

## Research Article

# Hierarchical Characteristics and Proximity Mechanism of Intercity Innovation Networks: A Case of 290 Cities in China

Xianzhong Cao <sup>1</sup>, Gang Zeng,<sup>1</sup> Lan Lin <sup>2</sup>, and Lin Zou <sup>1,3</sup>

<sup>1</sup>Center for Modern Chinese City Studies and Institute of Urban Development, East China Normal University, Shanghai 200062, China

<sup>2</sup>Institute of Urban and Population Development, Shanghai Academy of Social Sciences, Shanghai 200020, China

<sup>3</sup>Shanghai University of Engineering Science, Shanghai 201620, China

Correspondence should be addressed to Lan Lin; [linlan@sass.org.cn](mailto:linlan@sass.org.cn) and Lin Zou; [zoulin200618@163.com](mailto:zoulin200618@163.com)

Received 1 February 2021; Revised 8 April 2021; Accepted 18 May 2021; Published 25 May 2021

Academic Editor: Jing-Hu Pan

Copyright © 2021 Xianzhong Cao et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The formation mechanism of innovation networks is one of the core issues in the current research of innovation networks, and proximity plays an important role in the formation and development of innovation networks; however, which proximity is more important and how different proximities interact remain to be further researched. This study conducts a social network analysis and adopts a spatial interaction model to examine innovation networks among 290 Chinese cities. The results reveal that, first, the hierarchical characteristics of Chinese cities' innovation networks reflect a core periphery structure and the spatial patterns of large dispersion and small agglomeration. Further, bound by the Hu line, the hierarchy is high in the east and low in the west. Second, geographical, institutional, and cognitive proximities positively affect Chinese cities' innovation networking. Cognitive proximity, particularly, has the highest impact. Geographical proximity reinforces the effect of institutional proximity, and thus, their interactions are complementary.

## 1. Introduction

Knowledge and technological innovations have become the key driving forces of regional economic development. Innovation includes the production of new products, the adoption of new production methods, the development of new markets, and the expansion of new sources of supply or new forms of organization. Acquiring knowledge is a prerequisite for the implementation of innovation activities [1]. In fact, they are considered more important than traditional material capital and are essential strategic resources for sustained economic growth [2]. China's central government believes that innovations play a critical role in leading development and are strategic support in building modern economic systems. Cities accumulate talent, capital, information, enterprises, and other innovative elements and are an important platform for innovation-driven development [3]. The traditional model for closed innovation, along with

regional innovation systems and learning areas, can no longer match the needs of rapid economic development or effectively cope with dynamic competitive environments. Thus, local governments are increasingly pursuing innovative cooperation and knowledge promotion through innovative partnerships with other cities and the optimised allocation of innovative resources to achieve complementary advantages and win-win situations. The expected outcomes are the improved efficiency of city innovations, reduced innovative costs and risks, and enhanced city competitiveness. In this new era, intercity networking and collaborative innovations have become a new and frequent trend associated with city development [4].

The mode of regional innovation has changed from single-actor independent innovation to multiactor collaborative innovation. Moreover, the paradigm of innovation research in economic geography and regional economics has shifted from traditional locations to modern flow space.

Thus, the perspective of networks based on relationships has become an important starting point to analyse regional innovation and city development [5, 6]. It has been a common innovation mode for firms to innovate through cooperative networks; the innovation mode has successively gone through technology promotion, demand pull, interaction, and comprehensive; now, it has entered the fifth generation innovation mode with innovation networks, which is also the leading direction of future innovation research [7]. The most fundamental reason for innovation networking lies in the limited innovation ability of a single actor and the scarcity of resources; individuals can acquire more external knowledge and resources in the innovation networks [8]. The literature of economic geography focuses on the structure and formation mechanisms of innovation networks, particularly those formed by microinnovation actors such as enterprises, universities, and research institutions. Some scholars examine the spatial and topological structure and dynamic evolution processes of innovation networks [9], while others discuss the impact of proximity on innovation cooperation, knowledge flow, dynamic evolution, internal impact mechanisms, and innovation performance [10]. The formation of innovation networks is affected by many factors; first, the endogenous effect of network structure, including the embeddedness, externality, absorptive capacity, small world, and technical goalkeeper. Second, the characteristics of network organizational elements, including the nature, scale, and status of organizational elements; third, the perspective of multidimensional proximity, which mainly includes geographical proximity, social proximity, cognitive proximity, institutional proximity, and cultural proximity [11]. The role of proximity in innovation and interorganizational networks has received increasing attention over the past decade [12]. Bergé [13] investigates that how network proximity influences the structure of interregional collaborations and how it interacts with geography. However, few studies examine city structures from an innovation perspective, whereas a majority of the studies are limited to innovation network structures that fail to detail why such network structures are formed, which is a research-worthy topic. Which proximity has greater influence on the formation of innovation networks and how different proximities interact are still unsolved questions, which is the purpose of this paper.

Adopting an innovation networks' perspective, this study fills the gap in the literature by analysing the hierarchical structural characteristics of 290 Chinese cities, including the locational and spatial attributes of their innovation networks, and incorporating multidimensional proximity in a mechanism analysis of proximity. In doing so, it aims to understand the current collaborative innovation situation in Chinese cities and clarify the relationship between the formation of intercity innovation networks and proximity. The findings will serve as a reference to formulate more accurate regional innovation policies and a basis to enrich relevant innovation studies in economic geography.

The remainder of this paper is organised as follows. Section 2 presents the origin of innovation networks and the proximity framework. Section 3 describes the data and

empirical variables used to analyse the structural and proximity mechanisms of innovation networks. Section 4 conducts a social network analysis (SNA) on the network structure of 290 Chinese cities. Section 5 discusses the influence mechanisms of geographical, institutional, and cognitive proximities on the cities' innovation networks. Section 6 concludes the paper.

## 2. Theoretical Analytical Framework

Open collaborative innovations have become a new mode of city innovation and have further given rise to intercity innovation networks. The structure of intercity innovation networks not only reflects the contact way of each city in a network and but also determines the mutual position and relationship of each city. In other words, it directly affects knowledge exchanges and interactions among cities in a network [14], which are associated with the depth of integration and utilisation of innovation resources as key factors in determining the performance of city innovation [15]. The concept of innovation networks was originally proposed in the sociology literature, and later, economic geographers applied it to innovation research. Freeman [16] defines innovation networks as a new institutional arrangement that breaks away from the previous innovation model to realise systematic innovation that can also be recognised in academic circles. In essence, an innovation network is a closely related system formed by various formal and informal linkages among innovative actors including firms, universities and research institutions, governments, capital markets, and intermediaries. Boix and Trullén [17] measured the factors that affect the evolution of different intensities of knowledge in a region's cities. Researchers have defined innovation networks at the city level [18]. They believe it is a strategic collaborative process for a city to realise the joint complementation and optimal allocation of knowledge spillovers and innovative elements (i.e., talents, funds, and information), both of which can be responses to rapidly changing innovation demands in a knowledge economy era. Intercity innovation networks can also be viewed as an interactive form of city space.

The concept of proximity originated in Marshall's pioneering research on industrial cluster economies. It was originally defined as the spatial colocation of economic activity actors within the same cluster [19], thus emphasising geographical proximity in a given period. Economic geographers are currently extending the proximity perspective to analyse the impact factors, evolution dynamics, and mechanisms of innovation networks. Many studies focus on the relationship between geographical proximity and knowledge innovation and show that the former not only promotes firms' agglomeration but also affects the structure of innovation networks [20]. Notably, single-dimensional geographical proximity does not sufficiently explain interactive learning and cooperative innovation among innovation actors. To this effect, the French School of Proximity Dynamics considers a multidimensional proximity framework comprising geographical, organizational, institutional, cognitive, and social proximities [21, 22], thus shifting the

proximity discussion from single-dimensional proximity to multidimensional proximity. The Netherlands School of Utrecht has conducted an in-depth analysis of interactions among geographical, organizational, institutional, cognitive, and social proximities and their impact on firms' innovation cooperation [23], which is popular in multidimensional proximity analysis [24]. Capone and Lazzeretti [12] investigated the role of various forms of proximity in multiple informal interorganizational relationships. The literature has both qualitative and empirical studies that emphasise the importance of geographical, cognitive, and institutional proximities in knowledge flow and firms' innovation networking [25].

