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Agglomeration and green technology innovation efficiency of industrial enterprises – Based on spatial statistical analysis

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Abstract: Based on China's provincial panel data from 2009 to 2019, this paper empirically tests and analyzes the effects of industrial agglomeration and other important economic variables on industrial green technology innovation efficiency from the perspective of spatial statistical analysis. The results show that the efficiency of China's industrial green innovation has not changed much during the study period, exhibiting an obvious polarization phenomenon. Moreover, the improvement of the degree of industrial agglomeration is conducive to the regional green innovation efficiency level. This means that industrial agglomeration produces effective environmental and innovation benefits. In addition, the influence coefficient of enterprise-scale is negative, indicating that for Chinese industrial enterprises, the enlargement of the production scale weakens the promotion effect of R&D activities. The influence coefficient of human capital is negative, mainly because the direct effect has a small and positive value, while the indirect effect (spillover effect) has a negative and large value, indicating that the spillover effect of human capital between regions in China is deficient.

Introduction

Environmental pollution is an important global issue. Various models have been raised to solve this problem, such as coordination degree model (Haken, 1971), development level evaluation model (Wu & Zhao, 2016), space general equilibrium analysis model (Hirte, 2013), system dynamic model (Jeon, 2015), game theory model (Sun, 2019) and surrogate model (Silvia, 2016), etc. However, scholars believe that the next focus must be on management practices (Adu & Kumarasamy, 2020). They think that the new industrialization mode emphasizes the high efficiency and sustainable utilization of resources through the enhancement of management ability, so that industry development will change from resource-consuming to technology-oriented, including the establishment of scientific and technological innovation system (Wu, 2021), vigorously develop circular economy (Wang & Feng, 2018), formulate and improve laws and regulations (Kuznetsov & Kuznetsova, 2019), explore new regional development pattern (Wu, 2020), etc. Since the reform and opening-up, China's industrial economy has experienced several rounds of rapid growth and has now formed a mature system that is in a period of transformation, rising with great potential. However, the pollution caused by the extensive development of the industrial economy has caused serious disasters for human beings; the deterioration of the ecological environment has become a major challenge for the country while trying to meet the increasing needs of the sustainable development of the economy. China has the world's largest industrial scale, among which traditional high-pollution high--consumption industries, including coal, steel and petroleum, account for a large percentage. This situation will remain in the foreseeable future. Chinese development may not be like that of some small Western developed countries that focus on a few clean industries but instead will need to develop momentum in green technology innovation and implement it across the whole process of economic development. Therefore, the implementation of a green innovation development strategy is indispensable for China to promote a new development pattern based mainly on the domestic circular economy as well as to promote the sustainable and healthy development of the economy in this new development stage. For China, green innovation development has the following implications (Hu, 2014). First of all, it emphasizes the symbiosis of economic system, social system, natural system and the diversification of development goals, that is, the systematism, integrity and coordination of the three systems, which is very close to the natural view of "unity of man and nature" advocated in traditional Chinese philosophy. Second, it is based on the green economic growth model. The characteristic of the model is the proportion of green economy unceasing enhancement, green technology, green energy and green capital to stimulate the low energy consumption, and to adapt to the human health and environment friendly the constant improvement of the relevant industries in GDP.

According to new industrial organization theory, the scale economy is one of the key factors that determine market structures. The impact of the scale economy is to protect and play competitive vitality under market mechanisms and make full use of the economic agglomeration effect to improve the efficiency of resource allocation to obtain a higher level of social welfare. In essence, industrial agglomeration is a process of capital and labor assembly that promotes investment and attracts the participation of producers. In addition, the agglomeration of the same industry can make it easier for producers to obtain the assets of production and reduce transportation and information-collection processes of related enterprises during the industrial chain, thus saving costs. In addition, industrial agglomeration can make full use of public facilities, which is convenient for the exchange of scientific and technological achievements as well as information to improve product quality. Moreover, industrial agglomeration can exert a positive influence on various measures to protect the ecological environment. Because the concentration of industrial enterprises is conducive to the sharing of pollution control equipment and technology and the setting of unified environmental regulations by the government, thus reducing the unit cost of pollution treatments and improving the scale effect of pollution controls. For example, the agglomeration of producer industries in Shanghai is realized by relying on different spatial carriers, including modern service agglomeration zone, creative industry park, producer service functional zone and others. The establishment of these functional zones has accelerated the transformation of the old industrial zones with high energy consumption and pollution to functional zones for R&D producer services, international energy conservation and environmental protection industries (Liu, 2012). Also, diversified agglomeration has higher R&D efficiency and greater attraction to high-tech industrial zone (Duranton et al. 1999), so that the production technology is purified, thus significantly reducing industrial pollution emissions in regions. However, from the perspective of China's reality, the areas with high industrial agglomeration degree are also the most polluted areas (Zhang and Dou, 2016), which seems to be contradictory to the traditional agglomeration economic theory. Before the reform and opening up, China implemented a balanced development strategy for regional industrial development (Wu and Zhao, 2017). Under the common arrangement of census registers, employment and other welfare systems, the low-level industrial distribution in China's region seriously damaged the high efficiency of the industrial economy. After the reform and opening up, market-oriented economic system reforms greatly promoted industrial agglomerations (Li, 2014), which in turn realized self-strengthening through market expansion and technology diffusion effects, becoming an important force to promote China's economic development. For a long time, China's industrial enterprises have continuously concentrated in regions with superior geographical locations and rich natural resources and have gradually formed the industrial space pattern of the "center-periphery". Therefore, is the agglomeration of industrial enterprises conducive to the improvement of green innovation efficiency? This question is worth being tested.

