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*Original Paper*

# Spatio-Temporal Evolution and Mechanisms of Inter-city Cooperative Innovation Network in Sichuan and Chongqing

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***Abstract***
*This study examines the spatio-temporal heterogeneity and proximity mechanisms of innovation networks in Sichuan and Chongqing by social network analysis and a stochastic actor-oriented model. The findings reveal the following: (1) The quantity of innovation collaborations has significantly increased, resulting in a denser network. A core-periphery structure has emerged, with Chengdu and the Chongqing Central Urban Area serving as the core; (2) Chengdu has played a leading role in the network, while the cities in the Chongqing Central Urban Area have progressively gained importance since 2010, acting as a hub for innovation resource gathering and transit. However, there is a clear tendency toward innovative cooperation between cities within the province; (3) The initial establishment of innovation linkages incurs costs, with endogenous variables playing significant roles in network evolution. Multi-dimensional proximity has positive effects on network evolution, although the level of GDP per capita somewhat hinders innovative cooperation.*

***Keywords***
*Innovation Network, Technological Collaboration, Temporal-spatial Evolution, Multi-dimensional Proximity*

## 1. Introduction

Technology and knowledge innovation have steadily emerged as key components for increasing national competitiveness. China is moving from a fast growth stage, which is dependent on the production and manufacturing of resource factors, to a high-quality development stage, which is driven by technological innovation and knowledge. China is currently ranked among the most scientific and technologically inventive countries. By using externality, collaborative innovation can effectively shorten the interval between innovation production and application and make full use of technological advantages to increase each party’s capacity for independent innovation despite high input costs and multiple uncertain risks. Therefore, collaboration enhances the flow of innovation factors both within and between regions (Powell & Snellman 2004), and the ensuing innovation network facilitates coordination between various actors and platforms (Su et al., 2018). As a result, regional innovation progressively moves toward open innovation and advances the realization of an innovation ecosystem's virtuous cycle. Therefore, understanding the dynamic evolution process and spatiotemporal pattern of innovation networks is crucial for the governance of innovation systems and regional collaborative growth.

Starting with the notion of Space of Flows, economic geographers have built urban networks to describe the patterns of various types of elements in space. These networks have been protracted by the flow of capital and traffic (Yuan et al., 2019), information (Pinar & Volkan 2018), people and logistics (Li et al., 2023). In light of the innovation network portrayed by knowledge and technology flow, researchers primarily concentrate on the spatial differentiation of innovation elements within the region as well as the network structure, including network formation, the agglomeration trend of development and network mechanism. Scopes vary from the global (Liu et al., 2022b), national (Ma et al., 2015), urban (Li et al., 2022), provincial and municipal (Zhang et al., 2020) to enterprises and institutional organizations, under the condition of a similar knowledge structure. These have been contrasted with smaller scales such as inter-firm and individual inventors (Graf, 2011; Teng et al., 2021). Moreover, pertinent research has been conducted on several industry sectors and technological species (Beaudry & Schiffauerova, 2011), which reflects the various cooperation modes and traits associated with decision-making of subjects involved in the innovation process. Agglomeration theory and actor network theory have been used in urban studies to explain the operating mechanisms and phenomena of city elements (Scott & Storper 2015). Placing innovation activities on the city scale implies, at the foremost, that agglomeration has a huge impact on innovation. Agglomeration facilitates the geographical spread of knowledge, especially the spread of tacit knowledge (Wijngaarden et al., 2020). Thus, there are a proliferation of discussions on similarity and multidimensional proximity (Liu et al., 2022a). Surely, the heterogeneity (Corsaro et al., 2012) and diversity (Nieto & Santamar ía, 2007) of the individuals in a collaborative relationship in terms of their goals, knowledge base, culture, competence, status power, etc., have a greater impact on the development of innovation networks and the novelty of the innovation outcomes. Actor network theory regards both human and technology as dynamic subjects, and both human and non-human actors can participate in scientific and technological practices (Sayes, 2014), which provides a new insight into innovation from a network perspective.

The innovation capacity of Chinese cities shows large differences (Feng et al., 2022), which presents a diamond-shaped structure with Beijing-Tianjin-Hebei, Yangtze River Delta, Pearl River Delta, and Chengdu-Chongqing city clusters as the vertex (Ma et al., 2015). With the Chengdu-Chongqing Economic Circle rising to a national strategy in 2021, the Chengdu-Chongqing city clusters have narrowed the gap with the others, gradually becoming the emerging innovation hub. The number of patent applications has been rising (Yuan & Han, 2021), and the degree of internal connection has remarkably increased (Li et al., 2021a).

Sichuan and Chongqing (Figure) occupy strategically crucial positions in the national development pattern. In terms of geographic location, it is the intersection node of the Yangtze River Economic Belt and the “One Belt, One Road”, seen as a backbone for upholding the stability of the country. Furthermore, it served as the launching base of China-Europe Express Railway, connecting China’s hinterland with the Asian-European continent. It is an important corridor for trade and cultural exchanges between Southeast Asia and Europe and also a window for opening up western China. Sichuan and Chongqing share similar backgrounds of culture and industrial development history, characterized by a large proportion of a state-owned economy and outstanding strength of the equipment manufacturing industry. Broad market space and opportunities have been stimulated by the large population base and industrial scale, making the Sichuan and Chongqing regions the fourth pole of China’s economic growth, with strong innovation strength, which will certainly give its innovation network spatial and temporal structure and uniqueness of the innovation mode.

