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Study on the Spatial Association Network Structure of Urban Digital Economy and Its Driving Factors in Chinese Cities

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Abstract: The digital economy has become an important engine for global economic development by promoting optimal resource allocation and advancing industrial restructuring. Based on the panel data from 279 prefecture-level cities in China from 2012 to 2021, this paper constructs the spatial association networks of urban digital economy using a modified gravity model and analyzes the complex network characteristics and driving factors of urban digital economy growth by the social network analysis methods and the Quadratic Assignment Procedure (QAP). This study finds that (1) the level of urban digital economy in China shows a rising trend year by year and displays an uneven spatial distribution. (2) Spatial association networks of urban digital economy are relatively well-connected, with increasing density and stability of spatial associations, yet some hierarchical structure remains, and overall connectivity still needs to be improved. (3) Most cities in the east region occupy the core positions within the complex network, significantly influencing the overall complex network through a "siphon effect", while cities in the central region play more of a "bridge" role in the spatial association network. In contrast, cities in the northwest, northeast, and southwest regions are situated on the periphery of this spatial association network. (4) The economic development level, informatization level, technological innovation, urbanization level, industrial structure, and human capital contribute to the formation of the spatial association network of the digital economy. Based on these conclusions, specific policy implications for the future development of the spatial association network of the urban digital economy are proposed.

Keywords: digital economy; spatial association network; complex network analysis; driving factors; QAP analysis

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Academic Editor: Ludovico Minati

Received: 28 February 2025
Revised: 20 April 2025
Accepted: 23 April 2025
Published: 27 April 2025

Citation: Yang, W.; Yan, M.; Wang, X.; Shi, J. Study on the Spatial Association Network Structure of Urban Digital Economy and Its Driving Factors in Chinese Cities. *Systems* **2025**, *13*, 322. https://doi.org/10.3390/systems13050322

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1. Introduction

The report from the Communist Party of China's 20th National Congress has advocated for the establishment of digital industry clusters that are globally competitive, the rapid acceleration of the digital economy, and the close connection between digital and real economies [1]. A new economic paradigm is being created based on the economy driven by digital technologies. As the world's economies are changing, a new trend in global development is the merging of the digital and physical sectors. The rise of the digital economy has injected new momentum into China's economic and social progress, opening new fields and providing new driving forces [2]. It has rapidly become a key driver of economic growth and social development [3]. The digital economy, by leveraging modern information networks, has transcended geographical limitations, facilitated the networked sharing of knowledge, technology, and data, and strengthened economic linkages between

cities. This connection not only optimizes the economic cycle [4] but also promotes the coordinated development of urban economies [5].

However, there are significant differences in resource allocation, economic foundation, scientific and technological level, and policy environment among different regions in China that have implemented region-specific policies and investments, which cause apparent disparities in the growth of the digital economy across various areas. This discrepancy has a significant influence in several areas, including regional economic coordination and the balanced development of the digital economy itself.

Existing studies have preliminarily discussed the regional differences of the digital economy, mainly focusing on the construction of measurement indicators [6], the analysis of influencing factors [7,8], and the analysis of economic effects [9]. However, most of the existing literature treats regions as independent individuals and uses traditional geographical or statistical methods to analyze static differences, which fail to fully reveal the dynamic network properties of the digital economy's spatial correlation. Especially in the context of digital technology breaking through the limitations of space and time, the complex network correlation between regions through the flow of data elements, the collaboration of the digital industry chain, and the diffusion of technology is becoming a key mechanism to reshape the regional economic pattern. This network development mode makes the digital economy level of a single region not only depend on the local resource endowment but also be deeply affected by its place and function within the overall structure of the network. The complex network structure is an important feature indicating the connection of the digital economy, which is trans-regional and multithreaded. Therefore, a deep understanding of the complex network structural features of the spatial association in the digital economy, exploring its influencing factors and complex network effects, is of great significance for narrowing the digital divide between cities, constructing the development model of a new economy, and fostering high-level growth in China's economy.

The rest of this paper is arranged as follows: Section 2 includes a literature review and research hypothesis. Section 3 discusses the research methodologies, model setting, and variable selection. Section 4 examines the spatial association network of the urban digital economy in China. Section 5 presents a study of the driving elements of the digital economy spatial association network. Finally, Section 6 closes this article by discussing the policy implications.

2. Literature Review and Research Hypothesis

2.1. Research on the Development of Digital Economy

Don Tapscott [10] pioneered the idea of the digital economy and summarized its characteristics, including complete digitization, high knowledge intensity, pervasive virtualization, and interconnectivity. Some academics conducted in-depth research on how the digital economy developed. In China's quest for economic progress, the digital economy plays a crucial role as an integral part of the current economic system. According to Dan [11], by adjusting industrial structures and introducing new green technologies, the digital economy may propel top-notch green development. Wang and Chen [12] highlighted that the digital economy creates new opportunities for shaping the pattern of economic development. Wang et al. [13] emphasized that the important avenue digital economy has become a new engine for promoting top-notch economic development. Therefore, we make the following hypothesis:

H1: *The growth of the digital economy's spatial association network is positively impacted by the economic development level.*

With the quick advancement and widespread use of spatial econometric techniques in recent years [14], as well as complexity theory and social network analysis methods, an increasing number of academics have focused on the spatial correlation properties [15]. When it comes to quantifying the spatial correlation feature of the digital economy, scholars have widely used spatial weight matrices to construct Moran's index, a classic indicator that measures the similarity and spatial dependence of economic activities between regions. Additionally, the application of inverse distance spatial weight matrices [16] provides a geographically distance-based alternative for assessing spatial correlation. However, the digital economy network exhibits spatial heterogeneity and complexity, which can significantly influence how spatial relationships are formed [17]. It is challenging to create and sustain a direct spatial linkage of the digital economy between geographically disparate places despite the fact that digital technology has partially overcome the constraints of time and space. Therefore, we make the following hypothesis:

H2: *Geographical distance has a negative effect on the formation of spatial association network of digital economy.*

2.2. Research on the Driving Factors of Digital Economy

Dewan [18] carried out a comprehensive investigation on the advantages of Information and Communications Technology (ICT) investment in 36 countries, finding that a high degree of digital foundation in developed countries significantly impacts economic development. The development of information technology not only enables enterprises to share data, enhances the productivity of industrial sectors, and promotes industrial development, but also reduces regional disparities between cities. Therefore, the widespread application of digital technology offers economic and social advantages to countries worldwide [19]. Innovation in technology is the main engine propelling the growth of the digital economy. Recently, researchers have looked into the mechanism of technological innovation in the digital economy from multiple dimensions. Rammer et al. [20], based on the data of German enterprises, verified that AI technology can enhance the innovation ability of enterprises and improve the speed of product iteration, thus expanding the scale effect of the digital economy. Zhong et al. [21] noted that the development of spatial relational network structure benefits from technological progress. Therefore, we make the following hypothesis:

H3: *The degree of technical innovation and information technology has a favorable impact on the development of the digital economy's spatial association network.*

Urbanization level and industrial structure are important structural variables affecting the evolution of the digital economic landscape. Acemoglu and Restrepo [22] point out that urbanization accelerates the integration of digital technology across sectors through the agglomeration effect. According to the modular innovation theory of Yoo et al. [23], the increase in the proportion of service industries promotes trans-regional digital economy network connectivity by enhancing inter-industry technical compatibility. Li et al. [24] point out that urbanization and industrial structure are the primary drivers of the spatial association network and show significant variations over time and across different regions. Therefore, we make the following hypothesis:

H4: *Urbanization and industrial structure play a positive role in shaping the spatial association network of the digital economy.*

As the carrier of knowledge and skills, one key factor in the growth of the digital economy is human capital. The author of [25] emphasizes that human capital with advanced digital skills is the source of innovation in the digital economy. Zhang et al. [26] found that human capital narrows the urban–rural gap through fostering digital economic development. Wang et al. [27] point out that the difference in human capital level plays a key role in shaping the spatial correlation network. Therefore, we make the following hypothesis:

H5: *Human capital has a positive influence on the formation of the spatial correlation network of the digital economy.*

Although traditional theories hold that marketization can help improve the efficiency of resource allocation, some studies have shown that excessive marketization levels may inhibit the development of the digital economy due to problems such as market structure imbalance and lagging regulation. Song et al. [28] found that the degree of marketization has no significant influence on the role of the digital economy. Garcia-Murillo and MacInnes [29] pointed out that, in highly market-oriented economies, capital and talent are more likely to converge in developed regions with well-developed digital infrastructure, resulting in less developed regions falling into the "digital poverty trap". Therefore, we make the following hypothesis:

H6: *The level of marketization negatively affects the formation of the spatial correlation network of the digital economy.*

2.3. Research on the Digital Economy Spatial Association Network

Lately, the study of spatial association networks has garnered a lot of interest from international scholars. Fingleton [30] constructs a spatial association network of inter-regional economic ties and finds that the location of a region in the development of the economic network is closely tied to its inherent structure and interactions. By studying the spatial network, Dilworth et al. [31] found that the "digital divide" between British regions has intensified over time. There has not been much study performed on the structural characteristics and driving factors of China's digital economy spatial association network [32]. Some scholars have studied the spatial association and spatial spillover mechanism of the digital economy, but mainly at the provincial level. Zhu and Chen [33] have made an attempt to probe into the core role of the spatial distribution of the digital economy in the development of Hangzhou city. At the provincial level, the complex network structure is the primary focus of most of these studies, but few scholars have examined it at the prefecture-level city scale. Zhang et al. [34] discovered that the development shows significant spatial distribution differences, with noticeable disparities in the levels and capabilities of the digital economy across different regions, forming a differentiation between core and peripheral regions. Li et al. [35] hold the view that the progress in the realm of the digital economy promotes regional green innovation efficiency enhancement through spatial spillover effects. Technological innovation flow strengthens the digital economy links between different cities, forming a complex spatial association network structure. Spatial heterogeneity leads to significant differences in digital economic activities across different regions and the establishment of a complex network supporting the digital economy [36]. The driving factors contribute to shaping the spatial association network of the digital economy.

On the whole, the existing research focused on the economic advantages that the digital economy creates, and further study is needed on its characteristics in spatial association networks and the driving factors of spatial association network within China's urban digital economy. Therefore, the contributions of this paper are threefold. First, this paper makes

up the related research on digital economy from an overall complex network perspective. In order to investigate the spatial association characteristic across 279 Chinese cities at the prefecture level, we build the intricate topological network of the urban digital economy. We next examine the spatial association network distribution in each city at the network level. Second, the centrality of the spatial association network, along with the spatial clustering mode of the digital economy through block modeling and structural hole analysis, are examined in this paper. Finally, the driving factors influencing the formation of spatial association networks of urban digital economy are deeply explored using QAP (Quadratic Assignment Procedure) analysis in social network analysis. This study not only enriches the research content on the characteristics of the spatial association networks of the digital economy but also provides new perspectives and methods for future research.

3. Research Design

3.1. Research Methods

3.1.1. Modified Gravity Model

The gravity model theory, based on Newton's universal gravitation theory, has evolved through understanding and application into an economic gravity theory with broad application prospects [37]. In practical applications, we need to modify the gravity model according to the research question. Existing literature often uses the gravity model to establish spatial connections [38]. Considering the digital economy's cross-regional characteristics to calculate spatial associations in the digital economy, the gravity model used in this paper has been adjusted as follows:

$$R_{ij} = K_{ij}\frac{\sqrt[3]{G_iP_iE_i}\sqrt[3]{G_jP_jE_j}}{D_{ij}^2}, \quad K_{ij} = \frac{E_i}{E_i + E_j}, \quad D_{ij} = \frac{d_{ij}}{g_i - g_j} \tag{1}$$

where i and j denote cities; R_{ij} implies the spatial relevance distance of the digital economy between cities; P_i represents total population; G represents total GDP; E refers the digital economy development index; K_{ij} represents the contribution rate in the growth of digital economy link between cities; d_{ij} implies the geographical distance between cities; g represents the economic growing performance level, calculated by GDP per capital. According to Formula (1), we calculate the gravitational matrix of digital economy associations between cities, constructing a 279 × 279 directed binary asymmetric matrix.

3.1.2. Social Network Analysis

Through Social Network Analysis (SNA), researchers can investigate the complex web of connections that define relationships in societal networks [39]. It primarily includes three main components: whole network analysis, individual network analysis, and blockmodeling analysis. In China, the complex network attributes of the digital economy in general are usually described using four dimensions: network efficiency, network density, network hierarchy, and network association degree. Particular network characteristics are typically captured using three indicators: the centrality of degree, betweenness, and closeness. Main indicators and explanations are referenced in [40], as can be seen in Table 1.

The block model must be used as the main technique for spatial clustering analysis in social network analysis. It examines the functions of various locations (blocks) in the intricate network [41]. Moreover, this model divides the overall complex network into sectors with different responsibilities, revealing the information transmission paths between sectors. Based on an iteratively converging correlation matrix, nodes are classified and clustered to form a single module. This analysis method helps delve into the association relationships between nodes within and between clusters after clustering.

Table 1. Key indicators and descriptions of the urban digital economy spatial network structure.

Indicator	Calculation Formula	Formula Description	Indicator Meaning
Network Density	$D = L/[N \times (N-1)$	Actual number of relationships/Maximum possible total number of relationships	The higher the density, the closer the spatial association relationships between cities.
Network Connectivity	$C = 1 - V/[N \times (N-1)/2$	Degree to which any two members in the network are directly or indirectly reachable	Higher connectivity indicates stronger stability of the overall network structure.
Network Hierarchy	$H = 1 - K/\max(K)$	Degree of asymmetric reachability among members in the network	Higher hierarchy indicates a more stringent network structure, with some cities having stronger dominant positions.
Network Efficiency	$E = 1 - M/\mathrm{mzx}(M)$	Degree of redundancy in network connections	Lower efficiency indicates more spillover paths and a more stable network structure.
Degree Centrality	$DC = n/(N-1)$	Number of members directly connected to a member/Maximum possible number of direct connections	Higher degree centrality indicates stronger control of one city over others.
Closeness Centrality	$CC = \sum_{j=1}^{N} d_{ij}$	Sum of shortest distances from a member to all other members in the network	Higher closeness centrality means shorter distances between members, leading to closer association and collaboration.
Betweenness Centrality	$BC = \frac{2\sum_{j}^{N}\sum_{k}^{N} b_{jk}(i)}{N^2-3N+2}$ $b_{jk}(i) = \frac{g_{jk}(i)}{g_{jk}}$	Extent to which a member acts as an intermediary for other members	Higher betweenness centrality indicates a more prominent intermediary role of a city in the network.

Note: N is the network's total number of members. The actual number of relationships is L. V represents the number of member pairs in the network that cannot reach each other. K denotes the count of symmetrically accessible member pairs in the network. In the other case, M is the network's number of redundant connections. The number of members that are directly related to a particular member is denoted by n. $b_{jk}(i)$ is the likelihood that member i is on the shortest path between j and k, with $j \neq k \neq i$ and $j < k$. g_{jk} is the number of shortest paths between members j and k, while $g_{jk}(i)$ is the number of those paths that pass through member i.

Ronald Burt initially presented the structural hole theory in his book "Structural Holes: The Social Structure of Competition". It emphasizes that structural holes within a social complex network can provide organizations or individuals located in these positions with advantages in information and other resources. This concept is significant for analyzing social complex network structures under the internet economy. In the digital economy's spatial complex network structure, if two cities lack direct contact and must connect through a third city, then the third city occupies a structural hole. This type of city has information and control advantages and can attract more resources and benefits. Structural holes are typically characterized by four indicators: effective size, efficiency, constraint, and hierarchy, and the calculation methods for these indicators are as follows:

Effective size: The effective size is used to calculate and measure the overall influence and importance of a node. The formula to calculate the effective size of a node is as follows:

$$ES_i = \sum_j (1 - \sum_q P_{iq}P_{jq}) = n - \frac{1}{n}\sum_j \sum_q P_{jq} \quad (2)$$

where n is the magnitude of node i, j represents the adjacent nodes of node i, and the nodes that are adjacent between node i and node j are represented by q. P_{iq} and P_{jq} are the proportions of node q in the adjacency of nodes i and j, respectively.

Efficiency: To calculate the efficiency of a node, it is necessary to divide its effective size by its actual size within the network. The calculating formula is as follows:

$$EF_i = \frac{ES_i}{n} \tag{3}$$

The calculation of i is determined by the number of nodes, and n represents the number.

Constraint: This indicates the extent to where a node is restricted by its peers in the network. A higher constraint implies stronger dependency and fewer structural holes. The calculation formula is as follows:

$$C_i = \sum_j C_{ij}\, C_{ij} = (P_{ij} + \sum_q P_{iq} P_{qj})^2 \tag{4}$$

where nodes i and j share an adjacent location with node q, and the percentage of node j among all nodes that are adjacent to node i, $P_{ij,}$ is indicated.

Hierarchy: This indicates how much constraint is concentrated on a particular node. The formula for calculating the hierarchical level of a node is as follows:

$$HI_i = \frac{\sum_j \left(C_{ij} / \frac{C}{N}\right) I_n \left(C_{ij} / \frac{C}{N}\right)}{NI_n(N)} \tag{5}$$

These indicators help understand the strategic positioning of cities within the digital economy network and the potential advantages or disadvantages they hold due to their specific structural roles.

3.1.3. QAP Analysis

To verify the existence of correlations between matrices, matrix data are permuted in a regression analysis using the Quadratic Assignment Procedure (QAP), which is commonly used for analyzing the factors affecting complex network structures [42]. In the study of the correlation between associated variables, traditional empirical tests often overlook problems such as autocorrelation among independent variables or multicollinearity [43]. QAP regression analysis, a non-parametric method, is used to permute matrix data in a regression analysis in order to confirm the presence of correlations between matrices. Accordingly, this study employs the nonlinear QAP analysis method from social network analysis to conduct an analysis of influencing and driving factors.

3.2. Model Setting and Variable Selection

The factors that have an effect on the improvement of the digital economy involve economic, social, and demographic characteristics. Therefore, this study selects eight factors: geographical distance, differentiated levels of economic development, industrial structure, urbanization level, information development level, human capital, marketization level, and technological innovation. Together, these elements have an impact on how China's digital economy spatial association network is formed and help to explain the network's more intricate structural changes. This serves as the foundation for this study's development of the subsequent model below:

$$Q = f\,(D, E, S, C, I, H, M, T) \tag{6}$$

In the above model, a spatial association matrix, which is represented by the dependent variable Q, is present in the digital economy of China. D is the matrix of geographical proximity; the matrix of variations in economic development levels is represented by the letter E, measured by the ratio of institutional deposits and loans to gross regional product (ECO); S represents the matrix of industrial structure disparities, calculated using the ratio of tertiary industry output to total production (ISL). C denotes the matrix of urbanization level disparities, based on the proportion of the urban population to the total population (UDL). I is the matrix of differences in the performance of information development, and I is computed by the ratio of broadband internet users to total population (IDL); H is the matrix of human capital differences, determined by the proportion of the numbers of middle school students to the total population (EDU); M is the matrix of marketization level differences, derived from the proportions of government spending to GDP (MAL). T is the matrix of technological innovation differences, measured by the percentage of government spending on technology and science compared to total fiscal expenditure (TEL).

3.3. Data Sources and Explanation

Different from previous studies, this study's focus is on 279 prefecture-level cities between 2012 and 2021, and uses panel data from them. The analysis data are from the "China Urban Statistical Yearbook" and the "China Urban Construction Statistical Yearbook". Both the China Digital Economy Development and Employment White Paper and the China Digital Economy Development Index White Paper are used to assess the digital economy's scale and development level. Geographic distances are calculated using the latitudes and longitudes of cities from Baidu maps. Data on geographical distance, economic development, industrial structure, and urbanization are sourced from city statistical yearbooks, while data on internet broadband access numbers are from the "China Communications Yearbook". The cities with many missing values are excluded, and the interpolation method is used to fill in the few missing values. Table 2 displays the descriptive statistical analysis of the variables.

