Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 11, No. 3, 2023

Spatio-temporal Features of Industrial Carbon Efficiency and Its Influence Elements Analysis

-- Empirical Evidence from China

Xinjun Li[1, a]

[1]School of History, Anhui Normal University, Wuhu, 241002, China
[a]lixinjun2000126@126.com

Abstract: The assessment of industrial carbon emission efficiency and the investigation of its influence elements are hot topics in environmental economics. Supported by SBM model, this paper uses the information of 30 provinces from 2005 to 2020 to study the spatial-temporal evolution of China's industrial carbon emission efficiency and its influencing factors. This paper believes that, in terms of direct effects, the energy structure, industrial structure, property rights structure, environmental control and foreign direct investment level will greatly influence the industrial carbon emission efficiency; with regard to indirect effects, the property rights structure, environmental control and foreign direct investment level significantly influence the industrial carbon emission efficiency.

Keywords: Industry Carbon Emission Efficiency, Super-efficient SBM model, Spatio-temporal characteristics, Spatial Panel Durbin Model.

1. Introduction

Decrease in carbon emission is greatly significant to sustainable economic growth in China and the green transformation of its growth mode. For realizing the objective of "carbon peak and carbon neutral", China makes a top-level design for "dual carbon", trying to build a "1+N" policy system for peak carbon neutrality. In the process of realizing the goal of "dual carbon", increasing efficiency while reducing carbon needs to be focused on in the industrial sectors. How to reduce the use of energy and increase efficiency in the industrial field should be rationally considered. The measurement of efficiency of carbon emission has been studied in two approaches. The first is to measure carbon emission efficiency by a single factor, it defines the carbon productivity as the proportion of CO2 emission to GDP [1]. The other way is based on the total factor perspective, including stochastic frontier analysis, M-L Index, information analysis Analysis and the improved model on basis of it [2]. In China, the special governance system and unique social and economic structure have resulted in the differentiation of its carbon emission efficiency, which has unique research value. At the same time, it is a path of innovative significance to separate out the influence factors of carbon emission efficiency on basis of Chinese empirical data and confirm their effectiveness in econometric means.

2. Literature Review

In terms of factors affecting carbon efficiency, scholars have analyzed some agents like the industrial structure, opening up to the outside world, environmental control and technological progress [3-6]. In addition, more literatures also use the control variable method to focus on a certain core variable affecting the efficiency of industrial carbon emissions. Some studies point out the impact of the indiscriminate use of burnable carbon products and market mechanisms on industrial carbon emissions; some dig the association between the external economy and carbon emission efficiency; and some try to know the impact of industrial agglomeration on carbon emission efficiency [7-9].

3. Research Design and Methodology

3.1. Measurement of industrial carbon emission efficiency

For measuring efficiency of industrial carbon emission, the Super-SBM model with unpopular output is adopted on basis of constant returns to scale, and selects input indicators including labor force (the number of staffs in industrial industries in different regions), capital (the net value of fixed assets in industrial industries above assigned size in different regions) and overall energy (the overall energy consumption in different regions)[10]. The output expected is represented by the operating income of industrial entrepreneur owners above designated size in different regions, and the undesired output is expressed as the CO2 emissions of industry in different regions. Among them, the industrial CO2 emissions by region are calculated by using eight fossil fuels including fuel oil, diesel oil and hard coke in each region of China based on the method in IPCC Guidelines for National Greenhouse Gas Emission Inventory 2006. All the information needed to calculate industrial carbon emission efficiency with the SBM model are official data with a time span of 2005-2020, and the regions include 30 provinces, municipalities directly under the Central Government and ethnic autonomous areas in China (excluding Macao, Hong Kong, Tibet and Taiwan because of the missing of their data), Mathlab2021a is used as the computing environment, and arcgis10.2 is used to draw the spatial distribution map. All information comes from the National Bureau of Statistics, China Statistical Yearbook, China Energy Statistical Yearbook, China Economic Census Yearbook and China Industry Statistical Yearbook. Among them, because the regional data of the usage of the eight fossil fuels used to calculate industrial carbon emission efficiency are missing in some years, the linear interpolation method and the near-mean interpolation method are used to complete the data the data.

