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Original Research

Analysis on Spatial Correlation Network of Green Innovation Efficiency of China's High-Tech Industry

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Abstract

Green innovation efficiency (GIE) determines the division of labor in high-tech industries in regional value chains. Currently, China's high-tech industries have not yet formed a systematic, balanced, and efficient green innovation network. Hence, to clarify the potential space structure of China's high-tech innovation activities, this study adopts the super-efficiency SBM model to measure efficiency and uses the improved gravity model and social network analysis method to construct the spatial correlation matrix and process network analysis. The results show that (1) the GIE of high-tech industries in different provinces differs considerably and the spatial distribution is uneven. The mean GIE values in the eastern, central, western, and northeastern regions are characterized by gradient decrease. (2) From 2012 to 2019, no significant change was observed in the GIE spatial correlation intensity of China's high-tech industry. (3) Henan, Shandong, Shaanxi, Guangdong, and Hunan are the important nodes in the correlation network. These provinces have a strong influence on the network and can effectively control the flow of innovative elements. (4) In the correlation network, the interaction within the block is stronger than that between the blocks. Blocks II and IV are the hinterland of Blocks I and III, respectively, providing Blocks I and III with innovative elements. The conclusions of this study provide a theoretical basis for policy makers to promote the efficient and sustainable development of the high-tech industry in China.

Keywords: green innovation efficiency, high-tech industry, social network analysis

Introduction

With economic development shifting from high-speed growth to high quality, China is facing the dilemma of industrial upgrading and environmental resource constraints and urgently needs high-quality industrial development to provide strong support for regional development. The high-tech industry, which is an industrial form with R&D technology at its core, shoulders the task of cultivating new growth drivers, and its development plays an important role in China's economic structure renewal and performance growth [1]. However, some Chinese high-tech industrial enterprises face problems with the production process with low value-added and insufficient supply of high technology, which not

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only restrains the improvement of the industrial value chain but also has certain negative effects on the environment [2].

Innovation-driven and green development are the only way for sustainable and high-quality economic development. Green innovation strategy is an effective prescription to solve the regional development dilemma and green innovation efficiency (GIE) is the key factor that affects the division of labor of high-tech industries in regional value chains [3]. The GIE of regional high-tech industries is the external embodiment of green innovation strength, while the correlation of GIE is the internal mechanism supporting the development of the overall innovation system network. Combining internal and external analysis can grasp the development state of the innovation ability of high-tech industries more accurately. The existing research on innovation performance of high-tech industry analyzes from the perspective of attribute data, and ignores the formation mechanism of innovation space network structure, but the attribute data are often determined by the structure. The purpose of this paper is to supplement the research on the spatial relationship of GIE of China's high-tech industries and explore the node positioning and spillover effect characteristics of provinces in the overall network. This study helps strategy makers of high-tech industry innovation to clarify the spatial texture of China's high-tech innovation activities and determine the division of regional function from the whole, to provide a theoretical basis for the policymakers to promote the efficient and sustainable development of China's high-tech industry.

Many studies have focused on the innovation efficiency of high-tech industries, including multi-dimensional and multi-stage performance evaluation and analysis of the influencing factors. Haschka and Herwartz empirically used the Bayesian stochastic frontier approach to measure innovation efficiency and examine the influence of different sources of knowledge externalities on the patenting activity of four high-tech industries in Europe [4]. Lin et al. adopted the DEA window analysis based on panel data to dynamically investigate the technological innovation efficiency of China's high-tech industries from the regional and industrial perspectives [5]. To solve the problem of ignoring the internal structure of the innovation process, Chen et al. divided the innovation stage of the high-tech industry into the R&D and the commercialization stages and use the conceptual model to measure their efficiency [6]. Chen et al. estimated the technological development efficiency and the holistic innovation efficiency of high-tech industries in China, and the spatial econometric model is used to analyze the factors influencing innovation efficiency [7]. Wang et al. empirically explored the efficiency of technological innovation of 18 high-tech industries in China and further explore the differences between sub-sectors [8]. Some scholars have considered the effects of the production process of high-tech industries on the ecological environment in the measurement of innovation efficiency, which opened up a way for research on the sustainability of the innovation efficiency of high-tech industries. Liu et al. studied the regional differences of influencing factors of green technology innovation efficiency of high-tech industrial clusters in China [9]. Chen et al. proposed a three-stage super-efficiency DEA model based on the cooperative game to investigate the R&D green innovation of Chinese high-tech industries for 29 provinces [10].