Table 2. Descriptive statistics.

Variable	Observed Value	Mean Value	Standard Deviation	Minimum Value	Maximum Value
DEL	2790	0.3341	0.113	0.07	0.80
ECO	2790	10.7886	0.562	9.01	13.06
ISL	2790	0.289	0.209	0.045	1.396
UDL	2790	5.7319	0.9585	0.6831	0.8019
IDL	2790	1.0889	0.6506	0.1679	7.4502
EDU	2790	6.6284	0.9135	3.8394	9.6397
MAL	2790	0.544	0.246	0.396	0.712
TEL	2790	0.003	0.003	0.000	0.063

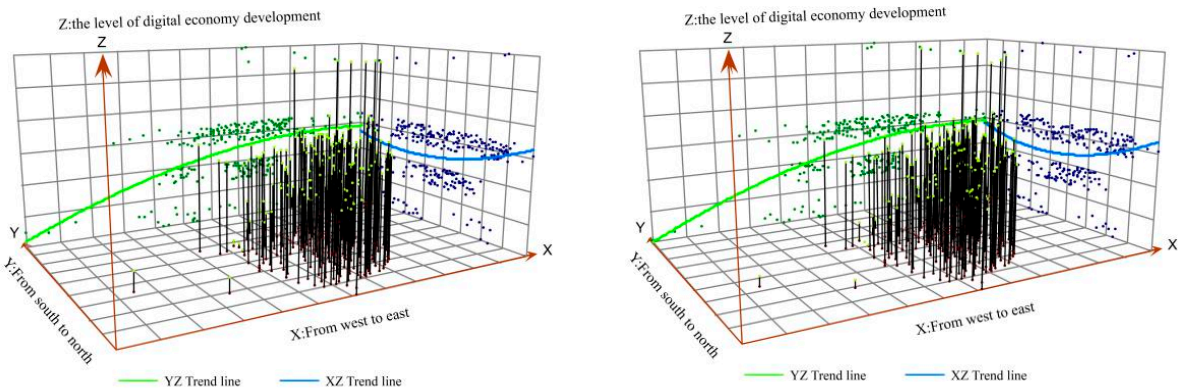
Note: D is the geographical location difference matrix, calculated by the longitude and latitude of the city. DEL stands for digital economy development level index. The seven variables in the table are calculated to form seven difference matrices of E, S, C, I, H, M, and T in this paper.

4. Characteristics of the Spatial Association Network in the Chinese Urban Digital Economy

4.1. Overall Trends in Digital Economy Development

As shown in Figure 1, this paper utilizes the trend analysis tool in ArcGIS 10.2 software to visually describe the spatial distribution trend of Chinese digital economy growing. Each vertical line represents the level (height) and position of digital economy progress in each city. In particular, the Z-axis is indicative of the progress of the digital economy. The X-axis moves from west to east, and, from south to north, the Y-axis moves. Both the 2012 and

2021 trend lines are similar; in the north–south direction, there is a rising trend line between the first and third quadrants, while the third and fourth quadrants have a slight U-shaped trend line in the east–west direction. Trend analysis from 2012 to 2021 denotes that year after year, Chinese cities have seen an increase in digital economy development, and these improvements are spatially dispersed, with an important pattern of uneven distribution.



(**a**) (**b**)

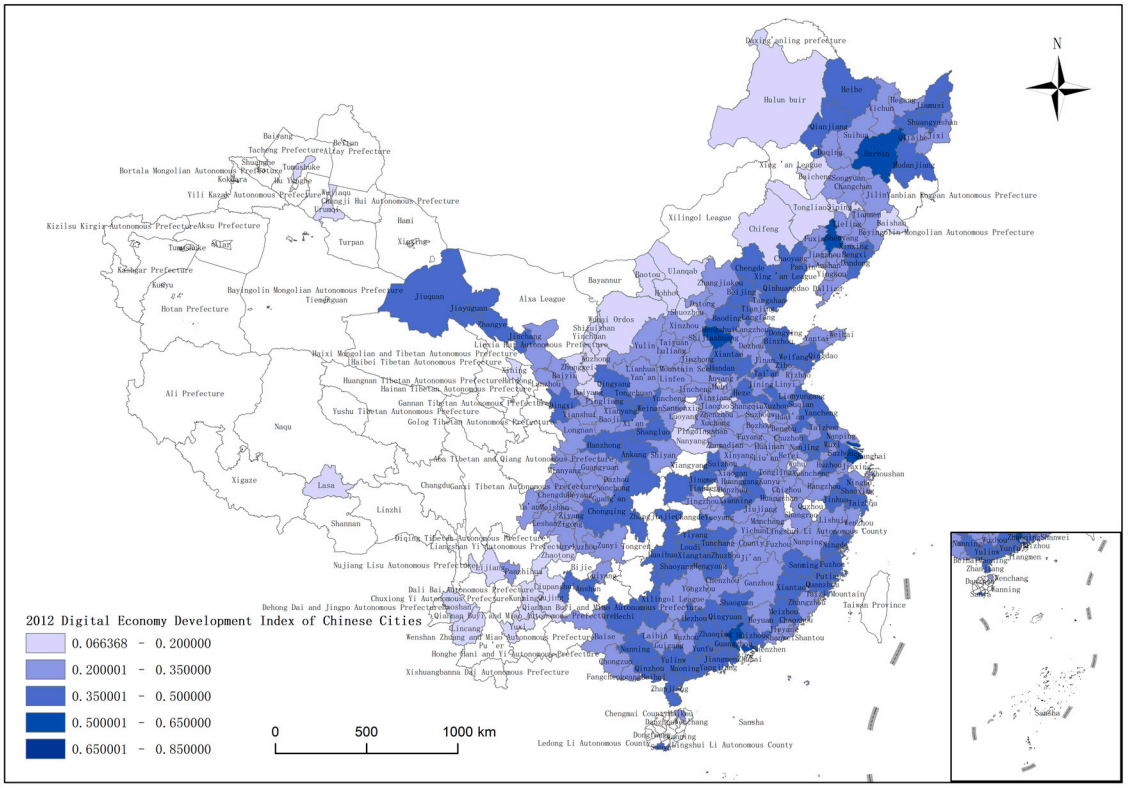
Figure 1. Spatial trend of city digital economy development in China. (**a**) 2012. (**b**) 2021.

Furthermore, this research paper utilizes the natural discontinuity method to map the spatial distribution of digital economy for 279 prefectural-level cities in China within the development performance between 2012 and 2021, and the results are shown in Figure 2. Overall, from 2012 to 2021, China's urban digital economy shows an obvious spatial differentiation between the east and the west according to the depth of color level, showing an "unbalanced" situation, and by comparing development level of less-developed western area, the level in eastern coastal cities is much higher. The level of improvement performance for digital economy in various cities is gradually rising, and by 2021, in most cities like East, South and central China, the level of growing performance for digital economy has improved significantly.

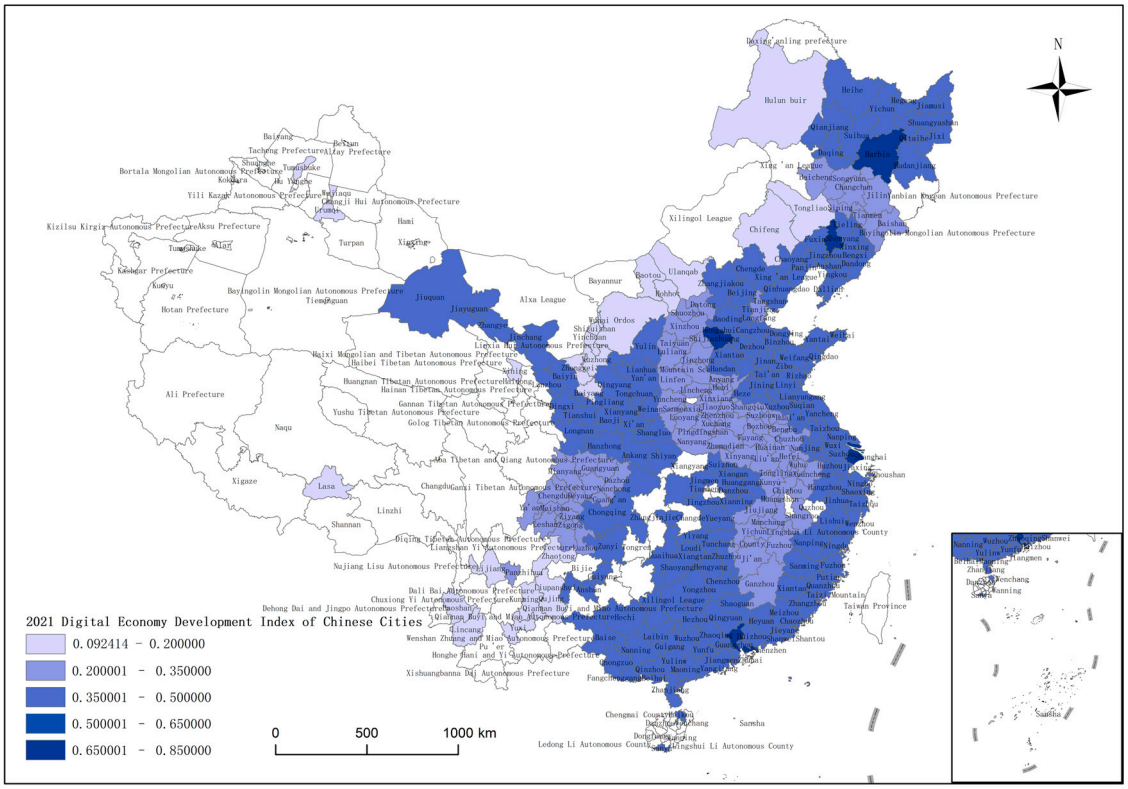
4.2. Overall Network Characteristics of China's Urban Digital Economy

4.2.1. Spatial Association Characteristics

The model of modified gravity was utilized to figure out the spatial associations on the growing performance levels of 279 prefecture-level cities in the digital economy, and a relationship matrix was constructed. Software calculations show that, in 2012, there was a total network density of 0.118 in the digital economy for the urban areas in China, but, in 2021, it showed a rise in network density of 0.123. Comparing the spatial complex network topology maps of these two years (Figure 3), we can see that there are no isolated cities in the intricate network and notable spatial connection linkages in the digital economy development level in Chinese cities. The total scale of network density and network relationships, between 2012 and 2021, showed an upward trend; second, from a regional perspective, the center of the network holds the majority of cities in the eastern and southern China regions. Conversely, the northwest and southwest provinces lie on the outskirts of the network, and this situation has not changed from 2012 to 2021; third, individual cities have experienced significant changes in network centrality and network status from 2012 to 2021; Fourth, cities located on the periphery of the network have a noticeable spillover effect, indicating that a large amount of digital economy resources are flowing out of these areas, posing great challenges to their own development and adversely affecting balanced regional development.

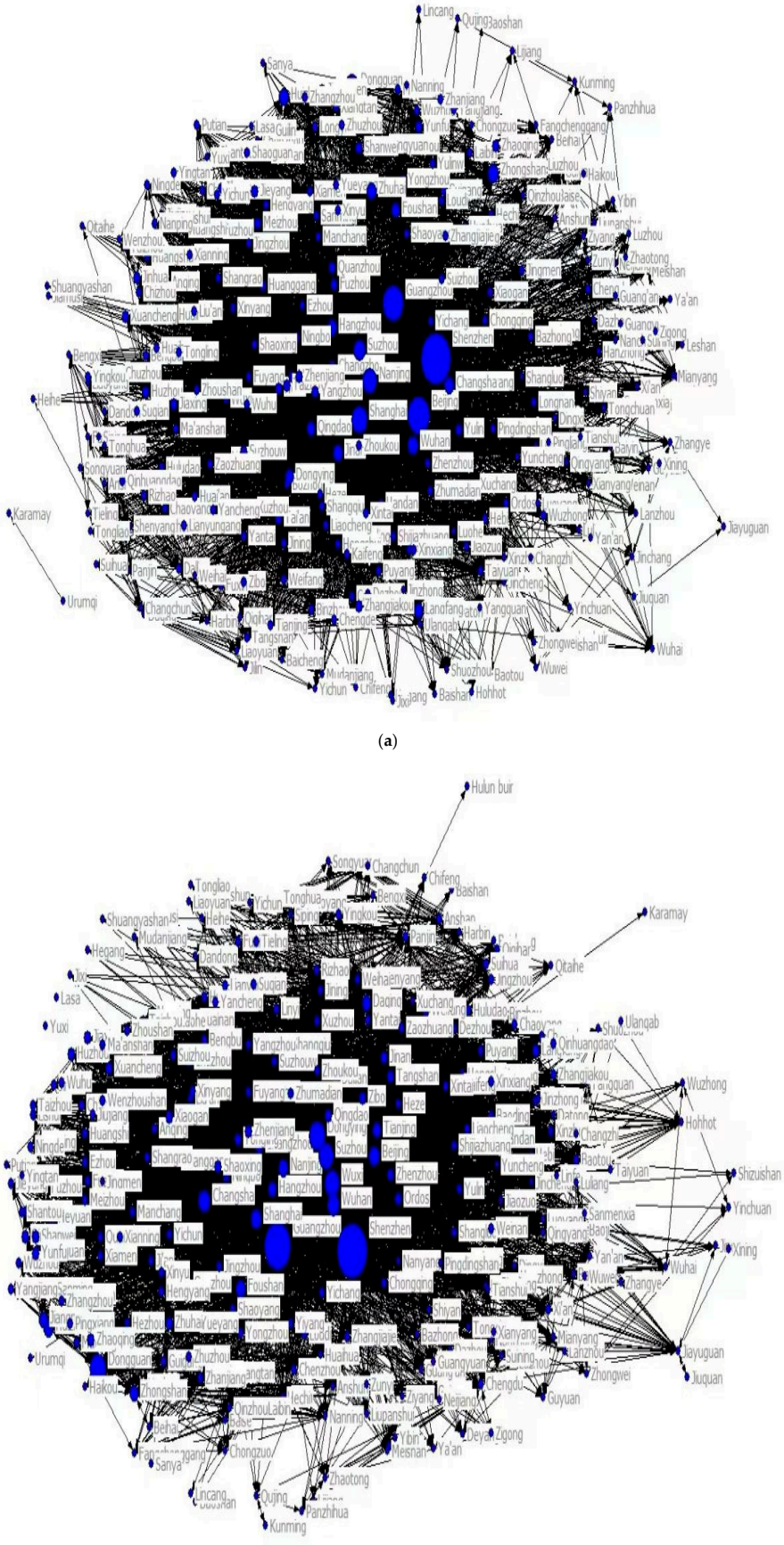


(**a**)



(**b**)

Figure 2. Spatial distribution of city digital economy development in China. (**a**) 2012. (**b**) 2021.



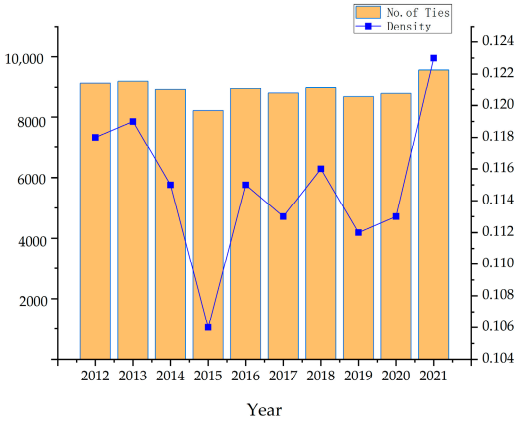
(**a**)

(**b**)

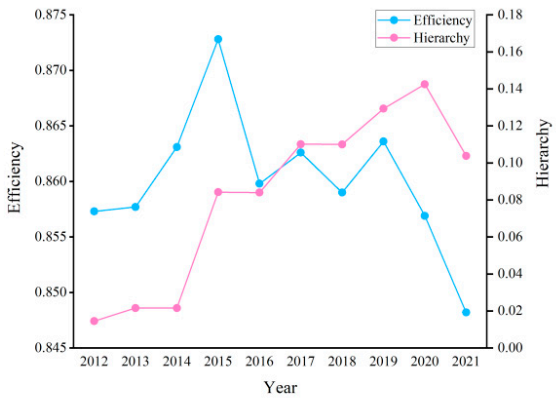
Figure 3. Spatial network topology map of urban digital economy in China. (**a**) 2012. (**b**) 2021.

4.2.2. Overall Network Structural Characteristics

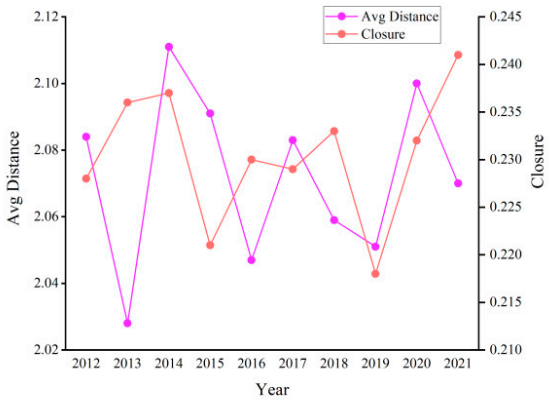
This paper calculates each year's intricate network architecture features utilizing UCINET 6.0 software and creates a dynamic feature map of the structure of the entire complex network (Figure 4). It is apparent from the measurement results that, from 2012 to 2021, the network association degree was consistently 1, indicating that all 279 prefecture-level cities were included in the complex network and maintained good connectivity with direct or indirect relationships. As shown in Figure 4a, there is an upward fluctuating trend in the density of the intricate network and the number of links between cities. Between 2012 and 2021, the number of network relationships rose from 9130 to 9562, and the network density grew from 0.118 to 0.123, depicting a rise in the closeness of spatial associations in the digital economy among cities. Figure 4b shows a generally fluctuating downward trend in network efficiency, indicating an increase in spatial association relationships among cities and rising network stability. There was a significant increase in network hierarchy, from 0.0145 in 2012 to 0.1038 in 2021, suggesting that cities that are developing a better digital economy are increasingly dominating their positions within the complex network.



(**a**) No. of Ties and Density



(**b**) Efficiency and Hierarchy



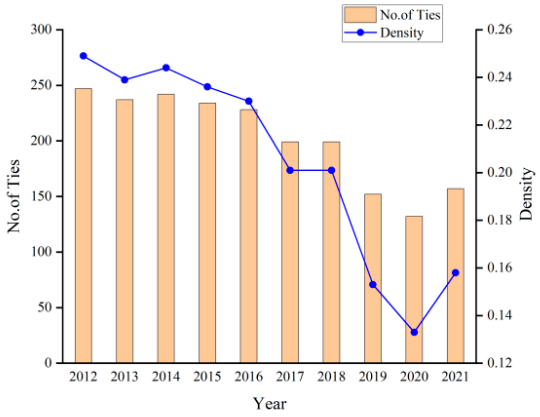
(**c**) Avg Distance and Closure

Figure 4. Dynamic feature of overall spatial network structure of urban digital economy in China.

