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Spatial Correlation Network and Driving Factors of Carbon Total Factor Productivity of Heavily Polluting Enterprises in China

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Abstract: *This paper takes 728 heavily polluting enterprises in A-share listed companies from 2013 to 2021 as the research sample, and takes provincial research as the scale.On the basis of a comprehensive measurement of its carbon total factor productivity, this paper uses social network analysis and QAP method.To explore the spatial correlation network and driving factors of carbon total factor productivity of heavy polluting enterprises in China. The results showed that (1) from 2013 to 2021,The carbon total factor productivity of heavy polluting enterprises in China has experienced three stages of fluctuation, which first increased, then decreased and then decreased.On the whole, there is still much room for improvement.(2) The spatial correlation network of carbon total factor productivity of heavy polluting enterprises in China has broken through the constraints of geographical proximity.The carbon total factor productivity of heavy polluting enterprises among provinces shows significant spatial correlation and spillover effect.However, the overall relevance of the network is low, but the stability is high.(3) Each region shows different status and function in the spatial correlation network.Shandong, Henan, Hubei, Anhui and other provinces have higher degree centrality, closeness centrality and intermediary centrality.It belongs to the "leader" and "middleman" in the network.(4)The spatial correlation network of carbon total factor productivity in heavily polluting enterprises can be divided into four sectors: net spillover, net beneficiary, two-way spillover and broker. There are significant spillover effects both within each sector and between different sectors, and the spillover effects between sectors possess obvious transmission characteristics.(5) There are differences in the effects of the factors affecting the spatial correlation network of carbon total factor productivity of heavy pollution enterprises in different years.Economic development level, informatization level, transportation level, innovation level and spatial adjacency relationship are all carbon factors for heavy pollution enterprises.Productivity has a significant impact on the formation of spatial correlation network.*

Keywords: *carbon total factor productivity; heavy pollution enterprises; SBM-GML model; spatial correlation network*

1. Introduction

Carbon total factor productivity, a key indicator for economic growth and environmental protection, measures the proportional efficiency of total factor inputs like capital, labor, energy and technology considering carbon emission constraints, output and various inputs [1]. Promoting it helps economic transformation, sustainable development, reduces carbon intensity and pollution, achieving a win-win. The exploration of it at home and abroad began with single factor carbon productivity, which is the ratio of GDP to CO2 emissions [2]. But as attention to carbon emission complexity grows, scholars find single-factor carbon productivity ignores the substitution of carbon emissions with energy, capital and labor, so it can't fully show the impact on "carbon peak" and "carbon neutralization". In contrast, carbon total factor productivity more comprehensively reveals the benefits of low-carbon economic growth and the process of economic and social transformation to low-carbon [3].

At present, scholars in multiple fields (agriculture, service, industry) conduct in-depth studies on CTFP's evaluation method, improvement reasons and influencing factors [4-8]. For CTFP growth measurement, it mainly involves parametric SFA and non-parametric DEA[9]. DEA, being simple without presetting production function, is widely used and developed in TFP change research. The SBM-DEA model and its derivatives have become the main means to measure CTFP [10]. It can

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calculate efficiency change under undesirable output constraint and further measure CTFP variation ratio by combining with non-radial distance function. When discussing CTFP growth reasons, most scholars deem technology progress and efficiency improvement crucial [11-12]. However, Zhang Ning's team's horizontal comparative study on carbon productivity shows that developed economies lead in technological progress while developing countries are better at efficiency improvement[13]. Researchers not only explore the contributing factors of CTFP improvement but also extend the focus to the mechanism of various factors (energy mix, environmental regulation, FDI, industrial agglomeration, technological innovation, carbon trading market, carbon exchange policy, etc.) affecting CTFP [14-19]. With the improvement of spatial analysis technology, based on previous research results, the spatiotemporal change trend and spatial spillover of CTFP are deeply discussed [20].

