

Spatial network structure and Socio-economic drivers of low-carbon energy consumption structure in China

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Abstract

Based on the data of Chinese provinces from 2004 to 2022, this paper constructs the low-carbon index of energy consumption structure. Then the systematical influencing factors and the spatial correlation network structure of inter-provincial energy consumption in China are analyzed through the social network analysis method. The degree centrality, betweenness centrality and closeness centrality of individual network structure show individual provincial role in the spatial energy transmission network. The block model analysis shows that 8 provinces have "bidirectional spillover"; 11 provinces have "net receiver"; 4 provinces have "net spillover"; and the other 7 provinces have "broker" roles. The analysis of influencing factors shows that the impact of energy intensity fluctuates, the positive impact of environmental regulation weakens, the impact of foreign investment turns positive, the positive effect of government intervention and industrialization declines, and the positive effect of technology market development and urbanization increases.

Keywords

Low-carbon energy transformation; modified gravity model; social network analysis; economical systematical drivers

1. Introduction

At present, the global energy consumption structure is transforming in the direction of low-carbon, but fossil energy is still dominant, but low-carbon energy such as hydropower, nuclear, wind, and solar energy accounts for about 20%, and shows a rapid growth trend. The changing trend of this energy structure shows that despite the rapid development of low-carbon energy, there are still many challenges to achieving deep decarbonization of the global energy system. In the future, as countries increase investment in clean energy and technological progress, the proportion of low-carbon energy in the energy consumption structure is expected to further increase. In this

context, China, as one of the world's largest energy consumers, is also actively promoting the low-carbon development of its energy consumption structure. In recent years, China has made significant investments and technological progress in the field of renewable energy, with the installed capacity of clean energy such as wind and solar energy continuing to grow, and important progress has also been made in low-carbon energy fields such as nuclear energy and hydropower. In addition, the Chinese government has continuously optimized its energy consumption structure and reduced its dependence on traditional fossil energy through policy guidance and technological innovation, laying a solid foundation for achieving the goals of carbon peak and carbon neutrality. However, due to the turbulence of global energy supply and consumption markets, the decarbonization process of global energy consumption structure has slightly stagnate (Evro et al., 2026), and due to the obvious imbalance between supply and demand spatial structure and the close correlation between carbon reduction space (Bilgen, 2014), each region has a certain dynamic equilibrium in the consumption of energy segments(C. Wei et al., 2025)。 As a major energy consumer, China's energy consumption structure also has certain spatial correlation characteristics (Chen and Zhang, 2024; Fang et al., 2025).This also makes it necessary to consider the overall consideration in the process of decarbonizing the energy consumption structure.

Energy is an important material foundation for human survival and development, which is related to international livelihood and national security. With the increasingly tightening of the "dual carbon" goal constraints and energy resource constraints, China's economic development is facing many energy challenges under the "new normal", such as the imbalance between energy supply and demand, the bottleneck of energy structure and renewable energy consumption, the technical and cost pressure of green and low-carbon transformation, and the stability of energy supply. On the one hand, the total energy consumption has shown a trend of rising year by year, reaching 5.41 billion tons of standard coal in 2022; on the other hand, under the combined effect of various factors such as economic transformation, industrial structure, and industrial chain resilience

and safety level, and energy endowment structure, energy consumption has shown significant spatial imbalance. To break the constraints of resources and environment, since the "14th Five-Year Plan" period, China has set stricter energy conservation targets and comprehensively considered factors such as economic and social development, interest, and resource characteristics of various regions to decompose the overall energy conservation goals of the country into provinces. If the energy consumption of each province is independent of each other, then the sum of the provinces' completion of their respective energy-saving tasks is the energy-saving task completed by the whole country. However, under the combined action of various factors, energy consumption between provinces does not exist independently, but presents a certain spatial correlation (Sun et al., 2025a). Therefore, in the case of obvious inter-provincial spatial correlation between energy consumption, provinces should not only consider their own energy consumption structure but also fully consider and effectively contain the energy consumption structure of related provinces in the process of promoting the low-carbon energy consumption structure in the province. With the implementation of engineering projects aimed at promoting cross-regional energy flow (such as west-to-east gas transmission, west-to-east electricity transmission, north-south coal transportation, east-to-west computing), marketization, digital economy, and artificial intelligence, the spatial connection between total energy consumption and structure has become more common and extensive, and has gone beyond the "near neighbor" relationship in the sense of geography alone, and gradually presents a complex network structure form with multiple threads. In this context, the structural characteristics and evolution trend of the spatial correlation network of the low-carbon trend of energy consumption structure are accurately described, the status and role of each province in the low-carbon spatial correlation network of China's energy consumption structure are clarified, the driving factors of the low-carbon spatial correlation network of China's energy consumption structure are explored, and the influence of the spatial correlation network structure on energy intensity (consumption)

is deeply revealed. It has important theoretical significance and application value for the formulation and implementation of energy policies, as well as the construction of a cross-regional collaborative energy-saving mechanism and a low-carbon system for energy consumption structure.

Existing studies have used exploratory spatial data analysis (ESDA) to reveal the significant spatial correlation and spatial agglomeration characteristics of China's energy consumption, but there are four limitations in existing studies: First, the explained energy spatial agglomeration characteristics only consider the geographical "proximity" or "adjacent" effect, and the resulting policy implications are often limited to "local", so it is difficult to grasp the spatial correlation characteristics between inter-provincial energy consumption as a whole, which is not conducive to the realization of China's overall energy consumption goal (dual carbon goal). Second, it is based on "attribute data" rather than "relational data", which makes it difficult to describe the overall network structure characteristics of spatial correlation of energy consumption, and the structure often determines the performance of attribute data, which has more analytical value. Third, it gives more descriptions of "quantity" rather than "quality" associations. The traditional spatial measurement method examines the spatial correlation structure and effect of energy consumption "quantity" based on spatial factors but cannot reveal the driving factors and influencing effects of the spatial correlation "relationship" in the dynamic process of low-carbon energy consumption structure. Based on the perspective of relational data and network, this paper uses the inter-provincial consumption data of various energy subdivisions in China from 2004 to 2022 to calculate the low-carbon index of energy consumption structure by cosine angle method, constructs a modified gravitational model to determine the spatial correlation relationship between low-carbon energy consumption structure, and uses social network analysis (SNA). The spatial correlation network structure, driving factors and influencing effects of low-carbon energy consumption structure were investigated. The overall characteristics and evolution trend of China's energy

consumption structure are reflected by measuring network density, network connection, network hierarchy and network efficiency. Through centrality analysis, the status and role of each province in the spatial correlation network of low-carbon energy consumption are examined. The spatial clustering mode of low-carbon energy consumption structure is revealed through block modeling. The driving factors of the spatial correlation network structure of decarbonization of energy consumption structure are empirically tested by QAP analysis, and the impact effect of decarbonization of energy consumption structure is empirically tested by OLS regression.

2. Methods and data

2.1 Measurement of low-carbon index of energy consumption structure

The general vector angle is used for weighting to construct the low-carbon index of energy consumption structure. Firstly, according to the level of carbon emission coefficient per unit calorific value of various subdivided energy, 9 types of subdivided energy are arranged in descending order. The terminal energy consumption is divided into nine categories, namely coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, natural gas and electricity energy consumption, and it is converted into 10,000 tons of standard coal according to the reference coefficient of various energy conversions in the China Energy Statistical Yearbook. To reflect the low-carbon energy consumption structure, the e^i carbon emission coefficients per unit calorific value will be arranged in descending order from high to low, as shown in Table 1 below:

Table 1 Carbon emission levels by energy types

type	rank	Carbon emission coefficient per unit calorific value
Coke	1	27.435

Raw coal	2	24.7878
Fuel oil	3	20.678
diesel	4	19.796
Crude oil	5	19.698
kerosene	6	19.11
Gasoline	7	18.522
Natural gas	8	15.147
Electricity	9	12.138

The proportion of nine types of energy consumption in total energy consumption constitutes a set of nine-dimensional space vectors, which are expressed as follows:
 $EC_0 = (ec_{1,0}, ec_{2,0}, ec_{3,0})$, Then combine the basic unit vector groups of the three types of energy consumption $EC_1 = (1, 0, 0)$, $EC_2 = (0, 1, 0)$, $EC_3 = (0, 0, 1)$, then the angles $\delta_1, \delta_2, \delta_3$ between EC_0 and EC_1, EC_2, EC_3 , is calculated separately

$$\delta_j = \arccos \left\{ \frac{\sum_{i=1}^3 (ec_{i,j} \cdot ec_{i,0})}{(\sum_{i=1}^3 (ec_{i,j}^2)^{1/2} \cdot \sum_{i=1}^3 (ec_{i,0}^2)^{1/2})} \right\}$$

$$j = 1, 2, 3$$

Finally, the low-carbon level index of energy consumption structure is calculated by linear weighted summing:

$$EC = \sum_{k=1}^3 \sum_{j=1}^k \delta_j$$

The larger it is, the higher the low-carbon level of the energy consumption structure. The measurement data in this paper is based on panel data from 30 provinces

(excluding Tibet, Hong Kong, Macao and Taiwan) from 2004 to 2022, and the data are from the China Energy Statistical Yearbook

2.2 Dagum Gini coefficient decomposes the spatial differentiation of low-carbon energy consumption structure between provinces in China

The Thiel index can measure the regional differences in the decarbonization of China's energy consumption structure through subgroup decomposition, but it cannot measure the overlap of inter-regional and intra-regional differences, which includes multidimensional poverty (Demsou, 2023), energy system resilience (T. Wei et al., 2025), carbon dioxide inequality (Demsou, 2023), and intra- and out-of-club disparities in renewable energy (Li et al., 2022).etc. Because Dagum Gini coefficient decomposition not only identifies intra-regional and inter-regional differences, it can also identify supervariable density, that is, the spatial difference caused by the overlapping part between different regions and can more accurately explore the contribution to the overall gap from the three parts of intra-region, inter-region and supervariable density.

There have been studies using the Gini coefficient to decompose inequality in the energy economy (Chen et al., 2025), etc., so this study refers to the related research on Gini coefficient decomposition (Tomson Ogwang., 2014; Wu and Chen, 2023), and used the Dagum Gini coefficient and its decomposition method to detect the spatial differences in the low-carbon energy consumption structure between provinces in China. The basic definition of the Gini coefficient is shown in Equation (1).

$y_{ji}(y_{hr})$ is the low-carbon index of the energy consumption structure of a province in the region $j(h)$, $\bar{y}$ represents the average value of the low-carbon index of energy consumption structure in each province, n represents the number of provinces, k is the number of regions, $n_j(n_h)$ is $j(h)$ the number of provinces in the region. When decomposing the Gini coefficient, the regions need to be sorted

according to the mean value of the decarbonization index of the energy consumption structure, as shown in Equations (1) and (2):

$$G = \frac{1}{2\bar{y}n^2} \left(\sum_{i=1}^n \sum_{r=1}^n |y_i - y_r| \right) \quad (1)$$

$$= \sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}| / 2n^2\bar{y}$$

$$\bar{Y}_h \leq \dots \bar{Y}_j \leq \dots \bar{Y}_k \quad (2)$$

Among them, n is the number of provinces; k is the number of subgroups, In the text, it refers to the eastern, central, western and northeastern regions respectively; n_j (n_h) is the number of provinces within a subgroup j (h); j and h are the numbers of subgroups divided, i and r are the numbers of provinces in the subgroup; G is the overall Gini coefficient, y_{ji} (y_{hr}) is the low-carbon index of energy consumption structure in any region j (h), $\bar{Y}$ represents the average of the decarbonization of energy consumption structure in all regions, Its calculation formula is: $\sum_{j=1}^k \sum_{i=1}^{n_j} y_{ij} / n$. The larger the Dagum Gini coefficient, the more unbalanced the low-carbon level of energy consumption structure between regions. The above method calculates the difference in the decarbonization level of the overall energy consumption structure.

