Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 13, No. 1, 2024

Research on the Influence and Spatial Effect of Carbon Trading Market on Green Innovation Efficiency of Industrial Enterprises

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Abstract: Based on the panel data of 30 provinces and cities in China from 2005 to 2020, a two-stage value chain model of green innovation of Chinese industrial enterprises is constructed and the green innovation efficiency of industrial enterprises is measured, in which coastal cities such as Guangdong, Beijing, and Shanghai have the highest innovation efficiency, and inland cities such as Ningxia, Inner Mongolia, and Gansu have the lowest efficiency. On this basis, a spatial double difference model is applied to reveal the effect of carbon trading market policies on urban green innovation efficiency and its spatio-temporal heterogeneity. The results show that the carbon trading market policy significantly affects the green innovation efficiency of industrial enterprises, and at the same time, the level of economic development, the level of foreign investment, and the industrial structure of each province and city also have a positive effect on the green innovation efficiency. There is also a spatial spillover effect of the carbon trading market policy, which not only has a significant incentive effect on the green innovation efficiency of the pilot cities, but also has a positive promotion effect on the green innovation efficiency of the neighboring cities. At the same time, the support of provincial and municipal governments significantly affects the spillover effect of carbon market policies.

Keywords: Carbon trading market; green innovation efficiency; spatial double difference; super-efficiency DEA.

1. Introduction

Climate change is a major challenge facing the world, and addressing climate change has a bearing on both China's domestic and international situations, as well as on the overall situation of development and the long term, and is not only an important tool for promoting high-quality economic development and ecological civilization, but also an important area for participation in global governance and adherence to multilateralism. The carbon emissions trading market, as a market-based environmental management tool, has been launched since June 2013 in seven pilot provinces and cities: Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen. The government carries out carbon emissions trading pilot work, using market means, actively inducing enterprises to carry out green technological innovation, while the technological progress of enterprises is a key factor in carbon dioxide emission reduction, reducing future carbon emissions, can effectively realize the low-carbon development of enterprises, and promote the green development of China's economy. In this context, assessing the actual policy effect of carbon emissions trading on enterprise green innovation has become a hot issue of concern for policy makers and academics. Under the regional coordinated development policy, the spatial correlation between different parts of the country should not be neglected, and it is of great significance to understand the current situation of China's carbon trading market and the development of green innovation of industrial enterprises as well as the spatial and temporal evolution patterns, and to deeply analyze the spatial effect of carbon market trading on the green transformation of industrial enterprises, in order to realize the coordinated governance of the region, and to promote the energy conservation and emission reduction of industry.

2. Literature Review

The operation of carbon markets as a policy tool for governments to regulate carbon emissions has implications in a number of ways, with Johnstone[1] et al. demonstrating that market-based instruments such as environmentally related taxes and trading licenses are more likely to induce innovation than direct regulations such as technology-based standards. Meanwhile, some scholars believe that environmental regulations will increase the production costs of enterprises to a certain extent[2] , while others believe that environmental regulatory policies will incentivize enterprises to innovate, thus improving the productivity of enterprises and bringing additional benefits[3] , both of which illustrate the policy effects of environmental regulations on enterprise innovation. Specifically for the carbon trading market, domestic scholars have studied the results of the carbon trading market from different perspectives. Wang Yong[4] et al. study the impact of carbon trading policy on the environment and find that the establishment of carbon market has the effect of improving carbon emission efficiency. Liu Chuanming[5] et al. used the synthetic control method to study the emission reduction effect of the policy at the national level, and found that the carbon trading policy brings obvious carbon emission reduction effect, but the emission reduction effect varies in different provinces due to the differences in the level of economic development and energy-saving technology. Lu Min[6] et al. used trend analysis and gray prediction model and found that carbon trading mechanism can effectively reduce the indirect carbon emission intensity of Shanghai's industrial sector, but the impact on direct carbon emissions is small. Xue Fei[7] et al. confirmed that there are carbon emission reduction effect and synergistic emission reduction effect of carbon trading market scale, the expansion of carbon trading market scale is conducive to the reduction of carbon emissions in the pilot area, and the carbon trading market scale can reduce sulfur dioxide emissions while realizing the carbon emission reduction and synergistic emission reduction effect at the same time. Ren Xiaosong[8] et al. studied the effect and heterogeneity of carbon trading policy on industrial carbon productivity, and found that the carbon trading policy significantly improved industrial carbon productivity, realizing the effect of "reducing carbon and promoting economic development", but there are some differences in the degree of response to the policy in each pilot region.

Green technological innovation has been regarded as an important means to reduce environmental pollution, and the research on green technological innovation can be traced back to the 1990s, when C. Fussler[9] and others firstly put forward and defined "green innovation", and regarded that green technological innovation is a kind of new product and new technology, which can bring good economic value to the enterprise, the consumer and the society. It is also considered that green technology innovation is a new product and technology that can bring good economic value to enterprises, consumers and society. Measurement of green technology innovation efficiency. To measure the efficiency of green technological innovation, it is mainly carried out from the aspects of evaluation object[10] and evaluation method[13] . Another research hotspot is the influencing factors of green innovation efficiency. Han Jing[16] et al. believe that foreign investment and the restructuring of productive service industries are conducive to the improvement of green innovation efficiency; Li Jinri[17] et al. believe that the degree of urban transportation, government support, the number of urban colleges and universities, as well as the development of tertiary industry have a positive effect on the promotion of green innovation efficiency; however, Yang Shuwang[18] et al. believe that there is not a significant relationship between the industrial structure and green innovation, and they believe that enterprise pollution cost, technology market and the development of the industry are not important factors. They believe that enterprise pollution cost, technology market maturity and market openness can promote the efficiency of green innovation.

To summarize, at present, most of the studies conducted by scholars at home and abroad on how the carbon trading market affects carbon emission efficiency and the efficiency of green technological innovation focus on the measurement of the efficiency of green technological innovation as well as the influencing factors. However, due to the late opening of the domestic carbon market, and because of the selection of indicators and different research perspectives, the conclusions of the relevant studies are also different. This literature lays a good foundation for the subsequent research of this paper, but there are still some limitations. First of all, in the measurement of green innovation efficiency, it does not take into account that green innovation is a process, but is simply viewed as a whole. Secondly, in terms of research content, the current scholars mostly focus on the direct impact of carbon market on enterprises' green technological innovation, and do not explore it from the perspective of spatial effect, especially under the strategy of regional synergistic development, the mutual influence between provinces in China is more and more important. Therefore, based on the synthesis of previous research, this paper firstly constructs a two-stage value chain model of green innovation of Chinese industrial enterprises through a two-stage DEA model, and empirically analyzes the spatial effect of carbon market on industrial green technological innovation based on this using panel data from 2005 to 2020, and comprehensively examines the incentive effect of low-carbon city construction on the efficiency of urban green innovation from the spatial perspective.