Literature Review

Industrial agglomeration and collaborative development are key issues in industrial organization theory and have received much attention from academia in recent years (Yang et al. 2016; Liu et al. 2017; Zhao and Lin, 2019; Shen and Peng, 2021). By definition, industrial agglomeration refers to an economic phenomenon in which the industries in a particular sector are interdependent and mutually complementary with the characteristics of specialization within a specific space (Storper, 1992). Krugman (1991 a;1991b; 1993) emphasized that market proximity is the motive of industrial agglomeration, constructed the market potential function based on the assumption of increasing returns to scale and its positive feedback mechanism (Krugman, 1992), and calculated the maximum salary that potential market entrants were willing to pay. Marshall (1920) believed that industrial agglomeration had effects such as labor pools, personnel flows and technology diffusion and could speed up information exchange in the agglomeration area, thus driving technology spillover and sharing. The rapid spread of knowledge and the spillover effect within the agglomeration area can accelerate the technological innovation of enterprises.

Later, Porter (1998) posited that, from the perspective of the industrial chain, upstream and downstream industrial agglomeration is more conducive to the sharing of production factors among enterprises and the reduction of transportation and communication costs, thus improving production efficiency and response speed to market demand, which is conducive to enterprises' long-term development. In addition, from the perspective of the spatial dimension, regional differences in the development foundation and the "point-surface" development model also make spatial heterogeneity an important feature of industrial development, which is manifested as an industrial spatial agglomeration phenomenon (Xiao and Du, 2017).

Scholars believe that against the background of today's knowledge economy, industrial agglomerations have gradually become a key driving force for national competitiveness (Turkina and Van Assche, 2018). Studies show that the vertical division of labor of middle and small enterprises provides a decisive advantage for industrial agglomeration, and that agglomeration drives the innovation of new products and the optimization and upgrading of production methods (Humphrey and Schmitz, 1996; Newman and Page, 2017; Kuznetsov and Kuznetsova, 2019).

Research on industrial enterprise agglomeration and green innovation efficiency mainly includes the following studies. Qu et al. (2021) examined the diversification and specialization of enterprises on green technological innovation efficiency, and Liu et al. (2020) empirically tested the effect and regional differences of industry clusters on regional green innovation efficiency. The results show that both diversification and specialization of industrial agglomeration significantly promote regional green technology innovation efficiency, and the effect of diversification is stronger. Ji et al. (2020) show that industrial agglomeration and regional green development efficiency have a short-term impact on technological innovation, while the influence of green development efficiency on industrial spatial agglomeration needs to be strengthened. Wang et al. (2019) found an inverted U-shaped relationship between industrial agglomeration and environmental pollution. Industrial agglomeration in most areas is an important cause of environmental pollution. Technological innovation and structural optimization play an important channel role in industrial agglomeration affecting environmental pollution. Chen and Golley (2014) found that environmentally friendly technological innovation is conducive to enhancing regional green development potential and improving regional green development efficiency.

In conclusion, scholars have performed many research studies on the green innovation effect of industrial agglomeration and have achieved fruitful results, but there is still room for improvement. Firstly, the research has had a narrow focus on the independent relationship between industrial agglomeration and green innovation efficiency, neglecting other important economic variables such as human capital, market environment, industrial structure and so on. Secondly, there are few studies from the perspective of spatial economics, and the research results are thus often incomplete with limited relevance for large countries such as China. Therefore, from the perspective of spatial differentiation and spillover, whether the agglomeration and scale effect of industrial enterprises can play a better role in green science and technology innovation is very important for China to develop effective industrial development, environmental protection and science and technology policies. Based on the perspective of spatial economics, this paper studies the relationship between industrial agglomeration and green science and technology innovation efficiency, hoping to provide a reference for the coordination of industrial, environmental and science and technology policy in China.

Calculation and dynamic analysis of green technology innovation efficiency

Green technology innovation efficiency measurement model – SEDEA

Data envelopment analysis (DEA), a digital elevation model, was proposed by Charnes, Cooper and Rhode in 1978. DEA is a linear programming model, expressed as the ratio of output to input. It tries to maximize the efficiency of service units by comparing the particular unit with the performance of a group of similar units with providing the same service. In this process, some units that achieve 100% efficiency are called efficient units, while other units that score less than 100% efficiency are called inefficient units. This method has many advantages, e.g., there is no need to determine the specific form of frontier production function, there is no need for input and output items to standardization, the efficiency can be evaluated through the decomposition efficiency value of the best and the gap, so as to find out the best way to improve efficiency. Therefore, DEA is widely used in terms of resource and environmental efficiency evaluation (Wu and Ma, 2016). According to the characteristics of the object, we select a super-efficient slack based model with unexpected output to measure the green innovation efficiency of provinces in China. Suppose there are n decision-making units (DMUs), denoted as DMU_j (j=1, 2, ..., n), and each DMU has m inputs, denoted as x_i (i=1, 2, ..., m) q_1 expected outputs, denoted as y_r (r=1, 2, ..., q_1), and q_2 unexpected outputs, denoted as b_t (t=1, 2, ..., q_2). Then, for a decision unit DMU_k (x_k, y_k, b_k), its production possibility set is:

$$P=\{(x_k, y_k, b_k) \,|\, x_k \ge \sum_{j=1, j\ne k}^{n} x_{ij}\lambda_j,\ y_k \le \sum_{j=1, j\ne k}^{n} y_{rj}\lambda_j,\ b_k \ge \sum_{j=1, j\ne k}^{n} b_{ij}\lambda_j\} \quad (1)$$