Next, build Gini coefficient of decarbonization of energy consumption structure G_{jj} and intra-regional variations G_w in the subgroup j , The specific calculation methods are as shown in (3) and (4):

$$G_{jj} = \left(\frac{1}{2\bar{Y}_j} \right) \sum_{i=1}^{n_j} \sum_{r=1}^{n_j} |y_{ji} - y_{jr}| / n_j^2 \quad (3)$$

$$G_w = \sum_{j=1}^k G_{jj} p_j^s \quad (4)$$

Among them, $\bar{Y}_j$ represents the average development of the low-carbon level of energy consumption structure in the region (subgroup), and other indicators are as described above.

Construct the subgroup j and h interregional Gini coefficient G_{jh} of the region and the difference G_{nb} in net worth between regions, The calculation is shown in equations (5) and (6):

$$G_{jh} = \left(\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}| \right) / n_j n_h (\bar{Y}_j + \bar{Y}_h) \quad (5)$$

$$G_{nb} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh} \quad (6)$$

The supervariable density G_t is then calculated. As shown in Eq. (7), the relationship $G = G_w + G_{nb} = G_t$ between them is satisfied,

$$G_t = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) 1 - (D_{jh}) \quad (7)$$

Among them, $p_j = n_j / \bar{Y}$, $s_j = n_j \bar{Y}_j / n \bar{Y}$ ($j = 1, \dots, k$). At the same time, this study will define D_{jh} the negative relative impact of the change of the low-carbon index of energy consumption structure between j and h regions, As shown in equations (8), (9), (10). $F_j(F_h)$ is respectively the cumulative distribution density function of the region j , h . d_{jh} is the difference between regions and the change of the low-carbon index of energy consumption structure, interpreted as mathematical expectation of summing all sample values $y_{ji} - y_{hr} > 0$ in the j , h region; p_{jh} is a supervariable first-order moment and it can be interpreted as the

mathematical expectation of the sum of all sample($y_{hr} - y_{ji} > 0$) values in the region.

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \quad (8)$$

$$d_{jh} = \int_0^{\infty} dF_j(y) \int_0^y (y - x) dF_h(x) \quad (9)$$

$$p_{jh} = \int_0^{\infty} dF_h(y) \int_0^y (y - x) dF_j(x) \quad (10)$$

2.3 Modified gravitational matrix model

Determination of relationships is key to network analysis. According to the existing literature, the relationship is mainly determined by the gravitational model (Bai et al., 2020; Sun et al., 2025b) and VAR Granger Causality test (GROENEWOLD et al., 2008). This paper refers to the existing studies and chooses to modify the gravity model to determine the spatial correlation relationship of low-carbon energy consumption structure, which is done for two reasons: first, the evolution trend of the network based on the VAR model cannot be visualized in space; Second, the VAR model is too sensitive to the selection of lag orders, which reduces the accuracy of network structure feature characterization to a certain extent. The gravitational model is not only more suitable for aggregate data and structural data but also can comprehensively consider the factors of economic and geographical distance, and then use cross-sectional data to describe the evolution trend of spatial correlation networks. Therefore, the use of gravitational model to construct a network is more advantageous in revealing the dynamic evolution trend of the spatial correlation network of the low-carbon process of energy consumption structure. Based on the above considerations, this paper introduces the gravitational model into the field of low-carbon process of energy consumption structure, and at the same time, in order to enhance its applicability,

the gravitational model is modified, and the modified gravitational model is shown in Equation (11):

$$y_{ij} = k_{ij} \frac{\sqrt[3]{P_i EC_i G_i} \sqrt[3]{P_j EC_j G_j}}{\left(\frac{D_{ij}}{g_i - g_j} \right)^2}, k_{ij} = \frac{EC_i}{EC_i + EC_j} \quad (11)$$

i 、 j represents the province. y_{ij} represents the gravitational pull of the low-carbon index of the province's energy consumption structure between provinces i and j ; EC_i and EC_j represents respectively the low-carbon index of the energy consumption structure of the province and the province. P_i 、 P_j is the total population of the province i and the province j at the end of the year; G_i and G_j is the real GDP of the province i and the province; k_{ij} indicates the contribution rate of provinces in the low-carbon linkage of energy consumption structure between province i and province j . In order to consider the influence of economic distance and geographical distance factors on the spatial correlation of low-carbon energy consumption structure between provinces. This paper uses the distance D_{ij} between provincial capitals to compare the difference between province i and province i per capita GDP to characterize the "distance" between provinces. According to Equation (11), the gravitational matrix between the low-carbon energy consumption structure of the province is calculated. The average of each column of the gravitational matrix is taken as the critical value, and the gravity is higher than the critical value of the column as 1, which means that the province in this column has a correlation with the low-carbon energy consumption structure of the province. On the contrary, if the gravity is lower than the critical value of the column, it is recorded as 0, indicating that there is no

correlation between the province and the low-carbon energy consumption structure of the province.

2.4 Social network analysis

Social network analysis is an interdisciplinary analysis method for "relation data" that has been widely used in sociology, economics, management and other fields, and has become a new research paradigm.

2.4.1 Overall network characteristics.

The overall network structure characteristics are usually characterized by network density, network correlation, network hierarchy and network efficiency. Among them, network density can reflect the tightness of the spatial correlation network of low-carbon energy consumption structure (Lv et al., 2019). The greater the network density, the closer the connection between the low-carbon energy consumption structure of the inter-provincial energy consumption structure, and the greater the impact of the network structure on the low-carbon energy consumption structure of each province. The network correlation degree reflects the robustness and vulnerability of the energy consumption spatial correlation network itself. If many lines in the network are connected to a province, then the spatial correlation network of the low-carbon energy consumption structure is highly dependent on that province, in other words, once the province is excluded, the network may collapse. The higher the network hierarchy, the stricter the hierarchical structure between provinces in the low-carbon spatial correlation network of energy consumption structure, and the more provinces will be in a subordinate and marginal position in the low-carbon spatial correlation network of energy consumption structure. Network efficiency reflects the connection efficiency between provinces in the low-carbon spatial correlation network of energy consumption structure. If the network efficiency is lower, it means that there are more connections between provinces, and the closer the connection between the low-carbon energy consumption structure of provinces, the more stable the spatial correlation network of low-carbon energy consumption structure, and the easier it is to promote

the spatial flow and transmission of low-carbon energy consumption structure through the low-carbon spatial correlation network of energy consumption structure, and narrow the gap between provinces in the low-carbon process of energy consumption structure.

2.4.2 Network characteristics of each node.

According to the social network analysis method, the network characteristics of each node can be described by network centrality indicators such as degree centrality, intermediary centrality and proximity centrality. Degree centrality can measure the degree of centrality in the low-carbon spatial correlation network of energy consumption structure according to the number of connections in the network. Betweenness centrality reflects the extent to which a province controls the correlation between other provinces, and the higher the intermediation centrality, the more it can control the interaction between the low-carbon energy consumption structure of other provinces, and the more the province is at the center of the network. Closeness Centrality describes the extent to which a province in the network is "not controlled by other provinces" in the process of decarbonizing the energy consumption structure. The higher the proximity to the center of a province, the more direct correlation there is between the province's energy consumption and other provinces, which are the central actors in the network.

2.4.3 Spatial cluster analysis.

The block model is the main method for spatial clustering analysis in social network analysis. Block models can analyze the roles of individual locations (blocks) in the network (Sun et al., 2025c). Through block model analysis (Lu et al., 2023), the development of low-carbon spatial correlation networks of energy consumption structure can be investigated from a new dimension, the internal structure of low-carbon spatial correlation networks of energy consumption structure can be revealed and described, the number of plates in the network and the provinces contained in each plate can be found, and then the relationship between plates and connection methods can be

analyzed. This paper divides the roles of blocks in the low-carbon spatial correlation network of energy consumption structure into four types. The first is the net beneficiary role, in which members of such sectors accept relationships from both members of other sectors and members within the sector, and receive significantly more relationships from outside the sector than it spills over to other sectors. the second is the net spillover role, which is significantly more connected to other sectors than other sectors to this sector; the third is the two-way overflow role, in which such sector members both send and receive contacts from other sectors, while there are more contacts from members within the sector; The fourth is the role of the broker, which not only sends contacts to other sectors, but also receives contacts from other sector members, and the sector has more connections with other sector members.

2.5 The QAP method

QAP regression methods are widely used in social network analysis to explore the "relationship" between two relational variables (Lv et al., 2019; Sun et al., 2025b). This paper uses QAP regression to verify the influencing factors of low-carbon energy consumption structure in China, and the specific steps are as follows: the low-carbon network matrix and the difference matrix of influencing factors in China's provincial energy consumption structure from 2004 to 2022 are matched according to the provincial name. In order to present concise and clear results, 2004, 2010, 2016 and 2022 were selected at 6-year intervals, and divided into four groups, each including the low-carbon network matrix of energy consumption structure, the energy intensity difference matrix (EI), the environmental regulation difference matrix (ER), the foreign investment level difference matrix (FDI), the government expenditure level difference matrix (GOV), the industrial development scale difference matrix (IND), and the technology market development difference matrix(TMD) Urbanization Level Difference Matrix (URB).

Reducing energy intensity (EI) can reduce high-carbon energy demand, promote clean energy use (Degirmenci et al., 2025), and encourage enterprises and research

institutions to invest more in energy technology innovation (Pan and Lin, 2025).; Environmental regulation (ER) promotes the low-carbon energy consumption structure by restricting high-polluting and energy-consuming enterprises and promoting environmental protection investment. The level of foreign investment (FDI) can introduce clean energy technologies, promote the transformation of energy consumption structure, provide financial support and market promotion, and help the development of low-carbon energy industries (Viglioni et al., 2025); The scale of government expenditure (GOV) can directly affect the adjustment of energy consumption structure, promote energy technology innovation, affect the formulation and implementation of energy policies and regulations (Pan and Lin, 2025), and promote low-carbon development. Although the expansion of industrial development scale (IND) has increased energy demand, it has also promoted the transformation of energy consumption structure, promoted technological innovation and energy efficiency improvement; Technology market development level (TMD) promotes energy technology innovation and clean energy technology promotion (Hua et al., 2022); Urbanization level (URB) improves energy efficiency, promotes clean energy use, changes energy consumption structure, and drives energy technology innovation, but it also faces the challenge of energy demand growth, and energy planning and management need to be strengthened. Therefore, the selected variables are shown in Table 2.

Table 2 Selection of influencing factors of spatial correlation between low-carbon energy consumption structure in China

Variable symbols	Meaning	Hypothesis testing
EI	Differences in energy intensity	Energy intensity determines fossil and clean energy demand, and will the magnitude of the difference have an impact on the decarbonized network?
ER	Differences in	Will environmental regulation improve energy efficiency, promote renewable energy,

	environmental regulation	adopt cleaner production technologies, and develop electric mobility and energy storage technologies have a positive impact on decarbonized networks?
FDI	Differences in foreign investment	Foreign investment can promote the development and utilization of low-carbon energy with new technologies, capital and management experience, thereby promoting the decarbonization of the energy consumption structure
GOV	Differences in government spending	Will the difference in government spending determine the level of government funding for fossil energy and clean energy development technologies have a positive impact on low-carbon networks?
IND	Differences in industrial development	The difference in the scale of industrial development determines the total amount and structure of energy supply
TMD	Differences in technology market	The difference in the technology market determines the degree of diffusion of low-carbon technology, and whether the large difference in diffusion will have a positive impact on the low-carbon network
URB	Differences in urbanization	Does the increase in urbanization rate enhance the rigidity of energy demand, and the low quality of urbanization development reduces the level of energy demand.

