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Research on Influencing Factors of Provincial Energy Efficiency in China Based on the Spatial Panel Model

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ABSTRACT

The Super-SBM model was used first to assess the energy efficiency of 30 Chinese provinces from 2012 to 2017. After that, an energy efficiency spatial correlation test was conducted, and finally, the influencing elements of energy efficiency were analyzed using a geographic panel model. The findings show that the amount of regional economic development has a substantial positive impact on energy efficiency, whereas the level of regional urbanization and the severity of environmental restrictions have a considerable negative impact on energy efficiency in China's provinces. Other regions' energy structure and technical innovation have a substantial positive spillover effect on the region's energy efficiency, whereas other regions' economic development and foreign direct investment have a significant negative spillover effect on the region's energy efficiency.

INTRODUCTION

The development and utilization of energy are required for both continual economic growth and continuous societal development. Energy is a crucial component of societal production. Energy usage is steadily growing as industrialization progresses. According to a report by the International Energy Agency, worldwide energy consumption will increase by 37% by 2040. Although sufficient and stable energy input can maintain national energy security and promote healthy economic development, energy shortage is one of the main challenges in the economic and social development of developing countries. As the largest developing country in the world, China's energy consumption has shown explosive growth along with its economic development. In 2019, the total energy consumption reached 4870 MTCE, and the external dependence on natural gas and oil has exceeded 40% and 70%. Clean energy is relatively scarce, and the long-lasting energy crisis will cause more serious development problems and bring a heavy burden to China. The coal-based energy structure and crude economic expansion have frequently broken through the bottom line of environmental carrying capacity throughout the past 40 years of reform and opening up, and pollutant emissions significantly surpass the global average.

There is a serious shortage of energy resources in China, and the environmental carrying capacity is close to the upper limit. It is necessary to slow down the growth rate of total energy demand, accelerate structural transformation, promote the formation of new ways of green and circular development, improve energy consumption structure, and make energy development in the direction of low-carbon and clean energy. The energy issue is one of the bottlenecks restricting the sustainable development of China's economy and society. It's worthwhile to consider and investigate how to make the most of limited energy. For China to accomplish ecological civilization construction and high-quality economic development, this is critical. Therefore, the evaluation of energy efficiency and the study of its influencing factors have become the focus of attention of many scholars.

Past Studies

At present, research on energy efficiency at the inter-provincial is mainly focused on energy efficiency calculations and influencing factors.

For the study of energy efficiency measurement, the data envelopment analysis (DEA) model is the current mainstream method. It does not need to consider the influence of dimensions and weights, nor does it need to set the production function in advance. It can evaluate complex systems with multiple inputs and multiple outputs. Wang et al. (2018) have used the DEA method to measure energy efficiency. With the increasingly serious pollution problem, to measure and evaluate energy efficiency more scientifically and rationally, more and more scholars have begun to consider undesired output in the DEA model. By weighting the emissions of the "three industrial wastes," Zhou & Zhang (2016) portrayed environmental pollution emissions as undesirable output. Tone (2003) included the undesirable output in the SBM model, recognizing the various proportional changes between the expected and undesired outputs. Guan & Xu (2015) used the SBM model of undesirable output to investigate the spatial distribution characteristics and evolution of energy efficiency. Wang et al. (2017a) found that improving energy efficiency is vital for slowing global warming through an improved SBM model study. Meng et al. (2016) used the hybrid SBM model to measure the provincial energy efficiency under the haze constraints in China and found that there is a problem of energy waste. Qin et al. (2016) used the DEA-SBM model of undesired output to measure the energy efficiency of the eastern coastal area and found that energy efficiency is greatly affected by undesired output.