It is clear from the discussion above that most of the literature examines the independent effect of proximity on the various dimensions of innovation networks. However, the proximity of different dimensions is not divided and independent; rather, it is interactive [26]. Recently, empirical studies have examined the impact of multidimensional proximity interactions [13] although they remain in their infancy, thus warranting the strengthening of related empirical tests and theoretical discussions. The proximity framework generally includes three dimensions, geographical dimension (characterized by the difference of physical distance between members of innovation networks), cognitive dimension (characterized by the degree of knowledge similarity), and institutional dimension (degree of common ownership, strength of social ties, degree of sharing standards, habits, regulations, and laws), and is widely used in related research such as regional coordinated development and innovation networks. This study also employs the three proximities to explain structural differences in intercity innovation networks.

### 3. Methodology and Data

**3.1. Data Sources.** Given the difficulties associated with collecting large amounts of network data, most scholars apply a modified spatial interaction model (i.e., gravity or gravity model) with a city output or comprehensive index system to measure innovation linkages between cities. Joint patent applications represent knowledge flow among various innovation actors in different cities and more effectively reflect the innovative relationship between cities. Thus, an increasing number of scholars are using data on joint patent applications to measure innovation networks. Among various patents, such as appearance design and utility model patents, invention patents are more representative of original technology and technological innovation performance [27]. Therefore, this study uses data on joint invention patent applications to examine intercity innovation networks in China.

Patent data are obtained from the patent retrieval and analysis system of the National Intellectual Property Administration (<http://www.pss-system.gov.cn/sipopublicsearch/patentsearch/table> Search-showTableSearchIndex.shtml). In China, it takes 18 months for patents to be publicly released. This study uses data on invention patent applications by two or more actors for 290

cities in 2014. The data of patent application in 2014 was selected because it was published in 2016, but the new patent law was implemented in 2017, and there were new restrictions and regulations on patent application. The data before 2017 was stable, and the data after that was unstable, so the data of patent application in 2014 was selected.

First, the researchers logged into the patent retrieval and analysis system and searched for Chinese invention patents for the scope, "201401 20141231" for application date, and "?; ?;" for applicant names of the 290 cities for applicant address (e.g., Beijing, Shanghai, Guangzhou, and Shenzhen). Second, data for the following criteria were deleted to ensure reliable network data: (i) less than two joint applications for institution patents by applicants including individuals or joint applications between individuals and one institution, (ii) individual applications in which it is difficult to determine applicants' city, and (iii) foreign applicants since this study focuses on innovation linkage among 290 cities in Mainland China. Finally, the analysis conducts a two-to-two estimation for invention patent applications by three or more institutions. In addition, information on applicants' city is extracted to establish an omnidirectional intercity innovation network. Data on 63,108 joint invention patents have been collected since April 2017. Following a screening and processing, data for 42,921 patents, including 286 city nodes, were retained.

## 4. Methodology

**4.1. Social Network Analysis.** The SNA is commonly used to describe innovation network structures. Ter Wal and Boschma [28] conducted an SNA on innovation networks and portrayed and visualized network structures and evolution. SNA has been deemed "the most promising empirical analysis tool."

This study uses centrality and network density to measure the local and overall structure of intercity innovation networks. In addition, it uses the UCINET software to analyse the local and overall structures.

- (i) *Network Density.* Network density reflects the degree of node connections in networks: the higher the network density, the closer the node connections. The formula is as follows:

$$D = \sum_{i=1}^k \sum_{j=1}^k \frac{d(n_i, n_j)}{k(k-1)}, \quad (1)$$

where  $D$  is network density,  $k$  is a node, and  $d(n_i, n_j)$  is the connection between nodes  $i$  and  $j$ .

*Network Centrality.* Network centrality measures mainly the degree of node centrality in the network and can be formulated as follows:

$$CD(n_i) = \sum_{j=1}^n X_{ji}, \quad (2)$$

where  $CD(n_i)$  is network centrality and  $X_{ji}$  is the contact strength between nodes  $i$  and  $j$ .

*Network Centrality Potential.* Network centrality potential measures the network's degree of centralisation and reflects the degree of deviation in a network by examining the overall structural characteristics of the network. The formula is as follows:

$$C = \frac{\sum_{i=1}^n (C_{\max} - C_i)}{\max[\sum_{i=1}^n (C_{\max} - C_i)]}, \quad (3)$$

where  $C_{\max}$  is the maximum degree of centrality for the nodes in the network and  $C_i$  is the degree of centrality for node  $i$ .

*4.2. Spatial Interaction Model.* Early proximity studies have ignored the effect of spatial interaction in a multiregional context. Wanzenböck [29] proposed a new measure for assessing the network proximity between aggregated units, based on disaggregated information on the network

$$\begin{aligned} \text{COL}_{ij} = & \alpha + \beta_1 \text{PAT}_i + \beta_2 \text{PAT}_j + \beta_3 \text{RDE}_i + \beta_4 \text{RDE}_j + \beta_5 \text{HUC}_i + \beta_6 \text{HUC}_j + \beta_7 \text{GPC}_i + \beta_8 \text{GPC}_j + \beta_9 \text{GEO}_{ij} \\ & + \beta_4 \text{INS}_{ij} + \beta_5 \text{COG}_{ij} + \varepsilon, \end{aligned} \quad (4)$$

where explained variable  $\text{COL}_{ij}$  is innovation cooperation between cities measured by the number of joint applications for invention patents by cities  $i$  and  $j$  in 2014. Control variables conclude patent applications ( $\text{PAT}_i$  and  $\text{PAT}_j$ ), R&D expenditure ( $\text{RDE}_i$  and  $\text{RDE}_j$ ), human capital ( $\text{HUC}_i$  and  $\text{HUC}_j$ ), and GDP per capita ( $\text{GPC}_i$  and  $\text{GPC}_j$ ).  $\text{PAT}_i$  and  $\text{PAT}_j$  are the total number of invention patent applications by cities  $i$  and  $j$  in 2014 and are used to measure a city's technological innovation capability. This study incorporates these variables in its model to examine the spatial interaction effect between the two cities.  $\text{DIS}_{ij}$  is the geographical proximity between city  $i$  and city  $j$ . According to Balland et al. [10];  $\text{GEO}_{ij} = 10 - \ln(\text{DIS}_{ij} + 1)$ , where  $\text{DIS}_{ij}$  is the spatial spherical distance between city  $i$  and city  $j$  and is calculated using ArcGIS.  $\text{INS}_{ij}$  is the degree of similarity in institutional environments—this includes informal systems such as culture, language, social values, norms, and formal systems; for example, law and regulations and regional development policies—between city  $i$  and  $j$ . As in the study by Ejeremo and Karlsson [35], this study sets  $\text{INS}_{ij}$  as a virtual variable that takes the value of 1 if the two cities belong to the same province; otherwise, 0.  $\text{COG}_{ij}$  denotes similarity in the technical knowledge structure between two cities. In the study by Jaffe [36],  $\text{COG}_{ij} = (\sum_{m=1}^8 \text{PAT}_{im} \text{PAT}_{jm} / \sqrt{\sum_{m=1}^8 \text{PAT}_{im}^2 \text{PAT}_{jm}^2})$ ,  $\text{PAT}_{im}$ , and  $\text{PAT}_{jm}$  are the number of invention patent applications under the  $m$ -th number of the International Patent Classification for cities  $i$  and  $j$ . Data on classified patents can be collected from the patent retrieval and analysis system of the National Intellectual Property Administration (see Table 1).

distance of actors. Scherngell and Barber [30] categorised factors influencing regional interactions into scale factors and distance variables that symbolise tension and resistance using a gravity model. Scherngell and Hu [31] proposed a spatial interaction model that addresses limitations in previous research. Since then, their model has been widely applied in innovation research by economic geographers. Montobbio and Sterzi [32], for example, analysed factors influencing international technical cooperation. Kunze [33] explored the relationship between innovation and trade in Europe. Gui et al. [34] discussed the proximity mechanism of the global cooperation network for scientific research papers. This study adopts this model, which is based on the conceptual framework of multidimensional proximity, to develop a proximity mechanism model for intercity innovation networks as follows: R&D expenditure, human capital, and GDP per capita:

## 5. Empirical Results

The empirical results highlight that 286 Chinese cities (or 98.6%) established innovation networks and, in particular, 42,921 innovation linkages, in 2014 (see Figure 1). However, innovation cooperation is relatively weak in China's intercity innovation networks, reporting a density of only 0.05. In other words, it is difficult to initiate innovation cooperation among cities because the average path length is 2.07, which is greater than that of random networks of the same scale. Moreover, it necessary to strengthen the intensity of innovation cooperation among cities where the average degree of centrality is 15.