With the acceleration of the marketization process, various resources and elements of the innovation subject have strong mutual attraction, and the spillover effect is a significant feature of innovation activities. The importance of social networks analysis for innovation diffusion has been widely recognized in practice and scientific disciplines [11]. Krätke conducted a network analysis of R&D-related partnerships between public research institutions and private enterprises in German metropolitan areas and examined the effects of knowledge networks on innovation spillovers of regional firms [12]. Liu et al. employed the complex network theory and conducted in-depth research on the patent collaboration network of smart grids field in China [13]. Based on green patent authorization data, Liu et al. use social network analysis and quadratic distribution programming to analyze the evolution of green innovation networks and the influence of multi-dimensional proximity on its formation [14]. Although social network analysis has been widely used in the field of innovation, no research has focused on green innovation in high-tech industries. Therefore, it is necessary to establish a spatial correlation network of green innovation in high-tech industries and analyze the regional green innovation capability and function.

Material and Methods

Super-Efficiency SBM Model

Compared with the traditional DEA model, the ordinary SBM model considers the slack variables in the objective function, which solves the problem of slack of input-output variables. However, the decision-making unit (DMU) efficiency values are distributed between (0,1), among which the efficiency values of effective DMUs are all 1, and thus, the effective DMUs cannot be compared [15]. To solve this problem, Tone developed the super-efficiency SBM model, which allowed the DMU efficiency value to be greater than 1, and effective DMUs can be compared further, thereby improving the accuracy of comparison results [16-18]. This study uses the Super-SBM model to measure the GIE of China's high-tech, and the evaluation model is as follows:

$$\min\rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{ik}}}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\frac{y^d}{y_{sk}^d}+\sum_{q=1}^{r_2}\frac{\overline{y^u}}{y_{qk}^u}\right)}$$

$$\text{s.t.}\begin{cases} \bar{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j; \overline{y^d} \leq \sum_{j=1,\neq k}^{n} y_{sj}^d\lambda_j; \\ \overline{y^d} \geq \sum_{j=1,\neq k}^{n} y_{qj}^d\lambda_j; \bar{x} \geq x_k; \overline{y^d} \leq y_k^d; \overline{y^u} \geq y_k^u; \\ \lambda_j \geq 0; i = 1,2,\dots,m; j = 1,2,\dots,n; \\ s = 1,2,\dots,r_1; q = 1,2,\dots,r_2 \end{cases} \quad (1)$$

where ρ is the green innovation efficiency value of the high-tech industry, N is the number of provinces, m is the number of inputs, r_1 and r_2 represent the number of expected and unexpected outputs, respectively, x, $y^{d,}$ and y^u correspond to the elements of the input matrix, expected output matrix, and unexpected output matrix, respectively.

The measurement of GIE considers reducing the effects on the environment from two aspects of production sources and final products [19]. The input indicator of GIE includes three aspects: labor, capital, and energy [20]. High-tech industry R&D full-time personnel equivalent and internal expenditure o n R&D represent labor input and capital input, respectively [21]. The energy consumption of high-tech industries is selected as the energy input indicator to measure the green attribute of innovation efficiency of high-tech industries and energy effectiveness [22]. In terms of output indicators, patents are the most commonly used agents to study innovation trends and dynamics, and thus, patent application is selected to measure the output capacity and potential market benefits of innovative technologies [23]. Sales revenue of new products is selected to measure the market transformation ability and direct economic value of high-tech industry innovation products [24]. As an unexpected environmental output, sulfur dioxide emissions from high-tech industries reflect the negative externality of the production process to the ecological environment [25].

Improved Gravity Model and Spatial Correlation Matrix

The gravity model is a mathematical model abstraction of the complex interaction state between real regions, which is widely used in the research of distance attenuation effect and spatial interaction [26]. Based on the characteristics of the development of GIE of high-tech industries, not limited to geographical proximity effect, and considering the influence of economic and social environment on the flow of green innovation elements, the improved gravity model is used to determine the GIE relationship between provinces in this study. Referring to the practices of Fan, the geometric mean of GIE of high-tech industries, GDP, and permanent resident population are taken as a regional mass [27], and the improved gravity model is as follows:

$$R_{ij} = K_{ij} \times \frac{\sqrt[3]{P_i E_i G_i} \times \sqrt[3]{P_j E_j G_j}}{D_{ij}^2}, \quad K_{ij} = \frac{E_i}{E_i + E_j}, \quad (2)$$

where R_{ij} represents the correlation strength of GIE of high-tech industry between province i and province j, K_{ij} indicates the difference of GIE structure between province i and province j, P_i and P_j represent the permanent resident population in province i and province j, respectively, E_i and E_j represent the GIE value of high-tech industries in provinces, G_i and G_j represent the GDP of the province, and D_{ij} indicates the shortest road distance between province i and province j. The spatial correlation matrix created by interactive relationships is the premise of social network analysis. The average value of each row of data in the matrix is taken as the threshold. If R_{ij} is greater than the threshold, the value is 1, indicating that a spatial correlation between province i and province j exists, otherwise, the value is 0, thereby creating a spatial binary matrix of GIE of China's high-tech industries.