3. Model Construction and Variable Description

3.1. Super-efficiency DEA model

Traditional DEA models are mainly based on CCR or BBC, and with the deepening of research, DEA models have been optimized and extended, deriving such models as DEA-SBM, DEA-RAM, etc. Although these models solve the problems of input-output slack variables and non-desired outputs in the evaluation of efficiency, they all look at the innovation process as a whole and only consider the overall inputs and outputs and thus neglect the stages of the innovation process. Based on the innovation value chain theory proposed by Qian Li[19] et al. in this paper, we constructed a two-stage value chain model of green innovation for Chinese industrial enterprises, as shown in Figure 1.

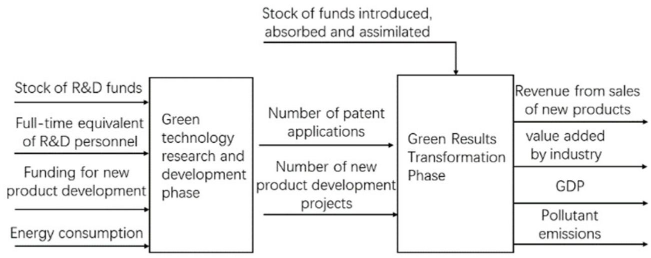

Figure 1. Two-stage value chain model of green innovation in industrial companies

In this study, the super-efficiency DEA model is used to calculate the green science and technology R&D efficiency and green achievement transformation efficiency of industrial enterprises in 30 provinces of China from 2005 to 2020, respectively, and the overall green innovation efficiency is expressed by the product of science and technology R&D and achievement transformation efficiencies, which is borrowed from the study of Yu Yongze[20] et al. The formula of the super-efficiency DEA model is:

$$\begin{cases} \text{Min } \theta \\ \sum_{i=1 j\neq 1}^{n} X_j\lambda_j + S^- = \theta X_0 \\ \sum_{i=1 j\neq 1}^{n} Y_j\lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, j = 1,2 \ldots, k-1, k, \ldots, n \\ S^- \geq 0, S^+ \geq 0 \end{cases} \quad (1)$$

where θ denotes the efficiency values ofX_j andY_j denote the input and output variables of the jth decision unit, respectively.S^- andS^+ denote slack variables, n denotes the number of decision units, and λ is a column vector.

3.2. Double Difference Spatial Durbin Model (SDM-DID)

3.2.1. Parallel trend test

The double difference model (DID) is valid provided that the parallel trend assumption is satisfied. Double differencing does not require that the experimental and control groups are identical, but it does require that the experimental and control groups have the same trend over time. Therefore a parallel trend test is required before using the double difference model. The event study method is used to empirically test the dynamic effect of carbon trading policy. The model is as follows:

$$GIE_{it} = \beta_0 + \sum_{t=2005}^{2020} \beta_t\, d_{it} + \beta_4 \sum x_{it} + \gamma_t + \lambda_j + \varepsilon_{it} \quad (2)$$

where GIE_{it} denotes the green innovation efficiency of each province in each year, and x_{it} denotes the control variables; d_{it} is the combined dummy variable, the $d_{it} = d_i * d_t$ and d_i and d_t are all 0-1 variables. d_i The assignment is when the year is defined as 0 in the year before the implementation of the carbon emissions trading policy (2005-2013) and 1 in the year after the implementation of the carbon emissions trading policy (2014-2020). d_t Indicates whether the province has implemented the carbon emissions trading policy or not, and the regions that have implemented it (Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong) are assigned the value of 1, while the remaining 24 provinces are assigned the value of 0. γ_t denotes time fixed effects. λ_j denotes individual fixed effects, and ε denotes the random error term. β_t The coefficients of the estimates are insignificant if they contain 0, and significant if they do not. If the coefficient of the interaction term before policy implementation is not significant and the coefficient of the interaction term after policy implementation is significant, it means that there is no significant difference between the control group and the experimental group before policy implementation, and the parallel trend test is passed.

3.3. Double Difference Modeling (DID)

The double difference model is often used to evaluate the effect of policy implementation, the principle of which is to divide the research subjects into experimental group and control group, and compare the effect before and after policy implementation by controlling the systematic difference between the two groups. The change before and after the control group represents the change brought about by time, and the change before and after the experimental group represents the change brought about by policy interference and time at the same time, and the change brought about by policy implementation can be obtained by subtracting the change in the experimental group from the change in the control group. This paper establishes the following model based on the double difference method. The experimental group is set to be the six provinces and cities where the policy is implemented, and the control group is set to be other provinces and cities; at the same time, 2013, the year before the implementation of the policy, is used as the base period, and the year dummy variable is defined, with the year after 2013 defined as 1 and the year before 2013 defined as 0. The model is constructed as follows:

$$GIE_{it} = \beta_0 + \beta_1 d_{it} + \beta_2 d_i + \beta_3 d_t + \beta_4 \sum x_{it} + \gamma_t + \lambda_j + \varepsilon_{it} \quad (3)$$

The definitions of the variables in this model are the same as in the previous model.

3.4. Spatial measurement models

Since different types of spatial econometric models assume different spatial transmission mechanisms and economic significance, the selection of spatial econometric models is of great importance[21] . In order to obtain a better fitting effect, a series of spatial econometric model tests are carried out with reference to Elhorst[22] et al. before the regression is carried out, and then the spatial econometric model suitable for the study of this paper is selected. First, the LM test and the robust LM test are used to determine the corresponding fit of the SEM model, the SAR model, and the SDM model; second, the LR test is conducted to further determine whether the SDM model degrades into the SAR or SEM model; finally, the Hausman test is used to determine whether to select the random-effects or the fixed-effects model for the study. The testing process followed the path of spatial autocorrelation model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). To eliminate the effect of heteroskedasticity, the non-ratio variables in the model were logarithmized.

(1) Spatial Autocorrelation Model (SAR)

The spatial autocorrelation model, also known as the spatial lag model (SLM), in which spatial dependence between variables leads to spatial correlation, and there is unidirectional spatial correlation between regions. The model contains a lag term for the spatial dependent variable. The following equation:

$$Y_{it} = \propto + \gamma W Y_{it} + X_{it}\beta + c_t + u_i + \varepsilon_{it} \quad (4)$$

where W denotes the spatial weight matrix and WY_{it} denotes the Y_{it} the spatial lag term, and c_t denotes the time-fixed, the u_i denotes individual fixed, and ε_{it} denotes the random error term.

