The Evolution of Interurban Knowledge Collaboration Networks of China: Structures and Mechanisms

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Proefschrift aangeboden tot het behalen van de graad van Doctor in de Wetenschappen: Geografie

Door

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December 2019

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Acknowledgements

It has been over 5 years Since I started my Ph.D. Losses and gains, bitter and sweet, laughter and tears, every piece of those memories a kind of precious treasure. There are two stages of my Ph.D. life, one is in Tongji and the other is in Ghent. Along the way, too many people need to be acknowledged. I will start with the deepest gratitude to my two supervisors/mentors, Professor Zhenwei Peng and Professor Ben Derudder, for their profound roles in my Ph.D. Without their help and support, this work would not exist.

In my first half in Tongji, I started with confidence and ambition. However, faced with a flood of new ideas and knowledge, it soon turned out to be a tough journey with self-abasement and self-doubt of my ignorance. I will never forget the simple but powerful encouragement from Professor Peng: "Do not be afraid of failures, do not question if you can do, but question if you do it hard", which has been a motto throughout these years. My interests in urban network research are from Professor Peng. Five years ago, Peng offered me an opportunity to participate in his research project about "Shanghai in global city networks". After lots of discussions with him, I fixed my research topic on urban networks, he then encouraged me to go abroad to access to the academic front. After I came back from Ghent, it seemed that I had lost the ability of writing a standard Chinese dissertation, which might because of two years' training in English writing. He devoted lot of time and energy to help me establish the framework and organization, as well as the wording and phrasing of this thesis, which is particularly memorable.

In my second half in Ghent, I have grown from a rookie to a researcher who can write a qualified and sound scientific paper. I cannot tell the process of how I came to know what scientific research is without mentioning the important role of Professor Derudder. He is the guide for me to enter the center of urban network research. I admire his profound knowledge, never-ending inspirations and rigorous academic attitude. What I cannot forget is, when first came to Ghent, he offered me a valuable chance to work with him on a Chinses Geographical Science paper, from which I built a lot of confidence. For each of my manuscript, he patiently and relentlessly criticized, revised and proof-read word by word, quite often from far-away places and regardless the working day or holiday. I have learned from him how to do research and what a researcher should be like. In addition, I will never forget his comforting and encouraging words when I felt down and struggled with my research. And of course, I will always remember his praise of "keep up the good work", which has always been my biggest motivation.

I would like to thank the other member of my examination committee, Professor Zilai Tang, Professor Miaoxi Zhao, Professor Shangwu Zhang, Professor Bindong Sun, Professor Qiyu Tu, Professor Frank Witlox and Dr. Long Cheng, for your insightful suggestions and comments.

Doing the same thing for five years will drive anyone crazy. Therefore, I would like to express my gratitude to a couple of people who distracted me from the brain-racking work and brought me laughter and joy. First, I owe thanks to the member of Peng family in Tongji, including Dr. Jing Gao, Jia lu, Shubei Li, Dr. Bin Pan, Dr. Baojun Fan, Dr. Weipeng Lin, Dr. Xiaoxi Li and Dr. Xiaoyan Zhao. I will never forget your help and support during my Ph.D. I thank my comrade Dr. Zuquan Wu, Dr. Wei hou, Dr. Xu Guo and Dr. Hongzhou He, the exiting discussions with you were always inspiring.

I wish to express my gratitude to my colleagues in Ghent, and the SEG family in particular, Dr. Jonas De Vos, Dr. Tom Storme, Freke Caset, Filipe Marques Teixeira, Jorn Koelemaij, Leen De Paepe and Dr. Galuh Syahbaba. Your hospitality made me feel like home. I thank to Dr. Weiyang Zhang, Dr. Liang Dai, Kunbo Shi and Rui Shao: thanks for your companionship during my stay.

I sincerely acknowledge the financial support provided by the China Scholarship Council, which enable me to complete my Ph.D. in Belgium.

Last but not the least, I would like to dedicate this work to my family. They have provided me with what appeared to be never ending support throughout my Ph.D. I am sorry for the absences of many family reunions and events, I promise that I'll try to make up for it.

Zhan Cao

Shanghai, December 2017

Abstract

Innovation is the primary force that drives economic development. It has been widely acknowledged by governments and officials that innovation is the strategic support for China's modernization system, also the key to improve China's international status and overall competitiveness. Cities act as incubators for innovation, this is because, on one hand, cities provide tangible assets for innovation activities such as requisite human resources, capital investments, spaces and infrastructures. On the other hand, cities also provide intangible but favorable assets such as social capital, innovation milieus and institutional arrangements for innovation. Innovation is also the engine for cities to keep their competitiveness and maintain sustainable development. However, the knowledge pool and innovative resources of one single city is limited. Against the backdrop of increasingly fiercer global competition, endogenous development might easily lead to technological lock-in. It is necessary for cities to participate in the KCNs that beyond the local boundaries to avoid the lock-in traps. More importantly, by occupying advantageous network positions in collaboration networks, cities could, to some extent, compensate for their own weaknesses such as disadvantageous locations, underdeveloped infrastructures and insufficient scale economies. Against this background, this study takes the "interurban knowledge collaboration networks (IKCNs)" as main research object and takes the "structural characteristics" and the "influencing mechanisms" as the starting point of the empirical framework.

Based on a comprehensive literature review, this study discusses the geographical dimension of innovation processes, the internal mechanisms of the IKCNs, the application of social network analysis and the extended horizon of urban network studies. By doing so, two main hypotheses are introduced: (1) the evolution of the IKCNs follows the general pattern of "space dependency" and "path dependency". (2) the evolution and formation of the IKCNs are jointly affected by "macro-structural factors" and "micro-initiative factors".

With the Web of Science paper index library being the data source, the research constructs the IIKCNs across different geographical scales, i.e. a transnational knowledge collaboration network consists of 165 sovereign states and territories, a global IKCN consists of 500 world cities, a national IKCN consists of 217 Chinese cities, and regional IKCNs of 20 city-regions of China. With the aid of various methods and techniques, such as spatial analysis, social network analysis and econometric analysis, the "structural characteristics" and "influencing mechanisms" in the evolution processes of the IKCNs are systematically examined. Firstly, the evolution of the "spatial configurations" and "topological structures" of the IKCNs in different spatial

scales are discussed. Secondly the influencing mechanisms of the evolution and formation of the IKCNs are discussed both from “macro” and “micro” perspectives. The main conclusions are as follows:

First, the evolutions of the spatial and topological structures of the IKCNs both present gradual and steady development trajectories which comply with the general patterns of “space dependency” and “path dependency” respectively. Meanwhile, cities in the IKCNs occupy different positions and play different roles, while a city may have different functions in different spatial scales of the IKCNs. Further, the evolutionary paths of the cities are closely related with their innovation stage and the costs trade-off of the actors. Besides, the differences of territorial contexts account for the differences of evolutionary paths of cities in the IKCNs. Last, the topological properties have double-sided impacts on the innovation performance of cities: occupying an advantageous position will boost a city’s innovation performance, however, excessive embedding in networks might be detrimental.

Second, the evolution and formation of the IKCNs is jointly affected by “macro-structural factors” and “micro-initiative factors”. By an in-depth investigation on the “Sino-Belgium joint laboratory for geo-information” program, several “macro-structural factors” are introduced, including the transformation of scientific research paradigm, the complementation of basic resources and the support of collaborative environment. Based on a qualitative and quantitative combined analysis of the medical science inter-organizational knowledge collaboration network of the “Jiangsu-Zhejiang-Shanghai” city region, multidimensional proximity has been detected as the “micro-initiative factors”, i.e. geographical proximity, institutional proximity, social proximity, cognitive proximity as well as cultural proximity.

On one hand, this research has deepened the understanding of the spatial mechanism of innovation processes as well as the interactive mechanism between “space of place” and “space of flow”, further provide empirical references for the integration of innovation theories and spatial science. Besides, it also extends the horizons for urban network studies by systematically and comprehensively uncovering the structural characteristics and internal mechanism of urban systems in regional, national and global IKCNs. On the other hand, this research also has practical significance which helps to evaluate cities’ network positions and functions, helps to clarify and judge cities’ evolutionary path and development trend and helps to ascertain the barriers and bottlenecks of cities’ innovation development, further to facilitate the spatial planning and policy making in practices.

Keywords：Interurban knowledge collaboration networks, Evolution，Structural characteristics, Influencing mechanisms，China

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Chapter 1 Introduction

1.1 Research background

1.1.1 Innovation is the primary force that drives economic development

Scientific and technological innovation has invariably been the driving force and the source of the development in human society throughout history. The history of modernization is also the history of scientific and technological innovation progress as well. Every significant evolution of modern society is closely related to the revolutionary breakthrough of science and technology. Science and technology are the “engines” of modernization because they can enhance productivity, boost economic and social development and enrich human spiritual and material wealth. Innovation not only supports current development, but also leads the future progress.

Over the past 40 years since the reform and opening up, China has become a world factory due to its great labor pool. The socio-economy has developed rapidly with great improvement in people’s livelihood and China’s rising international status. However, compared with developed countries, there is still a gap lying in the capability of independent innovation especially in core science and technology. The report of the 18th National Congress of the Communist Party of China clearly proposed the implementation of the “innovation-driven development” strategy; the report of the 19th National Congress of the Communist Party of China emphasized that: “Innovation is the primary force that drives development as well as the strategic pillar underpinning China as a modernized economy.” At present, in face of the historical transition of the socialism with Chinese characteristics and of economy from high-speed growth to high-quality development, it is necessary to emphasize that “innovation-driven development” is the key to China’s future, the key to enhance China’s economic power and the key to improve China’s international competitiveness and status.

1.1.2 Cities act as incubators for innovation

American economist Edward Glaeser emphasizes in his book *Triumph of the City* that innovation is a key driving force for urban development and an important clue to understand the booms and busts of cities (Edward Glaeser, 2012). Sociologist Lewis Mumford points out in his book *The City in History* that cities are containers for preserving, maintaining and incubating diversified knowledge that provide a practicing field for stimulating innovation (Lewis Mumford, 2005). American geographer Richard Florida and his colleagues published *The City as Innovation Machine* in *Regional Studies*. They argue that innovation is not merely produced in cities, and it couldn’t be produced without cities. Because cities not only provide tangible assets for innovation such as requisite human resources, financial supports, spaces and infrastructures, more importantly, they provide intangible assets such as social capital, innovation milieus and institutional arrangements. (Florida et al., 2017)

On the other hand, innovation is of great significance for cities' sustainable development and overall competitiveness. In the era of globalization and "knowledge-based economy", the innovation competition among nations is embodied in that of cities. Building world-class innovation-oriented cities has become a strategic and normative action to cope with a new round of international scientific and technological competition. For instance, a plan to build New York into the "East Silicon Valley" and "The Capital of Innovation" has been drawn up by the government of the US, which will prioritize developing high-tech industries such as biotechnology and communication technology, in order to establish a diversified innovation center. London also made a "Innovation Strategy and Action Plan" to build a "Mini Silicon Valley" to transform itself into a "leading innovation city". Strategic goals and related technological innovation strategies for making global or regional innovation centers have also been deployed in cities such as Tokyo, Paris, and Seoul Major cities in China like Beijing, Shanghai, Guangzhou, Shenzhen. Various plans with the goal of building world-class innovation-oriented cities have also been developing. It appears to be particularly important that close attention should be paid to urban innovation in this setting.

1.1.3 Interurban knowledge collaboration networks and urban innovation

American science historian Keith Simonton believes that the era of "scientific genius" represented by Newton and Einstein has come to an end, and the era of "big science" has just begun (Simonton, 2013). He emphasizes that contemporary cutting-edge science has become complex and specialized with unprecedented high risks and uncertainty, so that much of the cutting-edge work these days tends to emerge from large, well-funded, inter-organizational, inter-city, inter-regional and international collaborative teams.

However, a city's knowledge pool and resources are limited. Against the backdrop of increasingly fiercer global competition, endogenous development might easily cause technological lock-in and economic recession. Therefore, to achieve sustainable development, it is necessary for cities to continuously update existing knowledge by accessing itself into trans-local collaboration networks. In this process, not only can cities acquire new knowledge, but also can they obtain new innovative resources and new market information to conduct self-adjustments. Cities can benefit from the knowledge spillovers and knowledge diffusion in collaboration networks. In summary, in addition to local endowments, the participation in the KCNs has become more and more important for cities to achieve innovation competitiveness. Therefore, as incubators of innovation, cities are also the “hinges” in the KCNs that connect other cities across different geographical scales. Through knowledge collaboration, cities from different regions and countries are interlinked. And at this time, knowledge spread and diffuse, and then, innovation emerge.

In view of this, the research on the IKCNs has theoretical significance: it can deepen our understanding of the spatial network process of innovation and of the interaction between “space of place” and “space of flow”. It also can broaden the horizon of interurban network research and deepen our understanding, discussion and interpretation of the IKCNs. On the other hand, the research on the IKCNs also has vital practical significance: it helps to evaluate cities’ network positions and functions, clarify and judge cities’ evolutionary paths and development trends and ascertain the barriers and bottlenecks.

1.1.4 The bottlenecks of city networks research

Since the 1990s, the conceptualization, theorization, empirical exploration and normative application of “city network” have become the frontier areas of human geography, economic geography and urban planning research. The “rise of the network society” reshapes the geospatial formation of social practices and territorial organization logic. Cities are interconnected vertically and horizontally through flows of capitals, people and commodities, which is distinct from a traditional “central place” system. Since the early 21st century, based on the conception of “city networks”, “relational data” and network analysis methods have been widely applied, which have opened a new chapter for the empirical research on city networks, the achievements and breakthroughs are obvious. However, after nearly 20 years of development, empirical research on interurban networks has encountered “bottlenecks”. Specifically, they are:

（1）Due to the limitations of data, there goes the problem of “scale discontinuity” in city networks research. City networks are trans-scalar and continuous and nested from globe to local: every city is embedded and situated both in local networks and global networks to varying degrees. In addition, a city might have different statuses and roles in city networks of different geographical scales. However, on account of the difficulty of relational data collection, much of the existing studies focus on a single spatial scale which can hardly help us to grasp the whole picture of city networks. Therefore, it is imperative to exploit appropriate relational data, and build continuous trans-scalar city networks.

（2）Due to the limitations of analysis techniques, there goes the problem of “using new data with old methods to explain a novel phenomenon, but usually only to get outdated conclusions”. Since the formation of the concept and theory of “city network”, it was considered to be a new explanation of the spatial organizations of contemporary urban systems that challenged and even subverted the traditional “central place theory”. However, even with the emergence of relational data, much of the existing literature are constrained in the traditional thinking set of urban system research and always focus on the “rank-size” or “hierarchical structures” of cities in city network. Therefore, the discussions are often limited within “city rankings” and “morphological configurations”. Thus, it is necessary to use more advanced network analysis techniques to expand the scopes and contents of empirical research on city networks. In recent years, the development of complex network theories and the rise of social network analysis have provided new tools for network research, and their potentials in urban network research need to be deeply explored.

（3）Due to the limitations of perspectives, there goes the problem of “favoring phenomenon descriptions but ignoring mechanism discussions” in city networks research. The spatial structures and geographical configurations of city networks as well as the sizes and positions of cities in the network are the focuses and mainstreams of current city network research. However, there are relatively few studies that systematically discuss the underlying mechanisms of interurban network formation and evolution. Therefore, it is necessary to carry out research on the issue of the mechanisms of city network formation.

To sum up, the keys to breaking through the bottlenecks of city network research are (1) to use appropriate relational data to build continuous trans-scalar networks from global to local, and put cities in open networks for research, (2) to enrich the contents of city network research with new methods and techniques, (3) to pay attention to the internal mechanisms of evolution and formation of the interurban network

1.2 Research questions and research objects

1.2.1 Research questions

Based on the research background, this thesis takes China’s IKCNs as the research objects and focuses on two basic questions: (1) What are the “structural features” of the evolution of China’s IKCNs at different spatial scales? (2) What are the “influencing mechanisms” of the evolution and formation of China’s IKCNs?

1.2.1.1 Spatial and topological structures of the IKCNs

The "structural features" of the IKCNs are the first research question of this thesis. Specifically, the "structural features" of urban knowledge collaboration networks include "spatial structures" on one hand and "topological features" on the other hand (Ter Wal and Boschma, 2009). First, the examinations of "spatial structures" of the KCNs focus on the projection and embeddedness processes of the networks in geographical space, including organizational forms, geographical configurations and hierarchical orders of the urban system in networks, as well as the positions and power of individual cities in networks. Second, the examinations of "topological features" of the KCNs mainly focus on the "overall network properties" and "ego network properties". The former aims to investigate the "small-world" properties, "scale-free" properties, "global efficiency", "core-periphery structure", "center-hinterland structure", etc. The latter is mainly designed to inspect "centrality", "power" and "connection dimension", etc. (Phelps et al., 2012).

What needs to be emphasized is that the "spatial scale" is the geographical reference for examining the "structural features" of the IKCNs as well as the main logical thread of the empirical framework of this thesis: (1) At global scale, the main goal is to investigate the structural features of transnational knowledge collaboration networks and global interurban networks. Besides, further attention is payed to China and its major cities, especially their differences with other countries/cities. (2) At national scale, the main goal is to explore the structural features of the IKCNs of China. (3) At regional level, the main goal is to observe the structural features of the IKCNs of different city-regions in China, and compare the differences of structural features of the IKCNs within three major city-regions, i.e. the Yangtze River Delta city-region, the Beijing-Tianjin-Hebei city-region and the Guangdong-Hongkong-Macao Great Bay Area city-region.

1.2.1.2 **Macro- and micro-influencing mechanisms of the formation of IKCNs**

The "influencing mechanisms" of the evolution and formation of China's IKCNs is the second research question of this thesis. The formation of the IKCNs is the micro actor of innovation in cities, that is, the integration of the process of the interactions among researchers or organizations, and the process of selecting their collaborative partners is not random, therefore the KCNs present specific structures and forms. The representations of the IKCNs are embodiments of the collaborative behaviors of the actors involved. (Knoben and Oerlemans, 2006). The initiatives and incentives of collaborative practices are not random, they are, to a large extent, shaped and constrained by both macro and micro contexts. The former denotes the macro-external factors, such as globalization trends, institutional settings or local contextual embeddedness etc., that externally influence the specific trajectories of social practices. The later refers to the micro-internal factors, such as economic rationality, transaction costs trade-offs and preferential interests etc., that internally determine the behavioral logic of individual actors.

First, at the macro level, structural factors, such as scientific research paradigms, collaborative appeals, local resource endowments, socio-economy backgrounds and institutional arrangements indirectly but profoundly influence the collective behavior of actors in their social practices. The collaborative networks formed by actors are embedded in and attached to this structural social context. Therefore, exploring these external macro-structural factors is of great significance for understanding the formation of the IKCNs.

Second, at the micro level, knowledge collaboration can be seen as a social behavior by nature, the collaborative behavior is thus a certain type of rational economic behavior. In the processes of searching partners, establishing and maintaining collaborative relations take money and time, the stable and efficient collaborations between different actors only can be found when benefits are higher than costs. From this perspective, studying the behavioral logic and trade-off process of actors in the course of collaboration are the keys to deeply understanding the underlying organization process of the KCNs.

In summary, this thesis will exam the "influencing mechanisms" of the evolution and formation of China's IKCNs from the both macro and micro perspectives.

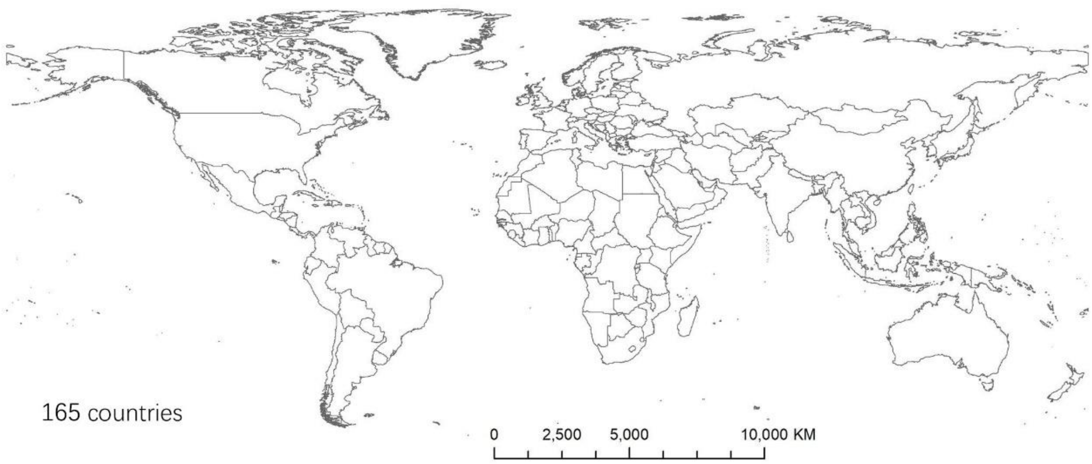
1.2.2 Research objects

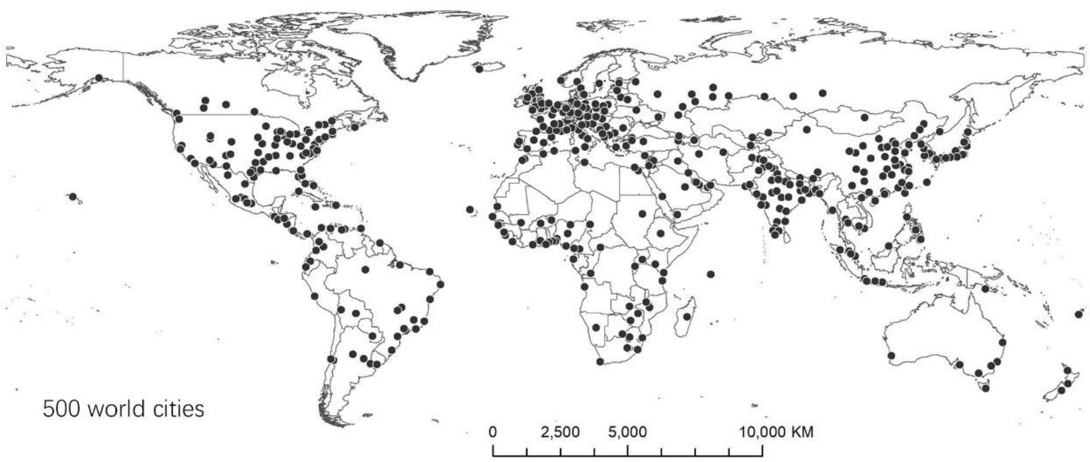
1.2.2.1 Spatial dimensions

Firstly, as shown in Figure 1-1. the spatial dimensions of the research on the structural features of the KCNs range from global to national and regional scales. (1) On the global scale, the basic units are "countries" and "cities" for transnational and global IKCNs respectively. The former includes 233 sovereign countries and regions, while the later includes 500 cities worldwide, and the selection of cities in line with the research on world city network that being conducted by Globalization and World City research group (GaWC) (Taylor and Derudder, 2015).[1] Among them, there are 44

1 Taylor and Derudder selected cities with the population of more than 1.5 million, and capitals with population more than 1 million (based on 2008 demographic data). The selected cities mostly are important cities such as capitals, economic centers and administrative centers of each country.