Social Network Analysis

Social network analysis shifts the focus from the attributes of research objects to the relationships among research objects [28]. First, the network density, connectedness, hierarchy, and efficiency are selected to analyze the overall network characteristics of the spatial correlation network of GIE of China's high-tech industries. Second, the position and role of each province in the network are revealed by degree centrality, closeness centrality, and betweenness centrality. Third, the block model analysis was carried out to classify all provinces into blocks, and the characteristic functions of each block were defined. Finally, the middleman analysis of all units is carried out to determine the intermediary function of each province in the block interaction.

Data Source

The research object of this paper covers 30 provinces (municipalities and autonomous regions) in China (excluding Tibet, Hong Kong, Macao and Taiwan, because of the unavailability of data), and the indicator data come from China Statistical Yearbook in High Technology Industry (2013-2020). China Statistical Yearbook on Environment (2013-2020), China Energy Statistical Yearbook (2013-2020), and China Statistical Yearbook (2013-2020). Indicator data that cannot be obtained directly are converted based on the contents of the above material.

Results and Discussion

Spatial-Temporal Evolution and Characteristics of GIE in China's High-Tech Industries

This study takes 2012-2019 as the main research period (excluding 2017, because of the lack of data). The Super-SBM model is used to measure the GIE of high-tech industries in 30 provincial-level units during the study period, as shown in Table 1. The GIE of high-tech industries in different provinces differs considerably and the spatial distribution is uneven. During the study period, the GIE of high-tech industries in various provinces had a certain fluctuation. GIE values rose or fell in provinces, but the entire region maintained an upward trend. The mean GIE value in the eastern, central, western, and northeastern regions is characterized by gradient decrease, and significant regional differences can be observed. The developed and open eastern region where the GIE average is always higher than the national average focuses more on innovation and sustainable development, and the high-level innovation infrastructure platform is easy to build. Beijing, as the capital, is the capital and talent highland of China's high-tech green innovation, and its GIE always ranks first in China. It is worth noting that the growth rate of GIE in the central, western, and northeastern regions is higher than that in the whole country and the eastern region, indicating that the relatively backward areas of GIE can target the developed eastern region based on the concept of sustainable innovation and development and achieve rapid growth through learning and practice.

Analysis on Spatial Correlation Network of GIE in China's High-Tech Industry

The spatial correlation binary matrix of GIE of China's high-tech industries is introduced into the Ucinet software and analyzed using the social network method.

Overall Network Characteristics

Using the binary matrix constructed by the improved gravity model and social network theory, Ucinet draws the spatial network topological graph of GIE of China's high-tech industries and selects three sections in 2012, 2016, and 2019 for analysis (Fig 1-3). The spatial correlation of GIE of high-tech industries is not limited to the local geographical space, and some provinces can have a direct spatial spillover effect with non-adjacent areas, forming a complex GIE relationship set. The total number of network relationships in 2012, 2016, and 2019 is 203, 201, and 204, which is far from the theoretical maximum number of connections, and the network density is 0.233, 0.231, and 0.234, respectively. During the study period, the network correlation degree was all 1, indicating that direct or indirect paths between any two provinces exist, and that the network is robust. The hierarchy degree is about 0.24, and the asymmetry in the network is not very significant. The network efficiency is about 0.72, indicating that the superposition of the GIE spatial spillover effect is not obvious. Although the GIE of the whole country has a steady and moderate growth change during the research period, the inter-regional spatial network interaction has not changed significantly, and the overall spatial network structure remains relatively stable.

Network Individual Characteristics

The degree centrality is used to measure the connectivity of each province in the network. The stronger the connectivity, the greater the influence of the region and the more it is in the local center position of the network. In 2019, the average value of degree centrality in 30 provinces was 0.234, and 13 provinces were above the mean. Henan, Shandong, Hunan, and Shaanxi ranked in the top four, and these provinces had a strong direct relationship with other provinces. Among the 13 provinces, Shaanxi and Sichuan belong to the western region, while the other provinces come from the eastern and central regions. Henan, as an important comprehensive transportation hub and the center of human and information flow, occupies the central position of the network. Shandong is a key node in complex network relations despite its low GIE. The out-degree indicates the ability to influence the network, and the in-degree indicates the extent to which nodes are affected. The area where the out-degree is greater than the in-degree is the overflow area, otherwise, it is the benefits area. In 2019, except for Beijing, Fujian, Guangdong, Hainan, and Jiangxi, other provinces in the eastern and central regions were benefit areas. Beijing, which had the highest GIE, has some spillover effects but is not at the core of the network. Guangdong, which also had a high level of GIE, has a strong spillover effect and is the key node of the network. Except for Sichuan and Chongqing, provinces in the western and northeastern regions are spillover areas. Sichuan and Chongqing, as the two driving cores of the western region development, need a lot of resources. The three northeastern provinces with poor spatial correlation are on the edge of the network.