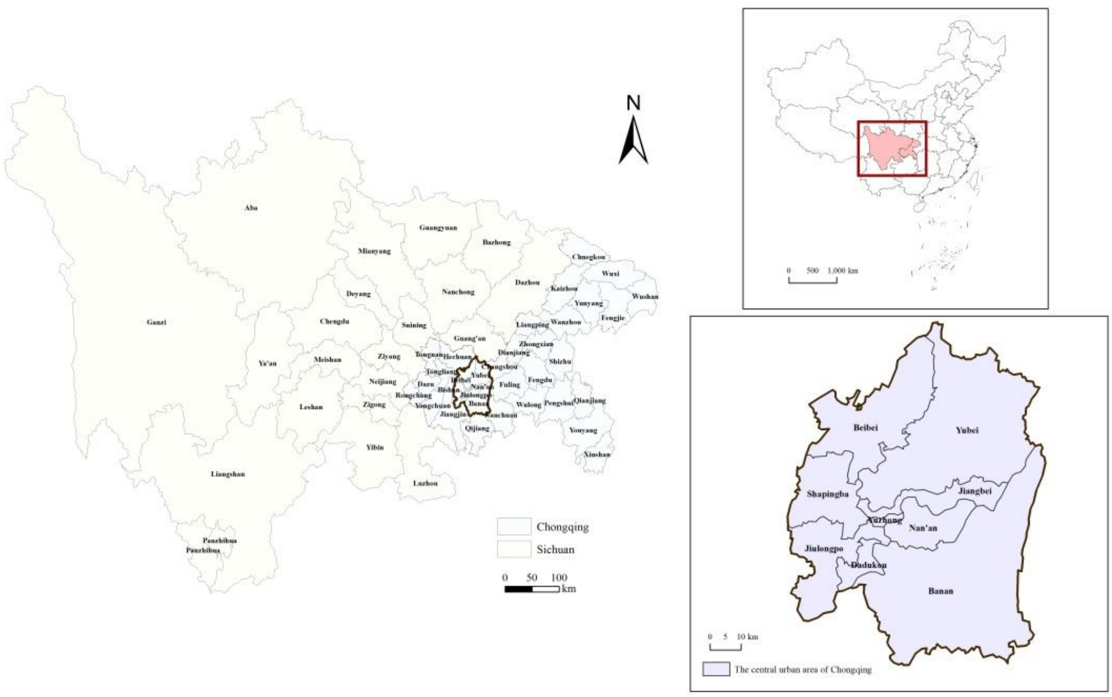


**Figure 1. Scope of Sichuan and Chongqing**

Research on innovation networks targeting the Chengdu-Chongqing Economic Circle is emerging. Scholars have analyzed innovation characteristics such as knowledge transfer (Zeng et al., 2022), the theme of collaborative innovation according to governmental texts (Cao et al., 2022), and innovation capacity. Comparative studies of innovation networks within the Chengdu-Chongqing city cluster (Sun et al., 2022b) and with other city clusters (Han & Yang, 2021) have grown gradually. Meanwhile, the relationship between the innovation network and innovation performance (Sun et al., 2022a), and the factors hindering its development (Han & Yang 2022) have also been identified. It is noticeable that there have been analyses of knowledge innovation network mechanisms in this region using collaborative thesis data (Hou et al., 2023), while the simulation of innovation network evolution mechanisms from the perspective of technology innovation is still absent.

Against this backdrop, we established an innovation network between cities in Sichuan and Chongqing through cooperative patents from 2000 to 2019. We adopt a social network analysis and stochastic actor-oriented model to explore the spatio-temporal evolution of the innovation network from the perspective of multi-dimensional proximity. An analysis of its evolution mechanism is carried out to enrich the research results of the innovation network in the time series data spanning a large period of time and to provide a reference for the decision-making of the innovation development of the Sichuan-Chongqing region.

The rest of the article is structured as follows. The second section reviews the theoretical background of innovation and innovation network. The third section introduces the data resources and research methods applied in this study. The fourth and fifth sections present the results of the research, including the spatio-temporal evolution of the innovation network in the Sichuan-Chongqing region and its proximity effects. The final section concludes the study by summarizing the main findings and providing further discussion.

## 2. Literature Review

### *2.1 Research in Innovation*

Schumpeter, for the first time, proposed the definition of innovation and summarized the main forms of innovation in 1912. In his book “The Theory of Economic Development”. Many discussions of innovation were subsequently launched, laying a theoretical foundation for innovation research. W. Rupert Maclaurin expanded Schumpeter’s philosophy and categorized technological innovation processes into several phases (Godin, 2008). One of his contributions was the linear model of innovation (Godin, 2006), which states that innovation is a chain of processes ranging from basic sciences to applied sciences, design, manufacturing, and then sales. This paved the way for subsequent quantitative research on innovation. Researchers have subdivided the types of innovation into disruptive and continuous innovation, radical innovation (Sandberg & Aarikka-Stenroos, 2014), incremental innovation, and adaptive innovation (Zheng et al., 2021), according to the process and characteristics of innovation. The process of innovation has also been investigated. The division of innovation stages and quantitative indicators have been summarized (Dziallas & Blind, 2019), and the innovation resistance brought about by network externalities and consumer characteristics at different stages has been explored (Anonymous, 1989; Huang et al., 2021). Innovation capability is also an essential topic. The influencing factors of innovation capability, such as natural resources and the degree of urbanization, are examined (Chen et al., 2020), as well as its effects, such as the trend of regional development caused by inequality (Xu et al., 2022).

In addition, it is found in the study that open innovation has already become the mainstream of innovation forms compared to the traditional innovation of closed innovation (Vidmar et al., 2020), which has brought about alliances (Dong & McCarthy, 2019), inter-organizational technology, and knowledge flow and spillover. Then, the tendency of networking is obvious. Roger's theory of innovation diffusion delineates the diffusion process into five stages and considers that the number of innovation adopters in the process of innovation diffusion shows an S-shaped curve over time. In addition, scholars have been engaged in exploring the interaction mechanism among innovation subjects. Higher education institutions and research institutes are regarded as the main places where innovation activities are held (Ankrah & Al-Tabbaa, 2015). Since the concept of triple helix has migrated from the field of biology to the study of social sciences, Henry Etzkowitz et al. analyzed the interaction among universities, industries, and the government and explored the intrinsic relationship of industry-university-research innovations from the perspective of knowledge spillover (Etzkowitz & Leydesdorff, 2000; Perkmann et al., 2011). It provides a new paradigm in the study of innovation, that is, to consider the impacts of knowledge outputs on cooperative relationships and factors from the viewpoint of the subjects involved in the cooperation (de Wit-de Vries et al., 2019).

*2.2 Space of Flows*

Castells first advocates the concept of space of flows, which considers that complex geographic processes are carried by "space of flows" (Castells, 1999). It not only includes flows (capital flow, logistics, population flow, information flow, etc.) and characteristics of flows but also covers carriers (transportation network, Internet, etc.), nodes, and boundaries (Jin et al., 2021). Economic globalization and the booming development of information technology are key factors in the formation of space of flows. The restriction of geographical distance on "flows" has been significantly reduced, and the spatial form has been transformed from geographic space to geographic network space. It is believed that the space of place and the space of flows dominate the interactions of short and long distances, respectively (Li et al., 2017). Distance, density, spatial distribution patterns and geo-centrality are generally used to quantify the spatial patterns of flows. As the emergence of virtual networks has weakened the hierarchical nature of networks, the traditional "space of place" and "space of flows" have been visualized as "actor cyberspace" constructed by undifferentiated actors. However, it is undeniable that the social, historical, and cultural factors in the "space of place" cannot be replaced, and the cost of material mobility due to geographical distance still exists and has an impact on various networks (Yang et al., 2008).