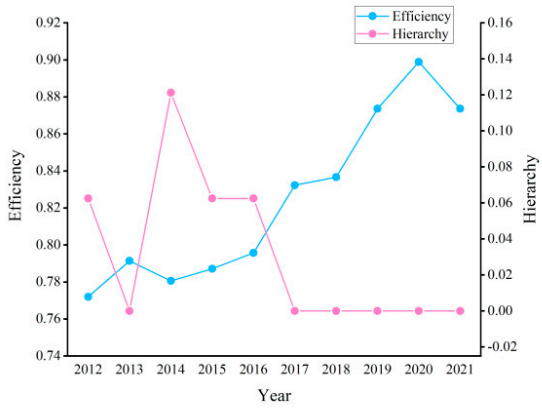
The accessibility of the complex network of spatial connections that make up the digital economy is typically measured using network small-world characteristics, typically characterized by the average path length and clustering coefficient, as detailed in Figure 4c. Overall, from 2012 to 2021, the spatial association network of cities' digital economies exhibited significant small-world characteristics. The average path length generally ranged

from 2 to 3, indicating that any two city nodes in the network could establish a complete connection through from 2 to 3 intermediary cities. The general trend of the clustering coefficient showed significant fluctuations, indicating frequent contacts and strong mutual influences in the improvement of digital economy in cities.

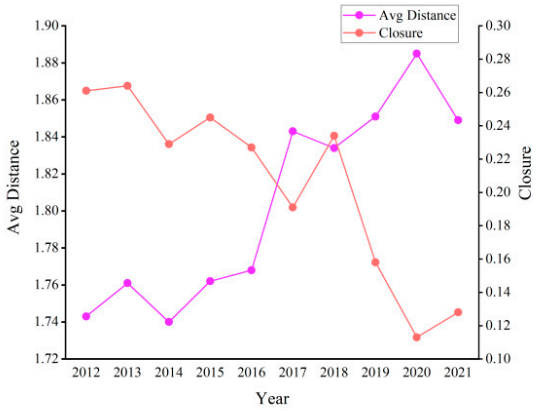
In order to further examine the structural variations in the digital economies of Chinese cities, this research divides China into seven main regions: North China, Northeast China, Northwest China, East China, South China, Southwest China, and Central China (City classification see Appendix A). As shown in Figure 5a, there is a downward fluctuating trend in the network density and number of connections in North China. This indicates a year-over-year decline in the closeness of the spatial relationship between cities in North China's digital economy is spatial. The general pattern of network efficiency is upward, but fluctuating, as shown in Figure 5b, indicating fewer spillover paths between cities and a decrease in network structural stability. A less stringent city network hierarchy and a decline in the dominant position of cities that are developing a more efficient digital economy. According to Figure 5c, the overall trend of the clustering coefficient shows a decrease of significant magnitude signifies a decrease in the frequency of contacts, and weaker mutual influence in digital economy development among cities.



(**a**) No. of Ties and Density



(**b**) Efficiency and Hierarchy

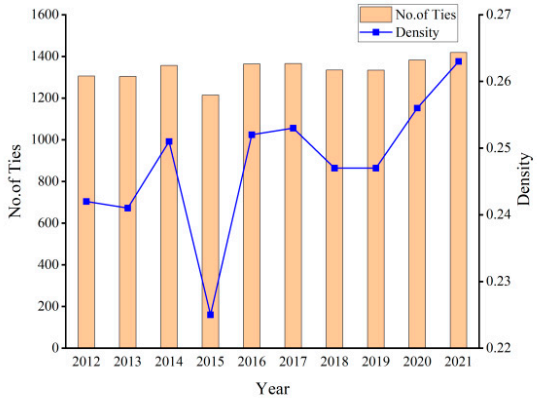


(**c**) Avg Distance and Closure

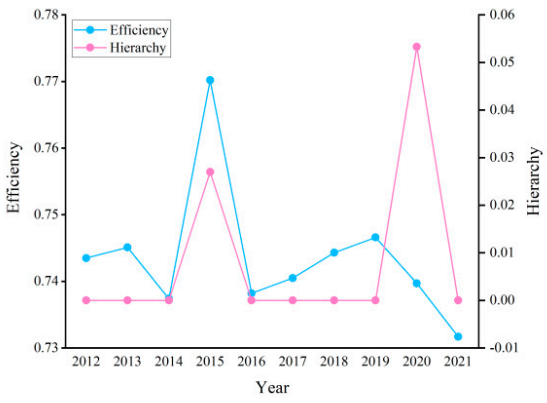
Figure 5. Dynamic feature of spatial network structure of urban digital economy in north region.

Figure 6a indicates an increase in the cities' digital economy with the closeness of spatial associations. The observation in Figure 6b is that the network's comprehensive operational efficiency is subject to a variable but generally declining trend, implying that

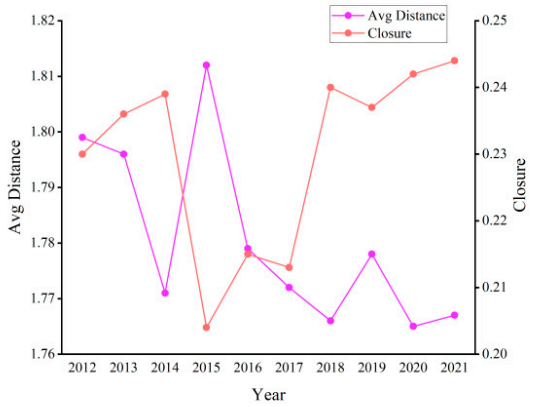
spatial association relationships among cities in the digital economy are increasing and network stability is rising. A consistently stringent city network hierarchy with no significant change in the dominant position of cities with better digital economy development. As seen in Figure 6c, the overall trend of the clustering coefficient shows significant fluctuations, indicating an increase in the frequency of contacts and mutual influence in digital economy development among cities.



(**a**) No. of Ties and Density



(**b**) Efficiency and Hierarchy

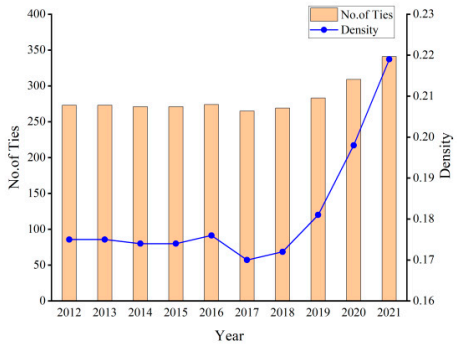


(**c**) Avg Distance and Closure

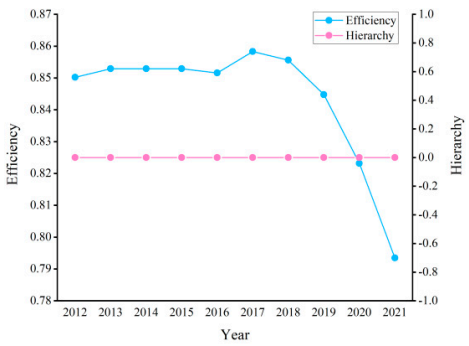
Figure 6. Dynamic feature of spatial network structure of urban digital economy in east region.

As shown in Figure 7a, a rise in the proximity of spatial links in the digital economy between cities is shown by the higher trend in the number of connections and network density in these cities. Figure 7b reflects that the overall network efficiency exhibits a downward trend, suggesting an increase in spatial association relationships among cities and rising network stability. There has been no change in network hierarchy. In Figure 7c, the overall trend of the clustering coefficient shows no significant fluctuations, indicating that the frequency of contacts and mutual influence in digital economy development among cities has not changed significantly.

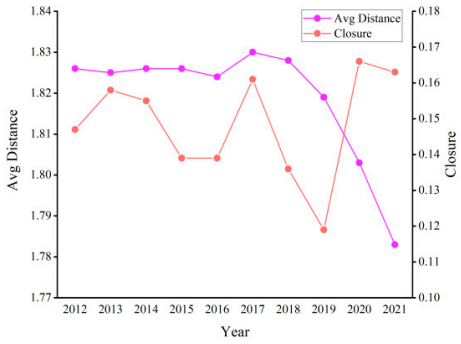
As shown in Figure 8a, the closeness of spatial associations in the digital economy among cities has essentially remained unchanged. Figure 8b indicates that fewer spillover paths between cities and a decline in network structural stability. It shows an unstable city network hierarchy and an unstable dominant position of cities with better digital economy development in the network. As shown in Figure 8c, the overall trend of the clustering coefficient shows a downward fluctuation, indicating a weakening of contacts and mutual influence in digital economy development among cities.



(**a**) No. of Ties and Density

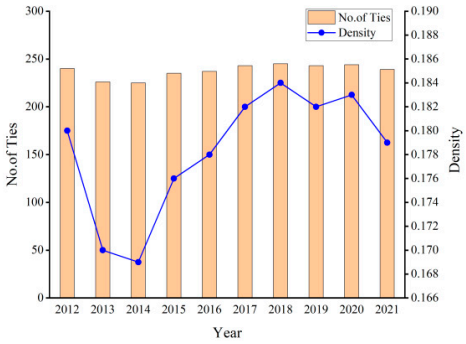


(**b**) Efficiency and Hierarchy

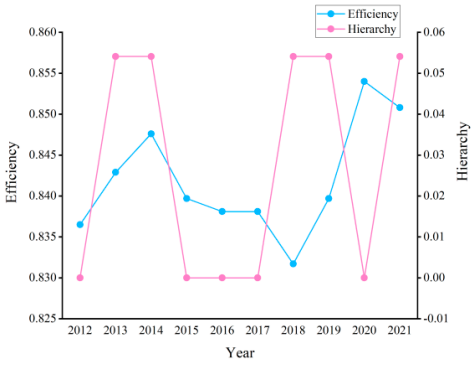


(**c**) Avg Distance and Closure

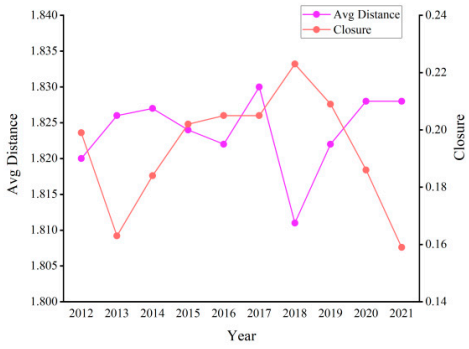
Figure 7. Dynamic feature of spatial network structure of urban digital economy in central region.



(**a**) No. of Ties and Density



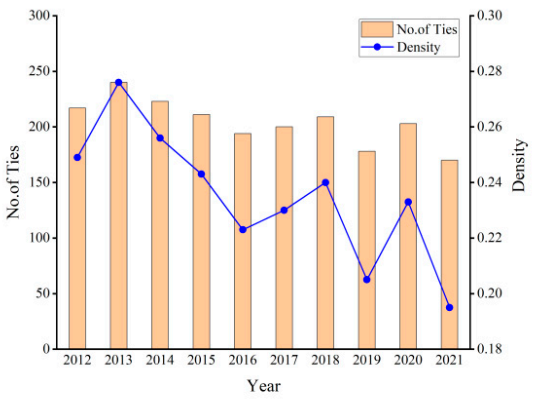
(**b**) Efficiency and Hierarchy



(**c**) Avg Distance and Closure

Figure 8. Dynamic feature of spatial network structure of urban digital economy in southern region.

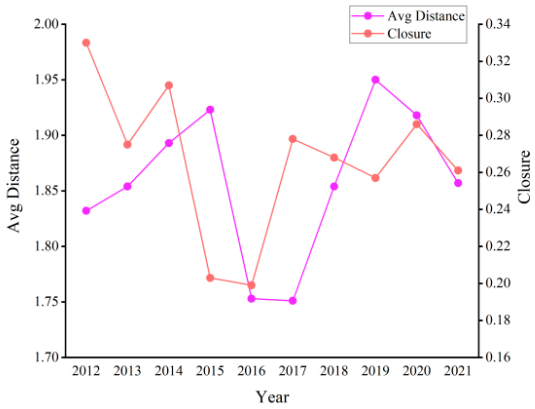
Figure 9a indicates a decline in the closeness of spatial associations in the digital economy among cities. Figure 9b reflects that the spatial association relationships among cities are reducing in the digital economy, and network stability is declining. There is a gradually more stringent city network hierarchy, with cities that have better digital economy development gaining a dominant position in the network. As shown in Figure 9c, the overall trend of the clustering coefficient shows a fluctuating decrease, indicating a decline in the frequency and mutual influence of digital economy development contacts among cities.



(**a**) No. of Ties and Density



(**b**) Efficiency and Hierarchy

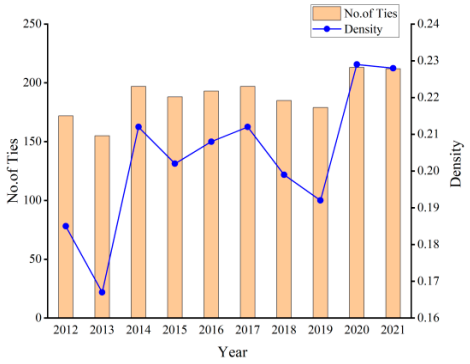


(**c**) Avg Distance and Closure

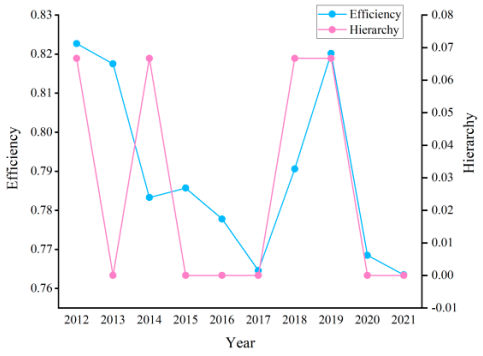
Figure 9. Dynamic feature of spatial network structure of urban digital economy in northwest region.

Figure 10a shows an increase in the closeness of spatial associations in the digital economy among cities. Figure 10b reflects an overall fluctuating downward trend in network efficiency and an increase in spatial association relationships among cities and rising network stability. As shown in Figure 10c, the overall trend of the clustering coefficient shows significant fluctuations, indicating frequent contacts and strong mutual influences in digital economy development among cities.

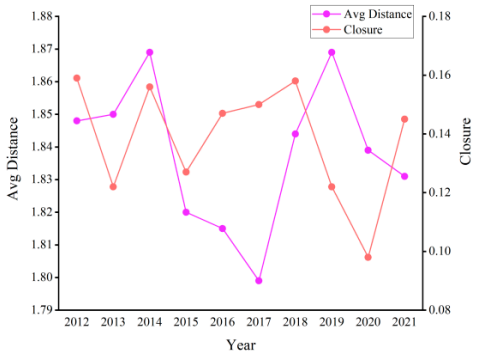
As shown in Figure 11a, the closeness of spatial associations in the digital economy among cities is increasing. Figure 11b reflects an overall fluctuating downward trend in network efficiency, indicating an increase in spatial association relationships among cities and rising network stability. As detailed in Figure 11c, the overall trend of the clustering coefficient exhibits a noticeable decline, indicating a weakening of contacts and mutual influence in digital economy development among cities.



(**a**) No. of Ties and Density

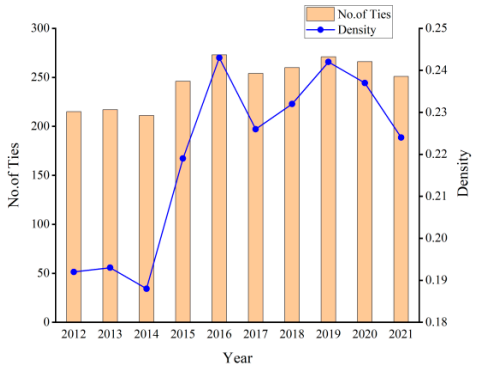


(**b**) Efficiency and Hierarchy

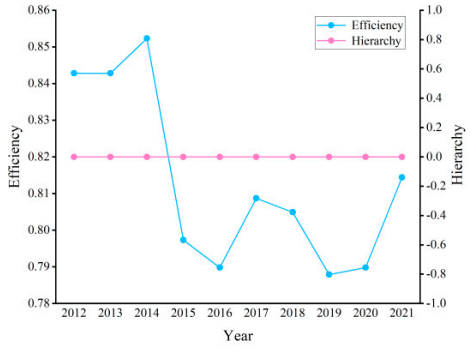


(**c**) Avg Distance and Closure

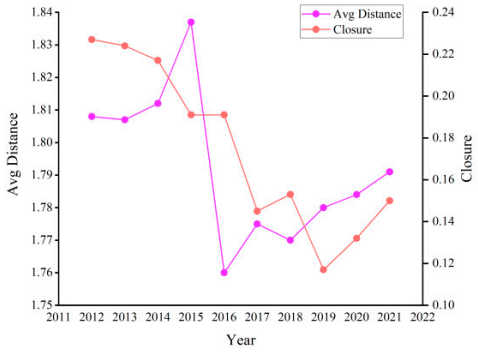
Figure 10. Dynamic feature of spatial network structure of urban digital economy in southwest region.



(**a**) No. of Ties and Density



(**b**) Efficiency and Hierarchy



(**c**) Avg Distance and Closure

Figure 11. Dynamic feature of spatial network structure of urban digital economy in northeast region.

4.3. Analysis of Individual Network Characteristics

4.3.1. Degree Centrality

By analyzing the features of the entire network complexity, this research further uses UCINET software to compute the centrality of degree, betweenness, and closeness of the 279 prefecture-level cities in China in 2021, to discuss the position and responsibility of complex network in each city. Due to space limitations, only the top fifty and the bottom fifty cities are displayed (See Appendix A for results).

The spatial association network of the digital economy in Chinese cities in 2021 has an overall average degree centrality of 15.348. The top fifty cities have an average degree centrality of 39.583, which is greater than the average for all cities. It indicates that there are more connections of these cities than others and occupy a central spot in relation to the spatial connotation network. The majority of cities in the eastern coastal regions, with high levels of centrality are located, suggesting that cities in these regions have affected the economy with digital technologies in other regions profoundly. Conversely, the average degree centrality of the bottom fifty cities is 2.7144, significantly below the overall average, indicating these cities have fewer connections with other cities and occupy a peripheral position in the complex network. Cities with low level of centrality are mainly in the Northwest and Southwest regions, indicating these cities have less direct impact on the digital economy of other regions (see Figure 12 for details).



Figure 12. Analysis of degree centrality in the spatial association network of digital economy.

The average out-degree of the fifty largest cities is 103.32, according to the latest analysis of out-degree and in-degree, and the average in-degree is 74.54. Among them, 39 cities show dominance in outgoing over incoming interactions, indicating these cities are more connected with other cities, demonstrating stronger dissemination and influence capabilities. The bottom fifty cities have an average out-degree of 2.48 and an in-degree of 7.18, indicating these cities are less connected and have weaker influence, importance, and dissemination capabilities within the complex network.

4.3.2. Betweenness Centrality

In 2021, the network of spatial associations that presented in China's urban digital economy has an average centrality of 0.355. It can be shown that the average betweenness centrality of the top fifty cities is 1.703, higher than the overall average for Chinese cities (Figure 13). These cities have higher betweenness centrality, demonstrating that they are important nodes that have a controlling influence on the intricate network. These cities establish many connections externally, with noticeable benefit effects, and possess high influence and control within the network, serving as "mediators" and "bridges". Conversely, the average betweenness centrality of the bottom fifty cities is 0.003, significantly below the overall average, indicating that these cities have fewer digital economy resources, smaller digital economy scales, less noticeable benefit effects, and lesser influence in the digital economy spatial association network.