Carbon total factor productivity is a significant topic in academia, drawing scholars' attention with abundant research results yet room for improvement. This paper has marginal contributions: (1) Current research often focuses on industry, agriculture, and fishery, lacking in heavy pollution enterprises, especially enterprise-level data analysis. This study zooms in to provinces' heavy pollution enterprises, aiding in capturing their characteristics and change mechanisms, providing a more detailed basis for targeted low-carbon transformation. (2) Previous enterprise carbon total factor productivity research mainly considered geographical proximity. With modern transportation and information network progress, spatial impacts exceed geographical limits, forming complex networks. This study fills the gap in analyzing this aspect. (3) Existing studies overlooked cross-regional spatial association network effects on enterprise carbon total factor productivity. This study reveals the importance of spatial correlation network for improving correlation efficiency, promoting regional collaborative energy-saving and balanced development, and providing support for enterprises' harmonious development under environmental constraints. However, current study's shortcomings might impede further enterprise carbon total factor productivity growth.

In view of the shortcomings of the existing research, this paper draws lessons from the research results of enterprise carbon total factor productivity and spatial correlation network.This study selects 728 heavy polluting enterprises in China's A-share listed companies as the research object, and takes the provincial scale as the research scale.The carbon total factor productivity of these enterprises was measured between 2013 and 2021.Based on the modified gravity model and social network analysis method,This study focuses on the analysis of the spatial correlation network structure characteristics of the carbon total factor productivity of heavy pollution enterprises.By mean of QAP regression analysis,Various driving factors affecting the spatial correlation network of carbon total factor productivity of heavy pollution enterprises are discussed in depth.The purpose is to provide a scientific reference for promoting the low-carbon coordinated development of enterprises.

2. Description of research methods and data

2.1. Research methods

2.1.1. Carbon total factor productivity analysis method for heavy pollution enterprise

(1) Measure mode. Data Envelopment Analysis (DEA) is not restricted by specific function, dimension or price information.It is often used to evaluate the efficiency of resource utilization of various decision making units.Based on this, people have further developed BBC, CCR, SBM and other models [21] to ensure that in some specific scenarios,These models have good adaptability. The model not only takes into account the interactive factors among departments,But also the waste generated in the production process is included in the calculation.Tone [22], in order to more deeply solve the problem that multiple DMUs all have full efficiency (i.e., the efficiency value is 1),An SBM model based on modified slack variables is proposed.Therefore, this study uses the SBM model of undesirable output to measure the carbon total factor productivity of heavy polluting enterprises.The specific operation steps can be referred to the relevant literature.

The SBM (Slack-based Measure) model effectively solves the problem of overestimation of the efficiency of decision-making units (DMUs) by traditional directional distance functions when there is excessive resource input or insufficient output by incorporating slack variables into the objective function. Suppose there are n decision-making units, and the inputs, desired outputs, and undesired outputs are represented as $x \in R^m$, $y \in R^{s_1}$, $b \in R^{s_2}$ respectively. Define matrices X, Y, B as: $X = [x_{1,\cdots,}x_n] \in R^{m\times n}$, $B = [b_{1,\cdots,}b_n] \in R^{s_2\times n}$. Drawing on the ideas of Tone (2001, 2003), the SBM model for decision-making unit $DMU_0(x_0, y_0, b_0)$ including undesired outputs is constructed as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i-1}^{m}\frac{S_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r-1}^{s_1}\frac{s_r^g}{y_{r0}} + \sum_{r-1}^{s_2}\frac{s_r^b}{b_{r0}}\right)}$$

$$\begin{aligned} s.t. \quad & x_0 = X\lambda + S^- \\ & y_0 = Y\lambda - S^g \\ & b_0 = B\lambda + S^b \\ & S^-, S^g, S^b, \lambda \geq 0 \end{aligned} \tag{1}$$

Among them, S is the slack of input and output. For a specific DMU, the decision-making unit is efficient if and only if $\rho = 1$, that is, $S = 0$, $S^g = 0$, $S^b = 0$.