(2) Spatial Error Model (SEM)

In the SEM model, technological innovation spillovers are due to random shocks whose spatial effects are mainly transmitted through the error term, and the model includes the random error autocorrelation term as the spatial error term. The following equation:

$$Y_{it} = \propto + X_{it}\beta + c_t + u_i + \varepsilon_{it} \quad (5)$$

$$v_{it} = \rho\gamma W Y_{it} + \varepsilon_{it} \quad (6)$$

where W is a known spatial weight matrix and there is a spatial dependence of the perturbation term, if the coefficient of the perturbation term $\rho = 0$, then the model can be reduced to a general linear regression model.

(3) Spatial Durbin Model (SDM)

In the SDM model, both the change in the error term due to the spatial lag of the dependent variable and the spatial interactions between regions are taken into account, as modeled below:

$$Y_{it} = \propto + \gamma W Y_{it} + X_{it}\beta + \theta W X_{it} + c_t + u_i + \varepsilon_{it} \quad (7)$$

where W is the known spatial weight matrix, WX denotes the effect of explanatory variables from neighboring regions, and other variables have the same meaning as above.

3.5. Double Difference Spatial Durbin Model (SDM-DID)

The non-spatial double-difference method only studies the impact of the policy implementation on the local area, ignoring the impact of the policy implementation on the neighboring areas of the implementation area. By implementing the carbon trading policy in the pilot province, the government promotes green technology innovation in the province, thus achieving the effect of reducing carbon emissions in the pilot area; at the same time, because the pilot city and the surrounding cities are not independent of each other, and have extensive economic ties, when the distance between the provinces is closer, the closer the ties between the provinces are; therefore, when the carbon trading market policy is implemented, the pilot city's surrounding cities will also be indirectly affected. Therefore, to evaluate the impact of carbon trading market policy, it is not only necessary to consider the impact on the pilot provinces, but also need to consider the spillover effect on the green innovation efficiency of the neighboring provinces of the pilot provinces. Therefore, in order to study the impact of carbon trading market policy on carbon emission efficiency and its spatial spillover effect, this paper introduces the spatial weight matrix on the basis of the non-spatial double-difference model, and constructs the following double-difference spatial model:

$$GIE_{it} = \alpha_0 + \alpha_1 d_{it} + \alpha_2 W * d_{it} + \alpha_3 \sum x_{it} + \gamma_t + \lambda_j + \varepsilon_{it} \quad (8)$$

where W in Eq. denotes the spatial weight matrix. The following two spatial weight matrices are used in this paper.

The spatial adjacency matrix, constructed based on whether or not each province is in a geospatially adjacent position, When two provinces are adjacent，w_{ij}=1；otherwise，w_{ij}=0

The economic distance matrix, a spatial weighting matrix constructed with the economic level of each province, is set as follows:

$$w_{ij} = \begin{cases} \dfrac{1}{\left|GDP_i - GDP_j\right|}, & i \neq j \\ 0, & i = j \end{cases}$$

Of these, theGDP_i andGDP_j denote the per capita GDP of provinces and provinces.

3.6. Description of data sources and variables

3.6.1. Explained Variables

In this paper, the green innovation efficiency of industrial enterprises in each province is taken as an explanatory variable and is calculated using the super-efficiency DEA model. According to the data availability and the consistency of statistical caliber, this paper finally selects the panel data of 30 provinces and cities in China except Tibet, Hong Kong, Macao and Taiwan from 2005 to 2020 to measure the green innovation efficiency of industrial enterprises in each province and city in China. The specific input-output indicators are as follows:

(1) Green technology research and development phase

In this paper, the input indicators of science and technology R&D stage are selected from three aspects: labor, R&D capital and energy consumption, which are measured by the full-time equivalent of R&D personnel, the stock of internal expenditure of R&D funding, the stock of new product R&D funding and the total amount of coal consumption, respectively. Among them, the internal expenditure stock of R&D funds is calculated by the perpetual inventory method with reference to Xiangdong Li[23] et al. The method is as follows:

$$K_{i,t} = I_{i,t} + (1-\theta) * K_{i,t-1} \quad (9)$$

Among them.$K_{i,t}$, the$K_{i,t-1}$ denote the stock of internal expenditure on R&D funding in province i in period t and period t-1, respectively, θ is the depreciation rate, and θ is taken to be 15%.$I_{i,t}$ is the constant price R&D funding internal expenditure of province i in period t. In which the calculation of the stock of internal expenditure of funding in the initial period is referred to Ying Li[24] et al. for the following calculation:

$$K_{i,0} = I_{i,1} / (g_i + \theta) \quad (10)$$

g_i denotes the average annual growth rate of internal expenditure of the constant price funding in province i, where the geometric mean method is used for calculation. And taking 2005 as the base period, the R&D deflator price index is utilized to deflate the funding category indicators, in which referring to the research of Zhu Pingfang[25] et al. the R&D deflator price index = 0.45*Fixed Asset Investment Price Index + 0.55*Consumer Price Index. Meanwhile, this paper adopts the number of professional applications and the number of new product development projects to measure the output of science and technology R&D stage.

(2) Green Results Transformation Phase

In this paper, in addition to the number of professional applications and the number of new product development projects, the stock of enterprise's introduction, digestion and absorption funding is also selected as an input indicator for the green results transformation stage, and as above, deflated and stocked calculations are carried out.

For the outputs of the transformation stage of green results, this paper adopts the sales revenue of new products, regional industrial added value, and regional gross domestic product as desired outputs, and selects carbon dioxide emissions, sulfur dioxide emissions, general industrial solid waste generation, and industrial smoke (dust) emissions as non-desired outputs.

3.6.2. Explanatory variables

Since June 2013, in order to implement the policy of gradually establishing a domestic carbon market in the 12th Five-Year Plan, the carbon market has been piloted in seven provinces and municipalities, namely Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen, and in order to unify the scope of the study, this paper combines Shenzhen with Guangdong Province. And the period of 2005-2013 is selected as the non-pilot period and the period of 2014-2020 as the pilot period; Beijing, Tianjin, Shanghai, Hubei, Chongqing, and Guangdong are taken as the experimental group, and the remaining 24 provinces and municipalities are taken as the control group.

Variables d_i is defined as 0 when the year before the implementation of the carbon emissions trading policy (2005-2013), and 1 when the year after the implementation of the carbon emissions trading policy (2014-2020), and the variabled_t denotes whether the province has implemented the carbon emissions trading policy, and the regions that have implemented it (Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong) are assigned the value of 1, while the remaining 24 provinces are assigned the value of 0. The variable$d_{it} = d_i * d_t$ as explanatory variables to indicate the net effect of carbon trading market policies.

3.6.3. Control variables

This paper takes into account the variability in the level of economic development, the degree of openness to the outside world, the industrial structure, the strength of government support and the population density of the city, as well as the fact that these factors may have an impact on the efficiency of green innovation, and so the above factors are used as control variables.

