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Network centrality, support organizations, exploratory innovation: Empirical analysis of China's integrated circuit industry

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A B S T R A C T

Exploratory innovation is critical to the breakthrough of core technologies in the integrated circuit (IC) industry, and cooperative innovation is a promising form of IC industry development. According to the viewpoint of social network, this paper constructs intercity networks of the IC industry by using a data set of cooperation patents from 2011 to 2020 in China. We uncover the evolution characteristics of the innovation networks, explore the relationship between network centrality and exploratory innovation in a city, and consider universities and development zones, named support organizations, as moderating variables. The results of the social network analysis (SNA) and dynamic panel system generalized method of moments model (System-GMM) are given as follows: Cities are increasingly inclined to collaborate with counterparts over time for innovation, but the overall network scale remains small. Beijing occupies core position in the networks. A cooperative innovation model driven by peripheral cities has been formed as the number of the peripheral cities has gradually increased. The network centrality of a city has a positive effect on its exploratory innovation. Both universities and development zones positively moderate the effect of network centrality on exploratory innovation. Based on the characteristics of the network, our study reveals the importance of taking the internal structure of the network and the node support environment into the same framework, which provides guidance for the innovative development of the world IC industry.

1. Introduction

Being the core of the information industry, the IC industry is the key force that leads a new round of technological revolution and industrial transformation. The U.S., Japan and the Western European widespread attention to the development of the IC industry which has driven the growth of computers, consumer electronics, telecommunications, and other related industries [1]. The IC industry, as an important industry in Singapore's economy, adds considerably to jobs, exports, and high per capita incomes [2]. Korea adopted policies for IC industry development, such as bringing in several foreign companies and encouraging them to import advanced technologies [3]. However, many countries still face the problem of insufficient innovation capacity. Indeed, technology-driven innovation is the main model in the IC industry. Further, innovation can be clarified by exploratory innovation and exploitative

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innovation [4]. Exploratory innovation (*EI*) entails the discovery, development, and pursuit of new knowledge and drives a different technology trajectory [5]. That is, exploratory innovation represents significant deviations from current organizational capabilities because it creates of entirely new goods, new technologies, and new production processes with a high level of creativity and challenge. As for the IC industry, which is highly sensitive to new technologies, the improvement of exploratory innovation capabilities is critical to its core technology development.

According to the research of Vermeer and Thomas [6], a growing number of collaboration has developed in high-tech industries. Numerous firms and organizations participate in collaborative R&D through a range of various modalities of partnership in high-tech industries, to form a closer network of inter-organizational cooperation. In particular, the IC industry has an obvious characteristic of R&D cooperation [7]. The important role of inter-organizational collaboration, interaction and exchange in technological innovation has long been recognized in economics [8]. Indeed, enterprises, universities, and research institutes all participate in collaborative innovation, and these organizations build industrial network together. Furthermore, cities are integral elements of an interdependent system, and they are not isolated entities but connected nodes in a flowing space. Extra-local interactions in the interdependent system of cities need to be investigated in research on cities and innovation [9]. Consequently, we focus on intercity network in the IC industry. The important feature of the knowledge network structure is network centrality (*NC*), which denotes a high position in a status hierarchy [10]. High network centrality means that node has a certain network position and can more easily access the knowledge and information needed for exploratory innovation. Accordingly, it is necessary to investigate how to promote exploratory innovation from a network perspective.

Further, city is not a simple, single actor but a huge, internally complex, spatially diffused collective [11]. Obtaining resources from a higher network centrality is not sufficient to promote exploratory innovation because of the lack of knowledge, technical skills, and local interaction and communication. Network participants are located in different positions in the network and are embedded in the local environment which includes a series of support organizations. Previous study described the rise of these organizations to serve support functions, including strengthening organizational capacities, mobilizing resources, and providing information [12]. In view of this, network participants rely on interactions with local support organizations.

To sum up, we propose three research questions in the IC industry:

Q1. What are the evolution features of the innovation network?
Q2. Does network centrality have a positive effect on exploratory innovation?
Q3. Do support organizations promote the impact of network centrality on exploratory innovation?

In 2020, the market scale of China's IC industry exceeded US$137.85bn (RMB 880bn), making China the fastest growing country in the world.[2] As a representative of the emerging economy, China relies heavily on imports of integrated circuit products. Severe technological bottlenecks in the IC industry make it difficult to build core competitiveness and form a strong foundation for seizing the high ground in science and technology [13]. The manner in which China breaks through "bottleneck technology" is a conundrum that needs to be resolved. Therefore, this paper takes China as an intriguing case for study to follow further directions for the IC industry and to serve as a point of reference for other countries. Specifically, by establishing IC innovation networks from 2011 to 2020 in China, we apply the SNA method and System-GMM method to uncover the evolutional features of the innovation networks, to explore the impact of network centrality on exploratory innovation, and to detect the moderating effect of support organizations on the *NC-EI* relationship.

This paper has three contributions: First, we contribute to the extant literature by revealing evolutional characteristics of intercity innovation networks in the IC industry based on the construction of collaboration networks among enterprises, universities, and research institutes at the city level. Specifically, the network topology is depicted and the parameters of the IC network features are calculated. By using the block model, we detect the change in the relative position of cities and the cooperative innovation model. Second, this paper explores the influential mechanism of network centrality on exploratory innovation and empirically tests the positive impact of network position on exploratory innovation in IC industry. Third, the internal structure of the network and the node support environment are incorporated into the same framework in our study. We find that both universities and development zones have significant positive moderating effects on the *NC-EI* relationship. It means that the support organizations are accelerators in enhancing the level of exploratory innovation in industrial innovation network.

The rest of this study is structured as follows. The literature review is presented in Section 2. Section 3 lays out our theoretical foundation and hypothesis development. The methodology is shown in Section 4, including sample, variables, empirical approach. Our empirical results are reported in Section 5. Discussion is given in Section 6. Finally, conclusions and implications are presented in Section 7.

2. Literature review

The research about construction of industrial innovation network mainly from the perspective of patent. Some works on innovation network focused on inventors, particularly in the US [14,15], while other works built innovation network according to the partners of the enterprise [16,17]. Further, scholars conducted rich research on the construction of high-tech industrial innovation network. By

[2] China's integrated circuit industry becomes the world's largest. Data is available at http://www.chinadaily.com.cn/a/202106/10/WS60c18361a31024ad0bac4dc2.html (accessed 30 Mar 2023).

using the innovative organizations from North America, Europe and Asia as samples, Guan and Liu [18] examined the structural characteristics of inter-organizational cooperation and knowledge networks in the emerging nano-energy industry. Bai and Liu [19] illustrated the features of Asian innovation networks by calculating the network centrality indicators of the four technologies: 3D printing technology, big data technology, integrated circuit technology, and carbon nanotubes and graphene technology. Meng, Liu [20] took the example of Chinese new energy automobile industry to build an innovative network evaluation model and perform empirical testing. Zhang, Qian [21] studied the multi-dimensional proximity mechanism and the evolutionary characteristics of the biomedical innovation network architecture. Tseng, Lin [22] concentrated on the study of social network indicators in the worldwide semiconductor industry, and tracked the evolution of innovation networks.