2.6 Analysis of the influence effect of network structure characteristics

The performance of attribute data often depends on the structure, and the analysis of structural characteristics on specific issues can be examined. On the basis of describing the network structure characteristics of the low-carbon spatial correlation between China's inter-provincial energy consumption structure, this paper is more related to the effect of the network structure of the low-carbon spatial correlation between energy consumption and consumption structure on the "attribute data" of national energy intensity and provincial energy intensity standard deviation. In order to reveal the effect of the low-carbon spatial correlation network of energy consumption structure, this paper empirically investigates the impact of low-carbon energy consumption structure on national energy intensity and inter-provincial differences from the perspective of the overall network structure using the OLS method.

2.7 Data sources

This paper empirically examines the spatial correlation between low-carbon energy consumption structure in 30 provinces in China (excluding Tibet, Hong Kong, Macao and Taiwan), and the sample spans from 2004 to 2022. The sources and processing of the data required for the gravity model are as follows: the low-carbon index of energy consumption structure by province is derived from the comprehensive index measured by the general cosine angle method, and the data of energy consumption by province are derived from the "China Energy Statistical Yearbook" of the corresponding year; The GDP and population at the end of the year are derived from the China Statistical Yearbook of the corresponding year, in which the GDP is deflated according to 2004=100 to eliminate the impact of price factors on GDP. The geographic distance between provinces is expressed as the spherical distance between provincial capitals and is calculated by ArcGIS. Therefore, this paper studies the spatial differentiation of low-carbon energy consumption structure and examines the structural characteristics of the spatial correlation network of low-carbon energy consumption structure in China.

In the process of using QAP analysis to explore the driving factors of low-carbon energy consumption structure, this paper selects the node years of low-carbon energy consumption structure, namely 2004, 2010, 2016 and 2022, and then conducts QAP regression to compare and analyze the influencing factors affecting the low-carbon energy consumption structure. In this paper, energy intensity (EI), environmental regulation level (ER), foreign investment level (FDI), government expenditure level (GOV), industrial development scale (IND), and urbanization level (URB) are selected As a variable indicator. The data sources used in the study are the National Bureau of Statistics, the China Statistical Yearbook and the provincial statistical yearbooks. The difference matrix is established based on the difference of each variable as the explanatory variable, and the difference in the low-carbon index of the energy consumption structure in each year is used as the explanatory variable. The data comes from the statistical yearbook of each province. In order to remove the dimensional influence, the margin standardization method is used for processing.

Among them, energy intensity (EI) refers to the amount of energy consumed per unit of gross domestic product (GDP). It is mainly expressed by the ratio of total energy consumption to the GDP of the region. Environmental regulation (ER) is expressed as the ratio of industrial pollution control investment to industrial added value. The level of foreign investment (FDI) is expressed as the ratio of the total value of trade imports and exports to the regional GDP. Government expenditure scale (gov) is a general expression of government intervention, referring to the existing indicators in the statistical yearbook, using the local fiscal general budget expenditure (100 million yuan) to the regional GDP. The scale of industrial development (IND) is expressed as the ratio of industrial added value to the GDP of the region. The development level of the technology market (TMD) is based on the multi-dimensional subject analysis of the technology market, and the output contract turnover of the technology market is used to measure the development level of the technology market, and the turnover of the

technology market is expressed by the ratio of the GDP of the region. The level of urbanization (URB) is expressed as the ratio of urban population to the total population.

3. Results and discussion

3.1 Decomposition results of Dagum Gini coefficient

Based on the calculated low-carbon index of energy consumption structure, this paper uses the Gini coefficient and decomposition method to measure the overall Gini coefficient, intra-regional Gini coefficient, inter-regional Gini coefficient and contribution rate of the decarbonization of energy consumption structure in China and the four major regions from 2004 to 2022, and the measurement results are shown in Table 3, Table 4 and Table 5. Fig. 1 depicts the change trend of the Gini coefficient of the low-carbon index of energy consumption structure in the country and the four major regions during the study period, and it is found that the Gini coefficient of the low-carbon level of energy consumption structure at the national level increased from 0.0157 to 0.0246 during the entire sample period, with an average annual growth rate of 2.5%, of which the Gini coefficient in 2020 reached the maximum value (0.0251), indicating that the spatial differentiation of low-carbon energy consumption structure at the national spatial scale showed an overall upward trend. From the perspective of the spatial differentiation within the four regions, the low-carbon level of energy consumption structure in the eastern and western regions has the largest degree of spatial differentiation (the average Gini coefficient of the eastern and western regions was 0.0222 and 0.0172, respectively during the study period), followed by the spatial differentiation in the central region (the average Gini coefficient in the central region was 0.0087 during the study period), and the lowest spatial differentiation in the northeast region (the average Gini coefficient in the northeast was 0.0066 during the study period). From the perspective of the changing trend, the eastern and northeastern regions showed an overall trend of rising first and then falling, and the Gini coefficient in the central and western regions showed an overall trend of rising. The Gini coefficient in the western region has the largest change (the difference between the

maximum value and the minimum value is 0.0114), the second largest change in the Gini coefficient in the northeast region (the difference between the maximum value and the minimum value is 0.0034), the change in the Gini coefficient in the central region is the second (the difference between the maximum value and the minimum value is 0.0090), and the change in the Gini coefficient in the eastern region is the smallest (the difference between the maximum value and the minimum value is 0.0080). At the same time, combined with Table 3, it is found that there are still significant spatial differentiation characteristics in the low-carbon level of energy consumption structure in China, and the degree of low-carbon differentiation of energy consumption structure in the eastern and northeastern regions is shrinking, and the degree of regional spatial differentiation in the central and western regions is expanding.

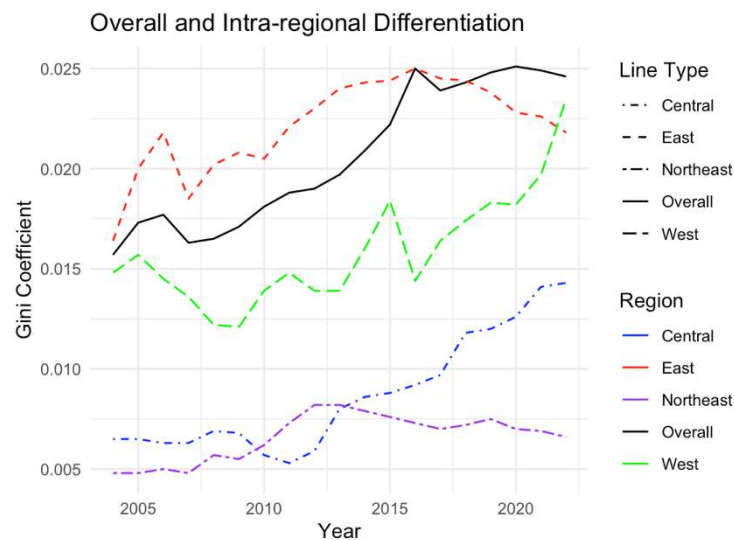


Fig. 1 Overall and intra-regional differentiation

Table 3 Overall and regional differentiation of Dagum Gini coefficient

year	G	east	middle	west	northeast
2004	0.0157	0.0164	0.0065	0.0148	0.0048
2005	0.0173	0.02	0.0065	0.0157	0.0048
2006	0.0177	0.0218	0.0063	0.0145	0.005
2007	0.0163	0.0185	0.0063	0.0136	0.0048

2008	0.0165	0.0202	0.0069	0.0122	0.0057
2009	0.0171	0.0208	0.0068	0.0121	0.0055
2010	0.0181	0.0205	0.0057	0.0139	0.0062
2011	0.0188	0.0221	0.0053	0.0148	0.0073
2012	0.019	0.023	0.0059	0.0139	0.0082
2013	0.0197	0.024	0.008	0.0139	0.0076
2014	0.0209	0.0243	0.0086	0.016	0.0079
2015	0.0222	0.0244	0.0088	0.0184	0.0076
2016	0.0226	0.025	0.0092	0.0175	0.0073
2017	0.0239	0.0245	0.0097	0.02	0.007
2018	0.0243	0.0244	0.0118	0.0217	0.0072
2019	0.0248	0.0238	0.012	0.0228	0.0075
2020	0.0251	0.0228	0.0126	0.0236	0.0069
2021	0.0249	0.0226	0.0141	0.0236	0.007
2022	0.0246	0.0218	0.0143	0.0235	0.0066
Mean	0.0205	0.0222	0.0087	0.0172	0.0066

Figure 2 depicts the trend of the Gini coefficient between the eastern, central, west and northeast regions of China's energy consumption structure during the study period from 2004 to 2022, with the average Gini coefficient between the eastern region and the central region being 0.0284, and the degree of spatial differentiation ranking first among the regions, and then arranging the degree of spatial differentiation in descending order of mean: east and northeast (0.0256).), eastern and western (0.0255), central and western (0.0154), western and northeastern (0.0137), and the spatial differentiation degree of central and northeastern regions was the smallest (0.0100). From the perspective of the change trend, the Gini coefficient fluctuated little between regions on the whole, and the difference in the low-carbon level of energy consumption structure in the central and northeastern regions, the western and northeastern regions

showed a narrowing trend, of which the most obvious decrease in the degree of spatial differentiation was in the eastern and central regions, with an average annual decrease of 0.0014%; The difference between the Gini coefficient between the east and the center, the east and the west, the east and the northeast, and the central and western regions showed an upward trend, with the most obvious increase in the degree of interregional spatial differentiation in the eastern and northeastern regions, with an average annual increase of 0.1%. Overall, since 2004, the difference in the level of decarbonization of energy consumption structure between most regional pairs has generally shown an upward trend, especially after 2010. Table 4 Specifically, the interregional differences between the east and the center, the east and the west, and the west and the northeast increased significantly after 2010, while the differences between the central and northeastern regions and the central and western regions also increased, but they were relatively stable. This indicates that over time, there have been greater differences in the progress of decarbonization of energy consumption structure in different regions, which may be affected by various factors such as regional economic development level, energy resource distribution, policy orientation, and technological progress.