(1) Level of economic development (PGDP)

The level of economic development has a great impact on carbon emissions. Rapid economic development accelerates the demand for goods and services by individuals and enterprises, which leads to an increase in industrial production activities and ultimately leads to an increase in carbon emissions, while provinces and cities with higher carbon emissions have a more urgent need to improve the efficiency of green innovation. So this paper refers to the research of Zhu Huan[26] et al. and selects the logarithm of per capita GDP of each province and city to measure the economic development level of each province and city.

(2) Level of Foreign Investment (FDI)

Foreign investment will bring competition effect to the provinces and cities where foreign investment is introduced. In order to seize the market with local enterprises, foreign-invested enterprises must reduce costs, improve product quality, and enhance their innovation ability; at the same time, when foreign-invested enterprises enhance their innovation ability, local enterprises will enhance their innovation ability in order to prevent being eliminated from the market. This paper refers to the practice of Liu Haiyun[27] et al. and selects the logarithm of the level of foreign direct investment in each province and city to measure foreign investment.

(3) Industrial Structure (IS)

Compared with other industries, the secondary industry has a higher intensity of energy demand and utilization, so the higher the proportion of the secondary industry, the higher the energy consumption, which will lead to a larger carbon emission, and it will be more necessary to improve the efficiency of green innovation. In this paper, we refer to Li Wenhong[28] et al. who choose the logarithm of the ratio of the value added of the secondary industry to the GDP of each province and city to measure the industrial structure of each province and city.

(4) Level of government support (GS)

Local governments are an important support for technological innovation activities in provinces and municipalities, and government support can increase the motivation of innovative enterprises and thus improve their innovation efficiency. In this paper, we refer to Xiao Liming[29] et al. and select the logarithm of the ratio of local government education plus S&T expenditures to the GDP of each province and city to measure the strength of government support in each province and city.

(5) Urban Population Density (UPD)

According to the IPAT model (Environmental Impact = Population*Affluence*Technology) proposed by Ehrlich and Holdren[30] , regional human activities also have an impact on environmental change, which affects the regional green innovation efficiency, and therefore urban population density is included in the model as a control variable. .

The specific variables are described in the table below.

Table 1. Description of variables

control variable	notation	Description of calculations
Level of economic development	PGDP	GDP of provinces and municipalities / resident population of provinces and municipalities; logarithmic scale
Level of foreign investment	FDI	FDI in provinces and municipalities/GDP in provinces and municipalities; logarithmic scale
industrial structure	IS	Value added of secondary industry in provinces and municipalities/GDP in provinces and municipalities; logarithmic scale
Government support	GS	Local government expenditure on education plus science and technology/GDP of provinces and municipalities; logarithmic scale
Urban population density	UPD	Number of resident population in provinces and municipalities/area of provinces and municipalities; logarithmic scale

3.6.4. Data sources

In this paper, panel data of 30 provinces and cities in China from 2005 to 2020 are selected, and Tibet, Hong Kong, Macao and Taiwan are not included in the analyzed samples due to their serious missing data. The raw data of this paper come from China Statistical Yearbook, China Environmental Statistical Yearbook, China Science and Technology Statistical Yearbook, China Energy Statistical Yearbook, China Trade and Foreign Economy Statistical Yearbook, as well as statistical yearbooks of provinces and cities. According to the two-stage DEA model in the previous section, the green innovation efficiency of industrial enterprises in 30 provinces in China from 2005 to 2020 is calculated as shown in the following table:

According to the table we can know that the provinces with high green innovation efficiency are Guangdong, Beijing and Shanghai, while the provinces with low green innovation efficiency are Ningxia, Inner Mongolia and Gansu, and the ones in the middle ranking are mostly the provinces and cities located in the center. Because the innovation efficiency is closely related to the economic development and other conditions of the provinces and cities, the cities located in the coastal area will be higher than the innovation efficiency in the inland area, and at the same time, this also reflects a certain aggregation of high innovation efficiency.

Table 2. Green innovation efficiency of industrial enterprises, 2005-2020

GIE_{it}	2005	2006	2007	2008	2009	2010	2011	2012
Anhui	0.801	0.809	0.818	0.824	0.835	0.855	0.859	0.864
Beijing,	0.883	0.888	0.918	0.914	0.891	0.897	0.894	0.893
Fujian	0.895	0.897	0.907	0.910	0.913	0.919	0.914	0.911
Gansu	0.782	0.803	0.816	0.814	0.811	0.831	0.831	0.832
Guangdong	0.950	0.958	0.956	0.955	0.956	0.964	0.966	0.963
Guangxi	0.829	0.839	0.849	0.848	0.845	0.855	0.858	0.854
Guizhou	0.766	0.775	0.784	0.798	0.798	0.808	0.810	0.816
Hainan Island	1.007	1.012	1.010	1.001	1.000	1.004	1.001	0.962
anhui	0.839	0.849	0.860	0.869	0.861	0.867	0.857	0.858
He'nan	0.852	0.866	0.879	0.892	0.888	0.897	0.893	0.895
Heilongjiang	0.842	0.847	0.855	0.863	0.854	0.857	0.861	0.865
Hubei	0.822	0.826	0.841	0.849	0.857	0.874	0.875	0.885
Hunan	0.841	0.853	0.863	0.867	0.869	0.880	0.879	0.882
Jilin	0.759	0.769	0.784	0.798	0.860	0.816	0.822	0.829
Jiangsu	0.876	0.885	0.894	0.900	0.901	0.907	0.899	0.904
Jiangxi	0.835	0.851	0.861	0.870	0.873	0.895	0.896	0.901
Liaoning	0.786	0.797	0.806	0.821	0.823	0.822	0.823	0.826
Inner Mongolia	0.781	0.794	0.801	0.809	0.816	0.816	0.810	0.816
Ningxia	0.804	0.799	0.787	0.791	0.790	0.810	0.790	0.796
Qinghai	1.011	1.005	0.906	0.883	0.862	0.838	0.824	0.835
Shandong	0.861	0.875	0.882	0.885	0.889	0.890	0.878	0.881
Shanxi	0.787	0.793	0.809	0.819	0.812	0.828	0.835	0.834
Shaanxi	0.854	0.864	0.868	0.876	0.877	0.889	0.886	0.894
Shanghai	0.906	0.913	0.918	0.914	0.904	0.915	0.908	0.904
Sichuan	0.809	0.825	0.838	0.852	0.860	0.870	0.875	0.882
Tianjin	0.818	0.833	0.827	0.835	0.832	0.840	0.835	0.843
Xinjiang	0.937	0.926	0.893	0.888	0.851	0.880	0.876	0.870
Yunnan	0.857	0.865	0.873	0.874	0.867	0.907	0.862	0.871
Zhejiang	0.875	0.881	0.892	0.894	0.890	0.902	0.895	0.898
Chongqing	0.834	0.844	0.849	0.851	0.856	0.869	0.874	0.880
GIE_{it}	2013	2014	2015	2016	2017	2018	2019	2020
Anhui	0.869	0.870	0.869	0.872	0.885	0.891	0.890	0.909
Beijing,	0.903	0.915	0.926	0.939	0.967	0.972	0.998	1.022
Fujian	0.911	0.915	0.919	0.914	0.929	0.936	0.935	0.965
Gansu	0.832	0.829	0.818	0.815	0.820	0.828	0.835	0.847
Guangdong	0.965	0.971	1.001	1.029	0.997	1.000	0.999	1.008
Guangxi	0.854	0.855	0.864	0.872	0.880	0.884	0.877	0.886
Guizhou	0.827	0.838	0.852	0.859	0.863	0.870	0.881	0.890
Hainan	0.929	0.931	0.941	0.985	0.975	0.995	1.000	1.023
anhui	0.851	0.851	0.856	0.870	0.876	0.874	0.880	0.895
He'nan	0.898	0.900	0.908	0.924	0.944	0.949	0.955	0.970
Heilongjiang	0.863	0.858	0.844	0.839	0.843	0.854	0.857	0.862
Hubei	0.891	0.896	0.904	0.919	0.931	0.943	0.945	0.945
Hunan	0.885	0.886	0.892	0.899	0.899	0.903	0.916	0.931
Jilin	0.829	0.838	0.841	0.851	0.854	0.866	0.855	0.865
Jiangsu	0.903	0.903	0.911	0.917	0.928	0.942	0.954	0.982
Jiangxi	0.905	0.904	0.903	0.903	0.908	0.908	0.912	0.998
Liaoning	0.830	0.824	0.822	0.825	0.829	0.835	0.840	0.852
Inner Mongolia	0.816	0.817	0.821	0.827	0.841	0.849	0.855	0.861
Ningxia	0.798	0.788	0.785	0.784	0.797	0.798	0.798	0.803
Qinghai	0.858	0.852	0.838	0.870	0.887	1.000	0.961	1.001
Shandong	0.882	0.878	0.882	0.893	0.901	0.901	0.905	0.920
Shanxi	0.829	0.822	0.810	0.814	0.844	0.856	0.863	0.868
Shaanxi	0.896	0.897	0.892	0.898	0.918	0.949	0.964	0.906
Shanghai	0.899	0.899	0.899	0.917	0.958	0.966	0.971	0.985
Sichuan	0.888	0.887	0.893	0.901	0.906	0.913	0.922	0.929
Tianjin	0.866	0.861	0.869	0.887	0.873	0.883	0.891	0.903
Xinjiang	0.869	0.885	0.862	0.857	0.884	0.926	0.970	0.954
Yunnan	0.879	0.882	0.883	0.879	0.888	0.898	0.898	0.904
Zhejiang	0.904	0.908	0.924	0.947	0.941	0.951	0.965	1.002
Chongqing	0.888	0.892	0.896	0.908	0.905	0.902	0.908	0.929