3.2. Variable selection and data selection

On basis of the previous study outcomes, seven explanatory variables are selected: per capita GDP (per GDP), energy structure (ES), property rights structure (PS), industrial structure (IS), environmental regulation (ER), foreign investment level (FDI), and the technology choice index (TCI). $TCI = \frac{AVM}{GDP} / \frac{LM}{L}$. The greater the intensity of the intervention, the greater will be this deviation and the higher will be the TCI. Therefore, the TCI index can be a desirable proxy variable for government intervention.

3.3. Spatial Econometrics Methods

To test the influence elements of carbon emission efficiency, the spatial econometric model is set up:

$$\begin{aligned} CE_{it} = {} & \alpha_0 + \rho W * CE_{jt} + \alpha_1 LNPERGDP_{it} + \alpha_2 ES_{it} + \alpha_3 IS_{it} + \alpha_4 PS_{it} + \alpha_5 LNER_{it} \\ & + \alpha_6 FDI_{it} + \alpha_7 GI_{it} + \alpha_8 W * LNPERGDP_{jt} + \alpha_9 W * ES_{jt} + \alpha_{10} W * IS_{jt} \\ & + \alpha_{11} W * PS_{jt} + \alpha_{12} W * LNER_{jt} + \alpha_{13} W * FDI_{jt} + \alpha_{14} W * GI_{it} + \gamma_i \\ & + \pi_t + \mu_{it} \end{aligned}$$

In the above formula, CE_{it} means the carbon emission efficiency of province i in the t year, which is the explained variable in this paper. $W * CE_{jt}$ refers to the spatial lag term of carbon emission efficiency. $LNPERGDP_{it}$ represents the natural logarithm of per capita GDP of province i in the t year. ES_{it} stands for the energy structure of province i in the t year. IS_{it} refers to the industrial structure of province i in the t year. PS_{it} refers to the property rights structure of province i in the t year. $LNER_{it}$ means the environmental regulation intensity of province i in the t year. $W * LNPERGDP_{jt}$、$W * ES_{jt}$、$W * IS_{jt}$、$W * PS_{jt}$、$W * LNER_{jt}$、$W * FDI_{jt}$、$W * GI_{it}$ are the spatial lag terms of the corresponding variables, which are adopted to assess the spatial spillover effect of each variable on the carbon emission efficiency. ρ means the spatial autoregressive parameter. γ_i and π_t are the provincial fixed role and the year fixed role, the inclusion of two fixed roles can greatly relieve the omission variable bias. μ_{it} means the random disturbance term.

4. Temporal and Spatial Evolution Features Analysis

For analyzing the changing features of industrial carbon emission efficiency more directly, this paper draws the time series change chart of China's industrial carbon emission efficiency by region and the spatial distribution chart of China's industrial carbon emission efficiency. In each year, the efficiency values of East China, Central China, West China and Northeast China and the whole country are expressed by average, which is the sum of the efficiency values corresponding to all geographical units within a certain space, minus the number of geographical units in the space.

4.1. Temporal characteristics

As can be observed from the figure below, the overall trend of China's industrial carbon emission efficiency is a floating rise. The mean efficiency of the national and four regions appeared a V-shaped inflection point in 2010, which may be related to Chinese economic recovery after the global financial crisis in 2008. The average efficiency of the national and three regions showed a trend of sharp increase in 2018, which is related to the important measures in 2017: in this year, Beijing, Shanghai and other places successively introduced the 13th Five-Year Plan for controlling greenhouse gas emissions; the carbon financial market in Shanghai, Hubei and other places began to flourish; the national carbon market quota allocation plan was announced; and the national carbon emission trading system was launched. The growth trend was hit in 2019, and the cause of this phenomenon may be the global production stagnation and soaring costs caused by COVID-19. In terms of regions, all regions have improved their industrial carbon emission efficiency, with the most important improvement in the western area and the slowest efficiency growth in the eastern area. In addition, the central region and northeast region also experienced varying degrees of growth.