This study uses ArcGIS 10.2 and employs Jenks natural breaks' optimisation and further divides the link intensity of China's intercity innovation networks into four grades: high (1,149–3,109), medium (362–1,149), low (89–362), and lower (1–89) intensities. Figure 2 shows that an increase in connection strength causes a rapid decline in the number of intercity linkages. Moreover, a majority of the city innovation linkages demonstrate low strength; that is, 1,626 groups (76.99 percent of total linkages) report less than 10 linkages. Only 3 and 16 groups show high and medium strength, which is less than 1% of total linkages. These results highlight that most cities in China have a relatively low degree of innovation cooperation. While intercity innovation networks are large in scale and wide in coverage, there are obvious problems such as loose links, poor accessibility, and knowledge spillovers, and thus, the functions of intercity innovation networks need to be further enhanced. Boix and

TABLE 1: Definitions of variables in the proximity mechanism model for intercity innovation networks.

Variable	Index	Definition	Measure method
Explained variable	Innovation cooperation ( $COL_{ij}$ )	Ties for innovation cooperation between two cities	Number of joint invention patents for cities $i$ and $j$
	Geographical proximity ( $GEO_{ij}$ )	Geographical proximity between two cities	$GEO_{ij} = 10 - \ln(DIS_{ij} + 1)$
Explanatory variable	Institutional proximity ( $INS_{ij}$ )	Degree of similarity in institutional environments between two cities	1 or 0
	Cognitive proximity ( $COG_{ij}$ )	Similarity in technical knowledge structure between two cities	$COG_{ij} = (\sum_{m=1}^8 PAT_{im} PAT_{jm}) / \sqrt{\sum_{m=1}^8 PAT_{im}^2 PAT_{jm}^2}$
	Innovation performance (PAT)	City's technological innovation capability	Number of invention patents
Control variable	Innovation input (RDE)		R&D expenditure
	Innovation talent input (HUC)	Human capital	Number of personnel with bachelor degree or above
	Economic development (GPC)		GDP per capital

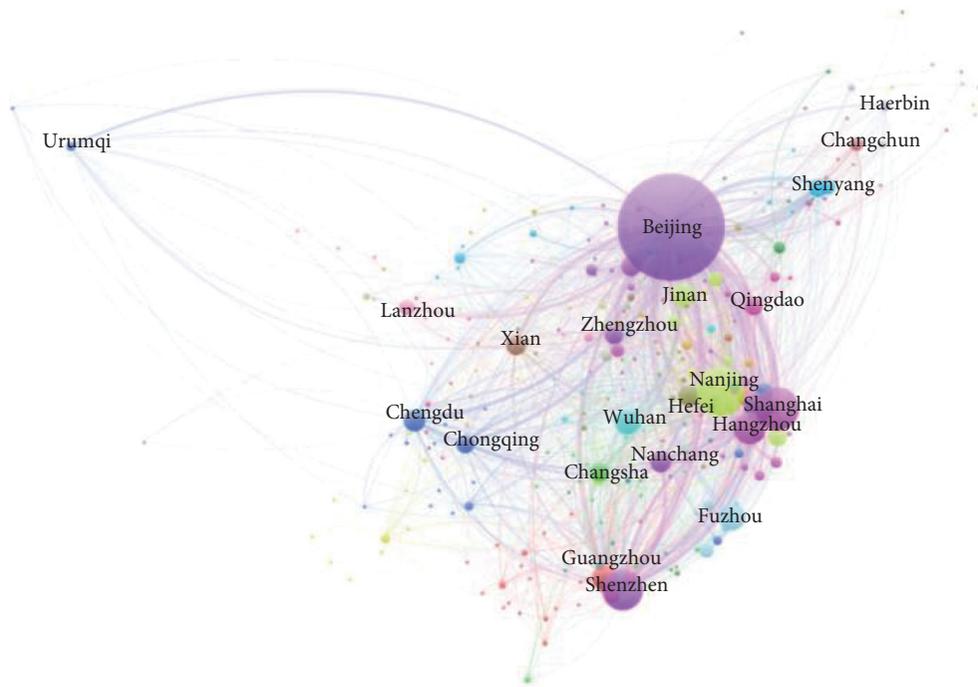


FIGURE 1: Topological structure of China's intercity innovation networks in 2014.

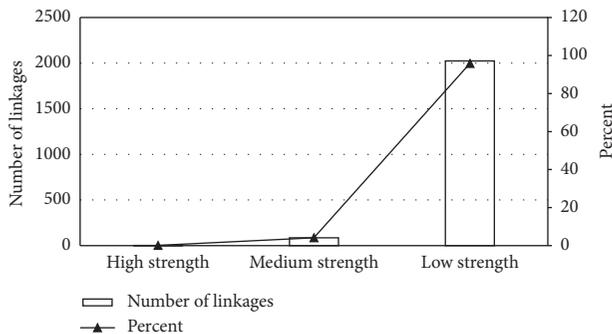


FIGURE 2: Linkage strength in China's intercity innovation networks for 2014.

Trullén [17] also found that higher growth rates are associated with higher levels of technology and knowledge, and the growth of the different kinds of knowledge is related to local and spatial factors (agglomeration and network externalities), and each knowledge intensity shows a particular response to these factors. Bettencourt et al. [37] found that the structure of the patent coauthorship network weakly correlated to increasing rates of patenting.

The Hu line has largely contributed to the east-west inequality in innovation linkages between cities. The linkages in eastern cities are greater than those in western cities. High-intensity innovation linkages are observed mainly among few big cities, such as Beijing-Nanjing, Beijing-Tianjin, and Beijing-Shanghai. The geographical spatial

pattern of medium-intensity innovation linkages demonstrates a “single-centre radiation” feature, in which Beijing is at the centre and radiating outward. Low-intensity innovation linkages, on the other hand, report “single-centre radiation and local networking,” where Beijing is at the centre. Complex and interactive network linkages can also be observed in Yangtze River Delta and Pearl River Delta. The researchers found that network linkages to the east of the Hu line tend to have varying intensities, while those in the western cities have low intensity.

The network centrality potential of China’s intercity innovation networks is 0.95, indicating a “core edge” structure. Using the Pajek 4.08 software and a hierarchical clustering algorithm for the block model, this study divides China’s intercity innovation networks into five levels: strong core, core, strong semi-edge, weak semi-edge, and edge (see Table 2). Next, it uses the network map drawing tool in VOSviewer 1.6.5 to draw the hierarchical structure diagram of China’s intercity innovation networks (see Figure 3). The results show that only Beijing is at the strong core of the network; 17 cities including Shanghai, Nanjing, and Wuhan are at the core; 30 cities consisting of Hefei, Wuxi, and Dalian are at the strong semi-edge; 75 cities comprising Yueyang, Beihai, and Jinmen are at the weak semi-edge; and, 163 cities including Guyuan, Sanmenxia, and Bazhong are at the edge. Figure 3 shows that cities in the strong core of the network are deeply connected with cities that are at the core, are lower in the hierarchy, and have fewer innovation linkages with other cities.

According to Table 2 and Figure 4, the case cities can be divided into five types: strong core city, core city, subcore city, subperiphery city, and periphery city. See Figure 4 for a visualisation using ArcGIS 10.2. Similar to the distribution of network linkages, the city hierarchy is bound by the Hu line. That is, a majority of the core and subcore cities are located to the east of the Hu line, and the overall distribution is relatively scattered. Few cities concentrated in the Yangtze River Delta and Pearl River Delta report the geographical distribution characteristics of “large dispersion and small agglomeration.” By contrast, most of the cities to the west of the Hu line are subperiphery or periphery cities. Cities at the top of China’s intercity innovation networks are mainly administrative such as Beijing, Shenzhen and Suzhou, which are provincial capitals or municipalities, are core cities possibly because China’s national or regional innovation system is significantly influenced by the government. The research of van der Wouden and Rigby [18] shows that metropolitan regions with more local and nonlocal network ties outperform cities where economic agents are isolated, and coinventor networks differ between cities that produce specialized and diversified knowledge. Many important scientific research institutions and universities are located in administratively central cities, such as Beijing, Shanghai, Nanjing, Wuhan, Guangzhou, and Hangzhou, and this increases the possibility of innovation networking [38,39]. Lobo and Strumsky [40] also found that agglomerative features of metropolitan areas are more important determinants of metropolitan patenting productivity than the structural feature of the inventive networks.

## 6. Mechanism for City Innovation Networking in China

Using formula (4), a model for the relationship between intercity innovation networks and geographical, institutional, and cognitive proximities is established. The correlation coefficients for the explanatory variables indicate that, except institutional and geographical proximities, which are 0.707, the other variables are less than 0.2. The variance inflation factor (VIF) for all explanatory variables is less than 3. Therefore, there is no multiple collinearity problem among the explanatory variables in the relationship model, and their reliability is high. For the explained variables, which report a nonnegative integer, it is necessary to use a discrete counting model such as the Poisson regression or negative binomial regression models. The data of the explained variables are excessively dispersed since the variance of the explained variables is 10739.98, while the expected value is only 20.32, which is significantly less than the variance. This study employs a negative binomial regression model to test the proximity mechanism of China’s intercity innovation networking (see Table 3).