4. Empirical Analysis and Results

4.1. Parallel trend test

The prerequisite for the realization of the double-difference method is to pass the parallel trend test, and the following figure shows the parallel trend dynamic effect test plot of this paper, where the vertical dashed line indicates thed_{it} the 95% confidence interval of the regression coefficient, in order to avoid multicollinearity, this paper sets the year before the implementation of the policy, which is 2013, as the base period. According to the figure, we can see that in the first five years of policy implementation, the 95% confidence intervals of the regression coefficients contain 0, indicating that the regression coefficients are not significant; while in the first year after the implementation of the policy, the 95% confidence intervals of the regression coefficients cross the horizontal line, indicating that the regression coefficients are significant, and the coefficients change from negative to positive, which indicates that the implementation of the policy has a positive effect on the promotion of the explanatory variables and has been influential for several years after the implementation. has been influential for several years afterward.

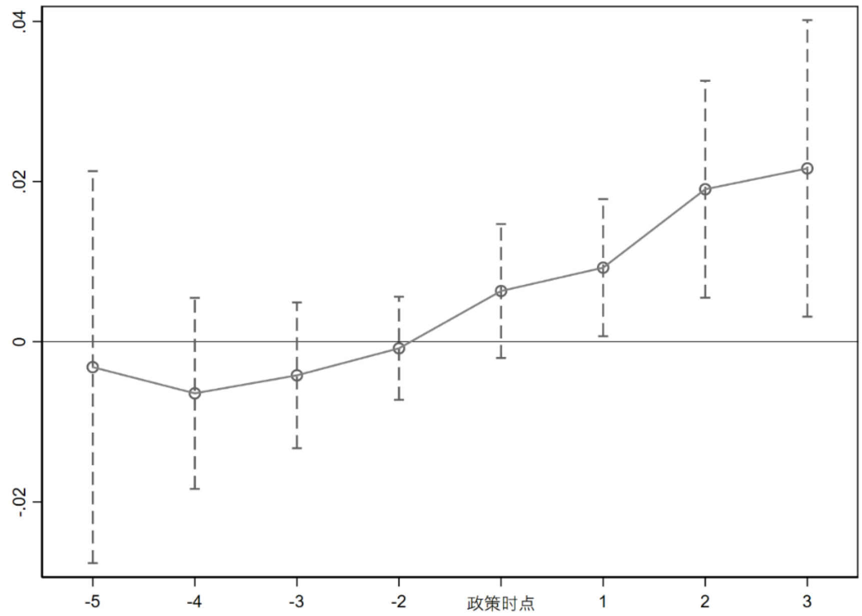

Figure 2. Plot of the test for the dynamic effect of parallel trends

4.2. Spatial correlation analysis

Airflow, water flow and industrial transfer affect carbon emissions in neighboring provinces, which indirectly affects the efficiency of green innovation in neighboring provinces. Therefore, in order to scientifically verify the spatial correlation of carbon emissions, this paper constructs a 0-1 proximity matrix based on geographic proximity, and measures the Moran's I value of carbon emissions of 30 provinces in China from 2005 to 2020. The results are shown in the following table, the Moran's indices of carbon emissions are all positive and pass the significance level. This indicates that there is a certain spatial clustering effect of carbon emissions among Chinese provinces, which provides a scientific basis for borrowing spatial measurement as an analytical tool.