Chinese cities including all capital cities and some economically advanced cities.（2）On the national scale, 217 prefectural-level cities or above are selected as the research objects.（3）On the regional scale, 20 city-regions are selected as the research objects, including 5 national-level city-regions (Yangtze River Delta city-region, Beijing-Tianjin-Hebei city-region, Guangdong-Hong Kong-Macao Greater Bay Area city-region), and 8 regional city-region (Central South city-region, Shandong Peninsula city-region, West Coast of the Taiwan Straits city-region, Harbin-Changchun city-region, Central Plains city-region, Guanzhong city-region, Guangxi Beibu Gulf city-region, North Slope of Tianshan Mountain city-region), and 6 local city-regions (Central Shanxi city-region, Hohhot-Baotou-Ordos city-region, Central Yunnan city-region, Central Guizhou city-region, West Lanzhou city-region and Ningxia Yanhuang city-region) and East Coast of the Taiwan Straits city-region.





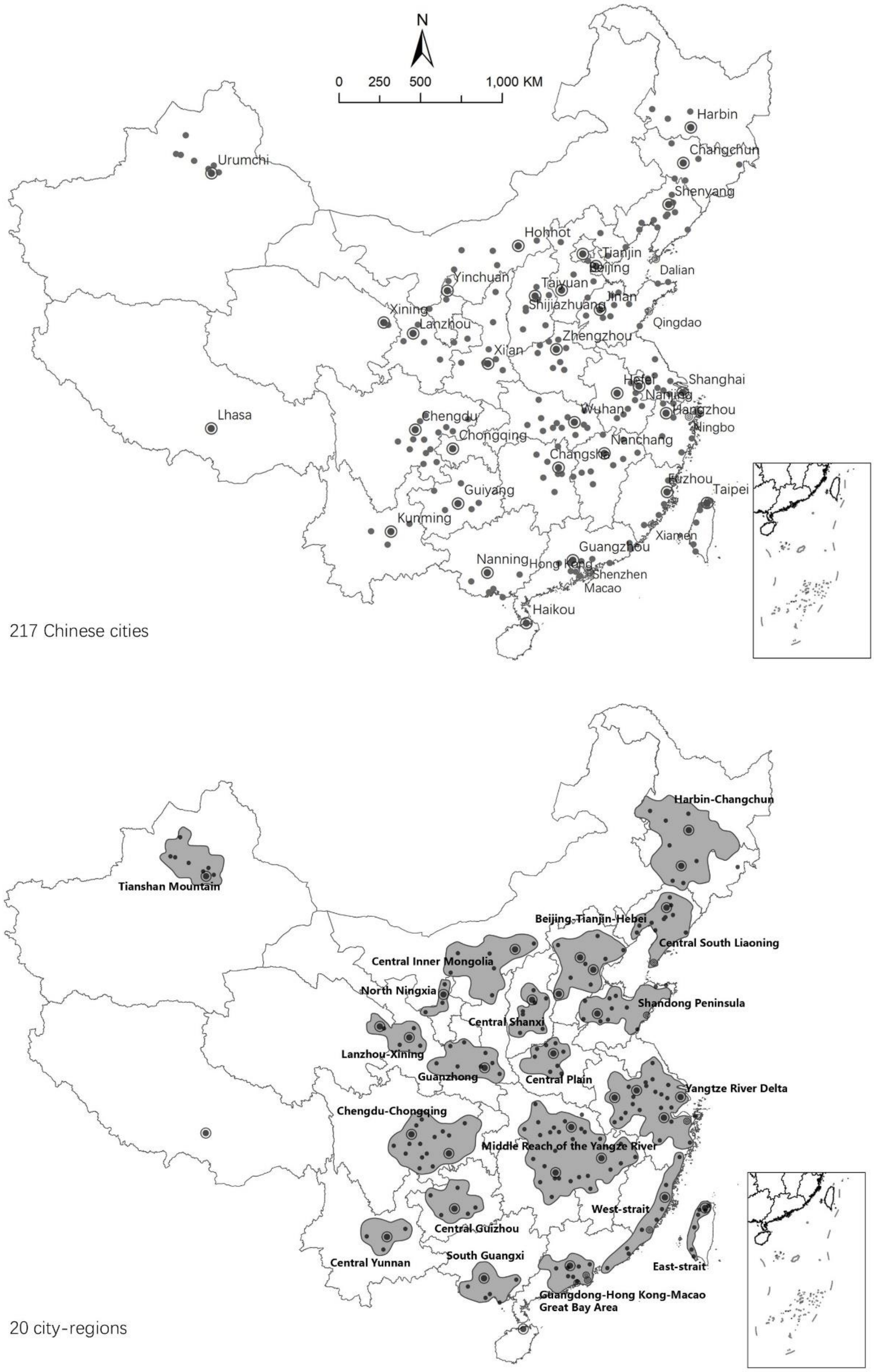


Figure 1-1 Spatial dimensions of the research

Source: author

1.2.2.2 Time dimensions

About time dimensions, it needs to be emphasized that there is “time lag” effects existing in scientific research or any other R&D activities. Specifically, there is a “lag” between the actual innovation activities and innovation output. which might lead to fluctuations of yearly output. Besides, this “time lag” effect becomes more apparent as the spatial scale gets degraded. In line with the existing literature, the time dimensions of transnational collaboration networks range 3 cross-sections of 1995, 2005 and 2016. For studies on interurban collaboration network across different spatial scales, a 5-year moving window are applied to minimize the lag effects. More specifically, two consecutive 5-year periods of 2002-2006 and 2012-2016 are designated, and the data of each cross-section are aggregated by raw data of 2002-2006 and 2012-2016 respectively.

Table 1-1 Time dimensions of the research

Spatial scales	Time dimensions	Research objects
Global scale	1995、2005、2016	233 sovereign countries and regions
Global scale	2002-2006, 2012-2016	500 cities worldwide
National scale	2002-2006, 2012-2016	217 prefectural-level or above cities in China
Regional scale	2002-2006, 2012-2016	20 city-regions in China

Source: author

1.3 Research framework

1.3.1 Research contents

This thesis is organized as follows:

The first part (Chapter 1-3) includes research background, literature review and research design. In Chapter 1, under the context of knowledge-based economy and the need of innovation-driven development, the significance and necessity of studying the IKCNs are put forward. Further, two main research questions are proposed: What are the “structural features” of the evolution of China’s IKCNs at different spatial scales? (2) What are the “impact mechanisms” of the evolution and formation of China’s IKCNs? In Chapter 2, the existing literature centered on the geography of innovation is systematically reviewed, the KCNs and city network research paradigm. In Chapter 3, the main hypotheses are proposed, and the data and methodology are introduced and the empirical framework is built.

The second part (Chapters 4-8) is the main body of the empirical examinations. First, in Chapters 4-7, the “spatial structures” and “topological features” of the IKCNs at different spatial scales are investigated. In Chapter 4, countries are taken as basic units and the evolution of the transnational KCNs is examined, and the emphasis is laid on China's network features, which provides the macro context for the following research. In Chapter 5 the evolution of the IKCNs of 500 cities around the world is examined and more attention is paid to Chinese cities. In Chapter 6, the evolution of China's IKCNs of 217 cities is analyzed. In Chapter 7, the evolution of the IKCNs of 20 Chinese city-regions is discussed. In addition, the evolution of the IKCNs of the Yangtze River Delta city-region, the Beijing-Tianjin-Hebei city-region and the Guangdong-Hong Kong-Macao Greater Bay Area city-region is compared and analyzed. in Chapter 8, the underlying mechanisms of the evolution and formation of the IKCNs are explored from both macro and micro aspects.

The third part (Chapter 9) provides an inductive overview and comprehensive explanation of the evolution of China's IKCNs. Further, some policy implications are proposed.

1.3.2 Research framework

The research framework is as follows (Figure 1-2):

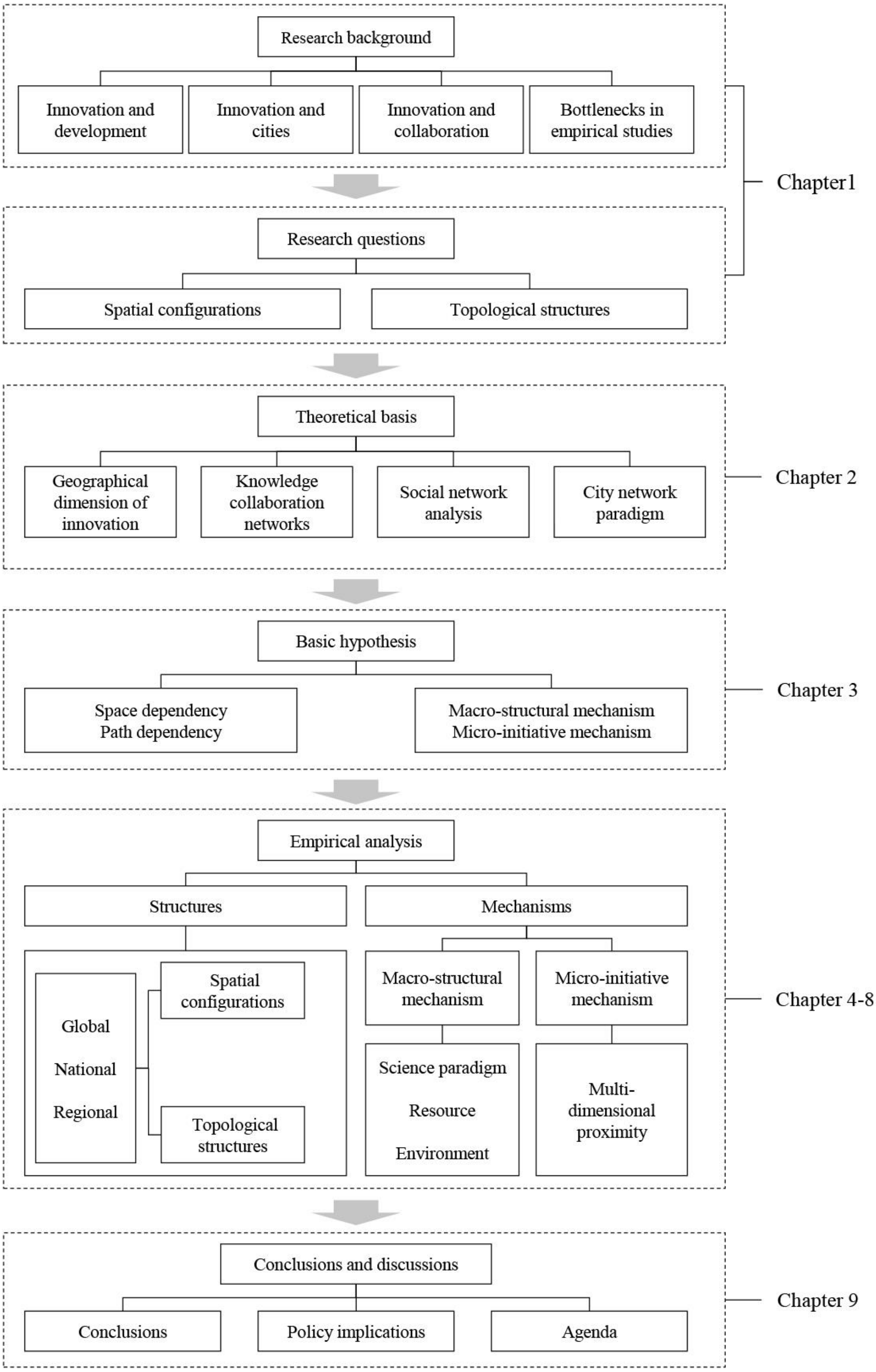


Figure 1-2: Research framework

Source: author

Chapter 2 Literature review

2.1 The territorial embeddedness and network embeddedness of innovation process

2.1.1 The geographical dimensions of the innovation process

In the field of economic geography, the “Regional Innovation System” is one of the earliest theories on the geographical connotations and spatial attributes of the innovation process. This concept, initially proposed by Professor Cooke（1992）of Cardiff University, refers to a regional system within a certain geographical boundary characterized by territorial embeddedness, within which firms, higher education institutions and public research institutions are inter-connected with specialization and synergy. A regional innovation system encourages the rapid diffusion of knowledge, skills and know-how, which in turn boost innovation. With regard to the definition of “region”, Cooke and Schienstock (2000) and Cooke (2001) have respectively put forward two definitions: in the first definition, the region is described as geographical space with clear boundary (generally the administrative boundary) featuring self-organizing and specific functions. It refers to one country, one city-region, one city or one specialized cluster. In the second definition, more stress is laid on the non-spatial but intangible region-specific elements, such as social capital, institutional arrangement and cultural belonging, which have significant impacts on innovation performance of cities.

It should be pointed out that unlike the perception of innovation in economics and sociology, regional innovation theory particularly focuses on the geographical and spatial dimension of innovation process. Firstly, the production and collaboration of knowledge hinge on spatial agglomeration. Agglomeration provides actors with more possibilities of face-to-face interactions, which can facilitate exchange of knowledge and information, In turn, it also encourages innovation; Secondly, the fact that the territorial embeddedness created by the spatial agglomeration fosters place-specific relational assets, within which actors share similar values, routines, culture and mutual trust. These local assets are embodied as social networks which is of importance for knowledge diffusion and production (Asheim and Gertler, 2005; Asheim and Isaksen, 2002; Gertler, 2001).

2.1.2 The organization of innovation network

The core of the regional innovation system theory and its analysis framework is to emphasize the interactions between different actors, i.e., innovation networks, especially the interactive behaviors of individuals and organizations actors like study, cooperation and alliance. (Cooke, 1996; Cooke and Morgan, 1993; Zeng et al., 2018; Lian, 2016; Lu, 2014b; Miao and Wei, 2007; Yan et al., 2018; Zou et al., 2018). However, in the current research on regional innovation systems, the definition of "innovation network" is still relatively vague. The research on "network behavior" between actors is rather limited—much research is on the basis of case studies that discuss the organizational process of innovation activities between different institutions and its coupling paths to the local institutional context. Generally, these studies have fallen into two main streams: micro perspective and macro perspective. The former focuses on the interaction between several or a small number of key actors in a certain region/agglomeration, (Asheim and Coenen, 2005; Murray, 2002) but falls short of analyzing the overall network structure of the region (Stuck et al., 2016). The latter one though stresses more on the overall social network context of a certain region, but still limited to local activities of actors. (Dicken and Malmberg, 2001). Relatively few studies involve the overall structure of innovation network and their networking processes (Grabher, 2006). Ter Wal and Boschma (2009) argue that these two analytical frameworks have obvious limitations both in theoretical evolution and empirical support. First, they failed to grasp the whole picture of network process of the actors in the regional innovation system, namely, the direct or indirect social relationship between them (Stuck et al., 2016). Second, a considerable number of studies on regional innovation systems focus on analyzing specific cases, and tend to pay much attention on geographical proximity and regional institutional contexts (Asheim, 1999). However, the topological structure of knowledge networks, the underlying processes of knowledge spillovers and creation in innovation networks and also the impacts of networks on regional innovation system are rarely discussed (Giuliani, 2007a, 2009; Ter Wal and Boschma, 2009; Yan et al., 2018; Zou et al., 2018).

Stuck et al. (2016) state that social network analysis based on complex network theory is absent in the early research on regional innovation system. In fact, at the incipient stage of conceptualization of the regional innovation system, Cooke (1996) also put forward the term of "regional innovation network". He points out that regional innovation network is the key support for the running of regional innovation system. The regional innovation network in its essence is the processes of social construct of actors in regions or the networking processes of social relationships (Cooke, 2002). Pyka (2002) believes that regional innovation network plays a vital role in maintaining the operation, development and evolution of regional innovation system. Its main functions include, leveraging the collective advantages of network members, reducing the R&D costs of individual actors and providing thick social assets for actors. More importantly, it can regulate, control and supervise the behaviors of actors in complex innovation processes, in order to reduce risks and uncertainties and further to maximize the opportunities of innovation.

2.1.3 Trans-scalar nature of innovation networks

Si et al. (2016) argue that the research on innovation network in human and economic geography can be divided into local approach and global approach: one is the "new regionalism" genre that is in line with industrial districts and agglomeration economy theories and focuses on local industrial clusters and the local innovation system. This approach focuses on the formation and function of regional embeddedness, institutional thickness and local relational assets in the process of knowledge exchange and production (Asheim, 1999; Cooke, 2001; Storper and Venables, 2004a). The other is "relational economic geography" with the global production network and the global innovation network as its core. This approach takes globalization as its analysis background, and put more emphases on the division of labor and collaboration in the transnational and trans-regional production systems, as well as collaborative innovation produced within them (Coe et al., 2004; Dicken et al., 2001; Gereffi, 1996). Maskell and Malmberg (1999), Scott and Storper (2003) agree that although innovation depends on local assets, overly thick relational assets will lead to detrimental path dependency and regional lock-in. Therefore, in order to sustain the development of regional innovation network, it is necessary to continuously update the old relational assets and break the rigid social network structure. Globalization provides opportunities for the reconstructing regional innovation networks: via accessing into transnational networks, actors can acquire new knowledge and market information from other regions, thus it could make adjustments to ensure sustainable competitiveness (Asheim and Isaksen, 2002; Lechner and Dowling, 2003; He, et al., 2018; Si et al., 2016).Thus, it is of great importance to fully understand the interactive processes between local networks and global networks (Castells, 1996; Swyngedouw, 2004; Cao and Zeng, 2018; Miao, 2006; Si,et al., 2016).

Bathelt et al. (2004) established a conceptual model of "local buzz" and "global pipelines". On the basis of clarifying the dialectical relationship between globalization and localization, they pointed out that the process of regional innovation depends not only on local innovation milieus but also on the stable collaboration partnership in other innovation regions. "local buzz" refers to knowledge exchange and interactive learning among actors in clusters, cities or regions through face-to-face communication, contacts and meetings on a daily basis which literally resembles buzzing bees. This concept is essentially in consistent with the conceptions of "relational assets" (Scott and Storper, 2003), “untraded interdependencies” (Storper, 1995) and the “innovation milieu” (Capello, 1999). “global pipelines” refer to a long-distance channel that convoys knowledge spillovers and exchange among actors in different places. Bathelt explicitly emphasizes the importance of establishing a “global pipelines”: in spite of the huge cost, they, once effectively established, can introduce new knowledge and market information into local clusters so as to avoid the lock-in.

Bathelt also points out that the interaction between “local rumors” and “global pipelines” do not absolutely secure sustainable development in the region. The imbalance between them will still pose a threat to regional development. For example: (1) overly dense “local buzz” will breed information overload which increases the cost of searching for effective information and undermines the establishment of “global pipelines”[2]; (2) too many strong “global pipelines” will weaken the flexibility and self-organizing of “local buzz” and could be harmful for the formation of local innovation milieu[3].

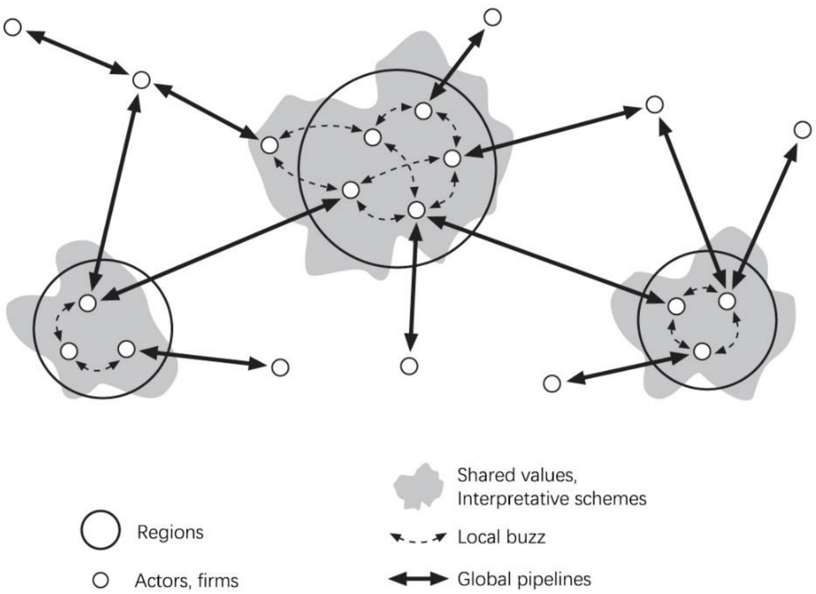


Figure2-1 “Local buzz” and “global pipelines” dynamics
Source: Bathet (2007)

2 For instance, the Swiss watch industry has formed a fairly profound “local buzz” system due to its long-term historical accumulation. However, such overly dense local industrial environment throws the local watch industry into a great crisis from 1970 to 1980-because it was too self-enclosed and thus ignored the revolutionary impact of electronic technology applied in the watch industry. This crisis was gradually lifted until the “global pipelines” were established, so that the internal institutional arrangements were adjusted in time.

3 For instance, large multinational firms set up factories in Southeast Asia countries where the industrial bases are weak. The dominance of these multinational firms in resource allocation and production technology often adversely affect the local industrial environment and then destroy local production systems; or under the control of multinational corporations, the local industrial chain and production system are changed, gradually obey their input-output arrangements, get limited to the situation of providing basic raw material or preliminary product supply , and eventually the local production system will suffer a structural lock-in.

Liefner and Hennemann (2011) point out that the innovation capabilities and development paths of regions are the outcome of the interaction between local networks and global networks. they particularly stressed on that the characteristics of knowledge spillovers and production in local knowledge networks are closely related with their positions in the global knowledge networks. Based on this argument, they divided the regions into four different types (figure 2-2). The first type is the “knowledge-access” regions. As gateways or hubs in the global innovation network, such regions with both high-quality “global pipelines” and dynamic “local buzz” can acquire external knowledge efficiently, meanwhile, quickly spread the external knowledge within the local region, enormously driving the overall innovation ability of the region. The second type is “knowledge gateway” regions. Although having “global pipelines”, such regions can barely develop well because of being less embedded in local innovation networks and less efficient in diffusion of external knowledge. The third type is “bypassed” regions. Although it enjoys strong innovation ability and efficient innovation network, there is a risk of regional technological lock-in with the absence of the key “global pipelines”. The fourth type is “peripheral” regions which do not have highly active “local buzz” and high-quality “global pipelines”, and therefore the overall innovation capacity and competitiveness in such regions are rather limited.