A broad range of literature has found that the structure of the network is important for innovation [23]. Scholars have focused on constructing innovation network at the corporate or regional level to further investigate the relationship between network centrality and innovation. In terms of enterprise, there is debate on whether network centrality can appropriately enhance corporate innovation performance. Zeng, Liu [24] deemed that betweenness centrality positively influenced biopharmaceutical companies' technological innovation. Sun and Lee [25] suggested that network centrality has a negative influence on innovation in the electronics and information technology industries. Li, Li [26] and Ma, Zhang [27] discovered that cooperative network centrality displayed an inverted U-shape relationship with exploratory innovation by using samples of AI and low-carbon energy enterprises, respectively. Furthermore, a recent line of research connected to this field is that which seeks to connect network theory with regional sciences and urban economics in order to investigate the innovative capacity of cities and regions. van der Wouden and Rigby [28] found that knowledge network structure was relevant for regional innovation in U.S. Innocenti, Capone [17] thought that the structure of inventor networks enhanced the inventive capacity of Italian provinces. Yao, Li [9] conducted a network analysis of China's national innovation system and revealed positive effects of the degree centrality on urban innovation. Bai, Wu [29] established a global 3D printing cooperative innovation network of 34 economies and discovered that network centrality correlated with industrial performance.

We summarize the relevant literature on the factors influencing the relationship between network centrality and innovation, which examined moderating variables concerning the characteristics of the network itself or the node's external environment. Lyu, He [30] and Shi, Lu [31] found that technology clusters enhanced the linear relationship between network centrality and innovation. Potter and Wilhelm [32] studied how degree centrality influenced the Japanese supplier innovation network and the moderating effect of corporate structural embeddedness. Wang and Jiao [33] identified that scientific cooperation positively moderated the U-shaped relationship between network centrality and technological innovation. Wang, Zhao [16] suggested that formal institutions positively moderated the relationship between network centrality and innovation performance, whereas informal institutions moderated the relationship negatively.

In summary, there is still much room for research: First, although the innovation network of high-tech industry has been attached importance, current research lacks the construction of IC innovation network and the analysis of network characteristics and cooperative innovation model. Second, the direction of the influence of network centrality on innovation is not uniform (i.e., positive, negative, and nonlinear). Moreover, the extant studies have analyzed the direct consequences of network position on innovation performance without further classification of innovation types [27,34]. According to the recent line of research connected network theory with regional sciences and urban economics, the effect of network centrality on exploratory innovation for IC industry at the city level has not been well explained. Third, there is a lack in existing research of including supporting organizations into innovation network. How support organizations moderate the relationship between network centrality and exploratory innovation remains to be explored.

3. Theoretical foundation and hypothesis development

3.1. Social network theory and network centrality

Social network theory (SNT) presumes that the interdependence of social actors has a substantial impact on both their individual behavior and the large social group that they compose [35]. SNT suggests that a city will be more inventive if it demonstrates stronger social relationship. With the growing complexity and specialization of R&D projects, technological innovation depends more and more on collaborative efforts [36]. Cities that build and sustain cooperation with one another form linkages that grow into an intercity cooperation network. Cities in the network can be affected by the direct connection nodes as well as the indirect connection nodes [9], because knowledge, technology, and information flow through different paths. Resources got access from the ego network of actors could enhance their future performance. Network centrality is one of the most significant structural aspects in network research, as it represents the status of the actor [37]. The network centrality of a city reflects the status in the hierarchical as well as the degree of independence it has in accessing valuable resources and other network members [38]. Cities with a high centrality have easier access to resources come from many different nodes. To summarize, this study is based on the social network theory.

3.2. Network centrality and exploratory innovation

Remarkable network actors can obtain knowledge, attract partners, and efficiently use knowledge, which is conducive to exploratory innovation. First, High network centrality might make it easier to acquire knowledge [39]. Since a high network centrality node, which is located close to other nodes, receives information flows faster, it reflects quick access to external diverse knowledge, resource exchange, and information transmission. Information obtained from high network centrality nodes could expand the scope of their knowledge base [40]. The knowledge base lays the foundation for exploratory innovation. Second, cities with high network centrality have a good reputation and trust level in the network, which releases a signal of trustworthiness [41], so as to attract and amplify the willingness of other innovators to collaborate. Moreover, building and sustaining relationships with innovation collaborators can be easier and more efficient in cities with higher network centrality [42], making the cooperation relationships more stable and reliable. A large quantity of direct collaborative links suggests increased access to resources and the ease of collecting additional information, which stimulates the growth of exploratory innovation [43]. Third, the majority of knowledge paths pass through the node at the center of the network which called pivot [44]. The advantage of the pivot is to screen and understand the possible worth of knowledge [45]. Furthermore, the central network position brings the node knowledge benefits such as accessibility, timeliness, and reference [46]. Therefore, cities with a central position could indeed efficiently leverage knowledge and thus promote the level of exploratory innovation.

However, cities with high centrality face the risk of high costs, absorption saturation, and knowledge lock-in, which diminish the benefits of the central position. First, the significant barrier to innovation is cost [47]. Cities with high network centrality have higher transaction costs within the cooperative network. Cities with higher central position have more extensive cooperation and the need for sustained investment of time, passion, and other resources, which puts pressure on coordination mechanisms and managerial attention [48]. Moreover, partners could be unwilling to share knowledge because opportunism makes information sharing more difficult [49]. As a result, the cost of collaboration has increased. Exploratory innovation involves pursuit of new knowledge and is more susceptible to cost constraints. Second, cities with high centrality may be at risk of not being able to absorb the high diversity of knowledge they gain from their network position. According to the absorption capacity theory, not all external knowledge can be completely assimilated [50]. With more information accessed, the prospective absorptive capacity of the city approaches saturation and makes it more difficult for the node to assimilate any further knowledge. It means high network centrality increases the difficulty of knowledge uptake. And successful exploratory innovation requires high levels of absorption [51]. Third, over-embedding in current relationships reduces the enthusiasm of network participants for altering their ties and discovering new ideas [52]. The route dependency impact thus grows with time. Additionally, knowledge gained through partners loses value over time [53]. The novel combining mode for knowledge elements in a network tends to be exhausted [54]. Cities are not exposed to new knowledge and ideas, and the knowledge tends to be homogenized. As a result, cities have the risk of knowledge lock-in. Nevertheless, exploratory innovation demands diverse knowledge [55].

Based on the analysis above, the association between network centrality and innovation is generally inconclusive [41]. In high-tech industries, a large number of innovation organizations are engaged in joint R&D through a variety of different modes of partnerships, to form a closer network of inter-organizational cooperation. The high-tech industry is distinguished by a quickly evolving, complicated, and distributed knowledge base, and it would expect valuable advantages from network cooperation for inventive productivity (e.g. Ref. [56]). Among the high-tech sectors, the IC industry is typical of interorganizational network, high capital concentration, and extreme system uncertainty. The IC industry has an extremely high degree of technological complexity and short product life cycles [57], it is urgent to improve the capacity of innovation from cooperation network. Consequently, we believe that network centrality will benefit exploratory innovation in the IC industry.

Based on the above reasons, this paper proposes the following hypothesis.

H1. The network centrality of a city positively affects its exploratory innovation in the IC industry.