Knowledge and technology diffusion and regional innovation network development complement each other. In the context of the knowledge era, it is crucial to understand the evolutionary path of the combination of innovation factors in the space. Knowledge flow can be divided into informal and formal. The former is an unconscious knowledge flow without a fixed pattern, while the latter is a conscious exchange of knowledge between subjects without the need to use the spatial advantage (Moreno & Miguelez, 2012). This implies that knowledge flow has both social and spatial attributes, and its network has unique characteristics compared with the typical network in topology and spatial form (Sorenson et al., 2006). Knowledge spillover, knowledge diffusion, knowledge transfer, and independent learning of innovative subjects all contribute to knowledge flow through the mobility of talents, technology transfer, and collaborative innovation. The purpose of knowledge exchange and the generation of new knowledge can be achieved in which tacit knowledge is more influential and difficult to quantify in comparison with explicit knowledge for innovation (Song & Ma, 2022).

### *2.3 Innovation Networks*

Although discussions on cooperative behaviors such as linkages and contracts in the innovation process have begun since the rapid progression of economic theories, the formal application of the term innovation network was published in Freeman's article "Networks of innovators: A synthesis of research issues" in 1991 (Freeman, 1991), in which he defined innovation network and pointed out the significance of time-series research and different regional scale innovation networks for economic development policy insights. The resulting researches on innovation networks can be divided into the following areas:

#### 2.3.1 Spatial Structural Differentiation of Innovation Networks

In previous studies, scholars have used the approach of social network analysis to explore the characteristics of topological networks and the role of nodes in the network by calculating network density, clustering coefficients, average path lengths, etc. (Ye & Xu, 2021). The spatial agglomeration of innovations (Andrews & Whalley, 2022) and how innovation networks are embedded in geographical space in structural or relational ways are also inquired (Ba et al., 2021; Boxu et al., 2022). Innovation is a growth strategy for organization where cooperation and competition are symbiotic, giving rise to a monocentric, multi-cluster structure (Andersson et al., 2014; Wang & Yang, 2022) with a spatial hierarchy (Taalbi, 2020; Wang et al., 2020). Most innovation networks present a core-periphery framework, featuring small-world and scale-free traits (Liu et al., 2022a). For specific industries, cooperative innovation may be temporary (Richardson, 2016), but in general, the stability of cooperative networks is critical for industrial development (Kumar & Zaheer 2019), and structural holes (Guan et al., 2015) is one of the important indicators of stability. At last but not least, scholars have also described the structural changes of the innovation network from the time dimension (Sun, 2016), comparing the innovation network with other city networks(Guan et al., 2022).

#### 2.3.2 Factors Influencing Innovation Networks and Externalities

To address the matrix form of the innovation network, studies usually use the quadratic assignment procedure (QAP) (Li et al., 2021b; Liu et al., 2021), multinomial logit model (Palumbo & Manna 2018), and others to examine the factors influencing the quantity of innovative connections, interactivity between them, and coordinated relationship with economic development (Chen & Zhang, 2021), etc. More scholars have used topological network indicators in regression models, or GEOdetector (Chen & Zhang, 2021) to calculate the possibility of variables fitting. For example, the impact of variables on the collaborative patenting outcomes (Miguelez, 2019) has been analyzed by tracking the work background and geographical mobility of knowledge producers. In addition, it is estimated that the innovation network or nodes' positions in the network affects the innovation performance (Zhang et al., 2022), efficiency (Zhang & Wu, 2021), and aggressiveness (Lyu et al., 2020), which demonstrates that the evolution of the innovation network promotes the adjustment of the organization's knowledge structure, as well as the management of innovation and the commercialization of innovation outcomes.

2.3.3 Evolution Mechanisms of Innovation Network

Johannes summarized three trajectories of geographic network evolution: selection, retention, and variation. He stated that network evolution is subject to the cumulative mechanism of retention and relies on the path dependence of the selection of nodes in the network (Gluckler, 2007). Complex network theory assumes that network evolution is determined by a combination of endogenous and exogenous effects. Preferential attachment, node similarity, and proximity are the most frequently considered promoters of these mechanisms. Since the introduction of multidimensional proximity, typical proximity metrics, such as geographic proximity, institutional proximity, social proximity, cognitive proximity, and organizational proximity (Boschma, 2005), have been introduced into the framework of network research, such as flow space, organizational cooperation, and trade.

Due to the fact that it is possible for all proximity dimensions to change over time (Balland et al., 2015), the analysis of regional network evolution requires not only relational data but also time-series-based data over a considerable period of time (Gluckler, 2007). Therefore, a growing number of researchers have attempted to explain network evolution using dynamics models. Among them, models such as the Exponential Random Graph Model (ERGM) and the Stochastic Actor-Oriented Model (SAOM) can simulate endogenous and exogenous variables simultaneously. ERGM can analyze the effects of multi-level mechanisms of networks in only two periods. Later, TERGM, STERGM, and other optimization models have been developed, which can analyze networks of more than two periods, similar to SAOM. However, the modeling of nodes as "individual actors in a social network" is still the strength of SAOM. SAOM has been used in the fields of economic geography, evolutionary economics, sociology, management, etc. The relevant researches include innovation network and diffusion (Greenan, 2015), transportation network (Hu et al., 2023), friendship network (Ellwardt et al., 2012), etc. which focus on both micro-level and municipal-level (Akçomak et al., 2023).

## 3. Materials and Methods

### *3.1 Data Sources*

To maximize the collection of patent information, which takes up to three years from filing to disclosure of domestic patents, we searched and exported the information of cooperative invention patents from Jan. 1, 2000 to Dec. 31, 2019. Each patent data collected is required that the number of applicants more than 1 and the addresses of applicants located in Chongqing or Sichuan Province. Finally, we obtained information on cooperative invention patents with the international patent classification and the address of each applicant, including the filing date of each invention. After sorting and cleaning, 27805 cooperative patent information was obtained from the counting principle, as shown in Table 1. Neglecting the intra-city cooperation, 10298 inter-city cooperation contacts were finally acquired, and a 59×59 matrix of inter-city invention patent cooperation between Sichuan and Chongqing cities is constructed:

$$\begin{bmatrix} 0 & x_{1,2} & \cdots & x_{1,59} \\ x_{1,2} & 0 & & x_{2,59} \\ \vdots & & \ddots & \vdots \\ x_{1,59} & x_{2,59} & \cdots & 0 \end{bmatrix}$$

**Table 1. Counting Rules for City Innovative Connections**

| City | A, B | A, B, C | $A_1$, $A_2$, B | $A_1$, $A_2$, B, C |
|---|---|---|---|---|
| Counting rule | AB=1 | AB=1, AC=1, BC=1 | AB=2 | AB=2, AC=2, BC=1 |

Some of the missing enterprise address information was traced and entered through an authoritative website (https://www.tianyancha.com/). Statistics (GDP per capita, urbanization rate, etc.) for each city were taken from the Chongqing Statistical Yearbook and the Sichuan Statistical Yearbook. The data for Dazu District and Shuangqiao District, Qijiang District and Wansheng Economic Development Zone before 2012 are merged as a result of the reorganization of administrative divisions in 2011. The latitude and longitude of each city are taken from the Baidu Map.