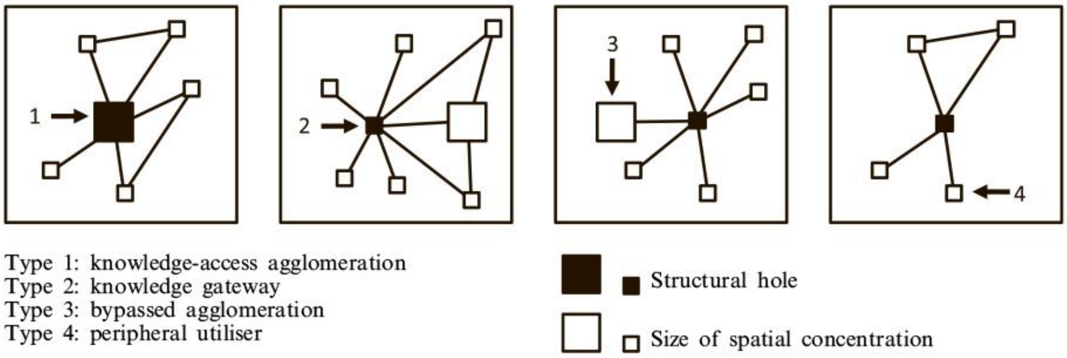


Figure2-2 Typology of spatial concentrations in knowledge networks
Source: Liefner and Hennemann (2011)

Si et al. (2016) proposes the concept of “global-local innovation network”. They stress that the global-local innovation network is not a simple aggregation of innovation networks in different regions. Instead, they should be regarded as a whole at first, and the growth and each regional innovation system needs to be discussed in a broader picture of national and global innovation network. Miao and Ai (2009) propose an analysis framework of “learning field” based on the “technology-organization-region” trinity model proposed by Storper (1997). They particularly emphasize that the regional innovation processes are interactive learning processes between different regional innovation networks across different geographical scales.

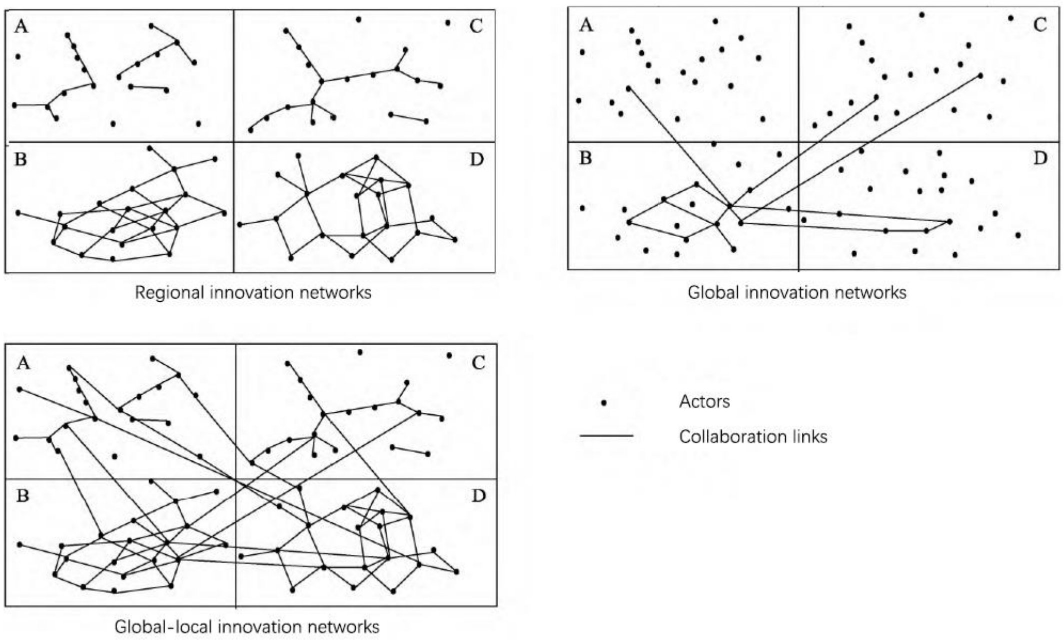


Figure2-3 Comparison of regional innovation system, global innovation network and global-local innovation network

Source: Si et al (2016)

2.2 Knowledge, knowledge networks and knowledge collaboration networks

2.2.1 Knowledge

Knowledge is the foundation of innovation and the key competitiveness of innovation actors (Phelps et al., 2012). Different types of knowledge determine and influence the mechanisms of knowledge creation and diffusion. Thereby the structural features, evolution process and spatial configuration of knowledge networks are shaped. Polanyi (1967) was the first to explore the types of knowledge and divided it into two types: explicit knowledge and tacit knowledge[4] (Table 2-1). Explicit knowledge refers to objective and rational knowledge that can be recorded, expressed and diffused via language, words, symbols and images. It can be documented and codified in paper trails, so some scholars also term it as "codified knowledge" (Foray and Lundvall, 1996). This type of knowledge is usually produced and spread in the forms of product appearance, recorded files, databases, books and computer coding. It has less adherence to the

[4] It had also been have translated into "intangible knowledge" or "silent knowledge" by some scholars.

knowledge owners and is not strongly bounded within local institutional contexts. Therefore, codified knowledge can, to some extent, disseminates beyond time and spatial boundary (Asheim and Isaksen, 2002; Gertler, 2008; Gertler and Levitte, 2005). Conversely, tacit knowledge usually refers to knowledge that cannot be disseminated in a coded form, which resembles the concept of know-how in industrial district theory. This type of knowledge is strongly embedded in regional or local contexts: its production, acquisition and diffusion processes often highly depend on spatial agglomeration and face-to-face communication (Gertler, 2003; Gertler and Wolfe, 2004).

Table 2-1 Characteristics of coded knowledge and tacit knowledge

feature	Coded knowledge	Tacit knowledge
Form of expression	Various	Single
Ways of exchange	Formal	Informal
Diffusion difficulty	Easy	Relatively hard
Geographical scale	Global	Local/region

Source: Cao et al. (2016)

Bathelt et al. (2004) argue that codified knowledge and tacit knowledge are not two opposite concepts. They state that both codified and tacit knowledge can be disseminated at local and global scales in some cases. He stresses the success of regions, to a large extent, depends on their capabilities to absorb and integrate these two types of knowledge. Similarly, some scholars such as Ashiem believe that there is no absolute codified knowledge or absolute tacit knowledge. These two can be mutually transformed. The scholars divided knowledge into analytical, synthetic and symbolic types in terms of creation patterns, expression forms and spatial dimensions (Table 2-2). They believed that different knowledge exists in different places and their discrepancies also reflect the different development paths of different regional innovation systems.

Table 2-2 Three types of knowledge

	Analytical	synthetic	symbolic
Importance	Importance of scientific knowledge often based on deductive processes and formal models	Importance of applied, problem related knowledge (engineering) often through inductive processes	Importance of interpretation, creativity, cultural knowledge, sign values, implies strong context specificity
Goals	Developing new knowledge about natural systems by	Applying or combining existing	Creating meaning, desire, aesthetic qualities, affect,

	applying scientific laws; know why	knowledge in new ways; know how	intangibles, symbols, images; know who
Production	Collaboration within and between research units	Interactive learning with customers and suppliers	Learning by doing, in studio, project teams
Representations	Patents, publications, documents	Skills, inspirations, way of thinking	Films, TV shows, art work, design
Codified/tacity	Strong codified knowledge content, highly abstract, universal	Partially codified knowledge, strong tacit component, more context specific	Reliance on tacit knowledge, craft and practical skills and search skills
Spatial dimension	global	Global and local	local

Source: Asheirn (2007), Asheim and Coenen (2005), Moodysson et al. (2008)

Zou (2018) further divided the codified knowledge into basic knowledge and applied knowledge according to the characteristics of the research actors in innovation networks. Basic knowledge refers to the knowledge from non-profit organizations like universities and research institutions aiming to discover and create new knowledge. In many cases, this kind of knowledge cannot be quickly transformed into products with commercial and productive value, but mainly in the forms of scientific papers. On contrary, applied knowledge is mainly generated by the profit-oriented enterprises. This kind of knowledge is produced to be applied into technical research or to meet the demand of market products and services, usually in the forms of patents or new products.

2.2.2 Knowledge Networks

Knowledge creation and knowledge flow are core issues in industrial district theory, innovative milieus theory and regional innovation systems theory (Capello, 1999; Cooke, 1992; Drucker, 1969; Storper, 1992). Since Drucker (1969) proposed the concept of "knowledge economy", it have been confirmed by a large number of studies that both the development of global and that of local economies increasingly rely on intensive knowledge production, diffusion, absorption and application (Powell and Snellman, 2004). Knowledge and innovation have become the core variables in maintaining economic growth, preventing technological lock-in and middle-income traps for cities, regions and even countries (Porter, 1996, 1998). In economic geography, studies on regional innovation and knowledge spillovers can be roughly divided into two schools. The first school takes the neo-classical economies as their theoretical foundation, and the knowledge production function as their empirical framework to explore the influencing variables affecting the innovation performance and evolutionary paths of regions (Autant-Bernard, 2012; Basile and Mínguez, 2018; Jaffe, 1989). Under this framework, regional knowledge investments such as R&D expenditure, human capital and technological foundation are deemed as determinate factors in regional knowledge output. Additionally, geographical proximity is deemed as an important factor in facilitating the knowledge spillovers. The measurements based on spatial weight matrices are widely used in this research. However, some scholars point out that regional innovation capability and knowledge output do not solely depend on local inputs and endowments but also on knowledge spillovers from other regions. This is because the knowledge spillovers are not geographically restricted. Trans-regional and even transnational knowledge diffusion and spillovers are very important in maintaining competitiveness and sustained development of regional innovation systems (Bathelt et al., 2004; Hoekman et al., 2010; Hoekman et al., 2009). In view of this, the second type of research began to focus on network factors, especially the important role of knowledge networks plays in the processes of regional innovation and knowledge production (Araújo et al., 2018; Autant-Bernard et al., 2007b; Boschma and Ter Wal, 2007; Maggioni and Uberti, 2011; Wanzenbock et al., 2014).

New knowledge derives from creative integration of existing knowledge that unevenly distributed among different actors (Fleming, 2001). Phelps (2010) define a knowledge network as a set of nodes—individuals or higher-level collectives that serve as heterogeneously distributed repositories of knowledge and agents that search for, transmit, and create knowledge—interconnected by social relationships that enable and constrain nodes' efforts to acquire, transfer, and create knowledge. Phelps et al. (2012) further point out that knowledge networks are coupled with the social networks, and the structure of the social network is of importance in shaping the patterns of knowledge diffusion, interaction and creation among actors in a certain community. Therefore, prior to understanding innovation, the structural representation, organizational process and internal mechanism of knowledge networks should be understood first, which is the key to further understand the development paths of regional innovation systems (Owen-Smith, 2006; Powell et al., 1996; Reagans and McEvily, 2003)

2.2.3 Knowledge Collaboration Network

Singh (2005) points out that collaboration is the main channel for knowledge spillovers and also the formation of knowledge networks. The underlying mechanism of knowledge network formation is the direct or indirect collaboration activities between actors, which can bring benefits to network members (Powell et al., 1996; Powell et al., 2005). The formation of knowledge network is coupled with the processes of partner selection, collaboration or break collaboration. Wang et al. (2014) and Xie et al. (2018) argued that knowledge networks and the KCNs are somehow decoupled. They believe that the individual innovation process is rooted in the collaboration network and the knowledge network at the same time. The collaboration network is a social network weaved by researchers or institutions, while the knowledge network is composed of different but related knowledge elements or bases. With different structural features, these two different types of networks have different effects in stimulating individual innovation. Nevertheless, Wang et al. (2014) also emphasize that the integration processes of different knowledge elements in knowledge networks require the social networks between actors as the carriers. In a word, the KCNs and innovation are inextricably linked. And seeking for collaboration increasingly matters for innovation actors as knowledge innovation has become more complex, more competitive with higher costs and risks (Powell et al., 1996; Teixeira et al., 2008). Table 2-3 shows the main reasons and motivations for innovation actors to collaborate and access to knowledge cooperation networks.

Table 2-3 The main motivations for involvements in knowledge collaboration

Incentives	Descriptions
Complexity of technological development	Access to new technological knowledge and to complementary technologies, which allow for different research lines to be followed
	To achieve scale and scope economies and to respond rapidly in the marketplace despite technological uncertainty
The reduction and sharing of uncertainty and costs	Alliances as a mechanism of intermediate governance between the market and the hierarchy. The more complex the available technology, the more inefficient the market, as the place in which firms can acquire the necessary knowledge and technology
	The possibility of acquiring and internalizing the abilities and competencies of partners, so as to create new valid competence for the firm
	By combining their efforts, firms can reduce the uncertainty derived from the expected result not being obtained, not appearing with sufficient speed, or requiring more financial or technological funds than were originally expected and increase the possibilities of obtaining a positive result
	The probability of an innovation achieving success also depends on aspects such as the complementarity of the resources and the increase in R&D investments, which is favored by cooperation
Market access and the search for opportunities	As demands, preferences and needs of consumers change at great speed, the excessive period of time that may pass between the invention of the product and its final appearance on the market also implies a high risk for the firm and thus one objective is to shorten it
	Help to avoid the duplication of unnecessary R&D efforts and to achieve scale economies

	To absorb the knowledge and abilities which they lack, and which is represented by the tacit knowledge of their partner, that is to say, its know-how, both in the area of technology and in other spheres
	The aim of extending the range of products, or substituting those that already exist because they are found in mature sectors
	Access to larger domestic and foreign markets, thereby improving their expectations of recovering the investment
	The standardization of products or processes, aimed at excluding possible competitors by implementing a strategy based on differentiation or cost advantages that will act as a barrier to the entry of new firms in the sector

Source: Teixeira et al. (2008)

In a nutshell, innovation is the engine to improve the overall economic performance and sustain long-term development for organizations, regions and countries. The generation of new knowledge depends on the integration of existing knowledge. However, knowledge is distributed unevenly across places, and different places possess heterogenous knowledge. In the processes of innovation, knowledge networks act as channels for knowledge diffusion and integration across different geographical entities and embodied as “buzz” and “pipelines” (Bathelt et al., 2004). Meanwhile, the knowledge networks are embedded in the social networks which formed and maintained by direct or indirect collaborative activities between actors (Wanzenbock et al., 2014). Engagements in the KCNs not only can benefit actors themselves, but also have a positive effect on the overall innovation capability of the region (Asheim and Isaksen, 2002; Zeng et al., 2018).

2.2.4 Construction of the KNCs

Knowledge, especially tacit knowledge, remains as an intangible asset that can hardly be quantified and measured, so are the KCNs. There are four main approaches to measure the KCNs in existing literature: the scientific research collaboration networks extracted from co-authored publications, the technological collaboration networks drawn from co-invented patents, the joint R&D research network derived from R&D collaboration projects, and the collaboration network attained by field research (mainly interviews and surveys) on certain collaborative activities (Lata et al., 2015; Scherngell and Barber, 2011; Wanzenbock et al., 2014).

The KCNs built by co-authored papers mainly reflect the academic knowledge exchange and creation. The collaboration purpose is to achieve academic value of new knowledge in certain specialized fields (Ponds et al., 2007). The KCNs are built in accordance with the co-appearance of authors, institutions, cities and countries in a paper. The hypothesis of such network construction logic is that the co-authored papers can somewhat reflect the formal collaborative relations between actors, which embodied as formal publications (Ponds et al., 2009; Ponds et al., 2007). This approach is adopted in this thesis.

The KCNs built by co-invented patents mainly reflect the collaboration of technological knowledge. This kind of collaboration pays more attention to the commercial value new knowledge and is more exclusive in comparison with the scientific collaboration network (Maggioni et al., 2007). Similar to scientific collaboration networks, the joint applications for patents can also reflect knowledge exchange between the actors, so that can be widely used in construction of the KCNs (Ter Wal and Boschma, 2009).

The wide use of above-mentioned two network construction techniques is because they cannot only reflect the real KCNs, but also enjoy the advantages of openness, accessibility and richness in data mining. Many professional scientific paper index databases and patents query databases provide scholars with abundant data sources. The widely used open-access scientific paper databases include Web of Science of Thomson Reuters, Scoupus of Elsevier, as well as Chinese databases like “CNKI”, “Wanfang” and “Cqvip”. Frequently-used patent databases include European Patent Office (EPO), United States Patent and Trademark Office (USPTO) and National Intellectual Property Administration (NIPA) of China. More importantly, these databases also provide detailed information that is useful for the construction of the KCNs. Taking Web of Science as an example, apart from basic information like the title, abstract, citations, authors, it also systematically records the scientific fields of the papers, the authors’ affiliations and their detailed addresses, etc. This provides great convenience and flexibility for the construction of the KCNs. Besides, since the databases of scientific publications and inventive patents are huge, the use of such data can make it possible to construct multi-scalar KCNs.

The third approach of the KCNs construction is based on the joint R&D network such as government-funded research projects and enterprise-led joint R&D projects. Such knowledge collaboration may produce both the basic knowledge and the applied knowledge (Lata et al., 2015; Scherngell and Barber, 2011; Wanzenbock et al., 2014). Lata et al. (2015) investigate the European Framework Programme and point out four characteristics of project-based KCNs: First, the actors involved are diverse, including individuals, companies, universities and other non-profit research institutions. Second, the research mostly centers on presumptive[5] scientific research projects. Third, the incentives of collaboration are less market-oriented. Fourth, the collaboration projects have long-term cycles.

The fourth approach to build the KCNs is based on qualitative surveys, such as interviews and field research. By applying this approach, one can capture more details in the process of knowledge spillovers and generation within the KCNs. For example, by using questionnaires, Huggins et al. (2012) investigates the businesses KCNs of different regions, i.e. North England region, Thessaloniki region in Greece and Istanbul region in Turkey. He finds that collaboration networks have a significant positive effect on regional innovation performance, and the regional contexts also profoundly affect the structural features and evolutionary paths of the knowledge collaboration network. Huber (2012) constructs an interpersonal knowledge collaboration network through interviewing professionals in the Cambridge IT industrial clusters and explores the impacts of different dimensions proximity on innovation performance. Compared with aforementioned approaches, the sample sizes of such survey-based network construction technique are rather small, which can hardly illustrate the whole picture of the KCNs.

2.3 The application of social network analysis the KNCs research

As mentioned above, the formation and evolution of the KCNs is a social construct by nature. Therefore, the KCNs share some general attributes and characteristics with social networks in common. Many scholars suggest that the relevant theories and techniques of social network analysis (SNA) can provide new ideas and analytical frameworks for studies of regional innovation systems and the KCNs (Durugbo et al., 2011; Muller and Peres, 2018; Stuck et al., 2016; Ter Wal and Boschma, 2009; Yokura et al., 2013).

There are three propositions need to be focused when applying SNA to knowledge collaboration networks research. The first proposition relates to the structural features of networks , including the overall topological properties of the knowledge collaboration network, the status and centrality of the network members and their impacts on innovation performance of regions and the actors within it (Ahuja, 2000; Muller and Peres, 2018; Reagans and McEvily, 2003; Ter Wal and Boschma, 2009).

The second proposition focuses on the dynamics and evolution of regional innovation networks, as well ason exploring the mechanisms that influence the evolutionary paths of the networks (Boschma and Frenken, 2010; Glückler, 2007; Ter Wal and Boschma, 2009; Ter Wal, 2009). The third proposition emphasizes the spatial dimensions of the KCNs: on one hand, it is imperative to explore the relation between network and space, i.e., the territorial embeddedness of the local and trans-local KCNs (Asheim and Isaksen, 2002; Maggioni and Uberti, 2011); on the other hand, it is important to explore the interactions between different scales of KCNs, in another word, the interactions between "local buzz" and the "global pipelines" and their impacts on regional innovation performance (Bathelt, 2007; Bathelt et al., 2004).

2.3.1 Social Network Analysis and the KNCs

Social network analysis (SNA) was first proposed by sociologist Barnes based on the early quantitative studies of psychological research in US during the 1930s (Barnes, 1954, 1969). SNA is designed to examine the structures, evolution processes and driving mechanisms of social networks on the basis of complex network theory and graph theory. It characterizes networked structures in terms of nodes (individual actors, people, or things within the network) and the ties, edges, or links (relationships or interactions) that connect them, and it offers effective tools for molding, visualizing and explaining them. Until now, social network analysis has developed as a key technique in modern sociology. It has also gained significant following in anthropology, biology, demography, communication studies, economics, geography, history, information science, organizational studies, political science, social psychology, development studies, sociolinguistics, and computer science and is now commonly available as a consumer tool (Lin Juren, 2009; John Scott et al., 2007).

Ter Wal and Boschma (2009) point out that SNA has great potential in economic geography and can be applied to at least three research topics, namely, industrial clusters, regional innovation systems and knowledge spillovers[6]. Based on social network theory, Muller and Peres (2018) point out that the topological properties of the KCNs are closely related to regional innovation performance, diffusion and production patterns of knowledge in the networks. They argue that the concepts of "cohesion", "connectedness" and "conciseness" are often used to describe the structural characteristics of social networks are also applicable to testing and evaluating the overall performance of the KCNs. Firstly, the cohesiveness of the network refers to how close the connections between network members are. A network is cohesive if they have characteristics like close collaboration, mutual trust and common relational assets that influence the spread and diffusion of knowledge. Secondly, the network connectedness reflects the topological distance and the strength of connection between the network members. A network is connected if the average network member has a large number of ties, if social hubs (particularly well-connected members) are prominent, and if network distances between members are small. Third, the conciseness of the network is used to describe the number of redundant connections in the network. A network is concise if its level of redundancy is low, i.e., social circles are sufficiently distinct from one another, so that each connection makes a meaningful contribution to the flow of information.

2.3.2 Topological properties of the KNCs

In the SNA analysis framework, the topological features of the networks have three dimensions, namely, global characteristics, node characteristics and dyadic characteristics (Newman, 2003). Firstly, the global characteristics refer to the macro structural characteristics displayed by a certain network. For example, a firm or a village can be seen as a social network, within which actors interact in certain ways and display certain organizational structures. At the same time, the network structure also has an impact on members' behaviors (Liu, 2004). Secondly, the node characteristics are about the position, power and connectivity of a focal network member in a certain network, and the similarities and differences between different network member (Muller and Peres, 2018). Thirdly, the dyadic characteristics mainly focus on the bilateral relation between two network members. This connection determines the interaction between network members and also affects the overall structure of the network (Stuck et al., 2016).

Innovation emerges from interaction and collaboration between diverse actors and hence it is embedded in the formation and evolution of the KCNs (Owen-Smith and Powell, 2004). On one hand, knowledge collaboration network rooted in the social interactions between the innovation actors and is closely related to actors' behaviors and logic. Therefore, the different actors choose their collaboration partners in different ways which in turn display different topological features in the KCNs. On the other hand, the impacts of the collaboration networks on the behaviors, preferences, initiatives and innovation performance of different innovation actors vary. In the same knowledge collaboration network, actors who occupy the center of the network have more advantages in knowledge acquisition and information exchange (Chiu, 2009;

Ozkan-Canbolat and Beraha, 2016; Zaheer and Bell, 2005.; Qian et al, 2010a). In the following text, the global characteristics and individual characteristics of the topology of knowledge collaboration network will be discussed:

2.3.2.1 **Global network properties: network size, network density, small-world network, scale-free network**

(1) Network size / Network density

Network size and network density are basic indicators that describe the overall characteristics of networks. Network size refers to the total number of actors in the network. Network density is a measure of the proportion of possible ties which are actualized among the members of a network. In the KCNs, the network size can reflect the overall size of potential partners and their knowledge pool. The network density can reflect the speed and efficiency of information and knowledge spread and diffusion in the network.