3.3. *Moderating effect of support organizations*

A social network is made up of multiple social actors and relationships that connect them together. Notably, these actors are ultimately embedded in a localized environment, especially affected by the local support organizations. We need to focus not only on the actors but also on the support organizations' effects on the role of the actors. Therefore, this study incorporates the internal structure of network and the node support environment into the same framework. In other words, it is important to take support organizations into consideration when we investigate the relationship between the network centrality and exploratory innovation. Lynn, Reddy [58] referred to support organizations as "superstructure organizations" because they offered collective goods to network members. Referring to the research of Belso-Martinez, Diez-Vial [59], support organizations acted as brokers to build mutual understanding between different actors so that technical and commercial information could be disseminated over the network. Therefore, we believe that support organizations can accelerate knowledge acquisition and interaction, which helps the city in a central position to improve the degree of exploratory innovation. In particular, Wolf, Cantner [60] classified support organizations into two main groups: technical intermediaries, such as universities, vocational training centers, or research institutes, and knowledge exchange intermediaries, i.e., organizations often created and supported by government funding to encourage knowledge transfer. We thereby divide the support organizations into universities and development zones as representatives of the two types, respectively. Then we discuss their roles in the influence of network centrality on exploratory innovation.

3.3.1. *Moderating effect of universities*

Bramwell, Nelles [61] discovered that universities were mentioned much more often as sources of innovation than government research institutions or technology transfer centers. We argue that universities have the potential to both amplify the good benefits of network centrality on exploratory innovation and attenuate the negative implications. The aspects of enhancing the positive effects are shown as follows. First, universities help cities increase access to knowledge exchange, which reinforces the central position of the city. Universities can create contact channels between local organizations and external organizations, such as leading companies, and research institutes, helping high-centrality nodes access more information and external knowledge. Second, universities strengthen the city attraction and help it build partnerships. Schartinger, Rammer [62] found industry tended to look for university with better research output. Moreover, university graduates often pursue the opportunity to develop, maintain, and construct their professional networks [63], which increases the connection between node city and other cities to some extent. Finally, universities cultivate talents to help organizations efficiently use information and knowledge. The high-technology firms often suffers from high turnover rates and difficulty in recruiting the right talent [64]. According to the research of Gertler and Vinodrai [65], universities serve as "anchors of creativity" in attracting highly skilled researchers and students. A higher level of human capital increases the likelihood that an organization would connect with knowledge providers (i.e., universities and public research institutes) [66], which helps to effectively use knowledge.

We also illustrate the aspects of mitigating the negative effects: First of all, the transaction costs of the organization can be reduced by establishing partnerships with local universities. Hewitt-Dundas, Gkypali [67] deemed that the past experience of collaborating with a university significantly enhances the chance of the organization to participating in such cooperation again. Repeated interactions increase the confidence of organizations, thereby reducing transaction costs. Secondly, universities could boost the absorptive capacity of organizations. Qi Dong, McCarthy [68] argued that organizations with a higher percentage of private partners, such as universities, could better deal with the problems of absorptive capacity that occur as network centrality grows. In fact, university graduates improve organizations' absorptive ability [69]. Thirdly, universities can expose organizations to a broad range of new ideas [70]. Diez-Vial and Montoro-Sanchez [71] believed that links with universities are analogous to having extensive social network. These links provide new ideas, experiences, and knowledge from the diverse sources offered by the companies and other institutions that have already interacted with the university. Access to diverse new knowledge enables cities to reduce the risk of information lock-in.

Based on the overall reasons, the following hypothesis is proposed.

H2. The relationship between network centrality and exploratory innovation is positively moderated by universities.

3.3.2. Moderating effect of development zones

A development zone is a government-designated region for industrial and commercial development [72], which plays a critical role in industrialization [73]. The establishment of development zones is becoming a common approach adopted by many nations. In China, the majority of IC organizations are in development zones which provide a platform for promoting the innovative growth of the industry. Therefore, this research focuses on the important role of development zones between network centrality and exploratory innovation.

Concerning the aspects of enhancing the positive effects: First, the organizations in the development zones can exchange knowledge and information more easily. Vásquez-Urriago, Barge-Gil [74] deemed agglomeration of industrial activity could foster local knowledge exchange and promote innovation. Development zones supply public goods (i.e., network cohesiveness), which makes it easier to create and exchange knowledge between organizations. Since development zones have a certain amount of capital and labor, it is easier to make knowledge flow within the development zones at a high speed. Moreover, organizations in development zones have access to the cutting-edge technology, scientific knowledge, and human resources [75]. Liu and Yang [76] found that a development zone promotes industrial connection among the firms located inside it. This connectivity assists organizations in introducing innovative manufacturing machinery and technology. Organizations in the area could benefit from accessible circumstances thanks to the establishment of development zones. As a result, the attractiveness of the development zones increased. Organizations outside the city are more willing to establish partnerships with organizations in the zone. Third, development zones make more productive firms more likely to enter and stay in the development zones through selection effects [77]. To be specific, development zones deter inefficient

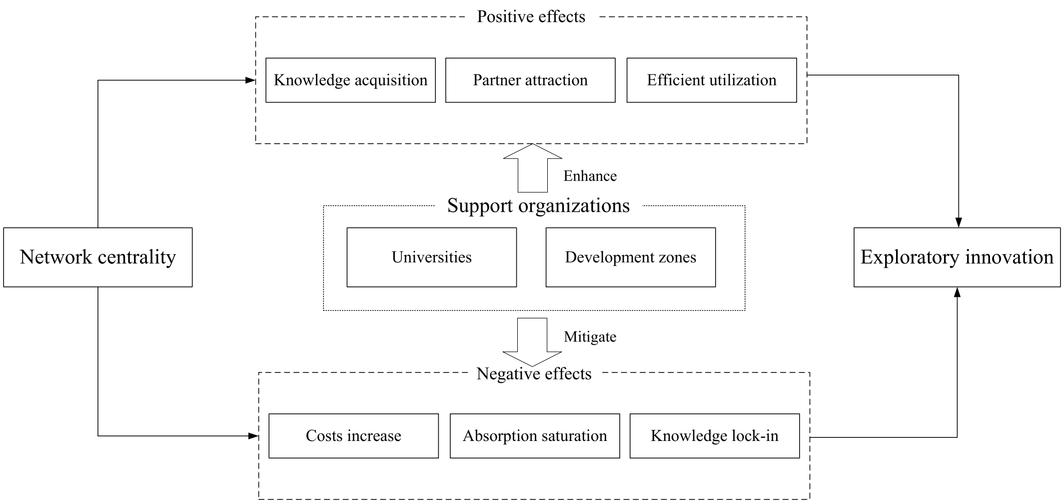

Fig. 1. Theoretical model.

companies from entering by setting entry thresholds. Increasing competition between firms in the zone forces low-productivity firms to exit. High productivity means knowledge converts inputs into outputs quickly.

In terms of the aspects of mitigating the negative effects: First, Chang [78] believed that innovative organizations in development zones may benefit from government management. The development zones have been given a variety of preferential policies by the government, including government subsidies, tax returns, and inexpensive land [79]. Such policies help companies in lowering costs and increasing disposable profits. Indeed, combining different policies could produce synergistic effect [80]. Second, the development zones house a variety of companies and research organizations which have a similar range of knowledge and a certain degree of technological similarity. Absorption of knowledge can be facilitated by knowledge partners that have technological commonalities [81]. High-tech similarities may lessen the challenges that knowledge receivers have in recognizing and absorbing knowledge [82]. Thereby development zones make it easier for organizations to absorb knowledge. Third, development zones progressively developed an industrial correlation effects among firms and nearby academic institutes by absorbing diverse kinds of companies and talents [75]. The new ideas and knowledge flow in the development zones among organizations. Regional organizations may absorb information selectively, thus increasing the knowledge diversity so as to reduce the organizations' risk of knowledge lock-in.