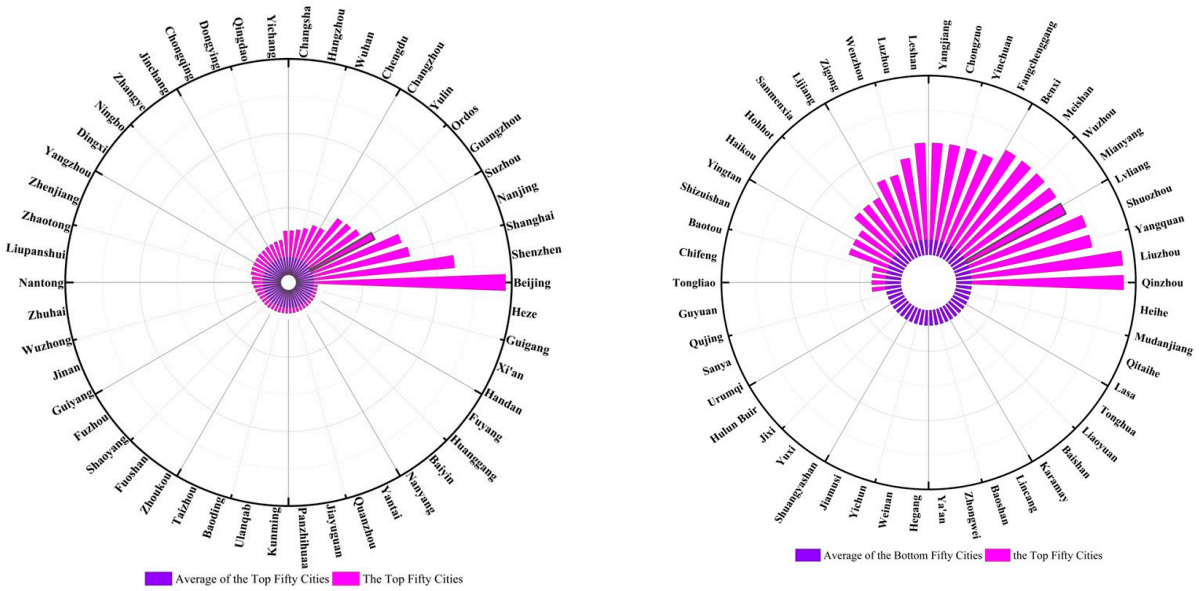


Figure 13. Analysis of betweenness centrality in the spatial association network of digital economy.

4.3.3. Closeness Centrality

In network analysis, closeness centrality is employed to assess a node's average distance to all other nodes. In 2021, the average closeness centrality of the 279 prefecture-level cities in China was 16.980, showing little variation, which denotes that the ability of cities within complex network of spatial associations to connect with other cities has gradually strengthened. According to the calculations shown in Figure 14, the average closeness centrality of the top fifty cities is 17.499. These cities have high closeness centrality, indicating that they can establish connections with other cities quickly and efficiently, and they are at the forefront of the digital economy with network, with strong resource acquisition capabilities. On the other hand, the average closeness centrality of the bottom fifty cities is 15.921. These cities have fewer spatial connections with other cities and are situated around the edges of the digital economy complex network, with lower benefit effects and lacking the capacity to significantly affect other cities.

When examining the degree of centrality, betweenness, and closeness in conjunction, it is evident that the East and South China regions consistently score above the national average and above other regions, occupying central positions in the digital economy's geographical network. On the other hand, the Northwest and Southwest regions score below the national average, with a significant difference from the East and South China regions, placing them on the periphery.

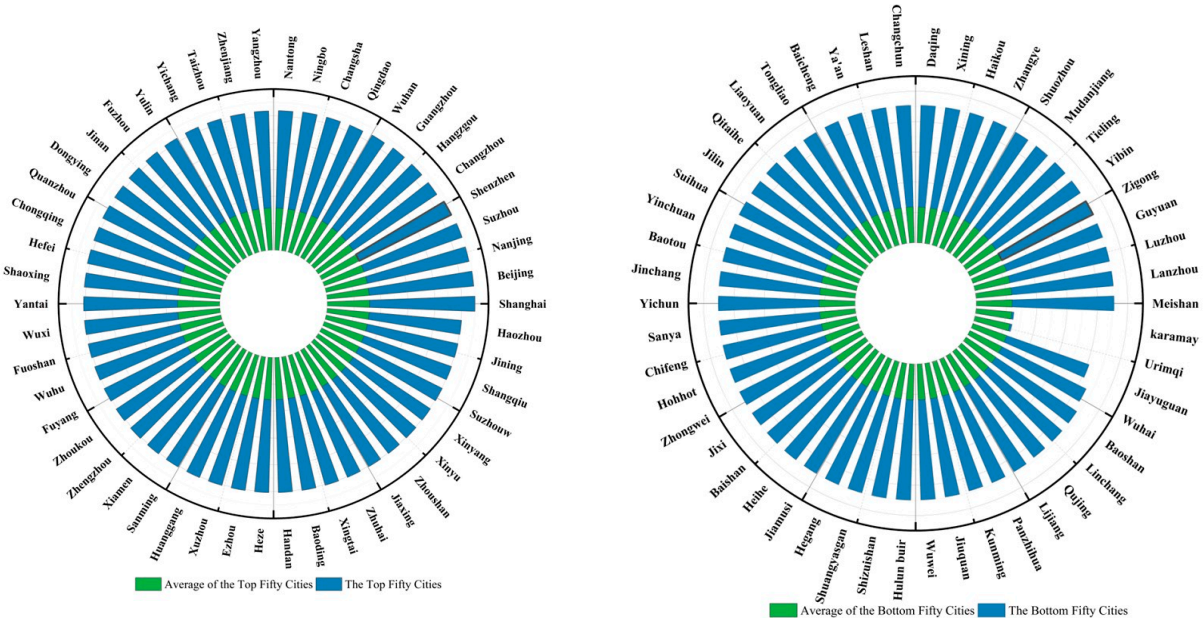


Figure 14. Analysis of closeness centrality in the spatial association network of digital economy.

Cities at the local level with top rankings in all three individual network characteristics include Beijing, Shanghai, Nanjing, Shenzhen, Suzhou, Guangzhou, Changzhou, Wuhan, Hangzhou, and Changsha. The prominence of these cities is due to their robust economic foundations, strong science and education resources, rich talent reserves, advantageous geographic locations with convenient transportation, well-developed digital economy infrastructure, and tight connections with surrounding areas. They exhibit a significant "siphon effect", attracting substantial external resources, capital, and talent inflows, with clear benefit effects, while also having a technological spillover effect on surrounding cities.

Conversely, cities ranking low in all three individual network characteristics include Urumqi, Hulunbuir, Karamay, Zhongwei, Jixi, Hegang, Lijiang, Jiamusi, Baishan, and Lincang. These cities, due to their remote geographic locations, weak economic foundations, insufficient research investment, and underdeveloped digital economy infrastructure, struggle to attract external resources, information, and talent. This results in fewer spatial connections with other cities, positioning them on the outskirts of the network in the digital economy, with low benefit effects and an inability to significantly influence other cities or establish efficient and close connections. This situation leads to a "Matthew effect" in the spatial network that exists within the urban digital economy of China, where the strong become stronger and the weak become weaker.

4.4. Cohesive Subgroups Analysis of China's Urban Digital Economy Spatial Network

4.4.1. Block Model Analysis

This study utilizes the CONCOR module, which is a component of the UCINET software module, to investigate the block characteristics of the spatial association network of the urban digital economy. Because of that, discovering spatial clustering characteristics within China's digital economy association network is allowed. The maximum division was set at 2, and the convergence criteria were 0.2%, which resulted in the spatial network map of 279 prefecture-level cities being divided into four blocks: Block I includes 135 cities, mainly located in North China, Southwest China, and Northeast China. Block II consists of 88 cities, primarily in the Northwest and Central China regions. Block III encompasses 33 cities, mainly from the Central and South China regions. Block IV comprises 23 cities which predominantly in the Southeastern region (See Appendix A).

According to the block model analysis results (Table 3), the internal relationship percentages within each block are 15.63%, while the inter-block relationship percentages are 84.37%, indicating significant spillover effects in the advancement of the digital economy among cities. The roles of blocks within the Chinese urban digital economy spatial association network are categorized into four types:

1. Net Beneficiary Blocks: Members of these blocks both receive relationships from external members and from within the block and have a far higher number of entering relationships than exiting ones. Block II, for instance, has 664 outgoing relationships, 306 internal relationships, and receives 950 relationships from other blocks, qualifying it as a "Net Beneficiary" block.
2. Net Outflow Blocks: Compared with what they received, these blocks send out significantly more connections to other blocks. Block IV, with 2832 outgoing relationships, 167 internal relationships, and receiving 1753 from other blocks, is classified as a "Net Outflow" block, where members not only satisfy their own digital economy resources but also provide resources to other regions.
3. Bidirectional Outflow Blocks: Members of these blocks both send out and receive relationships, having a comparatively greater quantity of interactions originating from inside the block. According to the definition, Block I is a "Bidirectional Outflow" block, with 3889 outgoing relationships to other blocks and receiving 3777 relationships, having more contacts from within the block.
4. Brokerage Blocks: These blocks have fewer internal relationships but play the role of connectors and bridges by both sending out and receiving relationships from other blocks. Block III, with 2177 outgoing relationships, only 208 internal relationships, and receiving 1587 external relationships, has extensive contacts with other blocks, qualifying it as a "Brokerage" block.

Table 3. Inter-block connections in the urban digital economy's spatial association network.

Block Type	Relationships Received		Relationships Overflow		Expected Internal Relationship %	Actual Internal Relationship %	Block Type Description
	Internal	External	Internal	External			
Block I	814	3777	814	3075	48.20	20.93	Bidirectional Outflow
Block II	306	960	306	358	31.29	40.08	Net Beneficiary
Block III	208	1587	208	1969	11.51	9.83	Broker
Block IV	167	1753	167	2665	7.91	5.90	Net Outflow

Note: The total number of received relationships within a block (outgoing relationships) is calculated as the sum of relationships on the main diagonal of the reception matrix; the sum of the relationships in each column (row) outside of its own block represents the total number of outgoing relationships (received relationships) from outside the block. The formula "(Number of cities within the block − 1)/(Total number of provinces in the network − 1)" is used to determine the expected internal relationship proportion, and "Internal relationships within the block/Total spillover relationships of the block" is used to determine the actual internal relationship proportion.

In constructing the density matrix for each block, the combined Chinese cities' total network density in 2021 was 0.123, this value is used as a benchmark to compare the density of each block. Substituting 1 for the corresponding block density occurs when it is higher than or equal to 0.123, otherwise, it is replaced with 0. This creates a likeness matrix for the Chinese urban spatial association network, as it can be seen in Table 4.

Table 4. Density and likeness matrix between blocks in spatial association network of urban digital economy.

Block Type	Density Matrix				Likeness Matrix			
	Block I	Block II	Block III	Block IV	Block I	Block II	Block III	Block IV
Block I	0.045	0.014	0.303	0.502	0	0	1	1
Block II	0.014	0.040	0.036	0.043	0	0	0	0
Block III	0.356	0.095	0.197	0.141	1	0	1	1
Block IV	0.652	0.251	0.175	0.332	1	1	1	1

4.4.2. Structural Hole Analysis

To further reveal the spatial clustering characteristics within China's digital economy complex network, this study uses UCINET software to calculate the structural hole metrics of the Chinese urban digital economy spatial association network (See Appendix A). The results from the years 2012 and 2021 are presented and compared, so SWOT analysis is used to carry out the structural hole.

(1) Strengths: Dominance of Core Cities in Structural Holes

Major cities, such as Shanghai, Beijing, Shenzhen, Guangzhou, Nanjing, etc., exhibit high effective size indices (an average of 30.03 in 2021, up from 28.35 in 2012), indicating their pivotal roles as structural holes in the digital economy network. These cities act as critical information hubs, facilitating efficient resource integration and exerting significant influence over the network. The rising average efficiency index (from 0.6282 to 0.6425, 2012–2021) further underscores their ability to leverage structural holes for enhanced control and information flow.

The average constraint index decreased from 0.2024 in 2012 to 0.1874 in 2021. Cities with decreasing constraints may occupy more structural hole positions, gaining more opportunities to utilize their positions within the digital economy complex network to acquire more control benefits and information resources.

(2) Weaknesses: Marginalization of Peripheral Cities

Geographically remote cities like Sanya, Kunming, Yinchuan, Lijiang, Urumqi, Baoshan, etc., face high constraint indices and low effective size/efficiency scores due to underdeveloped digital infrastructure. Their limited connectivity restricts their ability to bridge structural holes, perpetuating their exclusion from key network benefits. These cities struggle with "structural hole isolation", as evidenced by their inability to establish sufficient connections within the spatial network.

(3) Opportunities: Dynamic Structural Hole Expansion

The declining constraint index and rising effective size suggest opportunities for emerging cities (e.g., Chengdu, Chongqing) to exploit untapped structural holes. Investments in digital infrastructure could enable these cities to bridge gaps and enhance their network roles. National initiatives like the "East Data West Computing" project could empower western cities (e.g., Yinchuan, Jiuquan) to overcome geographic constraints by improving connectivity and reducing dependency on coastal hubs.

(4) Threats: Core–Periphery Polarization

The widening gap between core and fringe cities is likely to exacerbate regional disparities. Over-reliance on core cities for information poses systemic risks. Thus, it will spread to the whole digital economy spatial association network. Peripheral cities face difficulties, including insufficient policy support and funding, that limit their ability to develop spatial association networks.

5. Analysis of Factors Driving the Structure of the Digital Economy Spatial Association Network

5.1. QAP Correlation Analysis

To explore the construction mechanisms of China's urban spatial association network, this study selects the most recent year, 2021, as the representative year and uses an analysis of QAP (Quadratic Assignment Procedure) correlation to examine the relationships between China's urban digital economy spatial association network and various influencers. Table 5 displays the results that indicate that six out of the eight factors passed

the significance test, affirming that the development of China's urban digital economy spatial association network is significantly influenced by these six factors. Specifically, the coefficients for geographical location differences and marketization level differences are negative, suggesting that greater distances between cities and larger disparities in marketization levels are detrimental to the development of the urban digital economy that is being encouraged by the establishment of a spatial association network. The suppression of these factors results in spillover effects within the spatial complex network.

Table 5. QAP correlation analysis results.

Variable	Actual Correlation Coefficient	Significance Level	Mean Coefficient	Standard Deviation	Minimum Value	Maximum Value	$p \geq 0$	$p \leq 0$
D	−0.076	0.000	0.000	0.011	−0.023	0.066	1.000	0.000
E	0.132	0.000	0.000	0.011	−0.026	0.049	0.000	1.000
S	0.013	0.130	0.000	0.012	−0.025	0.059	0.130	0.871
C	0.001	0.170	0.000	0.012	−0.032	0.049	0.170	0.830
I	0.032	0.008	0.000	0.011	−0.030	0.044	0.008	0.993
H	0.013	0.097	0.000	0.011	−0.025	0.072	0.097	0.903
M	−0.026	0.001	0.000	0.012	−0.027	0.058	1.000	0.001
T	0.074	0.000	0.000	0.013	−0.026	0.070	0.000	1.000

Conversely, the positive coefficients for the other four influencing factors indicate that increases in the disparities of these factors can facilitate the formation of China's urban digital economy spatial association network. These factors include economic development level differences, information development level differences, human capital differences, and technological innovation differences. Each of these positively correlated factors contributes to strengthening the connectivity and flow of information and resources across cities, enhancing the network's overall cohesion and effectiveness.

By understanding these relationships, policymakers and urban planners can better strategize on reducing negative impacts while enhancing positive drivers to foster a more interconnected and robust digital economy landscape across various urban areas in China. This strategic approach can lead to more balanced urban development, leveraging digital economic strengths and mitigating weaknesses effectively.

5.2. QAP Regression Analysis

This study used QAP regression analysis to investigate the relationships between the influencing elements and the spatial connection matrix of China's urban digital economy. The outcomes are presented in Table 6. The analysis indicates that a significant negative value exists in the regression coefficient for the geographical distance difference matrix at the 1% level, indicating that the development of a spatial association network for the digital economy is hampered by larger physical distances between cities. This is primarily due to geographical constraints; cities that are geographically closer can more easily form spatial associations, as the cost of digital economic element flow is relatively lower between adjacent cities, leading to tighter spatial associations. Conversely, non-adjacent cities face higher costs in the flow of digital economic elements and less efficient information exchange, resulting in looser spatial associations. Thus, Hypothesis H2 is supported.

The highest and most statistically positive coefficient in the economic development level difference matrix is 0.134, suggesting that growing disparities in economic development levels aid in the growth of the urban digital economy spatial association network This suggests that disparities in economic development can lead to a "siphon effect", where resources are drawn more towards cities with advanced digital economy, which are mainly distributed in the southeast coastal areas. These economic disparities concentrate various resources in these cities. Hypothesis H1 is verified.

Table 6. QAP regression analysis results.

Variable	Unstandardized Regression Coefficient	Standardized Regression Coefficient	Significance Probability	Probability A	Probability B
D	−0.001	−0.075	0.000	1.000	0.000
E	2.479	0.134	0.000	0.000	1.000
S	0.485	0.006	0.224	0.224	0.776
C	0.065	0.02	0.387	0.387	0.613
I	0.131	0.013	0.070	0.070	0.930
H	0.086	0.016	0.055	0.055	0.945
M	−2.864	−0.041	0.000	1.000	0.000
T	4.608	0.016	0.064	0.064	0.936

Both the informatization level and technological innovation difference matrix's regression coefficient have a significant level of positivity at the 10% level, suggesting that advancements in information technology provide efficient channels for information circulation and improve the utilization efficiency of various resources between cities, thereby tightening inter-city connections and promoting the formation of urban digital economy spatial associations. They are key factors influencing digital economy development. Therefore, Hypothesis H3 is supported.

The regression coefficients for the difference matrix between industrial structure and urbanization level are 0.006 and 0.002, respectively, but the factor's failure to pass the significance test suggests differences in industrial structure and urbanization levels among cities are not a significant factor in the creation of a network spatial associations that exists in China's digital economy. Therefore, Hypothesis H4 is supported

The regression coefficient of the human capital variance matrix shows a significant positive value. This indicates that the expansion of educational disparities is conducive to the formation of the digital economy spatial association network. This factor significantly enhances the circulation of digital economy elements, promotes the connection of urban digital economy, and thereby facilitates the formation of the network. Therefore, Hypothesis H5 is supported.

Conversely, at the 1% level, the marketization level difference matrix's regression coefficient has a significant negative impact, which suggests that larger disparities in marketization levels between cities are detrimental in the digital economy to the creation of a spatial association network. The primary motive is that the market is a key player in the digital economy; greater differences in city marketization levels lead to larger disparities in resource allocation, which, in turn, increase differences in innovation and competition between cities, affecting the digital economy's healthy growth and impeding the establishment of the network. Therefore, Hypothesis H6 is supported.

In this research, we take a closer look at the elements that affect the urban digital economy in China and how the spatial correlation matrix relates to regression analysis. The research breaks down the 279 cities in China that are at the prefecture level into Eastern, Central, Western, and seven distinct regions: China's North, South, East, Central, Southwest, Northwest, and Northeast regions (See Appendix A). The estimation results are presented in Table 7.

From Table 7, it is clear that all four levels of industrial structure, informatization, human capital, and marketisation had notably positive regression coefficients at the 10% level. An ideal setting in which the digital economy can take root network for spatial correlation among Eastern region cities, is one in which there are larger variations in these four parameters. Among them, the difference matrix for the informatization development level has the largest impact coefficient, at 0.260, indicating that the expansion of informatization development level differences is the most important factor in fostering the development of the digital economy spatial association network in eastern cities. Cities in the east typically have better geographical locations, higher levels of economic development and urbaniza-

tion, and advanced technological innovation, so it's no surprise that these factors failed the significance tests. Hence, the development of the Eastern region's digital economy spatial correlation network is unaffected by these four elements. The Central area includes 97 cities. With the greatest regression coefficient of 0.263, there is a positive link between human capital and the difference matrices at the 1% level and between geographic location and the amount of informatization development at the 10% level. Out of the seven components that were considered, only three had a statistically significant impact on how cities in the Central region's digital economy spatial correlation network came to be. The Western area includes 83 cities. While the regression coefficients for the difference matrices of industrial structure and informatization development level are notably positive at the 10% level, there is a noticeable positive trend at the 1% level in the regression coefficients for both geographical location and economic development level, according to the regression results. Amplification of the differences in these four factors supports the formation of a spatial correlation network among cities in the Western region. Here, for the difference matrix of human capital, the regression coefficient is notably negative at 10%, suggesting that a digital economy spatial correlation network would be less feasible if there were more disparities in human capital among the western cities. There was no statistical significance for the other three variables.