The global Malmquist-Luenberger index successfully solves the linear programming problem that the traditional Malmquist-Luenberger index may encounter when measuring across periods.The problem of solution.This study is based on the global Malmquist-Luenberger index (GML index) and refers to Oh [23] et al.The carbon emissions of heavily polluting enterprises are regarded as undesirable outputs.By constructing the global SBM directional distance function, the carbon total factor productivity of heavy pollution enterprises is measured, and the calculation formula is as follows:

$$\begin{aligned} & GML^{i,t+1}\left(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}\right) = \frac{1 + D^G\left(x^t, y^t, b^t\right)}{1 + D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \\ & = \frac{1 + D^t\left(x^t, y^t, b^t\right)}{1 + D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)} \cdot \frac{\left[1 + D^G\left(x^t, y^t, b^t\right)\right] / \left[1 + D^t\left(x^t, y^t, b^t\right)\right]}{\left[1 + D^G\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right] / \left[1 + D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}\right)\right]} \end{aligned} \tag{2}$$

(2)Selection of input and output indicators. This paper takes micro-heavily polluting enterprises as the research object. Referring to relevant literature, the input indicators include capital input, labor input and energy input. Among them, for capital input, the perpetual inventory method [23] is used to estimate the capital stock. The calculation formula is: $K_t = (1-\delta)\cdot K_{t-1} + (I_t / P_t)$. Here, $K_{t\text{-}1}$ is the current capital stock, K_t is the capital stock of the previous period, I_t is the current fixed asset input, P_t represents the fixed asset investment price index of the province where the enterprise is located, and δ is the depreciation rate. This paper draws on the research of Shan Haojie [24] and others. The depreciation rate is set at 10.96%. Labor input is measured by the number of employees at the end of the year. Energy input includes seven items of energy consumption such as enterprise water consumption, electricity consumption, raw coal consumption, natural gas consumption, gasoline consumption, diesel consumption, and centralized heating. These are converted to unified standard coal according to the conversion coefficient on the official website of the energy bureau. The output indicators include two aspects: one is the desired output, measured by operating income; the other is the undesired output, represented by operating income and enterprise carbon emissions. Among them, operating income is based on 2012 as the base period and deflated according to the price index of the province where the enterprise is located. Enterprise carbon emissions include emissions from combustion and energy fuels, emissions from production processes, emissions from solid waste incineration, emissions from sewage treatment, and emissions from changes in land use methods. These are calculated according to the "Enterprise Greenhouse Gas Emission Accounting Method and Reporting Guidelines" for different industries released by the National Development and Reform Commission.

2.1.2. Modified Gravitational Model

In this paper, the modified gravity model of Shao Hanhua [25] is used to establish the carbon total factor productivity network of heavy pollution enterprises. The modified gravity model is as follows:

$$X_{ij} = K_{ij}\frac{M_i M_j}{D_{ij}^{\lambda}}, K_{ij} = \frac{F_i}{F_i + F_j} \tag{3}$$

Among them, X_{ij} is the correlation intensity of carbon total factor productivity of heavily polluting enterprises. K_{ij} represents the gravitational coefficient. F_i and F_j are the GDP of the provinces where heavily polluting enterprises are located. M_i and M_j respectively represent the average values of carbon total factor productivity of heavily polluting enterprises in province i and province j. D_{ij} represents the geographical distance between province i and province j. λ represents the distance attenuation coefficient and is usually set to 2.

Using the modified gravity model, the binary matrix of carbon total factor productivity of heavy pollution enterprises was computed. The average of each row in the matrix was then taken as the threshold for binarization. If above the threshold, a value of 1 was assigned, signifying a correlation in carbon total factor productivity of heavy pollution enterprises among provinces; otherwise, a value of 0 was given, indicating no such correlation. [26].

2.1.3. Social Network Analysis

Cyberspace, a constantly changing spatial layout composed of various economic units, enables the diversified flow of material and non-material elements. Essentially in the technology spillover field, it emphasizes functional connections and external effects of different nodes. SNA can deeply analyze cyberspace by describing its interconnections and structural properties based on the social relationship matrix. This study will analyze the spatial correlation network of carbon total factor productivity of heavy pollution enterprises from the three dimensions of overall network characteristics, individual network characteristics and block model. The overall network structure is analyzed from density, correlation degree, efficiency and level. Individual network characteristics are discussed from degree centrality, intermediate centrality and closeness centrality. The block model is a core tool for evaluating clustering in the spatial association network. Referring to relevant research, the spatial correlation network of carbon total factor productivity of provincial heavy pollution enterprises is classified according to the definitions of "broker", "net spillover", "two-way spillover" and "net benefit". The detailed calculation formulas of related indexes, block model analysis and plate definition can be found in [25].