Considering the above discussion, this paper comes up with the following hypothesis.

H3. The relationship between network centrality and exploratory innovation is positively moderated by development zones.

In summary, we visualize the theoretical model in Fig. 1 by using the Visio software.

4. Methodology

4.1. Sample

Since China released the Notice of the State Council on Issuing Several Policies on Further Encouraging the Development of the Software and Integrated Circuit Industries in the year2011,[3] the Chinese IC industry has grown rapidly. Therefore, we present an analysis of the IC industry in cities at the prefecture level and above derived from 31 provinces, municipalities and autonomous regions of mainland China during 2011–2020. Joint patent applications are a common type of cooperation [83]. This paper focuses on the cooperation network built by intercity collaborative relationships. In reference to the research of Sun, Geng [84], this paper defines cooperative patents based on patentees. If the patentees include multiple patentees from universities, research institutions, and enterprises, the patent is considered a collaborative patent. The steps to construct the IC industry cooperation network are given as follows. Step 1: The patent information for the IC industry can be retrieved and collected on the China Key Industries Patent Information Services Platform. Step 2: We delete patent applications where patentees only include individuals because individuals do not have geographic information at the city level. Step 3: In order to ensure the availability of variable data for regression analysis (see Table 1), we select the patentees located in mainland China. Step 4: The patent cooperation matrix is established by matching the detailed addresses of each patentee to the city. Furthermore, real-world network is dynamic. Cities or collaborative relationships may appear or disappear in network, which describes the compositions and interactions dynamically. We therefore construct networks in different time periods according to empirical research needs.

4.2. Variables

4.2.1. Dependent variable

Patents are extremely important in the IC industry. It is considered a necessary condition for innovative organizations to maintain their technological competitiveness through having intellectual property rights in the IC industry [1]. The People's Republic of China's Patent Law classifies patents into three types of invention, utility, and design patents. In contrast to utility and design patents, invention patents need to satisfy the standards of uniqueness, ingenuity, and practical application [85]. Indeed, invention patents pursue radical changes, whereas utility patents and design patents pursue incremental changes. Furthermore, exploratory innovation reflects the ability to change old technologies into something significantly new [4]. Invention patent thereby is in line with the nature of exploration innovation. Especially, Yu and Chen [86] took new invention patents as a reliable and valid indicator of exploratory innovation. Per the rationale aforementioned, we utilize the cities' IC invention patent counts as a measure of exploratory innovation.

4.2.2. Independent variable

This paper adopts network centrality as independent variable. The network centrality can be evaluated by closeness centrality, degree centrality, and betweenness centrality [37]. Each indicator reflects the unique role of nodes in social network, but with different definitions and measurements [87]. Closeness centrality determines the accessibility of a node to all nodes along the shortest paths [88]. Moreover, closeness centrality allows a node to efficiently acquire information and achieve competitive advantage [89], which is efficient in small network [90]. Thus, we choose closeness centrality as the metric of network centrality. It may be computed using the equation below [91]:

[3] The information of this administrative document can be seen at http://www.gov.cn/zwgk/2011-02/09/content_1800432.htm (accessed 30 Mar 2023).

Table 1
Variable specification.

Category	Variable name	Variable symbol	Variable description
Dependent variable	Exploratory innovation	*EI*	Logarithm of the invention patent amount
Independent variable	Network centrality	*NC*	Closeness centrality
Moderating variables	Universities	*UN*	The share of university students in the resident population
	Development zones	*DZ*	Logarithm of the development zone amount at the provincial level and above
Control variables	Economic development	*ED*	Logarithm of GDP
	City size	*CS*	Logarithm of the registered population
	City innovation	*CI*	Logarithm of the local patent applications
	Digital industrial infrastructure	*DII*	Logarithm of the per capita year-end mobile phone users

Note: The data of dependent variable can be retrieved and collected on the China Key Industries Patent Information Services Platform. The independent variable data can be calculated by Equation (1) based on the construction of innovation network. The data of moderating variables and control variables come from the China City Statistical Yearbook (2012–2021), the China Statistical Yearbook (2012–2021), the China Urban Construction Statistical Yearbook (2012–2021), the China Economic Development Zone Audit Announcement Catalogue (2018 edition), and the website of China development zones (https://www.cadz.org.cn/).

$$NC_i = \frac{n-1}{\sum_{j=1}^{n} d_{ij}} \tag{1}$$

where NC_i is the closeness centrality of city i. n indicates the overall city count. d_{ij} is the shortest length connecting cities i and j. The closeness centrality of a node reveals how fast it can reach other nodes [9]. That is, the higher the *NC* score of a city is, the easier the city is to access additional nodes. Furthermore, multiple measurements of centrality could lead to improved parameter significance testing and estimation accuracy over those studies with a single measurement [92], we thereby conduct robustness test by using degree centrality as independent variable in Section 5.6.

4.2.3. Moderating variables

We classify support organizations into two main groups: universities and development zones. Referring to the study of Su, Hua [93], we use the share of university students in the resident population of a city to measure universities. Development zones are calculated by development zone counts at the provincial level and above (e.g. Ref. [94]).

4.2.4. Control variables

Exploratory innovation is not only determined by network characteristics but also influenced by city factors. To eliminate endogenous errors caused by urban characteristics, we add economic development, city size, city innovation, digital industrial infrastructure as control variables. This study selects the GDP to measure the economic development (e.g. Ref. [9]). City size can be represented by registered population (e.g. Ref. [95]). The quantity of local patent applications is calculated to gauge city innovation (e.g. Ref. [96]). Digital industrial infrastructure can be measured by the per capita year-end mobile phone users (e.g. Ref. [97]).

To minimize the impact of heteroskedasticity, relevant variables are transformed logarithmically (e.g. Ref. [98]). Table 1 displays specifics about the variables in this study.

4.3. Empirical approach

4.3.1. Social network analysis

Social network analysis is a quantitative method to identify how actors interact with each other within a network [99]. This method exerts an increasingly important role in field of innovation cooperation [100]. In a network, nodes and edges are used to represent entities and their interactions, respectively, to help us analyze the characteristics and location of network (e.g. Refs. [101,102]). Specifically, in this paper, entities and interactions refer to cities and cooperative relationship, respectively, and the steps to construct the IC industry cooperation network are given in Section 4.1. Further, the parameters of the overall network characteristics and the block model are shown as follows.[4]

(1) The overall characteristics of the network

The overall network characteristics can be quantified by size, tie, density, average path length, and clustering coefficient (e.g. Refs. [103–105]). The parameter specification is given in Table 2.

(2) The block model

[4] The characteristics of the network can be described from two levels, namely the overall network and the individual network [101]. The structural features of network individuals are evaluated by degree centrality, closeness centrality, and betweenness centrality, which has been discussed in Section 4.2.1.

Table 2
Parameter specification.