A stepwise regression test was conducted on the models, and the results show that Models 1–3 reject the original hypothesis ( $\alpha=0$ ) at the 5% level, thus reiterating the rationality of the negative binomial regression model. The  $p$  values for the three models are zero, and the results do not reject the null hypothesis. A majority of the estimated parameters for the explanatory variables are significant at the 1% level, demonstrating the reliability of the test results above (see Table 4).

Models 1–3 show that geographical proximity is significantly positive at the 1% level, suggesting that greater geographical proximity between two cities renders innovation networking more likely. The contrary also holds true. Innovation is a process of strong interactive learning and communication along with the obvious characteristics of knowledge exchange and transfer, particularly tacit knowledge, and requires frequent face-to-face interactions among innovation actors [41, 42]. Huggins et al. [43] also pointed out that the springboard effect and the geography of external knowledge networks are associated with the regional economic context, Capone and Lazzeretti [12]; Knoblen [44] underlined the heterogeneous impact of various forms of proximity on the different relationships and the strong impact of social ties on innovation. This also explains the criticality of geographical proximity. Increasing geographical distances between cities will increase the time and economic cost of face-to-face interactions and create obstacles in cooperative efforts. Moreover, it significantly decreases the potential for innovation networking among cities. This finding strongly refutes the views of “the death of geographical proximity” and “geographical death” proposed by Cairncross [45] and Friedman [46]. Further, it proves that geographical proximity continues to play a vital role in China’s intercity innovation networks, even though transportation and information technology are highly developed,

TABLE 2: Hierarchy of China's intercity innovation networks.

Network hierarchy	Number of cities	Network centrality	Average of network centrality potential	Cities
Strong core	1	255	255	Beijing
Core	17	54–140	77	Shanghai, Nanjing, Suzhou, Wuhan, Zhengzhou, Tianjin, Xian, Jinan, Chongqing, Chengdu, Changsha, Shenzhen, Hangzhou, Guangzhou, Shenyang, Qingdao, and Changchun
Strong semiperiphery	30	23–52	34	Hefei, Wuxi, Dalian, Dongguan, Ningbo, Kunming, Xiamen, Lanzhou, Foshan, Taiyuan, Changzhou, Nanchang, Xuzhou, Yantai, Guiyang, Nanning, Zhenjiang, Urumqi, Nantong, Yinchuan, Fuzhou, Zhuhai, Yangzhou, Luoyang, Taizhou (Jiangsu), Yichang, Yancheng, Shijiazhuang, Haerbin, and Lianyungang
Weak semiperiphery	75	9–22	13	Yueyang, Beihai, Jinmen, Jian, Kaifeng, Yichun, Zhongwei, Huizhou, Jiangmen, Chuazhou, Anyang, Qinhuangdao, Chifeng, Jiaozuo, Huainan, Fuxin, Dezhou, Jilin, Luan, Huaibei, Suqian, Huangshan, Tongling, Bengbu, Changde, Zhaoqing, Langfang, Qingyuan, Shantou, Sanya, Guilin, Liuzhou, Shizuishan, Hengyang, Shaoguan, Huzhou, Heyuan, Zhangzhou, Zhongshan, Zhuzhou, Anqing, Tongliao, Handan, Weifang, Weihai, Taian, Chuzhou, Jiujiang, Mianyang, Jinhua, Zibo, Lishui, Zhoushan, Quzhou, Wenzhou, Taizhou (Zhejiang), Xiangtan, Wuhu, Jining, Shaoxing, Jiaxing, Zhanjiang, Haikou, Xuchang, Xining, Pingdingshan, Maanshan, Changzhi, Dongying, Huaian, Tangshan, Zhangjiakou, Baoding, and Anshan
Periphery	163	1–8	4	Remaining 163 cities

and geographical distance is a crucial factor in innovation actors choosing innovative partners.

Models 2 and 3 show that institutional proximity also significantly promotes innovation networking among Chinese cities, and the probability of innovation cooperation among cities with institutional proximity is higher. A city is not a simple geospatial unit but a comprehensive carrier of various natural and human elements. In the course of their historical development, cities develop different humanistic qualities that contribute to varying institutional environments, including informal institutional environments such as culture, language, and norms. However, these differences create institutional barriers in intercity innovation networking. Thus, cities with similar institutional environment factors create more conducive environments to enhance mutual trust between their innovation actors. This reduces uncertainty in the innovation networking process, decreases the costs of exchange, and enhances the possibility of innovation networking between cities. This finding is consistent with the viewpoint of Maillat and Kebir [47], who highlighted that special informal norms play a crucial role in forming innovation networks among regional innovative actors and similar institutions facilitate interregional innovation networking.

Model 3 shows that cognitive proximity is significantly positive at the 1% level, indicating that cognitive proximity promotes innovative cooperation among Chinese cities. In other words, cities with similar cognitive levels are highly likely to become innovative partners. Cognitive convergence renders two cities similar in technology specialisation, thus ensuring effective communication in innovation networking

and the identification and absorption of new knowledge. This finding is consistent with those of Guellec [48], Ponds et al. [49], and Guellec [48], who found that countries with similar technical expertise are more likely to engage in innovation cooperation. Ponds et al. [49] examined the industry-university-research cooperation in the Netherlands and showed that technological proximity is a necessary prerequisite for innovative cooperation among cross-regional enterprises, scientific research institutions, and universities.

Some scholars believe that the proximity of various dimensions affects and interacts with each other, and there may be some substitution or complementary effects [50, 51]. This study conducts a variable interactions' test to further examine the interaction among geographical, cognitive, and institutional proximities in China's intercity innovation networks. Because geographical and cognitive proximities are continuous variables, institutional proximity is considered a category variable. To ensure that the method is correct and the results are reliable, the study uses one proximity type among geographical, cognitive, or institutional proximities as the main variable, and the other two are considered regulatory variables to examine interactions between two proximities (see Table 5).

Using geographical proximity as the main variable and cognitive proximity as the regulatory variable, Model 4 is constructed to test the regulatory effect of cognitive proximity on geographical proximity. Similarly, Model 5 is constructed to test the regulatory effect of geographical proximity on cognitive proximity. Since both geographical and cognitive proximities are continuous variables, an

