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Original Research

The Spatial Temporal Evolution Pattern and Influencing Factors of Green Innovation Efficiency: Based on Provincial Panel Data of Chinese Industrial Enterprises

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Abstract

Based on the panel data of 30 provinces in China from 2009 to 2017, the Super-SBM model with undesirable output is used to measure the green innovation efficiency (GIE) of Chinese industrial enterprises, and the Moran's I is used to analyze the spatial correlation. Then, spatial-temporal distribution characteristics are analyzed. Finally, the spatial panel model is used to examine the influencing factors of GIE. The results show that the GIE of Chinese industrial enterprises is at a low level, but it shows an upward trend in the time dimension. The changing trends of industrial enterprise's GIE in various regions are different. The GIE of industrial enterprises in eastern China is changing in a wave-like manner. The central and western are on an upward trend, which is consistent with the overall. Spatially, the GIE of industrial enterprises decreases from east to west. Most of the areas where the GIE of industrial enterprises is above the mid-high level are located in the southeast coast. The green innovation efficiency of industrial enterprises in various provinces has an obvious positive spatial correlation, but it has weakened in recent years. The level of economic development, environmental regulations, opening to the outside world, and technological innovation environment have a positive impact on the green innovation efficiency of industrial enterprises, while the level of urbanization has a significant negative impact on it. At last, this paper presents recommendations for the development of green innovation efficiency of Chinese industrial enterprises according to the findings.

Keywords: industrial enterprises, green innovation efficiency, spatial-temporal characteristics, Super-SBM model, spatial econometric model

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Introduction

Green innovation and green finance are two important components of sustainable development. Green innovation aims to achieve the dual goals of economic development and ecological protection [1, 2]. In 2015, the Fifth Plenary Session of the 18th CPC (the Communist Party of China) Central Committee put forward the development concept of innovation, coordination, green, openness, and sharing. At the same time, it emphasized that we must place innovation at the core of development, uphold the concept of innovative development. In 2020, the Fifth Plenary Session of the 19th CPC Central Committee emphasized that we will uphold the core position of innovation in China's modernization drive. Both enterprises and governments have increased their investment in technological innovation in recent years. Innovation capabilities of various regions have improved, and the position of innovation is becoming more prominent. Among many forms of innovation, green innovation pursuing resource conservation and environmental protection has increasingly become a vital driving force for green development. According to reports that in 2020, CO_2 emissions of China's gross domestic product (GDP) of 10,000 yuan decreased by 1.0%, coal consumption as a percentage point of total energy consumption dropped by 0.9% year-on-year, and clean energy consumption in total energy consumption has increased by 1.0% year-on-year. Green innovation has achieved remarkable results in China's economic development. Stokey and Aghion, Howitt pointed out that for achieving the best way of sustainable development, the economy must be equipped with growth engines and pollution-free industries [3, 4]. However, Akao did not fully agree with their views. That path may not be enough to achieve sustainable development, because sustainable development relates not only efficiency but also intergenerational equity [5]. Therefore, to evaluate the GIE of Chinese industrial enterprises and their spatial-temporal distribution characteristics, and to conduct spatial econometric analysis on the influencing factors of the green innovation efficiency of industrial enterprises is the focus of this article.

Green innovation refers to all forms of innovation that use natural resources in the most effective way to minimize environmental damage. Green innovation efficiency refers to the greening degree of regional innovation efficiency, which comprehensively considers pollution of the environment and energy consumption. It is the green index of innovation quality [6]. The development of green technology is the main source of value created by multinational companies, which gained environmental competitive advantages through green innovation activities [7]. Existing research on green innovation efficiency is abundant. Oduro and Takalo et al. gave a comprehensive overview of the research status and evolution of green innovation [8, 9]. There are two main aspects to the research on the GIE: the measurement method and evaluation of GIE, and the other is the impact of influencing factors on the GIE. As far as methods, Data envelopment analysis (DEA), stochastic frontier analysis (SFA), Malmquist index, and other methods have been used in the measurement of the GIE extensively. DEA is a linear programming model expressed as the ratio of output to input. SFA is a method for efficiency estimation using stochastic frontier production functions, and the Malmquist index method is based on the DEA method. The productivity changes in the next period are measured and calculated on the Malmquist Total Factor Productivity Index, to conduct a dynamic analysis of efficiency. Existing studies have used a three-stage DEA model with undesirable output measured green technology innovation efficiency in various provinces of China [10, 11]. The GIE of Chinese cities or the Yangtze River Economic Belt is calculated based on super slacks-based measure [12, 13]. Li et al. used SFA to analyze the GIE of regional high-end manufacturing and its influencing factors [14]. Zeng et al. used the global Malmquist-Luenberger index to measure the GIE [15]. Ye and Cheng found that the green technology innovation efficiency of various provinces in China showed significant spatial autocorrelation, and the overall green technology innovation efficiency was low. The financial ecological environment and its composition, GDP per capita, the introduction of foreign capital, environmental regulations have a significant role in promoting GIE [16]. Li and Du (2020) analyzed the influence of environmental regulations on GIE from the perspective of the spatial correlation of prefecture-level cities in China. They concluded that the spatial spillover effect of environmental regulations on GIE is significant. It is first inhibited and then promoted, whether local or neighboring [12]. Zhang et al. used a slacks-based measure of directional distance functions model, took Xi'an as an example for research. They found that there was an inverted U relationship between environmental regulations and the GIE. Regional education level was significantly related to the GIE, while government support has no significant impact [17]. The GIE of industrial enterprises is of great significance to the realization of sustainable economic development. The whole green technology innovation efficiency in China's industrial industries is low, and companies rely on the scale to a high degree. However, the GIE in most provinces is improving, and there are significant regional differences [18-20]. In addition, some scholars have evaluated the GIE of Chinese industrial enterprises and high-tech manufacturing from the perspective of the innovation value chain, and discussed the GIE in the R&D phase and the achievement transformation phase [21, 22]. Zhong et al.. (2019) constructed a non-radial directional distance function-data envelopment analysis three-stage evaluation model to measure the GIE of China's heavy polluting industries [23].