Name	Calculation formula	Description	Explanation
Scale	n	n denotes the city number.	The larger size represents more cities in the network.
Tie	$\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}, i<j$	Tie is the total number of network edges. And there is a connection between city i and city j; then $a_{ij} = 1$; otherwise $a_{ij} = 0$.	The bigger the tie is, the more partners the cities have.
Density	$\frac{2m}{n(n-1)}$	m refers to Tie.	The higher density indicates a closer relationship among cities.
Average distance length	$\frac{2}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}$, $i<j$	d_{ij} stands for the shortcut route between cities i and j.	Longer average distance length indicates looser linkages.
Clustering coefficient	$\frac{1}{n}\sum_{i=1}^{n}\frac{2e_i}{k_i(k_i-1)}$	e_i is the number of real lines that connect adjacent cities of city i, and k_i is the number of adjacent cities of city i.	The higher the clustering coefficient is, the stronger the connection of the overall network structure is.

Source: The content is collated by the authors according to Refs. [103–105].

The block model can be applied to analyze network location [102]. We thereby use the block model to analyze the core–periphery structure of the IC cooperative innovation network. This approach breaks the network nodes into a number of separate subsets that we referred to as "blocks", with the aim of examining the connections among each "block". The block model builds a new matrix by continuously computing row-column correlation. The blocks in the matrix have two types: One is the empty type (symbolized by a hyphen) without a corresponding cooperative structure. The other is the full type (illustrated by com) which has a similar framework for collaboration. This matrix, called an image matrix, represents intra-block interactions [101]. In summary, the block model describes the overall structure of the network and describes the locations and relationships of each city in the network structure.

4.3.2. Dynamic panel system generalized method of moments model

To investigate the impact of network centrality on exploratory innovation and to identify the moderating effect of support organizations between network centrality and exploratory innovation. We use the equation as follows:

$$EI_{i,t} = \beta_0 + \beta_1 EI_{i,t-1} + \beta_2 NC_{i,t} + \beta_3 \left(NC_{i,t} {*} Z_{i,t}\right) + \beta_4 Z_{i,t} + \sum \beta_n X_{i,t} + \delta_i + \pi_t + \varepsilon_{i,t} \tag{2}$$

Where i means the city, t refers to the year. The $EI_{i,t}$ and $EI_{i,t-1}$ represent the exploratory innovation. $NC_{i,t}$ is represented as the network centrality. $Z_{i,t}$ means the universities or development zones. $X_{i,t}$ refers to the control variables. δ_i and π_t are city and year fixed effects, respectively. $\varepsilon_{i,t}$ stands for the robust standard error. It should be noted that the model needs panel data, we thereby establish IC innovation networks annually from 2011 to 2020 to obtain the values of $NC_{i,t}$.

To estimate Equation (2), we utilize the System-GMM method. Problem with endogeneity can be resolved [106], as this method can eliminate the need for strictly exogenous instruments by using lagged variables as instruments [107]. In particular, it is possible to overcome endogeneity caused by bidirectional causation between the explained and explanatory factors [108]. System-GMM estimation may address the issues of weak instruments and small sample sizes better than Difference-GMM estimation [109]. When the data is an unbalanced panel, System-GMM estimate performs better than Difference-GMM [110]. Furthermore, the regression model also takes all time-invariant unobserved heterogeneity variabilities as well as citywide time-specific impacts into account.

5. Empirical results

5.1. Analysis of network evolutionary features

This paper divides the period of the network into 2011–2015 and 2016–2020, to explore the evolution characteristics of IC networks and to avoid bias caused by data fluctuations in a single year. Fig. 2(a and b) depicts the network topology about the two-stage city cooperation based on the VOSviewer software. The larger the node is, the greater the number of intercity cooperative relationships the city has. The network links represent the cooperation relationships. Obviously, the linkages of intercity cooperation network increased significantly from 2011 to 2015 to 2016–2020. We can conclude that cities are increasingly inclined to collaborate with counterparts over time in the IC industry.

Further, Table 3 lists characteristic parameters of the IC network at each stage. The number of cooperation expands from 33 to 51 cities, and more cities engage in the cooperative innovation, while the total scale is still small. The collaboration across cities is becoming more intense, and the number of cross-city cooperation linkages more than doubled from 47 to 111. A decrease in network density shows that the cities are getting loosely linked. The tendency toward reduction of the average path length suggests that city connection is becoming more and more accessible. The value of the clustering coefficient is higher than the density. Thus, as compared to the random network, the IC cooperation network is substantially more clustered.

In order to detect the change in the relative position of cities and the cooperative innovation model, by using the block model, we divide the network into three blocks: core cities (CCs), semi-periphery cities (SPCs), and periphery cities (PCs). Table 4 depicts the changes in the core-periphery structure of network during two time periods. The findings indicate that Beijing is central to the

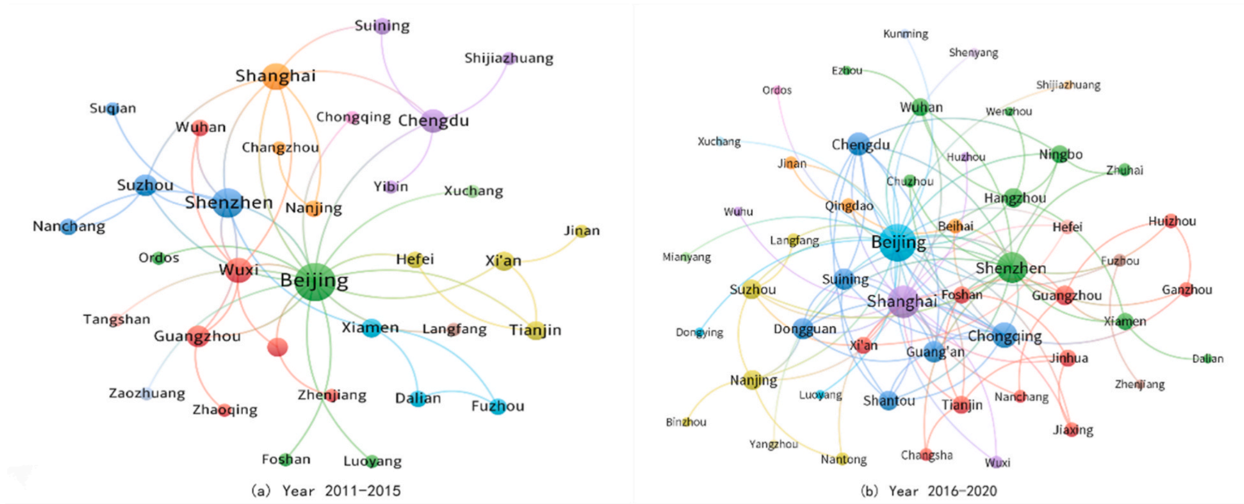

Fig. 2. Innovation network evolution of the IC industry.

Table 3
Information regarding the parameters of the IC network.

Period	Scale	Tie	Density	Average distance length	Clustering coefficient
2011–2015	33	47	0.089	2.657	0.564
2016–2020	51	111	0.087	2.388	0.529

Note: The values are calculated by the Ucinet software.

networks. The amount of semi-peripheral cities has decreased, and many cities are becoming increasingly marginalized. The peripheral cities count has risen to 42. Additionally, Table 5 presents the final image matrix, which illustrates that the cooperation model gradually changes from semi-peripheral cities to peripheral cities in the IC industry. In summary, we can conclude that the peripheral cities have increased in numbers and developed a cooperative innovation model that is driven by them.