2.2. Data sources

Based on the "Industry Classification Management Catalogue for Environmental Protection Verification of Listed Companies" and the "Guidelines for Environmental Information Disclosure of Listed Companies", combined with the standards of the "Industry Classification Guidelines for Listed Companies" (revised in 2012), this paper selects heavily polluting enterprises listed on the Shanghai and Shenzhen A-share markets from 2013 to 2021 as the research samples. The data in this paper are sourced from the "China Energy Statistical Yearbook", the "China Environmental Statistical Yearbook", as well as the State Intellectual Property Office of the People's Republic of China (SIPO) and the China Stock Market & Accounting Research (CSMAR) database. The following processing has been carried out on the original data: Firstly, samples of ST and *ST are excluded; secondly, samples with missing observations for all variables are excluded; thirdly, Winsorization processing has been conducted on all continuous variables at the 1% quantile. Eventually, 728 observed enterprises and 6,552 observed values are obtained.

3. Spatial Correlation Network Analysis of Carbon Total Factor Productivity of Heavy Pollution Enterprise

3.1. Spatial network characteristics of carbon total factor productivity of heavy pollution enterprises

Based on the measured CTFP of heavy pollution enterprises, its gravity is obtained via formula (2). A spatial correlation matrix of carbon TFP in heavy pollution enterprises was constructed. It was found that from 2013 to 2021, the spatial correlation effect of CTFP of heavy polluting enterprises in 31

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provinces (municipalities and autonomous regions) has surpassed geographical proximity, forming a nationwide spatial correlation network. Hence, a detailed analysis of the structural characteristics of the spatial correlation network of carbon TFP of China's heavy polluting enterprises is carried out based on social network analysis.

3.1.1. Analysis of that characteristic of network

This study employed Ucinet 6.0 software to quantitatively assess the spatial correlation network of carbon total factor productivity of heavy polluting enterprises in China from 2013 to 2021 via comprehensive characteristic indicators. Table 3 indicates that during the studied period, the network density and correlation degree of carbon total factor productivity of heavy polluting enterprises in China. From 2013 to 2021, the network density of carbon total factor productivity of heavy polluting enterprises in China exhibited a fluctuating downward trend. By 2021, it reached the lowest point, with an average network density of 0.2148 during the study period. This implies that there is a definite spatial relationship among the carbon total factor productivity of heavy polluting enterprises across the country, yet the tightness of this spatial connection is relatively low. Thus, there is significant potential for cooperation and exchanges among heavy polluting enterprises in the low-carbon production field in various provinces. Simultaneously, in different research years, the network correlation degree has consistently maintained a stable level of 1.000. This means that although the network density of carbon total factor productivity of provincial heavy polluting enterprises shows an unstable trend each year, its overall network structure remains relatively stable and accessible. Table 3 also shows that during the study, the spatial correlation of carbon total factor productivity of heavy pollution enterprises and the change trends of network efficiency and network rank. The network efficiency fluctuated within the range of 0.7310 during the studied time period, with a relatively small fluctuation amplitude. This indicates that the spatial correlation network of carbon total factor productivity of heavy polluting enterprises has low redundancy, and the carbon TFP correlation efficiency of heavy polluting enterprises between different provinces is relatively stable, but there is still room for further enhancement. Additionally, during the studied period, the network rank degree showed a pattern of first fluctuation and then stability. In most years, the network grade was stable at 0.1330. This shows that the spatial correlation network did not form a strict hierarchical order, and there was no obstacle to network connectivity. The correlation degree of carbon total factor productivity of heavy polluting enterprises between provinces was continuously increasing.

Table 3 The overall structural characteristics of the spatial correlation network of carbon total factor productivity of heavypolluting enterprises in China from 2013 to 2021

	2013	2014	2015	2016	2017	2018	2019	2020	2021
Network density	0.2226	0.214	0.2183	0.2097	0.2226	0.2097	0.214	0.2151	0.2075
Network relevancy	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Network level degree	0.133	0.1912	0.1330	0.1310	0.1894	0.1912	0.1931	0.1912	0.1376
Network efficiency	0.7218	0.7379	0.7287	0.7356	0.7310	0.7517	0.7310	0.7287	0.7563

3.1.2. Analysis of network characteristics of individuals

This research uses the centrality analysis method to describe the individual network structure characteristics of heavily polluting enterprises in China. Considering the limitations of the article's length, we have adopted three key indicators, namely degree centrality, closeness centrality and betweenness centrality, and finally presented the specific situations of degree centrality, betweenness centrality and closeness centrality of the carbon total factor productivity network of heavily polluting enterprises in 2013, 2015, 2017, 2019 and 2021.