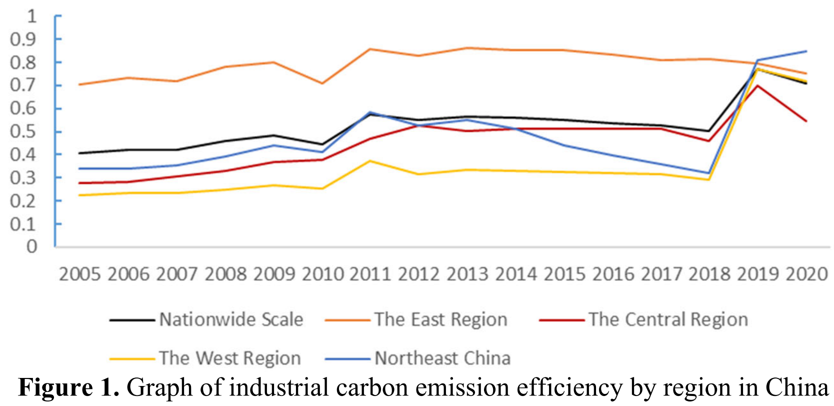

Figure 1. Graph of industrial carbon emission efficiency by region in China

4.2. Spatial characteristics

From the spatial perspective, before 2015, the industrial carbon emission efficiency displayed the features of high in the east and low in the west. However, since 2015, the situation has changed. The efficiency value of the original low-efficiency zone has begun to increase, while the industrial carbon emission efficiency of the high-efficiency zone and the extremely high-efficiency zone has begun to decline. The industrial carbon emission efficiency of China has begun to appear high in the west and low in the east. This change may be related to the change in China's growth strategy. With the transfer of industrial industries to the inland and the strong support of the eastern and central areas for the development of high value-added and low-energy usage industries, the energy consumption of the eastern and central areas has begun to decline, and the consumption of carbon products of industrial enterprises has gradually decreased. There is no more room for efficiency improvement in daily civil carbon products, so the overall efficiency value calculated by the SBM model has declined. However, the western area is deep in the inland, and based on bearing the transfer of eastern industries, it uses new technologies to improve efficiency.