For the study of energy efficiency influencing factors, Cui et al. (2014) found that technological progress has a significant impact on energy efficiency. Wang et al. (2011) believed that energy efficiency will be affected by government intervention, degree of opening to the outside world, and industrial structure. Yao et al. (2012) found that optimizing the industrial structure can improve energy efficiency. Wu & Du (2018) based on the data of 11 provinces in the Yangtze River Economic Belt found that skewed technological progress has a positive effect on total factor energy efficiency. Ruipeng & Boqiang (2017) believed that improving technical production methods, increasing per capita GDP, optimizing the energy structure, and increasing foreign direct investment can improve energy efficiency. Liu et al. (2008) studied that increasing the relative price of energy will have a positive impact on energy efficiency, but Li et al. (2014) analyzed that the effect of energy price on energy efficiency is not significant. Jiang & Ji (2020) believed that the level of urbanization has a negative inhibitory effect on energy efficiency, while Song et al. (2020) believed that the level of urbanization has a positive effect. Wang et al. (2017b) analyzed that environmental regulations inhibit the improvement of energy efficiency by increasing the operating costs of enterprises. Wang & Zhong (2015) indicated that environmental regulation improves energy efficiency through innovation compensation effects. Dai & Fu (2020) believed that the impact mechanism of environmental regulations is different for regions with different energy efficiency.

This article draws on the work of earlier researchers and expands on two points: On the one hand, due to the vast number of input and output indicators, the standard DEA model will have several decision-making units that are rated as successful, but it cannot be distinguished further. As a result, the Super-SBM model of undesirable output is employed in MaxDEA software to assess energy efficiency; on the other hand, the energy usage efficiency of various locations and its influencing factors are usually spatially associated. The use of traditional panel models will ignore this problem. However, the spatial panel model can test whether the energy efficiency has spatial relevance, and can decompose its effects.

MATERIALS AND METHODS

Construction of the Theoretical Model

Super-SBM model: The Super-SBM model can solve the evaluation and ranking of relatively effective units. When evaluating the j-th decision-making unit, the input and output of the j-th decision-making unit will be replaced by the linear combination of the inputs and outputs of all other decision-making units, and the j-th decision-making unit will be excluded.

Suppose there are n decision-making units (DMU_j, j = 1, 2,...,n), and each DMU uses m types of inputs (i=1,...,m) to produce s types of outputs (r=l,..., s), mark the DMU to be evaluated as DMU_j (j=1,...,n). Let x_{ij} be the i-th input of the j-th DMU, and y_{rj} be the r-th output of the j-th DMU. The model of the Super-SBM under variable returns to scale is as follows:

$$Min\delta=\frac{s}{m}\left(\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{io}}\Big/\sum_{r=1}^{s}\frac{\bar{y}_r}{y_{ro}}\right)$$

$$\bar{x}\geq\sum_{\substack{j=1\\j\neq o}}^{n}\lambda_j x_j,\ \bar{y}\leq\sum_{\substack{j=1\\j\neq o}}^{n}\lambda_j y_j,\ \sum_{\substack{j=1\\j\neq o}}^{n}\lambda_j=1,\ \bar{x}\geq x_o,\ \bar{y}\leq y_o \quad ...(1)$$

The Super-SBM model considering undesired output is:

$$Min\delta=\frac{\frac{1}{m}\sum_{t=1}^{m}\frac{x_t}{x_{to}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{y_r^g}{y_{ro}^g}+\sum_{r=1}^{s_2}\frac{y_r^b}{y_{ro}^b}\right)}$$

$$x\geq\sum_{\substack{n=1\\n\neq i}}^{N}x_n\cdot\lambda_n,\ y^g\leq\sum_{\substack{n=1\\n\neq i}}^{N}y_n^g\cdot\lambda_n,\ y^b$$

$$\geq\sum_{\substack{n=1\\n\neq i}}^{N}y_n^b\cdot\lambda_n,\ \sum_{\substack{n=1\\n\neq i}}^{N}\lambda_n=1$$

$$x\geq x_o,\ y^g\leq y_o^g,\ y^b\geq y_o^b,\ \lambda\geq 0 \quad ...(2)$$

Where, δ is the target efficiency, x, $y^{g,}$ and y^b represent input, expected output, and undesired output respectively; s denotes the relaxation vector, which can avoid the deviation that may be caused by the radial and angle selection; λ indicates the weight vector.

Spatial Correlation

Moran's I test is a hypothesis test method for spatial correlation. The global Moran's I statistic is defined as:

$$\text{Global Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{n} x_i$$

$$s^2 = \frac{1}{N}\sum_{i=1}^{n}(x_i - \bar{x})^2 \quad ...(3)$$

Where, i, j are regions, x_i and x_j denote the observed values of energy efficiency, $\bar{x}$ represents the mean value, and w_{ij} is the (i, j) element of the spatial weight matrix.