The green innovation efficiency with unexpected output is:

$$min\ \rho^* = \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}}+\sum_{t=1}^{q_2}\frac{s_t^{b-}}{b_{tk}}\right)} \quad (2)$$

$$s.t.\ \begin{cases} \sum_{j=1, j\ne k}^{n} x_{ij}\lambda_j - s_i^- \le x_{ik} \\ \sum_{j=1, j\ne k}^{n} y_{rj}\lambda_j + s_r^+ \ge y_{rk} \\ \sum_{j=1, j\ne k}^{n} b_{tj}\lambda_j - s_t^{b-} \ge b_{tk} \\ 1-\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}}+\sum_{t=1}^{q_2}\frac{s_t^{b-}}{b_{tk}}\right) > 0 \\ \lambda \ge 0,\ s^- \ge 0,\ s^+ \ge 0 \end{cases} \quad (3)$$

where s_i^- represents the relaxation of the i_{th} input; s_r^+ represents the relaxation of the r_{th} expected output; s_i^{b-} represents the relaxation of the t_{th} undesired output; and λ represents the weight vector.

Selection of input and output variables and data sources

After introducing the method, we need to select indicator variables. The selection process should conform to scientific, comprehensive and reasonable principles. The measurement of green innovation efficiency needs to include input variables, expected output variables and unexpected producer variables. For green innovation systems, input refers to the costs paid in the innovation process, including not only economic and human investment in scientific and technological innovation but also efforts for economic development and ecological environment improvement. The output is divided into expected and unexpected output. The former includes the number of invention patents and innovation generated by direct economic benefits, which measures the returns gained by investments in science and technology. The latter includes industrial "three wastes" emissions, which measures the extent to which technological innovation and ecological environmental governance investment reduce pollution emissions.

The area where the system works includes an administrative unit with a provincial agglomeration covering part of the area (Korol and Zawartka, 2019). So, for research objects, we select 30 provinces (municipalities and autonomous regions) in mainland China and measure their green innovation efficiency over 11 years from 2009 to 2019 within the framework of total factor analysis. Tibet, Hong Kong, Macau and Taiwan were not included due to the lack of data. Data were obtained from the China Statistical Yearbook, the China Industrial Yearbook and the China Environmental Statistical Yearbook from 2010 to 2020. Cooper et al. (2001) noted that the number of decision units in the DEA algorithm needs to meet the condition of $n \geq \max\ \{m \times s,\ 3(m+s)\}$ to ensure the accuracy of the results, where n represents the number of DMUs and m and s represent the number of variables for input and output, respectively. The paper meets this condition.

According to econometrics, the more data sets, the smoother the efficiency frontier can be constructed. In this paper, we took all the input-output data within the sample period as the reference technology set of the current period and used MaxDEA Pro 6.6 to calculate the eco-scientific and technological innovation efficiency values of various regions in China from 2009 to 2019. The results are as shown in Table 2 and Figure 1. The draw of Figure 1 is based on the average value.

From 2009 to 2019, the efficiency value essentially shows a small fluctuation, without an obvious variation, which reflects the stability presented by China as a huge economy in development. Considering different provinces, Beijing (1.409), Shanghai (1.166), Guangdong (1.12) and Zhejiang (1.064) are the four provinces with the best performance (their efficiency values are all greater than 1). We can clearly see that these provinces are the most economically developed provinces located in the southeast coastal areas. In recent years, with the deepening transformation of manufacturing industries and the gradual improvement of industrial structure, the labor-intensive, high pollution and high energy-consumption enterprises in these regions have gradually moved to relatively more backward economic areas where the prices of other production factors are lower. The economic development of these regions is going through a painful period of transformation, and the speed has decreased correspondingly. However, the quality and sustainability level of regional development has been comprehensively guaranteed. The Chinese government's plan for the future of these provinces, which continues to develop fully due to their geographical, technological and financial advantages, seeks to have them become the world's most important high-tech research and high-end industrial manufacturing centers (Wu and Zhao, 2016).

The worst performing provinces (with efficiency scores less than 0.2) are Yunnan (0.197), Shanxi (0.173), Heilongjiang (0.163) and Inner Mongolia (0.134). These provinces are the most economically backward regions of China, all relying on traditional manufacturing industries as their economic base. The most prominent feature of their development is that they all take the traditional industrialization road of high pollution and high consumption, and their scientific and technological innovation ability is relatively weak. According to the government's regional planning, the future direction of these regions is to implement the strictest management system to optimize resource allocation, further improve utilization efficiency, accelerate the transformation of the production mode and energy and resource consumption, strengthen punishment for pollution, and avoid further deterioration of the ecological environment. In addition, more support should be given to such areas to help them build a system for technology--led industrial transformation and upgrades to narrow the development gap with other regions.

Dynamic evolutionary analysis of green technology innovation efficiency

We further sketch the trend and dynamic evolution of China's industrial green innovation efficiency by using the nonparametric estimation method (called kernel density analysis). Its basic principle is to let the probability density estimation equation of the variable X at point x be as follows:

$$\hat{f}_n(x) = \frac{1}{nh^p} \sum_{i=1}^{n} K\left[\frac{x - X_i}{h}\right] \tag{4}$$

where $K(\square)$ is the kernel function, h is the bandwidth, and n is the sample number. The kernel function and bandwidth should

Table 1. An evaluation index system of regional industrial green technology innovation

Indicator type	Indicator name		Indicator description and unit
Input indicators	Science and technology innovation labor input		Total wastewater discharged (Man-year)
	Science and technology innovation capital investment		Total wastewater discharged (10,000 yuan)
	Ecological and environmental improvement investment		Completed investment in industrial pollution control (10,000 yuan)
	Energy input		Total industrial energy consumption (10,000 tons standard coal)
Input indicators	Expect output	Innovation patent	Inventions in force (Piece)
	Expect output	Innovative economic benefits	Revenue from sales of new products (10,000 yuan)
	Undesired output	Industrial „three wastes" discharge	Total waste water discharged (10,000 tons)
	Undesired output		Sulphur dioxide emissions (10,000 tons)
	Undesired output		Common industrial solid wastes produced (10,000 tons)