Degree centrality exhibits significant provincial differences in the spatial correlation network of carbon total factor productivity of heavy polluting enterprises. Regions above average are closer to the center, supplying key elements. The number of such regions in 2013, 2015, 2017, 2019, and 2021 was 12, 13, 13, 17, and 17 respectively, with degree centrality differences decreasing over time. Ningxia, Shandong, etc., are at the core, and their productivity growth may have spillover benefits. Closeness centrality of heavy polluting enterprises' carbon total factor productivity declined from 54.682 in 2013 to 51.746 in 2021 due to regional centers like Qinghai, Shaanxi, and Hebei in 2021, yet most provinces maintain a central role with fluctuating proportions above average. Betweenness centrality rose from 4.457 in 2013 to 4.568 in 2021, likely due to improved networks and strategies. The number of regions above average in relevant years was 13, 13, 13, 15, and 15. Provinces like Shandong and Henan, in key

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channels and nodes, rank top ten, enhancing their "bridge" role and control, though overall improvement is needed.

3.1.3. Analysis of plate network characteristics

In order to further understand the role and position of each province in the spatial correlation network of carbon total factor productivity of heavy polluting enterprises, to describe the interaction between provinces, this study selected the data of 2021.The clustering characteristics of the spatial correlation network of carbon total factor productivity of heavy pollution enterprises were analyzed by using Ucinet software CONCOR iterative convergence methodIt is determined that the maximum value of the segmentation depth is 2 and the concentration criterion is 0.2000.

As per Table 5, in the spatial network of carbon total factor productivity of heavy polluting enterprises in 31 provinces, there are 187 spatial associations. 117 are intra-plate relationships (62.57% of total network relationships), and 70 are inter-plate ones (37.43%). It shows that the spatial correlation path mainly focuses on each plate, with sparse inter-plate connections. Heavily polluted enterprises' carbon total factor productivity has a geographical agglomeration tendency, perhaps due to resource complementarity and economic interaction among adjacent regions. The out-of-plate relationship reflects the spillover effect, i.e., improvement in one place can positively impact surrounding areas. Also, there are diverse relationship patterns both between and within different plates.

Table 5 Spatial correlation of carbon total factor productivity of heavily polluting enterprises in 31 provinces(municipalities and autonomous regions) in China in 2021

	Plate I	Plate II	Plate III	Plate IV	Receive correlation factor		Overflow correlation factor	Proportion of expected internal relationship	Actual interrelationship ratio
					Inside	Outside			
Plate I	26	14	7	0	26	16	21	20	55.32
Plate II	6	50	4	0	50	35	10	40	83.3
Plate III	10	21	33	10	33	15	41	20	44.59
Plate IV	0	0	4	8	8	10	4	10	66.67

Plate I consists of seven provinces like Anhui, Shanghai, etc. Its internal correlation coefficient is 26, higher than the external ones for receiving (16) and spillover (21) plates. The actual internal relations proportion (83.33%) exceeds the expected (40%), showing "two-way spillover" as its spatial connections mainly focus within the plate.Plate II includes 13 provinces such as Gansu, Guizhou, etc. It has the largest number of internal members with 50 internal relations. The correlation coefficient outside the receiving plate (35) is notably higher than that outside the overflow plate (10). With the actual internal relationship percentage (55.32%) exceeding the expected (20%), it's classified as a "broker" sector.Plate III covers seven provinces including Tianjin, Shanxi, etc. There are 33 internal correlation coefficients and 41 for the spillover plate's external ones. The actual internal relationship ratio (44.59%) exceeds the expected (20%), featuring "net spillover".Plate IV includes four provinces like Heilongjiang, Inner Mongolia, etc. Its internal correlation coefficient is 8, while the receiving plate's correlation coefficient is 10. As the internal coefficient is lower than the sum of external ones and the actual internal relations proportion (66.67%) exceeds the expected (10%), it's a "net beneficiary" sector.