5.2. Descriptive statistics and correlation analysis

The means, standard deviations, and correlations of variables are shown in Table 6. The average *EI* is 2.165, while the standard error is 1.816. The *NC* has a mean value of 30.883, and its standard deviation is 15.073, suggesting considerable network centrality inequality. It can be seen from the Pearson Correlation matrix that there is a positive correlation between *NC* and *EI*. In addition, the average VIF of 1.424 and the maximum VIF of 2.005 are both considerably less than 10, indicating that multi-collinearity is not a severe concern in this study.

5.3. Stationarity test

This study uses unit root testing to prevent the possible pseudo regression. Table 7 depicts the results of the ADF-Fisher test and the PP-Fisher test. All variables are found to be stationary.

5.4. Endogeneity test

Before estimating the GMM model, we effectively separate endogenous variables from exogenous variables by performing the endogeneity test [111]. The explanatory variable is exploratory innovation. The instrumental variables are the lagged one-period terms of independent variables, moderating variables, and control variables, respectively. All the variables are regressed using two-stage least squares in turn. In order to determine whether each variable is endogenous, the Wu-Hausman F test and the Durbin-Wu-Hausman chi-square test are applied, respectively. The results are represented in Table 8. We find that only *NC* is an endogenous variable.

Table 4
"Core–periphery" cities of the IC industry network.

Period	CCs	SPCs	PCs
2011–2015	1 (Beijing)	18 (Chengdu, Ordos, Hefei, Langfang, Shanghai, Shenzhen, Tianjin, Xi'an, Suzhou, Wuxi, Chongqing, Nantong, Foshan, Tangshan, Guangzhou, Luoyang, Xuchang, Zaozhuang)	14 (Dalian, Suining, Wuhan, Xiamen, Suqian, Jinan, Zhaoqing, Zhenjiang, Fuzhou, Shijiazhuang, Nanchang, Changzhou, Nanjing, Yibin)
2016–2020	1 (Beijing)	8 (Chengdu, Shanghai, Shenzhen, Chongqing, Dongguan, Suining, Guang'an, Shantou)	42 (Beihai, Binzhou, Dalian, Ordos, Foshan, Fuzhou, Guangzhou, Hangzhou, Hefei, Huizhou, Mianyang, Ningbo, Xiamen, Suzhou, Tianjin, Wuxi, Wuhan, Changsha, Jiaxing, Jinhua, Kunming, Nanjing, Wenzhou, Wuhu, Zhuhai, Chuzhou, Jinan, Qingdao, Yangzhou, Luoyang, Nanchang, Xi'an, Nantong, Dongying, Shenyang, Xuchang, Shijiazhuang, Huzhou, Langfang, Ezhou, Zhenjiang, Ganzhou)

Note: The results are measured by the Pajek software.

Table 5
Final IC network picture matrix.

Period		CCs	SPCs	PCs
2011–2015	CCs	–	–	–
	SPCs	–	com	–
	PCs	–	–	–
2016–2020	CCs	–	–	com
	SPCs	–	com	–
	PCs	com	–	–

Note: The results are calculated by the Pajek software.

5.5. Regression analysis

We conduct the System-GMM regression based on the endogeneity test results.[5] The parameter estimation results are listed in Table 9. The coefficient of AR (1) is significant whereas the correlation coefficient of AR (2) is not, which indicates that the difference of random disturbance terms has a first-order auto-correlation. Moreover, the p-value of Sargan test is greater than 0.1, revealing that the choice of instrumental variables does not lead to over-identification. Therefore, the System-GMM estimator is valid.

Only control variables are included in Mode l. Model 2 shows that the coefficient of NC is positive and significant, which indicates that cities with high network centrality tend to have better exploratory innovation performance. H1 can be verified. As shown in Model 3 that the network centrality, and the interaction between universities and network centrality are significantly positive, which indicates that universities strengthen the *NC-EI* relationship. It is consistent with H2. Moving on to Model 4, the coefficient of network centrality (*NC*) and the interaction between development zones and network centrality (*NC*DZ*) is positive and significant. In other words, the development zones enhance the relationship between network centrality and exploratory innovation. H3 can be supported. When the moderating variables are taken into consideration, the coefficients of *NC* in Models 3 and 4 are larger than those in Model 2. They jointly demonstrate that it is important to consider the reinforcing effect of support organizations when exploring the *NC-EI* relationship in the IC industry. To gain further insights into these moderating effects, we visualize the effects that how support organizations moderate the relationships between network centrality and exploratory innovation in Fig. 3(a and b) by using the Origin software. As shown in Fig. 3(a and b), the network centrality responds to better exploratory innovation with high values of the moderating variables.

5.6. Robustness check

In this section, we use degree centrality as the new independent variable (i.e., *NC'*) for robustness test. We define the degree centrality by using Equation (3) [91]:

$$NC_i^{'} = \frac{b_i}{n-1} \tag{3}$$

where $NC_i^{'}$ is the degree centrality of city *i*. b_i is the number of cities which are directly connected to city *i*. *n* is the total number of cities

[5] With respect to the endogeneity of interaction term, Ebbes, Papies [117] proposed that when one variable of interaction term is endogenous and the other is exogenous, we should treat the interaction as a separate endogenous variable. Therefore, we regard NC*UN and NC*DZ as endogenous variables, as NC is endogenous, and UN and DZ are exogenous (see Table 8).

Table 6
Statistical summary and correlation analysis.

Variables	N	MEAN	SD	*EI*	*NC*	*UN*	*DZ*	*ED*	*CS*	*CI*	*DII*	VIF
EI	206	2.165	1.816	1								(1.424)
NC	206	30.883	15.073	0.351***	1							1.135
UN	206	3.599	2.981	0.040	−0.031	1						1.139
DZ	206	2.932	0.655	0.253***	0.101	0.149**	1					1.595
ED	206	8.960	0.830	0.753***	0.282***	0.114	0.493***	1				1.883
CS	206	6.405	0.695	0.362***	0.184	0.233***	0.579***	0.606***	1			2.005
CI	206	4.304	0.954	0.063	−0.136*	0.044	0.082	0.151**	0.077	1		1.064
DII	206	4.331	0.949	−0.188***	−0.006	−0.225***	−0.145**	−0.224***	−0.073	−0.098	1	1.148

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The results are estimated by the Stata software.

Table 7
Results of unit-root testing.

Variables	ADF-Fisher test	PP-Fisher test
EI	59.373*	130.881***
NC	17.708**	153.178***
UN	19.296**	150.756***
DZ	18.571**	67.980**
ED	82.722***	133.250***
CS	83.573***	101.920***
CI	12.881	143.529***
DII	16.828**	230.123***

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The results are estimated by the Stata software.

Table 8
Results of endogeneity test.

Null hypothesis	H0: Variable is exogenous.						
Variables	*NC*	*UN*	*DZ*	*ED*	*CS*	*CI*	*DII*
Instrumental variables	NC_{t-1}	UN_{t-1}	DZ_{t-1}	ED_{t-1}	CS_{t-1}	CI_{t-1}	DII_{t-1}
Wu-Hausman F test [P]	0.006	0.972	0.671	0.854	0.839	0.731	0.715
Durbin-Wu-Hausman chi-square test [P]	0.004	0.970	0.646	0.842	0.826	0.709	0.692

Note: The results are estimated by the Stata software.

Table 9
Results of the System-GMM model.