Table 2. Calculation results of provincial green technology innovation efficiency from 2009 to 2019

GTE	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average	Ranking
Beijing	1.200	1.503	1.442	1.367	1.192	1.180	1.208	1.130	1.054	1.044	3.184	1.409	1
Tianjin	1.048	1.042	1.124	1.104	1.177	1.117	1.130	1.139	0.825	0.675	0.457	0.985	5
Hebei	0.189	0.175	0.206	0.213	0.232	0.227	0.217	0.268	0.238	0.304	0.246	0.229	23
Shanxi	0.149	0.134	0.170	0.169	0.191	0.175	0.146	0.174	0.177	0.218	0.196	0.173	28
Inner Mongolia	0.141	0.118	0.119	0.110	0.111	0.109	0.107	0.122	0.168	0.187	0.183	0.134	30
Liaoning	0.289	0.241	0.307	0.295	0.336	0.315	0.283	0.303	0.280	0.364	0.240	0.296	19
Jilin	1.458	1.058	1.125	1.112	0.201	0.274	0.192	1.072	1.155	1.049	1.283	0.907	8
Heilongjiang	0.158	0.158	0.147	0.170	0.162	0.153	0.142	0.150	0.168	0.184	0.199	0.163	29
Shanghai	1.213	1.134	1.144	1.116	1.195	1.088	1.056	1.097	1.357	1.348	1.073	1.166	2
Jiangsu	0.517	0.647	1.002	0.791	0.792	1.067	1.053	1.033	1.018	1.012	0.521	0.859	9
Zhejiang	1.020	1.060	1.109	1.037	1.100	1.077	1.131	1.092	1.035	1.034	1.014	1.064	4
Anhui	0.378	1.014	1.060	1.032	1.070	1.153	1.117	1.184	1.044	1.056	0.492	0.964	7
Fujian	0.391	0.357	0.389	0.367	0.399	0.400	0.429	0.457	0.427	0.410	0.289	0.392	16
Jiangxi	0.167	0.187	0.198	0.221	0.284	0.338	0.352	0.539	0.596	0.545	0.438	0.351	18
Shandong	0.417	0.416	0.430	0.415	0.446	0.433	0.419	0.387	0.363	0.351	0.263	0.395	15
Henan	0.253	0.231	0.237	0.231	0.283	0.291	0.316	0.289	0.287	0.310	0.237	0.270	20
Hubei	0.327	0.341	0.346	0.345	0.415	0.415	0.499	0.435	0.444	1.007	0.378	0.450	12
Hunan	0.491	0.470	0.488	0.604	1.013	0.714	0.571	1.001	1.039	1.021	0.376	0.708	10
Guangdong	1.275	1.165	1.010	0.693	0.772	1.030	1.110	1.319	1.356	1.365	1.221	1.120	3
Guangxi	0.268	0.261	0.223	0.236	0.336	0.291	0.313	1.000	1.030	1.012	0.252	0.475	11
Hainan	1.004	1.052	0.378	0.297	0.337	0.256	0.203	0.258	0.226	0.211	0.196	0.402	14
Chongqing	1.043	1.097	1.069	1.006	1.013	1.084	1.243	1.149	1.020	0.591	0.360	0.970	6
Sichuan	0.335	0.314	0.310	0.362	0.386	0.422	0.449	0.423	0.374	0.334	0.268	0.362	17
Guizhou	0.215	0.252	0.267	0.242	0.219	0.233	0.188	0.258	0.222	0.243	0.180	0.229	22
Yunnan	0.186	0.176	0.197	0.206	0.213	0.217	0.174	0.217	0.212	0.219	0.151	0.197	27
Shaanxi	0.203	0.223	0.232	0.204	0.213	0.212	0.195	0.218	0.224	0.256	0.222	0.218	25
Gansu	0.139	0.216	0.225	0.237	0.271	0.270	0.227	0.172	0.194	0.197	0.214	0.215	26
Qinghai	0.127	0.056	0.027	0.036	0.044	0.030	0.083	0.124	0.255	1.074	1.008	0.260	21
Ningxia	0.153	0.189	0.185	0.231	0.277	0.206	0.249	0.215	0.248	0.280	0.203	0.222	24
Xinjiang	0.121	0.190	0.206	0.227	0.275	1.003	0.239	0.256	0.246	1.015	1.066	0.440	13
Average	0.496	0.516	0.512	0.489	0.498	0.526	0.501	0.583	0.576	0.631	0.547	0.534	–

be selected in the specific estimation. The key to the fitting result is the setting of the optimal bandwidth. The basic idea of bandwidth selection is to minimize the mean square error. There are many forms of kernel functions, and we choose the most common function – Epanechnikov. The paper selected the four years 2009, 2013, 2017 and 2019 as the investigation sections, and the distribution diagram of the kernel density function for each year is shown in Figure 2.

Figure 2 shows that the dynamic evolution of the green innovation efficiency distribution of Chinese industrial enterprises presents two obvious characteristics. First, the distribution peak did not change much from 2009 to 2019, indicating that most provinces in China did not improve during this period, but instead, the performance of industrial enterprises in green innovation stagnated. Second, all efficiency values present a "twin peaks" model in four years, and the width between the peaks did not change obviously. The efficiency of industrial green innovation tends to be centralized and close to two equilibrium points, one at a lower level (approximately 0.4) and the other at a higher level (approximately 1.2), indicating that the efficiency of industrial green innovation in China presents an evident polarization phenomenon during the research period, during which the gap between provinces does not shrink. In addition, it is worth mentioning that the peakedness of the two peaks in 2019 was significantly higher than that in the other three years, indicating that the data series in 2019 had more extreme values and more serious polarization, which means that more areas were concentrated near the value of inefficiency.