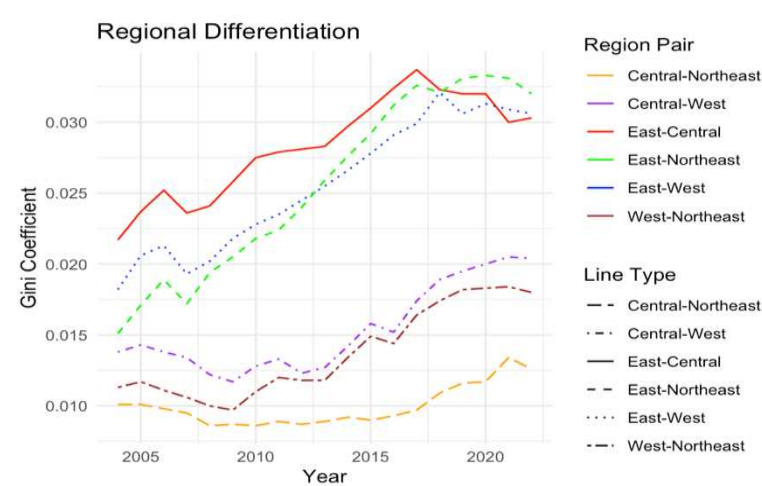


Fig. 2 Degree of differentiation between regions

Table 4 The degree of regional differentiation of Dagum Gini coefficient

year	East- Central	East- West	East- Northeast	Central- West	Central- Northeast	West- Northeast
2004	0.0217	0.0182	0.0151	0.0138	0.0101	0.0113
2005	0.0237	0.0206	0.0171	0.0143	0.0101	0.0117
2006	0.0252	0.0213	0.0189	0.0138	0.0098	0.0111
2007	0.0236	0.0193	0.0172	0.0134	0.0095	0.0106
2008	0.0241	0.0202	0.0194	0.0122	0.0086	0.01
2009	0.0258	0.0218	0.0205	0.0117	0.0087	0.0097
2010	0.0275	0.0228	0.0218	0.0128	0.0086	0.011
2011	0.0279	0.0235	0.0224	0.0133	0.0089	0.012
2012	0.0281	0.0245	0.024	0.0123	0.0087	0.0118
2013	0.0283	0.0255	0.0259	0.0127	0.0089	0.0118
2014	0.0297	0.0266	0.0276	0.0142	0.0092	0.0134
2015	0.031	0.0278	0.0292	0.0158	0.009	0.0149
2016	0.0324	0.0291	0.0312	0.0152	0.0093	0.0144
2017	0.0337	0.0299	0.0326	0.0174	0.0097	0.0164
2018	0.0323	0.0299	0.0321	0.0189	0.0109	0.0174
2019	0.032	0.0306	0.0331	0.0195	0.0116	0.0182
2020	0.032	0.0313	0.0333	0.02	0.0117	0.0183
2021	0.03	0.0309	0.0331	0.0205	0.0134	0.0184
2022	0.0303	0.0306	0.032	0.0204	0.0126	0.018
Average	0.0284	0.0255	0.0256	0.0154	0.01	0.0137

Figure 3 depicts the trend of the contribution rate of Gini coefficients within regions, between regions, and supervariable densities to the overall Gini coefficient from 2004 to 2022. After decomposition, it was found that the Gini coefficient between regions contributed the most to the overall spatial differentiation, and the overall trend showed a trend of increasing first and then decreasing. The contribution rate of intra-

regional differentiation to the overall spatial differentiation during the study period changed little, and the contribution rate of supervariable density to the overall spatial differentiation showed a trend of decreasing first and then increasing during the study period, decreasing from 2004 to 2010 and increasing from 2011, and its contribution rate was always the smallest. Combined with Table 6, it is found that the Gini coefficient between regions is mainly derived from inter-regional differences in the low-carbon index of energy consumption structure, followed by intra-regional differentiation, and finally supervariable density, that is, the low-carbon level of energy consumption structure overlaps between the four major regions, and the contribution of inter-regional differences to the overall difference is always at the level of 50%.

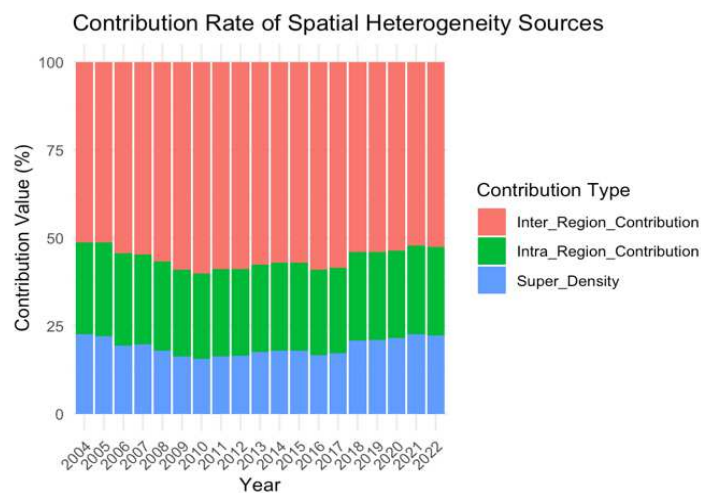


Fig. 3 The degree of spatial differentiation of low-carbon energy consumption structure in China and its sources

Table 5 Spatial differentiation degree and source of Dagum Gini coefficient

year	Within the area (%)	Inter- regional (%)	Supervariable density (%)
2004	26.0458	51.3764	22.5778
2005	26.6565	51.3354	22.0081
2006	26.2504	54.3848	19.3648

2007	25.5311	54.7204	19.7486
2008	25.3671	56.7875	17.8454
2009	24.7347	58.9672	16.2982
2010	24.29	60.2014	15.5086
2011	24.8874	58.8012	16.3114
2012	24.6943	58.8558	16.4499
2013	24.8032	57.5772	17.6196
2014	24.9454	57.0658	17.9889
2015	25.0981	57.0108	17.8911
2016	24.3404	59.0577	16.6019
2017	24.3332	58.4516	17.2152
2018	25.1675	54.0426	20.7899
2019	25.075	53.9706	20.9544
2020	24.8458	53.6038	21.5505
2021	25.2197	52.2234	22.5569
2022	25.1312	52.5767	22.2921
Average	25.1272	55.8426	19.0302

3.2 Network structure characteristics of low-carbon spatial correlation between China's inter-provincial energy consumption structure

3.2.1. The overall network structure characteristics and its evolution trend

Based on the modified gravitational model, the spatial correlation relationship between provinces is determined and the relationship matrix is established, as shown in Figs. 4 and 5 below. In order to show the structure of the low-carbon spatial correlation network of energy consumption, this paper uses ArcGIS and UCINET visualization tools Netdraw to draw the spatial correlation network map of China's energy consumption structure in 2004, 2010, 2016 and 2022, respectively, and the spatial network correlation topology of China's energy consumption structure decarbonization.

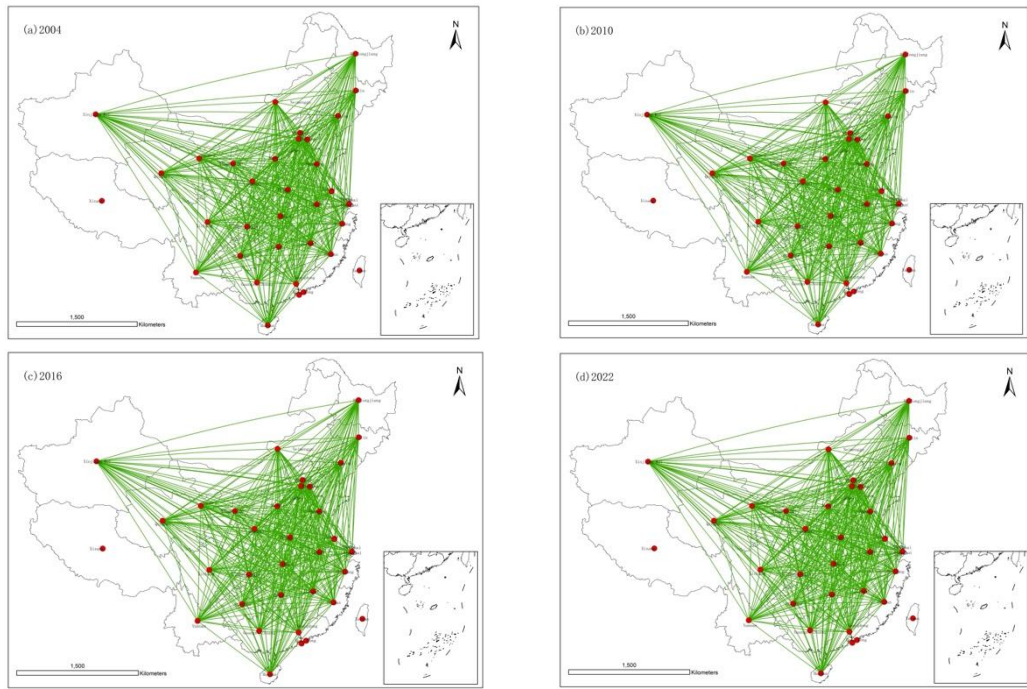


Fig. 4 Spatial correlation network of low-carbon energy consumption structure in China

Combined with the availability of data and the feasibility of ensuring the measurement method, this paper selects 30 provinces and cities in Chinese mainland (except Tibet, Hong Kong, Macao and Taiwan) as research samples of low-carbon spatial correlation networks of energy consumption structure, and uses the method of modified gravity model to obtain the spatial correlation network (i.e., "0-1" matrix) of low-carbon energy consumption structure, and on this basis, the node years 2004, 2010, and 2010 are plotted with the help of Ucinet6.0. The topology of the low-carbon spatial correlation network of energy consumption structure in 2016 and 2020 is compared and analyzed, and the network topology characteristics of Figure 5 are deeply explored based on the network map in Fig. 4. The nodes in the low-carbon spatial correlation network of energy consumption structure represent 30 provinces. The connections of the nodes indicate their spatial correlation, and the direction of the arrows is used to characterize their overflow direction. The low-carbon energy consumption structure of China's provincial energy consumption presents a more typical network structure form. The spatial correlation of low-carbon energy consumption structure between provinces breaks through the traditional limitation of geographical proximity, which not only

produces linkage benefits for energy consumption in neighboring provinces, but also produces spatial correlation with non-neighboring provinces, thus presenting a stable and complex spatial relationship between them.

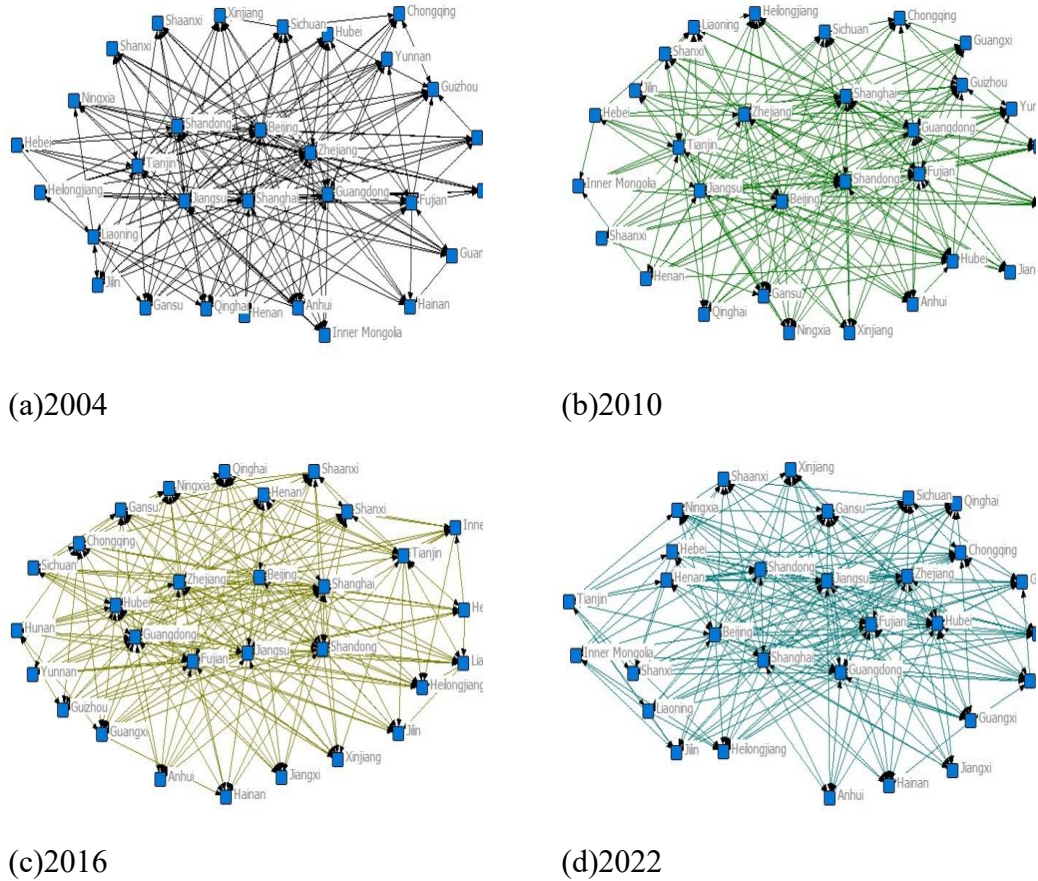
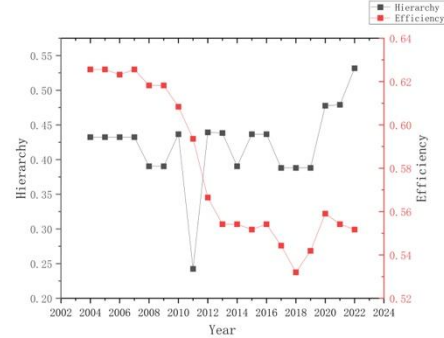
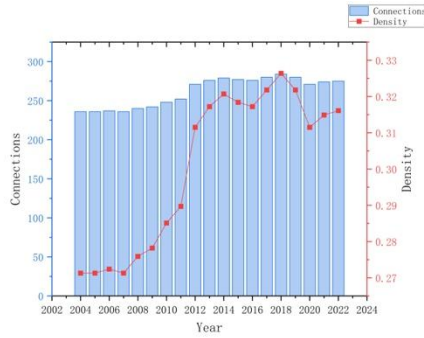