The closeness centrality measures the approach extent of each node to other nodes. In 2019, the average value of closeness centrality was 55.223, and 14 provinces including Henan, Shandong, Shaanxi, Hubei, Hunan, and Jiangsu, etc. exceeded the average value. These provinces are closer to the geometric center of the network and are not easily controlled by other provinces. These provinces also tend to be associated with other provinces, which can effectively promote the development of green innovation in other provinces. Meanwhile, the three northeastern provinces are still on the edge of the network because of their poor

Table 1. Results of GIE in China's high-tech industry.

DMUs	2012	2013	2014	2015	2016	2018	2019
Beijing	1.7950	1.7684	1.9115	2.1971	1.7683	2.4660	2.3386
Tianjin	1.1371	1.1474	1.0808	1.0150	1.1179	0.6586	0.6151
Hebei	0.2649	0.2662	0.3089	0.3229	0.3611	0.4111	1.0464
Shanxi	0.2814	0.2835	0.2998	0.2707	0.1288	0.2542	0.3859
Inner Mongolia	0.1760	0.1965	0.1883	0.2303	0.2787	1.0302	1.0303
Liaoning	0.3266	0.4054	0.3776	0.5179	0.6271	0.5332	0.4421
Jilin	0.3250	0.4425	0.3631	0.2803	0.3288	0.4615	0.5488
Heilongjiang	0.2455	0.2534	0.3236	0.3565	0.4526	0.2995	0.5883
Shanghai	0.4059	0.4709	0.4874	0.5035	0.5794	0.6780	0.6214
Jiangsu	0.6736	0.5917	0.7103	0.8083	0.7864	0.6525	0.6199
Zhejiang	0.5894	1.0538	1.0365	1.1037	1.1296	1.0669	1.0523
Anhui	1.0796	1.0574	1.1106	1.1269	1.0918	1.0431	0.7143
Fujian	1.0259	0.5458	0.4974	0.5832	0.6307	0.5532	0.5529
Jiangxi	0.2951	0.3571	0.4564	0.4954	0.6152	0.5584	0.7200
Shandong	0.4770	0.4332	0.4211	0.5565	0.6209	1.0223	0.5170
Henan	0.3377	1.1958	1.1992	1.1862	1.1980	1.2533	1.1132
Hubei	0.3558	0.4001	0.3590	0.4482	0.5962	0.6439	1.0113
Hunan	0.5494	0.6272	0.5911	0.6307	0.7114	0.5727	0.5453
Guangdong	0.6401	0.6850	0.6923	0.7478	1.0674	1.1065	1.1467
Guangxi	0.2766	0.3788	0.3313	0.3098	0.3140	1.1149	1.2607
Hainan	0.4110	0.4817	1.0586	0.3100	0.2245	0.1909	0.1464
Chongqing	0.5019	0.3861	0.5763	1.0657	0.7237	0.6285	0.6406
Sichuan	1.0087	0.4904	0.6947	0.6824	0.6904	0.4736	0.5256
Guizhou	0.4244	0.3740	0.5727	0.4001	0.4266	0.5027	0.4042
Yunnan	0.3715	0.3688	0.4067	0.3269	0.3788	0.4193	0.3336
Shaanxi	0.2405	0.2732	0.2727	0.3001	0.3250	0.2740	0.3261
Gansu	0.5159	0.4419	0.5299	0.5303	0.5328	0.4892	0.4002
Qinghai	0.0712	0.0889	0.1557	0.3076	1.2813	1.1186	0.7848
Ningxia	1.0993	1.2502	1.0273	0.4552	0.5989	1.0067	1.0971
Xinjiang	0.0710	1.0681	0.4380	1.1019	1.0163	0.5741	0.3716
China	0.5324	0.5928	0.6160	0.6390	0.6868	0.7353	0.7300
Eastern	0.7420	0.7444	0.8205	0.8148	0.8286	0.8806	0.8657
Central	0.4832	0.6535	0.6693	0.6930	0.7236	0.7210	0.7483
Western	0.4325	0.4834	0.4721	0.5191	0.5970	0.6938	0.6523
Northeast	0.2990	0.3671	0.3547	0.3849	0.4695	0.4314	0.5264

Notes: According to the China Statistical Yearbook in High Technology Industry, the eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The northeast region includes Liaoning, Jilin, and Heilongjiang.