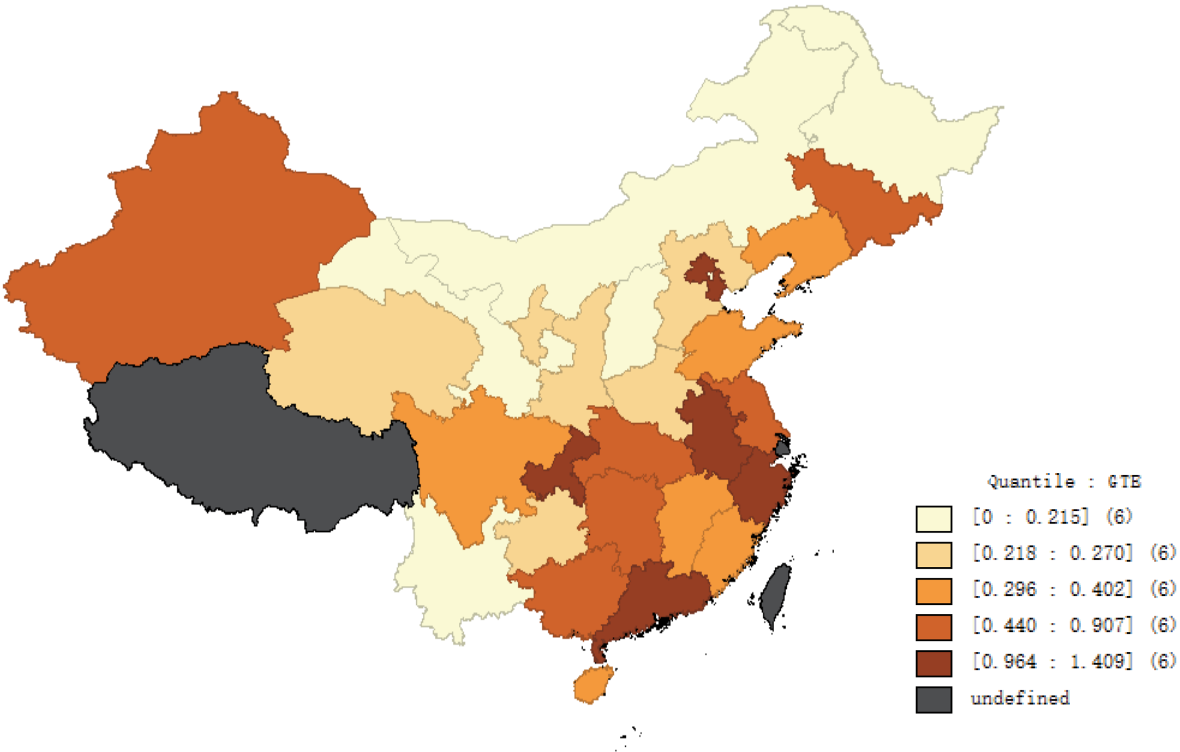

Fig. 1. Spatial differentiation of regional green innovation efficiency in China

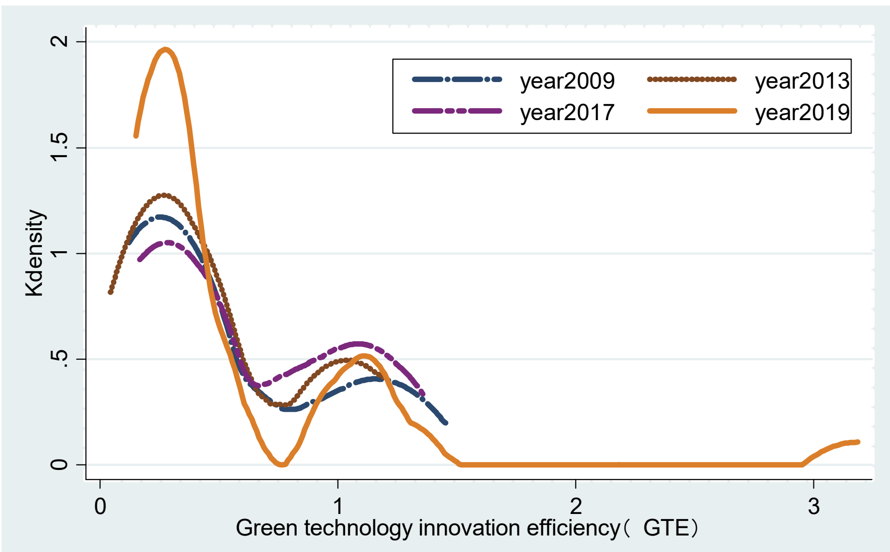

Fig. 2. Kernel density diagram of the green technology innovation efficiency of industrial enterprise

Spatial statistical analysis of the direct and spillover effects of industrial enterprise agglomeration on green technology efficiency

Method introduction

The most important aspect of the spatial statistical method is to combine the object of study with its geographical location. The first law of geography states that everything is related to everything else but more related to the near one (Wang et al. 2015). It should be noted that distance here is a broad concept that includes not only geographical location but also the closeness of economic cooperation and even the distance between interpersonal relationships. As we all know, the interaction between development elements can be investigated in the decision-making processes concerning management (Lukaszewska et al. 2021) and the spatial statistical technique (Wiatkowski et al. 2021; Pohl and Kostecki, 2020). Generally, scholars typically use the spatial weight matrix to sample the spatial distance of the research object. The setting of the spatial weight matrix must also meet the requirements of the first law of geography, i.e. , the spatial correlation of different subjects must decrease with increasing distance. The assumption of spatial correlation and dependence in spatial economics breaks the hypothesis that each research subject is independent of each other in classical economic theory and makes the performance of the research subject highly related to its geographical location, thus making the research more scientific and reasonable as well as more widely applied.