Variables	Model 1	Model 2	Model 3	Model 4
EI_{t-1}	0.797***	0.812***	0.860***	0.794***
	(0.024)	(0.058)	(0.090)	(0.104)
NC		0.036***	0.039**	0.041*
		(0.014)	(0.018)	(0.024)
*NC*UN*			0.039***	
			(0.011)	
UN			0.023	
			(0.046)	
*NC*DZ*				0.011**
				(0.006)
DZ				0.034
				(0.095)
ED	0.421***	0.231*	0.135	0.232
	(0.057)	(0.129)	(0.128)	(0.170)
CS	−0.173***	−0.190***	−0.195**	−0.223**
	(0.036)	(0.068)	(0.082)	(0.093)
CI	0.055***	0.064	0.079**	0.090**
	(0.021)	(0.039)	(0.038)	(0.045)
DII	−0.086***	−0.157***	−0.127***	−0.116**
	(0.030)	(0.057)	(0.045)	(0.052)
CONSTANT	−1.746***	−0.903	−0.565	−1.331
	(0.477)	(0.855)	(1.002)	(1.383)
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
AR (1) [P]	0.087	0.087	0.093	0.095
AR (2) [P]	0.329	0.167	0.173	0.180
Sargan [P]	0.577	0.489	0.649	0.531

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The robust standard errors are given in parentheses. The results are estimated by the Stata software.

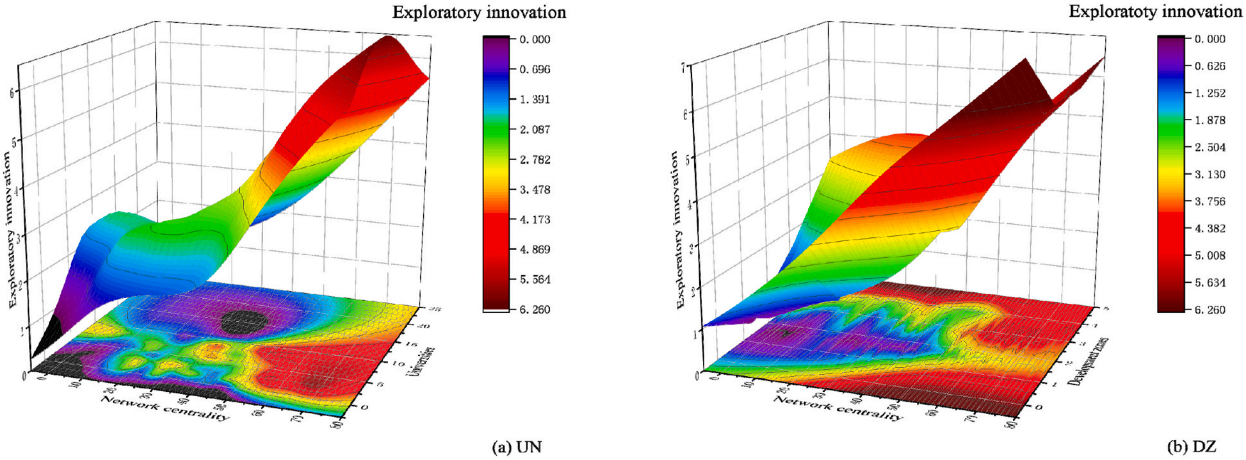

Fig. 3. Schematic diagram of the moderating effects of *UN* and *DZ*.

Table 10
Results of replacing the independent variable.

Variables	Model 2	Model 3	Model 4
EI_{t-1}	0.744***	0.796***	0.725***
	(0.094)	(0.102)	(0.102)
NC'	0.022***	0.027**	0.005
	(0.007)	(0.013)	(0.011)
*NC'*UN*		0.009**	
		(0.005)	
UN		0.042	
		(0.034)	
*NC'*DZ*			0.054**
			(0.027)
DZ			−0.016
			(0.100)
ED	0.360**	0.361*	0.520**
	(0.177)	(0.199)	(0.203)
CS	−0.189***	−0.285***	−0.236***
	(0.069)	(0.090)	(0.076)
CI	0.060	0.069	0.048
	(0.055)	(0.064)	(0.030)
DII	−0.133**	−0.131	−0.121*
	(0.063)	(0.084)	(0.074)
CONSTANT	−0.994	−0.689	−1.801
	(1.363)	(1.700)	(1.646)
City fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
AR (1) [P]	0.038	0.066	0.091
AR (2) [P]	0.145	0.274	0.410
Sargan [P]	0.521	0.950	0.980

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The robust standard errors are given in parentheses. The results are estimated by the Stata software.

in the network. The degree centrality shows how many cities in cooperation network that are directly connected to a city [112].

Through stationarity test, *NC'* is found to be stationary.[6] Only *NC'* is endogenous variable based on the endogeneity test.[7] We then perform System-GMM regression again. The regression results are given in Table 10. The coefficient of *NC'* in Model 2 is positive and significant at a significant level of 1%, which indicates that cities with high network centrality tend to have better exploratory innovation performance. In Model 3, the coefficient of *NC'*UN* is significantly positive, which illustrates the positive effect of network centrality and exploratory innovation can be enhanced by universities. Model 4 indicates that the coefficient of *NC'*DZ* is positive and significant, which means that development zones can boost cities in the network to improve the level of exploratory innovation.

[6] The ADF-Fisher test and the PP-Fisher test show that NC' is stationary (P-values are 0.000 and 0.005, respectively).

[7] The Wu–Hausman F test and the Durbin–Wu–Hausman chi-square test show that NC' are endogenous (P-values are 0.021 and 0.013 respectively).

Table 11
Results of replacing the dependent variable.

Variables	Model 1	Model 2	Model 3	Model 4
EI'_{t-1}	0.412**	0.713***	0.823***	0.477***
	(0.163)	(0.111)	(0.136)	(0.160)
NC		0.007	0.021	0.032
		(0.012)	(0.019)	(0.025)
*NC*UN*			0.015	
			(0.017)	
UN			0.005	
			(0.017)	
*NC*DZ*				0.005
				(0.007)
DZ				0.029
				(0.085)
ED	0.945***	0.476***	0.271	0.736**
	(0.295)	(0.164)	(0.197)	(0.305)
CS	−0.284**	−0.214**	−0.166	−0.357***
	(0.129)	(0.101)	(0.101)	(0.132)
CI	−0.092*	−0.054	−0.039	−0.034
	(0.048)	(0.047)	(0.048)	(0.046)
DII	−0.070	−0.088*	−0.052	−0.083
	(0.084)	(0.045)	(0.052)	(0.075)
CONSTANT	−4.432**	−1.586	−0.900	−3.649*
	(1.862)	(1.004)	(1.235)	(1.907)
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
AR (1) [P]	0.004	0.003	0.004	0.002
AR (2) [P]	0.122	0.157	0.223	0.188
Sargan [P]	0.481	0.251	0.484	0.390

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The robust standard errors are given in parentheses. The results are estimated by the Stata software.

Therefore, the results in Table 10 are consistent with previous states in Table 9, suggesting that the conclusions of this paper are robust.