*3.2 Methodology*

3.2.1 Social Network Analysis

Social network analysis through the quantitative statistics of the network nodes and the relationship between the network structure and attribute characteristics, including the overall network and node attributes. The overall attribute analysis of the network includes the network density and clustering coefficients. The details of the indicators and their meanings are presented in Table 2.

**Table 2. Implications and Descriptions of Selected Indicators**

| Variable | Function | Notations | Interpretations |
|---|---|---|---|
| Density | $D=\frac{n}{N(N-1)}$ | Where n refers to the number of connections and N is the number of nodes in the network | Closeness of the regional innovation spatial association network connection. |
| Clustering Coefficient | $CC=\frac{1}{n}\sum_{n}\frac{2d_i}{k(k-1)}$ | Where $d_i$ is the number of nodes that own the connection with i; k is the number of first-order neighboring nodes of node i | The tendency of nodes to aggregate measured by the ratio of triples in the network. |

| | | | |
|---|---|---|---|
| Average Network Distance | $L = \frac{1}{\frac{1}{2}N(N-1)}\sum_{i\geq j} d_{ij}$ | Where $d_{ij}$ represents the distance between i and j, and N is the number of nodes in the network | Reflects the degree of separation between nodes in the network. A smaller value represents a greater degree of connectivity of the nodes in the network. |

3.2.2 Community Detection

Community detection is an algorithm that identifies subgroups within networks based on the similarity of connection patterns (Stanley et al., 2018). Currently, there are two main types of partitioning methods supported by big data: first, by using the similarity of activity time-variant features or semantic sentiment associated with geographical units, similar regions are merged through clustering methods; second, by leveraging the strength of connections between geographical units, community detection algorithms are employed to partition geographical units with tight connections into the same region.

Community detection has been extensively applied in fields such as computer science, medicine, and biology, and has given rise to many community detection algorithms optimized for specific research needs (Girvan & Newman, 2002; Liu et al., 2007; Raghavan et al., 2007). Among these, community detection algorithms based on modularity optimization, such as the Fast Folding and Louvain algorithms, are commonly used in research (Newman & Girvan, 2004). Here, the Louvain community detection algorithm is employed to determine the community affiliation of objects by calculating modularity. The greater the modularity value, the better the community partitioning effect. The formula for the modularity calculation is as follows:

$$Q = \frac{1}{2m}\sum_{i.j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j) \tag{1}$$

$$\delta(u, v) = \begin{cases} 1, (u == v) \\ 0, else \end{cases} \tag{2}$$

Where Q represents the modularity; $A_{ij}$ denotes the weight of the edge between nodes i and j; $c_i$ indicates the community to which node i belongs; $k_i$ is the sum of the weights of all edges connected to node i; and m is the sum of the weights of all edges in the network.

3.2.3 Stochastic Actor-Oriented Model

The Stochastic Actor-Oriented Model (SAOM) is a dynamic model that views each network node as an independent actor. It considers competition and dependence in the connections between nodes. Network evolution is based on the process by which each actor creates, maintains, or terminates a connection with other actors. As it implements continuous-time Markov chain estimation through a series of iterations of the longitudinal network matrix, it verifies the evolutionary stability of the parameters of the variables and quantifies the manner, degree, and uncertainty associated with the longitudinal network evolution between these factors and the observations. In recent years, the study of the evolution mechanism of innovation networks has become one of the hotspots, and the evolution mechanism of innovation cooperation and technology transfer networks in various regions and fields has been attracting the attention of Chinese and foreign scholars.

SAOM is implemented through the RSiena program (Ruth M. Ripley, 2022), which requires that the input initial explanatory variables be binary adjacency matrices and that the number of observation periods be greater than two. In this study, the linkage matrices are binarized and added as a time-varying covariate (varDyadCovar); Secondly, the 59 urban nodes of the 20 year invention-patent cooperative linkages were split into four continuous observation periods from 2000-2004, 2005-2009, 2010-2014, and 2015-2019; Finally, a 59 × 59, four-period, one-mode, undirected cooperative innovation network was constructed. SAOM provides five modeling types for undirected networks, among which the unilateral initiative and reciprocal confirmation model is considered to be the most matched model for cooperative networks (Balland, 2012; Balland et al., 2013), i.e., when one actor sends an offer to cooperate and another actor accepts the invitation to cooperate, the linkage is reached. The basic form of the SAOM is as follows (Snijders et al., 2010):

$$P\{X(t) - x^0\} = \frac{exp\big(f_i(\beta, x)\big)}{\sum_{x=C(x^0)} exp\big(f_i(\beta, x)\big)} \tag{1}$$

$$f_i(\beta, x) = \sum_k \beta_k\, s_{ki}(x) \tag{2}$$

where P represents the probability that an actor i switches the current state $x_0$; x denotes the predicted state of the network; $f_i(\beta, x)$ denotes the network effect function of node i; $s_{ki}(x)$ is a function of the network structural effects, relational covariates, and individual attributes of the actors chosen in the article, and βk denotes the statistical parameters corresponding to $s_{ki}(x)$.

### *3.3 Variable Selection*

#### 3.3.1 Network Structure Factors

Transitivity represents the tendency to create closure triples in a network and refers to where node i is bound to node j, which is bound to node h, and node i is bound to node h, which means "whether a network node prefers to associate with nodes to which the node is already connected". The formula is as follows:

$$T_i(x) = \sum\nolimits_{j<h} x_{ij}\, x_{ih} x_{hj} \tag{3}$$

Preferential attachment refers to the phenomenon in which any new node entering the network has a higher probability of connecting to a node with high centrality. The larger the estimate of preferential attachment, the more likely a star structure around a high centrality node will appear in the network. It is given by:

$$Pa_i(x) = \sum_j x_{ij} \sqrt{\sum_h x_{hj}} \tag{4}$$

Where $Pa_i(x)$ denotes the state of the connections between cities. where i, j, and h represent the city nodes. Specifically, $x_{ij}=1$ signifies that city i maintains a cooperative relationship with city j, whereas $x_{ij}=0$ indicates the absence of such a cooperative relationship.

3.3.2 Proximity Factors

Geographic proximity characterizes the geospatial proximity of the innovation subject, expressed as the inverse of the spherical distance(Hong and Su 2013) calculated from the coordinates of the two locations.

$$Dist_{ij} = 6371 \cdot \{arccos[\sin(lat_i)\sin(lat_j) + \cos(lat_i)\cos(lat_j)\cos(|long_i - long_j|)]\} \tag{5}$$

$$Geo_{ij} = \frac{1}{Dist_{ij}} \tag{6}$$

where $lat_{i,j}$ and $long_{i,j}$ are the coordinates latitude and longitude of cities i and j, respectively.