When analyzing spatial econometric models, a benchmark model is needed for comparison and reference (Jiang, 2016). The ordinary least squares (OLS) model is the most common reference model. Therefore, spatial econometric modeling starts from the OLS model, and the Lagrange multiplier test (LM) is performed with the residuals after OLS regression. The test contains two statistics: **LM–Error** and ***LM–Lag***. If these two statistics are not significant, the OLS model is a suitable method. If only one statistic is significant, then the ***LM–Error*** statistical significance points to the spatial error model, while the ***LM–Lag*** statistical significance points to the spatial lag model. In the case if both statistics are significant, Anselin (1988) proposed a Lagrange multiplier test for robustness, which correspondingly contains two unified quantities, namely***, robust LM–error and robust LM–lag***. Among them, if the ***robust LM–error*** statistical value is significant, it points to the spatial error model, while the ***robust LM–lag*** statistical value is significant, it points to the spatial lag model.

The form of the spatial error model (SEM) is as follows:

$$GTE_{it} = a_i + b_i IND_{it} + \beta M_{it} + \varepsilon_{it} \tag{5}$$

$$\varepsilon_{it} = \lambda \sum W_{ik} \varepsilon_{kt} + \mu_{it} \tag{6}$$

where ***GTE*** represents industrial green technology efficiency; ***IND*** represents the agglomeration degree of industrial enterprises; μ is the normal distributed random error vector; λ is the space error coefficient of the $n \times 1$ cross-section dependent variable vector; and ε is the random error vector. Parameter β represents the influence of the control variable M on the dependent variable; and parameters λ are the influence degree and direction of the observed value of adjacent areas on this area.

The spatial lag model (SAR) takes the following form:

$$GTE_{it} = a_i + b_1 IND_{it} + \beta M_{it} + \mu \sum \omega_{ik} GTE_{kt} + \varepsilon_{it} \tag{7}$$

where ***GTE*** is the dependent variable; ω is the spatial weight matrix of $n \times n$ order; μ is the spatial regression coefficient; and ε is a random error vector.

Analysis of the impact of industrial enterprises' agglomeration on green technology efficiency

Before conducting spatial analysis, the paper first needs to select the spatial weight matrix. We did not use the traditional spatial proximity matrix (0–1 matrix) but instead chose the spatial distance weight matrix, which is based on the distance attenuation function between provincial capitals, and took the reciprocal of the shortest distance as the spatial weight. The advantage of this matrix is that the spillover of green innovation activities between spatially close but not adjacent provinces may influence and interact with each other.

Then, we used the global index ***Moran's I*** to analyze the dependence and correlation of the spatial distribution of China's industrial green technology efficiency. The test results show that the normal statistical value Z of ***Moran's I*** in the study year passes the significance level test of 5% (see Table 3), indicating that the industrial green technology efficiency is not a completely random distribution, and it is therefore necessary to analyze the influencing factors of the industrial green technology efficiency from the spatial dimension.

Then, the paper carried out a spatial autocorrelation test on the variables, the results of which are shown in Table 3.

From Table 3, we know that the spatial panel regression model is more appropriate than the traditional econometric model to investigate the impact of industrial agglomeration (***IND***) on the green technology efficiency (***GTE***) of industrial enterprises. Before establishing the relevant spatial panel model, the Hausman test should be used on the SEM and SAR models. Since the P-value is less than 0.05, the null hypothesis is rejected. Therefore, we use the fixed effect model rather than the random effect model. In addition, through the observation and judgment of the Lagrange multiplier lag, error and robustness test, we know that under the spatial distance weight matrix, the value of the ***LM–Lag*** is significantly greater

Table 3. Spatial autocorrelation test of estimated residuals in the linear panel model

Test variables	Statistic	P-value
Moran's I	0.263	0.046
Lagrange Multiplier (lag)	3.8202	0.000
Robust LM (lag)	3.7098	0.000
Lagrange Multiplier (error)	1.877	0.000
Robust LM (error)	1.243	0.003

than ***LM—Err*** and passes the significance level test. Thus, the spatial lag model (SAR) is better than the spatial error model (SEM). Therefore, we use the SAR model.

For the indicator, we use the number of large- and medium--sized industrial enterprises as the basic index to measure the level of regional industrial agglomeration (***IND***). In addition, we also select some other social conditions as control variables (Tomczyk and Wiatkowski, 2020), including human capital (***HUM***), which is represented by the number of students in colleges and universities per 100,000 inhabitants; Industrial structure (***STR***), represented by the proportion of the value of the secondary industry in GDP; Market environment (***MAR***), represented by technical market turnover; Enterprise-scale (***SCAL***), represented by the average number of employees in industrial enterprises; and Foreign trade (***TRA***), represented by the proportion of the total volume of foreign trade in GDP of provinces. In addition, because the logarithmic treatment does not change the original data structure and can eliminate possible heteroscedasticity, we take the natural logarithm of the above variables by ***lnIND***, ***lnHUM***, ***lnSTR***, ***lnMAR***, ***lnSCAL*** and ***lnTRA***.

The estimation results of the spatial panel SAR model are shown in Table 4.

From Table 4, we can see that all coefficients (ρ) of SAR are positive and pass the significance level test of 5% in the time-fixed, spatial-fixed or spatial-time dual fixed models, indicating that the industrial green technology innovation efficiency (***GTE***) presents a spatial agglomeration state. Among the three types of models, the time-fixed model has the highest fitness. Therefore, this paper mainly analyzes the time--fixed model in the following section.