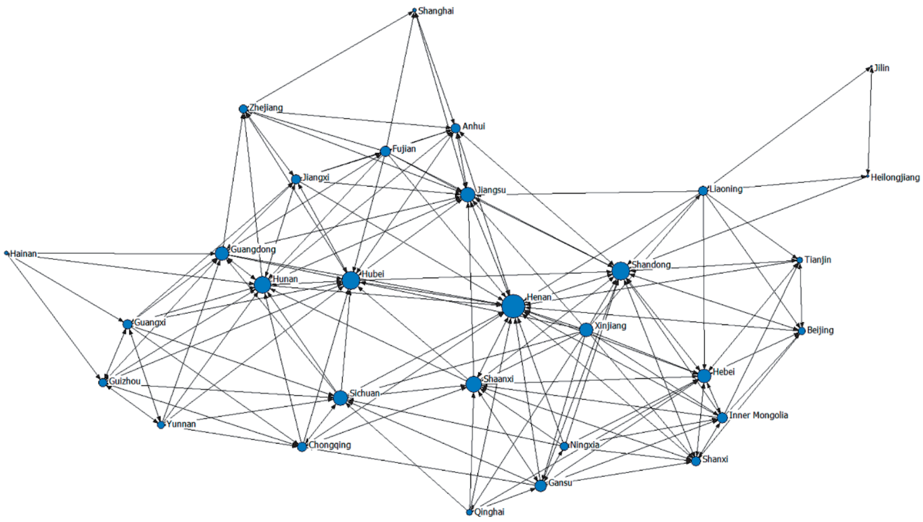

Fig 1. Spatial correlation network map of GIE in China's high-tech industry in 2012.

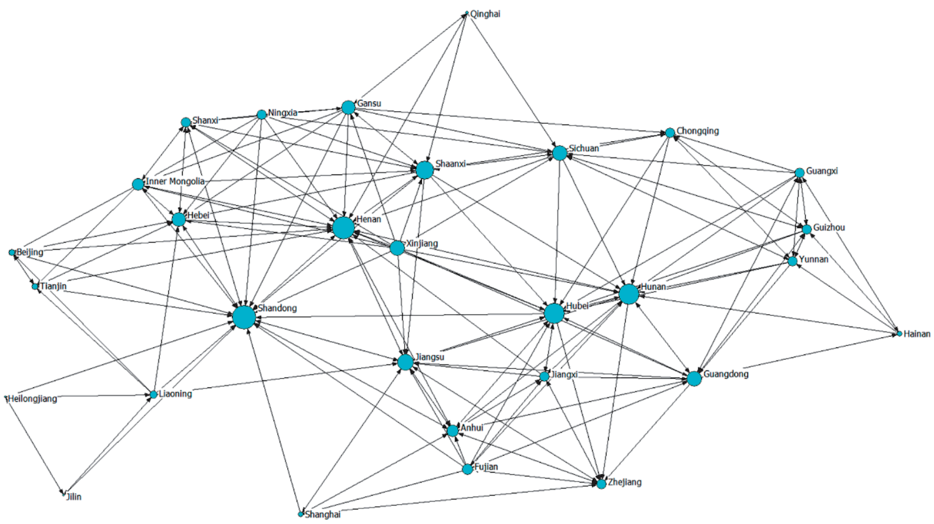

Fig 2. Spatial correlation network map of GIE in China's high-tech industry in 2016.

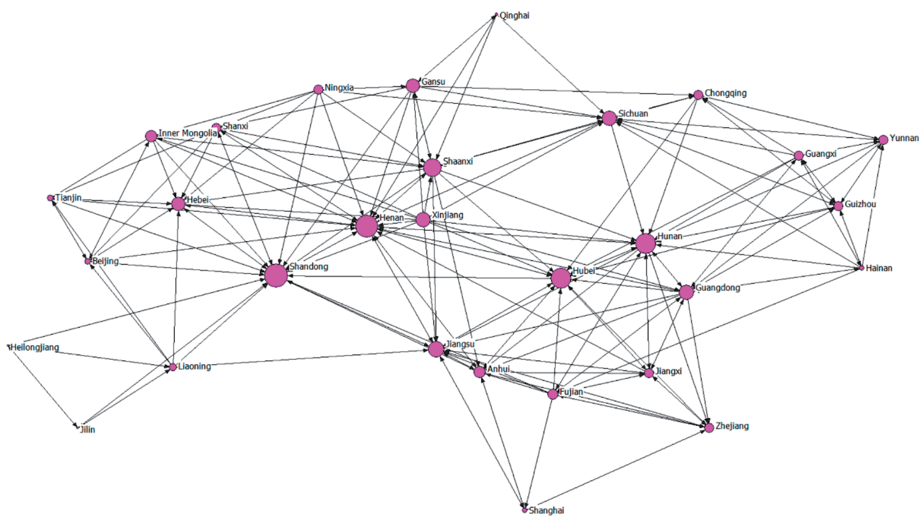

Fig 3. Spatial correlation network map of GIE in China's high-tech industry in 2019.

Table 2. Centrality analysis on the spatial correlation network of GIE in China's high-tech industry in 2019.