Economic proximity is reflected by multiplying the ratio of the smaller and larger per capita GDP values of the two regions by the mean value of the two regions. The closer the ratio of the economic development levels of the two regions is to 1, the smaller the difference between the economic development levels of the two regions and the higher the economic proximity. It is calculated by

$$Eco_{ij} = \frac{min(G_i, G_j)}{max(G_i, G_j)} \times \frac{G_i + G_j}{2} \tag{7}$$

Cognitive proximity is often referred to by the overlapping degree of technological fields and the similarity of industrial structures in previous studies. In this case, drawing on the technology vector pinch formula (Zhang et al., 2020) proposed by Jaffe (Jaffe, 1988). Patents for collaborative invention applications are categorized into 2,700 classifications according to the first five digits of the IPC. The degree of similarity in the field of technology in which patents are located between cities is given by:

$$Cog_{ij} = \frac{\sum_{k=1}^{n} p_{ik} p_{jk}}{\sqrt{\sum_{k=1}^{n} p_{ik}^2 \sum_{k=1}^{n} p_{jk}^2}} \tag{8}$$

Social proximity (Social proximity) Collaboration depends on similar social backgrounds among collaborators. Innovative nodes may be more willing to share knowledge and cooperate with objects in known social relationships, and establish cooperation with trust and reciprocity as a mechanism and tendency (Agrawal et al., 2008). It is commonly quantified by topological network distance (Lazzeretti & Capone, 2016; Schilling & Phelps, 2007) and whether there is a history of cooperation (Fernandez et al., 2021). Some studies have also used Salton's index and population mobility based on cell phone signaling data to measure the intensity of cooperation between two nodes. In this study, we denote the degree of similarity of cooperative members by the Jaccard similarity coefficient to calculate the social proximity between cities in Sichuan and Chongqing:

$$Soc_{ij} = \frac{C_{ij}}{N_i + N_j - C_{ij}} \tag{9}$$

Where $N_i$ and $N_j$ are the number of cities that own cooperated innovations with cities i and j, and $C_{ij}$ is the number of cities that have connections with both i and j.

3.3.3 Node Attributes

In addition, this study introduces two attribute variables: GDP per capita and urbanization rate. They are used to test whether the level of urban economic development and urbanization have prominent performance in the process of innovation network evolution. Meanwhile, they are added as control variables, which can be adjusted to optimize the model significance estimation.

## 4. Result

### *4.1 Evolution and Structural Features of Regional Innovation Networks*

The structural and evolutionary characteristics of the innovation network were analyzed using social network analysis by Ucinet. The results are shown in Table 3. Thereafter, the structural evolution of the collaborative innovation network between cities in four periods (Figure 3) was visualized using Arcgis 10.5.

4.1.1 Evolutionary Characteristics of Regional Innovation Networks

**Table 3. Statistical Characteristics of Urban Innovation Networks in Sichuan and Chongqing during the Period 2000-2019**

| Variable | 2000-2004 | 2005-2009 | 2010-2014 | 2015-2019 |
|---|---|---|---|---|
| Edge | 21 | 57 | 148 | 220 |
| Node | 19 | 36 | 51 | 53 |
| Network density | 0.0456 | 0.6891 | 2.2846 | 3.0655 |
| Standard variation of the network density | 0.6933 | 17.2489 | 29.9629 | 20.6545 |
| Clustering coefficient | 0.196 | 2.594 | 13.868 | 17.060 |
| Average network distance | 2.257 | 2.319 | 2.174 | 2.017 |

The frequency of innovation links between Sichuan and Chongqing has increased, and the scope of city cooperation is increasingly broadened. The number of cities involved in the partnership increased significantly, and the number of network edges increased from 21 to 220, with the network shape initially appearing. As Table 3 shows, cooperative innovation network is expanding, with an obvious agglomeration trend. In 2000-2019, the innovation network density of Sichuan and Chongqing cities showed a significant upward tendency. The standard deviation of network density also gradually rose to a higher value with the evolution of the network, illustrating that the development of the network has an imbalanced performance. The overall change in the average network distance is rather modest. It shows a slight decline after rising from 2.257 to 2.319 in 2005-2009, which reveals that the intermediary role of some core nodes in the network has gradually manifested itself. The clustering coefficient fluctuates and increases with an increase in the number of edges. This means that the polarization is still intensifying. The number of network links, density, and clustering coefficient increased significantly in 2010-2014, which shows that the innovation network is in a rapid expansion stage during this period. The newly joined cities slightly dilute the degree of aggregation of the network, and the breadth of cooperation gradually increases. Generally speaking, the triadic closure relationship among cities in the innovation network is becoming increasingly common and solid, and the core-periphery pattern is gradually formed.

Table 4 reflects the increase/decrease or maintenance status of connections in the network in four consecutive periods, and it can be seen that the number of new connecting edges and the growth rate have been on the rise. However, there are also a limited number of cases in which the original connection is broken, indicating that it is difficult to form long-term inter-city cooperation. Compared with the theoretical maximum number of network edges 59×(59-1)/2=1711, the network development is still immature, and most cities only cooperate with partners in the core position, and the connection is still loose.

**Table 4. Descriptive Statistics on the Evolution of Urban Innovation Networks in Sichuan and Chongqing**

| Period | Connection and break in the innovation network | | | |
|---|---|---|---|---|
| | 0→0 | 0→1 | 1→0 | 1→1 |
| T1~T2 | 1646 | 44 | 8 | 13 |
| T2~T3 | 1555 | 99 | 8 | 49 |
| T3~T4 | 1456 | 107 | 35 | 113 |

*Note*. $T_i$ denotes the observation time period, ~ denotes the evolution of the observation time period, and → denotes a change in the linkage status; 0 denotes no linkage and 1 denotes a linkage.

4.1.2 Innovation Network Space Evolution Analysis

From the space point of view, it shows the primary pattern of radiating to the surrounding cities with the main urban areas of Chongqing and Chengdu as the core. It can be seen from Table 5 that the innovation cooperation mainly focuses on between Chengdu and other Sichuan cities, Chengdu and Chongqing cities, and within Chongqing cities in the main urban area. The delineation of Chengdu-Chongqing Economic Zone (2011) and Chengdu-Chongqing City Cluster (2016) has promoted the agglomeration and overflow of innovation resources. The cooperative output of innovations and the lowering of transaction costs have pushed forward the cooperation and linkages between Chengdu and Chongqing. After 2010, most peripheral cities have established more stable connections with core cities, but linkages between fringe cities are still relatively scarce. As of 2019, all cities in Sichuan have been enrolled in the innovation network, while Nanchuan, Wulong, Pengshui, Youyang, Kaizhou, and Wuxi in Chongqing have not yet been joined, thus reflecting that communication between the cities in Southeast Chongqing and the rest of the cities is still relatively lackluster. Chengdu has an absolute position in the network, both in terms of the number of cooperation and various centrality indicators, and cities such as Mianyang, Deyang, Luzhou, and Meishan are progressively forming sub-centers, while the total amount of innovation in the central urban areas of Chongqing is steadily rising concurrently, bringing an obvious driving radiation effect to the surrounding cities. Cities such as Jiangjin, Yongchuan, and Fuling are more closely connected to the main city because of the incubation of new industrial parks.