Table 6 Spatial correlation plate matrix of carbon total factor productivity of heavily polluting enterprises in 31 provinces(municipalities and autonomous regions) in China in 2021

Like a matrix	Plate I	Plate II	Plate III	Plate IV
Plate I	1	1	0	0
Plate II	0	1	0	0
Plate III	0	1	1	1
Plate IV	0	0	0	1

Based on the analysis of the interaction between the four major plates in the spatial correlation network and the plate characteristics,we have preliminarily revealed the spatial distribution characteristics of carbon total factor productivity of heavy pollution enterprises.and the role characteristics of these plates are different.In order to understand the spatial connection between the

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plates more accurately, the density matrix of each plate was calculated by using Ucinet software.And further convert that density matrix into an image matrix.More specifically, we use the network density (0.2075) of carbon total factor productivity of provincial heavily polluted enterprises as the evaluation criteria.If the density of a particular plate exceeds this criterion, a value of 1 is assigned to it;On the contrary, the assignment is 0 [25], and the result of the image matrix can be referred to Table 6.

According to the image matrix, the elements on the diagonals of the four plates are all 1.This means that there is an obvious correlation between the carbon total factor productivity of heavy polluting enterprises in these four sectors.Further analysis shows that plate I, in addition to its own internal relations, also spills over to plate II.Plate II receives factor flows from plates I and III, and plate III is the main body of spillover effects.It mainly spills over to Plate II and Plate IV, and the main members of Plate III gather in the center of the central and eastern regions.It has convenient transportation location, and is generally a province with developed economy, good energy resources and high technology level.So it is at the core of the network.

4. Driving Factors of Spatial Correlation Network of Carbon Total Factor Productivity of Three Heavily Polluted Enterprises

According to the above analysis,this paper has clarified the spatio-temporal evolution status and spatial correlation network characteristics of carbon total factor productivity of heavy pollution enterprises from 2013 to 2021.Sign. In order to effectively plan the productivity network correlation strategy of carbon total factor productivity of heavy pollution enterprises in the future,it is necessary to identify the driving factors of the spatial correlation network.QAP analysis is suitable for network relational data, and has a broader requirement for the independence of variables.The regression results will be more robust than traditional econometric regression results. Therefore,this paper uses QAP regression analysis to study the driving factors of the spatial correlation network of carbon total factor productivity of heavy polluting enterprises in China.The results of the study are shown in Table 7.

Table 7 Estimation of the influencing factors of the spatial correlation network of carbon total factor productivity of heavypolluting enterprises in China from 2013 to 2021

	C	V	T	E	I
2013	0.57***	-0.04	-0.19***	-0.13**	0.01
2014	0.57***	0.04	-0.18**	-0.15**	0.01
2015	0.57***	0.01	-0.18**	-0.14**	0.03
2016	0.57***	0.07*	-0.14*	-0.15**	0.01
2017	0.55***	0.05	-0.22**	-0.20***	0.05*
2018	0.57***	0.17*	-0.10	-0.13***	0.09***
2019	0.54***	0.10*	-0.07	-0.12**	0.10***
2020	0.56***	0.13*	-0.08	-0.12**	0.09***
2021	0.56***	0.06**	-0.008	-0.02	0.01***

The spatial adjacency matrix (C) has a significant positive impact on the construction of the spatial correlation network of carbon total factor productivity of heavily polluting enterprises each year. Close geographical locations mean lower circulation costs of elements and closer economic development between regions, facilitating element flow and spatial connection. The innovation level (V) has a consistently significantly positive regression coefficient, showing that a greater difference in innovation levels benefits network formation as low-innovation-level regions introducing technologies from high-innovation-level ones promotes exchanges and cooperation in green and low-carbon development among regions. The transportation level difference (T) matrix is relatively significant with a always negative coefficient, meaning a smaller transportation level difference helps form the network as consistent transportation levels enable element transfer and industrial economic exchanges [ref]. The regression coefficient of economic development level difference (E) is always significantly negative, indicating that similar economic development levels are more favorable for network formation by strengthening the flow of production technologies, equipment, and talents . The information level difference (I) matrix impacts the network formation obviously in most years and has a positive coefficient when significant. A greater information level gap benefits network construction as in highly informatized regions, elements can be concentrated more efficiently to promote element flow and network establishment. The central region often occupies a core position in the network mainly due to its abundant information resources that can gather elements and strengthen node connections.