A review of the existing literature found that the current research on the GIE mainly focuses on measurement and evaluation, or the influencing factors of green efficiency and the economic consequences of green innovation. Existing research may have the following shortcomings: First, the measurement of GIE is mostly based on the traditional DEA method, and the use of the Super-SBM model with undesirable output is less. The empirical test of influencing factors used the Tobit model more, ignoring the spatial correlation of each region. Second, the research content is not rich, only to evaluate the GIE, less research on the influencing factors, and the literature on spatial-temporal characteristics of industrial enterprise's GIE are lacking. Therefore, this paper uses the provincial panel data of Chinese industrial enterprises from 2009 to 2017, adopts the Super-SBM model with undesirable output to measure the GIE of Chinese industrial enterprises, and evaluates its spatial-temporal distribution characteristics. Global and local space Moran's I is used to analyze the spatial correlation of industrial enterprise's GIE from the whole and local perspectives. The spatial panel model was used to test the influencing factors of GIE of industrial enterprises. Finally, suggestions are put forward for the development of the green innovation efficiency of Chinese industrial enterprises.

Material and Methods

Super-SBM Model with Undesirable Output

Data envelopment analysis (DEA) is a linear programming model, which represents the ratio of output to input. The traditional DEA model ignores the slackness of input and output, makes the measurement of efficiency value inaccurate. Tone successively proposed the SBM (slack-based measure) model, the Super-SBM model, and the SBM model to deal with undesirable outputs [24-26]. It solved the problem that the efficiency value of multiple DMUs equals 1 when the efficiency value is measured, and the DMUs can be effectively evaluated and ranked. The SBM model that only considers undesirable outputs may have multiple DMUs effective simultaneously, which is not conducive to sorting them. Thus, this article uses the Super-SBM model with undesirable outputs when evaluating the GIE.

Assuming that the production system has *n* DMUs, each province (region, city) is considered a DMU, consisting of three vectors: the input, desirable output, and undesirable outputs. These three vectors are, respectively, $x \in R^m$, $y_g \in R^{S1}$, and $y_b \in R^{S2}$. The definable matrix X, Y^g, Y^b is as follows:

$$X = [x_1, x_2, ..., x_n] \in R^{m\times n} > 0, Y^g = [y_1^g, y_2^g, ..., y_n^g] \in R^{i\times n} > 0, Y^b = [y_1^b, y_2^b, ..., y_n^b] \in R^{z\times n} > 0$$

Referring to the studies of Tone and Li et al., a limited possible production set that excludes the decision-making unit (x_0, y_0) is as follows [26, 27]:

$$P \setminus (x_0, y_0) = \{(x, \bar{y}^g, \bar{y}^b) \mid \bar{x} \geq \sum_{j=1}^{n} \tau_j x_j, \bar{y}^g \leq \sum_{j=1}^{n} \tau_j y_j^g, \bar{y}^b \geq \sum_{j=1}^{n} \tau_j y_j^b, \bar{y}^g \geq 0, \tau \geq 0\} \quad (1)$$

The super-SBM model with undesirable outputs is as follows:

$$\theta^* = \min \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{i0}}{\frac{1}{s_1+s_2}(\sum_{r=1}^{s_1} \bar{y}_r^g / y_{r0}^g + \sum_{l=1}^{s_2} \bar{y}_l^b / y_{l0}^g)}$$

$$\text{s.t.} \begin{cases} \bar{x} \geq \sum_{j=1,\neq 0}^{n} \tau_j x_j \\ \bar{y}^g \leq \sum_{j=1,\neq 0}^{n} \tau_j y_j^g \\ \bar{y}^b \leq \sum_{j=1,\neq 0}^{n} \tau_j y_j^b \\ \bar{x} \geq x_0, \bar{y}^g \leq y_0^g, \bar{y}^b \geq y_0^b, \bar{y}^g \geq 0, \tau \geq 0 \end{cases} \quad (2)$$

where θ* is the target efficiency value. x, y^g and y^b are the input, desirable output, and undesirable outputs, respectively. $\bar{y}$, $\bar{y}^g$ and $\bar{y}^b$ are the slack in the input, desirable output, and undesirable outputs. τ is the weight vector.