The global Moran's I is used to test whether each province has agglomeration in space, but it can't see how it is agglomerated. The local Moran's I scatter plot needs to be used to identify the type of aggregation in the local space of each area. The formula is as follows:

$$\text{Local Moran's I} = \frac{(x_i - \bar{x})}{s^2}\sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \quad ...(4)$$

Spatial Panel Model

Common spatial measurement models include the following three forms:

The spatial lag model: SLM assumes that the explained variable in the region depends on the explained variable in the neighboring region, namely:

$$Y = \rho WY + X\beta + \varepsilon \quad ...(5)$$

Y is the explained variable, X denotes the explanatory variable, ρ represents the spatial autoregressive coefficient, W indicates the spatial weight matrix, ε represents a random error, and β denotes the influence coefficient of X on Y.

The spatial error model: SEM assumes that there is a spatial correlation in the disturbance term, namely:

$$\begin{cases} Y = X\beta + \mu \\ \mu = \alpha W\mu + \varepsilon \\ \varepsilon \to N(0, \sigma^2 I_n) \end{cases} \quad ...(6)$$

α is the spatial correlation coefficient of the disturbance term.

The spatial Durbin model: SDM assumes that the explained variable in this region depends on the explanatory variable in the adjacent region, namely:

$$Y = \rho WY + X\beta + WX\delta + \varepsilon \quad ...(7)$$

$WX\delta$ represents the influence of explanatory variables from neighboring regions, and δ is the coefficient vector.

The spatial panel model: It can be expressed as:

$$\begin{cases} Y_{it} = \tau Y_{i,t-1} + \rho W_i^T Y_t + X_{it}^T \beta + W_i^T X_t \delta + \mu_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda W_i^T \varepsilon_i + \nu_{it} \end{cases} \quad ...(8)$$

Where, $Y_{i,t-1}$ is the first-order lag term of the explained variable, μ_i represents the individual effect, and γ_t denotes the time effect. If $\lambda = 0$, it is the SDM model; if $\lambda = 0$, $\delta = 0$, it is the SLM model; if $\tau = \rho = 0$, $\delta = 0$, it is SEM model.

RESULTS AND DISCUSSION

Data Source and Description

The data in this article comes from the 2013-2018 "China Price Statistical Yearbook" (Energy prices), "China Environmental Yearbook" (Strength of environmental regulations), and "China Statistical Yearbook" (Other indexes). The index system for the study of energy efficiency in various provinces in China is shown in Table 1.

It should be noted that to reduce the numerical difference between variables, logarithms are taken for all variables.

Calculation of Energy Efficiency

Use MaxDEA software to measure the energy efficiency of each province as shown in Table 2.

From 2012 to 2017, the energy efficiency of most provinces has shown an upward trend. Generally speaking, China's energy efficiency is constantly improving. Among them, the energy efficiency of Beijing, Tianjin, Shanghai, Jiangsu, and Guangdong is at the leading domestic level, with energy efficiency above 1; Heilongjiang, Guizhou, Yunnan, Gansu, Qinghai, Ningxia, and Xinjiang are at a relatively low level in China, and their energy efficiency doesn't exceed 0.5. In 2017, the average energy efficiency of China's provinces

Table 1: Index selection and description.

Model		Index	Description
Super-SBM model	Input	Capital investment	Total city investment in fixed assets
		Labor input	(Total number of employees at the end of the previous year + total number of employees at the end of the year)/2
		Energy input	Total energy consumption
	Output	Expected output	Industrial output
			GDP(Gross domestic product)
		Undesired output	Industrial wastewater discharge
			Industrial sulfur dioxide emissions
			Industrial smoke (dust) emissions
Space panel model	Explained variable	Energy efficiency	Use Super-SBM model to measure (Y)
	Explanatory variables	The level of economic development	GDP per capita (X1)
		Urbanization level	The proportion of the urban population in total population (X2)
		Energy structure	The proportion of natural gas consumption in total energy consumption (X3)
		Energy prices	Annual purchase index of industrial producers (fuel power category) (X4)
		Strength of environmental regulations	Sewage discharge fee collection amount (X5)
		Technological innovation	Research and development expenditure (X6)
		Foreign direct investment	The proportion of total investment of foreign-invested enterprises in GDP (X7)

was 0.606, most of the eastern provinces were higher than the national average and most of the western provinces were lower than the national average. From the east coast to the west interior, energy efficiency is gradually declining, and a significant divide exists between the central and western regions and the eastern coastal districts. The energy efficiency of provinces that are geographically close together is similar, implying that China's inter-provincial energy efficiency may be spatially related.