5. Research conclusion and suggestions

This paper selects 728 heavily polluting enterprises of China's A-share listed companies as samples and takes provinces as the research scale. It measures their carbon total factor productivity comprehensively, explains spatiotemporal evolution characteristics systematically, uses social network analysis to clarify the spatial network structure characteristics, and applies QAP regression analysis to explore driving factors. The conclusions are: (1) From 2013 to 2021, the carbon total factor productivity of heavily polluting enterprises nationwide went through three fluctuating stages (rising, decreasing, then falling again), with much room for improvement. In space, central, eastern and western regions had the same fluctuating trend, and the western region grew faster. (2) The spatial correlation network has broken geographical proximity limits. There's significant spatial correlation and spillover effect among provinces' carbon total factor productivity. The network has low overall correlation but high stability. (3) Each region has different status and roles. Some regions in Shandong, Henan, etc., have high centrality values and are "leaders" or "intermediaries". The centrality fluctuates over years. The eastern region, with a developed economy, is an element gathering place and has high centrality. Some western regions get element inflow via policy support and have high centrality. A few central regions have high centrality due to good locations. (4) The network can be divided into four sectors with significant spillover effects within and between them and obvious transmission characteristics between sectors. (5) Influencing factors' effects vary by year. Spatial adjacency, innovation, transportation, economic development and informatization levels all significantly affect the construction of the spatial correlation network of carbon total factor productivity of heavily polluting enterprises.

In view of the above conclusions, this paper presents policy suggestions: Firstly, to better handle environmental challenges, build a comprehensive spatial correlation network of carbon total factor productivity of heavy polluting enterprises and remove administrative boundary barriers. Heavy polluting enterprises should be active, enhance inter-provincial communication and cooperation, and form an efficient governance cooperation system. Strengthening city and provincial cooperation can boost overall improvement and break traditional administrative limits for broader environmental gains. Secondly, in network construction, consider sector characteristics for division of labor and cooperation. Deepen understanding of regional traits, combine sectoral advantages and resources, optimize coordination, and enhance growth linkage. The government, balancing incentives and constraints, should promote policy coordination to ensure inter-provincial collaborative growth. It needs to formulate measures based on local conditions and guide enterprises to improve carbon total factor productivity. Thirdly, increase cooperation intensity of carbon total factor productivity among neighboring heavy polluting enterprises. Given regional differences, construct a scientific division of labor system to leverage complementary industrial and informatization advantages, promote experience and technology sharing, and ensure the network's orderly and efficient operation. These suggestions aim to enhance carbon total factor productivity of heavy polluting enterprises, build a better network, and drive environmental governance, responding to current issues and ensuring future sustainable development.

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Table 4 Spatial correlation network centrality of carbon total factor productivity of heavily polluting enterprises in 31provinces (municipalities and autonomous regions) in China from 2013 to 2021