Province	Outdegree	Indegree	Degree centrality	Rank	Closeness centrality	Rank	Betweenness centrality	Rank
Beijing	6	5	0.190	20	50	19	1.186	17
Tianjin	5	6	0.190	20	50	19	0.333	24
Hebei	5	10	0.259	11	53.704	15	1.103	19
Shanxi	6	10	0.276	9	53.704	15	5.758	7
Inner Mongolia	7	4	0.190	20	52.727	17	0.591	22
Liaoning	7	2	0.155	24	50	19	0.85	20
Jilin	3	2	0.086	28	42.647	28	0	26
Heilongjiang	3	2	0.086	28	42.647	28	0	26
Shanghai	3	4	0.121	27	42.029	30	0	26
Jiangsu	6	13	0.328	5	64.444	6	4.962	10
Zhejiang	5	8	0.224	14	48.333	25	1.736	15
Anhui	7	11	0.310	8	61.702	8	5.566	8
Fujian	9	5	0.241	12	59.184	10	2.195	14
Jiangxi	8	6	0.241	12	55.769	13	3.347	11
Shandong	7	17	0.414	2	69.048	2	12.845	3
Henan	8	18	0.448	1	72.5	1	20.423	1
Hubei	7	12	0.328	5	65.909	4	3.343	12
Hunan	8	13	0.362	3	65.909	4	9.014	5
Guangdong	11	8	0.328	5	61.702	8	9.8	4
Guangxi	8	4	0.207	16	49.153	22	1.132	18
Hainan	7	2	0.155	24	49.153	22	0.511	23
Chongqing	6	6	0.207	16	51.786	18	2.928	13
Sichuan	6	10	0.276	9	58	11	5.437	9
Guizhou	7	6	0.224	14	49.153	22	1.635	16
Yunnan	6	5	0.190	20	46.032	27	0.842	21
Shaanxi	11	9	0.345	4	67.442	3	20.033	2
Gansu	8	4	0.207	16	56.863	12	7.219	6
Qinghai	4	1	0.086	28	48.333	25	0	26
Ningxia	8	1	0.155	24	55.769	13	0.117	25
Xinjiang	12	0	0.207	16	63.043	7	0	26
Mean			0.234		55.223		4.097	

location and industrial structure problems. Compared with the measure of degree centrality, the distribution of provinces exceeding the mean of closeness centrality extends to the hinterland, and the location is closer to the geographical center.

Betweenness centrality and index of control ability are used to study the extent to which one node is in between the other two nodes. In 2019, the average value of the betweenness centrality was 4.097, and 10 provinces, including Henan, Shaanxi, Shandong, Hunan, and Guangdong, exceeded the mean value. These provinces with strong control over innovation elements are the centers of complex network relations and play a significant intermediary role in the network. Five provinces had a betweenness degree of 0, all of which come from the western and northeast regions except for Shanghai.

From the comprehensive evaluation of centrality, Henan, which is located in the central region, ranks first in each centrality and is the absolute core

Table 3. Analysis of the block spillover effects and the block function definitions

Blocks	Receiving relationship				Number of block's member	Relations received from other blocks	Relations sent to other blocks	Characteristic
	I	II	III	IV				
I	24	9	3	0	7	20	12	Broker
II	16	29	12	7	8	18	35	Net spillover
III	4	6	51	3	9	29	13	Main benefit
IV	0	3	14	23	6	10	17	Bilateral spillover

Notes: Block I includes Beijing, Tianjin, Hebei, Jilin, Heilongjiang, Liaoning, Shandong; Block II includes Shanxi, Inner Mongolia, Qinghai, Shaanxi, Henan, Xinjiang, Ningxia, Gansu; Block III includes Jiangsu, Hubei, Hunan, Guangdong, Anhui, Fujian, Jiangxi, Shanghai, Zhejiang; Block IV includes Guizhou, Yunnan, Guangxi, Hainan, Chongqing, Sichuan.

of the network. Shandong in the eastern region is the key node of the network and ranks 2-3 in each centrality. Guangdong is the largest economic province in China, with strong investment in innovation and a high GIE level, and is an important node in the southeast coastal areas. Shaanxi, with the GIE at the bottom, is the key node in the western region and ranks 2-4 in each centrality. Beijing represents the highest level of GIE but has a non-significant influence on the network. Shanghai is an international innovation center of economy, science, and technology, but is in a marginal position in the evaluation of network centrality. Regions with high GIE of high-tech industry or developed economy do not mean they have greater influence in the network. Qinghai, Jilin, and Heilongjiang are at the bottom of each centrality.

Block Model and Clustering Characteristics

This study analyzes the role of each subgroup in the spatial correlation network of GIE in high-tech industries based on the block model theory. The maximum division depth was set to 2 and the convergence standard was 0.2. Through the iterative correlation convergence method CONCOR algorithm, the 30 provinces were divided into blocks, and the subgroup network density is calculated.