Spatial Correlation Test

The spatial weight matrix reflects the proximity of provinces in geographic space. This paper uses the modified adjacency weight matrix, which doesn't regard Hainan as an isolated island but is adjacent to Guangdong. According to the convention, all main diagonal elements are taken as 0, the formula is as follows:

$$W_{ij} = \begin{cases} 0, & i \text{ and } j \text{ are not adjacent} \\ 1, & i \text{ and } j \text{ are adjacent} \end{cases} \quad ...(9)$$

Calculate the global Moran's I index of the energy efficiency of China's provinces from 2012 to 2017 through the software Stata16.0. It can be seen from Table 3 that the spatial correlation test of each year is considered to have a positive spatial autocorrelation at a significance level of 10%.

Use GeoDa software to draw Moran's I scatter plot using 2017 energy efficiency data, as shown in Figure 1. Both the global Moran's I and the local Moran's I are represented in this diagram. The Global Moran's I index was shown to be significantly positive after 999 randomized permutations. The local Moran's I of each province is the product of the horizontal and vertical coordinates of these distributed sites.

Beijing, Tianjin, Shanghai, Shandong, Fujian, Jiangsu, and Zhejiang are in the H-H cluster (first quadrant), all provinces are located in the east. Based on the policy advantages in the early stage of reform and opening up and their own geographical advantages, the economic development started earlier. With the advancement of the industrial transfer process, the current main industries are tertiary industries with lower energy consumption; Jiangxi, Hebei, and Hainan belong to the L-H type (second quadrant), indicating that the energy efficiency of these three provinces is relatively low, but the energy efficiency of neighboring provinces is relatively high. Their economy is underdeveloped and they

Table 2: Inter-provincial energy efficiency values.

	2012	2013	2014	2015	2016	2017	Mean	Rank
Beijing	1.138	1.16	1.171	1.175	1.162	1.14	1.158	2
Tianjin	1.182	1.187	1.183	1.175	1.169	1.113	1.168	1
Hebei	0.534	0.532	0.51	0.489	0.519	0.512	0.516	21
Shanxi	0.433	0.383	0.352	0.316	0.296	0.538	0.386	25
Inner Mongolia	1.075	1.071	1.037	1.026	1.008	0.435	0.942	6
Liaoning	0.546	0.557	0.555	0.615	0.553	0.567	0.566	14
Jilin	0.615	0.641	0.639	0.618	0.644	0.589	0.624	11
Heilongjiang	0.437	0.459	0.471	0.446	0.397	0.362	0.429	23
Shanghai	1.059	1.091	1.089	1.108	1.117	1.199	1.111	3
Jiangsu	1.112	1.02	1.005	1.01	1.021	1.039	1.035	5
Zhejiang	1.002	0.786	0.826	0.804	0.866	0.834	0.853	7
Anhui	0.56	0.592	0.579	0.566	0.615	0.608	0.587	13
Fujian	0.635	0.689	0.718	0.721	0.815	0.774	0.725	8
Jiangxi	0.537	0.578	0.571	0.549	0.538	0.536	0.552	16
Shandong	0.701	0.712	0.685	0.676	0.697	0.693	0.694	9
Henan	0.584	0.556	0.537	0.526	0.571	0.602	0.563	15
Hubei	0.552	0.603	0.606	0.615	0.635	0.62	0.605	12
Hunan	0.56	0.645	0.656	0.656	0.652	0.622	0.632	10
Guangdong	1.063	1.069	1.055	1.064	1.056	1.042	1.058	4
Guangxi	0.496	0.546	0.553	0.559	0.558	0.456	0.528	20
Hainan	0.557	0.544	0.546	0.52	0.454	0.409	0.505	22
Chongqing	0.508	0.532	0.545	0.559	0.569	0.549	0.544	17
Sichuan	0.559	0.576	0.557	0.544	0.513	0.495	0.541	18
Guizhou	0.322	0.366	0.378	0.397	0.397	0.389	0.375	26
Yunnan	0.371	0.408	0.407	0.407	0.374	0.359	0.388	24
Shaanxi	0.582	0.554	0.536	0.499	0.505	0.514	0.532	19
Gansu	0.359	0.356	0.337	0.302	0.285	0.294	0.322	29
Qinghai	0.36	0.365	0.354	0.347	0.331	0.286	0.341	28
Ningxia	0.335	0.36	0.349	0.349	0.346	0.339	0.346	27
Xinjiang	0.328	0.333	0.33	0.299	0.277	0.274	0.307	30