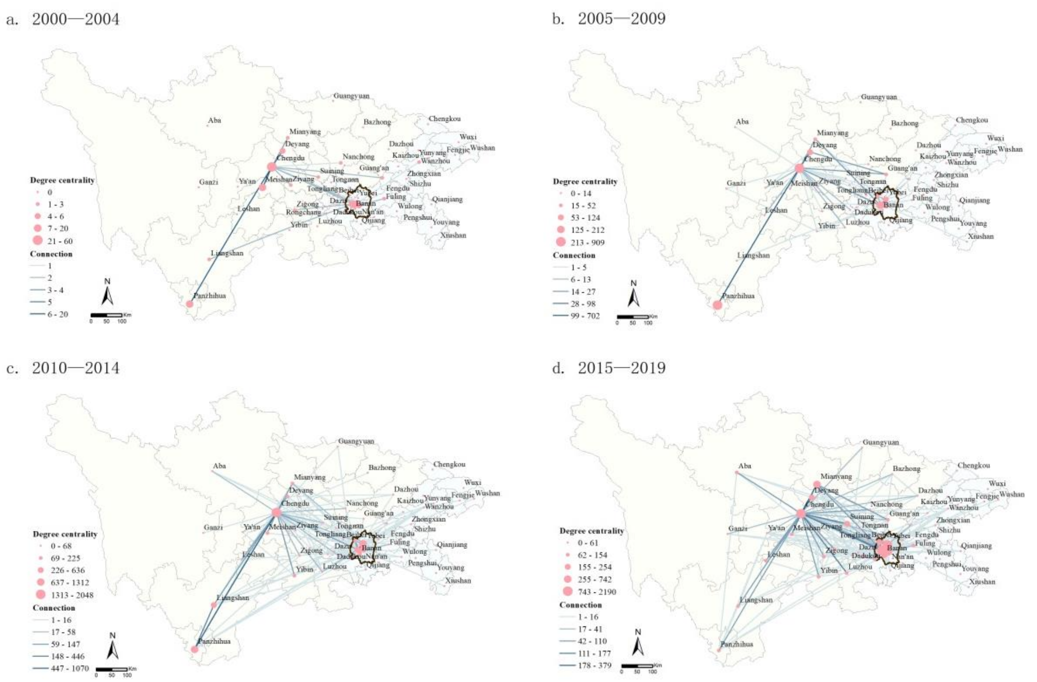


**Figure 2. Spatial Distribution of Innovation Collaboration between Sichuan and Chongqing Cities from 2000 to 2019**

4.1.3 Community Detection Result

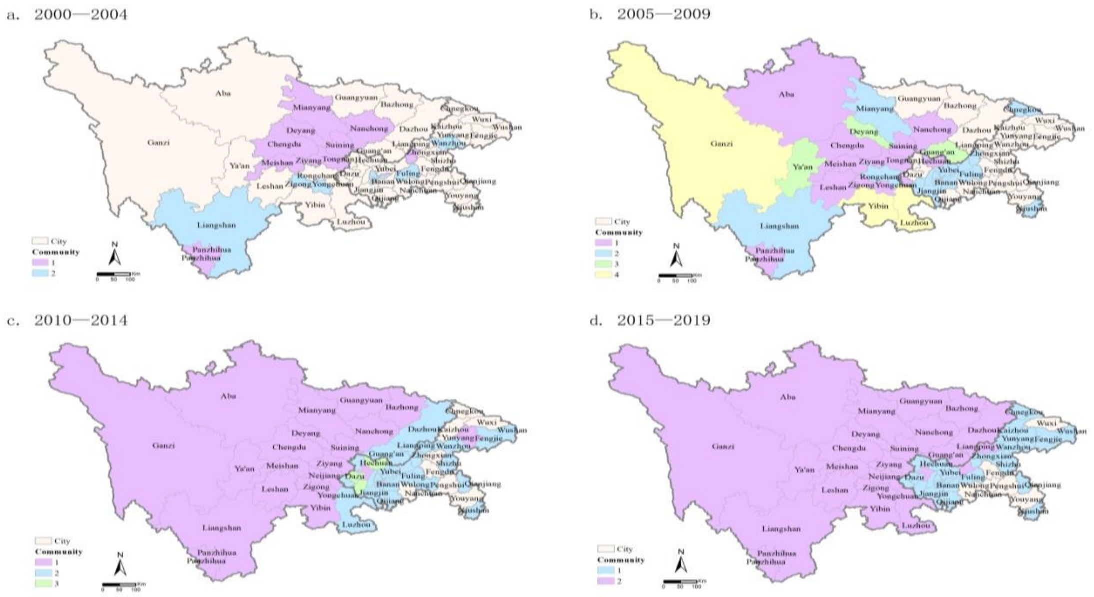


**Figure 3. Spatial Distribution of Inter-city Cooperative Innovation Communities in Sichuan and Chongqing**

The Louvain algorithm is implemented to detect inter-city collaborative innovation communities in the Sichuan and Chongqing regions across four periods from 2000 to 2019.

The results show that from a community size perspective, during 2000-2004, there were only two communities primarily divided due to the limited number of cities participating in innovation and the relatively weak connections between them. From 2005 to 2009, the number of communities reached its peak, with four distinct groups forming, and the number of members within each community gradually increased. However, after 2010, the number of communities began to decrease, returning to a partitioning pattern of two larger clusters.

From a spatial perspective, as shown in Figure, the innovation cooperation camps delineated by administrative boundaries have become increasingly clear. During the initial period from 2000 to 2004, the first community was centered on the "Chengdu- Mianyang- Deyang" cluster, which is also known for its strong industrial foundation. The second community mainly consisted of cities along the main and tributary streams of the Yangtze River, indicating that shipping transportation may have provided support for innovation cooperation. From 2005 to 2009, the community centered on Chengdu continued to expand, while Mianyang and Deyang became part of two other communities, leading to a diverse partitioning within Sichuan Province. From 2010 to 2014, the boundaries of communities between Sichuan and Chongqing became geographically distinct, with a clear spatial agglomeration pattern. From 2015 to 2019, except for Tongliang, Changshou, and Liangping, which still belonged to the "Sichuan" community, all other members of the community were from the same province (city), showing a significant trend toward localization. These cities are all at the border between the two provinces. Community affiliations for cities in such positions may also reflect the strength of attraction exerted by geographical proximity and institutional proximity on their intentions for innovation cooperation. For example, Tongliang, located on the central axis and border between Chengdu and the central urban area of Chongqing, has long played a pivotal role in the integrated development of Sichuan and Chongqing and Chongqing's westward development.