Table 3 shows 204 relationships can be found in spatial correlation networks of GIE of high-tech industries in 2019, including 127 within the blocks and 77 between the blocks. The interactive relationship within the blocks is stronger than the interactive relationship between the blocks. The member set of the four blocks are consistent with the geographical distribution of each province, indicating that the innovation correlation has certain limitations within the geographical area scope. The members of Block I come from the Bohai Rim region and the northeast region. Block I sends and receives external relations, and less connection is observed among internal members. Block I plays a bridge role in the spatial spillover effect and is defined as a broker block. The members of Block II come from the central and western regions. Block II had the largest amount of outgoing relations, while the amount of relations among internal members is less than the number of outgoing relations, and fewer external relations are received. Block II is characterized by net spillover. The composition of Block III is from the southeast coastal region and the central and southern regions. Block III has the largest amount of internal and receiving relations, while the outgoing relationship proportion is small. The spillover effect of Block III on other regions is small and thus, Block III is the main benefit block. The provinces of Block IV come from Southwest China. These provinces send out relations to other block members and internal block members but receive the least external relations, and so Block IV is a bilateral spillover block.

The density and image matrices (Table 4) show that each block has a relatively close internal connection. Block II, as the hinterland of Block I, unilaterally sends the relationship to Block I. Block III, which is the southeast coastal area, has a strong attraction to resources and accepts the relationship from Block

Table 4. Density and image matrices of the block.

Blocks	Density Matrix				Image matrix			
	I	II	III	IV	I	II	III	IV
I	0.571	0.161	0.048	0	1	0	0	0
II	0.286	0.518	0.167	0.146	1	1	0	0
III	0.063	0.083	0.708	0.056	0	0	1	0
IV	0	0.063	0.259	0.767	0	0	1	1

Notes: If the block density is greater than the overall network density, the value is 1 in the image matrix; otherwise, it is 0.

IV. Blocks I and II are benefit areas on the whole and cover the coastal areas of the Chinese mainland. Blocks II and IV cover the inland areas of China, and have the function of contributors as a whole. The green innovation elements of China's high-tech industries show the characteristics that the western region is attracted by the eastern region.

Middleman Role Analysis

Middleman analysis explores whether an internal trend in the exchange relationship between provinces exists and defines the nature of their intermediary behavior, as shown in Table 5. In the entire correlation network, 10 provinces act as liaisons. The Henan spent twice more time as a liaison than Shandong (Top 2).

Table 5. Analysis of the middleman role in spatial correlation network of GIE in China's high-tech industry.

Blocks	Province	Coordinator	Gatekeeper	Representative	Consultant	Liaison	Total
I	Beijing	0	0	6	0	0	6
	Tianjin	0	1	2	0	0	3
	Hebei	0	9	2	0	0	11
	Jilin	0	0	0	0	0	0
	Heilongjiang	0	0	0	0	0	0
	Liaoning	6	0	2	0	0	8
	Shandong	6	24	17	0	14	61
II	Shanxi	3	7	6	0	0	16
	Inner Mongolia	0	1	5	0	0	6
	Qinghai	0	0	0	0	0	0
	Shaanxi	4	5	33	0	9	51
	Henan	1	17	24	2	28	72
	Xinjiang	0	0	0	0	0	0
	Ningxia	1	0	1	0	0	2
	Gansu	7	0	4	0	0	11
III	Jiangsu	6	14	8	0	1	29
	Hubei	3	19	4	0	6	32
	Hunan	2	46	1	0	5	54
	Guangdong	0	25	10	2	7	44
	Anhui	8	10	8	0	0	26
	Fujian	6	6	4	0	1	17
	Jiangxi	8	0	2	0	0	10
	Shanghai	0	0	0	0	0	0
	Zhejiang	10	0	0	0	0	10
IV	Guizhou	3	3	5	0	0	11
	Yunnan	3	0	2	0	0	5
	Guangxi	3	3	2	0	0	8
	Hainan	0	2	1	0	0	3
	Chongqing	0	4	5	0	2	11
	Sichuan	1	13	9	0	3	26

Legend: Given flow 1>2>3, where 2 is the middleman. Coordinator: A>A>A (all nodes belong to the same block); Gatekeeper: B>A>A (source belongs to different block); Representative: A>A>B (recipient belongs to different block); Consultant: B>A>B (broker belongs to different block); Liaison: B>A>C (all nodes belong to different blocks)

These liaisons are the nodes that exchange resources most frequently between the different blocks and have the most vitality in the correlation network. They can connect different blocks. Among the 30 provinces, only Henan and Guangdong acted as consultants. As the two key innovation nodes, Henan and Guangdong had a certain trickle-down effect on other blocks. The top five provinces in terms of time in the role of middlemen are Henan, Shandong, Hunan, Shaanxi, and Guangdong. These provinces have unbalanced green innovation strength but play an outstanding role in the correlation network. Hence, the government should focus on improving the GIE of high-tech industries in Shandong, Shaanxi, and Hunan. Liaoning, Gansu, Jiangxi, Zhejiang, and Yunnan have more coordinating relations than their external relations, and these provinces act on the network connection within the block. Jilin, Heilongjiang, Qinghai, Xinjiang, and Shanghai have no middleman role inside or outside the block.