Table 3. Moran's I index of green innovation efficiency, 2005-2020

year	Moran's I	E(I)	Sd(I)	z	p-value
2005	0.148	-0.034	0.110	1.657	0.049
2006	0.152	-0.034	0.110	1.697	0.045
2007	0.177	-0.034	0.110	1.925	0.027
2008	0.173	-0.034	0.110	1.889	0.029
2009	0.172	-0.034	0.108	1.910	0.028
2010	0.223	-0.034	0.109	2.357	0.009
2011	0.247	-0.034	0.109	2.593	0.005
2012	0.290	-0.034	0.111	2.921	0.002
2013	0.357	-0.034	0.111	3.516	0.000
2014	0.339	-0.034	0.111	3.361	0.000
2015	0.354	-0.034	0.110	3.523	0.000
2016	0.292	-0.034	0.110	2.975	0.001
2017	0.287	-0.034	0.112	2.869	0.002
2018	0.170	-0.034	0.112	1.819	0.034
2019	0.166	-0.034	0.113	1.776	0.038
2020	0.350	-0.034	0.113	3.106	0.000

4.3. Model Testing

In order to scientifically demonstrate the relationship between variables, this paper introduces a variety of spatial econometric models to be empirically analyzed. Referring to the research conclusion of Anselin[31] , this paper successively conducts LM-Error test, LM-Lag test, LM-Error robust test, LM-Lag robust test, Hausman test and LR test, and the test results are shown in the following table, which can be seen that the values of the LM-Error test and LM-Lag test pass the 1% significance level test, indicating that the SDM model should be considered in a limited way; the Hausman test also passes the 1% significance level test, using fixed effects; while at the same time, the SDM model is used. significance level test, indicating that the SDM model should be considered in a limited way; the Hausman test also passes the 1% significance level test, using fixed effects; and also passes the LR test, with both the time and spatial fixed effects significant at 1%. So this paper uses a spatial panel Durbin model with time and space double fixed.

Table 4. Model Tests

Test Methods	statistical value	P-value
LM-Lag	80.042	0.000
LM-Lag(robust)	115.035	0.000
LM-Error	53.691	0.000
LM-Error(robust)	88.684	0.000
Hausman	84.20	0.000
LR-spatial fixed effects	43.40	0.000
LR-time-period fixed effects	509.16	0.000

4.4. Empirical results of spatial econometric modeling

Based on the above process, the empirical results of this paper are shown in the following table.

Table 5. Empirical results of DID and SDID models

variant	DID			SDID		
	Coef.	Std. Err	t	Coef.	Std. Err	t
d_{it}	0.028	0.005	4.87***	0.026	0.005	6.11***
PGDP	0.027	0.024	2.09**	0.043	0.128	3.38***
FDI	0.008	0.003	2.76***	0.006	0.002	3.40***
IS	0.079	0.025	3.12***	0.060	0.016	3.77***
GS	0.009	0.012	0.71	-0.010	0.007	-1.34**
UPD	-0.001	0.006	-0.54	-0.005	0.003	-1.670**
rho	-	-	-	0.269	0.062	4.33***
Sigma2_e	-	-	-	0.002	0.001	15.33***

Note: ***, ** and * sub-tables indicate significance levels of 1%, 5% and 10%.

From the above table, it can be seen that the explanatory variable in column DID d_{it} denotes the effect of carbon trading policy on green innovation efficiency, and its coefficient is 0.028 and is significant at 1% significance level, indicating that carbon trading policy has a significant positive promotion effect on green innovation efficiency in pilot cities. This is because the implementation of carbon trading policy in the pilot city promotes the carbon reduction behavior of industrial enterprises, and in order to achieve the carbon reduction target further motivates the green innovation efficiency of industrial enterprises. At the same time, the coefficients of the economic development level (PGDP), foreign investment level (FDI), and industrial structure (IS) passed the significance level test of 5%, with the coefficients of 0.027, 0.008, and 0.079, respectively, which indicates that these three control variables have a positive facilitating effect on green innovation efficiency. The level of economic development has a positive promotional effect on the green innovation efficiency of enterprises because regions with higher levels of economic development will have more sufficient funds to develop green production technology, and at the same time, it can also reduce carbon emissions while improving the efficiency of green innovation, forming a virtuous circle. The level of foreign investment promotes the level of green innovation because foreign-invested enterprises will have a competitive effect with local enterprises, foreign-invested enterprises will increase innovation to compete with local enterprises, and the same local enterprises will also increase innovation to ensure that they will not be eliminated, thus promoting the rise of the overall innovation capacity of enterprises in the region. The calculation of industrial structure in this paper is the ratio of the value added of the secondary industry to the GDP, and the secondary industry is mostly a high-energy-consuming industry, with more serious carbon emissions, so the rising industrial structure is even more necessary to improve the emergence of green production technology.

The explanatory variable in the SDID column d_{it} The coefficient of the SDID column is 0.026 and is significant at 1% significance level, which indicates that there is a positive spatial correlation effect of green innovation efficiency between regions, and this result is also in line with the results of the Moran index test. The geographic conditions of neighboring regions are similar, which means that the resource conditions are also similar, in addition, the economic trade and technology circulation in neighboring regions are more convenient and fast, and the carbon trading policy provides a platform for carbon trading between enterprises, which promotes the improvement of technological innovation efficiency even more.

4.5. Spatial spillover effects

Based on the above, it is known that there may be spillover effects due to the carbon trading policy on the green innovation efficiency of neighboring provinces. Therefore, drawing on the research results of LeSage[32] , partial differential equations are used to decompose the spatial effects into direct, indirect and total effects, of which the indirect effect is the spatial spillover effect, and the specific calculation results are shown in the following table.

Table 6. Decomposition of effects for the double difference spatial Durbin model

variant	LR_Direct	LR_Indirect	LR_Total
d_{it}	0.028***	0.032**	0.061***
	(6.35)	(2.42)	(4.10)
PGDP	0.042**	-0.018	0.023*
	(3.32)	(-1.07)	(1.13)
FDI	0.006**	-0.001	0.005*
	(3.37)	(-0.08)	(1.07)
IS	0.061***	-0.011	0.049
	(3.55)	(-0.27)	(0.93)
GS	-0.007	0.049***	0.041**
	(-0.95)	(3.75)	(2.71)
UPD	-0.006*	-0.011	-0.016*
	(-1.75)	(-1.28)	(-1.63)

Note: Numbers in parentheses are t-statistics, and ***, **, and * sub-tables indicate significance levels of 1%, 5%, and 10%.

From the table, we can see that the direct effect of carbon trading policy is 0.028, the spatial spillover effect is 0.032, and the total effect is 0.061, and all of them pass the significance test of 5%, which indicates that the carbon trading policy has a positive promotional effect on the innovation efficiency of the pilot cities, and there is also a positive spillover benefit, which not only improves the innovation efficiency of the pilot cities, but also improves the innovation efficiency of the neighboring It can not only improve the innovation efficiency of pilot cities, but also improve the innovation efficiency of neighboring provinces and cities. On the one hand, it is more convenient to circulate technology between neighboring cities, and under the pressure of green transformation, the policy dividend of the pilot city will drive the green innovation of the nearby cities, and on the other hand, the leading role of the pilot city will lead to the competition effect between the neighboring provinces and cities, so that there will be a spillover effect of the carbon trading policy on the green innovation efficiency of the pilot city. In addition, government support (GS) also has a positive spatial spillover effect, and government expenditure on education and science and technology positively affects innovation efficiency, while the existence of innovation city competition pressure from neighboring city governments helps neighboring cities to increase science and innovation expenditures and improve the level of innovation. And several other control variables do not pass the significance test, indicating that their spatial spillover effects are not formed.