Table 7. QAP regression analysis of eastern, central, and western cities.

Variable	Eastern City		Central City		Western City	
	Standardized Regression Coefficient	Significance Probability	Standardized Regression Coefficient	Significance Probability	Standardized Regression Coefficient	Significance Probability
D	0.000	0.898	0.000	0.048	0.000	0.001
E	0.108	0.267	0.103	0.260	0.319	0.008
S	0.227	0.017	−0.000	0.379	0.152	0.073
C	0.030	0.388	0.045	0.335	0.034	0.365
I	0.260	0.012	0.155	0.094	0.158	0.099
H	0.000	0.050	0.263	0.008	−0.000	0.011
M	0.229	0.036	0.140	0.171	0.118	0.206
T	0.061	0.343	−0.143	0.152	0.096	0.211

In the North China region, the network is mainly influenced by four factors: geographical location, human capital, technological innovation, and the level of informatization. The regression coefficients for the difference matrices of geographical location, human capital, and technological innovation are notably positive at the 10% level, and, at the 1% level, the informatization level's difference matrix is positively significant. Northern China is most facilitated by the expanding gap in human capital, according to the biggest regression coefficient for human capital (0.275), which is among these factors. According to the regression results, the four factors that contribute to the formation in the East China region are characterized by high levels of economic development, informatization, technological innovation, and human capital. At 0.527, the economic development level holds the most significant regression coefficient, indicating that a greater disparity in economic development is more conducive to the development of the digital economy spatial correlation network. The Central China region's urban digital economy spatial correlation network is primarily influenced by three factors: geographical location, economic development level, and marketization level. The regression coefficient for the difference matrix of geographical location is notably negative at the 10% level, indicating that there are geographical constraints between cities in the Central China region; the greater the geographical distance differences, the less conducive to the formation. At the 1% level of significance, there is a notably positive regression coefficient associated with the disparity matrix of economic development levels (with the largest coefficient at 0.542), suggesting that the economic development level plays a pivotal role in fostering the growth of the spatial correlation network in the Central China

region. The degree of industrialization, the degree of computerization (strongly positive at the 1% level), and the level of marketization (strongly positive at the 10% level) are the three parameters that impact building the urban digital economy's spatial correlation network in southern China. Like the East China region, the economic development level had the most significant regression coefficient (0.653), indicating that a greater gap encourages the growth of the spatial correlation network for the digital economy. Three factors primarily influence the formation of the urban digital economy spatial correlation network in southwest China: the difference matrices for human capital and informatization level are notably positive at the 1% level, and the regression coefficient for the industrial structure difference matrix is notably positive at the 10% level. The informatization level regression coefficient, at 0.298, is the biggest. The other five forces did not go through the significance test. The factors influencing the spatial association network of the digital economy in cities in the northwest region include industrial structure, human capital, urbanization level and marketization level. The most important influencing factor is industrial structure, with the largest regression coefficient at 0.438. The Northeast China region has the key elements that shaped the development of the urban digital economy network of spatial correlations, with five factors in total. Among these, at the 1% level, the informatization level has the biggest coefficient (0.431), whereas the difference matrices of geographical location, technical innovation, and informatization level all have positive regression coefficients. At the 10% level, the human capital regression coefficient is noticeably positive, but the urbanization level regression coefficient is noticeably negative. This suggests that larger disparities in urbanization level do not help form the digital economy's spatial correlation structure in the Northeast China region (Table 8).

Table 8. QAP regression analysis of seven regional cities.

	Regional	D	E	S	C	I	H	M	T
Standardized Regression Coefficient	North China	0.000	0.000	0.000	0.000	0.658	0.275	0.000	0.000
	East China	−0.000	0.527	−0.101	−0.002	0.403	0.129	0.039	0.459
	Central China	−0.000	0.542	−0.298	0.116	0.014	−0.572	0.529	−0.159
	South China	0.000	0.653	−0.025	0.064	0.447	0.391	0.195	0.014
	Northwest	0.000	−0.104	0.438	0.000	0.000	0.000	0.000	0.476
	Southwest	0.000	0.000	0.298	0.000	0.449	0.000	0.000	0.000
	Northeast	0.000	0.072	0.000	−0.224	0.431	0.000	0.000	0.000
Significance Probability	North China	0.036	0.393	0.800	0.651	0.000	0.019	0.336	0.030
	East China	0.336	0.000	0.107	0.500	0.000	0.087	0.351	0.000
	Central China	0.017	0.004	0.008	0.163	0.452	0.000	0.000	0.170
	South China	0.234	0.005	0.416	0.354	0.001	0.014	0.094	0.482
	Northwest	0.506	0.316	0.009	0.094	0.518	0.000	0.090	0.310
	Southwest	0.894	0.481	0.044	0.593	0.005	0.000	0.208	0.210
	Northeast	0.000	0.566	0.218	0.929	0.008	0.055	0.511	0.001

5.3. Study Comparison

In terms of digital economy development, compared with previous studies [44] mostly based on the provincial level, this paper studies the development trend and spatial distribution trend of China's urban digital economy. The statistical data can more accurately present the development status and differentiation of the digital economy.

In terms of spatial correlation research, most studies focus on spatial autocorrelation and the spatial spillover effect of the digital economy [45]. This paper focuses on the analysis of spatial correlation network characteristics of the urban digital economy in China. The block model and structural hole analysis are a new expansion on previous research.

In terms of driving factors, many factors that drive the development of the digital economy also drive the formation and development of the spatial association network, but there are also certain differences. Therefore, compared with previous studies on influencing factors of digital economy [46], this paper analyzes the driving factors of the

spatial association network of the digital economy, providing a new perspective for the development of the digital economy.

6. Conclusions and Policy Implications

6.1. Conclusions

This paper examines the spatial distribution and development trends of the digital economy in Chinese cities. While investigating the spatial linkage relationships of digital economies across cities, it also constructs a spatial association network. On this basis, the spatial complex network structural features and its driving factors are studied. The following conclusions are drawn:

First, China's cities are experiencing a fluctuating growth pattern with significant regional disparities in the economy within digital improvement. Cities in the southeast coastal regions exhibit notably higher levels of development compared to other areas.

Second, cities have established connections with neighboring and even non-neighboring cities, ensuring accessibility and tight linkages, with no isolated cities within the complex network. The closeness of spatial association relationships remains low and needs further enhancement. Cities that occupy central positions within the association network exert strong control over national digital economy resources and notably influence surrounding regions, demonstrating a pronounced "siphon effect". Conversely, the digital economy spatial association network places cities in the central area primarily in a "bridge" role, with cities in the northwest, northeast, and southwest regions positioning themselves on the network's periphery. This is a new development on the basis of previous research.

Third, according to cluster analysis, there is a reduction in the number of internal connections within each block, while inter-block connections are tight, showing clear spillover effects and significant regional heterogeneity within the network. From the structural hole analysis, cities like Beijing, Shanghai, Nanjing, Suzhou, Shenzhen, and Guangzhou occupy structural hole positions, underscoring their importance and influence within the digital economy spatial network structure. These cities gain considerable "informational advantages" and "control advantages". This is a new discovery that has not been found in previous studies.

Fourth, the development level of economic growth significantly impacts the establishment of the association network. Divergences in urbanization levels, human capital, and technological innovation contribute positively to the creation of spatial association networks in the digital economy. Geographical proximity and differences in marketization levels are negatively correlated with network formation, which hinders the construction of a spatial association network. This is a new development on the basis of previous research.

6.2. Policy Implications

As one of the most dynamic economic forms of the 21st century, the digital economy has not only transformed the traditional economic models of cities but has also profoundly influenced their development paths. The spatial association network of the digital economy is crucial in promoting the development of urban digital economies. This study reaches important conclusions at the urban level and, based on these conclusions, proposes the following policy recommendations:

Strengthening regional coordinated development strategies will foster balanced growth across different areas. Given the significant disparities between regions, especially between southeastern coastal cities and other areas, policies should be formulated to promote coordinated regional development and ensure a balanced distribution of digital economic resources across the country. The central and western cities are recommended to

act as a "bridge", enhancing cooperation with the eastern coastal cities to achieve interconnected development in the digital economy.

Enhancing city complex network connectivity contributes to improved collaboration and economic integration. Increasing investment in infrastructure, particularly in the digital economy sector, such as 5G networks and data centers, can improve the complex network connectivity and data transmission efficiency between cities. Strengthening intercity cooperation in the digital economy and promoting the use of resources will help form a more closely-knit network structure.

Optimizing the spillover effect of digital economy hub cities helps distribute benefits more widely: For cities in central positions, such as Beijing, Shanghai, Guangzhou, and Shenzhen, further leverage their spillover effects to spread advanced digital economy technologies and experiences to surrounding areas. These cities should disseminate advanced digital economy technologies and experiences to the surrounding areas. Additionally, long-term stable cooperative relationships should be established between these hub cities and peripheral cities to promote balanced development of the digital economy across the country.

Emphasizing policy guidance and differentiated management ensures tailored approaches that address specific regional needs in order to formulate differentiated digital economy development policies based on the specific characteristics of different regions and cities at various stages of development to ensure the targeted effectiveness of these policies. There has to be clearer policy direction to boost innovation, support digital economy integration with traditional industries, and raise digital economy's contribution to the national economy.

6.3. Limitations and Further Directions

The spatial association network of China's urban digital economy and its motivating elements are thoroughly examined in this article; however, there are still many shortcomings and research expansibility.

First of all, future research can further expand the regional scope so that it is no longer limited to cities, but extends specific research areas to city clusters, economic zones and even transnational regions. In addition, we can expand the international perspective and compare the structural differences and evolutionary laws of spatial correlation networks of digital economy in different countries.

Secondly, in terms of industry scalability, the research method of this paper can be applied to the production of digital products, the application of digital technology and other fields. In the future, the spatial association network of each industry should be constructed to analyze the characteristic differences in network structure, node centrality and association strength to enrich the research perspective.

Third, in terms of data, the current research is restricted by data acquisition conditions, the data used in this analysis mostly spans the years 2012–2021, and the urban digital economy's spatial association network may undergo more modifications over time. Follow-up studies should continue to update the data to track the latest trends and provide a more reliable basis for in-depth analysis.

Author Contributions: Conceptualization, M.Y. and W.Y.; methodology, X.W. and J.S.; software, M.Y.; validation, X.W. and J.S.; formal analysis, W.Y. and M.Y.; investigation, M.Y.; resources, W.Y.; data curation, M.Y. and X.W.; writing-original draft preparation, M.Y.; writing—review and editing, W.Y. and J.S.; visualization, M.Y. and X.W.; supervision, W.Y.; project administration, W.Y.; funding acquisition, W.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Major Special Project of the National Social Science Foundation of China under Grant no. 22VMG012, National Natural Science Foundation of China (NSFC) under Grant no. 71971131, the Research Project Supported by the Shanxi Scholarship Council of China under Grant no 2022-027, Wenying Young Scholars Program of Shanxi University and the Joint Laboratory of Tourism Big Data in Shanxi Province.

Data Availability Statement: Data will be provided upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Calculation results of degree centrality, betweenness centrality, and closeness centrality in 2021.

City	Out Degree	In Degree	Nrm Degree	City	Betweenness	City	Closeness
Shanghai	252	145	90.647	Beijing	12.88	Shanghai	19.633
Beijing	244	128	87.77	Shenzhen	9.502	Beijing	19.536
Nanjing	236	156	84.892	Shanghai	6.632	Nanjing	19.373
Suzhou	235	142	84.173	Nanjing	6.347	Suzhou	19.359
Shenzhen	220	124	79.137	Suzhou	4.767	Shenzhen	19.12
Guangzhou	196	91	70.504	Guangzhou	4.056	Hangzhou	18.746
Hangzhou	190	103	67.266	Ordos	3.84	Changzhou	18.746
Changzhou	188	133	65.827	Yulin	3.72	Guangzhou	18.733
Wuhan	167	112	58.993	Changzhou	2.521	Wuhan	18.558
Qingdao	156	71	55.755	Chengdu	2.474	Qingdao	18.35
Ningbo	154	86	54.676	Wuhan	2.087	Changsha	18.302
Changsha	148	91	52.878	Hangzhou	1.886	Ningbo	18.289
Nantong	142	74	51.079	Changsha	1.779	Nantong	18.146
Yangzhou	136	96	47.842	Yichang	1.753	Yangzhou	18.087
Taizhou	129	61	44.245	Qingdao	1.177	Zhenjiang	18.005
Zhenjiang	124	104	43.525	Dongying	1.145	Taizhou	17.97
Yichang	116	87	40.288	Chongqing	1.091	Yichang	17.947
Yulin	115	88	39.209	Jinchang	1.071	Yulin	17.866
Jinan	110	59	39.209	Zhangye	1.013	Fuzhou	17.809
Fuzhou	107	63	38.489	Ningbo	1.009	Jinan	17.809
Quanzhou	106	53	35.971	Dingxi	0.963	Dongying	17.752
Dongying	101	94	33.094	Yangzhou	0.931	Quanzhou	17.73
Hefei	98	64	32.374	Zhenjiang	0.922	Chongqing	17.617
Chongqing	91	24	31.295	Zhantong	0.883	Hefei	17.595
Yantai	87	52	29.137	Liupanshui	0.759	Shaoxing	17.495
Shaoxing	84	58	28.058	Nantong	0.748	Yantai	17.484
Foshan	82	54	26.619	Zhuhai	0.643	Wuxi	17.473
Ordos	81	95	24.82	Wuzhong	0.575	Wuhu	17.44
Zhenzhou	79	43	24.82	Jinan	0.512	Foshan	17.44
Zhoukou	76	54	24.46	Guiyang	0.467	Zhenzhou	17.429
Xiamen	73	57	24.46	Fuzhou	0.452	Fuyang	17.429
Fuyang	71	61	23.741	Foshan	0.443	Zhenzhou	17.429
Xuzhou	70	49	21.942	Shaoyang	0.443	Xiamen	17.386
Zhuhai	70	77	21.942	Taizhou	0.396	Sanming	17.364
Huanggang	70	57	21.583	Zhenzhou	0.396	Huanggang	17.353
Baoding	68	43	21.583	Baoding	0.388	Ezhou	17.342
Heze	65	44	21.583	Ulanqab	0.367	Xuzhou	17.342
Handan	63	47	20.504	Kunming	0.362	Heze	17.332
Xinyang	62	50	19.784	Panzhihua	0.357	Handan	17.321
Linyi	62	47	19.424	Jiayuguan	0.355	Baoding	17.321
Shijiazhuang	61	34	19.424	Quanzhou	0.338	Xinngtai	17.31
Shangrao	60	53	19.424	Yantai	0.334	Jiaxing	17.299
Xinyu	60	43	19.065	Nanyang	0.322	Zhuhai	17.299
Tongling	59	40	19.065	Baiyin	0.318	Zhoushan	17.299
Jining	58	42	19.065	Huanggang	0.31	Xinyu	17.289
Jiaxing	58	47	18.705	Fuyang	0.305	Xinyang	17.289
Yancheng	57	40	18.705	Handan	0.3	Suzhzhou	17.278
Shangqiu	57	48	18.705	Xi'an	0.275	Shangqiu	17.278
Tai'an	56	41	18.345	Guigang	0.263	Jining	17.267
Nanchang	56	41	17.986	Heze	0.263	Bozhou	17.267
Liaocheng	56	47	17.626	Xiamen	0.26	Nanchang	17.267
Sanming	55	56	17.626	Xining	0.258	Shangrao	17.267
Wuhu	55	71	17.626	Hefei	0.257	Liaocheng	17.267

Table A1. *Cont.*

City	Out Degree	In Degree	Nrm Degree	City	Betweenness	City	Closeness
Shaoyang	55	42	17.266	Shangrao	0.248	Linyi	17.256
Bozhou	54	52	17.266	Xinngtai	0.239	Yancheng	17.256
Huai'an	54	45	17.266	Huaihua	0.232	Shijiazhuang	17.256
Yueyang	54	38	16.906	Shijiazhuang	0.229	Tongling	17.246
Nanyang	54	41	16.906	Baoji	0.22	Nanyang	17.235
Xinngtai	52	56	16.187	Shangqiu	0.217	Shaoyang	17.235
Liu'an	52	48	16.187	Shaoxing	0.213	Huai'an	17.235
Suzhzhou	52	57	16.187	Yulin	0.212	Tai'an	17.235
Taiyuan	52	36	16.187	Linyi	0.204	Hengshui	17.224
Suizhou	52	38	16.187	Shenyang	0.195	Meizhou	17.224
Zhumadian	52	45	15.827	Longnan	0.193	Longyan	17.224
Zaozhuang	51	46	15.827	Liaocheng	0.192	Zhumadian	17.214
Weifang	50	29	15.827	Xinyang	0.189	Ma'anshan	17.203
Hengshui	49	46	15.468	Nanchong	0.185	Zaozhuang	17.203
Weihai	49	43	15.468	Ziyang	0.183	Ordos	17.203
Meizhou	49	48	15.468	Zhumadian	0.177	Yueyang	17.192
Dalian	49	27	15.468	Harbin	0.175	Liu'an	17.192
Ganzhou	49	35	15.108	Yibin	0.174	Taiyuan	17.192
Longyan	48	48	15.108	Pingliang	0.172	Suizhou	17.182
Dongguan	48	40	14.748	Hengshui	0.167	Huzhou	17.182
Zibo	47	38	14.748	Suzhzhou	0.162	Guigang	17.16
Fuzhou	46	44	14.388	Yan'an	0.161	Fuzhou	17.16
Jinzhou	46	40	14.388	Bazhong	0.161	Weifang	17.16
Jieyang	46	39	14.388	Zhengzhou	0.158	Zibo	17.15
Hengyang	45	35	14.388	Bozhou	0.153	Jinzhou	17.15
Chendu	45	22	14.388	Yongzhou	0.149	Huainan	17.15
Lianyungang	45	37	13.309	Taiyuan	0.143	Kaifeng	17.139
Anqing	45	39	13.309	Liu'an	0.14	Weihai	17.139
Yulin	44	39	13.309	Shangluo	0.13	Hengyang	17.139
Huzhou	44	45	13.309	Wuhu	0.126	Jieyang	17.139
Xinxiang	43	31	12.95	Tai'an	0.125	Xuchang	17.139
Zhuzhou	43	39	12.95	Jinzhou	0.124	Yulin	17.129
Yichun	43	33	12.59	Yuncheng	0.122	Chengdu	17.129
Wuzhong	43	15	12.59	Meizhou	0.121	Zhuzhou	17.118
Kaifeng	43	37	12.59	Zaozhuang	0.118	Zhangjiajie	17.118
Shengyang	42	25	12.59	Hechi	0.118	Bengbu	17.118
Yongzhou	42	41	12.59	Sanming	0.117	Lianyungang	17.118
Zhangzhou	42	30	12.23	Weihai	0.115	Yongzhou	17.118
Cangzhou	42	33	12.23	Xinxiang	0.108	Huaihua	17.118
Dezhou	42	34	12.23	Dalian	0.105	Ganzhou	17.118
Xianning	42	35	11.871	Cangzhou	0.104	Suqian	17.108
Huaihua	42	39	11.871	Kaifeng	0.103	Anqing	17.108
Huainan	41	45	11.871	Fuzhou	0.1	Dalian	17.108
Ji'an	41	34	11.871	Dongguan	0.1	Longnan	17.108
Bengbu	41	41	11.871	Wuxi	0.099	Huaibei	17.097
Guigang	40	42	11.871	Anyang	0.097	Yiyang	17.097
Suqian	40	40	11.511	Pingdingshan	0.091	Bazhong	17.097
Jinhua	39	30	11.511	Dezhou	0.089	Xianning	17.087
Yiyang	39	37	11.511	Fushun	0.088	Anyang	17.087
Wuxi	39	84	11.151	Yiyang	0.087	Dongguan	17.087
Ma'anshan	38	49	11.151	Jining	0.086	Shangluo	17.087
Chuzhou	38	37	11.151	Xuzhou	0.086	Puyang	17.087
Anyang	38	36	11.151	Longyan	0.086	Pingdingshan	17.087
Huizhou	38	32	10.791	Suizhou	0.086	Dezhou	17.087
Shantou	38	32	10.791	Ankang	0.084	Xinxiang	17.087
Pingdingshan	38	33	10.791	Zunyi	0.083	Cangzhou	17.076
Binzhou	38	34	10.791	Loudi	0.082	Chuzhou	17.076
Loudi	38	38	10.791	Jieyang	0.081	Binzhou	17.076
Xuchang	38	41	10.791	Hengyang	0.081	Huangshi	17.076
Ezhou	38	62	10.432	Ganzhou	0.08	Loudi	17.076
Puyang	38	36	10.072	Qingyang	0.08	Luohe	17.066
Qingyuan	37	35	10.072	Puyang	0.08	Tianjin	17.066
Tianjing	37	42	10.072	Zhoushan	0.078	Ji'an	17.066
Lishui	37	34	10.072	Zhangjiakou	0.077	Dingxi	17.066
Zhoushan	37	67	9.712	Huainan	0.076	Chaozhou	17.066
Jiujiang	37	31	9.712	Lanzhou	0.075	Huludao	17.066
Chaozhou	36	37	9.353	Xinyu	0.075	Chizhou	17.055
Chenzhou	36	33	9.353	Hanzhong	0.074	Zhangzhou	17.055
Nanping	36	32	9.353	Dazhou	0.074	Yichun	17.055
Ningde	36	26	9.353	Zhangjiajie	0.071	Hezhou	17.055