The coordinator plays an important role in promoting the innovation association between the provinces within the block. The main coordinators of Block I are Shandong and Liaoning. The main coordinators of Block II are Gansu and Shaanxi, while that for Block III are Zhejiang, Anhui, and Jiangxi, among which Zhejiang is the province that had the most time in handling coordinator functions among 30 provinces and does not have any intermediary responsibility for external relations. The main coordinators of Block IV are Guizhou, Yunnan, and Guangxi, and their statuses within the block are relatively balanced. Shandong is the main gatekeeper and representative of Block I, and its function in external relations is stronger than that in coordination within the block. Henan and Shaanxi are the main representatives of Block II and have obvious spillover effects on other blocks. Moreover, Shaanxi's time in the role of the representative is the maximum of the correlation network. Block III is the main benefit block, and its gatekeeper role in major provinces is stronger than the representative role. Hunan had the maximum time as the gatekeeper in the correlation network, while the time of role as representative is only 1. Sichuan is the main gatekeeper and representative of Block IV.

Conclusions and Suggestions

Conclusions

In this paper, the super-efficiency SBM model is used to measure the GIE of China's high-tech industry. The GIE spatial correlation network is constructed using the improved gravity model. The GIE network analysis is conducted using Ucinet software and the following conclusions can be drawn.

First, the GIEs of high-tech industries in different provinces differ considerably and the spatial distribution is uneven. During the study period, the GIE of high-tech industries in various provinces fluctuated. GIE values rose or fell in provinces, but the entire region maintained an upward trend. The mean GIE values in the eastern, central, western, and northeastern regions are characterized by gradient decrease and the GIE of the eastern region average is always higher than the national average.

Second, based on the characteristics of the overall network structure, the spatial correlation intensity of GIE in China's high-tech industries did not change significantly during the study period, and an overall relatively stable network structure is a prerequisite for the steady and moderate growth of GIE. The overall network density is low, and ample room for improvement in network efficiency can be observed.

Third, based on the individual characteristics of the network, Henan, Shandong, Shaanxi, Guangdong, and Hunan rank high in each centrality and these provinces are an important node in the correlation network. They have a strong influence on the network and can effectively control the flow of innovative elements. Meanwhile, Beijing and Shanghai, as super cities in China, do not play an important role in the related network. The results prove that having a high GIE of its high-tech industry or a developed economy dose not mean these regions have greater influence in the network.

Fourth, according to the block model analysis, the compositions of the four block members in the GIE spatial correlation network are consistent with the geographical distribution, and the interaction within the block is stronger than that between the blocks. Blocks II and IV are the hinterland of Blocks I and III, respectively, providing Blocks I and III with innovative elements.

Fifth, based on the analysis of the middleman role, Henan, Shandong, Hunan, Shaanxi, and Guangdong take the role of the middleman most of the time, and mainly undertake the intermediary behavior of the relations to external block.

Suggestions

The following suggestions are proposed to further enhance the GIE of China's high-tech industries and promote the coordinated development of regional innovation:

First, the key node provinces in the GIE spatial correlation network in China's high-tech industry that need to be focused on include Shandong, Hunan, and Shaanxi, which have important network status but low GIE level. Formulating targeted environmental regulations for the green development of high-tech industries and attracting high-quality high-tech industry talents are important. High-quality innovation resource elements should be channeled appropriately to these provinces to improve the GIE of these provinces and strengthen their innovation-leading position in the correlation network to achieve high-quality innovation.

Second, the feedback strength of the relationship among Blocks II to I and Blocks IV to III should be strengthened and provinces with consultant functions, such as Henan and Guangdong, should be cultivated. The platform for exchange and cooperation of green innovation technology in high-tech industries should be established to promote the equal development of regional innovation relations. The government should attach importance to the transmission function in the central region and narrow the spatial difference in the green innovation performance of the high-tech industries.

Finally, the government should focus on the edge of the network. A high-tech green innovation technology alliance should be built to absorb and assist the provinces on the edge of the network to enable them to enhance their innovation ability under environmental constraints, speed up fostering new growth drivers, better integrate into the high-tech green innovation network and benefit from it, and realize regional sustainable development.

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Conflict of Interest

The authors declare no conflict of interest.

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