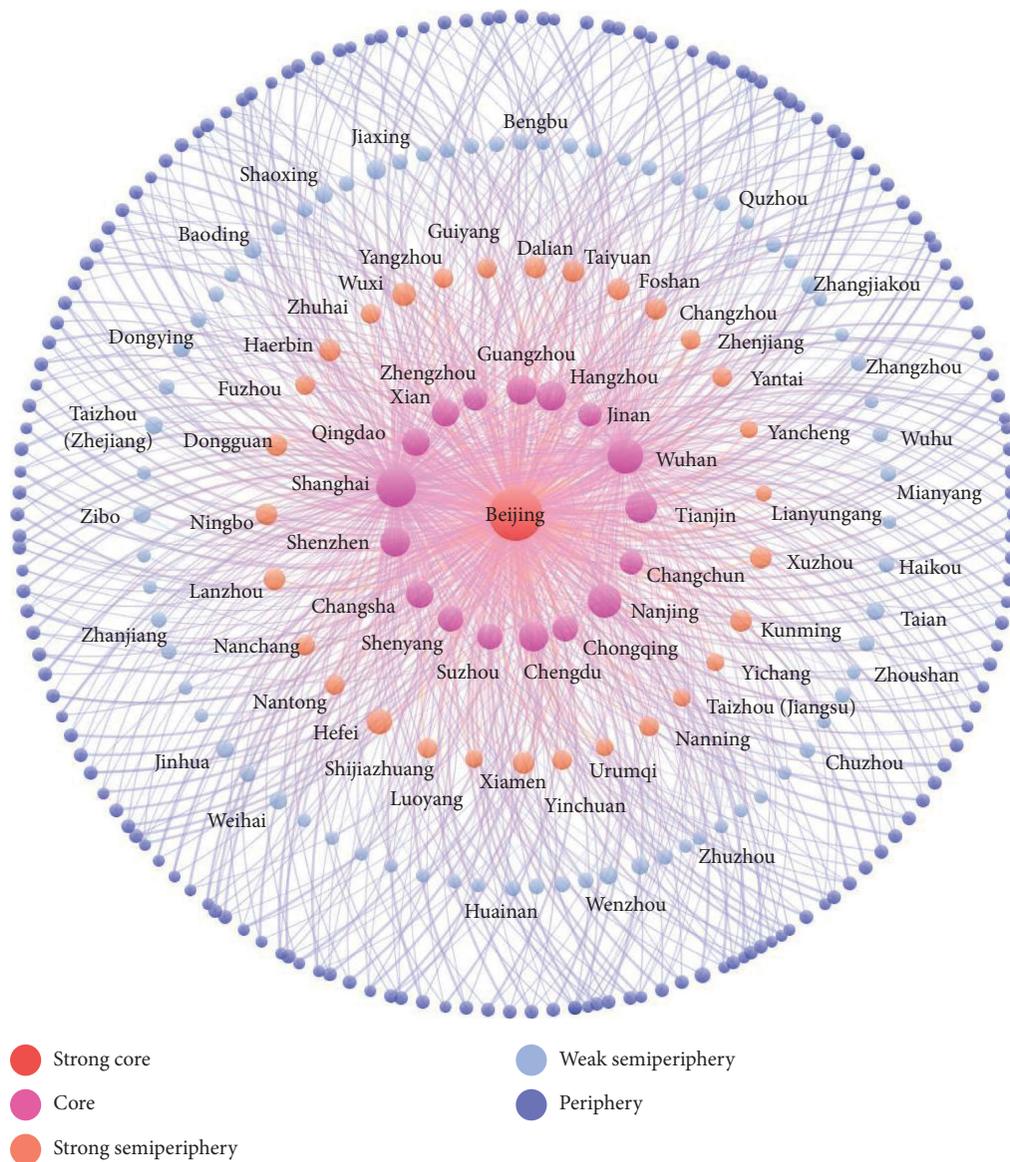


FIGURE 3: Hierarchical structure diagram of China's intercity innovation networks.

interaction term for the centralisation of geographical and cognitive proximities is added to the basic test model. Models 4 and 5 show that the interactive coefficient between geographical and cognitive proximities is significant at the 1% level, indicating significant interactions between both proximities. However, the significantly negative coefficient suggests that cognitive proximity will weaken the impact of geographical proximity on intercity innovation networking and vice versa. On the one hand, this substitution effect can be attributed to innovative cooperation with partners that are both cognitively and geographically close and that would otherwise be unable to access new information and knowledge, resulting in “excessive embedding” and “cognitive locking.” On the other hand, the scope for learning from each other considerably reduces for regions with similar geographical and cognitive proximity, and the risk of unconscious knowledge spillovers increases [52].

Next, institutional proximity is treated as the main variable, while geographical and cognitive proximities are considered regulatory variables. The interactive terms of  $INS_{ij} * GEO_{ij}$  and  $INS_{ij} * COG_{ij}$  are added to the basic model. Model 6 shows that the interactive coefficient for institutional and geographical proximities is significantly positive at the 5% level. In other words, the impact of institutional proximity on intercity innovation networking is positively regulated by geographical proximity and that of institutional proximity on intercity innovation networking will strengthen when the two cities are geographically close; this is a complementary effect. Model 7 shows that the interactive coefficient for institutional and cognitive proximities is also significant at the 5% level, but it is negative. This finding indicates that cognitive proximity will negatively regulate the relationship between institutional proximity and intercity innovation networking, which is a substitution effect.

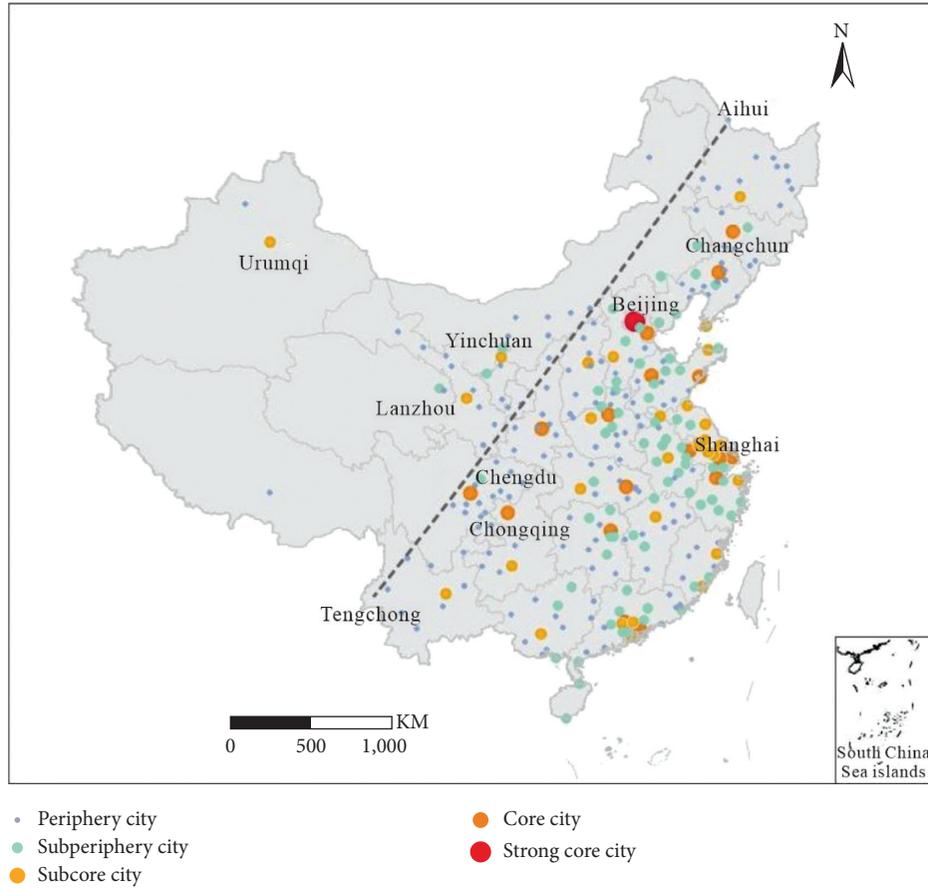


FIGURE 4: Hierarchical spatial distribution of China's cities.

TABLE 3: Descriptive statistical and correlation coefficient matrix of variables ( $N=2,112$ ).

Variables	Expected value	Variance	Max	Min	VIF	$COL_{ij}$	$DIS_{ij}$	$INS_{ij}$	$COG_{ij}$
$COL_{ij}$	20.32	10739.98	3109.0	1.00		1.00			
$GEO_{ij}$	3.57	0.88	7.00	1.85	2.020	0.016	1.00		
$INS_{ij}$	0.18	0.15	1.00	0.00	2.000	-0.024	0.707***	1.00	
$COG_{ij}$	0.81	0.02	1.00	0.25	1.035	-0.020	0.181***	0.153***	1.00

Notes. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ .

Next, this study uses both geographical and cognitive proximities as the main variables and institutional proximity as a regulatory variable to test the regulatory effect of institutional proximity on geographical and cognitive proximities. First, a group regression is conducted to divide the sample data into two groups depending on institutional proximity, and then, a negative binomial regression analysis is performed on the two sample groups (see Table 6). Models 8 and 9 show that geographical proximity actively promotes intercity innovation networking at the 1% level. However, the influence coefficient in the sample group for institutional proximity is larger, and the promotion effect is stronger, indicating that institutional proximity can enhance the positive influence of geographical proximity on intercity innovation networking, which is a complementary effect. The coefficient for cognitive proximity fails the significance test on the sample group for institutional proximity,

although it is significantly positive in the sample group for institutional nonproximity. This means institutional proximity will weaken the positive impact of cognitive proximity on intercity innovation networking, which is a substitution effect.

Figure 5 is a graph of the variables' regulatory effect and is created to better understand interactions between the different proximities. It shows the regulatory effect of geographical, cognitive, and institutional proximities. For cities with greater geographical proximity, the positive impact of cognitive proximity on intercity innovation networking weakens or even has a negative impact. In [13], the author points out that interregional network proximity is important in determining future collaborations but its effect is mediated by geography. However, the impact of institutional proximity on intercity innovation networking significantly increases. For cities with higher cognitive

TABLE 4: Regression test results for impact of three proximities on intercity innovation networking.