Spatial Autocorrelation and Spatial Econometric Model

Spatial autocorrelation is used to describe the degree of two which observations (values) at spatial locations (whether they are points, areas, or raster cells) are similar to each other. Generally speaking, it is the tendency for spatial locations that are close together to have similar values. In spatial statistics, the global Moran index (Moran's I) and local Moran's I are used in spatial autocorrelation tests widely. In addition, learning from existing literature [12, 28, 29], this article selects the spatial panel model in the spatial econometric to analyze the factors affecting the GIE. The general form of the spatial panel model is as follows:

$$\begin{cases} y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{it} + x'_{it}\beta + d'_i X_t \delta + \mu_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda m'_i \varepsilon_t + v_{it} \end{cases} \quad (3)$$

where W_{ij} is the element (*i*, *j*) of the spatial weight matrix, $d'_t X_t \delta$ represents the spatial lag of the explanatory variable, μ_i represents the individual regional effect, and γ_t is the time effect. If $\lambda = 0$, it is a spatial Durbin

model (SDM). If $\rho = 0$ and $\delta = 0$, it is a spatial error model (SEM).

It is necessary to test and choose the model before the spatial econometric analysis[1]. LM and LR tests were used to determine the spatial lag (SAR) model, spatial error model (SEM), and spatial Durbin model (SDM). Under the adjacent weight matrix, the LM-err and LM-lag test results are significant at the 1% or 10% level. Therefore, the results of the LR test support the SDM. Under the geographical distance weight matrix and the economic distance weight matrix, the test results of LM-err, R-LM-err, and LM-lag are significant at the 1% or 10% level, while the R-LM-LAG test rejects the null hypothesis, which indicates that the results support the spatial error model under the weight matrix of geographical distance and economic distance. The Hausman test results show that we should choose the model with fixed effects under the three spatial weights.

Variable Selection and Data Source

Selection of Indicators

Since green innovation is a complicated system that includes resource input, innovation output, and environmental benefits [30]. The measurement of the GIE should comprise undesirable outputs besides considering the capital, labor, energy input, and desirable outputs. According to the production function, the labor and capital factors are the fundamental input. Compared with the input factors of general innovation activities, green innovation involves energy and the environment. Therefore, the following variables are selected to construct a GIE indicator system for Chinese industrial enterprises. Capital input is represented by industrial enterprise R&D funds, labor input by the full-time equivalent of industrial enterprise R&D personnel, energy input by regional power consumption. The output indicators of green innovation efficiency of industrial enterprises include expected output and undesired output. Learn from exciting research [31, 32], the number of patent applications and sales revenue of new products are chosen as the desirable outputs. Undesirable outputs include three variables: regional wastewater discharge, sulfur dioxide discharge, and general industrial solid waste generated.

Learning from previous studies [29, 33, 34], this article selects economic development level (ECO), technological innovation environment (TECH), environmental regulation level (ER), and external degree of openness (OPEN), and the level of urbanization (UR) are variables that influence the GIE. These five variables are measured by the logarithm of regional gross domestic product (GDP) per capita, the proportion of local fiscal science and technology expenditure in the local government‘s general budget expenditure, the proportion of industrial pollution control investment in GDP, the proportion of total import and export in GDP, and the proportion of the urban population in total population at the end of the year.

Data Sources

According to the research purposes and availability of relevant data, this study analyzed the spatial-temporal evolution pattern and influence factors of regional GIE by using the data of 30 provinces and cities in China (except Hong Kong, Macau, Taiwan, and Tibet) from 2009 to 2017. Data on R&D expenditures of industrial enterprises, full-time equivalent of R&D personnel, number of patent applications of industrial enterprises, and sales revenue of new products are from the „China Science and Technology Statistical Yearbook.“ The data for electricity consumption, total wastewater discharge, sulfur dioxide discharge, and general industrial solid waste generation are from the „China Statistical Yearbook.“ The level of economic development, technological innovation environment, degree of opening to the outside world, and the level of urbanization can be calculated from the data obtained in the „China Statistical Yearbook“. The data of industrial pollution control investment comes from the „China Environmental Statistical Yearbook“. A small amount of data comes from the statistical yearbooks and statistical bulletins of each province, and individual missing data are filled in by linear interpolation.

Results and Discussion

Temporal Characteristics of Industrial Enterprise’s GIE

Using MaxDEA7.0 calculated the GIE of Chinese industrial enterprises from 2009 to 2017 (Table 1). It noted that there are differences in GIE under constant return to scale (CRS) and variable return to scale (VRS). The CRS model is more distinct than the VRS and can reduce systemic bias [35]. Therefore, this article chooses the CRS model as the basis for the evaluation of the GIE in Chinese industrial enterprises. The mean is 0.4, which is indicating that the GIE of Chinese industrial enterprises is low. The trend of industrial enterprise’s GIE in various regions of China from 2009 to 2017 is shown in Fig 1. From 2009 to 2017, the GIE rose from 0.255 to 0.472. The change indicates that the regional GIE of China is generally on the rising.