mainly operate traditional resource-based industries with high resource consumption and low output. The extensive economic development model leads to low energy efficiency. Therefore, optimizing the industrial structure and improving energy efficiency are issues that local governments need to pay attention to. The 14 regions of Heilongjiang, Inner Mongolia, Xinjiang, Gansu, Shanxi, Shaanxi, Ningxia, Qinghai, Yunnan, Guizhou, Sichuan, Chongqing, Liaoning, and Jilin are in the L-L aggregation (third quadrant). Most of them are located in the central and western regions and have abundant natural resources. Early economic development relied heavily on energy-intensive businesses like heavy industry. Energy efficiency has improved in recent years, but there is still a lot of room for improvement, and an upgrade of the industrial structure is on the horizon. Guangdong is the typical province in the H-L cluster (quadrant 4), indicating that its energy efficiency is improving quicker than that of its neighbors Fujian, Jiangxi, Hunan, Guangxi, and Hainan. The energy efficiency of China's 30 provinces showed an obvious spatial imbalance. The energy efficiency of the

Table 3: China's 2012-2017 global Moran's I Index of energy efficiency.

year	I	E(I)	sd(I)	z	p-value
2012	0.158	−0.034	0.112	1.727	0.042
2013	0.126	−0.034	0.111	1.441	0.075
2014	0.149	−0.034	0.111	1.647	0.050
2015	0.149	−0.034	0.111	1.647	0.050
2016	0.178	−0.034	0.112	1.897	0.029
2017	0.347	−0.034	0.111	3.442	0.000

central and western provinces showed a concentration of low efficiency, while the energy efficiency of the southeast coastal areas showed a concentration of high efficiency. The whole presents a stepped distribution.

Spatial Panel Model Analysis

Before analyzing the spatial panel model, it is necessary to judge the choice of SEM, SLM, or SDM through the LM test, Wald test, and LR test. Through the LM test, LM-Error and robust LM-Error, LM-Lag, and robust LM-Lag all reject the null hypothesis at the 1% significance level, that is, it is considered that there is a spatial error or a spatial lag. The spatial Durbin model is general in spatial econometrics. It can be judged whether SDM can be simplified to SAR or SEM through the Wald test and LR test. According to the test results, the p-values of the Wald test and LR test are both 0.000, that is, the SDM model is the best. Then through the Hausman test to determine whether to choose a fixed effect model or a random-effect model, the Hausman statistic is 88.84, the p-value is 0.000, and the null hypothesis of random effects is rejected at the 5% significance level, so the fixed effect model is constructed. In addition, to eliminate the influence of heteroscedastic and autocorrelation, a fixed-effects model with modified heteroscedasticity and autocorrelation robust standard errors is used. The estimation results comparing the traditional panel model and the spatial panel model are shown in Table 4.

In the fixed-effects model with traditional panel modified heteroscedasticity and autocorrelation robust standard errors, the level of economic development has a positive and significant impact on energy efficiency. The level of urbanization, the intensity of environmental regulations,