Variables	Model 1	Model 2	Model 3
PAT <sub>i</sub>	0.0000412*** (0.000)	0.000042*** (0.000)	0.000044*** (0.000)
PAT <sub>j</sub>	0.0000432*** (0.000)	0.0000455*** (0.000)	0.0000464*** (0.000)
RDE <sub>i</sub>	0.0000222** (0.000)	0.0000021*** (0.000)	0.0000004*** (0.000)
RDE <sub>j</sub>	0.0000231** (0.000)	0.0000025*** (0.000)	0.0000014*** (0.000)
HUC <sub>i</sub>	0.0000082 * (0.000)	0.0000079** (0.000)	0.0000052*** (0.000)
HUC <sub>j</sub>	0.0000063 * (0.000)	0.0000065** (0.000)	0.0000050*** (0.000)
GPC <sub>i</sub>	0.0000118** (0.000)	0.0000226*** (0.000)	0.0000076** (0.000)
GPC <sub>j</sub>	0.0000137** (0.000)	0.0000253*** (0.000)	0.0000069** (0.000)
GEO <sub>ij</sub>	0.4528901*** (0.000)	0.2658215*** (0.000)	0.252175*** (0.000)
INS <sub>ij</sub>		0.5930518*** (0.000)	0.6121559*** (0.000)
COG <sub>ij</sub>			1.338232*** (0.001)
CONS	1.01691*** (0.000)	0.9689111*** (0.000)	0.9120978*** (0.000)
N	2112	2112	2112
Prob. > chi2	0.0000	0.0000	0.0000
Log pseudolikelihood	-6791.1238	-6775.763	-6754.5513

Note. \*  $p < 0.10$ , \*\*  $p < 0.05$ , and \*\*\*  $p < 0.01$ . N represents the sample size in the model.

TABLE 5: Regression results of the interactive model for different proximities.

Variables	Model 4	Model 5	Model 6	Model 7
PAT <sub>i</sub>	0.0000437*** (0.000)	0.0000437*** (0.000)	0.0000441*** (0.000)	0.0000445*** (0.000)
PAT <sub>j</sub>	0.0000469*** (0.000)	0.0000469*** (0.000)	0.0000463*** (0.000)	0.0000469*** (0.000)
RDE <sub>i</sub>	0.0000232** (0.000)	0.0000221*** (0.000)	0.0000204*** (0.000)	0.0000204*** (0.000)
RDE <sub>j</sub>	0.0000252** (0.000)	0.0000225*** (0.000)	0.0000214*** (0.000)	0.0000234*** (0.000)
HUC <sub>i</sub>	0.0000462 * (0.000)	0.0000469** (0.000)	0.0000452*** (0.000)	0.0000433*** (0.000)
HUC <sub>j</sub>	0.0000336 * (0.000)	0.0000356** (0.000)	0.0000305*** (0.000)	0.0000325*** (0.000)
GPC <sub>i</sub>	0.0000118** (0.000)	0.0000122*** (0.000)	0.0000112** (0.000)	0.0000176** (0.000)
GPC <sub>j</sub>	0.0000168** (0.000)	0.0000132*** (0.000)	0.0000155** (0.000)	0.0000143** (0.000)
GEO <sub>ij</sub>	0.2566725*** (0.000)	0.2566725*** (0.000)	0.2548991*** (0.000)	0.2383039*** (0.000)
INS <sub>ij</sub>	0.6575141*** (0.000)	0.6575141*** (0.000)	0.1419111 (0.000)	0.7544208*** (0.000)
COG <sub>ij</sub>	1.029992** (0.012)	1.029992** (0.012)	1.378283*** (0.000)	1.097303*** (0.007)
GEO <sub>ij</sub> *COG <sub>ij</sub>	-1.195481*** (0.005)			
COG <sub>ij</sub> * GEO <sub>ij</sub>		-1.195481*** (0.005)		
INS <sub>ij</sub> *GEO <sub>ij</sub>			0.3993853** (0.022)	

TABLE 5: Continued.

Variables	Model 4	Model 5	Model 6	Model 7
$INS_{ij} * COG_{ij}$				-3.389262** (0.014)
CONS	0.933344*** (0.000)	0.933344*** (0.000)	0.806204*** (0.000)	0.9181173*** (0.000)
N	2112	2112	2112	2112
Prob. > chi2	0.0000	0.0000	0.0000	0.0000
Log pseudolikelihood	-6741.4869	-6741.4869	-6748.3122	-6741.4968

Note. \* $p < 0.10$ , \*\* $p < 0.05$ , and \*\*\* $p < 0.01$ .  $N$  represents the sample size in the model.

TABLE 6: Regulatory effect of institutional proximity on geographical and cognitive proximities.

Variables	Sample group of institutional proximity (Model 8)	Sample group of institutional nonproximity (Model 9)
$PAT_i$	0.0000783*** (0.000)	0.0000439*** (0.000)
$PAT_j$	0.0000494*** (0.000)	0.0000463*** (0.000)
$RDE_i$	0.0000652*** (0.000)	0.0000632*** (0.000)
$RDE_j$	0.0000572*** (0.000)	0.0000545*** (0.000)
$HUC_i$	0.0000486** (0.000)	0.0000415*** (0.000)
$HUC_j$	0.0000669* (0.000)	0.0000681** (0.000)
$GPC_i$	0.0000529** (0.000)	0.0000531*** (0.000)
$GPC_j$	0.0000547** (0.000)	0.0000533*** (0.000)
$GEO_{ij}$	0.5462855*** (0.001)	0.1794366*** (0.000)
$COG_{ij}$	-1.189488 (0.341)	1.682881*** (0.000)
CONS	0.7722817*** (0.001)	0.7867398*** (0.000)
$N$	376	1,736
Prob. > chi2	0.0000	0.0000
Log pseudolikelihood	-1250.723	-5475.5285

Note: \* $p < 0.10$ , \*\* $p < 0.05$ , and \*\*\* $p < 0.01$ .  $N$  represents the sample size in the model.

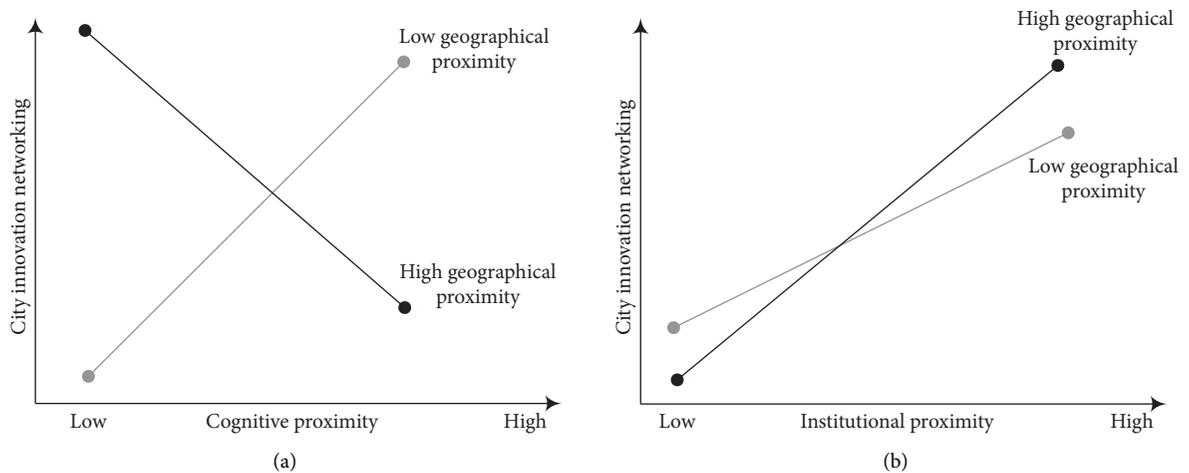


FIGURE 5: Continued.

