38 (01): 127-136.

[9] Zou Xuan, Jia Leiyu. The Optimal Path and Regional Differences of the Industrial Energy Consumption Structure [J]. Soft Science, 2017,31 (06): 46-50.

[10] Burke, P.J., Shahiduzzaman, M., Stern, D.I. Carbon dioxide emissions in the short run: The rate and sources of economic growth matter[J]. Global Environmental Change, 2015, 33: 109-121.

[11] Lin Boqiang, Li Jianglong. The Transformation of China's Energy Structure under the Constraint of Environmental Governance -- An Analysis Based on the Peak Value of Coal and Carbon Dioxide [J]. China Social Sciences, 2015 (09): 84-107+205.

[12] Ge Hong, Guo Yuwei, Han Weiyi. Effectiveness of Green Development and Environmental Governance – A Two-stage Non-radial Directional Distance Function Approach [J]. Operations Research and Management Science, 2017,26 (05): 142-150.

[13] Xu Shan, Fan Decheng, Wang Shaohua. Research on Evaluation of China's Energy Structure to Low Carbon Based on the Optimal Evaluation Met [J]. Science and Technology Management Research, 2016,36 (05): 186-192.

[14] Shi, Y., Pang, N., Ding, Y. Environment effects of energy consumption structure based on comprehensive grey correlation degree: from 1998 to 2006 in China[C]//2009 Asia-Pacific Power and Energy Engineering Conference. IEEE, 2009: 1-4.

[15] Tao Changqi, Li Cui, Wang Xiahuan. Research on the Relationship Between the Effect of Environmental Regulation on Total Factor Energy Efficiency and the Evolution of Energy Consumption Structure [J]. China Population, Resources and Environment, 2018,28 (04): 98-108.

[16] Liu Yaqin, Zhao Guohao. Analysis of the Evolution of China's Energy Consumption Structure under the Constraint of Energy Conservation and Emission Reduction [J]. Economic Iissues, 2015 (01): 27-33.

[17] Fang Debin, Dong Wei, Yu Qian. Optimization of China's Energy Consumption Structure under the Trend of Low-carbon Transformation [J]. Journal of Technology Economics, 2016,35 (07): 71-79+128.

[18] Chen Qiang. Econometrics and Stata Application [M]. Higher Education Press, 2015.

[19] Yu Zhuangxiong, Chen Jie, Dong Jiemiao. Road to Low Carbon Economy: Perspective of Industrial Planning [J]. Economic Research Journal, 2020,55 (05): 116-132.

[20] Wang Guixin, Li Gang. Effect of "Ecological Province" Construction on Carbon Emission Reduction in China [J]. Acta Geographica Sinica, 2020,75 (11): 2431-2442.

[21] Chen Qianli, Ma Xianlei, Shi Xiaoping, Zou Xu, Lan Jing. Does the Supply of Industrial Land Affect Industrial Energy Carbon Emissions? -- Based on the Analysis of Supply Scale, Method and Price [J]. China Population, Resources and Environment, 2019,29 (12): 57-67.

[22] Ren Yayun, Fu Jingyan. Research on the Effect of Carbon Emissions Trading on Emission Reduction and Green Development [J]. China Population, Resources and Environment, 2019,29 (05): 11-20.

[23] Yu Binbin. How Does Industrial Restructuring Improve Regional Energy Efficiency? – An Empirical Study Based on Two Dimensions of Magnitude and Quality [J]. Journal of Finance and Economics, 2017,43 (01): 86-97.

[24] Luo Chaoyang, Li Xuesong. Industrial Structure Upgrading, Technological Progress and China's Energy Efficiency -- An Empirical Analysis Based on the Non-dynamic Panel Threshold model [J]. Inquiry into Economic Issues, 2019 (01): 159-166.

[25] Huang Xianglan, Zhang Xunchang, Liu Ye. Does China's Carbon Emissions Trading Policy Fulfill the Environmental Dividend? [J]. Economic Review, 2018 (06): 86-99.

[26] Wang Ke, Li Chenxin, Wang Jiayu. China's Provincial Energy Efficiency Index (2010-2018) [J]. Journal of Beijing University of Technology (SOCIAL SCIENCE EDITION) 2021 (05): 1-16.