5.7. *Extended analysis*

Danneels [4] stated that innovation could be divided into exploratory innovation and exploitative innovation. Although we have already discovered the positive effect between network centrality and exploratory innovation in the IC industry, and enhanced impact of support organizations in that relationship. It is worth further thinking about whether network centrality can affect exploitative innovation and support organizations can moderate that relationship. In this section, this paper uses exploitative innovation as the new dependent variable (i.e., *EI'*), which is measured by the number of utility model and design patents granted [113]. Through stationarity test, *EI'* to be stationary.[8] And only *NC* is still a endogenous variable based on the endogeneity test.[9] Table 11 summarizes the results with System-GMM regression. Model 1 just includes control variables. The coefficient of *NC* in Model 2 is still positive but not significant. As shown in Model 3 and Model 4, the coefficients of interaction terms (i.e., *NC*UN*, *NC*DZ*) are not significant. We can conclude that network centrality does not affect the exploitative innovation in the IC industry and there is no moderating effect of the support organizations. The results reflect the necessity of focusing on exploratory innovation in this paper to some extent.

6. Discussion

This paper first constructs the innovation networks of the IC industry and explore the structural characteristics and core-periphery structure of the networks. Although previous studies have paid attention to the construction of high-tech industrial networks [18–22], the network characteristics of different industries are not the same. Actually, the innovative development of each industry has its specificity, and our exploration of the IC industry undoubtedly contributes to an increased understanding of this pioneering industry. Indeed, we find that the collaborative networks in the IC industry are small in scale, but the number of nodes involved in collaboration has increased year by year. A model of cooperative innovation driven by peripheral cities has been shaped in the Chinese IC industry. Additionally, this study constructs the IC industry network from a city perspective, beyond the research which focused on organizations in the IC industry network [114], and the study of network characteristics of the IC sub-industries (e.g., the integrated circuit design industry [91]). The findings can help the decision-makers of different institutions understand the collaboration characteristics of the IC industry, and look for appropriate partners at the city level.

[8] The ADF-Fisher test and the PP-Fisher test show that EI' is stationary (P-values are 0.001 and 0.000, respectively).
[9] The Wu–Hausman F test and the Durbin–Wu–Hausman chi-square test show that NC is endogenous (P-values are 0.017 and 0.011, respectively).

Second, this study uncovers the positive effect of network centrality on exploratory innovation in the IC industry, thereby supporting H1. Just as studies in biopharmaceutical industry [24] and 3D printing industry [29], this study also finds the advantages of cooperation in the IC industry. The role of intercity collaboration as a channel for knowledge exchange is essential for China that is transforming to an innovative country [36]. Especially for IC industry which the key technologies change continuously, technological cooperation has increasingly become a necessary path for innovative development. In addition, we identify the heterogeneous influences of network centrality between exploratory innovation and exploitative innovation. Network structure effects the two types of innovation differently because of the different intrinsic demands of innovation [18]. Exploratory innovation involves high-quality cooperative relationships to improve the capability of innovation. For the above reasons, exploratory innovation that creates entirely new goods, new technologies, and new production processes, is significantly important for the IC industry.

Third, this paper takes the internal structure of the network (i.e., network centrality) and the node support environment (i.e., supporting organizations) into the same framework. To be specific, we introduce universities and development zones, named support organizations, as relatively rare moderating variables. This paper relatively well illustrates the role of supporting organizations as a driving force for innovation. The results verify the rationality of the two-group classification of support organizations proposed by Wolf, Cantner [60] to some extent. Furthermore, industry, university, and government (i.e., IC industry, universities, and development zones) are put into a framework for discussion, a scheme that can find clues in the literature which presented a Triple Helix dynamics of university–industry–government relations that created a new mode of the production of scientific knowledge [115].

In summary, although this paper is an innovative study on China, the issues identified are widespread and demand the attention of all nations. The research framework provides a new prospective for the future research of industrial innovation based on intercity collaboration and the research models could be generalized to analyze the technological collaboration in other pioneering industries (e.g., biomedicine industry, artificial intelligence industry). Notably, each industry has specific characteristics, it is necessary to wait for more scholars to conduct empirical tests using data from other high-tech industries or countries, and we will keep an eye on related studies to compare with the results of this paper.

7. Conclusions and implications

7.1. Conclusions

By using the SNA method and System-GMM model, we reveal the evolution features of the innovation networks, and explore the *NC-EI* relationship in the Chinese IC industry when considering the moderating effect of support organizations. Our main research work includes: We first investigate the network evolutionary characteristics of the IC industry. Then we explore the influence of network centrality on exploratory innovation. Finally, we detect the moderating effects of universities and development zones, named support organizations, between network centrality and exploratory innovation.

The results of this study are as follows: First, cities are increasingly inclined to collaborate with counterparts over time in the IC industry, but the overall network scale remains small. Beijing occupies core position in the networks. A cooperative innovation model driven by peripheral cities has been formed as the number of the peripheral cities has gradually increased. Second, network centrality positively affects its exploratory innovation. Cities with high network centrality tend to have better exploratory innovation performance in the IC industry. Third, both universities and development zones positively moderate the effect of network centrality on exploratory innovation. Support organizations are accelerators in enhancing the level of exploratory innovation in industrial innovation network.

7.2. Theoretical implications

This study enriches the social network theory in four ways. First, we build a theoretical model from the perspective of social network lens. The action path of *NC* on *EI* is analyzed based on the concurrent investigation of positive effects (i.e., knowledge acquisition, partner attraction and efficient utilization) and negative effects (i.e., costs increase, absorption saturation, knowledge lock-in). Furthermore, the universities and the development zones, named support organizations, are taken into the analytical framework to explore how they enhance the positive effects and mitigate the negative effects. Second, based on the cooperation patents, this research constructs innovation networks at the city level, which answers the call from recent line of research connected network theory with regional sciences and urban economics. Further, the results of the network evolution characteristics are conducive to evaluate the applicability of social network theory with respect to specific industry (i.e., IC industry). Third, this paper suggests that *NC* positively influence *EI* in the IC industry. The incongruent results noted in prior literature may be due to different industries [41, 116]. Fourth, we detect that support organizations can act as moderators to reinforce the *NC-EI* relationship. We contribute to extant research as these types of moderation are relatively rare in social network research.

7.3. Practical implications

The government should encourage cities to strengthen their central position by cooperating with counterparts in IC industry. The government could remove the barriers to intercity interactions by building telecommunication and transportation infrastructure and providing financial assistance for intercity collaboration. The development of universities and the establishment of development zones should be encouraged by government because the advantages of a city's central position can be reinforced by the linkages among cities in the cooperation network.

Moreover, the companies should build a cooperative relationship with intercity organizations through patent cooperation, technology shareholding, joint operations, and other forms. The large amounts of knowledge from partners could enhance their scientific performance and impact. Companies should build a long-term partnership with universities through a "industry-university-research institute" collaboration network to continuously acquire new ideas and technologies from universities. Enterprises should make full use of the platforms provided by development zones to effectively develop a cooperation strategy and absorb technology inflows.

Additionally, universities should cultivate innovative and entrepreneurial talents who are proficient in technology. Universities strengthen the "bridge" and "intermediary" roles that they play in the collaboration network to establish links between different organizations through technical exchanges of researchers. To help companies acquire knowledge and advanced technology, development zones should deeply reform the mechanism of management system and introduce various technology industry associations, research and training institutions.

7.4. Limitations and future research

Several limitations should be mentioned. One limitation is that this study only uses patents to construct cooperation networks. Future research can consider other cooperation forms, such as joint operations, technology shareholding, etc. Second, this paper pays attention to inter-city network. The intra-city cooperation is another form in IC industry development. The differences in the structure of intra-city network and inter-city network could be synchronously considered in the future. Third, we consider universities and development zones as support organizations. Future research may take other organizations (e.g., research institutes, vocational training centers) into account.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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