(2) Small-world network / scale-free network

Many complex systems in the real world have the characteristics of complex networks, such as neural networks, the Internet, social networks and engineering power networks (Liu, 2014). Since the late 1990s, the rise and development of complex network theory and SNA have provided theoretical basis and analytical tools for describing, interpreting and simulating real-world complex networks (Kim and Wilhelm, 2008). Prior to this, network science was used to focus on the regular network[7] and the random network[8], however, the topological features of complex networks in the real world are neither completely regular nor random. The *Nature* and the *Science* have respectively published two articles about network science in 1998 and 1999, which are landmarks in this field. One is *Collective dynamics of "small-world"networks*, written by Watts and Strogatz. And it proposed "small-world network" in which most nodes are not neighbors of one another, but the neighbors of any given node are likely to be neighbors

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[7] In the regular network, the connection between any two nodes is subject to specific rules. Complete graphs (or global coupling graphs), star graphs (or star-shaped coupling graphs), neighboring node graphs (or nearest neighbor graphs) are common types of rule networks. For example, any two nodes in a complete graph are connected; there is a center point in the star map, and all other nodes are connected to the center and are not connected to each other. The characteristic path length and clustering coefficient of the rule network are relatively large.

8 The random network, regarded as an opposite extreme of the regular network, first proposed by the mathematicians Erdos and Renyi, so it is also called ER random network (Erdos and Renyi, 1960). In a random network, nodes are connected in a completely random manner. Unlike the regular network, the characteristic path length and clustering coefficient of the random network are relatively small, and the degree distribution comply with Poisson distribution. The ER stochastic network has been considered for a long time to be the best model for describing and interpreting networks in the real world.

of each other and most nodes can be reached from every other node by a small number of hops or steps. The other is *Emergence of scaling in random networks* by Albert and Barabási. And it proposed a "scale-free network" in which the degree distribution follows a particular mathematical function called power-law. It also implies the evolutionary process of complex networks displaying cumulative advantage and the Matthew effect.

The "small-world" of complex networks corresponds with the psychologist Milgram's "six degrees of separation" experiment and the theory that any person can be connected to another on the planet through a chain of acquaintances that has no more than five intermediaries (Milgram, 1967)[9]. This phenomenon suggests two most important characteristics of the interpersonal social network. First, each person's social community has a certain boundary, and people within such boundary are likely to know each other. In topological term, such networks display high clustering coefficients and highly clustered. Second, some "shortcuts" exist between different communities that make strangers in different circles can get acquainted through fewer intermediaries. From the perspective of topological properties, such networks have relatively small "characteristic path length" or "average shortest path"[10]. (Figure 2-4) It is generally believed that networks with small-world characteristics are generally less repetitive and redundant in information spread and diffusion.

[9] The six degrees of separation concept was examined in Milgram's 1967 "small-world experiment, which tracked chains of acquaintances in the United States. In the experiment, Milgram sent several packages to 160 random people living in Omaha, Nebraska, asking them to forward the package to a friend or acquaintance who they thought would bring the package closer to a set final individual, a stockbroker from Boston, Massachusetts. Each "starter" received instructions to mail a folder via the U.S. Post Office to a recipient, but with some rules. Starters could only mail the folder to someone they actually knew personally on a first-name basis. When doing so, each starter instructed their recipient to mail the folder ahead to one of the latter's first-name acquaintances with the same instructions, with the hope that their acquaintance might by some chance know the target recipient. Given that starters knew only the target recipient's name and address, they had a seemingly impossible task. Milgram monitored the progress of each chain via returned "tracer" postcards, which allowed him to track the progression of each letter. Surprisingly, he found that the very first folder reached the target in just four days and took only two intermediate acquaintances. Overall, Milgram reported that chains varied in length from two to ten intermediate acquaintances, with a median of five intermediate acquaintances (i.e. six degrees of separation) between the original sender and the destination recipient.

[10] Characteristic path length means the average length of the shortest path between any two connected nodes in a network.

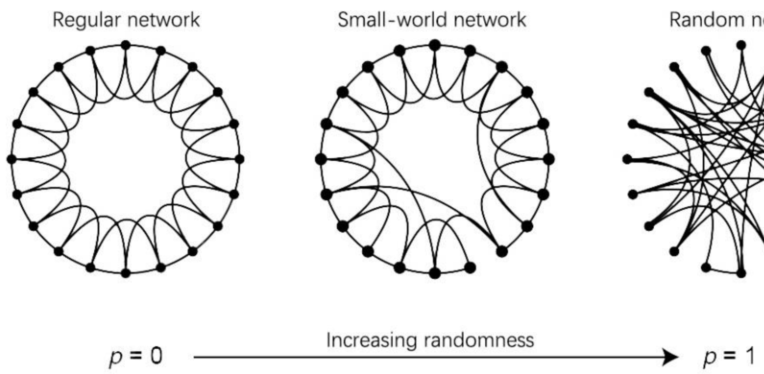

Figure 2-4 Regular, small-world and random network
Source: Watts and Strogatz (1998)

Recent interest in scale-free networks started in 1999 with work by Albert-László Barabási and colleagues at the University of Notre Dame who mapped the topology of a portion of the World Wide Web, finding that some nodes, which they called “hubs”, had more connections than others and that the network as a whole had a power-law distribution of the number of links connecting to a node. Such networks are called “scale-free networks” or “BA networks”. Degree distribution of nodes in scale-free networks is extremely uneven and subject to the power-law distribution, that is, a few nodes have a large number of connections while most nodes have very few connections (Barabási and Albert, 1999). It is believed that due to the existence of a few hubs, knowledge collaboration network with scale-free property are more efficient in spreading and diffusing \ information. Moreover, scale-free property also reflects the evolution principles of the complex networks, namely, the Matthew effect, cumulative advantage and preferential attachment.

Figure 2-5 is the comparison of the structural features in a random network, a small-world network and a scale-free network. The first column shows a series of diagrams which represent the three different networks. Each network contains 20 nodes. The second column shows degree distribution of each network, and the third column shows the adjacency matrix of each network. (A) Random network: nodes are connected in a random way, its degree distribution subjects to Normal or Poisson distribution. Nodes in adjacency matrix are randomly distributed. (B) Small-world network: most network members are connected by a small number of “shortcuts“. Degree distribution presents Poisson distribution. Nodes in the adjacency matrix are mainly concentrated near the diagonal. (C) Scale-free network: a few nodes have a large number of connections, and most of the nodes are sparsely connected. The degree distribution complies with the power-law distribution. Nodes in the adjacency matrix are unevenly concentrated in the upperleft.

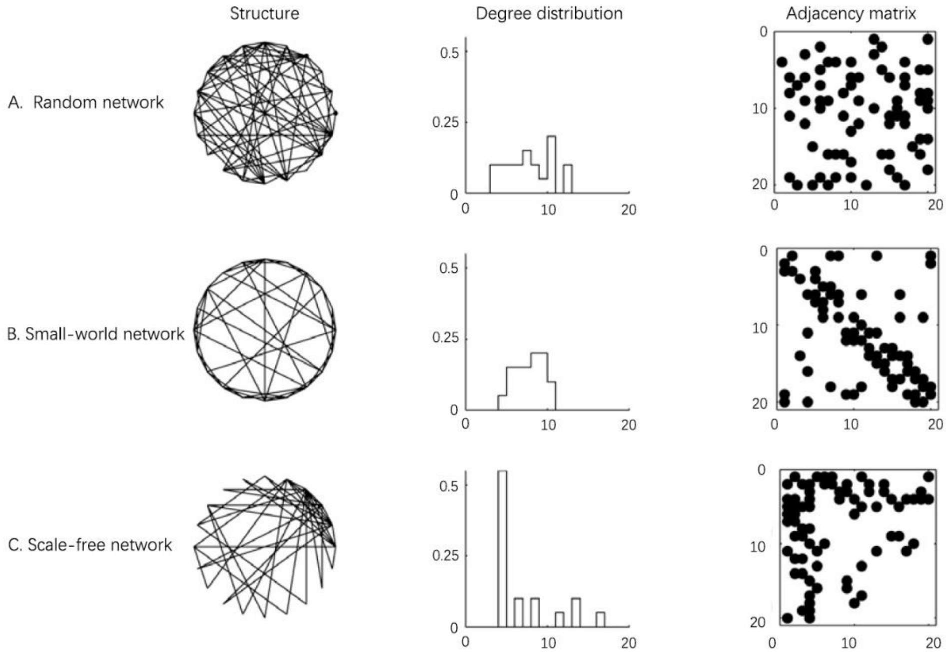

Figure 2-5 Topical properties of regular networks, random networks, small-world networks and scale-free networks

Source: Stobb et al. (2012).

(3) Other properties

With the advancement of SNA,in addition to “small-world” and “scale-free” properties, more and more topological features of complex networks have been discovered. For example: (1) Assortativity and disassortativity which is used to describe the selection tendency of nodes when accessing into networks. For example, In a knowledge collaboration network, if the members tend to collaborate with ones who have similar connectivity, such network exhibits assortativity, otherwise displays disassotativity. (Franceschet, 2011; Li et al, 2015; Maggioni and Uberti, 2009; Pepe and Rodriguez, 2010); (2) Community Structure which denotes the existence of sub-groups in the a network. The connections between different sub-groups are sparse but connections between the nodes in each group are relatively dense. In a knowledge collaboration network, a certain academic circle or a cluster consisting of closely connected people or enterprises can be called a community (Maggioni and Uberti, 2009; Newman, 2001; Onel et al., 2011; Palla et al., 2005; Lu Tianzan et al., 2016) (3) Core-periphery structure refers to a large number of connections in a network occur among only a few nodes that comprise the core of the network, while other nodes in the network are loosely connected and are located at the periphery. In a knowledge collaboration network, a few star scientists or large enterprises make up the core of the network and most other scholars or SMEs are sparsely connected around these core nodes (Lee, 2014; Leydesdorff et al., 2013; Duan, etc. 2018; Liu et al., 2017).

(4) Related empirical research

The famous physicist Mark Newman made outstanding contributions in the field of complex network research and pioneered in exploring the topological structure of the KCNs. Newman (2001) constructs four different KCNs with different dataset mined from four scientific papers index databases. He finds that all networks exhibits “small-world” and “scale-free” properties. Besides, he also discovered that the KCNs of different disciplines display different topological characteristics Using Web of Science paper data, Wagner and Leydesdorff (2005b) invstigate the topology structures of transnational KCNs of six different disciplines and obtain similar results with Newman (2001) that the degree distribution of the KCNs follow Power-law distribution, and display “scale-free” property. Similarly, they also observe that the power-law distribution is not perfect but with a hook-like tail. In this regard, Wagner and Leydesdorff (2005b) give two explanations: (1) “star scientists” who already have many partners and collaboration experiences, cannot have collaborations due to their aging; (2) adding new partners means higher marginal cost. These are the main differences between the KCNs and other typical “scale-free” networks. Since then, many scholars have conducted research on the KCNs of different databases or different disciplines, most of the results suggest the existence of “small-world” and “scale-free” properties of the KCNs (Barabâsi et al., 2002; Carayol and Roux, 2009; Dangalchev, 2004; Gay and Dousset, 2005; Moody, 2004; Uzzi and Spiro, 2005; Yu, 2018).

Scholars in China have also carried out considerable literature on the topological properties of KCNs in recent years (Xu et al., 2017; Zhang, 2015; Zhang et al., 2015). Liu et al. (2017) employ the data derived from the Web of Science database and discover that transnational KCN presents a typical “small-world” property. Duan et al. (2018) study the longitudinal evolution of patents transfer network between 2001 and 2015 in China and find that the “small-world” property of the network has been enhancing while the “scale-free” property tends to weaken. Wang (2013) uses scientific paper data from Web of Science to study the KCNs of biotechnology and nanotechnology in China, the results show that networks of these two disciplines present both “small-world” property and “scale-free” property albeit there exist differences between the two networks.

In research on KCNs, other topological properties of networks have also received extensive attention from scholars in addition to “small-world” property and “scale-free” property. For example, (1) based on the data of his previous studies, Newman (2004) examines the “assortativity” of KCNs and the results show that KCNs of different disciplines all present significant “assortativity”, which means researchers with more collaborators or collaboration experiences are more likely to collaborate with each other. Maggioni and Uberti (2009) study four networks related to knowledge flows or collaboration, i.e., Internet network, co-invented patents network, exchange students network (joint training) as well as funding projects collaboration network, they find that all types of networks exhibit high “assortativity”. Li et al. (2015) compare co-authored paper networks and co-invented patents networks in biotechnology from 2000 to 2009 in China. Unlike the aforementioned studies, the research shows both of the networks are disassortative, which means newly-joined members prefer to collaborate with members who already have many collaborators and collaboration experiences. (2) In the studies on community structure of KCNs, Palla et al. (2005) examine the collaboration networks of condensed matter research and find that there are several sub-communities in the networks and that these sub-communities are divided in line with the subdivisions of this discipline. Perianes-Rodriguez et al. (2010) find that the formation of communities relates to not only the discipline but also correlates with the researchers’ affiliations and research groups based on an investigation of the community structure of IT collaboration network. Onel et al. (2011) analyze community structure of the research collaboration network of nanotechnology and find that the distribution of the communities is obviously polarized with several giant communities and a large number of small communities (3) In the study of the core-periphery structure of networks, Hu and Racherla (2008) discover an obvious core-periphery structure of the collaboration networks in the field of hotel management. He also finds the core members of the network play important role in sustaining the whole network stable and resilient. Liu et al. (2017) and Leydesdorff et al. (2013) find the existence of core-periphery structure in global scientific collaboration networks, and such polarization is still being strengthened. Matthiessen et al. (2002) and Matthiessen et al. (2010) study global inter-city scientific collaboration networks and find clear-cut core-periphery structure with some large European and American cities as the center hubs.

2.3.2.2 Individual network properties: centrality, closure and structural holes

(1) Centrality

Centrality, including degree centrality (DC), betweenness centrality (BC) and closeness centrality (CC), is one of the basic indicators used to measure topological properties of nodes in networks. Centrality can be used to measure the statuses, power and functions of network members in KCNs.

Degree centrality (DC) is the number of connections a node has in network. In the KCNs, degree centrality directly reflects the "absorptive capacity" of innovation actors, namely, the ability to discover, absorb and create new knowledge (Cohen and Levinthal, 1990)[11]. Higher centrality indicates that the innovation actor has more collaborators, and in turn has more options in choosing collaborators with less dependency on one specific partner. Meanwhile, the degree centrality is also the criteria of judging the importance of actors in the KCNs.

Betweenness centrality (BC) for each node is the number of shortest paths between any two nodes that pass through the focal node, which reflects the node's bridging function and intermediary capability. In the KCNs, the betweenness centrality mirrors the reputation, control and intermediary capability of innovation actors in the network. Actors with higher betweenness centrality often hold more resources and control the knowledge and information flow in the networks.

Closeness centrality (CC) is calculated as the reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the network, which measures the accessibility of the nodes. In the KCNs, actors with higher closeness centrality are less dependent on other members. Thus it is outperformed in independent innovation.

In addition to the above-mentioned types, there are many other centrality measures, for example, eigenvector centrality, Katz centrality, PageRank centrality, cross-clique centrality, etc. Each of the centrality indicators have different meanings and applications.

(2) Closure

Closure, used to measure the cohesiveness of nodes in a network, refers to whether the neighboring nodes form a triadic closure. This structure is termed as the "tertius iungens" by Simmel and Wolff (1950). In the field of social sciences, the concept of "closure" is closely related to the concept of "social capital" and the social network structure that supports it (Granovetter, 2005; Guo Yi et al., 2003; Qi Jianwen and Li Pei-lin, 2018). Coleman (1988) points out that the more triadic closures one actor possesses, the tighter the actor is embeded in the social network. In turn it can use more social capitals and

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[11] The absorptive capacity is considered to be closely related to the innovation capability and performance of the innovation actor (Cohen and Levinthal, 1990).

benefits more. In a closed network with high cohesiveness, members can obtain information with higher credibility at a lower cost. Therefore, this type of network structure is conducive to fostering trust, to diffusing complex information and tacit knowledge, to promoting and maintaining collaborations, and thereby promoting the innovative performance of actors (Coleman, 1988; Granovetter, 2005). (Figure 2-6)

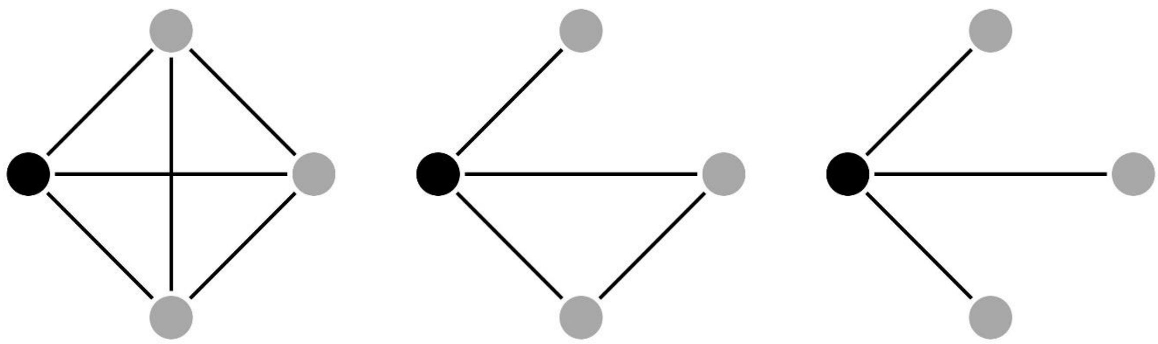


Figure 2-6 Examples of closure

Source: author

In three illustrations, the black dot is the focal node. In the left one, the three neighbors of the black node are all connected to it and to each other. Thus, the black node is in three triadic closures and display a higher level of embeddedness. In the middle one, the black node is in one triadic closure, so its network embeddedness is weaker than the node in left graph. In the right one, there is no triadic closure, so the embeddedness of the black node is the weakest.

(3) Structural holes

“Structural hole” is a concept from social network research, originally developed by Burt (1992). A structural hole is understood as a gap between two individuals who have complementary sources of information. An individual who acts as a mediator between two or more closely connected groups of people occupies the “structural hole” of the network, and could gain important comparative advantages. In particular, the position of a bridge between distinct groups allows him or her to transfer or gatekeep valuable information from one group to another. (Burt, 1992; Liang Lujin, 2011; Zhu Mengran, et al. 2018). Compared to “closure” discussed above, the concept of structural holes emphasizes the nodes are open in the network. As shown in Figure 2-7, there are three sub-groups of triadic closure in the network of graph A, in which they are all connected to node 1 but disconnected with others. The information exchange between these sub-groups must pass through node 1, that is to say, node 1 occupies the position of “structural hole” in the network and acts as a broker. In graph B, the node 1 is redundant, as the information exchange between the three sub-groups can be conveyed by direct connections between node 2, 3 and 4. Burt (1992) argues that structural holes are “separation between non-redundant contacts”. In KCNs, individuals occupying the structural holes have information benefits because such individuals are connected to individuals or groups with different knowledge backgrounds. And in turn they have more opportunities to acquire new knowledge. In addition, they also have control benefits because they can decide whether to fill the structural holes or not, and which party to be prioritized in the process of building collaboration.

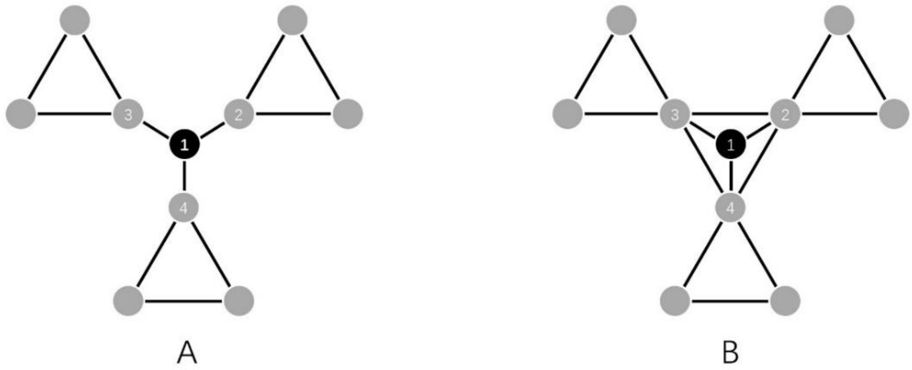


Figure 2-7 Structural holes
Source: author

There are two main types of structural holes measurement. The first is the structural hole index proposed by Burt (1992) and “constraint” is often used. The second is measured by the betweenness centrality, because both of the concepts are proposed to define the broker role of actors in networks.

2.3.3 Mechanisms of the evolution of the KCNs

The dynamic evolution of regional innovation networks and the KCNs is one of the key issues in the evolutionary economic geography (Boschma and Frenken, 2009; Frenken and Boschma, 2007; Glückler, 2007; Martin and Sunley, 2007; Ter Wal and Boschma, 2011; Wang et al., 2013; Yan and An, 2013). Evolutionary economic geography, regarded as the third method of economic geography research, takes social economic practices as an evolutionary process in both spatial and time dimensions and highlights the role of geography in determining the nature and trajectory of evolution of the economic system (Liu and Yin, 2006). It particularly focuses on two aspects: first, it highlights how the processes of path creation and path dependency interact to shape geography of economic development and transformation; second, it advocates that innovation activities and knowledge production are crucial to economic growth (Li, 2011; Liu and Cui, 2008). Glückler (2007) argues that the dynamic evolution of social networks is essentially a complex process of continuous formation and dissolution of ties between actors. This also applies to KCNs. Additionally, Ter Wal and Boschma

(2009) point out that in social network theory, the main factors influencing the formation and evolution of social ties between actors include proximity, preferential attachment and triadic closure. And the formation and dissolution of ties in the network are by no means random or accidental. Historical and cultural deposits, regional institutional contexts, proximity and actors' preference are also influencing the evolutionary paths of networks.