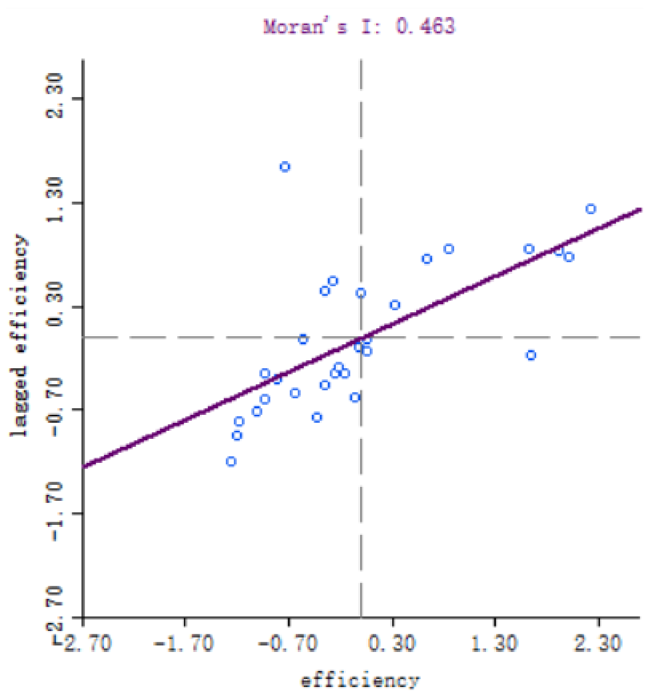

Fig. 1: Moran's I scatter plot.

Table 4: Model estimation results.

variable	A fixed-effects model with traditional panel modified heteroscedasticity and autocorrelation robust standard errors		Individual time double fixed effect spatial Durbin model	
	coefficient	p-value	coefficient	p-value
lnX1	0.512	0.007	0.988	0.000
lnX2	−1.573	0.002	−0.698	0.061
lnX3	0.005	0.875	−0.050	0.243
lnX4	−0.002	0.938	0.100	0.420
lnX5	−0.039	0.049	−0.053	0.031
lnX6	0.061	0.179	0.034	0.563
lnX7	−0.085	0.003	−0.038	0.254
W*lnX1			−1.258	0.000
W*lnX2			0.764	0.167
W*lnX3			0.271	0.001
W*lnX4			0.241	0.411
W*lnX5			0.050	0.251
W*lnX6			0.407	0.003
W*lnX7			−0.200	0.006

and foreign direct investment have a significant negative impact on energy efficiency. Compared with the traditional panel model, the spatial panel model considers the combined effects of the spatial error term and the spatial lag term, so it can more scientifically and reasonably reflect the direction and magnitude of the effects of various influencing factors. In the individual-time double fixed-effect spatial Durbin model, there is a significant positive impact on the level of economic development and a significant negative impact on the level of urbanization and the intensity of environmental regulations.

Then use the individual time double fixed effect spatial Durbin model to decompose its effects into direct effects, spillover effects (indirect effects), and total effects. The results are shown in Table 5.

In terms of direct effects, the level of economic development has a significant positive impact on energy efficiency, indicating that economic development can improve energy efficiency. With the continuous development of the economy and the improvement of the level of industrialization, a large number of advanced equipment and technologies have entered production and life, which has promoted the improvement of energy efficiency. The level of urbanization and the intensity of environmental regulations in the region have a significant negative impact on energy efficiency, indicating that the improvement of the two will reduce energy efficiency. The reason is that the acceleration of urbanization will increase people's demand for infrastructure, promote the rise of high-polluting industries such as steel and cement, and

Table 5: Effect decomposition results of spatial Durbin model.

variable	Direct effects		Spillover effects		Total effects	
	coefficient	p value	coefficient	p value	coefficient	p value
lnX1	1.017	0.000	−1.284	0.000	−0.267	0.303
lnX2	-0.731	0.046	0.818	0.123	0.087	0.869
lnX3	−0.050	0.232	0.259	0.002	0.209	0.005
lnX4	0.094	0.447	0.212	0.436	0.306	0.260
lnX5	−0.055	0.025	0.053	0.227	−0.002	0.965
lnX6	0.029	0.602	0.378	0.005	0.408	0.008
lnX7	−0.033	0.330	−0.185	0.009	−0.218	0.005

increase the demand for living energy, thereby inhibiting the improvement of energy efficiency. Increasing the intensity of environmental regulations means increasing the amount of pollution charges levied on enterprises. The environmental regulations are closely linked to the market, guide enterprises through market signals, and can produce continuous stimulus to enterprises. However, under the influence of the current factor market distortions in China, the deepening of regional capital is mainly biased towards high energy consumption and high pollution heavy chemical industries, making it difficult to achieve the incentive effect of environmental regulations on enterprise technological innovation, thereby inhibiting the improvement of energy efficiency.