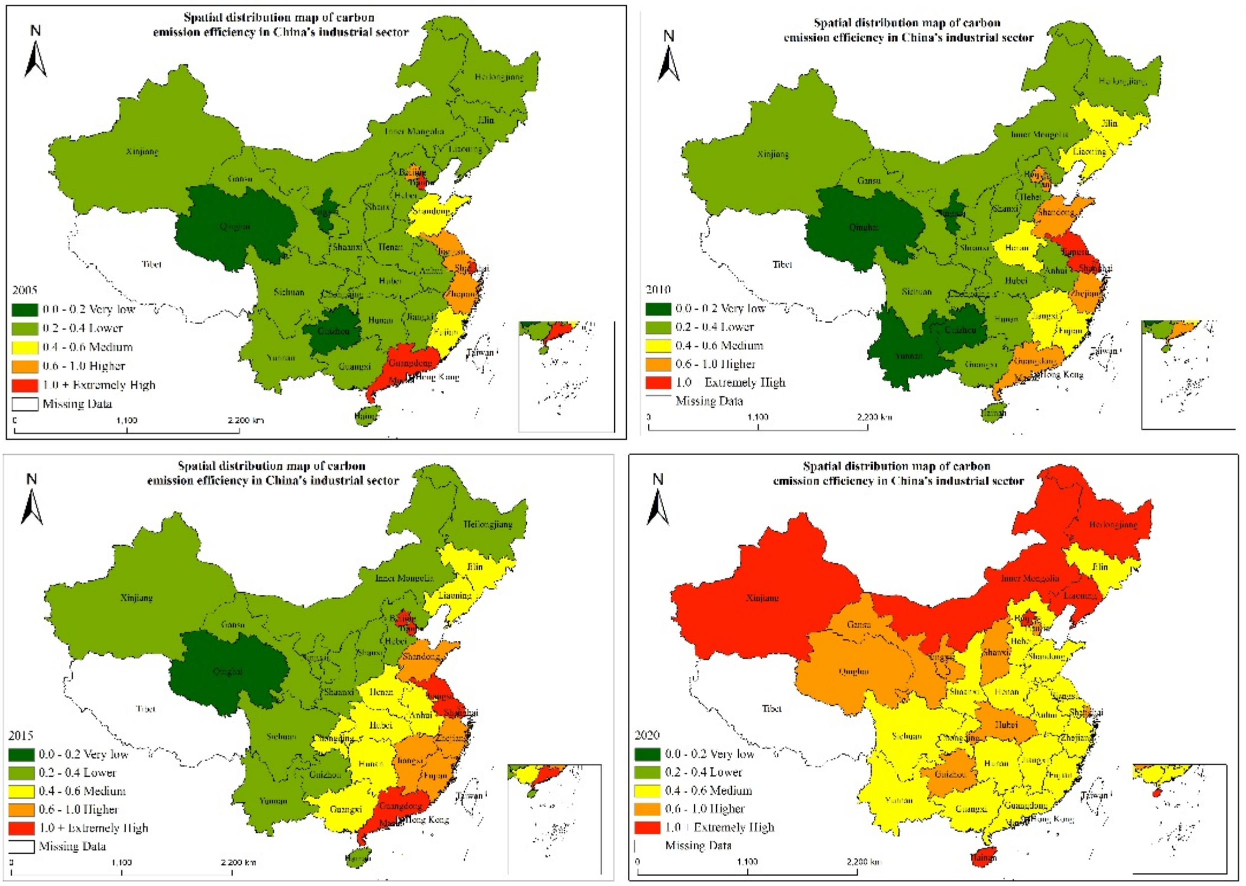

Figure 2.

5. Empirical Results

5.1. Variable descriptive statistics

For showing the data features of the sample, this paper presents the number, minimum, maximum, average and standard deviation of the observed values of the explained.

Table 1. Descriptive statistics

Variable	Meaning of variables	Obs	Mean	Std Dev.	Min	Max
CE	Industrial Carbon Emission Efficiency	480	0.529	0.314	0.154	1.633
LNPERGDP	Level of Economic Development	480	10.455	0.650	8.973	11.939
ES	Energy Structure	480	0.214	0.099	0.017	0.446
IS	Industry Structure	480	0.427	0.083	0.173	0.594
PS	Poverty Structure	480	0.394	0.185	0.107	0.823
LNER	Environment Regulation	480	11.773	1.041	8.236	13.769
FDI	level of Foreign Direct Investment	480	0.003	0.003	0.000	0.016
GI	Government Intervention	480	1.864	0.642	0.813	3.723

5.2. Spatial autocorrelation analysis

This paper describes the relationship between 30 provincial administrative regions with the inverse geographic distance spatial weight matrix, and tests the spatial correlation of carbon emission efficiency with the global Moran index. According to Table 2, it can be found that in most years of the investigated period, the Moran index is positive and very great, suggesting that the inter-provincial carbon emission efficiency show a great positive spatial association. Hence, the spatial econometric model is needed to be estimated.

Table 2. Moran's I of economic growth level based on geographic distance weight matrix

Year	Moran's I	Z-statistic	p-value	Year	Moran's I	Z-statistic	p-value
2005	0.098	3.886	0.000	2013	0.119	4.434	0.000
2006	0.109	4.196	0.000	2014	0.107	4.163	0.000
2007	0.112	4.318	0.000	2015	0.099	3.927	0.000
2008	0.116	4.341	0.000	2016	0.068	3.065	0.001
2009	0.112	4.197	0.000	2017	0.039	2.219	0.013
2010	0.141	5.118	0.000	2018	0.053	2.644	0.004
2011	0.122	4.466	0.000	2019	-0.051	-0.492	0.311
2012	0.110	4.128	0.000	2020	-0.019	0.484	0.314

5.3. Testing of the spatial model

The fixed effect and random effect models were selected with the Hausman test before the estimation of the spatial econometric model. For determining whether to adopt the individual fixed, time fixed or double fixed effect model, the LR test was further adopted for testing. Table 3 shows the test outcomes. The outcomes display that the double fixed effect should be adopted.

Table 3. Hausman Test

Type of inspection	Statistics value	P-Value	Conclusion
Hausman Test	15.22	0.033	Rejection
LR test (double fixation vs. single fixation)	45.01	0.000	Rejection
LR test (double fixed vs time fixed comparison)	214.51	0.000	Rejection

Because the spatial econometric model mostly includes SDM, SAR and SEM, it is necessary to test to decide which of the three models is more appropriate for analyzing this paper. This paper mostly uses WALDE test and LR test, and Table 4 shows the test outcomes. Based on Table 4, the WALD test outcomes support the use of spatial Durbin model.