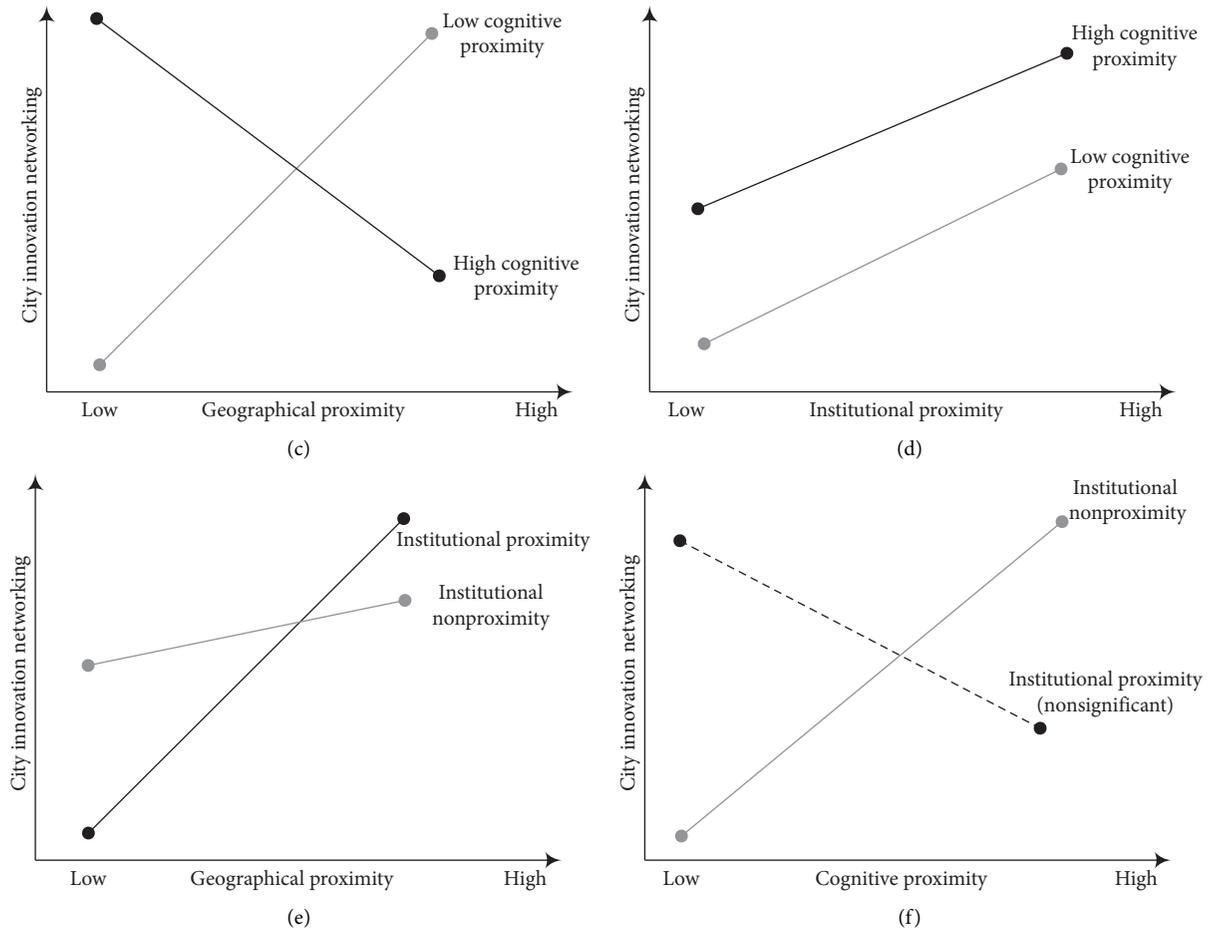


FIGURE 5: Regulatory effects of geographical, cognitive, and institutional proximities.

proximity, the positive impact of both geographical and institutional proximities considerably weakens. Finally, for cities with greater institutional proximity, the impact of geographical proximity strengthens and becomes more positive, while that of cognitive proximity is no longer significant.

## 7. Conclusions

There is growing concern regarding regional development and innovation in the economic geography literature [53–55]. In numerous recent studies on regional economic development, spatial proximity, density, and localised processes, which cannot explain new economic phenomena, global and local proximities have become increasingly important [50, 56, 57]. Adopting the innovation networks' perspective and conducting an SNA, this study analyses the structural characteristics, that is, the topology and spatial pattern of city networks in China. Drawing on Scherngell and Barber's [30] spatial interaction model, a model for the relationship between proximity and intercity innovation networks is established. The model is then employed to explain the interaction and impact of geographic, institutional, and cognitive proximities on China's intercity innovation networks.

The findings reveal that while the scale and scope of Chinese intercity innovation networks have been increasing, their density is lower and most cities are loosely connected. At the network level, the results suggest that the intercity innovation networks are more centred. That is, the agglomeration and hierarchy of innovation activities are prominent and develop into a core-periphery structure, which can be further divided into strong core, core, strong semiperiphery, weak semiperiphery, and periphery. Only Beijing is at the strong core of the network. Shanghai, Nanjing, and Wuhan are among the 14 cities at the core of network, and the remaining are at the strong semiperiphery, weak semiperiphery, or periphery of the innovation networks. According to the structure of innovation networks in the Chinese cities, we can divide the cities into five levels: strong core, core, subcore, subperiphery, and periphery. We find that the hierarchy of Chinese cities is high in the east and low in the west, with the core and subcore cities demonstrating a spatial pattern of "large dispersion and small agglomeration" and bound by the Hu line. To the east of the Hu line, the density and strength of innovation linkages between cities are higher, and thus, the networks are complex and efficient with Beijing as the strong core city. However, to the west of the Hu line, the innovation linkages are weaker and most cities are subperiphery or periphery cities.

## 8. Discussion

This study analyses mechanisms for intercity innovation networking in China and offers interesting conclusions consistent with the viewpoints of Maillat and Kebir [47], Guellec [48], Ponds et al. [49], and van der Wouden and Rigby [18], who argue that inventors in specialized cities value spatial proximity less and cognitive proximity more than inventors in diversified cities as they partner with nonlocal inventors. However, it refutes Cairncross [45] and Friedman's [46] views of "the death of geographical proximity" and "geographical death." The analysis reveals that geographical, institutional, and cognitive proximities positively impact innovation networks in Chinese cities. In particular, cognitive proximity has the strongest impact, followed by institutional and geographical proximities. The test results for variable interactions show significant interactions among geographical, cognitive, and institutional proximities. Geographical and institutional proximities positively regulate each other's relationship with intercity innovation networking, and the relationship between geographical and institutional proximities reports a complementary effect. However, there is a substitutive relationship between cognitive proximity and geographical and institutional proximities, and as a result, their role in promoting intercity innovation networking is weakened. This further confirms that cognitive proximity may result in increasingly weaker networks and is not conducive to the transformation of product structures in developing countries and regions [26].

Future research should consider further exploring data and methods to measure intercity innovation networks, introducing more proximity types, exploring the dynamics of the same proximity over time, and summarizing the regularity of each proximity type within the dynamic evolution of innovation networks.

## Data Availability

The data used to support the findings of the study are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

This work was supported by the National Natural Science Foundation of China (41801109 and 41771143) and Project of Science and Technology Commission of Shanghai Municipality (19DZ1203801).

## References

- [1] P. M. Cooke, *Regional Innovation System Barriers and the Rise of Boundary-Crossing Institutions*, Academia-Business Links, Palgrave, Macmillan, UK, 2004.
- [2] F. Quatraro and S. Usai, "Knowledge flows, externalities and innovation networks," *Regional Studies*, vol. 51, no. 8, pp. 1133–1137, 2017.
- [3] L. Lyu, Z. Liang, and R. Huang, "The innovation linkage among Chinese major cities," *Scientia Geographica Sinica*, vol. 35, no. 1, pp. 30–37, 2015.
- [4] F. Zhang and F. Wu, "Rethinking the city and innovation: a political economic view from China's biotech," *Cities*, vol. 85, pp. 150–155, 2018.
- [5] R. Huggins and P. Thompson, "A network-based view of regional growth," *Journal of Economic Geography*, vol. 14, no. 3, pp. 511–545, 2014.
- [6] R. Huggins and P. Thompson, "Networks and regional economic growth: a spatial analysis of knowledge ties," *Environment and Planning A*, vol. 49, no. 2, pp. 1–19, 2017.
- [7] R. Rothwell, "Successful industrial innovation: critical factors for the 1990s," *R&D Management*, vol. 22, no. 3, pp. 221–240, 1992.
- [8] X. Cao, G. Zeng, T. Teng, and Y. Si, "The best spatial scale of firm innovation networks: evidence from Shanghai high-tech firms," *Growth and Change*, vol. 49, no. 4, pp. 696–711, 2018.
- [9] I. Liefner and S. Hennemann, "Structural holes and new dimensions of distance: the spatial configuration of the scientific knowledge network of China's optical technology sector," *Environment and Planning A: Economy and Space*, vol. 43, no. 4, pp. 810–829, 2011.
- [10] P.-A. Balland, M. De Vaan, and R. Boschma, "The dynamics of interfirm networks along the industry life cycle: the case of the global video game industry, 1987–2007," *Journal of Economic Geography*, vol. 13, no. 5, pp. 741–765, 2013.
- [11] P. A. Balland, "Proximity and the evolution of collaboration networks: evidence from research and development projects within the global navigation satellite system industry," *Regional Studies*, vol. 46, no. 6, pp. 741–756, 2011.
- [12] F. Capone and L. Lazzarotti, "The different roles of proximity in multiple informal network relationships: evidence from the cluster of high technology applied to cultural goods in Tuscany," *Industry and Innovation*, vol. 25, no. 9, pp. 897–917, 2018.
- [13] L. R. Bergé, "Network proximity in the geography of research collaboration," *Papers in Regional Science*, vol. 96, no. 4, pp. 785–816, 2017.
- [14] D. Sudharshan, R. Madhavan, and S. C. Liu, "DiffuNET: the impact of network structure on diffusion of innovation," *European Journal of Innovation Management*, vol. 8, no. 2, pp. 240–262, 2005.
- [15] M. A. Schilling and C. C. Phelps, "Interfirm collaboration networks: the impact of large-scale network structure on firm innovation," *Management Science*, vol. 53, no. 7, pp. 1113–1126, 2007.
- [16] C. Freeman, "Networks of innovators: a synthesis of research issues," *Research Policy*, vol. 20, no. 5, pp. 499–514, 1991.
- [17] R. Boix and J. Trullén, "Knowledge, networks of cities and growth in regional urban systems," *Papers in Regional Science*, vol. 86, no. 4, pp. 551–574, 2007.
- [18] F. van der Wouden and D. L. Rigby, "Co-inventor networks and knowledge production in specialized and diversified cities," *Papers in Regional Science*, vol. 10, no. 98, pp. 1833–1853, 2019.
- [19] A. Marshall, *Principles of Economics*, Macmillan, London, UK, 1890.
- [20] J. Knoblen, "Localized inter-organizational linkages, agglomeration effects, and the innovative performance of firms,"