Table A1. *Cont.*

City	Out Degree	In Degree	Nrm Degree	City	Betweenness	City	Closeness
Xiaogan	36	31	9.353	Fuxin	0.07	Wuzhong	17.055
Luoyang	36	26	8.993	Jiaxing	0.068	Shenyang	17.055
Huaibei	36	39	8.993	Ezhou	0.068	Hebi	17.055
Heyuan	35	36	8.633	Nanchang	0.066	Qingyuan	17.055
Shaoguan	35	33	8.633	Xianning	0.065	Yuncheng	17.045
Huangshi	35	37	8.633	Wuwei	0.064	Xiaogan	17.045
Zhaoqing	35	25	8.633	Quang'an	0.064	Heyuan	17.045
Putian	35	22	8.633	Anqing	0.061	Zhangjiakou	17.045
Jingmen	34	31	8.633	Tongling	0.059	Huizhou	17.045
Maoming	34	21	8.633	Zhanjiang	0.058	Lishui	17.034
Shanwei	34	35	8.273	Xianyang	0.058	Hechi	17.034
Rizhao	34	31	8.273	Tianjin	0.057	Shanwei	17.034
Ulanqab	34	21	8.273	Yueyang	0.056	Zhongshan	17.034
Guilin	34	31	8.273	Yichun	0.052	Chenzhou	17.034
Yuncheng	34	33	8.273	Siping	0.052	Jiujiang	17.034
Zhanjiang	34	20	7.914	Ji'an	0.052	Shaoguan	17.024
Jiangmen	34	27	7.914	Huludao	0.05	Luoyang	17.024
Taizhou	34	25	7.914	Langfang	0.05	Pingliang	17.024
Langfang	34	27	7.554	Yancheng	0.049	Jincheng	17.024
Tangshan	33	34	7.554	Huaian	0.049	Shantou	17.024
Pingxiang	33	33	7.554	Bengbu	0.049	Jingmen	17.024
Luohe	33	35	7.194	Qingyuan	0.047	Xuancheng	17.024
Zhongshan	33	33	7.194	Xinzhou	0.046	Nanping	17.024
Yicheng	33	33	7.194	Jinhua	0.046	Rizhao	17.024
Nanning	33	19	6.835	Nanning	0.046	Xiangtan	17.024
Zhangjiakou	33	33	6.835	Chaoyang	0.046	Chaoyang	17.024
Zunyi	32	17	6.835	Qiqihar	0.046	Jinhua	17.013
Chaoyang	32	33	6.835	Jinzhou	0.046	Guilin	17.013
Huludao	32	37	6.835	Wuhai	0.044	Yingtan	17.013
Huangshan	32	32	6.835	Lishui	0.043	Huangshan	17.013
Guiyang	32	17	6.475	Luoyang	0.041	Pingxiang	17.013
Harbin	32	11	6.475	Jiaozuo	0.04	Linfen	17.003
Xi'an	31	26	6.475	Heyuan	0.04	Tianshui	17.003
Qinhuangdao	30	26	6.475	Chaozhou	0.04	Jiaozuo	17.003
Chengde	30	23	6.475	Panjin	0.039	Ankang	17.003
Xianyang	30	21	6.475	Jiuquan	0.039	Wuzhou	16.993
Chizhou	30	36	6.475	Xiaogan	0.039	Jiangmen	16.993
Jiaozuo	30	30	6.115	Daqing	0.039	Jinzhong	16.993
Jinzhou	30	26	6.115	Guilin	0.038	Yunfu	16.993
Baoji	30	22	6.115	Zhuzhou	0.037	Ningde	16.993
Yunfu	30	30	5.755	Laibin	0.036	Qingyang	16.993
Panjin	29	24	5.755	Huzhou	0.036	Fuxin	16.993
Yan'an	29	22	5.755	Shaoguan	0.035	Tangshan	16.982
Xiangtan	29	32	5.755	Ma'anshan	0.035	Changzhi	16.982
Anshan	28	22	5.755	Shiyan	0.035	Laibin	16.982
Changchun	27	10	5.396	Neijiang	0.035	Langfang	16.972
Hanzhong	27	21	5.396	Weifang	0.035	Xi'an	16.972
Beihai	27	19	5.396	Shantou	0.034	Xinzhou	16.962
Jincheng	26	32	5.396	Songyuan	0.034	Xianyang	16.962
Shiyan	26	23	5.396	Binzhou	0.034	Danton	16.951
Daqing	26	9	5.396	Shanwei	0.033	Chengde	16.951
Bazhong	26	39	5.396	Chenzhou	0.033	Jinzhou	16.951
Liuzhou	26	21	5.396	Danton	0.033	Qinhuangdao	16.951
Hechi	26	34	5.396	Guangyuan	0.033	Ulanqab	16.951
Yingkou	26	22	5.396	Chengde	0.032	Yan'an	16.951
Shangluo	26	38	5.396	Tangshan	0.032	Zhaoqing	16.951
Hezhou	25	36	5.396	Qinhuangdao	0.032	Baoji	16.951
Linfen	25	29	5.036	Linfen	0.031	Fushun	16.941
Longnan	25	39	5.036	Changchun	0.03	Taizhou	16.941
Ankang	25	30	5.036	Xuchang	0.03	Shiyan	16.941
Danton	25	26	5.036	Huaibei	0.03	Maoming	16.941
Dazhou	25	21	5.036	Suqian	0.03	Putian	16.941
Zhangjiajie	25	42	4.676	Pingxiang	0.029	Hanzhong	16.941
Wuhai	24	10	4.317	Yunfu	0.029	Qinzhou	16.931
Deyang	24	14	4.317	Jiangmen	0.029	Guiyang	16.931
Jinzhong	24	27	4.317	Hezhou	0.029	Ziyang	16.931
Tongchuan	24	19	4.317	Suining	0.028	Tongchuan	16.931
Changzhi	24	27	4.317	Zibo	0.028	Datong	16.931
Nanchong	24	18	4.317	Zhaoqing	0.028	Anshan	16.931
Yangjiang	24	22	3.957	Lianyungang	0.028	Yingkou	16.931
Fushun	23	24	3.957	Tianshui	0.028	Zhanjiang	16.931

Table A1. *Cont.*

City	Out Degree	In Degree	Nrm Degree	City	Betweenness	City	Closeness
Hebi	23	35	3.597	Jinzhong	0.028	Tonghua	16.92
Qinzhou	23	24	3.597	Tieling	0.027	Baiyin	16.92
Ziyang	23	24	3.597	Deyang	0.027	Siping	16.92
Laibin	23	29	3.597	Huizhou	0.027	Yangquan	16.92
Fuxin	22	30	3.597	Nanping	0.027	Liuzhou	16.91
Suining	22	14	3.237	Zhangzhou	0.024	Sanmenxia	16.91
Pingliang	22	32	3.237	Maoming	0.024	Nanning	16.91
Fangchenggang	22	18	3.237	Huangshi	0.023	Dazhou	16.91
Dingxi	21	36	3.237	Datong	0.022	Zunyi	16.91
Qingyang	21	29	3.237	Chuzhou	0.022	Liaoyang	16.9
Shuozhou	21	16	3.237	Jingmen	0.021	Yangjiang	16.9
Datong	21	23	3.237	Jilin	0.021	Guangyuan	16.889
Mianyang	20	12	3.237	Baicheng	0.02	Chongzuo	16.889
Quang'an	20	17	2.878	Jincheng	0.02	Panjin	16.879
Guangyuan	20	19	2.878	Suihua	0.02	Nanchong	16.879
Wenzhou	20	20	2.878	Zhongshan	0.019	Harbin	16.879
Lanzhou	20	11	2.878	Xuancheng	0.019	Quang Yen	16.879
Liaoyang	19	21	2.878	Anshan	0.018	Anshun	16.879
Baise	19	18	2.518	Taizhou	0.017	Wenzhou	16.879
Yangquan	19	22	2.518	sunshine	0.017	Beihai	16.879
Zhaotong	19	18	2.518	Jiujiang	0.017	Baise	16.879
Tieling	18	19	2.158	Luohe	0.017	Benxi	16.879
Luzhou	18	13	2.158	Xiangtan	0.016	Zhaotong	16.869
Benxi	18	18	2.158	Tongchuan	0.016	Suining	16.869
Yingtan	18	32	2.158	Hebi	0.016	Weinan	16.869
Sanmenxia	18	20	2.158	Baise	0.015	Qiqihar	16.869
Haikou	17	12	2.158	Huangshan	0.015	Liupanshui	16.859
Chongzuo	17	20	2.158	Changzhi	0.015	Neijiang	16.859
Xinzhou	17	26	2.158	Yingkou	0.015	Fangchenggang	16.859
Yibin	17	12	2.158	Ningde	0.014	Lvliang	16.859
Liupanshui	17	16	2.158	Chizhou	0.013	Deyang	16.859
Neijiang	17	17	2.158	Beihai	0.013	Songyuan	16.848
Wuzhou	16	30	2.158	Putian	0.012	Mianyang	16.848
Lvliang	16	16	1.799	Liaoyang	0.011	Meishan	16.828
Jinchang	16	8	1.799	Anshun	0.011	Luzhou	16.828
Hohhot	16	5	1.799	Qinzhou	0.011	Lanzhou	16.828
Siping	15	23	1.799	Liuzhou	0.011	Zigong	16.818
Baiyin	15	22	1.799	Yangquan	0.009	Guyuan	16.818
Tianshui	15	30	1.799	Shuozhou	0.009	Yibin	16.818
Qiqihar	14	18	1.439	Lvliang	0.008	Tieling	16.808
Zigong	14	13	1.439	Meishan	0.008	Zhangye	16.798
Leshan	14	8	1.439	Mianyang	0.008	Mudanjiang	16.798
Anshun	14	19	1.439	Benxi	0.008	Haikou	16.798
Yinchuan	13	6	1.439	Wuzhou	0.008	Shuozhou	16.798
Suihua	13	11	1.439	Chongzuo	0.007	Daqing	16.777
Sining	13	7	1.439	Fangchenggang	0.007	Xining	16.777
Songyuan	13	16	1.439	Yangjiang	0.007	Changchun	16.777
Ji Lin	12	13	1.079	Yinchuan	0.007	Leshan	16.767
Meishan	12	14	1.079	Leshan	0.007	Ya'an	16.767
Kunming	12	4	1.079	Luzhou	0.006	Baicheng	16.757
Baotou	11	8	1.079	Zigong	0.005	Liaoyuan	16.747
Wuwei	9	5	0.719	Wenzhou	0.005	Tongliao	16.747
Zhangye	9	9	0.719	Sanmenxia	0.004	Qitaihe	16.747
Tongliao	8	14	0.719	Lijiang	0.004	Jilin	16.727
Shizuishan	8	5	0.719	Hohhot	0.004	Suihua	16.707
Panzhihua	8	4	0.719	Haikou	0.003	Yinchuan	16.697
Chifeng	8	8	0.719	Shizuishan	0.003	Baotou	16.687
Baicheng	8	15	0.719	Yingtan	0.003	Jinchang	16.677
Ya'an	7	8	0.36	Tongliao	0.001	Sanya	16.667
Lijiang	7	4	0.36	Baotou	0.001	Yichun	16.667
Urumqi	7	0	0.36	Guyuan	0.001	Chifeng	16.647
Guyuan	6	12	0.36	Chifeng	0.001	Hohhot	16.637
Qujing	6	3	0.36	Ya'an	0	Zhongwei	16.617
Jiayuguan	5	2	0.36	Qujing	0	Jixi	16.607
Jiuquan	5	1	0.36	Zhongwei	0	Kiamusi	16.607
Sanya	5	7	0.36	Sanya	0	Baishan	16.607
Zhongwei	5	5	0.36	Baoshan	0	Hegang	16.607
Baoshan	5	1	0	Urumqi	0	Heihe	16.607
Lincang	5	2	0	Lincang	0	Shuangyashan	16.597
Hulunbuir	5	2	0	Hulunbuir	0	Shizuishan	16.587
Karamay	5	1	0	Karamay	0	Hulunbuir	16.567

Table A1. *Cont.*

City	Out Degree	In Degree	Nrm Degree	City	Betweenness	City	Closeness
Jixi	4	5	0	Jixi	0	Wuwei	16.518
Baishan	4	5	0	Baishan	0	Jiuquan	16.411
Yuxi	4	0	0	Yuxi	0	Kunming	16.267
Liaoyuan	4	15	0	Liaoyuan	0	Panzhihua	16.267
Shuangyashan	3	4	0	Shuangyashan	0	Lijiang	16.248
Tonghua	2	23	0	Tonghua	0	Qujing	16.116
Kiamusi	2	5	0	Kiamusi	0	Lincang	16.107
Lhasa	2	0	0	Lhasa	0	Baoshan	16.097
Yichun	2	7	0	Yichun	0	Wuhai	15.566
Qitaihe	1	7	0	Qitaihe	0	Jiayuguan	14.434
Weinan	1	17	0	Weinan	0	Urumqi	0.36
Mudanjiang	1	12	0	Mudanjiang	0	Karamay	0.36
Hegang	0	5	0	Hegang	0	Yuxi	0
Heihe	0	5	0	Heihe	0	Lhasa	0

Table A2. Calculation results of structural hole metrics in 2012 and 2021.

2012					2021				
City	Effsize	Efficiency	Constraint	Hierarchy	City	EffSize	Efficiency	Constraint	Hierarchy
Dongying	204.37	0.881	0.025	0.173	Beijing	224.44	0.92	0.023	0.170
Suzhou	199.36	0.882	0.029	0.229	Shanghai	221.28	0.878	0.023	0.162
Guangzhou	188.61	0.916	0.034	0.300	Nanjing	208.40	0.883	0.025	0.175
Shenzhen	188.13	0.904	0.032	0.263	Suzhou	204.86	0.872	0.026	0.190
Wuxi	185.88	0.877	0.029	0.205	Shenzhen	199.33	0.906	0.027	0.203
Shanghai	178.24	0.905	0.046	0.366	Guangzhou	181.65	0.927	0.035	0.316
Changsha	161.14	0.916	0.044	0.339	Hangzhou	166.04	0.883	0.041	0.308
Beijing	158.72	0.917	0.055	0.421	Changzhou	162.44	0.855	0.034	0.224
Ordos	149.75	0.886	0.032	0.171	Wuhan	149.92	0.898	0.047	0.323
Wuhan	145.20	0.891	0.053	0.356	Qingdao	137.48	0.881	0.06	0.380
Nanjing	141.10	0.887	0.051	0.345	Ningbo	136.36	0.885	0.043	0.275
Hangzhou	136.19	0.89	0.052	0.348	Changsha	134.71	0.91	0.053	0.354
Dalian	126.98	0.882	0.05	0.298	Nantong	122.63	0.864	0.061	0.355
Tianjin	116.97	0.886	0.061	0.344	Yangzhou	115.23	0.847	0.054	0.297
Qingdao	110.82	0.846	0.06	0.309	Zhenjiang	107.46	0.833	0.053	0.267
Foshan	102.14	0.904	0.079	0.445	Yichang	106.70	0.92	0.07	0.390
Changzhou	94.10	0.863	0.067	0.339	Yulin	104.86	0.912	0.059	0.333
Ningbo	93.77	0.852	0.063	0.301	Taizhou	99.85	0.805	0.063	0.288
Daqing	89.01	0.848	0.053	0.198	Jinan	92.87	0.844	0.073	0.324
Shaoxing	82.11	0.821	0.064	0.254	Fuzhou	91.59	0.856	0.071	0.334
Zhenjiang	75.42	0.82	0.071	0.285	Dongying	89.47	0.844	0.054	0.207
Tongling	74.57	0.829	0.067	0.237	Ordos	87.42	0.892	0.058	0.252
Shenyang	71.18	0.847	0.086	0.322	Quanzhou	82.19	0.814	0.068	0.267
Tangshan	69.86	0.794	0.08	0.271	Hefei	69.60	0.765	0.072	0.242
Zibo	69.34	0.806	0.078	0.271	Zhuhai	65.39	0.828	0.075	0.242
Zhuhai	66.58	0.843	0.077	0.273	Chongqing	64.50	0.741	0.064	0.168
Yulin	62.77	0.86	0.094	0.342	Yantai	63.35	0.782	0.083	0.262
Zhengzhou	60.32	0.783	0.084	0.249	Foshan	63.12	0.83	0.089	0.295
Baotou	59.87	0.832	0.082	0.248	Shaoxing	60.69	0.74	0.074	0.212
Jinan	58.20	0.727	0.073	0.193	Xiamen	60.27	0.826	0.083	0.25
Weihai	57.77	0.837	0.087	0.28	Wuxi	53.10	0.632	0.06	0.11
Yantai	52.63	0.731	0.083	0.209	Zhengzhou	50.66	0.724	0.079	0.175
Yichang	51.16	0.775	0.106	0.284	Zhoushan	50.09	0.737	0.082	0.189
Bozhou	46.69	0.64	0.058	0.043	Zhoukou	48.33	0.69	0.062	0.062
Heze	46.26	0.68	0.064	0.057	Fuyang	46.75	0.668	0.062	0.057
Zhoushan	45.62	0.76	0.093	0.207	Wuhu	46.60	0.656	0.074	0.143
Xiamen	45.34	0.796	0.104	0.251	Sanming	45.26	0.696	0.083	0.164
Fuyang	45.05	0.653	0.061	0.046	Huanggang	42.51	0.675	0.066	0.046
Xinyu	44.61	0.783	0.104	0.229	Ezhou	42.25	0.681	0.086	0.154
Huanggang	44.31	0.726	0.068	0.057	Handan	41.53	0.692	0.074	0.08
Chongqing	43.30	0.722	0.077	0.095	Baoding	41.36	0.689	0.074	0.077
Zhongshan	41.03	0.76	0.104	0.234	Heze	41.36	0.678	0.071	0.064
Zhoukou	38.60	0.677	0.075	0.057	Xinyang	38.48	0.675	0.074	0.062
Zhumadian	38.04	0.718	0.08	0.067	Nanyang	37.33	0.718	0.085	0.083
Lu'an	36.83	0.658	0.075	0.054	Xingtai	37.31	0.632	0.073	0.057
Shangrao	36.29	0.685	0.079	0.056	Shaoyang	36.81	0.708	0.083	0.074
Xingtai	35.85	0.629	0.073	0.041	Suzhou	36.71	0.644	0.076	0.061
Xiaogan	35.78	0.716	0.083	0.065	Linyi	36.10	0.669	0.079	0.062