However, there are differences in the changes in the GIE of Chinese industrial enterprises in various areas (Fig. 1). China‘s economic development is still in a transitional stage, and there are problems of redundant resource input and relatively low efficiency in the industrial production process. It leads to lower

[1] Due to space limitations, the table is not given in the manuscript. The test results can be obtained from the author.

Table 1. The results of provincial green innovation efficiency in China from 2009 to 2017.

Regions	2009	2010	2011	2012	2013	2014	2015	2016	2017	mean	rank
Beijing	1.084	1.140	1.095	1.121	1.122	1.116	1.165	1.130	0.755	1.073	1
Fujian	0.302	0.375	0.419	0.391	0.407	0.452	0.502	0.523	0.417	0.416	12
Guangdong	1.002	1.009	1.011	0.632	0.712	1.007	0.778	1.046	1.093	0.906	7
Hainan	0.305	0.396	0.439	0.378	0.410	0.314	0.223	0.305	0.331	0.338	16
Hebei	0.126	0.177	0.210	0.271	0.293	0.289	0.255	0.296	0.321	0.240	24
Jiangsu	0.477	0.687	1.002	0.744	0.702	1.009	1.009	1.024	0.622	0.783	9
Liaoning	0.225	0.269	0.324	0.341	0.395	0.374	0.346	0.377	0.366	0.331	17
Shandong	0.276	0.348	0.438	0.485	0.470	0.462	0.450	0.451	0.437	0.418	11
Shanghai	0.618	1.029	1.053	1.052	1.027	1.039	1.024	1.039	1.038	0.979	4
Tianjin	1.047	1.117	1.180	1.110	1.108	1.082	1.063	1.046	0.634	1.029	3
Zhejiang	1.076	1.067	1.056	1.049	1.098	1.074	1.096	1.069	1.011	1.066	2
East	0.472	0.578	0.645	0.609	0.631	0.656	0.616	0.665	0.578	0.603	
Anhui	0.340	1.012	1.043	1.026	1.044	1.067	1.067	1.083	1.048	0.925	6
Henan	0.167	0.236	0.260	0.247	0.347	0.340	0.346	0.371	0.377	0.290	20
Heilongjiang	0.108	0.153	0.172	0.183	0.198	0.172	0.162	0.163	0.191	0.165	28
Hubei	0.265	0.330	0.377	0.388	0.456	0.448	0.513	0.531	0.512	0.415	13
Hunan	1.192	1.143	0.571	0.626	1.013	0.772	1.000	0.807	0.616	0.831	8
Jilin	0.282	0.398	1.075	1.091	0.238	0.470	0.380	1.047	1.087	0.570	10
Jiangxi	0.112	0.165	0.224	0.321	0.381	0.396	0.377	0.565	0.568	0.307	18
Shanxi	0.099	0.140	0.169	0.200	0.221	0.190	0.160	0.217	0.252	0.177	27
Middle	0.223	0.326	0.377	0.409	0.401	0.408	0.403	0.495	0.496	0.384	
Gansu	0.108	0.171	0.258	0.333	0.344	0.334	0.233	0.186	0.256	0.233	25
Guangxi	0.176	0.203	0.309	0.358	0.470	0.374	0.435	1.000	1.044	0.408	14
Guizhou	0.144	0.291	0.333	0.325	0.314	0.308	0.264	0.271	0.283	0.275	21
Inner Mongolia	0.095	0.114	0.119	0.144	0.141	0.122	0.111	0.132	0.211	0.129	29
Ningxia	0.118	0.195	0.219	0.298	0.372	0.242	0.286	0.262	0.275	0.241	23
Qinghai	0.102	0.099	0.069	0.087	0.118	0.099	0.165	0.238	0.323	0.127	30
Shaanxi	0.152	0.239	0.279	0.231	0.261	0.224	0.204	0.208	0.247	0.225	26
Sichuan	0.240	0.288	0.350	0.427	0.447	0.457	0.472	0.408	0.437	0.383	15
Xinjiang	0.104	0.229	0.285	0.306	0.350	1.006	0.297	0.305	0.336	0.304	19
Yunnan	0.177	0.250	0.249	0.272	0.275	0.267	0.221	0.253	0.239	0.243	22
Chongqing	0.502	0.700	1.071	1.006	1.017	1.020	1.085	1.045	1.485	0.955	5
West	0.153	0.221	0.259	0.290	0.320	0.316	0.284	0.313	0.371	0.273	
National	0.255	0.349	0.400	0.417	0.436	0.442	0.414	0.466	0.472	0.400	