2.3.3.1 **Multidimensional proximity**

The concept of "proximity" could be traced back to Marshall's industrial district theory (Marshall, 1919) that face-to-face communication is more frequent in industrial districts because of the spatial proximity and co-location of actors. During these interactive processes, possibilities for knowledge exchange and interactive learning increase and the chances of innovation surge. In the 1990s, the French school of proximity dynamics conceptualized this spatial co-location as "geographical proximity". In addition, they proposed the concept of "organizational proximity" : whether organizations share the same or similar organizational patterns, values, rules and culture is also an important factor that determines trans-organizational interactions (Filippi and Torre, 2003; Torre and Gilly, 2000; Torre and Labelt, 2005). Boschma (2005), Knoben and Oerlemans (2006) further subdivide "organizational proximity" into "institutional proximity", "social proximity", "cognitive proximity" and "cultural proximity". They also point out that the combination of geographical proximity and non-geographical proximity promotes learning, collaborations and innovations among organizations. However, Boschma (2005) also argues that excessive proximity will have a negative impact on the establishment of collaboration. (Figure 2-8 and Table 2-4)

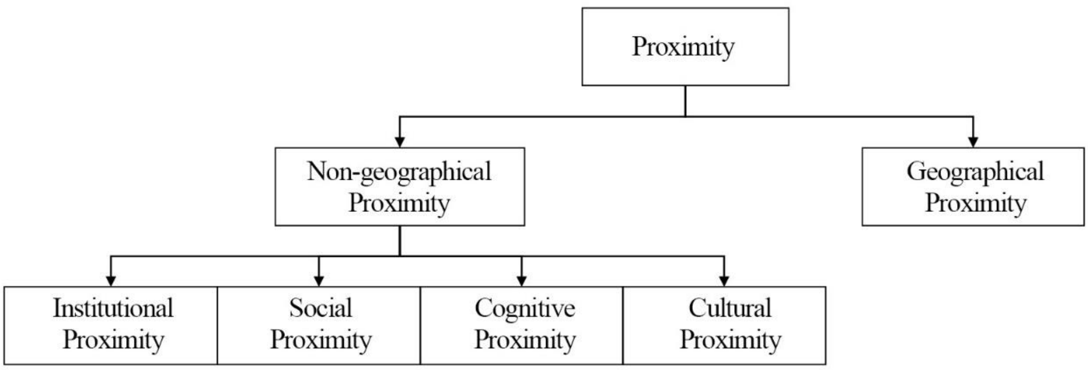


Figure 2-8 Multidimensional proximity
Source: author

Table 2-4 The definitions of multidimensional proximity

Multidimensional proximity	definition	Too little proximity	Too much proximity	Possible solutions
Geographical proximity	the absolute geographical distance that separates actors, the distance relative to the means of transport (travel times) or the perception of these distances by actors	No spatial externalities	Lack of geographical openness	Mix of “local buzz” and “global pipelines ”
Institutional proximity	actors whose interactions are facilitated by (explicit or implicit) rules and routines of behavior and that share a same system of representations, or set of belief	Opportunism	Lock-in and inertia	Institutional checks and balances
Social proximity	Relations between actors that socially connected by trust-based friendship, kinship, partnership and experience	Opportunism	No economic rationale	Mixture of embedded and market relations
Cognitive proximity	The similarities in the way actors perceive, interpret, understand and evaluate the world	Misunderstanding	Lack of sources of novelty	Common knowledge base with diverse but complementary capabilities
Cultural proximity	The similarities in sharing sets of values, such as ethic, religious and laguages	Misunderstanding	Lack of diversity	Diverse culture mixture

Source: Boschma (2005) and Knoben and Oerlemans (2006)

2.3.3.2 Preference attachment

In network theory, preferential attachment means that when the network scale is expanding, new nodes accessing into the network are more likely to connect with nodes that already have many connections (Barabasi and Albert, 1999). This concept describes the “Matthew effect” and “cumulative advantage” in the network evolution and growth: nodes at the core of the network enjoy more network resources and will continue to be strengthened, while those nodes situated in periphery will still linger within the peripheral area. This concept can explain the evolution of regional innovation networks from at least two aspects: first, the core-periphery structure is difficult to break in the evolution of KCNs (Orsenigo et al., 1997; Powell et al., 1996). Second, for a certain actor, having bigger number and wider range of collaborators can lead to more potential partners, which will further stimulate the exchange and production of new knowledge (Gulati, 1999).

2.3.3.3 Triadic closure

Triadic closure, a key concept in SNA that explains the evolution mechanism of the network, is used to indicate the transitivity in a three-nodes network: if there exist direct links between A-B and A-C, then there is a high possibility for B and C to establish a direct link. This concept implies that the probability of a new connection between two network members highly related to the partners the two nodes have in common. It can be used as an explanation of Granovetter's (1985) "social embeddedness" theory and the concept of "network capital" (Huggins, 2010): the closeness of social networks determines the formation and evolution of social norms, trust and collaborations among actors (Glückler, 2007; Kenis and Knoke, 2002; Ter Wal, 2014). Dahlander and McFarland (2013), Obstfeld (2005), Cassi and Plunket (2015) and other scholars confirm the impact of triadic closure on establishment of new collaboration among network members through different case studies.

2.4 City Networks and the IKCNs

2.4.1 City network paradigm

Since 2000, "city network" has been a new perspective and a new approach for scholars in human geography and urban planning in studying the organizations, processes and mechanisms of cities and city-regions in the context of globalization. With the rise of the network society, the hierarchical and vertical organization logic of urban systems based on the central place theory (Cristal, 2010) and the core-periphery theory (Hall, 1966) has been challenged. "Network" has become a novel spatial organization reflecting cities' synergy and interaction, that is, previously separated cities are interconnected through different types of flows such as people, goods, capitals and information (Taylor et al., 2010; Li, 2018; Ma and Li, 2012).

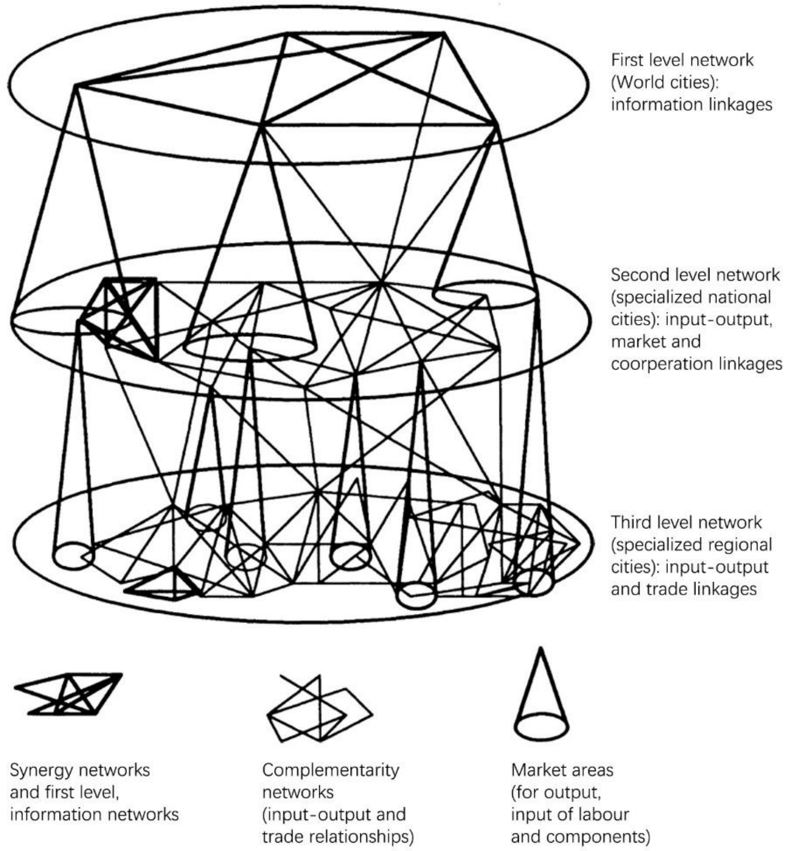


Figure2-9 Conceptual model of city networks
Source: Camagni (1993)

Research on city networks can be divided into two main streams of "regional city network" and "global city network". Although the spatial scale of their interests is different, their insights and analytical logic have generally gone through the transition from attribute thinking to relational thinking and the transition from hierarchy to network, respectively (Li, 2018). The studies of "regional city networks" preceded that of "global city networks". Early in the 1960s, Jacobs pointed that no city can succeed merely on its own but largely depend on the interactions with other cities. (Jacobs, 1969). In the same period, Burton proposed the concept of "dispersed city" that denoted an urban system within a number of spatially separated cities that are of similar size, administratively independent but highly integrated. (Burton, 1963). "City network" has been formally conceptualized since the 1990s. Batten compares the central place model and the network model of urban system and points that a city network evolves when two or more previously independent cities, potentially complementary in function, strive to cooperate and achieve significant scope economies aided by fast and reliable corridors of transport and communications infrastructure. He also argues that the collaborative mechanisms may resemble those of inter-firm networks in the sense that each urban player stands to benefit from the synergies of interactive growth via reciprocity, knowledge exchange and unexpected creativity. (Batten, 1995). (Table2-5)

Table2-5 Comparison between center place mode and city network mode

Central place system	Network system
Centrality	Nodality
Size dependency	Size neutrality
Tendency towards primacy and subservience	Tendency towards flexibility and complementarity
Homogeneous goods and services	Heterogeneous goods and services
Vertical accessibility	Horizontal accessibility
Mainly one-way flows	Two-way flows
Transport costs	Information costs
Perfect competition over space	Imperfect competition with price discrimination

Source: Batten (1995)

Camagni (1993) interprets the spatial logic underlying the organization of city networks from the perspective of economics. He sheds light on the synergy and collaboration among city networks, also on the advantages and benefits cities gain from being part of a network. He believes that both complementarity and synergy govern the operation mechanisms of city networks. The former one refers to the network made up of specialized and complementary centers, interlinked through a set of input-output and market relationships. Interurban division of labor at the same time ensures that there is a sufficiently large market area for each center and that scale and agglomeration economies are achieved. And the latter denotes city networks made up of similar, cooperating centers. In this case, the necessary economies of scale are provided by the network itself, which integrates the market of each single center. Examples of these networks are the already mentioned financial cities, whose markets are virtually integrated through advanced telecommunication infrastructures, or tourist cities connected through cultural or historical "itineraries". Camagni (2007) emphasizes that city networks are no longer organized for either minimizing transportation costs or maximizing non-overlapping markets, but for attaining scale economies with complementarity and synergy. (Table2-6)

Table2-6 The three kind of logic of spatial organization

Level	Aspect	Organizational logic		
		Territorial	Competitive	Network
Firm	Nature	Local market firm	Export firm	Network firm

	Crucial function	Production	Marketing	Innovation
	Strategy	Control of market areas	Control of market shares	Control of innovation assets and their trajectories
	Internal structure	Single unit	Specialized functional units	Punctually integrated units
	Entry barriers	Spatial friction	Competitiveness	Continuing innovatoin
Urban system	Principles	Domination	Competitiveness	Cooperation
	Structure	Nested Christallerian hierarchy	Specialization	City networks
	Sectors	Agriculture, government, traditional tertiary activities	Industry: industrial districts	Advanced tertiary activities
	Efficiency	Scale economies	Vertical/horizontal integration	Network externalities
	Policy strategy	None: size determines function	Traditionally: none, as export base determines growth. Nowadays: competitive advantage of each center	Intercity cooperation; intercity transport and communication; network provision
	Intercity cooperation goals	None (expect military or diplomatic goals)	Intercity division of labor	Economic, technological and infrastructure
	Networks of cities	Hierarchical, vertical networks	Complementary networks	Synergy networks, innovation networks
City	Nature	Traditional city	Fordist city	Information city
	Form	Relative internal homogeneity	Monofunctional zoning	Multifunctional zoning, polycentric city
	Policy goals	Power and image	Internal efficiency (clockwork city)	External effectiveness and attractiveness
	symbols	Square, church, market	Chimney, skyscraper	Airport, trade fair

Source: Camagni (1993)

Related research on “global city networks” is based on Friedmann’s “world city hypothesis”, Sassen’s “global city” and Castells’ “rise of the network society”. Friedmann (1986) links urban development with economic globalization and points out that world cities are the “basing points for global capital”. They serve not only as command and control centers for multinational corporations to organize global production and services, but also hubs that underpin the global transportation and communication network. Sassen (1991) also emphasizes that global cities are centers for global capital services particularly organized by advanced producer services (APS) firms such as banking, finance, insurance, law, management consulting and advertising. The rapid expansions of multinational companies worldwide require higher demands on functional integration, cost control and resource allocation. Therefore, they have been outsourcing production services, in turn, the APS networks are spatially match with global production networks. Castells (1996) argues that "space of flow" rather than "space of place" shapes the global urban system. "Space of flow" refers to the global economic network formed by flows of capital, information, and people etc., and "space of place" refers to cities that act as "hubs" and "nodes" in global economic network. From his perspectives, the sustained development of cities not only depend on their endogenous endowments but also on external resources flowing in city networks.

2.4.2 Diverse empirical paths

Early empirical research on city networks mainly was built upon "attribute data" such as GDP, population, the number of multinational corporations to describe the size distribution of city systems, or adopted indicators like industrial heterogeneity and homogeneity to indirectly reflect the interactive relations of cities' specialized division of labor. However, the "network" is often abstracted and conceptualized as the premise of city networks research due to the difficulties in exploiting relational data that directly captures the real flows among cities. Around 2000, based on Friedmann and Sassen's theories, some empirical studies have tried to construct world city networks by using location information of the headquarters and their branches of transnational firms. Since then, significant breakthroughs have been witnessed: various types of "relational data" and related analytical methods have been widely applied in global city networks research, and further extended to research of regional urban networks,

It is important that the organizational logic of the city networks is rooted in the interactive processes of exchange of people, goods and information between cities, within which different types of flows can be regarded as the vehicles or channels of the functional interactions between cities. The spatial configurations and topological structures of city networks depend on the type of flow and the urban functions it reflects. Furthermore, a city in different functions of city network may display different status and play different role (Table 2-7). Note that city networks with different functions are not exclusive and independent but are integrated and intertwined with one another, and such multi-functional connections are also beneficial for the overall resilience of the urban systems.

Table 2-7 Empirical paths of interurban networks

Type	Data type	Scholars	Function
Corporate network	Intra-organizational networks of advanced producer service firms	Taylor (2001), Derudder et al. (2003), Zhao et al. (2015),	Command and control in global capital services
	Headquarter-spinoffs intra-organizational networks of transnational firms	Alderson et al. (2010), Rozenblat (2010), Wall et al. (2011), Tang et al. (2015), Tang and Zhao (2010)	Command and control in global capitals
	Finance services networks between listed firms and IPO service firms	Pan et al. (2017), Pan et al. (2016)	Service capability in capital markets
Transport network	Airline networks	Smith and Timberlake (2001), Mahutga et al. (2010), Dai et al. (2018a), Zhang et al. (2016a), Wang et al. (2015)	Transport hubs
	Marinetime networks	Ducruet et al. (2010), Ducruet and Notteboom (2012), Ducruet et al. (2018), Wang and Zhu (2017)	
	Rail networks	Yang et al. (2018a), Yang et al. (2018b), Yang et al. (2019), Wang et al. (2014)	
Information network	Internet infrastructure networks	Choi et al. (2005), Townsend (2001), Malecki (2002), Wang and Ning (2006)	Information hubs
	Telephone or E-mail network	Hall and Pain (2006)	
Migration network	Commuting network	Burger et al. (2014), van Oort et al. (2010)	Attraction for people
	Location based services migration (social network and cellphone signals)	Huang et al. (2018), Zhang et al. (2016b), Niu et al. (2017), Wang et al. (2018)	
Socio-cultural network	Consumer networks, entertainment networks	Zhang et al. (2018), Cheng and Meng (2014)	Entertainment and culture centers
Innovation network	Co-authored networks	Matthiessen and Schwarz (1999), Li and Phelps (2017), Gui et al. (2018), Andersson et al. (2014)	Innovation centers
	Co-patents networks	Araújo et al. (2018), Guan et al. (2015), Chen (2018)	
	Collaborative projects networks	Kratke (2007), Kratke (2010)	

Source：author

2.4.3 Break the bottlenecks

The city network research has been experiencing rapid development for more than 20 years, and it has achieved significant progresses not only in theoretical constructions but also in empirical examinations. However, as discussed in Chapter 1, it has encountered several bottlenecks, particularly in empirical studies. First, due to the difficulties of data collections and the limitations of the data itself, most city networks studies only focus on one certain spatial scale. For instance, the GaWC uses the geographical information of the APS companies to construct global city networks. It can illustrate the overall configuration of the city networks at the global scale, but it can hardly grasp the complete city network structures at the national or regional scale because many APS companies only set up branches in one city in some countries (Robinson, 2005). Another example is that one can use flights network to outline the structures of global and national city networks, but it is difficult to conduct such approach at the regional scale, because in most cases, there are few flights among adjacent cities within the city-region. In contrast, relational data like co-publications or co-patents have significant advantages in building city network with continuous scales. Regardless of the size differences and distances between cities, cities can be incorporated into the network construction and analysis as long as they have external collaborations with other cities. In doing so, building trans-scale interurban networks from global to local can be accomplished. In addition, knowledge collaboration data can be utilized to build smaller and finer networks such as trans-organizational collaboration networks and interpersonal collaboration networks.

Second, in city networks research, the limitations of analytical methods and techniques lead the problem of "using new data with old methods to explain a novel phenomenon, but usually get outdated conclusions". Admittedly, the introduction of "relational data" and the application of basic network analysis methods have undeniable significance in understanding the organizational logic of "space of flow". However, most of current city network research still focuses on analyzing the spatial configurations of the city networks. In recent years, the progresses of complex network theories and social network analysis provide a new toolbox for city network research. As Ter Wal and Boschma stressed that the SNA has a huge potential to enrich the literature on clusters, regional innovation systems and knowledge spillovers. For example, the overall efficiency and effectiveness of the IKCNs can be examined through analyzing the overall network characteristics, roles and functions of cities in the IKCNs. It can be explored from multiple dimensions such as centrality, brokerage, command and control power in analyzing the individual network characteristics. In addition, through the application of block models, we can examine the “core-periphery” structure and the “center-hinterland structure” of the IKCNs.

Third, due to the limitations of research perspectives, discussions on the underlying mechanisms of the formation and evolution of city networks are relatively rare. In recent studies on the IKCNs, a few scholars have discussed the macro-mechanisms of network formation from different perspectives, such as research paradigm (Katz and Martin, 1997), policy support (Wagner and Leydesdorff, 2005b; Ma Haitao et al., 2018) and local contexts (Camagni, 1995; Storper and Venables, 2004a). Others also have endeavored to explain the micro behavior of actors’ collaborative initiatives and incentives from the perspective of complex networks (Newman, 2004). Such literature on the KCNs provide valuable references to further exploration of the mechanisms and the evolution and formation of city networks .

2.5 Summary

The primary issue in the research on the IKCNs is how to conceptually interconnect “knowledge”, “network” and “city” in parallel. To end this, in this chapter, firstly, regional innovation system theory is taken as the starting point, and then the geographical dimension of innovation processes is revealed: the processes of (re)production of knowledge are embedded both in “space of place” and “space of flow”. In addition, based on the theory of “local buzz” and “global pipelines”, the trans-scale property in the context of globalization is discussed in this chapter.

Secondly, the chapter systematically reviews related concepts and theories on “knowledge”, “knowledge networks” and “the KCNs” by (1) clarifying their definitions, types and characteristics, (2)highlighting the importance of “knowledge networks” in knowledge diffusion and creation, (3) reclaiming the definition and connotation of “the KCNs” and proposing the significance of conducting the KCNs research in innovation geography.

Thirdly, the application of social network analysis approach in the KCNs research is discussed, especially on the application of social network analysis and complex network theory in exploring the topological properties and underlying mechanisms of the KCNs.

Finally, this chapter put the proposition of the IKCNs into the center of this thesis. By a comprehensive review on the theoretical constructions and empirical examinations of city networks, three bottlenecks in the current city networks research are summarized: (1) the “scale discontinuity” problem due to limitations in acquiring appropriate relational data. (2) the problem of "using new data with old methods to explain a novel phenomenon, but usually get outdated conclusions" that caused by the constraints in analysis techniques. And (3) the problem of "favoring phenomenon descriptions but ignoring mechanism discussions" led by perspective limitations. In closing, the research on the IKCNs are claimed to be an empirical avenue for breaking these bottlenecks in city network literature.

Chapter 3 Basic hypothesis, empirical framework, and analytical methods

Based on the research background (Chapter 1) and the literature review (Chapter 2), this chapter first presents the basic hypothesis of the thesis, and then constructs the empirical framework, and finally introduces relevant analytical methods.

3.1 Basic hypothesis

3.1.1 Structures: "space dependency" and "path dependency"

As emphasized above, the geography of knowledge production and knowledge collaboration essentially are social practices that are projected in space, namely, territorial embeddedness (Heimeriks and Boschma, 2013; Martin and Sunley, 2007). First, the process of knowledge production and collaboration is coupled with the process of concentration and diffusion of innovation resources in space (Markusen, 1996). On one hand, spatial concentration can lead to scale economy with increasing returns: geographical proximity provides opportunities for local innovative production and innovative collaboration. On the other hand, the dynamic of knowledge spillovers enables the collaborative processes to transcend local boundaries and extend towards other places. Second, knowledge production is a spatially exclusive and contextually specified process (Asheim and Isaksen, 2002), that is, different places possess different specialized knowledge and technological know-how, meanwhile, under specific local contexts, the (re)production processes of knowledge also present distinct paths.

The generation of new knowledge is random, only the combination of specific knowledge under specific contexts can produce innovation. Therefore, the formation of collaborative networks is also not random, but always with specific purposes. It can be inferred that specific knowledge is attached to specific places, the collaborative connections between different places thus are in line with the way that the knowledge interaction is combined. Therefore, the spatial evolution of the KCNs presents specific inertia and development paths, which is called "space dependency" in this thesis.

In the theory of evolutionary economic geography, knowledge diffusion and knowledge creation are of "path dependency". The generation of new knowledge is mostly based on recombination and reinterpretation of existing knowledge (Boschma et al., 2015; Heimeriks and Boschma, 2013; Martin and Simmie, 2008). In term of knowledge collaboration behavior, the innovative actors are more likely to collaborate with whom they have worked with before, and this tendentiousness in the KCNs is also called "network routines" (Ye, 2017). Dang and Sun (2013) point out that network routines are norms, institutions and consensus that are accepted by most network members, at the same time, the behaviors of network members are constrained by these network routines. Ye (2017) argues that network routines can facilitate knowledge sharing and diffusion, and can help to maintain the stability of the KCNs. In a word, "network routines" reflect that the evolution of the topology of the KCNs is of "path dependency".

Based on this, the first basic hypothesis of this thesis is formulated: the evolution of the spatial configurations and topological structures of the IKCNs follows the general rules of "space dependency" and "path dependency" respectively.