Fig. 5 Spatial network association topology of low-carbon energy consumption structure in China

(1) Network density. Fig. 6 describes the evolution trend of low-carbon spatial correlation network density of inter-provincial energy consumption structure during the sample study period. It can be intuitively found from the figure that the total spatial correlation of low-carbon energy consumption structure between provinces during the sample study period showed a fluctuating and upward trend. The number of correlation relationships in 2004 was 236, and in 2022 it rose to 275, and correspondingly, the overall network density of low-carbon spatial correlation between inter-provincial energy consumption structures also showed a fluctuating upward trend, from 0.2713 in 2004 to 0.3161 in 2022. The fluctuation of network density indicates that the spatial

correlation between China's provinces and the decarbonization of energy consumption structure is becoming more and more close. However, this paper finds that the growth rate of spatial correlation network density fluctuates more frequently after 2012 than before 2012, mainly because after 2012, the implementation of electricity market-oriented reform, large-scale access to renewable energy, and inter-provincial trading mechanism has improved the allocation efficiency but also increased the instability of cross-regional allocation. In 2016, the dual control assessment of energy consumption covered the provincial level, and the carbon intensity constraints during the 12th Five-Year Plan period were included in the binding indicators, and the total carbon emissions in 2024 were included in the accounting system. The expansion of long-distance channels and the construction of multi-energy complementary bases will replace high-carbon provinces with low-carbon electricity and jointly promote the stable fluctuation of the low-carbon spatial correlation relationship between provinces and provinces.

Although the network density showed an upward trend during the sample period, the maximum number of possible relationships between all provinces was 870 (30×29), while the maximum actual relationship between the low-carbon energy consumption structure of the provinces was only 284 (2018), so there is still a lot of room for promoting the low-carbon relationship between provinces and provinces. At the same time, although the higher network density indicates that the spatial correlation between the low-carbon energy consumption structure of the province is becoming closer and closer, with the continuous improvement of network density, the redundant connections in the network may increase. Therefore, it is necessary to maintain appropriate network density to ensure the optimal spatial allocation and transmission of low-carbon energy consumption structure.



(a) Spatial correlation and network density of low-carbon energy consumption structure in China

(b) China's energy consumption structure low-carbon spatial correlation network level and network efficiency

Fig.6 Overall characteristics of the spatial network association topology of China's energy consumption structure for low-carbonization

(2) Network relevance. This paper uses the network correlation degree, network hierarchy and network efficiency in social network analysis to measure the network correlation of China's inter-provincial energy consumption structure low-carbon spatial correlation. The measurement results of network correlation showed that the network correlation degree from 2004 to 2022 was 1, indicating that the relationship between the low-carbon energy consumption structure of China's inter-provincial energy consumption structure is very close, and there is a very obvious spatial correlation and benefit effect. The measurement results of network rank show that the network level of the low-carbon spatial correlation between China's inter-provincial energy consumption structure during the sample study period shows an overall stable and fluctuating trend, as shown in Fig. 3. Among them, the network rating was stable at about 0.4324 before 2007, dropped to 0.3904 from 2008 to 2010, then dropped sharply to 0.2424 in 2011, and then rose to 0.5317 in 2022 in fluctuations, This result shows that the spatial correlation structure of low-carbon energy consumption structure has gradually become relatively strict, and the interconnection and mutual influence of low-carbon energy consumption structure between provinces have gradually increased, as

shown in Fig. 3. The measurement results of network efficiency show that the network efficiency of the low-carbon spatial correlation between China's inter-provincial energy consumption structure showed a downward trend year by year, from 0.6256 in 2004 to 0.5517 in 2022. This shows that the number of connections in the low-carbon spatial correlation network of the energy consumption structure has increased, and the stability of the network has been improved. Based on the measurement results of the above three indicators, with the continuous advancement of the "dual carbon" process, the constraints on energy resource allocation have been strengthened, and the low-carbon spatial structure of the energy consumption structure has been strengthened to a certain extent. At the same time, due to the gradual improvement of China's market system, especially the factor market system (national unified market), the role of the market in the allocation of energy resources has been continuously strengthened, which has reduced the transaction cost of the link between regional energy consumption, so as to increase the correlation between provinces in the low-carbon energy consumption structure, and then enhance the stability of the network.

3.2.2 Analysis of individual network characteristics

Based on the evolution of the overall network of low-carbon energy consumption structure in China, the individual network characteristics of each province in 2022 show new characteristics, so Table 7 reports the measurement results in 2022.

(1) Degree centrality

According to the calculation results of the degree centrality in Table 7, as of 2022, the average degree centrality in the 30 provinces of the country is 48.506, and there are 9 provinces higher than this average, from high to low: Beijing, Fujian, Henan, Guangdong, Hubei, Jiangsu, Shandong, Shanghai, and Zhejiang. These provinces have many relationships with other provinces in the low-carbon spatial correlation network of energy consumption structure. Among them, Shanghai's degree centrality is the highest at 93.103, because there is a spatial correlation and spatial spillover between Shanghai's low-carbon energy consumption structure and 27 other provinces, indicating

that Shanghai is in a central position in the low-carbon spatial correlation network of China's energy consumption structure. Except for Hubei, the provinces above the average degree centrality are in coastal areas, indicating that coastal areas have a strong influence on the spatial correlation and spatial spillover effect of low-carbon energy consumption structure. According to the measurement results in Table 7, Ningxia, Xinjiang, Shanxi, Jilin and Hainan rank in the last five in the country, indicating that the low-carbon energy consumption structure of these provinces has little relationship with other provinces. Energy production positioning and high-carbon lock-in make Shanxi, Xinjiang and Ningxia have a high proportion of "coal + coal chemical industry", low low-carbon index, lack of low-carbon output power, and UHV one-way power transmission makes it an isolated node in the low-carbon correlation matrix. Shanxi and Ningxia have overweight industrial structures, large technological gradient gaps, heavy low-carbon tasks, weak spillover capabilities, and lack of space for joint emission reduction cooperation. Xinjiang and Hainan are geographically and marginal in the market, with high transmission costs and limited low-carbon interaction. The five provinces have little spatial correlation between low-carbon due to high-carbon industry lock-in, one-way power transmission, and geography-market edge. The above reasons lead to the weak spatial correlation between its low-carbon energy consumption structure and other provinces.

Further, according to the calculation results of the point out degree and point in degree in Table 1, the average out-degree of 30 provinces in the country is 9, and there are 11 provinces with a out-degree greater than the mean, from high to low, there are Shanghai, Jiangsu, Beijing, Zhejiang, Fujian, Guangdong, Shandong, Hubei, Henan, Hebei and Tianjin. Some provinces have shown significant spillover effects in the low-carbon spatial correlation network of inter-provincial energy consumption structure due to their "high and low carbon capabilities" and "strong spillover channels". These provinces have a high level of local low-carbonization, low energy consumption per unit of GDP, and a high proportion of renewable energy consumption, taking the lead

in accumulating a "low-carbon technology-management" combination and spreading it to the whole country through standard output. At the same time, as provinces with "net input" of electricity and a "high proportion of green electricity", they reverse the low-carbon pressure to the sending provinces, driving the low-carbon of the entire network chain. In addition, these regions concentrate advanced manufacturing clusters, exporting low-carbon solutions and amplifying knowledge spillover through equipment sales, as well as advantages in carbon asset management, carbon trading, and green finance. The inter-provincial arbitrage generated by the carbon market and green electricity trading in the province has prompted enterprises in high-carbon industries to invest in renewable energy projects in neighboring provinces, forming a cross-provincial linkage of "capital-technology" and driving low-carbon development in neighboring provinces. At the same time, with their status as transportation and information hubs, these provinces have accelerated the flow of low-carbon factors and become distribution centers, with a radius significantly larger than other provinces. Through the five-fold mechanism of "standard output, green power procurement, equipment sales, carbon market arbitrage, and factor distribution", these provinces continue to pass on their low-carbon capabilities to other nodes in the network to promote the overall low-carbon process.

The average in-degree of the 30 provinces in the country is 9, and there are 16 provinces that are higher than the national average, namely Shanghai, Jiangsu, Fujian, Guangdong, Hubei, Chongqing, Guangxi, Gansu, Guizhou, Shaanxi, Heilongjiang, Qinghai, Ningxia, Xinjiang, Shanxi, Jilin, among which the provinces that are higher than their own out-degree are Chongqing, Guangxi, Gansu, Guizhou, Shaanxi, Heilongjiang, Qinghai, Ningxia, Xinjiang, Shanxi, Jilin, most of these provinces are located in remote areas, and the energy endowment is highly dependent on fossil fuels. Therefore, the process of decarbonization of energy consumption structure is relatively slow, and from the perspective of energy endowment, the endogenous driving force of low-carbon energy consumption structure in these regions is relatively weak, so it is

highly affected by the low-carbon energy consumption structure of other provinces, and other provinces will concentrate on the low-carbon spillover of energy consumption structure in these areas. Specifically, some provinces have shown "high in-degree and low out-degree" in the inter-provincial low-carbon network due to resource-policy passive output and industrial gradient transfer net benefit characteristics. On the one hand, Gansu, Qinghai, Ningxia, Xinjiang, Shanxi, Shaanxi and Guizhou, as large-scale renewable energy bases, have simultaneously exported low-carbon technical specifications in the receiving provinces when signing long-term agreements for many years, resulting in these sending provinces passively accepting low-carbon standards. On the other hand, Chongqing, Guangxi, Gansu, Guizhou and Shaanxi undertook the industrial transfer of large power-consuming households in the Yangtze River Delta and Pearl River Delta, but the transfer area lacked the reverse output of advanced low-carbon models, and the degree of point output remained low. The fundamental reason is that these provinces play the role of recipients of low-carbon resources and production capacity in the pattern of "west-to-east power transmission and westward industrial migration", and the coastal advanced low-carbon rules, funds and technologies are constantly imported, while there is a lack of mature model reverse output in the short term.