GIE of Chinese industrial enterprises. Since the National Science and Technology Conference put forward the strategy of independent innovation and building an innovative country in 2006, it‘s easy to see how much the country values innovation. Especially after the 18th CPC National Congress, innovation-driven development strategy is deeply root in people‘s hearts. National policy support and enterprise response positively make GIE of Chinese industrial enterprises have been improved steadily. In terms of the eastern area, the GIE of Chinese industrial enterprises rises and falls in a wave-like manner. In recent years, although

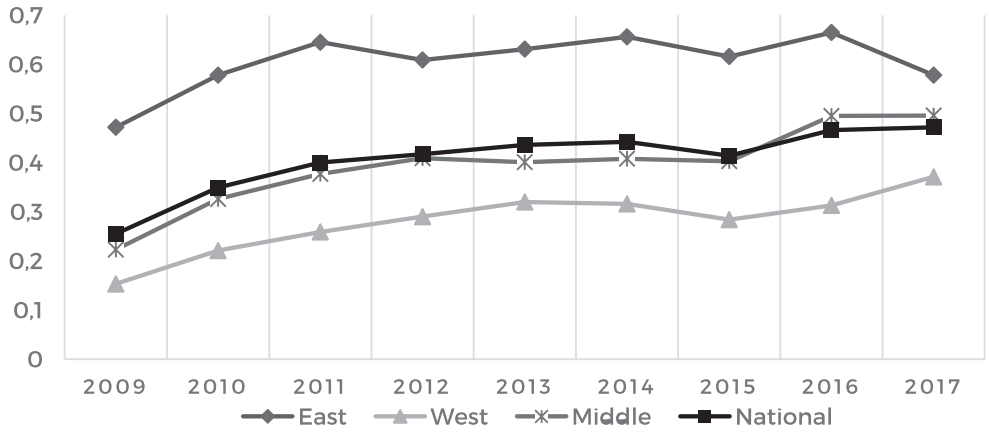

Fig. 1. Time trend of green innovation efficiency in various regions from 2009 to 2017.

various provinces have continuously increased human resources and funding in research and development investment, new product development, the application of new technologies, and the promotion of new ideas have cyclical. Innovation outputs such as the number of patents and the sales revenue of new products show a time lag, which led to a slight decline in the GIE of Chinese industrial enterprises at certain stages. In terms of the central and western regions, the GIE of Chinese industrial enterprises and the national level have remained consistent. From 2009 to 2014, it shows a steady upward trend year by year, and there is a slight decline in 2015, and there has been a significant increase since then. Because the industrial structure of the central and western regions is similar to a certain extent, and most of them rely on abundant energy resources for industrial production. Generally speaking, the larger the proportion of industry in regional industries, the more pollution emissions, the more likely it is adverse to the green development of the regional economy.

Spatial Characteristics of Industrial Enterprise's GIE

Spatial Correlation Test of Industrial Enterprise's GIE

1. Global spatial correlation test.

Using Stata15.0 calculated the Global Moran's I of China's GIE from 2009 to 2017 (Table 2). The results show that the Global Moran's I more than 0 and passed the significance test (except for 2017). It means that the spatial distribution of GIE is an obvious positive spatial correlation rather than random. Global Moran's I progressed a wave-like fashion, reached its maximum value in 2015, and then declined. It indicates that the spatial correlation fluctuations of GIE first increased and then decreased over time.

2. Local spatial correlation test.

The GIE agglomeration of provincial is divided into four types: high-efficient(H-H) agglomeration, hollow(L-H) agglomeration, low-efficient(L-L) agglomeration, and polarization(H-L) agglomeration [36, 37]. After the local spatial correlation test, it can be seen that Anhui, Beijing, Hunan, Jiangsu, Shanghai, Tianjin, and Zhejiang fall in the HH. Fujian, Guangxi, Guizhou, Hainan, Hebei, Hubei, Jiangxi, and Shandong fall in the L-H agglomeration. Gansu, Henan, Heilongjiang, Liaoning, Inner Mongolia, Ningxia, Qinghai, Shanxi, Shaanxi, Sichuan, Xinjiang, and Yunnan fall in L-L agglomeration. Guangdong, Jilin, and Chongqing fall in H-L agglomeration. High-efficient agglomerations such as Jiangsu, Zhejiang, Shanghai, and Anhui locate in the lower reaches of the Yangtze River. It is one of the most economically powerful regions in China. They are closely connected with the surrounding areas and have a strong ability to radiate and drive. The Beijing-Tianjin-Hebei region is the capital economic circle of China. Beijing and Tianjin are closely connected and have powerful collaborative development capabilities. However, industrial enterprise's GIE in Hebei is not growing as fast as them, so it is in a hollow agglomeration zone. Guangdong, Jilin, and Chongqing, which fall in the H-L agglomeration, have higher GIE than the surrounding areas, but the radiation driving ability is weak. Except for Liaoning, the provinces with L-L agglomeration located in the central and western regions. In general, more than half of the provinces fall within the H-H and L-L agglomeration, indicating that their GIE has a positive spatial correlation. That is to say, the provinces with high (low) GIE of industrial enterprises and their neighboring have higher (lower) GIE. Others fall in L-H and H-L agglomeration, which indicates that these provinces are not similar to the surroundings in GIE of industrial enterprises and are in the „highland" or „low-lying" land.