*4.2 Analysis of the Mechanism of Regional Innovation Network Dynamic*

The estimation of parameters is shown in Table 5. Model 1 is the default model, which contains the rate of change and network density variables for each observation period. On this basis, the influencing factors selected in this paper are added sequentially: firstly, two network endogenous variables, network transmissibility and preferential connectivity, are added to model 2, followed by the proximity indicator in model 3, and model 4 is the overall superposition model of all variables. After 1898, 2121, 2750, and 2926 iterations of computation, respectively, the overall maximum convergence ratios of the four models are 0.0955, 0.0625, 0.1623, and 0.137, respectively. The absolute values of the four models are lower than the standard value of 0.25, indicating that the network and variable data are applicable to the SAOM and are adequately fitted to the model. What is slightly not as accurate as it could be is that the parameters of the variables in the results are logarithmic ratios and have not been standardized, and therefore do not exactly reflect the degree of influence of each variable.

**Table 5. Estimation Results of the Stochastic Actor-Oriented Model**

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Rate parameter period 1 | 1.04 *** (0.15) | 4.94* (2.45) | 6.63* (2.92) | 3.36 *** (0.90) |
| Rate parameter period 2 | 2.40 *** (0.27) | 6.46 (36.04) | 6.20 *** (1.25) | 6.15 *** (1.13) |
| Rate parameter period 3 | 3.25 *** (0.33) | 3.12*** (0.30) | 3.53 *** (0.37) | 4.13 *** (0.46) |
| Density | -0.76 *** (0.08) | -3.63 *** (0.14) | -4.11 *** (0.19) | -4.17 *** (0.20) |
| Transitive Triads | | 0.37 *** (0.07) | 0.21 ** (0.06) | 0.21 ** (0.07) |
| Preferential Attachment | | 0.78 *** (0.06) | 0.85 *** (0.06) | 0.87 *** (0.06) |
| $Geo_{ij}$ | | | 71.05 *** (9.30) | 53.76 *** (12.55) |
| $Cog_{ij}$ | | | 1.66 *** (0.42) | 1.55 *** (0.41) |
| $Eco_{ij}$ | | | 0.12 (0.16) | 0.42 † (0.27) |
| $Soc_{ij}$ | | | 0.66† (0.39) | 0.58 (0.40) |
| GDP per capita | | | | -0.85 ** (0.3) |
| Urbanization rate | | | | 2.21 * (1.03) |
| Proportion of secondary and tertiary industries | | | | 0.47 * (0.23) |
| Iterations | 1898 | 2121 | 2750 | 2926 |

*Note*. *** denotes $p < 0.001$; ** denotes $p < 0.01$; * denotes $p < 0.05$; † denotes $p < 0.1$; Standard errors are in parentheses.

4.2.1 Network Structure Factors

The rate parameter represents the speed of evolution of the innovation network, whereas the density refers to the tendency of a node to connect with other nodes to the exclusion of other factors, which can also be interpreted as the "cost" of having a new connections (Ter Wal, 2014). For the Sichuan-Chongqing urban innovation network, the density parameter is always significantly negative, which means that generating the first cooperative connection between two cities requires a large investment, and this cost may set the threshold for participating in innovation cooperation. A trade-off exists between the cities' inputs and outputs of triggered innovation activities, which affects the formation of new connectivity edges of the network and, to a certain extent, hinders the joining of new nodes in the network.

The regression coefficient of transitivity is significant at the 1% level, indicating that the proximity based on the network structure plays an important role in the process of network evolution. A city prefers to cooperate with "friends" of "friends" in patenting, which leads to the formation of a solid closed triad among cities. The relationship between cities is more conducive to group collaboration and specialized division of labor in innovation cooperation. The inter-disciplinarity and output rate are enhanced, which promotes further expansion of the network and improves the quality of innovation. Moreover, transitivity also avoids the opportunistic behaviors of cities in cooperation (Gui et al., 2022). This enhances mutual trust and thus maintains long-term cooperative relationships among cities.

The preferential attachment parameter is positive and passes the significance test at the 0.1% level, which is identical to the outcome of other scholars' studies on cooperative networks (Cao et al., 2017). Nodes with a high degree of centrality are more likely to obtain new connections, thus developing a star structure that promotes the expansion of the innovation network. Furthermore, the inclusion of network exogenous variables and code attributes further amplifies the facilitating effect of preferred connections on network evolution. As a result, high-status cities have accumulated a large number of partners over time due to their proximity and level of development in previous collaborations, leading to the aggregation of more innovative resources. There is also a stronger likelihood that other cities that have not worked together are more likely to choose to work with them.

4.2.2 Proximity

Geographic proximity is significantly positive at the 0.1% level, indicating that geographic distance plays a weakly restrictive role in innovative cooperation. Geographical distance is greatly compressed by developed means of transportation, and the Internet has gradually become a communication tool. Hence, the influence of geographical barriers is not as strong as before (Ter Wal, 2014), whereas the role of geospatial space can still not be ignored as patent inventions possess the connotations of both dissemination and practical application of tacit knowledge dissemination.

Cognitive proximity is significantly positive at the 0.1% confidence level, with a regression parameter of 1.66. This indicates that the degree of technological overlap is a key factor in innovative cooperation. Industry and discipline similarity ensures that innovation subjects possess considerable overlapping knowledge accumulation, which makes their communication and exchange smoother. While their "exclusive" knowledge and technology can be effectively integrated (Yoo, 2017). Therefore, the innovation capacity of enterprises and organizations will be greatly increased.

Social proximity is significantly positive at the 10% level, which implies that social proximity facilitates the development of innovation networks. Consistent with the results of previous innovation cooperation studies, social proximity is the most important proximity factor for achieving collaboration (Ben Letaifa & Rabeau, 2013; Zhao et al., 2022), and nodes in the network tend to find new cooperation opportunities through high social proximity nodes exerting transitive functions. A higher overlap of partner cities denotes a higher degree of similarity in social relations between two cities and a lower cost of connection to a desired partner. Subsequently, the establishment of social relations relies on mutual trust, which leads to a significant reduction in the uncertainty of collaboration and an easier avoidance of opportunistic behaviors.

Economic proximity is found to be significantly positive at the 10% level. Cities with smaller economic disparities are more likely to generate new collaborations, which suggests that participation in the two-way exchange of innovations is based on a considerable economic base. On the one hand, developed cities fail to continue to expand cooperation with edge cities on the basis of existing connections, and this may be due to the mismatch of needs and intentions between the two cities with larger gaps or the lack of policy support for innovation activities in the edge cities; on the other hand, the edge cities have a weaker awareness of innovation, which renders it difficult to achieve innovative results between the two edge cities.