Fig.6 Individual network characteristics of low-carbon spatial correlation
network in China's energy consumption structure in 2022

Province	degree				betweenness		closeness	
	Out-degree	In-degree	Centrality	Rank	Centrality	Rank	Centrality	Rank
Shanghai	27	10	93.103	1	48.208	1	93.548	1
Jiangsu	26	10	89.655	2	41.498	2	90.625	2
Beijing	25	5	86.207	3	34.598	3	87.879	3
Zhejiang	23	8	82.759	4	34.422	4	85.294	4
Fujian	21	11	82.759	5	33.815	5	85.294	5
Guangdong	20	12	79.31	6	33.7	6	82.857	6
Shandong	20	7	68.966	7	28.544	7	76.316	7
Hubei	16	13	68.966	8	25.43	8	76.316	8
Henan	13	9	51.724	9	23.044	9	67.442	9
Hebei	13	5	48.276	10	18.248	10	65.909	10
Tianjin	10	5	44.828	11	15.928	11	64.444	11
Hunan	9	9	44.828	12	11.659	12	64.444	12
Sichuan	7	9	41.379	13	11.39	13	63.043	13
Chongqing	7	12	37.931	14	8.975	14	61.702	14
Anhui	6	6	37.931	15	7.777	15	61.702	15
Liaoning	6	8	37.931	16	6.937	16	61.702	16
Guangxi	6	10	37.931	17	6.098	17	61.702	17
Jiangxi	6	7	37.931	18	3.942	18	61.702	18
Gansu	4	12	37.931	19	3.648	19	61.702	19
Inner Mongolia	3	7	34.483	20	2.785	20	60.417	20
Guizhou	3	11	34.483	21	2.316	21	60.417	21
Shaanxi	2	10	34.483	22	2.13	22	60.417	22
Heilongjiang	1	11	34.483	23	0.582	23	60.417	23
Yunnan	1	9	34.483	24	0.327	24	60.417	24
Qinghai	0	10	34.483	25	0	25	60.417	25
Ningxia	0	11	31.034	26	0	26	59.184	26
Xinjiang	0	10	31.034	27	0	27	59.184	27
Shanxi	0	10	27.586	28	0	28	58	28
Jilin	0	10	24.138	29	0	29	56.863	29
Hainan	0	8	24.138	30	0	30	56.863	30
Mean	9.16667	9.16667	48.5058	-	15.5	-	67.5406	-

(2) Betweenness centrality

By 2022, according to the measurement results of the betweenness centrality in Fig.6, the average betweenness centrality of 30 provinces in the country is 13.533, and the provinces higher than this average are Shanghai, Jiangsu, Beijing, Zhejiang, Fujian, Guangdong, Shandong, Hubei, Henan, Hebei, and Tianjin from high to low. Among them, Shanghai's betweenness centrality is as high as 48.208, which is much higher than that of other provinces, indicating that Shanghai, as an international metropolis, is in a central position in the spatial correlation network of low-carbon energy consumption structure and plays the role of "intermediary" and "bridge". With the further establishment of Shanghai's central position in national resource trade, logistics

and shipping, energy information services, etc., this control and dominance role will be further strengthened. Jiangsu, Shandong, Zhejiang, Guangdong and other provinces are important landing, or transit ends of our country's main energy transmission channel, and they are also key nodes of LNG reception and natural gas transportation. Beijing, Shanghai, Guangdong, Hubei and other places are the core areas of the carbon market and green electricity trading, which have an important impact on the yield of low-carbon projects in neighboring provinces. The Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei regions are the core areas of low-carbon equipment manufacturing and standard formulation, which play a guiding role in the low-carbon development of other provinces. The scale of green funds and credit in six provinces, including Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang and Shandong, accounts for a high proportion of the country, which has an important impact on the pace of construction of renewable energy bases or industrial transfer projects in the west and northeast regions. In 2022, the total intermediary centrality of the low-carbon spatial correlation network of energy consumption structure is 406.001, and the sum of the intermediary centrality of the top 11 provinces accounts for more than 83% of the total, most of these provinces are in the eastern developed region, while the betweenness centrality of the last six provinces is 0.

(3) Closeness centrality.

According to the measurement results in Table 6, the average closeness centrality of 30 provinces in 2022 is 67.543, and there are 8 provinces higher than this average, from high to low, Shanghai, Jiangsu, Beijing, Zhejiang, Fujian, Guangdong, Shandong, and Hubei. The reason for this is that the eastern coastal provinces have high energy flow efficiency and strong energy acquisition capabilities. Shanghai is close to the center of 98.548, which is the center of the low-carbon spatial correlation network of energy consumption structure, and five provinces including Ningxia and Xinjiang are on the edge due to economic and geographical constraints. The closeness centrality measures the reciprocal of the average path from nodes to other nodes, and the shorter

the path, the higher the value and the faster the information propagation. Shanghai, Jiangsu and other 8 provinces and cities are leading, because of the shortening of physical, market and technical distances, low-carbon signals quickly reach the whole country. These provinces and cities are important nodes in the energy transmission network, which can quickly receive green electricity, low-carbon LNG and other energy, and carbon trading and green electricity trading are concentrated, and price signals can be quickly synchronized. At the same time, it has advantages in the formulation of zero-carbon factories, hydrogen energy and other standards, equipment production capacity, and green finance, and low-carbon factors can spread rapidly, promoting the low-carbon energy consumption structure of the country.

3.2.3 Block model analysis

The following paper reveals the spatial clustering characteristics of the low-carbon correlation network of energy consumption structure in each province through block model analysis. Using the CONCOR method (Convergent Correlations), the maximum segmentation depth is 2 and the centralized standard is 0.2. The 30 provinces in the country are divided into 4 blocks, of which 8 are in the I block, namely Anhui, Hebei, Henan, Sichuan, Guangxi, Guizhou, Jiangxi and Hunan, which are mainly located in the central and western regions. There are 11 members in the II block, namely Qinghai, Hainan, Gansu, Xinjiang, Liaoning, Jilin, Shanxi, Ningxia, Shaanxi, Heilongjiang and Yunnan, which are mainly concentrated in the western region and the northeast region. There are 4 members in the III block, namely Inner Mongolia, Beijing, Shandong and Tianjin, which have the characteristics of "high carbon carrying and low carbon spillover". There are 7 members in the IV block, namely Shanghai, Jiangsu, Guangdong, Hubei, Fujian, Zhejiang and Chongqing, which are in coastal areas or important nodes for energy transmission.

Table 6 Spillover effects of low-carbon spatial related blocks in energy consumption structure

Block	Total number of		Total spillover		Expecte	Actual internal
	receiving		relationships (units)		d internal	proportions
	relationships (units)				proportions	
	Within	Outside	Within	Outside		
	block	block	block	block		
Block I	4	62	4	59	0.24138	0.063492063
Block II	8	101	8	6	0.34483	0.571428571
Block III	7	17	7	51	0.10345	0.120689655
Block IV	23	53	23	117	0.2069	0.164285714

The following paper further reveals the position of the four blocks in the low-carbon spatial correlation network of energy consumption structure through block model analysis (Table 6). According to the previous calculations, there are 275 correlation relationships in the overall correlation network of energy consumption structure, 42 correlation relationships within blocks, and 233 correlation coefficients between blocks and blocks, indicating that there is obvious spatial correlation and spillover effect in the low-carbon energy consumption structure between blocks, as shown in Figure 8.

Among them, there are 63 spillover relationships in the I block, 4 relationships within the block, and 62 relationships that receive spillover from other blocks. The expected internal relationship ratio is 24.14%, and the actual internal relationship ratio is 6.35%, according to the previous definition, the I block is a "two-way spillover" block, the block members both send and receive contacts from other blocks, and the connections from the internal members of the block are relatively small.

There are 14 sending relationships in the II block, 8 relationships belonging to the block, and 101 relationships receiving other blocks. The proportion of expected internal relationships was 34.48%, and the actual internal relationship ratio was 57.14%. The members of this block are mainly provinces with Beijing as the center of geographical distance, and their energy consumption structure is greatly affected by the energy

allocation and low-carbon process of the capital Beijing and mainly receives transmission spillover from regions with a relatively advanced energy consumption structure low-carbon process, so the second block is the "net income" block.

There are 58 issuing relationships in the block III, 7 relationships belonging to the internal block, and 17 relationships receiving other blocks. The expected internal relationship ratio is 10.34% and the actual internal relationship ratio is 12.07%, so the III block is a "net spillover" block. While achieving low-carbon energy consumption structure, members of this block can drive other provinces to carry out low-carbon energy transformation.

There are 140 issuing relationships in the block IV, 23 relationships belonging to the block, and 23 relationships receiving other blocks. The expected internal relationship ratio is 20.69%, and the actual internal relationship ratio is 16.43%, so the IV block is the "broker" block, which not only sends relationships to other blocks, but also receives contacts from external members, playing the role of "intermediary" and "bridge" in the low-carbon spatial correlation network of energy consumption structure.

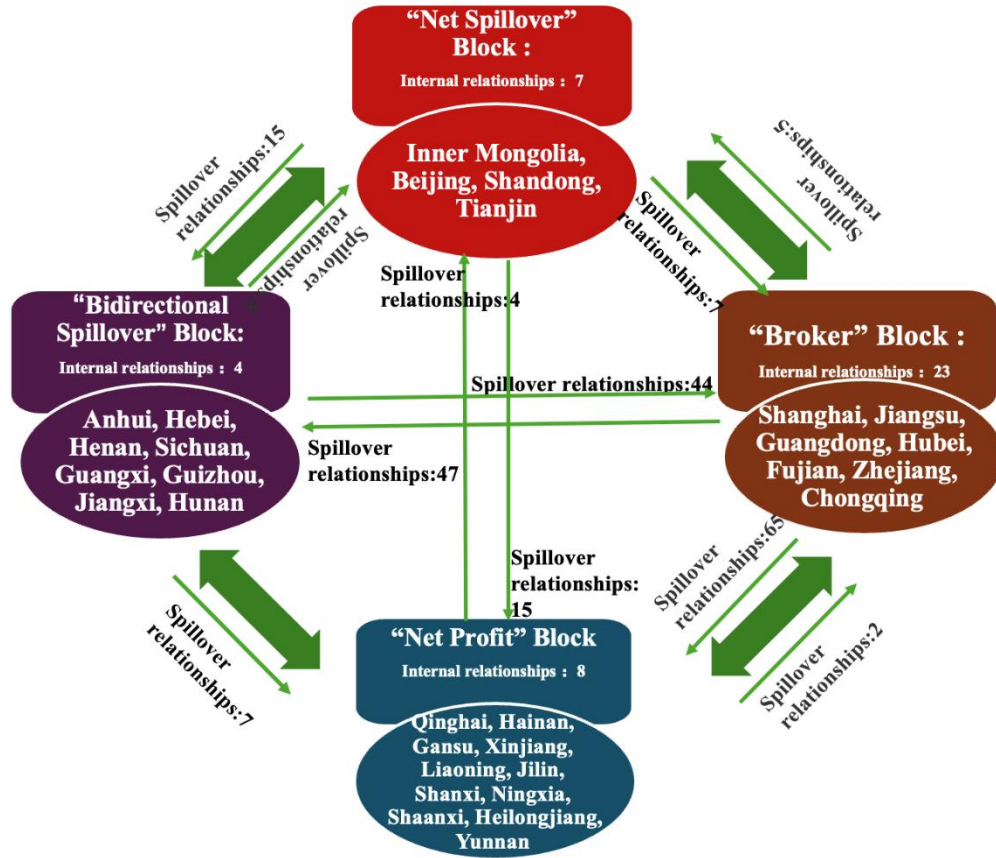


Figure 8 Correlation between the four major blocks of low-carbon energy consumption structure in China in 2022