The impact of energy structure, energy prices, technological innovation, and foreign direct investment on energy efficiency is not significant. In terms of energy structure, natural gas is low-carbon energy. Increasing its consumption can reduce pollution and improve energy efficiency. However, excessive natural gas consumption will cause a waste of energy. When energy is not fully utilized, energy efficiency will be inhibited and can't be improved, so the impact of energy structure on energy efficiency is not significant. In terms of energy prices, although price increases will force companies to invest in R&D of energy-saving and emission-reduction technologies, thereby improving energy efficiency. However, due to the time lag in the transmission mechanism of energy prices, the stricter price control of local governments, and the competition mechanism and monopoly mechanism among enterprises, it is difficult to form unified pricing in the energy market, which leads to inefficiency. Therefore, the impact of energy prices on energy efficiency is not significant. In terms of technological innovation, although technological progress can improve energy efficiency and reduce energy consumption, it will also produce a "rebound effect", thereby promoting economic growth, leading to an increase in energy demand and reducing energy efficiency. Therefore, the impact of technological innovation on energy efficiency is not significant. In terms of foreign direct investment, foreign investment can introduce advanced technology and efficient and cutting-edge production management methods to promote energy efficiency. However, excessive foreign investment will bring in a large number of foreign investment companies, including high energy consumption and high pollution companies, which will inhibit the improvement of energy efficiency. Therefore, the impact of foreign direct investment on energy efficiency is not significant.

In terms of spillover effects, adjacent areas' energy structures and technology innovation have a positive and considerable spillover effect on the region's energy efficiency, with the technological innovation spillover effect being bigger than the energy structure. The economic development level and foreign direct investment of neighboring regions have a significant negative spillover effect on the energy efficiency of the region, and the negative spillover effect of the economic development level is greater than that of foreign direct investment. The level of urbanization, energy prices, and the intensity of environmental regulations in neighboring regions do not have a significant impact on the energy efficiency of the region.

CONCLUSION

First and foremost, this paper uses the Super-SBM model to measure the energy efficiency of 30 provinces in China from 2012 to 2017 and finds that most provinces are increasing year by year. There is an obvious imbalance in energy efficiency among provinces, gradually decreasing from the east coast to the west inland; Besides, through the global Moran index test and the local Moran scatter plot, it is judged that energy efficiency has spatial correlation; Last but not least, the SDM model is judged by LM test, Wald test, and LR test, and the fixed effect model is judged by Hausman test. When the fixed-effects model is compared to traditional panel modified heteroscedasticity and autocorrelation robust standard errors, as well as the individual-time double fixed-effect spatial Durbin model, it is discovered that the latter can more scientifically and reasonably reflect the direction and magnitude of various influencing factors. Decomposing the effects of the individual-time double fixed-effect spatial Durbin model. In terms of direct effects, the level of economic development has a significant positive impact on energy efficiency, while the level of regional urbanization and the intensity of environmental regulations have a significant negative impact on energy efficiency, and other indicators are not significant. In terms of spillover effects, the positive spillover effects of technological innovation are greater than the energy structure, the negative spillover effects of economic growth are greater than foreign direct investment, and other indicators are not significant.

The recommendations are as follows: To start with, according to the spatial relevance of energy efficiency, promote the free flow and optimal allocation of energy between regions, thereby improving energy utilization efficiency. The improvement of energy efficiency in neighboring regions is conducive to the improvement of energy efficiency in the region. It is necessary to strengthen the coordinated development of energy efficiency between the region and neighboring provinces. In addition, develop the level of economic development in the region, increase per capita GDP, improve people's quality of life, strengthen inter-regional economic cooperation and technological exchanges, and thereby improve energy efficiency. But at the same time, it is necessary to avoid the negative spillover effect of the economic development of neighboring regions on the region. To improve the coordinated economic development between areas, the government should adopt corresponding guiding policies. Finally, provinces with higher energy efficiency should maximize the positive spillover effects of energy structure and technological innovation by encouraging neighboring regions to improve their energy structure and technological innovation, thereby improving energy efficiency and narrowing the energy efficiency gap. Deepen structural reforms on the energy supply side, expand expenditures for technology development, and enhance China's energy self-sufficiency.

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