Area	Point degree and center degree					Close to centrality					Intermediary centrality				
	2013	2015	2017	2019	2021	2013	2015	2017	2019	2021	2013	2015	2017	2019	2021
Anhui	33.333	36.667	36.667	36.667	40.000	56.604	57.692	57.692	56.604	57.692	9.048	11.740	6.743	9.500	9.827
Beijing	26.667	26.667	26.667	33.333	30.000	52.632	52.632	52.632	55.556	51.724	5.367	5.410	4.150	5.227	2.357
Fujian	26.667	26.667	26.667	20.000	26.667	49.180	49.180	49.180	47.619	49.180	2.747	1.813	2.449	1.017	1.159
Gansu	36.667	30.000	40.000	43.333	43.333	58.824	56.604	60.000	62.500	62.500	3.695	0.104	0.073	4.196	4.003
Guangdong	36.667	40.000	46.667	36.667	40.000	56.604	57.692	60.000	55.556	56.604	1.247	1.067	1.651	1.886	1.365
Guangxi	23.333	20.000	13.333	13.333	13.333	48.387	46.154	44.118	40.000	41.096	3.784	4.152	0.000	0.000	0.038
Guizhou	30.000	23.333	26.667	26.667	23.333	51.724	47.619	48.387	44.776	44.118	4.891	5.113	6.553	5.357	5.311
Hainan	36.667	30.000	40.000	36.667	23.333	52.632	56.604	60.000	52.632	49.180	0.828	2.182	0.000	0.000	0.000
Hebei	33.333	30.000	26.667	30.000	30.000	56.604	54.545	51.724	53.571	53.571	2.299	1.568	3.391	2.127	4.565
Henan	53.333	50.000	50.000	50.000	46.667	66.667	65.217	63.830	63.830	62.500	11.991	9.973	8.476	11.990	10.761
Heilongjiang	6.667	6.667	6.667	3.333	6.667	31.915	32.609	32.609	29.703	33.333	0.000	0.000	0.000	0.000	0.000
Hubei	50.000	50.000	50.000	46.667	43.333	65.217	65.217	65.217	58.824	60.000	10.235	8.982	10.082	10.994	10.506
Hunan	33.333	40.000	40.000	36.667	36.667	55.556	57.692	57.692	55.556	54.545	7.039	10.531	9.224	7.364	8.142
Jilin	13.333	13.333	13.333	13.333	20.000	44.118	45.455	45.455	41.667	47.619	4.901	4.901	4.108	6.092	4.598
Jiangsu	53.333	50.000	50.000	50.000	50.000	66.667	65.217	65.217	65.217	66.667	4.081	3.234	3.205	4.870	5.613
Jiangxi	36.667	33.333	36.667	33.333	30.000	58.824	55.556	57.692	53.571	51.724	6.257	4.905	6.322	8.990	7.285
Liaoning	20.000	20.000	20.000	16.667	20.000	45.455	46.875	46.875	42.254	42.857	7.513	7.513	3.432	6.207	7.354
Inner Mongolia	23.333	23.333	23.333	16.667	20.000	50.847	51.724	51.724	41.667	42.857	0.743	0.647	4.853	0.259	1.387
Ningxia	56.667	56.667	56.667	56.667	50.000	66.667	66.667	66.667	66.667	62.500	2.883	2.031	3.999	2.229	0.713
Qinghai	36.667	36.667	20.000	53.333	46.667	60.000	60.000	53.571	66.667	63.830	0.029	0.057	0.000	0.230	0.000
Shandong	56.667	63.333	63.333	50.000	50.000	69.767	73.171	73.171	63.830	63.830	19.705	22.449	19.353	14.442	12.938
Shanxi	33.333	30.000	36.667	36.667	36.667	55.556	54.545	56.604	56.604	55.556	3.578	2.944	7.538	5.755	6.640
Shaanxi	30.000	36.667	36.667	30.000	30.000	52.632	60.000	60.000	51.724	54.545	7.793	10.765	9.492	9.184	8.791
Shanghai	20.000	20.000	20.000	20.000	20.000	49.180	49.180	49.180	50.847	48.387	0.614	0.522	0.730	0.655	0.665
Sichuan	30.000	26.667	26.667	30.000	23.333	53.571	50.847	50.847	53.571	48.387	1.290	0.288	0.474	2.616	2.740
Tianjin	30.000	30.000	30.000	33.333	30.000	55.556	54.545	54.545	54.545	51.724	5.636	5.678	4.622	10.923	9.752
Xizang	50.000	46.667	36.667	40.000	3.333	65.217	63.830	60.000	61.224	39.474	0.000	0.000	0.000	0.000	0.000
Xinjiang	3.333	3.333	3.333	6.667	3.333	40.000	39.474	37.975	41.096	39.474	0.000	0.000	0.000	0.000	0.000
Yunnan	16.667	16.667	13.333	16.667	13.333	46.154	45.455	44.776	46.875	44.776	0.029	0.268	0.077	0.077	0.345
Zhejiang	26.667	30.000	26.667	26.667	23.333	53.571	54.545	52.632	52.632	50.847	0.758	0.704	0.600	0.997	0.819
Chongqing	43.333	40.000	36.667	36.667	33.333	58.824	56.604	55.556	55.556	53.571	9.181	7.700	7.024	5.123	5.047
Mean value	32.473	31.828	31.613	31.613	29.247	54.682	54.618	54.373	52.998	51.764	4.457	4.427	4.149	4.271	4.568