Table A2. *Cont.*

2012					2021				
City	**Effsize**	**Efficiency**	**Constraint**	**Hierarchy**	**City**	**EffSize**	**Efficiency**	**Constraint**	**Hierarchy**
Panjin	35.43	0.738	0.113	0.213	Shangrao	36.10	0.645	0.072	0.034
Xinyang	35.03	0.701	0.087	0.085	Shangqiu	36.08	0.644	0.075	0.051
Shangqiu	34.90	0.646	0.077	0.047	Nanchang	35.98	0.643	0.093	0.148
Suzhou	34.72	0.569	0.068	0.031	Chengdu	35.67	0.849	0.13	0.249
Chengdu	34.46	0.841	0.14	0.289	Bozhou	35.09	0.638	0.076	0.049
Shijiazhuang	34.09	0.568	0.07	0.036	Shijiazhuang	35.02	0.648	0.084	0.091
Baoding	33.94	0.722	0.094	0.098	Xinyu	34.82	0.6	0.084	0.114
Yangzhou	32.50	0.542	0.075	0.074	Taiyuan	34.54	0.72	0.114	0.197
Anqing	31.82	0.663	0.09	0.073	Liaocheng	34.48	0.627	0.077	0.055
Shaoyang	31.75	0.661	0.091	0.073	Meizhou	33.81	0.65	0.081	0.055
Handan	31.64	0.673	0.097	0.108	Weihai	33.77	0.689	0.103	0.16
Jingzhou	30.77	0.715	0.098	0.079	Zhumadian	33.65	0.673	0.085	0.061
Nanchang	30.52	0.598	0.093	0.111	Longyan	33.54	0.645	0.092	0.119
Nanyang	29.96	0.749	0.11	0.108	Tai'an	32.84	0.631	0.082	0.064
Hengshui	29.78	0.608	0.085	0.044	Dalian	32.22	0.7	0.121	0.204
Weinan	29.72	0.725	0.108	0.092	Hengshui	31.99	0.627	0.085	0.064
Yichun	29.70	0.691	0.1	0.074	Jingzhou	31.96	0.726	0.092	0.059
Linyi	29.62	0.581	0.081	0.04	Liu'an	31.57	0.644	0.085	0.053
Fuzhou	29.22	0.679	0.099	0.071	Fuzhou	30.98	0.674	0.09	0.055
Yuncheng	29.13	0.728	0.111	0.1	Guigang	30.79	0.669	0.094	0.069
Ganzhou	28.96	0.673	0.099	0.069	Zaozhuang	30.66	0.626	0.087	0.061
Shangluo	28.79	0.702	0.111	0.102	Jiaxing	30.59	0.527	0.078	0.076
Ji'an	27.37	0.702	0.109	0.078	Longnan	30.43	0.761	0.109	0.087
Chuzhou	27.21	0.618	0.095	0.05	Dongguan	30.43	0.676	0.111	0.157
Xuancheng	26.10	0.652	0.107	0.066	Zhangjiajie	30.40	0.724	0.107	0.1
Xinxiang	26.05	0.724	0.117	0.089	Huaihua	30.35	0.74	0.103	0.082
Suizhou	25.77	0.696	0.123	0.112	Xuzhou	30.28	0.488	0.067	0.035
Hengyang	25.76	0.678	0.116	0.098	Ganzhou	29.34	0.682	0.096	0.055
Xi'an	25.58	0.656	0.116	0.105	Hengyang	29.21	0.679	0.101	0.087
Kaifeng	25.40	0.669	0.113	0.083	Jieyang	28.96	0.643	0.093	0.055
Huangshan	24.89	0.638	0.11	0.068	Tianjin	28.84	0.687	0.119	0.163
Yongzhou	24.87	0.672	0.115	0.077	Yiyang	28.35	0.727	0.106	0.072
Xuzhou	24.78	0.459	0.074	0.015	Suizhou	28.07	0.597	0.092	0.07
Suqian	24.57	0.558	0.095	0.05	Huainan	27.71	0.616	0.094	0.061
Bengbu	24.44	0.555	0.098	0.061	Yulin	27.71	0.644	0.097	0.051
Meizhou	24.16	0.619	0.109	0.065	Kaifeng	27.71	0.644	0.101	0.08
Anyang	24.13	0.69	0.123	0.092	Bazhong	27.48	0.705	0.109	0.064
Yiyang	23.83	0.701	0.127	0.097	Dingxi	27.48	0.763	0.115	0.077
Ankang	23.72	0.698	0.132	0.105	Jining	27.36	0.498	0.076	0.036
Hefei	23.40	0.487	0.088	0.044	Yancheng	27.21	0.504	0.082	0.062
Dongguan	23.37	0.599	0.118	0.111	Shangluo	27.14	0.714	0.114	0.079
Quanzhou	23.28	0.529	0.1	0.07	Yongzhou	26.98	0.642	0.1	0.06
Nantong	23.10	0.481	0.087	0.038	Ji'an	26.93	0.709	0.109	0.071
Chizhou	22.78	0.633	0.118	0.072	Xinxiang	26.32	0.693	0.109	0.063
Xinzhou	22.72	0.71	0.141	0.123	Loudi	26.22	0.69	0.11	0.075
Dingxi	22.63	0.73	0.141	0.106	Pingdingshan	26.03	0.685	0.109	0.063
Zhangjiajie	22.54	0.704	0.139	0.109	Xianning	25.82	0.662	0.113	0.095
Jiujiang	22.53	0.663	0.132	0.116	Yichun	25.67	0.694	0.11	0.062
Lianyungang	22.32	0.587	0.111	0.069	Wuzhong	25.59	0.731	0.116	0.056
Liaocheng	22.32	0.558	0.107	0.065	Anyang	25.55	0.672	0.107	0.053
Weifang	22.25	0.556	0.107	0.062	Yueyang	25.13	0.513	0.086	0.046
Yancheng	22.20	0.541	0.102	0.052	Huaian	24.91	0.479	0.082	0.047
Tai'an	22.14	0.515	0.097	0.047	Puyang	24.75	0.651	0.111	0.064
Pingdingshan	22.13	0.714	0.139	0.11	Ma'anShan	24.40	0.498	0.089	0.063
Fuzhou	22.12	0.514	0.103	0.075	Anqing	23.90	0.583	0.102	0.061
Puyang	22.02	0.58	0.113	0.073	Yuncheng	23.88	0.702	0.122	0.071
Jining	21.96	0.488	0.093	0.042	Tongling	23.74	0.44	0.075	0.02
Huaian	21.78	0.519	0.098	0.046	Heyuan	23.62	0.656	0.116	0.061
Longnan	21.77	0.702	0.139	0.094	Hechi	23.60	0.694	0.126	0.082
Jiayuguan	21.74	0.87	0.136	0.082	Qingyuan	23.60	0.655	0.114	0.057
Xianning	21.58	0.654	0.134	0.102	Hezhou	23.54	0.654	0.115	0.055
Wenzhou	21.49	0.632	0.123	0.066	Shaoguan	22.94	0.675	0.123	0.071
Linfen	21.42	0.691	0.136	0.084	Pingxiang	22.88	0.693	0.127	0.079
Jiaxing	21.25	0.483	0.099	0.062	Chaozhou	22.66	0.596	0.112	0.068
Tianshui	21.05	0.702	0.144	0.099	Huludao	22.65	0.612	0.116	0.073
Taizhou	20.95	0.446	0.086	0.022	Zhangjiakou	22.55	0.663	0.128	0.091
Pingliang	20.91	0.697	0.147	0.103	Xiaogan	22.33	0.657	0.126	0.088
Jinzhong	20.78	0.67	0.142	0.104	Pingliang	22.12	0.691	0.131	0.073
Huludao	20.62	0.665	0.138	0.085	Guilin	22.01	0.688	0.128	0.065
Cangzhou	20.57	0.605	0.131	0.104	Lishui	21.97	0.628	0.119	0.062

Table A2. *Cont.*

2012					2021				
City	**Effsize**	**Efficiency**	**Constraint**	**Hierarchy**	**City**	**EffSize**	**Efficiency**	**Constraint**	**Hierarchy**
Heyuan	20.49	0.621	0.129	0.072	Cangzhou	21.91	0.592	0.116	0.075
Loudi	20.49	0.661	0.142	0.105	Huzhou	21.73	0.453	0.089	0.049
Zhangjiakou	20.33	0.726	0.15	0.102	Bengbu	21.68	0.516	0.104	0.065
Dezhou	20.04	0.557	0.122	0.08	Tangshan	21.67	0.637	0.137	0.128
Yulin	20.02	0.646	0.135	0.071	Ankang	21.59	0.72	0.144	0.1
Huaibei	19.98	0.512	0.113	0.073	Shenyang	21.37	0.577	0.115	0.062
Huainan	19.92	0.524	0.114	0.068	Chenzhou	21.11	0.621	0.123	0.067
Datong	19.89	0.71	0.155	0.109	Linfen	21.09	0.703	0.138	0.07
Huaihua	19.80	0.66	0.144	0.089	Zhuzhou	21.02	0.5	0.098	0.037
Ezhou	19.74	0.506	0.114	0.079	Tianshui	20.97	0.699	0.139	0.067
Qingyang	19.73	0.731	0.159	0.107	Jinzhong	20.87	0.72	0.146	0.087
Hanzhong	19.31	0.689	0.152	0.09	Weifang	20.69	0.46	0.092	0.034
Yan'an	19.28	0.622	0.141	0.1	Shanwei	20.53	0.587	0.122	0.072
Lvliang	19.26	0.741	0.163	0.109	Fuxin	20.53	0.684	0.145	0.107
Wuhai	19.20	0.8	0.229	0.368	Chaoyang	20.49	0.621	0.13	0.079
Zaozhuang	19.07	0.433	0.091	0.021	Jinhua	20.28	0.615	0.126	0.073
Luohe	19.01	0.594	0.146	0.123	Xinzhou	20.02	0.77	0.157	0.088
Guigang	18.82	0.607	0.133	0.058	Qingyang	19.92	0.687	0.144	0.075
Jieyang	18.75	0.625	0.139	0.074	Dezhou	19.79	0.521	0.111	0.06
Hezhou	18.58	0.619	0.142	0.072	Xuchang	19.50	0.453	0.093	0.019
Nanping	18.54	0.618	0.144	0.098	Ulanqab	19.32	0.773	0.153	0.08
Shiyan	18.16	0.673	0.162	0.104	Laibin	19.30	0.665	0.146	0.079
Ningde	17.98	0.666	0.156	0.092	Shantou	19.26	0.566	0.122	0.059
Tieling	17.89	0.688	0.164	0.114	Xuancheng	19.24	0.583	0.129	0.071
Ma'anShan	17.86	0.435	0.099	0.028	Huaibei	19.17	0.479	0.107	0.057
Chaoyang	17.57	0.703	0.16	0.076	Nanping	18.86	0.555	0.124	0.065
Chaozhou	17.55	0.585	0.143	0.079	Zibo	18.76	0.426	0.092	0.026
Shanwei	17.40	0.6	0.145	0.069	Jiaozuo	18.66	0.622	0.141	0.078
Shantou	17.40	0.6	0.145	0.076	Huangshan	18.50	0.487	0.111	0.053
Fuxin	17.31	0.641	0.157	0.089	Chengde	18.31	0.732	0.164	0.105
Chengde	16.70	0.726	0.167	0.072	Xiangtan	18.09	0.548	0.131	0.075
Huangshi	16.34	0.442	0.108	0.021	Jincheng	17.49	0.547	0.134	0.073
Zhuzhou	16.31	0.466	0.114	0.024	Yunfu	17.38	0.579	0.136	0.048
Yueyang	16.26	0.478	0.12	0.035	Huangshan	17.28	0.54	0.134	0.071
Hebi	16.16	0.539	0.146	0.083	Suqian	17.21	0.42	0.099	0.025
Xianyang	16.12	0.576	0.149	0.061	Jinzhou	17.06	0.656	0.164	0.101
Rizhao	16.07	0.459	0.118	0.045	Chizhou	17.00	0.472	0.12	0.065
Huzhou	16.05	0.411	0.104	0.026	Wuzhou	16.86	0.562	0.139	0.054
Qinhuangdao	15.96	0.665	0.172	0.094	Ziyang	16.41	0.684	0.163	0.056
Jingmen	15.89	0.53	0.145	0.08	Lianyungang	16.41	0.391	0.095	0.017
Qingyuan	15.80	0.632	0.162	0.066	Fushun	16.40	0.656	0.169	0.091
Chenzhou	15.54	0.576	0.157	0.081	Baiyin	16.30	0.741	0.176	0.081
Hechi	15.47	0.645	0.174	0.082	Binzhou	16.25	0.439	0.11	0.031
Liuzhou	15.45	0.533	0.144	0.065	Qinhuangdao	16.21	0.623	0.168	0.109
Lishui	15.42	0.617	0.173	0.113	Zhangzhou	16.13	0.448	0.114	0.036
Zhanjiang	15.38	0.615	0.163	0.065	Siping	16.00	0.696	0.173	0.091
Bazhong	15.23	0.609	0.168	0.072	Datong	15.86	0.69	0.181	0.098
Huizhou	15.16	0.474	0.126	0.039	Tonghua	15.83	0.688	0.174	0.067
Taiyuan	15.15	0.522	0.14	0.049	Danton	15.76	0.606	0.164	0.087
Changzhi	15.09	0.559	0.158	0.078	Panjin	15.56	0.623	0.173	0.109
Langfang	15.04	0.579	0.163	0.09	Zhanjiang	15.42	0.617	0.162	0.068
Baoji	15.03	0.557	0.151	0.052	Zhongshan	15.39	0.453	0.117	0.022
Yunfu	14.87	0.595	0.164	0.061	Hebi	15.29	0.437	0.118	0.036
Jinzhou	14.85	0.594	0.161	0.058	Huizhou	15.08	0.431	0.113	0.015
Zunyi	14.77	0.671	0.181	0.08	Langfang	15.07	0.558	0.157	0.082
Suihua	14.77	0.671	0.189	0.124	Yan'an	15.07	0.603	0.165	0.075
Jinhua	14.63	0.43	0.117	0.021	Luohe	15.05	0.418	0.113	0.03
Wuhu	14.55	0.416	0.115	0.024	Xi'an	14.96	0.554	0.145	0.031
Anshun	14.25	0.648	0.187	0.082	Guiyang	14.80	0.617	0.168	0.065
Shaoguan	14.24	0.57	0.168	0.079	Jiujiang	14.75	0.434	0.12	0.034
Jiaozuo	14.24	0.419	0.116	0.016	Luoyang	14.53	0.454	0.124	0.02
Nanchong	14.02	0.667	0.195	0.094	Xianyang	14.45	0.556	0.151	0.029
Danton	13.90	0.632	0.183	0.07	Jingmen	14.43	0.437	0.119	0.016
Tongchuan	13.63	0.619	0.2	0.12	Chuzhou	14.37	0.378	0.104	0.016
Taizhou	13.50	0.54	0.169	0.08	Baoji	14.30	0.572	0.157	0.038
Guangyuan	13.46	0.673	0.202	0.073	Dazhou	14.24	0.678	0.188	0.075
Wuwei	13.41	0.789	0.226	0.115	Rizhao	14.21	0.431	0.124	0.037
Longyan	13.39	0.432	0.128	0.023	Daqing	14.17	0.833	0.283	0.353
Xuchang	13.39	0.418	0.124	0.022	Hanzhong	14.13	0.589	0.167	0.048
Sanming	13.19	0.425	0.126	0.015	Jiangmen	13.91	0.449	0.129	0.025