The Spatial Distribution Characteristics of Industrial Enterprise's GIE

ArcGIS10.7 is used to draw the spatial distribution of GIE of Chinese industrial enterprises from 2009 to 2017 (Fig. 2). The blank space in the figure indicates

Table 2. Global Moran's I of Green Innovation Efficiency in China from 2009 to 2017.

Year	2009	2010	2011	2012	2013
Moran's *I*	0.171	0.231	0.202	0.192	0.294
Z Statistics	1.878	2.365	2.090	2.016	2.934
P Statistics	0.030	0.009	0.018	0.022	0.002
Year	2014	2015	2016	2017	□□
Moran's *I*	0.260	0.353	0.314	0.105	0.292
Z Statistics	2.604	3.484	3.064	1.260	2.898
P Statistics	0.005	0.000	0.001	0.104	0.002

the lack of data. According to the Natural Breaks (Jenks) classification method, the GIE is divided from high to low into five levels: high, medium-high, medium, medium-low, and low. The provinces with a higher level of Chinese industrial enterprise's GIE from 2009 to 2017 include Beijing, Tianjin, Shanghai, Chongqing, and Zhejiang, and the lower include Heilongjiang, Inner Mongolia, Shanxi, and Qinghai. It notes that the distribution of the GIE across the country is stepped from east to west, with the highest level of the GIE in the east (Fig. 1). Generally speaking, the higher the proportion of the secondary industry in GDP, the greater the number of pollutant emissions produced [38-40], while energy consumption and pollutant emissions are crucial inputs and outputs index for measuring the GIE. Compared with the central and western regions, there are higher economic levels, stronger technological innovation capabilities, greater population density, and a more reasonable industrial structure in the coastal areas. In particular, the three major economic circles of the Bohai Sea, the Yangtze River Delta, and the Pearl River Delta. They are the gathering place of outstanding talents, the leader of domestic technological innovation. Their excellent geographical location, sufficient social and economic conditions attracted many talented people and powerful enterprises, laying a foundation for the development of high-tech industries and progress of the GIE. Therefore, the GIE of Chinese industrial enterprises in the central and western is lower than in the eastern coastal areas. While the central and west regions, most of which are resource-intensive industries. Instead,

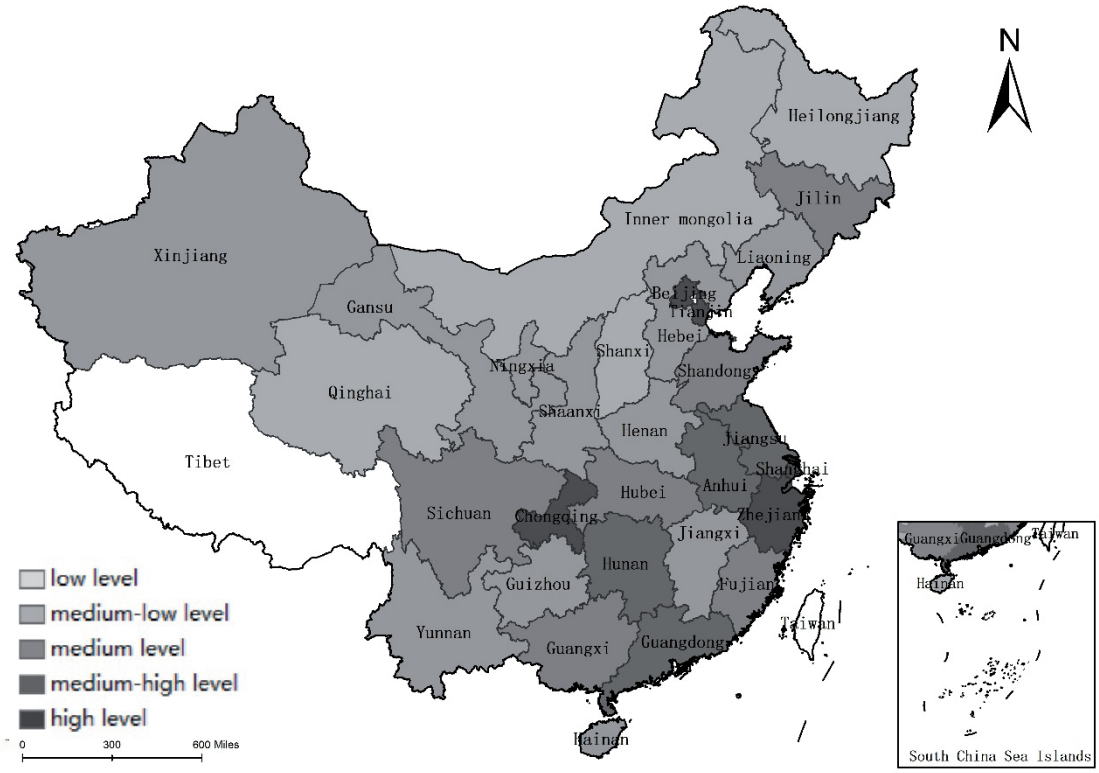

Fig. 2. Spatial distribution of green innovation efficiency of Chinese industrial enterprises in 2009-2017.