Table 4. Results of WALD test and LR test

Type of inspection	Null hypothesis	Statistics value	P-Value
WALD Test	SEM is superior to SDM	16.88	0.018
	SAR is superior to SDM	16.85	0.018
LR Test	SEM is superior to SDM	16.57	0.020
	SAR is superior to SDM	16.59	0.020

5.4. Model estimation results

Table 5. Estimation outcomes of spatial panel Durbin model

	Direct role	Indirect role	Total role
LNPERGDP	-0.0489(-0.450)	0.3179(1.578)	0.2690(1.554)
ES	0.3668**(2.184)	2.1212(1.162)	2.4880(1.302)
IS	1.2104***(3.401)	2.0640(1.091)	3.2744*(1.701)
PS	-0.4516***(-2.942)	2.0174*(1.658)	1.5658(1.252)
LNER	-0.0541***(-3.819)	0.1665*(1.762)	0.1124(1.152)
FDI	9.6310*(1.886)	-1.3e+02*(-1.919)	-1.2e+02*(-1.704)
GI	-0.0164(-0.426)	-0.6227(-1.501)	-0.6391(-1.478)
ρ		0.5339***(6.266)	
N		450	
intra-group R-squared		0.2857	

Note: *, ** and *** respectively show that the statistical significance test is passed at the great level of 10%, 5% and 1%; the t-statistic in brackets is calculated based on the heteroscedastic robust standard error.

Based on the outcomes of Hausman and LR tests, the spatial panel Durbin model is adopted by taking into account the fixed roles of province and year, and estimates the model by applying the quasi-maximum likelihood estimation approach. Nevertheless, due to nonlinear information production process of the spatial panel autoregressive model, the expected coefficient acquired by the spatial panel autoregressive cannot be directly used for partial role interpretation. The direct effect of explanatory variables shal be decomposed in a province on its own carbon emission efficiency, the indirect role (spillover role) in the carbon emission efficiency of geographically adjacent provinces, and the total role of the two based in the expression of data generation process. The decomposition herein is on basis of the approach of LeSage and Pace [11]. Table 5 shows the given estimated outcomes, indicating a positive spatial association between the carbon emission efficiency of different provinces, and the improvement of the carbon emission efficiency of the province will have a positive spatial spillover role in the carbon emission efficiency of the provinces geographically close to it. This is consistent with theoretical expectations that when a region's emerging technologies improve and its carbon trading mechanism is improved, such improvements tend to radiate to areas within a geographically similar space.

In terms of direct effect, negative but not statistically significant expected parameter of economic growth level is realized. The carbon emission efficiency can grow by about 0.004 for each 1 percentage point growth in the ratio of coal usage. The carbon emission efficiency can grow by about 0.01 for each 1 percentage point growth in the ratio of secondary industry. The carbon emission efficiency will decrease by about 0.005 for every 1% increase in the proportion of the operating revenue of state-owned industrial companies to the operating revenue of industrial companies above designated size. The carbon emission efficiency will decline by about 0.0005 for every 1% increase in the industrial pollution control fee. The estimated coefficient of the government intervention variable fails to pass the statistical significance test.

The above different estimated parameters have different economic significance. For the coefficient of energy structure, it seems that coal consumption is a contributor to the increase in carbon emission efficiency in a statistical sense, but this statement is obviously difficult to hold at the theoretical level. Excessive use of carbon products without considering the introduction of new technologies will most likely lead to environmental pollution and destruction. Secondly, for the industrial structure, its positive coefficient means that with the variation of economic structure and the upgrading of industrial structure, the efficiency of energy saving and environmental protection in the production process will become increasingly high, and in a higher level of industrial form, the industrial coal consumption rate will be greatly reduced. Moreover, for the property rights structure, the negative coefficient of property rights structure is consistent with the theoretical expectation because the monopoly of state-owned companies on production and distribution and the dictatorship over the widespread technologies lead to an inefficient consequence in the reform and innovation, impeding the healthy growth of market economy, and forces insufficient motivation to drive the enhancement of industrial carbon emission efficiency. Fourth, for environmental control, although the coefficient of environmental control variable is very small, it is also a negative coefficient corresponding to the results of previous empirical studies.

With regard to indirect effects, the proportion of state-owned economy and the improvement of environmental regulation level in geographically similar provinces both assist in enhancing the carbon emission efficiency of the province. The estimated parameter of foreign direct investment is greatly negative, and foreign direct investment exerts a negative spatial spillover role in carbon emission efficiency, namely, the improvement of foreign direct investment level in geographically similar provinces will inhibit the enhancement of carbon emission efficiency of the province.