Table A2. *Cont.*

2012					2021				
City	**Effsize**	**Efficiency**	**Constraint**	**Hierarchy**	**City**	**EffSize**	**Efficiency**	**Constraint**	**Hierarchy**
Jincheng	12.99	0.433	0.134	0.025	Zunyi	13.81	0.657	0.179	0.042
Siping	12.98	0.649	0.216	0.131	Anshan	13.80	0.575	0.174	0.076
Dazhou	12.95	0.617	0.195	0.082	Shiyan	13.76	0.573	0.17	0.063
Harbin	12.91	0.615	0.199	0.087	Anshun	13.70	0.721	0.213	0.101
Xiangtan	12.90	0.445	0.135	0.02	Maoming	13.59	0.523	0.153	0.041
Baiyin	12.89	0.678	0.22	0.11	Qinzhou	13.59	0.566	0.179	0.091
Hohhot	12.65	0.633	0.222	0.17	Liaoyang	13.53	0.644	0.195	0.084
Luoyang	12.31	0.44	0.141	0.024	Tongchuan	13.47	0.586	0.172	0.04
Zhangzhou	12.30	0.424	0.137	0.028	Baise	13.34	0.702	0.211	0.089
Anshan	12.27	0.533	0.19	0.112	Quang'an	13.32	0.74	0.21	0.086
Qiqihar	12.13	0.639	0.222	0.121	Yingtan	13.25	0.414	0.126	0.026
Yangquan	11.84	0.474	0.165	0.051	Changchun	12.98	0.764	0.271	0.267
Guilin	11.60	0.527	0.182	0.052	Zhaotong	12.98	0.721	0.192	0.052
Putian	11.49	0.547	0.19	0.066	Taizhou	12.95	0.498	0.159	0.064
Yingtan	11.16	0.465	0.177	0.071	Zhaoqing	12.79	0.474	0.146	0.029
Quang'an	11.00	0.611	0.227	0.092	Harbin	12.78	0.639	0.2	0.083
Laibin	10.79	0.568	0.216	0.082	Chongzuo	12.77	0.638	0.205	0.076
Qinzhou	10.69	0.594	0.219	0.062	Yingkou	12.68	0.528	0.174	0.067
Sanmenxia	10.52	0.457	0.169	0.021	Liupanshui	12.64	0.743	0.229	0.134
Tonghua	10.46	0.615	0.251	0.128	Qiqihar	12.59	0.699	0.204	0.062
Zhaoqing	10.27	0.446	0.169	0.023	Ningde	12.51	0.417	0.132	0.02
Binzhou	10.25	0.342	0.13	0.01	Changzhi	12.46	0.445	0.143	0.027
Liupanshui	10.24	0.64	0.257	0.115	Nanchong	12.25	0.681	0.213	0.084
Jiangmen	10.20	0.425	0.164	0.027	Wenzhou	12.00	0.6	0.204	0.08
Maoming	10.19	0.51	0.198	0.05	Guangyuan	11.85	0.624	0.211	0.076
Benxi	10.13	0.482	0.189	0.053	Lvliang	11.33	0.708	0.23	0.056
Pingxiang	10.10	0.439	0.177	0.049	Nanning	11.08	0.482	0.173	0.04
Suining	9.98	0.587	0.229	0.051	Wuhai	11.07	0.791	0.374	0.445
Nanning	9.97	0.475	0.185	0.03	Yangjiang	11.05	0.502	0.19	0.074
Lanzhou	9.45	0.675	0.271	0.085	Putian	10.62	0.408	0.152	0.024
Mianyang	9.24	0.66	0.268	0.064	Neijiang	10.59	0.623	0.237	0.089
Baicheng	9.17	0.611	0.271	0.106	Tieling	10.54	0.555	0.209	0.062
Wuzhou	9.13	0.435	0.191	0.043	Sanmenxia	10.44	0.497	0.189	0.039
Guiyang	9.04	0.532	0.232	0.056	Liuzhou	10.38	0.472	0.175	0.022
Yingkou	8.93	0.425	0.189	0.039	Suining	10.26	0.604	0.233	0.071
Neijiang	8.82	0.63	0.273	0.068	Meishan	10.18	0.727	0.266	0.077
Yibin	8.47	0.706	0.304	0.089	Yangquan	10.17	0.462	0.185	0.053
Luzhou	8.45	0.603	0.27	0.06	Weinan	10.12	0.595	0.225	0.021
Ziyang	8.24	0.588	0.276	0.063	Songyuan	10.05	0.628	0.234	0.079
Liaoyang	8.14	0.428	0.21	0.046	Deyang	9.69	0.606	0.236	0.077
Yangjiang	7.68	0.427	0.22	0.043	Benxi	9.54	0.477	0.199	0.041
Baise	7.67	0.548	0.278	0.069	Baicheng	8.88	0.592	0.248	0.051
Shuozhou	7.39	0.435	0.232	0.053	Beihai	8.78	0.439	0.194	0.032
Heihe	7.19	0.599	0.315	0.052	Liaoyuan	8.40	0.56	0.255	0.035
Panzhihua	7.05	0.783	0.388	0.229	Luzhou	8.34	0.596	0.272	0.064
Yichun	7.04	0.586	0.325	0.082	Zhangye	8.27	0.919	0.223	0.052
Changchun	7.00	0.5	0.304	0.134	Shuozhou	8.00	0.5	0.24	0.047
Chongzuo	6.84	0.526	0.3	0.073	Lanzhou	7.95	0.611	0.289	0.075
Zhaotong	6.64	0.604	0.329	0.059	Fangcheng gang	7.83	0.435	0.216	0.035
Fangcheng gang	6.38	0.425	0.257	0.049	Guyuan	7.69	0.641	0.321	0.078
Beihai	5.80	0.415	0.273	0.038	Mianyang	7.69	0.513	0.253	0.047
Leshan	5.80	0.725	0.381	0.08	Jilin	7.66	0.589	0.273	0.045
Zhangye	5.50	0.786	0.429	0.1	Zigong	7.32	0.563	0.295	0.059
Deyang	5.50	0.5	0.335	0.047	Yibin	7.22	0.556	0.294	0.057
Fushun	5.34	0.381	0.271	0.035	Tongliao	7.13	0.509	0.271	0.031
Qujing	5.31	0.759	0.4	0.132	Mudanjiang	6.96	0.58	0.317	0.069
Kiamusi	5.18	0.576	0.402	0.063	Jinchang	6.65	0.832	0.326	0.103
Zhongwei	5.17	0.646	0.481	0.2	Sining	5.73	0.716	0.421	0.146
Haikou	5.00	0.455	0.351	0.072	Ya'an	5.67	0.708	0.456	0.152
Meishan	4.94	0.706	0.451	0.056	Haikou	5.50	0.458	0.334	0.094
Jilin	4.65	0.422	0.351	0.073	Suihua	5.27	0.479	0.337	0.064
Zigong	4.64	0.58	0.447	0.112	Baotou	5.18	0.576	0.454	0.185
Guyuan	4.40	0.489	0.425	0.084	Leshan	4.17	0.521	0.43	0.067
Qitaihe	4.28	0.535	0.453	0.055	Qitaihe	4.07	0.582	0.536	0.15
Mudanjiang	4.10	0.512	0.458	0.071	Chifeng	4.05	0.506	0.449	0.051
Ya'an	4.07	0.679	0.49	0.096	Heihe	3.80	0.76	0.451	0.056
Chifeng	3.89	0.487	0.421	0.028	Zhongwei	3.75	0.75	0.557	0.187
Songyuan	3.68	0.408	0.39	0.038	Yichun	3.71	0.531	0.536	0.095

Table A2. *Cont.*

2012					2021				
City	**Effsize**	**Efficiency**	**Constraint**	**Hierarchy**	**City**	**EffSize**	**Efficiency**	**Constraint**	**Hierarchy**
Liaoyuan	3.67	0.367	0.378	0.053	Shuangyashan	3.50	0.875	0.406	0.055
Jixi	3.57	0.595	0.546	0.031	Yinchuan	3.25	0.542	0.587	0.158
Ulanqab	3.50	0.583	0.516	0.036	Baishan	3.20	0.64	0.737	0.245
Wuzhong	3.33	0.556	0.59	0.16	Hegang	3.20	0.64	0.737	0.245
Baishan	3.00	0.6	0.612	0.057	Jixi	3.20	0.64	0.737	0.245
Hegang	3.00	0.6	0.612	0.057	Kiamusi	3.20	0.64	0.737	0.245
Jinchang	2.72	0.544	0.612	0.057	Panzhihua	3.17	0.792	0.573	0.087
Lijiang	2.70	0.675	0.673	0.071	Kunming	3.14	0.786	0.542	0.05
Tongliao	2.42	0.346	0.495	0.035	Wuwei	3.07	0.614	0.537	0.011
Shuangyashan	2.29	0.457	0.651	0.04	Lijiang	2.90	0.725	0.69	0.162
Sining	2.00	1	0.5	0	Shizuishan	2.43	0.486	0.666	0.082
Yinchuan	1.64	0.411	0.781	0.075	Hohhot	2.40	0.4	0.561	0.039
Shizuishan	1.60	0.533	0.933	0.151	Qujing	2.13	0.708	0.797	0.057
Sanya	1.57	0.262	0.607	0.04	Sanya	2.13	0.304	0.527	0.04
Hulunbuir	1	1	1	1	Hulunbuir	2	1	0.5	0
Jiuquan	1	1	1	1	Jiayuguan	2	1	0.556	0.278
Karamay	1	1	1	1	Jiuquan	2	1	0.5	0
Kunming	1	1	1	1	Baoshan	1	1	1	1
Urumqi	1	1	1	1	Karamay	1	1	1	1
Baoshan	1	0.5	1.389	0	Lincang	1	0.5	1.389	0
Lincang	1	0.5	1.389	0	Urumqi	1	1	1	1
Lhasa	0	0	0	0	Lhasa	0	0	0	0
Yuxi	0	0	0	0	Yuxi	0	0	0	0
Mean value	28.35	0.628	0.202	0.112	Mean value	30.03	0.642	0.187	0.097

Table A3. City and region classification.

City	Regional Classification	Seven Regional Classification	Block Type
Ankang	Western region	Northwest	Block I
Anqing	Central region	East China	Block I
Anshun	Western region	Southwest	Block II
Anyang	Central region	Central China	Block I
Anshan	Eastern region	Northeast	Block I
Bazhong	Western region	Southwest	Block II
Baicheng	Central region	Northeast	Block II
Baishan	Central region	Northeast	Block II
Baiyin	Western region	Northwest	Block II
Baise	Western region	South China	Block II
Bengbu	Central region	East China	Block III
Baotou	Western region	North China	Block II
Baoji	Western region	Northwest	Block I
Baoding	Eastern region	North China	Block II
Baoshan	Western region	Southwest	Block II
Beihai	Western region	South China	Block III
Beijing	Eastern region	North China	Block II
Benxi	Eastern region	Northeast	Block I
Binzhou	Eastern region	East China	Block I
Bozhou	Central region	East China	Block I
Cangzhou	Eastern region	North China	Block IV
Changzhou	Eastern region	East China	Block I
Chaoyang	Eastern region	Northeast	Block I
Chaozhou	Eastern region	South China	Block II
Chenzhou	Central region	Central China	Block I
Chengdu	Western region	Southwest	Block I
Chengde	Eastern region	North China	Block II
Chizhou	Central region	East China	Block I
Chifeng	Western region	North China	Block I
Chongzuo	Western region	South China	Block II
Chuzhou	Central region	East China	Block III
Dazhou	Western region	Southwest	Block II
Dalian	Eastern region	Northeast	Block I
Daqing	Central region	Northeast	Block I
Datong	Central region	North China	Block II
Danton	Eastern region	Northeast	Block I
Deyang	Western region	Southwest	Block II

Table A3. *Cont.*

City	Regional Classification	Seven Regional Classification	Block Type
Dezhou	Eastern region	East China	Block IV
Dingxi	Western region	Northwest	Block III
Dongguan	Eastern region	South China	Block III
Dongying	Eastern region	East China	Block IV
Ordos	Western region	North China	Block II
Ezhou	Central region	Central China	Block IV
Fangchenggang	Western region	South China	Block IV
Foshan	Eastern region	South China	Block I
Fuzhou	Eastern region	East China	Block I
Fushun	Eastern region	Northeast	Block I
Fuzhou	Central region	East China	Block I
Fuxin	Eastern region	Northeast	Block I
Fuyang	Central region	East China	Block II
Ganzhou	Central region	East China	Block II
Guyuan	Western region	Northwest	Block II
Quang'an	Western region	Southwest	Block IV
Guangyuan	Western region	Southwest	Block I
Guangzhou	Eastern region	South China	Block II
Guigang	Western region	South China	Block I
Guiyang	Western region	Southwest	Block I
Guilin	Western region	South China	Block II
Harbin	Central region	Northeast	Block I
Haikou	Eastern region	South China	Block II
Handan	Eastern region	North China	Block IV
Hanzhong	Western region	Northwest	Block I
Hangzhou	Eastern region	East China	Block III
Hefei	Central region	East China	Block I
Hechi	Western region	South China	Block I
Heyuan	Eastern region	South China	Block I
Heze	Eastern region	East China	Block I
Hezhou	Western region	South China	Block I
Hebi	Central region	Central China	Block II
Hegang	Central region	Northeast	Block II
Heihe	Central region	Northeast	Block I
Hengshui	Eastern region	North China	Block I
Hengyang	Central region	Central China	Block II
Hohhot	Western region	North China	Block II
Hulunbuir	Western region	North China	Block I
Huludao	Eastern region	Northeast	Block III
Huzhou	Eastern region	East China	Block I
Huaihua	Central region	Central China	Block III
Huai'an	Eastern region	East China	Block I
Huaibei	Central region	East China	Block I
Huainan	Central region	East China	Block I
Huanggang	Central region	Central China	Block I
Huangshan	Central region	East China	Block I
Huangshi	Central region	Central China	Block I
Huizhou	Eastern region	South China	Block II
Jixi	Central region	Northeast	Block I
Ji'an	Central region	East China	Block II
Jilin	Central region	Northeast	Block III
Jinan	Eastern region	East China	Block I
Jining	Eastern region	East China	Block II
Kiamusi	Central region	Northeast	Block III
Jiaxing	Eastern region	East China	Block II
Jiayuguan	Western region	Northwest	Block I
Jiangmen	Eastern region	South China	Block I
Jiaozuo	Central region	Central China	Block I
Jieyang	Eastern region	South China	Block II
Jinchang	Western region	Northwest	Block I
Jinhua	Eastern region	East China	Block I
Jinzhou	Eastern region	Northeast	Block I
Jincheng	Central region	North China	Block I
Jinzhong	Central region	North China	Block I
Jingmen	Central region	Central China	Block I
Jingzhou	Central region	Central China	Block II
Jiujiang	Central region	East China	Block I
Jiuquan	Western region	Northwest	Block II
Kaifeng	Central region	Central China	Block II
Karamay	Western region	Northwest	Block III

Table A3. *Cont.*

City	Regional Classification	Seven Regional Classification	Block Type
Kunming	Western region	Southwest	Block I
Lhasa	Western region	Southwest	Block II
Laibin	Western region	South China	Block I
Lanzhou	Western region	Northwest	Block II
Langfang	Eastern region	North China	Block II
Leshan	Western region	Southwest	Block I
Lijiang	Western region	Southwest	Block I
Lishui	Eastern region	East China	Block I
Lianyungang	Eastern region	East China	Block II
Liaoyang	Eastern region	Northeast	Block I
Liaoyuan	Central region	Northeast	Block II
Liaocheng	Eastern region	East China	Block I
Lincang	Western region	Southwest	Block I
Linfen	Central region	North China	Block II
Linyi	Eastern region	East China	Block I
Liuzhou	Western region	South China	Block II
Lu'an	Central region	East China	Block IV
Liupanshui	Western region	Southwest	Block II
Longyan	Eastern region	East China	Block I
Longnan	Western region	Northwest	Block II
Loudi	Central region	Central China	Block I
Luzhou	Western region	Southwest	Block I
Luoyang	Central region	Central China	Block II
Luohe	Central region	Central China	Block III
Lvliang	Central region	North China	Block I
Ma'anShan	Central region	East China	Block II
Maoming	Eastern region	South China	Block I
Meishan	Western region	Southwest	Block II
Meizhou	Eastern region	South China	Block II
Mianyang	Western region	Southwest	Block IV
Mudanjiang	Central region	Northeast	Block II
Nanchang	Central region	East China	Block IV
Nanchong	Western region	Southwest	Block I
Nanjing	Eastern region	East China	Block I
Nanning	Western region	South China	Block III
Nanping	Eastern region	East China	Block I
Nantong	Eastern region	East China	Block II
Nanyang	Central region	Central China	Block IV
Neijiang	Western region	Southwest	Block I
Ningbo	Eastern region	East China	Block II
Ningde	Eastern region	East China	Block II
Panzhihua	Western region	Southwest	Block I
Panjin	Eastern region	Northeast	Block II
Pingdingshan	Central region	Central China	Block I
Pingliang	Western region	Northwest	Block I
Pingxiang	Central region	East China	Block I
Putian	Eastern region	East China	Block III
Puyang	Central region	Central China	Block II
Qitaihe	Central region	Northeast	Block I
Qiqihar	Central region	Northeast	Block I
Qinzhou	Western region	South China	Block I
Qinhuangdao	Eastern region	North China	Block III
Qingdao	Eastern region	East China	Block I
Qingyuan	Eastern region	South China	Block II
Qingyang	Western region	Northwest	Block II
Qujing	Western region	Southwest	Block IV
Quanzhou	Eastern region	East China	Block I
Rizhao	Eastern region	East China	Block II
Sanmenxia	Central region	Central China	Block IV
Sanming	Eastern region	East China	Block II
Sanya	Eastern region	South China	Block IV
Xiamen	Eastern region	East China	Block I
Shantou	Eastern region	South China	Block I
Shanwei	Eastern region	South China	Block I
Shangluo	Western region	Northwest	Block I
Shangqiu	Central region	Central China	Block IV
Shanghai	Eastern region	East China	Block I
Shangrao	Central region	East China	Block I
Shaoguan	Eastern region	South China	Block I
Shaoyang	Central region	Central China	Block IV
Shaoxing	Eastern region	East China	Block IV

Table A3. *Cont.*

City	Regional Classification	Seven Regional Classification	Block Type
Shenzhen	Eastern region	South China	Block I
Shenyang	Eastern region	Northeast	Block I
Shiyan	Central region	Central China	Block I
Shijiazhuang	Eastern region	North China	Block II
Shizuishan	Western region	Northwest	Block II
Shuangyashan	Central region	Northeast	Block II
Shuozhou	Central region	North China	Block I
Siping	Central region	Northeast	Block II
Songyuan	Central region	Northeast	Block IV
Suzhou	Eastern region	East China	Block I
Suqian	Eastern region	East China	Block I
Suzhou	Central region	East China	Block II
Suihua	Central region	Northeast	Block I
Suizhou	Central region	Central China	Block II
Suining	Western region	Southwest	Block I
Taizhou	Eastern region	East China	Block III
Taiyuan	Central region	North China	Block I
Tai'an	Eastern region	East China	Block III
Taizhou	Eastern region	East China	Block III
Tangshan	Eastern region	North China	Block III
Tianjin	Eastern region	North China	Block II
Tianshui	Western region	Northwest	Block II
Tieling	Eastern region	Northeast	Block I
Tonghua	Central region	Northeast	Block I
Tongliao	Western region	North China	Block II
Tongchuan	Western region	Northwest	Block I
Tongling	Central region	East China	Block I
Weihai	Eastern region	East China	Block III
Weifang	Eastern region	East China	Block I
Weinan	Western region	Northwest	Block II
Wenzhou	Eastern region	East China	Block I
Wuhai	Western region	North China	Block III
Ulanqab	Western region	North China	Block I
Urumqi	Western region	Northwest	Block II
Wuxi	Eastern region	East China	Block III
Wuhu	Central region	East China	Block III
Wuzhong	Western region	Northwest	Block I
Wuzhou	Western region	South China	Block I
Wuhan	Central region	Central China	Block IV
Wuwei	Western region	Northwest	Block II
Xi'an	Western region	Northwest	Block II
Sining	Western region	Northwest	Block II
Xianning	Central region	Central China	Block I
Xianyang	Western region	Northwest	Block II
Xiangtan	Central region	Central China	Block II
Xiaogan	Central region	Central China	Block I
Xinzhou	Central region	North China	Block I
Xinxiang	Central region	Central China	Block I
Xinyu	Central region	East China	Block IV
Xinyang	Central region	Central China	Block I
Xingtai	Eastern region	North China	Block I
Xuzhou	Eastern region	East China	Block III
Xuchang	Central region	Central China	Block I
Xuancheng	Central region	East China	Block I
Ya'an	Western region	Southwest	Block II
Yantai	Eastern region	East China	Block III
Yan'an	Western region	Northwest	Block II
Yancheng	Eastern region	East China	Block III
Yangzhou	Eastern region	East China	Block III
Yangjiang	Eastern region	South China	Block I
Yangquan	Central region	North China	Block II
Yichun	Central region	Northeast	Block II
Yibin	Western region	Southwest	Block II
Yichang	Central region	Central China	Block IV
Yichun	Central region	East China	Block I
Yiyang	Central region	Central China	Block I
Yinchuan	Western region	Northwest	Block II
Yingtan	Central region	East China	Block I
Yingkou	Eastern region	Northeast	Block I
Yongzhou	Central region	Central China	Block I
Yulin	Western region	Northwest	Block III

Table A3. *Cont.*

City	Regional Classification	Seven Regional Classification	Block Type
Yulin	Western region	South China	Block I
Yuxi	Western region	Southwest	Block III
Yueyang	Central region	Central China	Block I
Yunfu	Eastern region	South China	Block I
Yuncheng	Central region	North China	Block I
Zaozhuang	Eastern region	East China	Block I
Zhanjiang	Eastern region	South China	Block I
Zhangjiajie	Central region	Central China	Block I
Zhangjiakou	Eastern region	North China	Block I
Zhangye	Western region	Northwest	Block II
Zhangzhou	Eastern region	East China	Block I
Changchun	Central region	Northeast	Block II
Changsha	Central region	Central China	Block IV
Changzhi	Central region	North China	Block II
Zhaotong	Western region	Southwest	Block II
Zhaoqing	Eastern region	South China	Block I
Zhenjiang	Eastern region	East China	Block III
Zhengzhou	Central region	Central China	Block III
Zhongshan	Eastern region	South China	Block I
Zhongwei	Western region	Northwest	Block II
Chongqing	Western region	Southwest	Block II
Zhoushan	Eastern region	East China	Block III
Zhoukou	Central region	Central China	Block I
Zhuhai	Eastern region	South China	Block IV
Zhuzhou	Central region	Central China	Block I
Zhumadian	Central region	Central China	Block I
Ziyang	Western region	Southwest	Block II
Zibo	Eastern region	East China	Block III
Zigong	Western region	Southwest	Block II
Zunyi	Western region	Southwest	Block I

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