we should follow the path of low resource consumption, less environmental pollution, and uphold sustainable development. Among the provinces with low GIE of Chinese industrial enterprises, the problems of large resource provinces such as Inner Mongolia, Heilongjiang, and Shanxi are particularly prominent. The high input of energy resources usually accompanied by more pollution and emissions. Therefore, the GIE of Chinese industrial enterprises in central and western regions is generally low.

Analysis on the Influencing Factors of Industrial Enterprise's GIE

This article obtains the results of the spatial econometric model about the factors affecting the GIE of industrial enterprises (Table 3). Under the three spatial weight matrices, the impact of economic development on the GIE of industrial enterprises is significantly positive at the level of 1% or 5%. It shows that the higher the regional economic development level, the higher the regional GIE of industrial enterprises. Sufficient research and development funding is conducive to innovative industries' development and attracting high-end technical talents. The improvement of regional innovation efficiency and capacity is conducive to the formation of a virtuous circle of green economic development and industrial enterprise's GIE. The coefficient of spatial lag items -0.420 indicates that the economic development adverse to industrial enterprise's GIE in neighboring regions. The province with a high economic development level may attract talents and labor from neighboring, which is not conducive to innovation activities development and hinders GIE of industrial enterprises in neighboring.

The influence of environmental regulations on the GIE of industrial enterprises is positive but not statistically significant. It shows that environmental regulations promote the GIE of industrial enterprises to a certain extent, and the results support Porter's hypothesis. Appropriate environmental regulations can create a win-win situation in the conservation of the environment and economic growth by guiding enterprises' technological innovation, compensating part, or even covering their total compliance costs [41,42]. Environmental regulation is a factor that can promote green innovation development in China and contribute to promoting green technology innovation advances [43]. The improvement of technological innovation ability is conducive to improving energy efficiency, energy-saving, and emission reduction, thus promoting the GIE improvement. The coefficient of spatial lag -7.63 indicates that the increase of local environmental regulations intensity adverse the GIE of neighboring provinces. There is competition among local governments, and the increase in the intensity of local environmental regulations may lead border regions to follow blindly. Environmental regulations intensity is not as large as possible, and too large may exceed the critical value of promoting industrial enterprise's GIE.

The degree of opening up has a significant positive impact on the GIE of industrial enterprises. Opening up means domestic enterprises have more opportunities to exchange with foreign's. The exchange including many aspects such as technology and talent, which helps domestic enterprises to introduce advanced

Table 3. The results of spatial econometric model.

Variables	Adjacency matrix		Geographic distance matrix		Economic distance matrix	
	SDM	z-statistic	SEM	z-statistic	SEM	z-statistic
ECO	0.474**	2.565	0.382***	4.647	0.381***	4.708
ER	3.120	0.796	2.946	0.759	2.714	0.707
OPEN	0.440***	3.296	0.426***	3.443	0.426***	3.478
UBR	-1.919**	-2.400	-1.321*	-1.772	-1.290*	-1.731
TECH	1.234	0.537	0.795	0.349	0.800	0.351
W·ECO	-0.420	-1.568	-	-	-	-
W·ER	-7.630	-0.946	-	-	-	-
W·OPEN	0.109	0.492	-	-	-	-
W·URB	3.400**	1.965	-	-	-	-
W·TECH	2.585	0.735	-	-	-	-
R^2	0.357	-	0.396	-	0.401	-
Log-likelihhod	174.91	-	168.20	-	168.01	-
Observations	270	-	270	-	270	-

Notes: *** p<0.01, ** p<0.05, * p<0.1. "-" indicates that the item is empty.

technologies, improve existed processes. Thereby it contributes to saving energy, reducing pollutant emissions, and promoting industrial enterprise's GIE. Besides, environmental regulations may allow foreign enterprises with advanced technology to grant licenses to domestic enterprises that lack it and enhance innovation through technology transfer [44]. The regression coefficient of the spatial lag item is 0.109, which indicates that the degree of local opening up is positively affecting the GIE of industrial enterprises in neighboring provinces. Relevant local business contacts with foreign will promote the exchanges between neighboring provinces and foreign, and the advanced technologies introduced will promote progress, thus promoting industrial enterprise's GIE.