4.6. Robustness Tests

4.6.1. Robustness test of propensity score matched double difference model (PSM-DID)

In order to ensure the robustness of the empirical results, this paper adopts the propensity score matched double difference model (PSM-DID) to test the impact of carbon trading market. In this paper, the original panel data are matched and finally aggregated into the equilibrium panel data. The equilibrium test is conducted after the matching is completed, and the results are shown in the table below:

Table 7. Equilibrium test results

variant	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	T-test t	T-test P-value
PGDP	U	11.341	10.355	198.6	98.9	11.17	0.00
	M	11.341	11.053	2.3		1.62	0.083
FDI	U	-3.927	-4.298	40.1	902	2.28	0.023
	M	-3.927	-4.071	-3.9		1.95	0.085
IS	U	1.074	0.852	79.4	78.7	-6.66	0.00
	M	1.074	0.895	6.9		0.88	0.381
GS	U	1.473	2.037	53.6	93.0	1.91	0.062
	M	1.473	2.012	3.7		1.058	0.318
UPD	U	7.869	7.795	75.2	98.9	3.277	0.003
	M	7.869	7.862	-0.2		0.663	0.542

According to the table, we can see that the %bias value of the control variables after matching is less than 10% and is significantly smaller than the value before unmatched, which indicates that there is no obvious gap between the two groups and the balance assumption is satisfied. So the matched data were subjected to spatial double difference experiments, and the results are shown in the following table:

Table 8. Empirical results for propensity score matched double difference

variant	DID			PSM-DID		
	Coef.	Std. Err	t	Coef.	Std. Err	t
d_{it}	0.028	0.005	4.87***	0.535	0.005	7.62***
PGDP	0.027	0.024	2.09**	0.152	0.528	3.78***
FDI	0.008	0.003	2.76***	0.521	0.072	6.85***
IS	0.079	0.025	3.12***	0.236	0.028	5.28***
GS	0.009	0.012	0.71	-0.523	0.547	-2.12**
UPD	-0.001	0.006	-0.54	-0.105	0.054	-1.895**
rho	-	-	-	0.354	0.163	5.84***
Sigma2_e	-	-	-	0.562	0.001	16.54***

It can be known from the above table that the carbon trading market after matching has a more obvious positive promotion effect on innovation efficiency, and the effects of other control variables on innovation efficiency are not significantly different from those before matching.

4.6.2. Robustness tests for spatial spillovers

In order to ensure the robustness of the empirical results, this paper adopts the method of replacing the spatial weight matrix to carry out the robustness test, replacing the spatial adjacency matrix with the spatial distance squared matrix to carry out the regression analysis, and obtaining the results in the following table:

Table 9. Robustness test results

variant	LR_Direct	LR_Indirect	LR_Total
d_{it}	0.029***	0.005**	0.035***
	(4.27)	(1.85)	(4.19)
PGDP	0.152***	-0.028	0.057*
	(4.32)	(-0.98)	(1.08)
FDI	0.0246**	-0.021	0.015*
	(3.51)	(-0.06)	(1.17)
IS	0.074***	-0.024	0.047
	(3.88)	(-0.35)	(0.87)
GS	-0.014	0.045***	0.078***
	(-0.82)	(3.69)	(3.58)
UPD	-0.014*	-0.021	-0.048*
	(-1.85)	(-1.11)	(-1.25)

The comparison shows that the size, direction and significance level of the direct effect, indirect effect and total effect coefficients of the explanatory variables have not changed significantly; although the significance of some of the variables has changed, the direction of the coefficients is still the same. Overall, the results obtained after replacing the matrix are basically the same as those before replacement, indicating that the results of this paper are robust from the perspective of considering the spatial matrix.

5. Conclusions and Recommendations

5.1. Conclusion

Based on the two-stage DEA model, this paper constructs a two-stage value chain model of green innovation of Chinese industrial enterprises, measures the green innovation efficiency of industrial enterprises in each province and city in China, and explores the impact and spatial spillover effect of the carbon trading market policy on the green innovation efficiency of industrial enterprises in each province and city through double-difference method and spatial econometric modeling, and the main conclusions and contributions are as follows:

(1) The green innovation activities are decomposed into two stages: green science and technology research and development and green achievement transformation, and the green innovation efficiency of industrial enterprises in 30 provinces and cities in China is scientifically and reasonably measured. Among them, coastal cities such as Guangdong, Beijing and Shanghai have higher innovation efficiency, while inland cities such as Ningxia, Inner Mongolia and Gansu have lower efficiency.

(2) Carbon trading market policy significantly affects the green innovation efficiency of industrial enterprises, while the level of economic development, foreign investment level, and industrial structure of each province and city also have a positive effect on green innovation efficiency.

(3) There is a spatial spillover effect of the carbon trading market policy, which not only has a significant incentive effect on the green innovation efficiency of the pilot cities, but also has a positive promotion effect on the green innovation efficiency of neighboring cities. The robustness test shows that the spatial spillover effect still exists even if the spatial weight matrix is replaced. At the same time, the support of provincial and municipal governments significantly affects the spillover effect of carbon market policies.

5.2. Recommendations

(1) Emphasizing the spillover effects of carbon trading policies to improve the efficiency of green innovation

Carbon trading policy to improve the efficiency of provincial green innovation spillover effect is significant, to strengthen communication and cooperation between neighboring provinces and regions, across the provinces and regions to build a regular, all-round, multi-disciplinary technological innovation mechanism, regular meetings and communication system, effective use of the synergistic effect of the provincial policy, the pilot city of the carbon trading policy to play a demonstration leading role.

(2) Optimization of the regional industrial structure and increased investment

Strengthen the supply of low-carbon technologies, enhance the top-level design of the government's science and technology innovation system, promote the science and technology innovation-driven strategy, improve the incentive mechanism for science and technology innovation, and promote the upgrading of the industrial structure and optimization of the energy structure. Gradually increase the proportion of tertiary industry and accelerate the transition from secondary to tertiary industry. At the same time, increase foreign investment and raise the level of government support. Focus on building a platform for scientific and technological innovation and research and development, relying on scientific and technological innovation power to enhance the level of green innovation; adhere to the market orientation, optimize the circulation of innovation factors, highlight the status of the main body of enterprise innovation, optimize the allocation of resources, and improve the conversion rate of scientific and technological achievements, and make full use of the promotional effect of upgrading the industrial structure and foreign investment in the process of improving the efficiency of green innovation by the carbon trading policy.