3.1.2 Mechanisms: "macro-structural factors" and "micro-initiative factors"

Generally speaking, innovation, knowledge production and knowledge collaboration are fundamentally social practices governed by rational economic behaviors (Asheim and Coenen, 2006). Granovetter (1985) points out that socio-economic behaviors are socially situated and territorially embedded, economic actors of decision-making are not so much based on individual choices, but rather on social relationships, cultural values, moral concerns, politics, religion or the fear instilled by authoritarian leadership. Consequently, any analysis of economic behavior or incentive as an analytically distinct entity isolated from its socio-cultural, institutional and political context is flawed from the outset.

Katz and Martin (1997) point out that the shift of scientific research paradigm is one of the main reasons for the increase of trans-local knowledge collaboration: sciences have become much more complex, the knowledge bases have become more diverse and also specialized, and the costs and risks are higher. And much of the cutting-edge work these days tends to emerge from large, well-funded collaborative teams involving many contributors. Bi (2016) argues that since the innovation resources have been unevenly distributed across different places, the need for integration and complementation of different resource is another reason that account for the formation of the KCNs. Li et al. (2013) believes that the market environment, technological environment, policies and institutional environment, social and cultural environment are key exogenous factors that influence the formation of the KCNs. In summary, macro-structural factors like "scientific paradigm", "innovation resources" and "collaborative environment" might have considerable impacts on the formation of the KCNs.

From the micro perspective, the micro incentives and initiatives of individuals are governed by "economic rationality". Searching, engaging and maintaining collaborative relations with others cost time, energy and money, therefore, the micro processes of the formation of collaborative relations lie in actors' trade-off between their input and expected output.

Proximity is considered to be the "micro-initiative element" that influences the formation of the KCNs (Boschma, 2005; Knoben and Oerlemans, 2006; Torre and Labelt, 2005). Many studies have found that "geographical proximity" is necessary for collaborative interactions--spatial concentration of individuals and institutions are beneficial in facilitating face-to-face communication and nurturing trust-based milieus, which in turn encourages collaboration. However, in the era of big science, inter-city, inter-regional and even international cooperation has become more common, implying that the importance of “geographical proximity” on the formation of the KCNs has gradually been weakened. In the 1990s, the French school of proximity dynamics proposed that, in addition to “geographical proximity”, “non-geographical proximity factors” or “organizational proximity” are also influential for interpersonal or inter-organizational collaborations. (Filippi and Torre, 2003; Torre and Gilly, 2000; Torre and Callett, 2005). Boschma (2005), Knoben, and Oerlemans (2006) further divide “organizational proximity” as “cognitive proximity”, “social proximity”, “institutional proximity” and “cultural proximity”, etc. They also point out that the formation of knowledge collaboration is a combinedl interaction of “geographical proximity” and “non-geographical proximity” in the forms of complementation and substitution.

Based on this, the second basic hypothesis of this thesis is that the formation of the KCNs is influenced by both “macro-structural factors” and “micro-initiative factors”.

3.2 Empirical framework

Based on the hypotheses, the conceptual framework of this thesis is as follows (Figure 3-1):

First, this thesis investigates the “spatial configurations” and “topological features” of China’s IKCNs at different geographical scales. The overall empirical analysis logic follows the logic of “from global to local”, “from macro to micro” and “from whole to part” to ensure consistency, comparability and systematicness of the research. Specifically, spatial configurations and topological structures of the IKCNs are illustrated and interpreted through various spatial and network analysis techniques.

Second, the mechanisms of the formation of interurban knowledge networks are discussed from both macro and micro perspectives. At the macro level, the thesis takes “Sino-Belgium joint laboratory for geo-information” as a case, and conducts in-depth interviews with the participants Based on the results of the interviews, the study mainly discussed three macro-structural factors, i.e. “scientific paradigm”, “innovation resources” and “collaborative environment” that influence the formation of the IKCNs. At the micro level, taking the medical sciences collaboration networks of Jiangsu-Zhejiang-Shanghai city-region as an example, the impacts of “micro initiative performance factors”, i.e. geographical proximity, institutional proximity, social proximity, cognitive proximity, and cultural proximity, are quantitively and qualitatively examined.

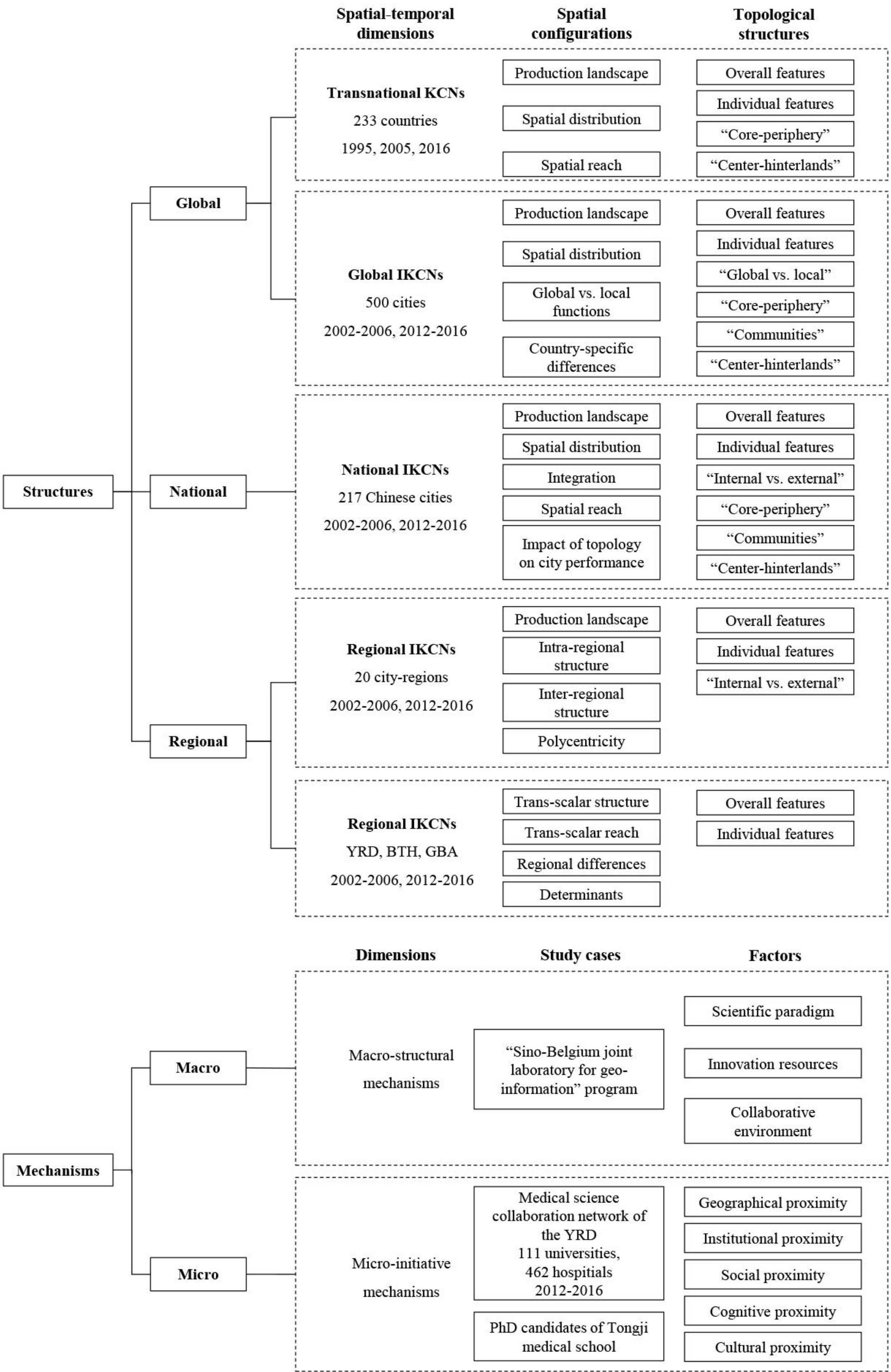


Figure3-1 Empirical framework

Source: author

3.3 Data

3.3.1 The Web of Science database

As intangible assets, knowledge and the KCNs are difficult to be empirically quantified and measured. There are four main methods for measuring the KCNs in existing research: scientific research collaboration networks based on co-authored papers, technical collaboration networks based on co-invented patents, and collaboration networks based on specific projects of R&D collaborations, and interpersonal collaboration networks built through field research like interviews and questionnaires (Lata et al., 2015; Scherngell and Barber, 2011; Wanzenbock et al., 2014). In this thesis, the construction of the IKCNs is based on the co-authored data mined from the Web of Science (WoS) database.

The WoS database is developed by Thomson Reuters, which includes more than 9,000 academic journals in the fields of natural sciences, engineering, biomedicine, social sciences, arts and humanities since 1975. It consists of three major citation indexes: Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI) and Arts & Humanities Citation Index (A&HCI). In addition to the basic information such as authors, titles, citations and research fields, the WoS database also provides detailed geographic information of each author's organization, which is of importance in building the IKCNs.

Another important reason is that the academic reputations and recognition of the WoS are trustworthy. Having academic papers been indexed in the three main databases has been considered as an important benchmark for evaluating the academic level of researchers or research institutions. Compared with some Chinese databases such as CNKI, WAN-FANGDATA and CQVIP, the research work indexed in the WoS is more internationally recognized and more globally comparable. This is especially critical for examining Chinese cities' evolution in the IKCNs at the global scale.

3.3.2 Construction of the IKCNs

The basic logic of the IKCNs construction is addressed as follows. As shown in Figure 3-2, the circles represent the co-authored scientific papers, the squares represent the institutions involved in scientific collaborations, the diamonds represent the cities where the institutions are located, and the triangles represent the countries that institutions/cities belong to. Graph 1 shows the "2-mode network" of institutions and scientific papers. It reflects the interactive relationships between organizations through scientific collaboration in the form of co-authored papers. For example, Institution *a* and Institution *b* are co-authors of Paper 1, then, the intensity of collaboration between Institution *a* and Institution *b* is counted as one. In this way, one can transform the "2-mode networks" between innovation actors and scientific papers into a "1-mode network" connected by different innovation actors. Then the result is the KCN of different institutions (Graph 2).

Obviously, the IKCNs are constructed by summing the knowledge collaboration relationships of different institutions from different cities: for example, there are two collaborative connections between City A and City B, which are the collaboration between Institution *c* and Institution *e*, and the collaboration between Institution *d* and Institution *f*, each of these two sets of collaborations is counted as one collaborative connection. Consequently, the intensity of collaboration between City A and City B is 1+1=2 (Figure 3). In a similar manner, a transnational KCN can be constructed (Figure 4).

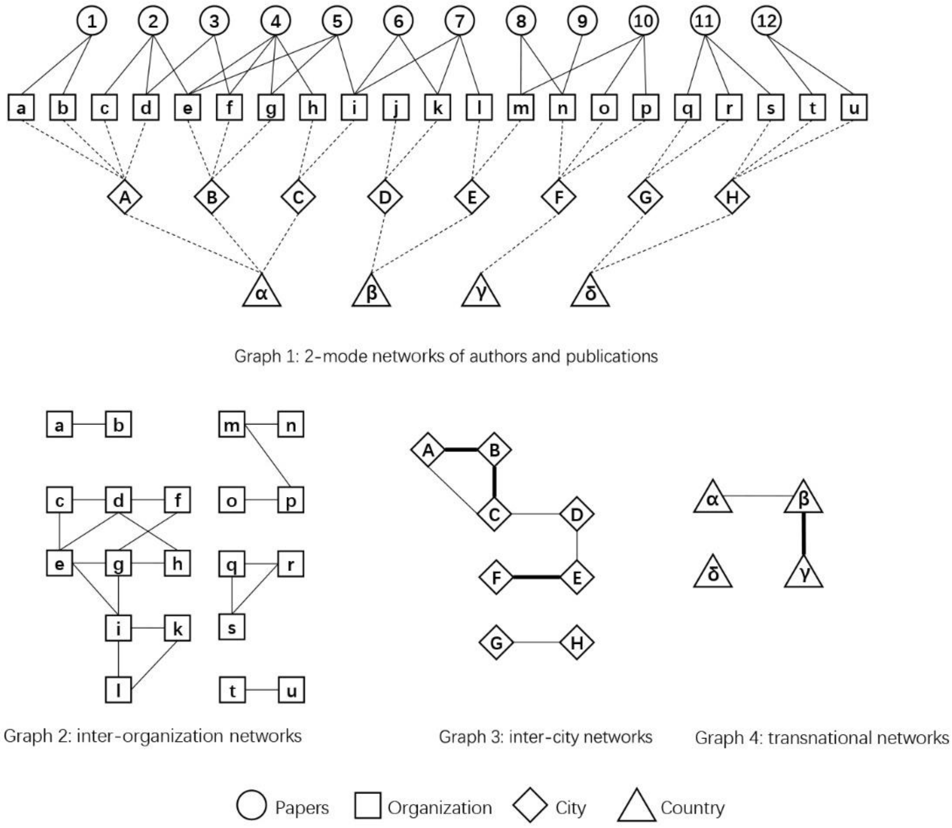


Figure 3-2 The logic of the IKCNs construction

3.3.3 Data collection and processing

Note that since this research deals with the KCNs of multiple spatial scales, the requirements for data accuracy are different, and in turn they demand different ways of data collection and processing. The network construction method introduced above is ideal but intricate. First, retrieve detailed information of all the scientific papers that produced in a focal city from the WoS database, including titles, research fields, authors' institutions and the detailed addresses of the institutions. If an article is co-authored by two or more institutions, then it can be considered that there are collaborative connections between these institutions. Then, the geographic information of these institutions can be utilized to construct IKCNs at different spatial scales.

The operationalization is as follows: first, log in the advanced search module of the WoS; second, set the target search range as “SCI-EXPANDED”, “SSCI” and “A&HCI”; third, set the time span as “2012-2016”; forth, set the language as “English”; and last, set the document type as “Article”.

Take New York as an example, type “CI=New York” in the search bar of the page, and 109,254 records are retrieved. That is, in 2012-2016, the number of scientific papers produced in New York is 109,254. Then, download the detailed information of all the records and obtain relevant information from them, including article titles, disciplines, authors’ institutions and detailed addresses. Lastly, after the raw data being sorted and corrected, the KCNs can thus be constructed based on those information and related analysis. It should be pointed out that there are mismatches and errors in the raw dataset. For example, in the WoS database, the standard name of New York University is “New York Univ”, but there are also errors in the raw dataset, such as “Newyork Univ” or “Univ New York”. Therefore, the raw data needs to be checked and corrected one by one. In addition, The WoS has strict restrictions that users can only download 10,000 records maximum for one retrieval. Therefore, this data collection approach is only suitable for research on specific regions with selected disciplines.

Another approach is more direct and easier. Take New York as the example again with the aim of retrieving all the scientific papers’ information that co-authored by institutions in New York and London. First, type “(CI=New York) AND (CI=London)” in the search bar, which indicates that the institutions involved in knowledge collaboration should be from New York and London. Then there are 5,043 records, that is, in 2012-2016, the intensity of collaboration between New York and London was 5,043. Similarly, to obtain the intensity of collaboration between the United States and the United Kingdom during 2012-2016, thus the searching condition is “(CU=USA) AND (CU=(England OR Scotland OR Wales OR North Ireland))”.Note, the searching condition for the UK is not “CU=UK” or “CU=Great Britain”, which means that when conducting such searching, it is also necessary to repeatedly check whether the input language is consistent with the standards of the database. The advantage of this approach is that the workload of data processing is relatively small, but the workload of data gathering is more intensive.

The second approach of network construction is less accurate when compared to the first. More specific, in figure 3-2, by the first approach, the strength of connection between City B and City C is 3, consisting of the connection between Institution *e* and Institution *i*, the connection between Institution *g* and Institution *i,* and the connection between Institution f and Institution *h* respectively. By the second approach , the strength of connection between City B and City C is 2, that is, the collaborations happened in Article 4 and Article 5. This is because the system itself is not able to distinguish that Institution *e* and Institution *g* are two different institutions in City B. Nonetheless, many existing empirical studies have shown that if the spatial scales of the objects are high and the number of records is large at the same time, the network construction results by this approach are solid and sound.

In summary, considering different research objects, research purposes and operational feasibility, different data collection strategies and data processing methods are adopted accordingly. The first research question mainly focuses on the structures of the IKCNs, and the spatial scales and data volume are rather large, therefore, the second method is more suitable. The second research question mainly focuses on the institutions of certain regions and certain disciplines, thus the first approach is more accurate and operable.

3.4 Research methods and techniques

This thesis is an empirical research with the aim of investigating both the structures and mechanisms of the evolution of the IKCNs in China. To end this, various analytical methods and techniques are adopted, including big data mining and processing, spatial analysis, social network analysis, econometric analysis, visualization techniques and semi-structural interviews:

3.4.1 Big data mining and processing

With over 1.2 million times of searching and over 3 million records, the data volume in this thesis is considerable. By accessing the Application Programming Interface (API) service provided by the Web of Science, a large scale of data collection was conducted with the aid of Eclipse program during September 2018, and the mining took more than 300 hours. The author spared no efforts to check and correct all the mismatches and errors in the raw data. Besides, in order to manage and operate the data more efficiently and precisely, Python, Access and other programming tools were also used.

3.4.2 Spatial analysis

Spatial analysis softwares like ArcGis10.3 and GeoDa are used as platforms. This thesis employs different spatial analytical techniques, including Gastner-Newman cartogram, spatial statistics, spatial clustering and spatial autocorrelation to describe, outline and analyze the geographical layout of innovation output as well as the spatial configurations of the IKCNs. Plus, some existing methods are improved and employed to further discuss multidimensional spatial features of the IKCNs, such as relative strength of connections, morphological polycentricity, functional polycentricity and spatial integration, etc.

3.4.2.1 **Gastner-Newman Cartogram**

A cartogram is a map in which some thematic mapping variables – such as travel time, population, or GDP – are substituted for land area or distance. The geometry or space of the map is distorted in order to convey the information of this alternate variable. Gastner and Newman (2004) propose a density-equalizing algorithm of cartogram for representing data for areas that modifies the size of the area to take account of different denominator populations. It's an approach that allows sizes of the areas to be equalized so they are visually comparable, while remains the overall geographic relations and topological attributes of the map. This technique is applied in visualizing and analyzing the spatial distribution of knowledge innovation output.

3.4.2.2 Coefficient of variance, Gini coefficient and rank-size analysis

In geographical research, it is crucial to investigate the spatial concentration and dispersion of the special properties within and between groups so as to qualitatively describe the overall geographical features. Indicators like variance or standard deviation are often used. But directly applying these two indexes to compare two groups of data is biased when their measurement scales or dimensions differ. The coefficient of variation is defined as the ratio of the standard deviation to the mean of a certain group of variables. The actual value of the coefficient of variation is independent of the unit in which the measurement has been taken, so it is a dimensionless index. For comparison between data sets with different units or widely different means, one should use the coefficient of variation instead of the standard deviation. The larger the coefficient of variation, the more discrete the variables within the group. Its expression is:

$$CV = \frac{\sigma}{\mu} \qquad (3\text{-}1)$$

In this thesis, σ and μ are respectively the standard deviation and average of the knowledge innovation output or network connectivity in a given year of observed countries or cities.

In economics, the Gini coefficient is a measurement of statistical dispersion and it is intended to represent the income or wealth distribution of a nation's residents. And it is the most commonly used measurement of inequality. In human geography literature, the Gini coefficient is widely employed to exam the degree of the (in)equal development of regions or countries, i.e., the gap between the developed entities and undeveloped entities (Yang et al., 2018). Larger value of the Gini coefficient indicates a more uneven development among regions within which most of the resources are concentrated in a few regions. It is expressed as follows:

$$G = \frac{1}{2n^2\overline{X}} \sum_{i=1}^{n} \sum_{j=1}^{n} | X_i - X_j | \qquad (3\text{-}2)$$

In this thesis, n is the number of countries or cities, $\overline{X}$ is the average of X_{ij}, and X_i, X_j are the innovation output or network connectivity of the country/city i and j respectively. G is the Gini coefficient (valued between 0 and 1). According to international standards, the spatial distribution is relatively of balance when $0.2 < G < 0.4$; the spatial distribution is relatively of imbalance when $0.4 < G < 0.5$; when $G > 0.5$, it corresponds to a rather uneven spatial distribution (Hu, 2004).

In the rank-size analysis, the hierarchical orders of the urban systems based on the correlation between its size and rank are mainly measured, which can also be applied to countries or regions (Chen, 2004). The size can be measured by indicators that represent the absolute mass of a country/city, such as GDP and population. In this thesis, the size can also be referred to the innovation performance and capability of the countries or cities via total amount of knowledge innovation output or networks connectivity. Specifically:

$$P_i = P_1 \times R_i^{-q} \tag{3-3}$$

P_i is the innovation output or network connectivity of the country/city i. P_1 is the knowledge innovation output or network connectivity of the primate country/city, R_i is the ranking of the country/city i in innovation output or networks connectivity. q reflects the overall degree of spatial concentration of innovation output and network connectivity of countries or cities. If $|q| > 1$, it indicates that the distribution of innovation output is uneven as the core countries or cities have absolute advantages. If $|q| < 1$, it implies relatively balanced distribution because small and medium-sized countries or cities also have high innovation output or network connectivity. Furthermore, for a certain country/city, if $|q|$ increases over time, it shows the existence of the Matthew effect at large that the innovation output or network connectivity of larger countries or cities grows faster than that of the smaller ones. On the contrary, if $|q|$ decreases over time, it indicates a diffusing trend that the innovation output or network connectivity of smaller countries or cities grows at a faster speed than the larger ones (Chen and Zhou, 2002).

3.4.2.3 K-means clustering analysis

Spatial clustering is an important indicator for describing the similarity and difference between spatial entities and further categorizing them in accordance with the variabilities. Spatial clustering can be defined as the process of group objects with certain dimensions into groups so that objects within a group exhibit similar characteristics when compared to those that are in the other groups. It is an important part of spatial data mining since it provides certain insights into the distribution of data and characteristics of spatial clusters. (Li et al., 2017). K-means clustering is a method of vector quantization, which is originally from signal processing and popular for cluster analysis in data mining. K-means clustering aims to partition observations into K clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This thesis uses K-means clustering to divide the countries or cities into different groups according to their innovation output or network connectivity. Therefore, we can better understand the hierarchy and variabilities of the geographical feature of the innovation system.