#### 4.2.3 Node Attributes

The parameters of urbanization rate, proportion of secondary and tertiary industry, and urban GDP per capita are significant at the 5%, 5%, and 1% levels. The urbanization rate is positively correlated with innovation network evolution. The urbanization rate characterizes the modernization level of the city, scientific and technological innovation capacity, etc. It confirms the importance of factors such as improvement of the public infrastructure and the presence of scientific research units and higher education institutions in the city in promoting the development of the innovation network. The higher the proportion of secondary and tertiary industries, the more likely a city is to join the innovation network early, suggesting that the network's development depends on a strong industrial base. The effect of GDP per capita on the evolution of the innovation network is negative, similar to the findings of some researchers on the influencing factors of cooperation and innovation of cities within province (Li & Ye, 2021). Cities with stronger innovation capacity tend to link with cities of similar level and cooperate less with edge cities other than core cities. Although the number of cooperation and innovation outcomes are increasing, the network fails to achieve breakthroughs in new nodes and new links. Considering this in conjunction with the positive results for economic proximity, innovative cooperation between Sichuan and Chongqing cities occurs more often between developed cities with comparable economic levels.

#### 4.2.4 Goodness of Fit

The fit of various variables during the evolution of the innovation network was calculated using the Monte Carlo Markov distance-based test method proposed by Lospinoso and Snijders (2019). The observed values are represented by red nodes, and the simulated statistical data are depicted in violin plots (Figure 4). The dashed lines indicate the 95% confidence intervals. As shown in the figure, the overall p-value is 0.16, which falls within the 95% confidence interval of the expected value and is greater than the standard threshold of 0.05, indicating a high fit of the overall model and credible parameters.

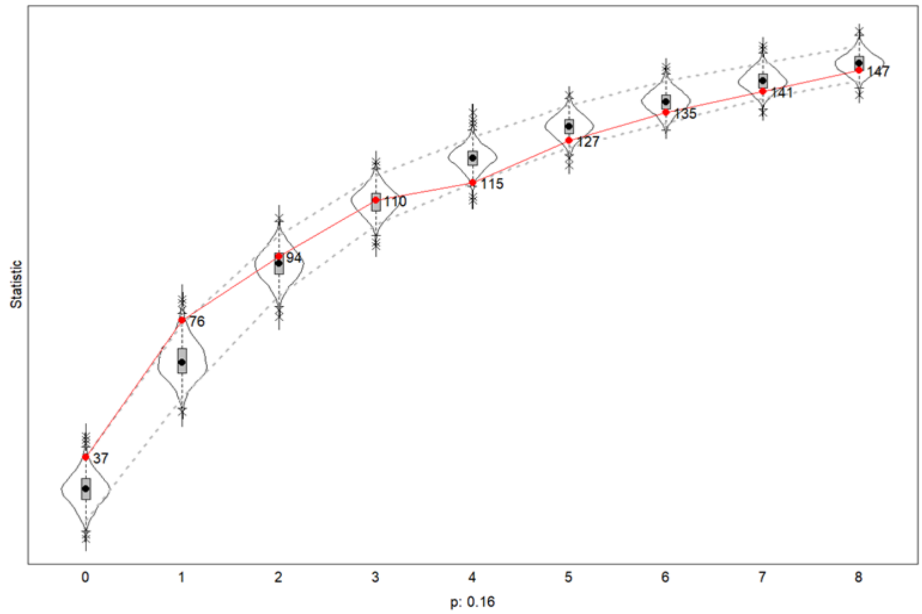


**Figure 4. Result of the Goodness of Fit**

## 5. Conclusions and Discussion

This paper examines the spatio-temporal pattern of innovation networks in Sichuan and Chongqing cities, mainly based on data of cooperative invention patents from 2000 to 2019, and analyzes the evolution factors of innovation networks using the dynamics model under the multidimensional proximity framework. The major conclusions are as follows:

First, the quantity of innovative cooperation between Sichuan and Chongqing cities has grown noticeably, and the number of nodes and connecting edges of the innovation network has increased over the past 20 years, and the growth rate has increased. However, the network is growing denser, and a core-periphery pattern centered on the Chengdu and Chongqing Main Urban Area has been spatially formed. Except for the core cities, most nodes are linked to a single object. Second, Chengdu plays a leading role in the network, and several main districts of Chongqing gradually improve their position in the network and become a hub for innovation resource collection and distribution. However, the results of detecting communities indicate that the number of clusters engaged in innovative collaborations is declining, and their geographical demarcation are aligning closely with administrative divisions. Third, all variables show high correlation in the simulation of the innovation network evolution mechanism. The initial establishment of innovation linkages is quite a challenge, and network transitivity and preferential attachment positively affect to network evolution; geographic proximity, cognitive proximity, economic proximity, and social proximity all play a positive role in network evolution; the level of urbanization is a key factor in the achievement of inter-city innovation cooperation, whereas the level of per capita GDP does not promote the further development of the network. This suggests that innovative collaborations in the Sichuan-Chongqing region are more likely to occur between core cities with comparable economic levels.

This paper conducts a preliminary study on the characteristics and driving mechanism of the evolution of innovation networks in Sichuan and Chongqing cities, where the area has gained little attention for now. Information storage in the Internet era provides conditions for quantitative research. Scholars use patents, scientific research papers, and awards for innovative achievements (Song & Zhang, 2021), and the flow of scientific and technological talents to refer to various innovation elements and to construct innovation networks by refining the nodes and links. To make up for one-sided analysis with a single type of innovation networks, many studies have chosen to use more than one type of data to construct multi-layer networks (Feng et al., 2022; Ma & Xu) to obtain a more comprehensive and rigorous analysis. However, patent data on inventions are used in this paper, which reflects the characteristics of technology innovation, compared to the multiple innovation networks established; However, given the availability of city-level statistics, only some of the proximity factors are considered when selecting the indicators of influencing factors, and some of the variables that strongly relate to the evolution of innovation networks are not taken into account, such as R&D input and the ratio of educated population.

We demonstrate an interesting result that in terms of innovation development, innovation cooperation among Sichuan and Chongqing cities is increasingly inclined toward cooperation within the same province. Although multiple innovation cooperation initiatives for the Sichuan-Chongqing region have been introduced and exchanges between Sichuan and Chongqing cities have deepened, it is difficult to compensate for the fragmentation caused by administrative boundaries. This implies that cooperation between the two centers within the region is full of challenges. In future studies, the characteristics of the innovation networks within each city or specific industry and the coupling of the innovation networks with other kinds of city networks are urgently needed to be further explored. A deeper investigation at the industrial and enterprise levels, coupled with a thorough comprehension of knowledge-technology flow dynamics, can significantly enhance our holistic analysis of regional innovation.

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