(3) Rationalizing Carbon Trading Policies and Synergistically Enhancing Green Innovation Efficiency

Rationally allocate the total amount of carbon trading among provinces and cities according to the process of emission reduction, and design a carbon quota allocation system in line with the industrial and energy structure. At the same time, it will improve the synergistic governance system among cities, actively explore the green innovation policy of regional integration and synergy with pilot cities to drive the surrounding cities, establish a provincial carbon emission monitoring mechanism, adjust the strength of scientific and technological innovation policies in a timely manner, and promote the upgrading and transformation of the regional economic structure, energy efficiency and industrial structure, so as to realize the enhancement of the efficiency of green innovation.

References

[1] Johnstone N, Haščič I, Kalamova M. Environmental policy design characteristics and technological innovation: Evidence from patent data[J]. 2010.

[2] Kneller R , Manderson E .Environmental regulations and innovation activity in UK manufacturing industries [J]. Resource & Energy Economics, 2012, 34(2):211-235.

[3] Porter M E , Linde C V D .Toward a New Conception of the Environment-Competitiveness Relationship[J].Journal of Economic Perspectives, 1995, 9(4). 97-118.

[4] WANG Yong,ZHAO Han. Impact of China's carbon trading market launch on regional carbon emission efficiency[J]. China Population-Resources and Environment,2019,29(01):50-58.

[5] LIU Chuanming, SUN Zhe, ZHANG Jin. Research on the carbon emission reduction policy effect of China's carbon emissions trading pilot[J]. China Population-Resources and Environment, 2019,29(11):49-58.

[6] LU Min, CANG Yuquan, LI Yanyan. Impact of carbon trading mechanism on industrial carbon emission intensity and competitiveness in Shanghai[J]. Technical Economy, 2018, 37(07):114-120.

[7] Xue Fei, Zhou Minliang. Research on the emission reduction effect of China's carbon trading market size[J]. East China Economic Management,2021,35(06):11-21.

[8] REN Xiaosong, MA Xi, LIU Yujia, ZHAO Guohao. Impact of carbon trading policy on industrial carbon productivity and transmission mechanism[J]. China Environmental Science, 2021, 41(11): 5427-5437.

[9] Fussler C, James P . Driving eco-innovation: a breakthrough discipline for innovation and sustainability[J]. pitman pub, 1996.

[10] Nasierowski W , Arcelus F J . On the efficiency of national innovation systems[J]. Socio-Economic Planning Sciences, 2003, 37.

[11] Cao Xia, Yu Juan. Research on regional innovation efficiency in China under the perspective of green low-carbon[J]. China Population-Resources and Environment,2015,25(05):10-19.

[12] JINRI LI,CHAO LI,ZEYU LI. Evaluation of urban green innovation efficiency and analysis of its influencing factors[J]. Statistics and Decision Making,2017(20):116-120.

[13] ZHANG Feng,REN Shijia,YIN Xiuqing. Green technology innovation efficiency of high-tech industries and its scale quality threshold effect[J]. Science and Technology Progress and Countermeasures,2020,37(07):59-68.

[14] WANG Hailong, LIAN Xiaoyu, LIN Deming. Empirical analysis of the impact of green technology innovation efficiency on regional green growth performance[J]. Science and Science and Technology Management,2016,37(06):80-87.

[15] Lv Yanwei, Xie Yanxiang, Lou Xianjun. Study on the spatial and temporal jump and convergence trend of green innovation efficiency in Chinese regions[J]. Research on Quantitative and Technical Economics,2020,37(05):78-97.

[16] Han Jing. Research on regional green innovation efficiency in China[J]. Research on Financial Issues,2012(11):130-137.

[17] JINRI LI, ZEYU LI, CHAO LI. An empirical study of urban green innovation efficiency--evidence from city clusters in the middle reaches of the Yangtze River[J]. Journal of Jiangxi University of Finance and Economics,2016(06):3-16.

[18] YANG Shu-wang, WU Ting, LI Zibo. Research on the spatio-temporal differentiation and influencing factors of green innovation efficiency in the Yangtze River Economic Belt[J]. Macroeconomic Research,2018(06):107-117+132.

[19] QIAN Li, XIAO Renqiao, CHEN Zhongwei. Research on green technology innovation efficiency of industrial enterprises in China and its regional differences--Based on common frontier theory and DEA model [J]. Economic Theory and Economic Management, 2015 (01): 26-43.

[20] Yu Yongze. Research on technological innovation efficiency of China's high-tech industry and its influencing factors--A two-stage analysis based on the perspective of value chain[J]. Economic Science,2009(04):62-74.

[21] Huang G, Zhang J, Yu J, et al. Impact of transportation infrastructure on industrial pollution in Chinese cities: a spatial econometric analysis [J]. Energy Economics, 2020, 92: 104973.

[22] Elhorst J P. Matlab software for spatial panels[J]. International Regional Science Review, 2014, 37(3): 389-405.

[23] LI Xiangdong,LI Nan,BAI Junhong,XIE Zhongqiu. Analysis of R&D innovation efficiency in high-tech industries[J]. China Soft Science,2011(02):52-61.

[24] Li Ying. Measurement and spatial characterization of R&D capital stock in Chinese provinces[J]. Soft Science, 2019, 33(07): 21-26+33.

[25] ZHU Pingfang,XU Weimin. The impact of government's science and technology incentive policy on R&D investment and its patent output of large and medium-sized industrial enterprises--an empirical study in Shanghai[J]. Economic Research,2003(06):45-53+94.

[26] ZHU Huan,ZHENG Jie,ZHAO Qiuyun et al. Economic growth, energy structure transition and carbon dioxide emission - an empirical analysis based on panel data[J]. Economic and Management Research,2020,41(11):19-34.

[27] LIU Haiyun,YAO Weiwei. Two-way FDI, environmental regulation and green innovation efficiency[J]. Ecological Economy, 2022, 38(10): 131-138+157.

[28] Li W.H., Cao W.L. FDI, environmental regulation and regional green innovation efficiency[J]. Statistics and Decision Making, 2020, 36(19): 118-122.

[29] XIAO Liming, GAO Junfeng, LIU Shuai. Changing trends of green technology innovation efficiency in China's regions based on spatial gradient - an empirical analysis of inter-provincial panel data[J]. Soft Science,2017,31(09):63-68.

[30] Ehrlich P R, Holdren J P. Impact of Population Growth: complicacy concerning this component of man's predicament is unjustified and counterproductive[J]. Science, 1971, 171 (3977): 1212-1217.

[31] Anselin L, Bera A K. Introduction to spatial econometrics[J]. Handbook of applied economic statistics, 1998, 237(5).

[32] LeSage J, Pace R K. Introduction to spatial econometrics [M]. Chapman and Hall/CRC, 2009.`