Regardless of which model is selected, the regression elasticity coefficient of industrial agglomeration is significantly positive, which means that the improvement of industrial agglomeration is conducive to regional green innovation efficiency. To some extent, industrial agglomeration can promote both competition and cooperation among industries in relevant knowledge, technology, infrastructure, energy conservation and emission reduction. (Liu et al. 2020). Therefore, collaborative agglomeration among industrial enterprises can improve regional green innovation capacity and efficiency through technology spillover, enhancing industrial competitiveness and strengthening industrial cooperation (Liu et al. 2020). Specifically, the industrial enterprise cluster can, on the one hand, effectively reduce the related enterprises in material and information resources sharing and transfer costs in time and space, thus speeding up the spread of invisible intangible resources exchange such as knowledge and technology, and playing a spillover effect to realize the sharing and optimized configuration of resources. On the other hand, industrial clusters also drive the development of the circular economy by upstream and downstream enterprises, further improving the efficiency of energy utilization, reducing pollution emissions, shortening production time, improving production efficiency, and reducing the product price and production costs to gain greater competitive advantage and market position, all of which promote the virtuous cycle of regional green innovation. In addition, the agglomeration of industrial enterprises can also deepen the complementarity, interaction and integration between industries by improving green technology trading mechanisms and building information-sharing platforms to achieve win-win cooperation between industries. Finally, the

Table 4. Estimation results of spatial panel SAR model

GTE	Spatial-Fixed Effects Model	Time-Fixed Effects Model	Spatial- and Time-Fixed Effects Model
lnIND	0.0096** (0.43)	0.3105*** (6.94)	0.297** (3.45)
lnHUM	0.031 (0.18)	0.26** (4.27)	0.311* (1.88)
lnSTR	0.0707*** (0.37)	0. 0643** (3.72)	0. 0391 (0.5)
lnMAR	0.0117** (1.07)	0.0452*** (5.36)	0.058** (3.45)
lnSCAL	-0.044** (-0.98)	-0.4632*** (-9.72)	-0.466*** (-5.16)
lnTRA	0.0138** (0.9)	0.188*** (12.52)	0.1798*** (8.31)
cons	0.142 (0.09)	-4.092*** (-6.36)	-4.21** (-2.92)
sigma_u	0.36	0.3	0.16
sigma_e	0.23	0.326	0.332
ρ	0.715**	0.46***	0.188**
R^2	0.505	0.7279	0.436

Note: *, **, and *** represent significance at the levels of 10%, 5%, and 1%, respectively. The value in brackets is T-statistic.

agglomeration of industrial enterprises also helps to make environmental regulation measures more targeted and more able to effectively alleviate the problems of large energy consumption and serious pollution emissions of industrial enterprises.

Among the other control variables, only the coefficient of enterprise-scale is negative, indicating that an increase in Chinese industrial enterprise size is not conducive to green technology innovation. The perspective of academia is that the impact of enterprise-scale on productivity depends on two mechanisms: the effect of pure economic scale and the indirect improvement of productivity through technological innovation activities (Sun et al. 2014). There exists an inverted U-shaped relationship between enterprise-scale and productivity. According to the model results, the enlargement of the Chinese industrial enterprise production scale is conducive to the effect of the scale economy, thus weakening the promotion effect of R&D activities, which is a phenomenon worthy of entrepreneurs' attention. Other factors, including the improvement of human capital, industrial structure and market environment, all have a positive effect on green technology innovation, which also conforms to common sense.

Analysis of the spillover effect of industrial enterprises' agglomeration effect on green technology efficiency

To further investigate this issue, the paper divides the effect of industrial agglomeration on industrial green innovation efficiency (***GTE***) into a direct effect and an indirect (spillover) effect based on the regression results of the SAR model. The specific results are shown in Table 5.

The indirect effect is the spatial spillover effect. In the spatial panel model, the coefficient of explanatory variables cannot represent the real partial regression result, and the coefficient of the spatial lag term cannot reflect the spatial spillover effect. Therefore, the spatial effects of industrial agglomeration and other control variables on green innovation efficiency need to be decomposed.

We can see that both the direct and indirect effects of industrial enterprise agglomeration on industrial green technology innovation efficiency pass the significance test at the 1% level. The direct effect accounted for 8.1% of the total effect, and the indirect effect accounted for 91.9%. This means that the weight of the indirect effect is greater than that of the direct effect. Specifically, an industrial agglomeration increase of 1% can promote an increase in local industrial green innovation efficiency of 0.051%, but an increase of 0.579% in adjacent regions indicates that the enhancement of regional industrial agglomeration not only promotes the improvement of green innovation efficiency but also promotes efficiency in neighboring regions. The results show that the agglomeration of industrial enterprises has mainly worked through competition effects, imitation effects and correlation effects (Luo and Liang, 2017). Yet, with the continuous development of marketization in China, the trade opening channels between domestic regions are gradually unblocked, accelerating the diffusion of technology capital and leading to an obvious indirect technology spillover effect. Therefore, for Chinese enterprises, local enterprises must enhance their innovation ability based on product competition, imitation and learning to ensure the level of regional innovation.

For other control variables, only human capital (***lnHUM***) and enterprise size (***lnSCAL***) have negative influence values, while the other variables have positive influence values. Enterprise-scale has already been explained. For human capital, the direct effects are positive, but the value is small, while the indirect effects are negative, but the value is large, indicating that the higher the education level of the residents of a particular area, the higher the green innovation efficiency. A possible explanation is that green innovation capability strengthens with an increase in the per capita level of education. In addition, people with higher education often focus more on enjoying life and have stricter requirements for environmental quality. In addition, people with a high degree of education usually have a strong awareness of environmental protection, which has a supervisory effect on industrial enterprises. For industrial enterprises with high pollution and high consumption, people tend to take up the weapon of law to protect their own rights and interests, forcing enterprises to choose between implementing cleaner methods of production or leaving.