- The Annals of Regional Science*, vol. 43, no. 3, pp. 757–779, 2009.
- [21] M. Bradshaw, “Multiple proximities: culture and geography in the transport logistics of newsprint manufactured in Australia,” *Environment and Planning A: Economy and Space*, vol. 33, no. 10, pp. 1717–1739, 2001.
- [22] J. Knoblen and L. A. G. Oerlemans, “Proximity and inter-organizational collaboration: a literature review,” *International Journal of Management Reviews*, vol. 8, no. 2, pp. 71–89, 2006.
- [23] R. Boschma, “Proximity and innovation: a critical assessment,” *Regional Studies*, vol. 39, no. 1, pp. 61–74, 2005.
- [24] P.-A. Balland, J. A. Belso-Martínez, and A. Morrison, “The dynamics of technical and business knowledge networks in industrial clusters: embeddedness, status, or proximity?” *Economic Geography*, vol. 92, no. 1, pp. 35–60, 2016.
- [25] T. Broekel and R. Boschma, “Knowledge networks in the Dutch aviation industry: the proximity paradox,” *Journal of Economic Geography*, vol. 12, no. 2, pp. 409–433, 2012.
- [26] C. He, L. Jin, and Y. Liu, “How does multi-proximity affect the evolution of export product space in China?” *Geographical Research*, vol. 36, no. 9, pp. 1613–1626, 2017.
- [27] C. Zhou, G. Zeng, and X. Cao, “Chinese inter-city innovation networks structure and city innovation capability,” *Geographical Research*, vol. 36, no. 7, pp. 1297–1308, 2017.
- [28] A. L. J. Ter Wal and R. A. Boschma, “Applying social network analysis in economic geography: framing some key analytic issues,” *The Annals of Regional Science*, vol. 43, no. 3, pp. 739–756, 2009.
- [29] I. Wanzenböck, “A concept for measuring network proximity of regions in R&D networks,” *Social Networks*, vol. 54, no. 54, pp. 314–325, 2018.
- [30] T. Scherngell and M. J. Barber, “Spatial interaction modelling of cross-region R&D collaborations: empirical evidence from the 5th EU framework programme,” *Papers in Regional Science*, vol. 88, no. 3, pp. 531–546, 2009.
- [31] T. Scherngell and Y. Hu, “Collaborative knowledge production in China: regional evidence from a gravity model approach,” *Regional Studies*, vol. 45, no. 6, pp. 755–772, 2011.
- [32] F. Montobbio and V. Sterzi, “The globalization of technology in emerging markets: a gravity model on the determinants of international patent collaborations,” *World Development*, vol. 44, no. 4, pp. 281–299, 2013.
- [33] K. Kunze, “Empirical analysis of innovation and trade in Europe: a gravity model approach,” *International Journal of Trade and Global Markets*, vol. 9, no. 3, pp. 197–211, 2016.
- [34] Q. Gui, C. Liu, and D. Du, “Does network position foster knowledge production? Evidence from international scientific collaboration network,” *Growth and Change*, vol. 49, no. 4, pp. 594–611, 2018.
- [35] O. Ejermo and C. Karlsson, “Interregional inventor networks as studied by patent coinventorships,” *Research Policy*, vol. 35, no. 3, pp. 412–430, 2006.
- [36] A. B. Jaffe, “Technological opportunity and spillovers of R&D: evidence from firms’ patents, profits, and market value,” *American Economic Review*, vol. 76, no. 5, pp. 984–1001, 1986.
- [37] L. M. A. Bettencourt, J. Lobo, and D. Strumsky, “Invention in the city: increasing returns to patenting as a scaling function of metropolitan size,” *Research Policy*, vol. 36, no. 1, pp. 107–120, 2007.
- [38] D. E. Andersson, S. Gunessee, C. W. Matthiessen, and S. Find, “The geography of Chinese science,” *Environment and Planning A: Economy and Space*, vol. 46, no. 12, pp. 2950–2971, 2014.
- [39] Q. Wang, G. Zeng, and G. Lyu, “Structural evolution of innovation networks of China’s equipment manufacturing industry,” *Acta Geographica Sinica*, vol. 71, no. 2, pp. 251–264, 2016.
- [40] J. Lobo and D. Strumsky, “Metropolitan patenting, inventor agglomeration and social networks: a tale of two effects,” *Journal of Urban Economics*, vol. 63, no. 3, pp. 871–884, 2008.
- [41] B. Veelen, “The new oxford handbook of economic geography,” *Local Environment*, vol. 23, no. 8, pp. 900–901, 2018.
- [42] G. L. Clark, M. S. Gertler, and M. P. Feldman, “The oxford handbook of economic geography,” *Economic Geography*, vol. 78, no. 3, pp. 387–392, 2002.
- [43] R. Huggins, H. Izushi, and D. Prokop, “Regional advantage and the geography of networks: explaining global-local knowledge sourcing patterns,” *Papers in Regional Science*, vol. 60, no. 98, pp. 1567–1584, 2019.
- [44] J. Knoblen, *Firm Mobility and Organizational Networks: Innovation, Embeddedness and Economic Geography*, Edward Elgar Publishing, Cheltenham, UK, 2008.
- [45] F. Cairncross, *The Death of Distance 2.0: How the Communications Revolution Will Change Our Lives*, Texere, Knutsford, England, UK, 2001.
- [46] T. L. Friedman, “The world is flat: a brief history of the twenty-first century,” *International Journal*, vol. 9, no. 1, pp. 67–69, 2005.
- [47] D. Maillat and L. Kebir, *The Learning Region and Territorial Production Systems*, Springer, Berlin, Heidelberg, 2001.
- [48] D. Guellec and B. van Pottelsberghe de la Potterie, “The internationalisation of technology analysed with patent data,” *Research Policy*, vol. 30, no. 8, pp. 1253–1266, 2001.
- [49] R. Ponds, F. van Oort, and K. Frenken, “The geographical and institutional proximity of research collaboration,” *Papers in Regional Science*, vol. 86, no. 3, pp. 423–443, 2007.
- [50] R. Crescenzi, M. Nathan, and A. Rodríguez-Pose, “Do inventors talk to strangers? On proximity and collaborative knowledge creation,” *Research Policy*, vol. 45, no. 1, pp. 177–194, 2016.
- [51] P. D’Este, F. Guy, and S. Iammarino, “Shaping the formation of university–industry research collaborations: what type of proximity does really matter?” *Journal of Economic Geography*, vol. 13, no. 4, pp. 537–558, 2013.
- [52] R. Crescenzi and S. Iammarino, “Global investments and regional development trajectories: the missing links,” *Regional Studies*, vol. 51, no. 1, pp. 97–115, 2017.
- [53] H. Bathelt, P. Li, and Y. Zhu, “Geographies of temporary markets: an anatomy of the canton fair,” *European Planning Studies*, vol. 5, pp. 1–19, 2017.
- [54] R. Martin, “Roepke lecture in economic geography—rethinking regional path dependence: beyond lock-in to evolution,” *Economic Geography*, vol. 86, no. 1, pp. 1–27, 2010.
- [55] S. Zhu, C. He, and Y. Zhou, “How to jump further and catch up? Path-breaking in an uneven industry space,” *Journal of Economic Geography*, vol. 17, no. 3, pp. 521–545, 2017.
- [56] C. He and H. Chen, “Participation in global production networks and export product upgrading,” *Acta Geographica Sinica*, vol. 72, no. 8, pp. 1331–1346, 2017.
- [57] E. Uyarra, “Regional innovation systems revisited: networks, institutions, policy and complexity,” *Openloc Working Papers*, vol. 27, no. 6, pp. 697–711, 2011.