3.4.2.4 Spatial autocorrelation

According to Tobler's First Law of Geography, the social practices of regions are not dependent but somewhat interrelated, that is, neighboring regions will affect each other in various social and economic activities (Tobler, 1970). The aforementioned indicators can measure the overall distribution of knowledge innovation output or network connectivity of countries and cities but fail to grasp the interactions between them. In this manner, spatial autocorrelation measures the correlation of a variable with itself through space. The results of spatial autocorrelation can be positive or negative: positive spatial autocorrelation occurs when similar values occur near one another, while negative spatial autocorrelation occurs when dissimilar values occur near one another. (Yang et al., 2018; Zhang et al., 2007). Spatial autocorrelation analysis includes Global Moran's I and Local Moran's I). The former reflects the overall correlation of spatial entities while the latter examines the correlation between selected spatial entities (Chen, 2004). The expression is as follow:

$$GMI = \frac{\sum_{i}^{n}\sum_{j}^{n} W_{ij}(X_i - \overline{X})(X_j - \overline{X})}{S^2 \sum_{i}^{n}\sum_{j}^{n} W_{ij}} \qquad (3\text{-}4)$$

$$S^2 = \frac{\sum_{j}(X_j - X)^2}{n-1} \qquad (3\text{-}5)$$

$$LMI = \frac{(X_i - \overline{X})}{\sum_{i}(X_i - \overline{X})^2} \sum_{i=1}^{n} W_{ij}(X_i - \overline{X}) \qquad (3\text{-}5)$$

GMI and *LMI* represent the global autocorrelation index and the local autocorrelation index, respectively. *n* is the number of spatial units involved and refers to the number of countries or cities in this thesis. X_i and represent the knowledge innovation output or networks connectivity of the country/city *i* and that of *j*, respectively. W_{ij} is the spatial weights matrix based on Euclidean distance. If *GMI* is close to 1, it indicates that the distribution of innovation output or networks connectivity of countries/cities is spatially concentrated at the global level. If *GMI* is close to -1, it indicates that the distribution of innovation output or network connectivity is spatially dispersed. According to the *LMI* index, the spatial autocorrelation is divided into four types: (1) high-high correlation type, that is, the knowledge innovation activities or network connectivity of a focal country/city and its neighboring countries/cities are all high, which suggests the existence of spatial agglomeration effect and significant clustering trend; (2) low-low correlation type, that is, the degree of innovation activities and network connectivity of a focal country/city and its neighboring countries/cities are all low, which shows the absence of spatial agglomeration and low level of spatial interactions; (3) high-low correlation type, that is, the innovation output and network connectivity of a focal country/city are high, while that of its neighboring countries/cities are low, showing a "polarized" structure; (4) low-high correlation type, that is, the innovation output and network connectivity of a focal country/city are low, while that of its neighboring countries/cities are high, presenting a "basin" structure (Yang et al., 2018).

3.4.3 Social network analysis

The KCNs are complex networks by nature. Therefore, the "social network analysis" (SNA) is employed in this thesis to examine their topological properties. With social networks analysis toolboxes such as UCINET, Pajek and R language, in this thesis, on one hand, the overall topological properties of the IKCNs are investigated, such as "small-world" property, "scale-free" property, "core-periphery" structure, "center-hinterland" structure. On the other hand, the topological properties of individual networks, i.e. multidimensional centralities are examined.

3.4.3.1 **Topological structures of networks**

（1） Overall topological properties of networks

The overall network topological properties are examined, i.e. average degree, density, global efficiency, degree-degree correlation, small-world property and scale-free property. The algorithms and descriptions are listed in Table 3-1:

Table3-1 Measurements of overall topological properties of networks

Indicator	Algorithm	Description	Interpretation
Average degree	$\bar{D}_G = \frac{1}{2n}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}$	The average number of ties of a node in a network. In the function, *n* is the number of nodes in the graph *G*. x_{ij} is number of connections between node *i and node j*	More ties per node will lead to farther and faster information penetration
Density	$d_G = \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}$	The ratio of overall number of network ties to number of all possible ties. In the function, x_{ij} is number of connections between node *i and node j*	Higher density is associated with more contacts and faster diffusion of knowledge
Global efficiency	$E_G = \frac{1}{n(n-1)}\sum_{i \neq i}^{n} \frac{1}{d(i,j)}$	Sum of the reciprocals of the characteristic path length	Higher global efficiency means higher level of

			between any two nodes. In the function, $d(i,j)$ is the characteristic path length between node *i* and node *j*	overall connectivity of the network，which can lead higher information exchange efficiency
	Assortativity	$k_{nn}(k) = \frac{1}{N_k}\sum_{i,k_i=k} k_{nn,i}$	A measure of the preference for a network's nodes to attach to others that are similar in some way. In the function, node j is adjacent to node i, k_j is the degree of node j，$N_k$is the number of the nodes whose degrees are k. If the value is positive, the network presents assortative; otherwise, the network presents disassortativity	On the one hand, information reaches social hubs quickly, via their social hub neighbors; thus, high assortativity is expected to facilitate growth. On the other hand, assortativity can compromise the network's conciseness due to an increase in redundancy
Small-world property	Clustering coefficient	$C_G = \frac{1}{N}\sum_{i=1}^{N}\frac{2E_{Gi}}{k_i(k_i-1)}$	A measure of the degree to which nodes in a graph tend to cluster together. Global clustering coefficient is the average of the local clustering coefficients of all the nodes. In the function, E_i indicates the actual number of edges between the neighbors of node i, k_i is the number of neighbours of a node	in a network with a relatively high level of clustering, each member is more likely to receive communication on the innovation from multiple network members, hence increasing awareness and concentrating peer influence and learning rate
	Average characteristic path length	$L_G = \frac{2}{N(N-1)}\sum_{i=1}^{N}\sum_{j=i+1}^{N} d_{ij}$	The average characteristic path length is calculated by finding the shortest path between all pairs of nodes, and taking the average over all paths of the length thereof. In the function, is the shortest path length between node *i* and node *j*	If the average characteristic path length is small, it suggests there exist short cuts in the network, which can interconnect different groups of actors and can be beneficial for information diffusion
	Small-world quotient	$Q_G = \frac{C_G/C_{Gr}}{L_G/L_{Gr}}$	Q_G is the small-world quotient of graph G, C_G is the clustering coefficient of graph G, L_G is the average characteristic path length of graph G; C_{Gr} and L_{Gr} are	A small-world network is considered to engender faster information flow than are regular lattice networks or random networks, due to the shortcuts between nodes

			the clustering coefficient and average characteristic path length of a random graph that has the same size with graph G. If Q_G is bigger than 1， it indicates the network presents a small-world property	
Scale-free property	Degree distribution	$P(k)\sim k^{-\gamma}$	A scale-free network is a network whose degree distribution follows a power-law. In the function, the fraction $P(k)$ of nodes in the network having k connections to other nodes goes for large values of k. If the value of γ is between 2 and 3, then the network can be considered as a scale free network	Because the existence of few hubs in the network, the efficiency of information diffusion is high

Source：Author

（2） Individual topological properties of network members

Zooming in on the node level, not all members of a network are equal: some perform better than others. This is due to their different positions in the network, which can be measured by indicators of individual network properties, such as node centrality, structural holes and closure. The algorithms, descriptions and interpretaions of these indicators are listed in Table 3-2:

Table3-2 Measurements of individual topological properties of network members

Indicator		Algorithm	Description	Interpretation
Node centrality	Degree centrality	$DC_{Gi}=\sum_{i=1}^{N} e_{ij}$	The number of ties a node has compared to other nodes in the network. In the function, e_{ij} is the number of ties between node i and node j	A node's degree centrality in the network is positively correlated with its ability to spread content and ideas throughout the network, and can be used to measure the importance of a node in the network
	Betweenness centrality	$BC_{Gi}=\sum_{i\neq j\neq k}\frac{\sigma_{jk}(i)}{\sigma_{jk}}$	The extent to which a node is an important intermediary between other members' connections in the network。 In the function, σ_{jk} is sum of	Nodes whose betweenness centrality is very high, as they connect communities that otherwise would have been disconnected from each other,

			the number of the characteristic path length between node j and node k, $\sigma_{jk}(i)$ is the number of those paths that pass through node j	are related to, and sometimes called brokers, or bridges. A node with higher betweenness centrality is considered to have more power in control the flow of information
	Closeness centrality	$CC_{Gi} = N \Big/ \sum_{j=1, j\neq i}^{N} d_{ij}$	The reciprocal of the sum of the length of the shortest paths between the node and all other nodes in the graph, which measures how close a node is to each of the other nodes in the network. In the function, d_{ij} is the characteristic path length between node i and node j	Network members with higher closeness centrality are assumed to be better connected, i.e., have easier access to information and to sources of influence. In addition, higher closeness centrality also implies the nodes have more information resources and does not depend on a few members, which can be interpreted as having more capability of independent innovation
Structural holes	Constraint	$C_{Gi} = \sum_{j}(p_{ij} + \sum_{q} p_{iq}p_{qj})^2$	The extent to which time and energy is concentrated within a single cluster. In the function, q *is the number of third-party nodes to which both node* i *and node* j *are connected and is the number of the focal node* i*'s network contacting with* j（p_{iq} *and* p_{qj} *are defined analogously*）	An actor with rich structural holes is more likely to acquire novel and heterogeneous information, have non-redundant ties and enjoy autonomy benefits
Closure		$LC_{Gi} = \sum_{i=1}^{N} \frac{2E_{Gi}}{k_i(k_i - 1)}$	Closure reflects the number of neighbors that two connected network members have in common. It can be measured by local clustering coefficient. In the function, E_{Gi} indicates the actual number of edges between the neighbors of node i, k_i is the number of neighbours of a node	Actors with higher local clustering coefficient are more embedded in the network, thus can acquire information more easily

Source：Author

3.4.3.2 Block model, "core-periphery" structure and "community" structure

The block model is a generative model for random graphs. This model tends to produce graphs containing communities, subsets characterized by being connected with one another with particular edge densities. For example, edges may be more common within communities than between communities. (Liu, 2014). The block model splits into blocks, within which all nodes are "structural equivalent" in terms of how they connect to the rest of the network (Scott, 1988). Two nodes of a network can be considered as "structurally equivalent" if they share the same neighbors and they can replace each other's "location" in the network without changing the structure of the whole network. Block model is highly flexible, capable of modeling a wide variety of topological structures, including not only the conventional network modules, but also disassortative, core-periphery or mixed community structures. (Figure. 3-3)

The examinations of the "core-periphery" structure of the IKCNs are conducted by hierarchical clustering algorithm while the investigations of the "clusters" structure of the IKCNs are operationalized by "community detection" techniques (Girvan and Newman, 2002). It should be noted that the "community detection" has different algorithms, such as "Girvan-Newman" algorithm, "fast-greedy" algorithm, "multi-level optimization" algorithm, "walk trap" algorithm, etc. each of them has a certain range of application. Since this thesis focus on large-scale weighted indirect networks, the "multi-level optimization" algorithm is more suitable (Blondel et al., 2008).

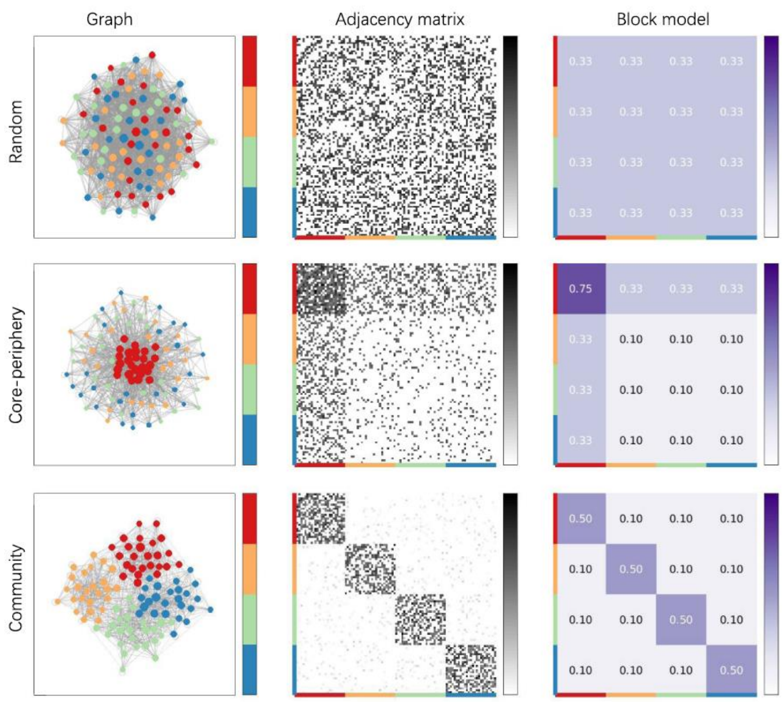


Figure 3-3 Block models and "core-periphery" structure and "community structure"
Source: Faskowitz et al. (2018)

3.4.3.3 “Center-hinterlands” structure

The detection of “center-hinterlands” structure of city network system was first proposed by Nystuen and Dacey (1961) based on the organizational logic of cities-regions, which is in line with the central place theory. This technique is designed to refine information of the complex networks and extract their backbones so as to identify the hierarchical relationships between cities. The division of cities into primate centers, sub-center and subordinate center can directly depict the “nodal-region” structure of the urban systems (Dai et al., 2018b; Deng et al., 2018). This thesis thus employs this method to identify the “nodal-region” structure of the IKCNs.

As shown in Figure 3-4, the basic roles of detecting the “center-hinterlnd” structure are: (1) the largest flows will be the ones that outlines the backbones of the urban networks; (2) the sizes of the cities are defined as the degree centrality of cites in the networks; (3) if city A’s size is bigger than city B, city B can be considered as city A’s subordinate when the strength of connection between them is largest; (4) a city is “independent” if its largest flow is to a smaller size city; (5) if city A is subordinate to city B and city B is subordinate to city C, then city A is subordinate to city C.

Matrix of city-dyads

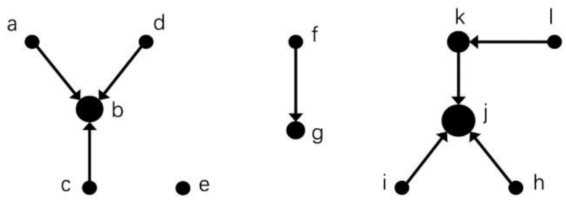
	a	b	c	d	e	f	g	h	i	j	k	l
a	0	75	15	20	28	2	3	2	1	20	1	0
b	69	0	45	50	58	12	20	3	6	35	4	2
c	5	51	0	12	40	0	6	1	3	15	0	1
d	19	67	14	0	30	7	6	2	11	18	5	1
e	7	40	48	26	0	7	10	2	37	39	12	6
f	1	6	1	1	10	0	27	1	3	4	2	0
g	2	16	3	3	13	31	0	3	18	8	3	1
h	0	4	0	1	3	3	6	0	12	38	4	0
i	2	28	3	6	4	4	16	12	0	98	13	1
j	7	40	10	8	5	5	17	34	98	0	35	12
k	1	8	2	1	0	0	6	5	12	30	0	13
l	0	2	0	0	0	0	1	0	1	6	12	0
Degree	113	337	141	128	290	71	118	65	202	311	91	39

Largest flow from these cities is to a “smaller” city where “size” is determined by the column totals

Network backbone

	a	b	c	d	e	f	g	h	i	j	k	l	
a		1											
b													*
c		1											
d		1											
e													**
f							1						
g													*
h										1			
i										1			
j													*
k										1			
l											1		

Blank spaces represent zero elements.
*terminal point, **Trivial terminal point



“Center-hinterlands” structure of the network

Figure 3-4 Calculation of the “center-hinterland” structure
Source: Nystuen and Dacey (1961)

3.4.3.4 “Globalization” and “localization”

In the city network research, the examinations of the “localization” and “globalization” features (or “internal reach” and “external reach”) of cities are useful in investigating their roles and functions in the city networks. A related concept is “knowledge gatekeepers”, first proposed by Allen (1977), and it has received a lot of attention. It refers to the actors who perform a crucial interfacing function between the local and the external knowledge systems, i.e. screening external sources, accessing them and conveying new knowledge to local actors. Therefore, knowledge gatekeepers are of significance in channeling external knowledge flow and spillovers, as well as in promoting the local innovation capabilities.

Borgatti (2006) proposes a measurement of the “external reach” and “internal reach” of network members based on path length. Breschi and Lenzi (2013) and Araújo et al. (2018) apply this method to examine the internal and external connectivity of cities in the KCNs and also to identify the “knowledge gatekeepers”. The specific algorithm of “localization” is as follows:

$$IR_{im} = \sum_{i=1}^{n_m} \frac{1}{d_{ik}} \tag{3- 6}$$

In the function, IR_{im} is the localization index of city i in country m. It is the sum of the geodesic distance (i.e. characteristic path length) between city i and other cities within its country. d_{ik} is the characteristic path length from city i to city k，both of which are located in the same country. Note, d_{ik} values 0 when city i and k are not interconnected. IR_i values between 0 and n_m（the number of cities of the country m. IR_{im} *is* valued as 0 when city i are not interconnected with any other city of the country, and it is valued as n_m when city i is interconnected with all cities of the country.

The mathematical measurement of “globalization” is:

$$ER_{im} = \sum_{i=1}^{n_o} \frac{1}{d_{ik}} \tag{3-7}$$

In this formula, ER_{im} is the globalization index of city i in country m. It is the sum of the geodesic distance between city i and other cities in foreign countries. ER_{im} is valued between 0 to n_o （ER_i is valued as 0 when city i is not connected with any other foreign cities, and it is valued as n_m when city i is connected with all foreign cities.

Based on this, the globalization and localization index of the whole country can be calculated, that is, the average of the globalization indexes of all the cities and average of the localization indexes of all cities, respectively (Figure 3-5). These two indexes are defined as follows:

$$ER_{im} = \frac{1}{n_m}\sum_{i=1}^{n_m}\sum_{k=1}^{n_o}\frac{1}{d_{ik}} \qquad (3\text{-}8)$$

$$IR_{im} = \frac{1}{n_m}\sum_{i=1}^{n_m}\sum_{k=1}^{n_m}\frac{1}{d_{ik}} \qquad (3\text{-}9)$$

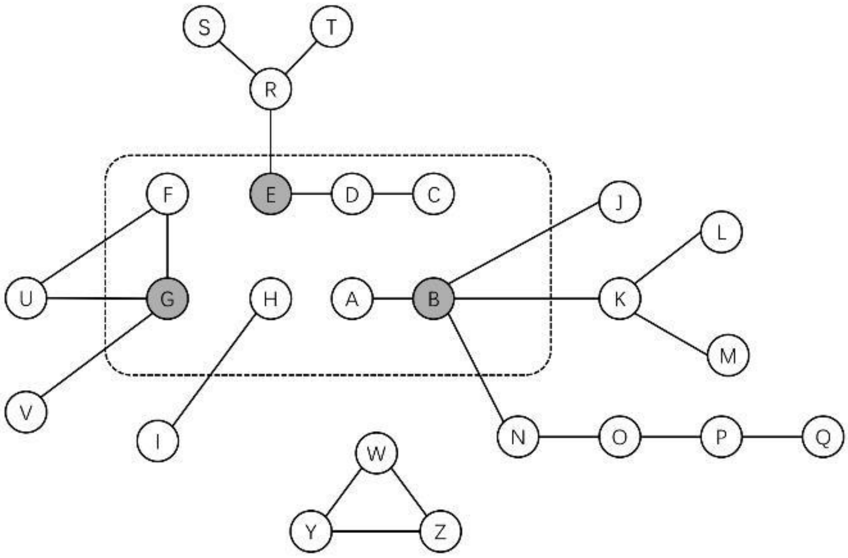


Figure 3-5 Measures "globalization" and "localization"
Source: Breschi and Lenzi (2015)

In the figure, circles represent cities, and the dotted line represents the boundary of a nation. City A to city H are located in the same country, among which, city B, E and G all function as brokerages between domestic cities and foreign cities, so they can be defined as "knowledge gatekeepers". For example, if city A need to collaborate with city J, it has to contact city B first, and the characteristic path length between A and J is 2 steps. Similarly, the characteristic path lengths between A and L is 3 steps. In this manner, the geodesic paths between city A and all other cities can be calculated. Then the globalization index of city A can be obtained: ER_A = 1 / 2 + 1/2 + 1/3 + 1/3 + 1/2 + 1/3 + 1/4 = 2.75. Accordingly, the country's overall globalization index ER = 1/8 ($ER_A + ER_B + ER_C + ER_D + ER_E + ER_F + ER_G + ER_H$) = 1 / 8 (2.75 + 5.08 + 0.83 + 1.16 + 2 + 1.5 + 2 + 1) = 2.04.

It should be pointed out that this method does not take the intensity of connection into consideration. In fact, when the geodesic lengths are the same, higher intensity of collaborative connections means higher accessibility. Therefore, this thesis uses the "weighted characteristic path length" introduced by Opsahl et al. (2010):

$$wd_{ik} = \min\left(\frac{1}{(CO_{ih})^a} + \ldots + \frac{1}{(CO_{hk})^a}\right) \qquad (3\text{-}10)$$

In this function, $wd_{ik.}$ is the weighted characteristic path length between city *i* and *k*. CO_{ij} is the intensity of collaboration between city *i* and *j*. *h* is the intermediary between *i* and *j*. *a* is the tuning parameter and is set as 1.5 in this research as Opsahl et al. did（2010）.

3.4.4 Econometric analysis

In order to measure the similarity, integration, determinants and performance of the IKCNs, various econometric models have been adopted, such as Quadradic assignment procedure (QAP) regression model, Poisson regression model, negative binomial regression model, zero-inflated negative binomial regression model etc.

3.4.5 Visualization

Data visualization helps to intuitively reflect research results. This study uses ArcGIS10.3 to visualize the spatial configuration of the IKCNs. The visualization of the topological structures of the IKCNs is done by softwares such as Gephi, Pajek, VOSviewer.

3.4.6 Semi-structural interview

Qualitative research is a scientific method of observation to gather non-numerical data. This type of research refers to the meanings, concepts, definitions, characteristics, metaphors, symbols, and description of things, not their "counts or measures". This type of research answers why and how a certain phenomenon may occur rather than how often. Through interpersonal interactions with the research object, explanatory understandings of its behavior could be attained. The qualitative research can be a complementation for the quantitative research by collecting and analyzing first-hand data which normally are difficult to quantify through quantitative approaches. This thesis uses in-depth interviews to provide first-hand information for examining the mechanisms of the IKCNs.

The author has been engaged in the joint PhD training program in the department of Geography of Ghent University in Belgium from 2016 to 2018. The author has conducted in-depth interviews with relevant members of the "Sino-Belgium joint laboratory for geo-information"，which is jointly found by the Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences and the department of Geography of Ghent University. The topics of the interviews are of the issues related to the macro mechanisms of the formation of the KCNs.

In addition, in September 2019, the author conducted random interviews with several PhD candidates in Tongji University School of Medicine on the issues related to the micro mechanisms that affect the formation of the IKCNs.

3.4.8 Summary

Table 3-3 lists the aforementioned empirical methods and their corresponding chapters.