In the indirect role, the negative coefficient of property rights structure can be derived as follows: in the process of gathering state-owned capital of adjacent provinces, the state-owned capital of this province is also attracted. When the local state-owned capital is exported, the local property rights structure is improved, the phenomenon of state-owned economy crowding out market resources and monopolizing resources is alleviated, and the conditions are created for the local use of emerging technologies and the de-distortion of the carbon trading market. In addition, as for environmental regulation, the improvement of environmental supervision in neighboring provinces reduces the negative externalities produced by enterprises in the production process, which assist in the improvement of environmental governance and the use of new technologies in the province. In the meantime, the environmental governance of neighboring provinces plays a demonstration role in the local. Third, the negative coefficient of foreign direct investment is derived from the inducement effect and the aggregation effect. When the good investment environment and favorable investment policies in neighboring provinces lead to capital inflow, due to the aggregation effect, the latecomers of capital are more likely to gather there. When the capital of this province may flee, the new capital will flow into the neighboring provinces with high probability. Therefore, it is difficult to realize the use of foreign capital to improve technology and improve carbon emission efficiency.

6. Conclusion

The empirical outcomes display that (1) From 2005 to 2020, Chinese overall industrial carbon emissions efficiency grew fluctuantly and greatly enhanced, with the average industrial carbon emissions efficiency rising from 0.41 to 0.72. (2) Chinese industrial carbon emissions efficiency has spatial heterogeneity. Specifically, the basic structure was high in the east and low in the west before 2015, and gradually appeared high in the west and low in the east after 2015, which may be related to the direction of national policies. (3) The growth of industrial carbon consumption in adjacent areas and local areas will drive the enhancement of industrial carbon emissions efficiency in a statistical sense, but it is not economically theoretically meaningful to only consider the change of energy consumption structure during the increase in industrial carbon emissions efficiency. (4) The upgrading of industrial structure in adjacent areas and local areas help improve industrial carbon emissions efficiency, and higher industrial forms are usually corresponding to lower industrial carbon emissions efficiency. (5) The improvement of local property rights structure and the reduction of the ratio of state-owned capital are conducive to improving local carbon emissions efficiency, and the enhancement of state-owned enterprises in adjacent areas positively influences the enhancement of local carbon emissions efficiency in a statistical sense. (6) The strengthening of local environmental regulation makes the hidden danger of the green paradox, but the strengthening of the regulatory intensity in adjacent areas assists in improving the local carbon emission efficiency. (7) The increase in local foreign investment level help improve local industrial carbon emission efficiency, but the increase in foreign investment level in adjacent areas may compete with the local, and thus negatively influence the local emission reduction and efficiency increase. (8) The parameter of per capita GDP and government intervention intensity failed to pass the test and is not significant.

References

[1] Kaya Y, Yokobori K. (1997). Environment, energy, and economy: Strategies for sustainability. United Nations University Press, Tokyo.

[2] Lin L, Heng Z. (2021). Study on the relationship between the integration of "Two industries" and carbon emission efficiency. Economic Survey, 38(5): 71-79.

[3] Yingqi X, Yu C, Jing W. (2022). Spatio-temporal evolution and influencing factors of carbon emission efficiency in low-carbon pilot cities in China. Journal pf Natural Resources, 37(5):1261-1276.

[4] Jian L, Min W. (2022). Dual environmental regulation, FDI and green Total factor productivity: a case study of three urban agglomerations in the Yangtze River economic belt. East China Economic Management, 36(1):31-41.

[5] Sanliang J, Caibao L. (2022). Externalities and heterogeneity of environmental regulation on carbon emission efficiency: an analysis based on the agglomeration synergy of producer services. East China Economic Management, 36(10):56-69

[6] Li Y, Liang H. (2022). Impact of different types of capital-biased technological progress on carbon emission efficiency. Science and Technology research, 42(14):211-218

[7] Guangming L, Weijie Z. (2017). Study on industrial carbon emissions and emission reduction mechanism under crbon trading in China. Chinese Journal of Population Resources and Environment, 27(10): 141-148.

[8] Hui W, Yijie B, Shuqiao W. (2016). Dynamic Evolution and spatial spillover of export trade, industrial carbon emission efficiency. Journal of Quantitative & Technical Economics, 12(1):3-19.

[9] Chenyao Qu. (2017). Impact of industrial agglomeration on carbon emission efficiency of China's manufacturing industry and its regional differences. Soft Science, 6(1):34-38.

[10] Tone K. (2003). Dealing with undesirable outputs in DEA:A slacks-based measure(SBM) approach. GRIPS Research Report Series 1, 0005.

[11] LeSage, J., and K. Pace. (2009) Introduction to Spatial Econometrics. CRC Press, Boca Raton.