To investigate the correlation between blocks in the decarbonization of energy consumption structure, this paper calculates the network density matrix of each block according to the distribution of correlations among blocks (as shown in Table 6). At the same time, according to the previous calculations, the network density of the low-carbon spatial correlation of China's inter-provincial energy consumption structure in 2022 is 0.3161, and the network density of any of the four blocks is higher than 0.3161, that is, the network density of the block is greater than the overall network density, so the low-carbon energy consumption structure will be more concentrated in this block. In this paper, the case of block network density greater than the overall network density is assigned to 1, and the case of block network density is less than the overall network density is assigned to 0, and the multi-value density matrix can be converted into an

image matrix, the density matrix and the image matrix are shown in Table 3, and Figure 4 intuitively describes the correlation between the four major blocks. According to Table 3 and Figure 4, block I (including Anhui, Hebei, Henan, Sichuan, Guangxi, Guizhou, Jiangxi, and Hunan, which are "two-way spillover" blocks) and Block II (including Qinghai, Hainan, Gansu, Xinjiang, Liaoning, Jilin, Shanxi, Ningxia, Shaanxi, Heilongjiang, and Yunnan, which are "net income" blocks) not only have a low-carbon correlation with their own energy consumption structure, but also receive "net spillover" from block III (including Inner Mongolia, Beijing, Shandong, and Tianjin) block) and block IV (including Shanghai, Jiangsu, Guangdong, Hubei, Fujian, Zhejiang, and Chongqing, which are the "broker" blocks), indicating that regions with low energy endowments, low economic development levels, and industrial structures that need to be further optimized need to play a leading role in low-carbon transformation in other provinces, especially in leading areas in the low-carbon transformation of energy consumption structure.

Block III (Inner Mongolia, Beijing, Shandong, Tianjin) holds green electricity and resources, Block IV (Shanghai, Jiangsu, Guangdong, Hubei, Fujian, Zhejiang, Chongqing) holds channels and standards, while Block I includes Anhui, Hebei, Henan, Sichuan, Guangxi, Guizhou, Jiangxi, and Hunan, which are "two-way spillover" blocks, and Block II (Qinghai, Hainan, Gansu, Xinjiang, Liaoning, Jilin, Shanxi, Ningxia, Shaanxi, Heilongjiang, and Yunnan, which are "net income" blocks) have both high-carbon "carbon reduction needs" and "undertaking capabilities" Therefore, green current, technology flow, and capital flow can only be poured into Block I and Block II first, and then consider internal mutual assistance.

As a leading low-carbon transformation of the energy structure, Beijing-Tianjin-Hebei, Yangtze River Delta and Pearl River Delta, as well as central energy nodes Hubei and western energy nodes Chongqing, can become the engine in the low-carbon spatial correlation network of the national energy consumption structure. In addition, there is also a low-carbon spillover effect of the energy consumption structure of Block

I to Block IV and Block II to Block IV, which indicates that the comparative advantage between the blocks in the inter-provincial energy consumption correlation network is exerted, and the linkage effect of "a game of chess across the country" is becoming more and more obvious.

Table 7 Density matrix and image matrix of low-carbon space related blocks of energy consumption structure in 2022

Block	Density matrix			
	Block I	Block II	Block III	Block IV
Block I	0.071	0.08	0.25	0.786
Block II	0	0.073	0.091	0.026
Block III	0.469	0.659	0.583	0.25
Block IV	0.839	0.844	0.179	0.548

Block	Adjacency Matrix			
	Block I	Block II	Block III	Block IV
Block I	0	0	0	1
Block II	0	0	0	0
Block III	1	1	1	0
Block IV	1	1	0	1

Table 7 shows the density matrix and image matrix of the low-carbon space correlation blocks of energy consumption structure. The density matrix shows the correlation strength between different blocks, among which the correlation between block 3 and block 2, and block 1 and block 4 are high, which are 0.659 and 0.786, respectively, while the correlation between block 4 and block 3 is the lowest at 0.179. The matrix shows how each block is related to other blocks, where block 3 and block 4 are associated with all other blocks, while block 1 and block 2 are not directly related to other blocks. Overall, Block 3 and Block 4 play a central role in the spatial correlation of low-carbon and are key factors in promoting the decarbonization process.

3.3 QAP regression analysis

As shown in Table 8, in the regression of the QAP difference network, the difference network of various factors driving the decarbonization of energy consumption structure shows different influences in different years.

Table 8 Results of QAP regression analysis

year	2004	2010	2016	2022
Intercept	-0.019507	-0.014638	-0.018166	0.208099
EI	0.004406**	-0.026482*	-0.04162***	0.094247**
ER	0.047653***	0.011887	0.10167***	0.060484
FDI	-0.006848**	0.000489	0.052422***	0.130433***
GOV	0.338774**	0.204926***	0.227486***	0.073097*
IND	0.401063***	0.56347***	0.434177***	0.067519
TMD	0.019784*	0.036303***	0.038128***	0.063956*
URB	0.23457***	0.233394***	0.246561***	0.390337***
R ²	0.875	0.866	0.88	0.502
Adj-R ²	0.874	0.865	0.88	0.498
Observations	870	870	870	870

Note: ***, **, and * indicate significant at the statistical levels of 1%, 5%, and 10%, respectively

1. Energy intensity difference network analysis

In 2004, 2010, 2016 and 2022, the energy intensity difference network (EI) showed a significant level of 5%, 10%, 1% and 10%, respectively, which had a positive to negative impact on the correlation between the low-carbon network of energy consumption structure and from negative to positive. The energy intensity of each province varies greatly, the low-carbon transition is difficult to be consistent, and the demand for low-carbon funds and technology is strong in high-energy-intensity regions. There are differences in energy endowments in different energy intensity regions in our country, and cross-regional energy transportation has become the norm. From 2004 to 2022, the difference in energy intensity between provinces promotes the spatial correlation of low-carbon energy consumption structure for two reasons: First, resources and technologies complement each other. Areas with high energy intensity

are rich in resources but backward in technology, and cooperation with areas with low energy intensity can introduce low-carbon technology and management experience. For example, the western region has high energy intensity, including coal and wind energy, and cooperates with the east to introduce clean utilization and wind power development technologies to achieve low-carbon transformation. On the contrary, areas with low energy intensity have advanced technology but lack resources and cooperate with areas with high energy intensity to ensure energy supply and promote low-carbon development. The second is the complementary advantages of industrial synergy. develop low-carbon industries in areas with high energy intensity, such as new energy equipment manufacturing; Technical support and market access are provided in areas with low energy intensity. For example, the east provides new energy vehicle technology for the west, and the west develops the new energy vehicle industry to achieve a win-win situation.

2. Analysis of environmental regulation difference network

The difference in environmental regulation level (ER) had a positive impact on the low-carbon spatial spillover of energy consumption structure at the significance level of 1% in 2004 and 2016 but had no significant impact in 2010 and 2022. This shows that in 2004 and 2016, the complementarity of differentiated environmental regulations led to the formulation of suitable low-carbon strategies in different provinces. The eastern region has strong environmental regulations, and the application and promotion of low-carbon technologies are rapidly promoted through strict emission standards and technological innovation incentives. The environmental regulations in the central and western regions are relatively relaxed and coordinated emission reduction can be achieved through cooperation with the eastern region and the introduction of low-carbon technology and management experience. Differences in environmental regulations promote regional cooperation, such as establishing cross-regional environmental governance alliances, sharing emission reduction technologies and funds, promoting low-carbonization, reducing regional carbon emission differences, and driving low-carbon development in the surrounding area through spatial spillover effects. Strict and effective environmental regulations encourage enterprises to adopt environmentally friendly energy technologies and production methods, and promote the low-carbon energy consumption structure.

3. Analysis of foreign direct investment difference network

Except for the insignificant impact in 2010, the difference in foreign direct investment level (FDI) experienced a shift from negative to positive impact on the spatial spillover of low-carbon energy consumption structure in 2004, 2016 and 2022. In the negative stage, foreign investment tends to be in areas rich in energy resources, where the industrial structure is single, high energy consumption and high pollution, foreign investment may consolidate high-carbon industries, and foreign enterprises pay attention to their own profits in the early stage, low-carbon technology transfer lags behind, and there is technological asymmetry, which limits local enterprises from absorbing low-carbon technologies. In the positive stage, after the increase in foreign investment, technical cooperation with local enterprises will be carried out, low-carbon technology and management experience will be spread to promote technological upgrading and industrial transformation. In 2022, differences in foreign investment will promote regional coordinated development, and low-carbon technologies will flow and share in different regions, creating spatial spillover effects and promoting the formation of low-carbon networks. Over time, foreign enterprises and local enterprises have deepened their cooperation, technology spillover effects have emerged, and environmental regulatory policies have been improved, prompting foreign enterprises to increase investment in low-carbon technologies and optimize the energy consumption structure.

4. Analysis of government expenditure difference network

In 2004, 2010, 2016 and 2022, the difference in government expenditure level (GOV) had a positive effect on the spatial spillover of low-carbon energy consumption structure, but the size of the promotion effect was gradually declining. Initially, areas with high intervention levels became low-carbon development demonstration zones, taking the lead in implementing policies such as carbon emission trading, green taxation, and energy conservation and emission reduction subsidies, promoting the application and promotion of low-carbon technologies, and demonstrating and driving the low-carbon process in low-intervention areas. With the narrowing of the difference in the level of government intervention, the adaptability of each region is enhanced, and the marginal effect of policy differences is decreasing. After the improvement of the market mechanism, the necessity of government intervention is reduced, and the positive effect of the level of intervention on the spillover of low-carbon space has weakened.

5. Analysis of the difference network of industrialization process

The IND of various regions had a gradually weakening positive effect on the spatial spillover of low-carbon energy consumption structure in 2004, 2010, and 2016, but it had no significant effect in 2022. The difference in the process of industrialization has led to different industrial structures and energy consumption structures in different provinces. In areas where the industrial structure is optimized, the progress of energy utilization technology and the application of new energy have improved the energy utilization efficiency of the industrial sector and reduced unit carbon emissions. In 2004, China's industrialization accelerated, and the level of industrialization varied greatly among provinces. Due to its strong economy, highly industrialized areas take the lead in applying low-carbon technologies, which have a positive spatial correlation with the surrounding area, and also transfer high-energy-consuming industries to the surrounding area to expand the spatial correlation of low-carbon. In 2010, low-carbon policies were promoted, and the relationship between high-industrialized areas and surrounding low-carbon spaces was strengthened, and their own low-carbon level was improved, driving the low-carbon development of the surrounding areas. In 2016, the industrialization differences in various provinces narrowed, the low-carbon effect in highly industrialized areas was remarkable, the improvement space was limited, the spatial correlation effect of low-carbon was attenuated, and the development of low-carbon energy technology attenuated the marginal effect of industrialization differences on low-carbon spatial correlation. In 2022, the difference in industrialization between provinces will be further narrowed, and low-carbon development will be balanced across the country.