Conclusions

Based on the relationship analysis between industrial agglomeration and green innovation efficiency, this paper establishes a spatial panel model of how the industrial agglomeration level and some other important economic variables affect industrial green innovation efficiency. The results show that (1) China's industrial agglomeration has

Table 5. Decomposition of direct impact, spillover impact and total impact effect based on the SAR model

Variable	Based on spatial distance					
	Direct	T-value	Indirect	T-value	Total	T-value
lnIND	0.051*	0.64	0.579**	3.44	0.63***	3.85
lnHUM	0.282*	1.62	-1.506***	-3.85	-1.224**	-3.2
lnSTR	0.061*	1.38	0.035	0.38	0.096	1.07
lnMAR	0.024**	1.21	0.089**	1.77	0.113**	2.36
lnSCAL	-0.207*	-2.35	-0.471**	-3.09	-0.678***	-5.15
lnTRA	0.017*	0.35	0.01	0.1	0.026	0.3

Note: *, **, and *** represent significance at the levels of 10%, 5%, and 1%, respectively.

a positive impact on industrial eco-efficiency, indicating that industrial agglomeration has produced good environmental benefits and innovation benefits. (2) According to the estimation results of the SAR model, the influence coefficient of enterprise scale is negative, indicating that for Chinese industrial enterprises, the enlargement of production scale weakens the promotion effect of R&D activities on productivity, which is worth being concerned about. (3) Based on the analysis of the spatial spillover effect, the indirect effect of China's industrial agglomeration on the efficiency of industrial green innovation is much greater than the direct effect. In addition, the impact of human capital is negative, mainly because the direct effect is positive but the value is small, while the indirect effect is negative and the value is large, indicating that the spillover effect of human capital is weak.

As China's economy enters its new stage, the structural contradictions in industrial economic development become increasingly prominent. It can be predicted that the key point of China's industrial economic development in the future will no longer be the speed of development, but rather the mode of transformation and structural adjustment; it will no longer be just about increasing the total amount, but rather improving innovation and ecological efficiency. At present, China's industrial economy, with a high degree of external orientation, is still faced with problems such as immature market development, insufficient innovation ability, the poor added value of products and increasing pressure of energy consumption and resource and environment constraints. China's future development needs to adapt to the new situation, new tasks and new requirements as well as to strive to resolve and break through deep-rooted problems that have created bottlenecks in the industrial economy.

The next most important task of the Chinese government is to promote the ecological transformation and technological upgrading of industrial clusters and to improve the form of industrial chains. In China, spatial agglomeration is an important form of industrial development. However, in recent years, the model of some industrial agglomeration areas has been blind expansion and extensive development. In addition, China's industrial layout is scattered, and the scale and pattern of development are unbalanced, leading to spatial imbalance and to the internal vicious competition among industrial zones. Accelerating the ecological transformation and technological upgrading of agglomeration areas is an important measure to improve the efficiency of industrial green innovation. Firstly, the government should adhere to the principle of prioritizing energy saving and improving energy efficiency. In addition, industrial enterprises need to increase R&D investment in energy-saving technology to promote energy-intensive industries and key enterprises to speed up technology upgrading, technology innovation, equipment updating, and the implementation of comprehensive energy-saving transformation; there is a need to drive industrial energy-saving technology from the local level, to the whole process. Secondly, the government should push stricter cleaner production audit systems to reduce the emission intensity of pollutants. For example, transforming cleaner production technologies in key polluting industries, improving and promoting cleaner production models based on ecological progress, and making the industrial chain "longer" and "thicker". On the one hand, based on the positioning of leading industries, in-depth investigation and research should be carried out around the missing and supporting links of the ecological development of the industrial chain to accelerate bringing in leading high--quality and high-tech enterprises and cultivating local enterprises to continuously improve the industrial chain. On the other hand, the coupling agglomeration of industrial industries should be accelerated to promote the concentration of homogeneous and related industries to form industrial chains and networks while realizing dislocation competition and improving the output ratio of resources and competitiveness.

In addition, the SAR regression coefficient and spatial spillover effect at the corporation scale are both negative, and the spatial spillover effect of human capital is negative. For these two variables, first, the enlargement of enterprise--scale has a negative impact on the improvement of green innovation efficiency, indicating that, from the perspective of efficiency, the technological innovation efficiency of large enterprises is offset by the low efficiency of their scale. Due to the obvious advantages of vitality, flexibility and the forces that drive competitive innovation, small- and medium-sized enterprises are better than large enterprises in technological innovation efficiency. In the future, regions are more likely to benefit from clusters other than increasing their size. Therefore, local governments should formulate targeted policies to bring in some advantageous scale-forming industrial enterprises integrated into interregional industrial clusters to formulate effective development patterns. The strategies should be implemented primarily in provinces where reduction potential is the largest (Bochenska and Rzeznik, 2019). Second, the spatial spillover effect of human capital is negative, which indicates that there are problems in China's regional human capital flow mechanism. Therefore, the next important step is to improve the environment and mechanism for the flow of human capital. In China, the important reason for differences in China's human capital stock is the state's unbalanced investment (Wu and Zhao, 2017). Therefore, the state should adjust investment policies appropriately to narrow the gap of unbalanced investment between different regions. Strengthening the dynamic management of human capital, i.e., improving the management mechanism of human capital, enhances workers' sense of competition and efficiency.

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