The level of urbanization has a significantly negative impact on the GIE of industrial enterprises. It indicates that the intensification of urbanization has restrained industrial enterprise's GIE. The expansion of the scale of cities and the increase in the number of enterprises have led to a rapid increasing in society's demand for energy, resulting in more pollutants and a decline in energy efficiency [45]. Energy efficiency and pollutant emissions reflect the low efficiency of innovative research and development activities to a certain extent, which is not conducive to the improvement of the GIE. The regression coefficient of the spatial lag item is 3.4, which is significant at the 5% level, indicating that the urbanization level positively affects the GIE of neighboring provinces. The expansion of cities will attract more labor and talents, attract more enterprises, correspondingly consume more energy, and produce more pollutants. By this time, the undesirable outputs of green innovation in neighboring provinces will decrease while the GIE of industrial enterprises improving.

The environment of technological innovation has a positive impact on the GIE of industrial enterprises, but it is not significant. It shows that the stronger the atmosphere of technological innovation, the more conducive to advancing the GIE of industrial enterprises. The larger the proportion of local fiscal expenditures on science and technology in the local government general budget, the more funds are used for innovation activities. The government actively encourages innovation and creates a deep innovation atmosphere in the whole society, which will help promote the transformation and upgrading of enterprises and further improve. Local innovation capabilities have improved the GIE of industrial enterprises. The coefficient of the spatial lag item is 2.585, which indicates that the technological innovation surrounding has a positive impact on the GIE of industrial enterprises in neighboring provinces. The competition among local governments has urged regions to increase technological innovation investment and create a good atmosphere for innovation. The increase pointed out by local technological innovation will stimulate the catch-up behavior of neighboring provinces, increasing technological innovation investment and promoting industrial enterprise's GIE.

Conclusions

This article uses panel data from 30 provinces in China (except Hong Kong, Macau, Taiwan, and Tibet) from 2009 to 2017. It calculates and analyzes the temporal-spatial distribution characteristics and influencing factors of the GIE of industrial enterprises at the provincial level. On the whole, the GIE of Chinese industrial enterprises is at a low level, but the overall trend is improving. There are differences in the changes in the GIE of industrial enterprises in various regions. The GIE of industrial enterprises in the eastern region has changed in a wave-like manner. While the central and western have maintained consistency with the overall level, showing an upward trend. From the perspective of spatial distribution, the spatial distribution of GIE of industrial enterprises is not random but has a conspicuous positive spatial correlation. Most provinces belong to high-efficiency agglomeration or low-efficiency agglomeration, which is similar to the GIE of industrial enterprises in neighboring provinces. The GIE of industrial enterprises is the highest in the eastern region, followed by the central, and the lowest in the western. The province with high-level GIE of industrial enterprises lies in the southeast coastal areas mostly. In particular, the three major economic circles of the Bohai Sea, the Yangtze River Delta, and the Pearl River Delta. In terms of influencing factors, the economic development level and the degree of opening up have a significant positive impact on the GIE of industrial enterprises. It indicates that the higher the level of economic development and opening up, the more conducive to advancing the GIE of industrial enterprises. The urbanization level has a significant negative impact on the GIE of industrial enterprises. It indicates that the expansion of urbanization has inhibited the GIE of industrial enterprises to a certain extent. The influence of environmental regulations and the technological innovation environment on the GIE of industrial enterprises is not statistically significant.

In response to the above conclusions, this article proposes the following suggestions. First, improving the green innovation evaluation and incentive mechanism, building a green innovation pattern that supports the modernization of the ecological environment governance system and governance capabilities, and create new advantages for regional development. The government should increase its support for science and technology, improve the innovation mechanism of reward and punishment, encourage enterprises to innovate actively, and take the path of green development. Following the requirements of the quality and management of the ecological environment

in different regions, governments should lead the way in innovation, optimize the layout of scientific research, and promote the support of scientific and technological achievements to lead the modernization of the ecological environment governance system and governance capabilities. In eastern coastal areas, they can actively develop new-generation network technologies such as big data, cloud computing, and the Internet of Things to improve resource allocation efficiency. In the central region, they can reduce pollutant emissions by accelerating the deep unite of industrialization and informatization and developing green manufacturing technologies with smart. In the western, they should promote modern energy technology with safe, clean, and efficient. The government should focus on optimizing the energy structure and improving energy-efficient, thereby promoting the transition of energy applications to clean and low-carbon energy. Regions should reduce undesirable outputs by improving the efficiency of factor input. Second, the Chinese government should advocate a change in the economic development model and continue to adhere to the basic state policy of opening up. The economic basis determines the superstructure, and enterprises should actively change their production methods, promote industrial transformation and upgrading, and lay the material foundation for green innovation.

At the same time, enterprises should actively learn and introduce foreign advanced technologies, and achieve energy conservation, emission reduction, and environmental protection through improvements to adapt to local needs, thereby increasing the GIE. Third, the Chinese government should attach importance to the role of environmental regulation and appropriately control the process of urbanization. The government can formulate appropriate environmental policies for different regions, and control the intensity of environmental regulations within a range conducive to innovation, to promote regional innovation efficiency. The degree of urbanization is not as high as possible. Local governments should appropriately control the process of urbanization to reduce environmental pollution and the occupation of green land for construction and promote the development of urban green.

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Conflict of Interest

The authors declare no conflict of interest.

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