6. Analysis of the difference network of technology market development

The development of the technology market (TMD) has had a gradually increasing positive effect on the low-carbon space spillover of the energy consumption structure in 2004, 2010, 2016 and 2022. In terms of technology diffusion and innovation spillover, advanced regions disseminate low-carbon technologies through demonstration projects, etc., and promote the diffusion of low-carbon technologies in various ways among provinces with different levels of technology market development. In terms of optimizing market mechanisms and resource allocation, provinces with the development level of high-tech markets have established and improved technology trading platforms, and tilted resources to low-carbon fields through policy guidance and market mechanisms. In terms of regional low-carbon technology collaborative allocation, the difference in the development level of technology markets has prompted

regional cooperation to strengthen cooperation, form a coordinated development pattern, optimize resource allocation, and enhance the spatial correlation impact on the low-carbon energy consumption structure

7. Urbanization level difference network analysis

The level of urbanization (URB) has a gradually increasing positive effect on the spatial spillover of low-carbon energy consumption structure in 2004, 2010, 2016 and 2022. With the evolution of urbanization, infrastructure continues to improve, and areas with high urbanization increase investment to improve energy efficiency, such as smart grid upgrades, transportation optimization, and demonstration drives other regions. At the same time, it takes the lead in applying low-carbon technology, investing in research and development, launching innovative achievements such as new energy vehicles, and rapidly spreading to low-urbanization areas through the improvement of the technology market. In the process of industrial transfer and upgrading, low-urbanization areas receive industries and upgrade, eliminate backward production capacity, introduce low-carbon technologies, optimize the energy consumption structure, drive surrounding low-carbon development, form synergies, and optimize the national energy consumption structure.

3.4 Analysis of the impact effect of low-carbon spatial correlation network structure of China's inter-provincial energy consumption structure

In this paper, the standard deviation of inter-provincial energy consumption intensity and national energy intensity are used as interpreted variables, and simple OLS regression is carried out on the three overall network characteristic indexes of network density, network hierarchy and network efficiency (both explanatory variables and dependent variable are taken as natural logarithms).

Table 9 OLS regression results of overall network structure effects

		Standard deviation of inter-provincial energy intensity
	National energy intensity	
Network density	-4.880***	-2.890*

	(-9.418)			(-1.783)
Network hierarchy		-0.381		0.011
		(-0.638)		(0.134)
Network efficiency			5.987***	-3.597*
			(9.978)	(-1.826)
_cons	-6.189***	-0.647	2.968***	-5.053
	(-9.902)	(-1.218)	(8.976)	(-1.671)
N	19	19	19	19

According to the regression results in Table 9, the regression coefficients of network density, network hierarchy and network efficiency of the low-carbon spatial association of energy consumption structure are -4.880, -0.381 and 5.987, among which the regression coefficients of network density and network efficiency are significant, indicating that the network structure of the low-carbon spatial correlation of energy consumption structure has a significant impact on energy intensity, and the fluctuation of the overall density of the low-carbon spatial correlation network of energy consumption structure and the decrease of network efficiency can significantly reduce the energy intensity. On the one hand, the increase in network density means an increase in the overall number of network links, which effectively limits and narrows the spatial difference in energy intensity between provinces (the low-carbon systematic energy consumption structure effectively narrows the spatial difference in energy intensity between provinces, which will help reduce energy intensity). Therefore, from the perspective of improving energy density, in order to promote the low-carbon energy consumption structure in a systematic, orderly and coordinated manner, we should continue to play the role of the government and the market, create more "channels" for the low-carbon transformation of the energy structure from the whole country, and continuously strengthen the spatial connection of the low-carbon energy consumption structure. On the other hand, the reduction of network efficiency means that the connection in the low-carbon spatial correlation network of the energy consumption

structure has increased, breaking the "comparative advantage" of some provinces in the process of low-carbon transformation, so that the gap between provinces in the network in terms of economy, technology, and talents has been narrowed, thereby effectively reducing their respective energy intensities. Therefore, from the perspective of reducing network efficiency, we should continue to accelerate the construction of energy market system and carbon trading market, reduce the cost of low-carbon spatial communication and connection of energy consumption structure, and improve the stability of low-carbon spatial correlation network of energy consumption structure.

This paper uses the standard deviation of inter-provincial energy intensity to measure the difference between provinces, which also reflects the spatial equity of energy consumption to a large extent. According to the regression results in Table 10, the regression coefficient of network density is -2.890, indicating that there is a negative correlation between its improvement and the decarbonization of energy consumption structure. Specifically, the increase in network density will lead to an increase in the difference in energy intensity between provinces (measured by standard deviation), which in turn will reduce the spatial equity of decarbonization of energy consumption structure. The reason may be that the increase in network density has allowed some regions to occupy a more favorable position in the energy network and obtain more energy resources or more efficient energy distribution, while others are at a disadvantage, exacerbating the spatial imbalance in the energy consumption structure. At the same time, the regression coefficient of network efficiency is -3.597, and the absolute value is larger, indicating that its improvement has a more significant negative impact on the spatial fairness of the low-carbon energy consumption structure. This may be because the improvement of network efficiency makes energy use more efficient in specific regions, attracting more energy consumption to be concentrated in these regions, further widening the difference in energy intensity between regions, and reducing the spatial equity of decarbonizing energy consumption structure.

4. Conclusion and countermeasures

4.1 Conclusion

Based on the data of Chinese mainland provinces from 2004 to 2022, this paper constructs a low-carbon index of energy consumption structure based on the angle cosine method and investigates the difference in the low-carbon level of energy consumption structure by using the Dagum Gini coefficient decomposition based on the indexed index. The influencing factors and effects of the spatial correlation network structure of inter-provincial energy consumption in China are empirically investigated by using social network analysis.

From the perspective of the region, the spatial differentiation degree of low-carbon energy consumption structure in the eastern and western regions is stronger than that in the central region and the northeast region, and the spatial differentiation between the eastern and central regions is the largest, and the contribution rate of the Gini coefficient between regions to the overall spatial differentiation degree is the largest, showing a trend of increasing first and then decreasing as a whole.

From the perspective of the overall network structure characteristics, during the sample study period, the network density of the low-carbon spatial association of China's inter-provincial energy consumption structure showed a fluctuating and upward trend, and the low-carbon connection between provinces became more and more close. The measurement results of network correlation degree show that the low-carbon spatial correlation network of China's inter-provincial energy consumption structure has a good connectivity effect, and the low-carbon energy consumption structure between provinces has a general spatial correlation and spatial spillover effect. At the same time, the network efficiency is decreasing year by year, the network hierarchy is getting stricter year by year, the network stability is gradually improving, and the spatial structure of "strict hierarchy" is stable in fluctuations.

From the perspective of individual network structure characteristics, the degree centrality of Beijing, Fujian, Henan, Guangdong, Hubei, Jiangsu, Shandong, Shanghai

and Zhejiang is higher than the national average, while the degree centrality of Ningxia, Xinjiang, Shanxi, Jilin and Hainan ranks in the last five in the country. The betweenness centrality of 11 provinces in Shanghai, Jiangsu, Beijing, Zhejiang, Fujian, Guangdong, Shandong, Hubei, Henan, Hebei and Tianjin is higher than the national average, and the sum of the betweenness centrality of the top 11 provinces accounts for more than 83% of the total, and the betweenness centrality of the bottom 6 provinces is 0. Shanghai, Jiangsu, Beijing, Zhejiang and other economically developed provinces play an important role as intermediaries and bridges in the low-carbon spatial correlation network of energy consumption. The eight provinces of Shanghai, Jiangsu, Beijing, Zhejiang, Fujian, Guangdong, Shandong and Hubei are higher than the national average and play the role of central actors in the network, while Ningxia, Xinjiang, Shanxi, Jilin and Hainan, which rank the last five in terms of closeness centrality, play the role of marginal actors in the network.

The analysis results of the block model show that the blocks composed of eight provinces in the eastern, central and western regions, Anhui, Hebei, Henan, Sichuan, Guangxi, Guizhou, Jiangxi and Hunan, play a "two-way spillover" role in the low-carbon spatial correlation network of energy consumption structure. The blocks composed of 11 provinces in Qinghai, Gansu, Xinjiang, Ningxia, Shanxi, Jilin, Liaoning, Heilongjiang, Shanxi and Yunnan concentrated in the northwest and northeast regions play a "net beneficiary" role in the network; The four provinces of Inner Mongolia, Beijing, Shandong and Tianjin play a "net spillover" role in the low-carbon spatial correlation network of energy consumption structure. The other seven provinces play the role of "brokers" in the network.

The results of the analysis of influencing factors show that in 2004, 2010, 2016 and 2022, the impact of energy intensity on the low-carbon network of energy consumption structure has a positive impact from positive to negative, and then from negative to positive, the positive impact of environmental regulation has decreased, the impact of foreign investment has changed from negative to positive, the positive effect

of government intervention and industrialization has existed but continued to decline, and the positive effect of technology market development and urbanization has gradually increased. The results of effect analysis show that the network structure of the low-carbon spatial correlation of energy consumption structure has a significant impact on the national energy intensity, the fluctuation and increase of the overall network density negatively impact the national energy intensity, and the decrease of network efficiency and network grade can significantly positively affect the energy intensity. Strengthening the network structure of low-carbon spatial correlation between energy consumption structure has become an important driving mechanism for the convergence of energy intensity between regions.

4.2 Policy enlightenment and suggestions

The above analysis conclusions provide a strong empirical basis for policy formulation. To translate these findings into actionable strategies, we propose a comprehensive policy framework that covers the following key actions:

First, comprehensively understand the spatial differentiation of low-carbon energy consumption structure, spatial correlation and network structure characteristics: establish a low-carbon monitoring system for energy consumption structure, regularly evaluate spatial differentiation and network structure characteristics, and promote multidisciplinary cooperation to study the formation mechanism of spatial differentiation, correlation and network characteristics.

Second, adjust and optimize the spatial correlation network structure of low-carbon energy consumption structure: formulate differentiated policies for the eastern, central, western and northeastern regions to promote coordinated regional development, and establish cross-regional cooperation mechanisms to promote resource sharing, technology exchanges and industrial cooperation.

Third, fully consider the plate structure characteristics of the low-carbon spatial correlation network of energy consumption structure: support Anhui, Hebei and other provinces to play a leading role in the "two-way spillover" sector and promote the

diffusion of low-carbon; strengthen infrastructure construction and technology introduction in Qinghai, Gansu and other provinces, and improve the capacity of the "net benefit" sector; use the radiation effect of Inner Mongolia, Beijing and other provinces to play the leading role of the "net overflow" plate; Clarify the functional positioning of other provinces and optimize the participation of regional cooperation in the "broker" sector.

Fourth, in terms of driving factors, precise policies should be implemented according to the changing trend of energy intensity to optimize the energy consumption structure. strengthen environmental supervision and formulate differentiated environmental regulatory measures; encourage foreign investment in low-carbon fields and strengthen project environmental assessment; shift from direct intervention to create a policy environment and promote the upgrading of industrial structure; Improve the technology trading market, accelerate urbanization, and improve energy efficiency.

Fifth, give full play to the positive role of the overall and individual network structure: strengthen inter-provincial cooperation, improve network density and efficiency, and promote the optimal allocation of energy resources; Support provinces with high centrality and intermediary centrality to drive surrounding development, and at the same time help low-value provinces to enhance their network status.

5. Research limitations and future directions

Current research mainly focuses on the direct relationship between low-carbon energy consumption structure and provincial energy intensity, while less consideration is given to the structural effect of individual networks. The individual network structure effect refers to the influence of each province's position and connection relationship in the spatial correlation network of energy consumption on economic resilience. For example, a province at the heart of the network may have easier access to energy technology innovation resources and energy cooperation with other provinces, positively impacting economic resilience. However, current research has not

constructed effective indicators of individual network structure to measure this effect, leading to insufficient analysis of the role of individual network structure in it.

Declarations

Competing Interests: The authors have no relevant financial or non-financial interests to disclose.

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

Data availability statements: The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

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