Table 3-3 Empirical methods and their corresponding chapters

	Methods	Chapters
Spatial analysis	Gastner-Newman catogram Coefficient of variation, Gini coefficient and rank-size analysis K-means clustering Spatial autocorrelation	Chapter 4 – Chapter 7
Social network analysis	Overall network topological properties Individual network topological properties Block models, “core-periphery” structure, “community” structure, “Center-hinterland” structure Globalization and localization indexes	Chapter 4 – Chapter 7
Econometric analysis	QAP Counts regression models	Chapter 4 – Chapter 8
Data visualization		Chapter 4 – Chapter 8
Qulitative analysis	In-depth interviews	Chapter 8

Source: author

Chapter 4 The evolution of the transnational knowledge collaboration networks

National contexts should be considered when studying the city systems where they are embedded. The international status, geopolitics, history, socio-economy and cultural background of countries are all important factors in determining the trajectories of urban development (Brenner, 2009). Wagner et al. (2019) emphasized that the status of a focal country in the transnational KCN is closely related to the structure and performance of its national innovation system. Guan et al. (2015) examined the interactions between transnational KCNs of countries worldwide and the IKCNs of those countries and found that a focal city's innovation performance is not only affected by the network position of its country at the global scale but also by its network position in the IKCN at the national scale. Therefore, in this chapter, the evolution of transnational KCNs with the country as the basic spatial unit is examined with the intension to outline the macro-structural, country-specific contexts for the further analysis of the IKCNs.

The era of "science genius", such as Newton and Einstein, is probably something of the past. Contemporary cutting-edge science is characterized by higher level of complexity, interdisciplinarity, uncertainty. Against this background, international scientific collaboration has gradually become the dominant force that drives the scientific and technological progress. Many scientific and technological breakthroughs today often come from large-scale international collaboration（Simonton, 2013). Royal Society[12], in a report on transnational scientific collaboration, points out that among all SCI and SSCI publications around the world, the proportion of transnational collaboration publications in 2011 reached 35%, which was 10% higher than that of 1995. Meanwhile, the transnational KNCs have witnessed a significant growth in terms of spatial range and collaboration intensity (Royal Society, 2011). Therefore, accessing into the transnational knowledge collaboration network and reaching the global

[12] The Royal Society, formally The Royal Society of London for Improving Natural Knowledge, is a learned society and the United Kingdom's national academy of sciences. Founded on 28 November 1660, it was granted a royal charter by King Charles II as "The Royal Society". It is the oldest national scientific institution in the world. The society fulfils a number of roles: promoting science and its benefits, recognizing excellence in science, supporting outstanding science, providing scientific advice for policy, fostering international and global co-operation, education and public engagement. It also performs these roles for the smaller countries of the Commonwealth.

innovation frontier turn out to be increasingly important for promoting countries' international competitiveness and maintaining the long-term prosperity.

4.1 The evolution of the landscape of the global scientific knowledge production

4.1.1 The rapid growth and expansion

In terms of resource input, the R&D expenditure in 1995 worldwide only accounted for 1.90% of the total GDP. In 2016, the share of the R&D expenditure rose to 2.31%. In 2016, R&D employees reached 1,473.2 per million people compared with 1,070.5[13] per million people in 2010. In terms of total output, the global scientific publications increased from 512,031 in 1990 to 1,498,140 in 2016--an increase of 192.6%, with the average annual growth rate of 7.2%. (Figure 4-1) It is obvious that the growth of global knowledge innovation output is closely related to the global economic growth trend. But at the same time, the growth of global innovation output does not necessarily go with the fluctuation of the global economy. For example, knowledge innovation still maintains steady growth even in the downturn of the 1990s and during the global financial crisis in 2008. It can be inferred that innovation has become an increasingly important national strategy, that is, to some extent, it is independent with the up and downs of the economy.

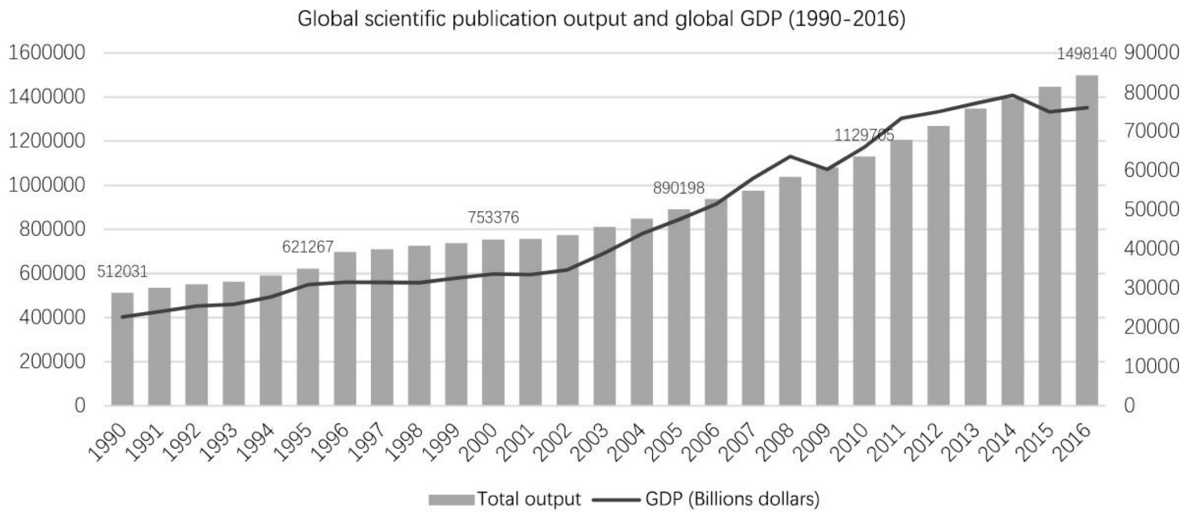


Figure 4-1 Global scientific publication output and global GDP (1990-2006)
Source: author

In terms of spatial range, the number of countries that actively participate in global knowledge innovation has increased and the spatial range of the scientific output has also been enlarged.

[13] Source: World Bank database.

In 1995, 189 of the 233 countries and regions studied have produced at least one paper in the WoS, and 51 have published more than 500 publications. The figures rose to 192 and 68 in 2005, respectively. By 2016, the number of countries with more than one paper published and more than 500 publications published was 207 and 93 respectively. As shown in Figure 4-2, in terms of spatial distribution, in 1995, the countries with less than 500 publications published are spread across all continents with the exception of North America, especially in most countries in Africa, Central Asia, the Middle East and Southeast Asia. By 2005, in some countries in Southeast Asia, Iran in the Middle East, Algeria in North Africa “enclaves” in those innovation “deserts” have gradually emerged. By 2016, these “deserts” have further shrunk. It is worth noting that some of the better-developed countries in East Africa (Ethiopia, Tanzania and Kenya, etc.) and West Africa (Nigeria and Cameroon) have gained strong momentum. In Table 4-1, the significant increase of the maximum and mean of the national scientific output further confirms this feature. At the same time, the coefficient of variation has gradually decreased from 5.00 in 1995 to 3.67 in 2016. The Gini coefficient and the global Moran’s I index have also gradually declined. These results indicate that more and more countries have become more active in being engaged in innovation and meanwhile, the gaps among countries have been gradually narrowed. In summary, innovation is becoming more and more globalized (Pavitt, 2002; Wagner and Leydesdorff, 2005a; Liu et al., 2017) and has become a “global enterprise” (Royal Society, 2011).

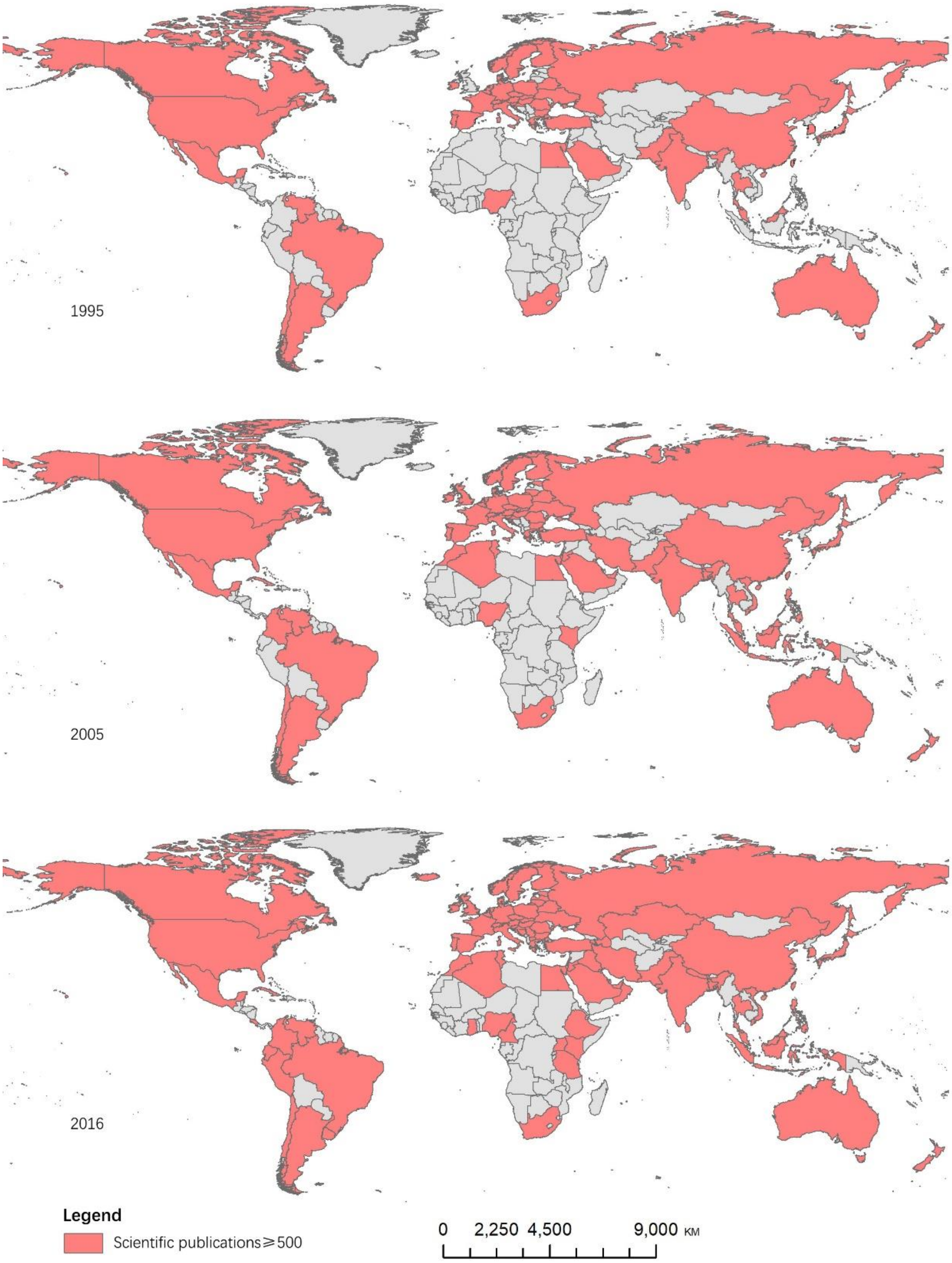


Figure 4-2 Countries with more than 500 scientific publications (1995-2016)

Source: author

Table 4-1 Descriptive statistics of the global scientific output (1995-2016)

	1995	2005	2016
Observations	189	192	207
Max	229,713.00	282,711.00	414,391.00
Min	1.00	1.00	1.00

Mean	3,647.49	5,800.95	10,605.52
Coefficient of variation	5.00	4.08	3.67
Gini coefficient	0.92	0.90	0.88
Moran's I	0.179	0.175	0.168

Source: author

4.1.2 The emergence of the multipolar structure

Figure 4-3 is the Gastner-Newman cartogram of the global scientific output from 1995 to 2016, in which the total number of the national scientific publications is proportional to the area of the countries. It shows that during 1995-2016, the geographical configuration of global scientific output experienced a significant shift. The "North America-Western Europe-Japan" tripod structure with the US as the core has been gradually rescaled. Emerging economies such as China, India, Brazil and South Africa have entered the stage in recent years, which is in accordance with the rapid growth trends of their national economy. By 2016, the China-India in the East Asia has become the "fourth pole" of the global scientific production landscape. However, the dominance of the "North America-Western Europe – Japan" axis, especially the US, has not been fundamentally challenged. As it can be seen from Figure 4-3, the number of scientific publications published in the United States in 1995 accounted for nearly 37.0% of the global total amount, and it is 27.4% higher than the UK, which ranked the second. Meanwhile China and India accounted for only 2.51% and 2.08% of the global total respectively. In 2016, although the global share of knowledge innovation output in the US declined, it was still as high as 27.7%. In the study period, among the top 20 countries in terms of scientific output, the EU countries monopolize, which reflects the high innovation performance of the region. By the end of the study, China has surpassed Western European countries, Japan and South Korea and become the world's second largest country in terms of scientific output, with a global share of 18.9%. In addition, South Korea, India and Brazil also entered the top 20 club.

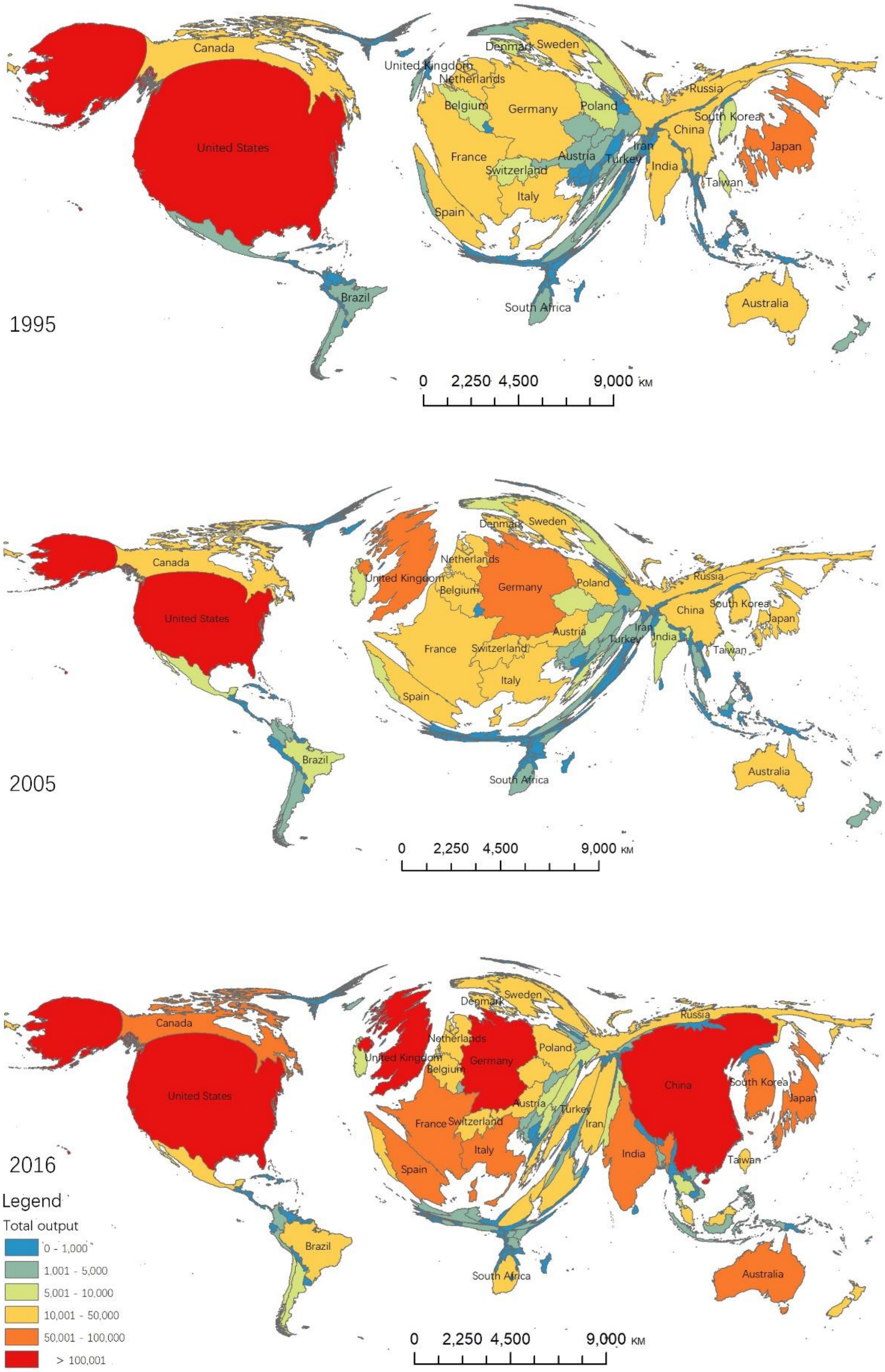
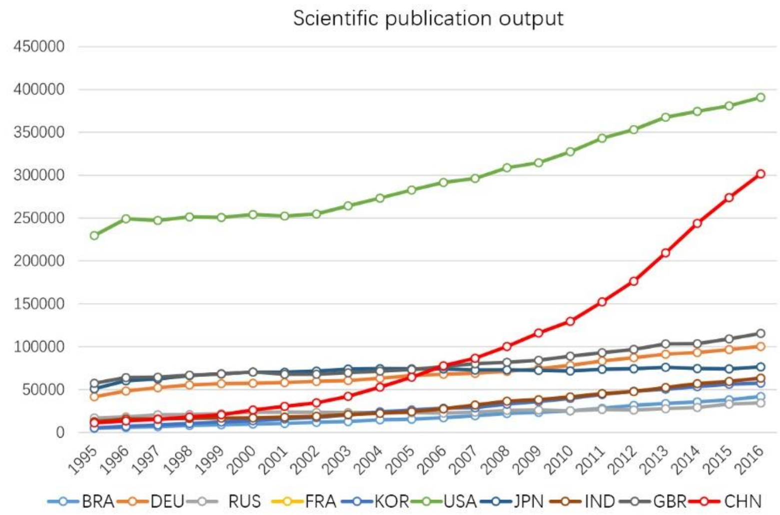


Figure 4-3 Total amount of the global scientific output (1995-2016)

Source: author



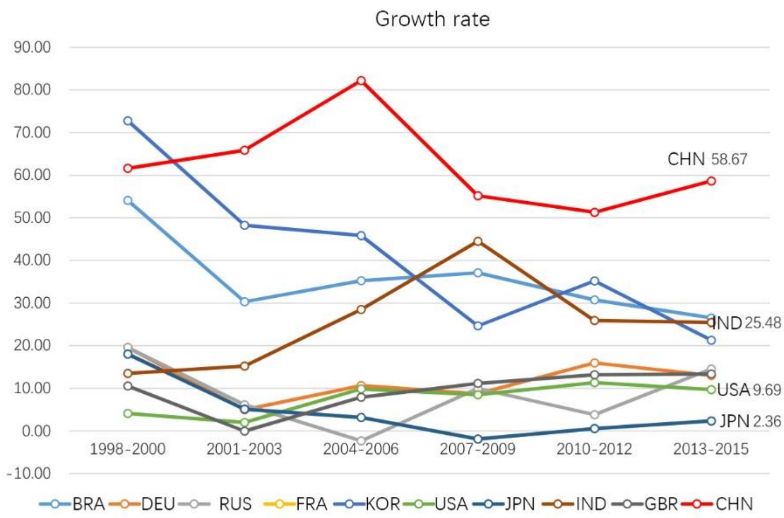


Figure 4-4 The total amount and growth rate of scientific output of major countries

Source: author

Table 4-2 Top 20 countries in the total amount of scientific publications published and their global shares (1995-2016)

	1995			2005			2016		
Rank	Country	Total amount	Share	Country	Total amount	Share	Country	Total amount	Share
1	United States	229,713	36.97	United States	282,711	31.76	United States	414,391	27.66
2	United Kingdom	59,625	9.60	United Kingdom	77,559	8.71	China	282,546	18.86
3	Japan	50,966	8.20	Japan	74,052	8.32	United Kingdom	128,911	8.60
4	Germany	41,543	6.69	Germany	66,343	7.45	Germany	101,559	6.78

5	France	31,838	5.12	China	64,485	7.24	Japan	80,007	5.34
6	Canada	30,821	4.96	France	47,111	5.29	India	78,301	5.23
7	Italy	22,790	3.67	Canada	41,395	4.65	France	69,893	4.67
8	Russia	16,800	2.70	Italy	38,754	4.35	Canada	69,454	4.64
9	Australia	16,400	2.64	Spain	28,353	3.19	Italy	66,960	4.47
10	Netherlands	15,402	2.48	Korea	26,039	2.93	Australia	65,064	4.34
11	China	15,282	2.46	Australia	25,652	2.88	Korea	59,673	3.98
12	Spain	13,402	2.16	India	24,219	2.72	Spain	54,778	3.66
13	India	12,668	2.04	Russia	22,971	2.58	Brazil	40,663	2.71
14	Sweden	12,221	1.97	Netherlands	22,565	2.53	Netherlands	39,351	2.63
15	Switzerland	9,451	1.52	Sweden	16,518	1.86	Russia	37,643	2.51
16	Israel	7,571	1.22	Taiwan, China	16,069	1.81	Iran	34,669	2.31
17	Belgium	7,126	1.15	Switzerland	15,470	1.74	Turkey	31,855	2.13
18	Poland	6,868	1.11	Brazil	15,360	1.73	Switzerland	28,894	1.93
19	Taiwan, China	6,031	0.97	Turkey	13,971	1.57	Poland	28,685	1.91
20	Denmark	5,866	0.94	Poland	13,122	1.47	Sweden	27,707	1.85

Source: author

Table 4-3 further confirms the aforementioned conclusions[14]. First, based on the national income, in 2016, the scientific output of high-income countries accounted for nearly 70% of the global total production, but its global share decreased by nearly 20% compared with 1995. In contrast, the output of middle-income countries grew rapidly. Then, from the perspective of the geoscheme, all regions have experienced considerable growth in the total amount of knowledge innovation. The growth rate of innovation output in all other regions in 1995-2016 has quadrupled or more except for Europe and North America. At the same time, in terms of the global share, it can be seen that the Asia Pacific region has become another innovation highland along with the Europe and North America. Finally, in terms of the transnational alliances, the emerging economic blocks of the BRICS countries (Brazil, Russia, India, China and South Africa) and the East Asia (China, Japan, Korea and ASEAN) have witnessed significant growth. During 1995-2016, the total amount of the scientific output of the BRICS countries increased by 7.6 times, and its global share also increased by 13.3%. This considerable contribution owes to China's rapid rise. In contrast, the EU, the North American Free Trade Agreement countries (the United States, Canada and Mexico) and the Four Asian

[14] The study involved the classification of countries by region and income level, the World Bank classification method has been adopted (http://datatopics.worldbank.org/sdgatlas/the-world-by-region.html). Among them, there are seven regions: North America, Latin America and the Caribbean, Europe and Central Asia, Middle East and North Africa, Sub-Sahara Afric, South Asia and East Asia and Pacific. There are four types according to income levels: high income countries, upper middle income countries, lower middle income countries, and low income countries.

Tigers (Singapore, Hong Kong, Taiwan and South Korea) have lower growth rates and their global shares declined. A notable rising star is Iran in the Middle East (Table 4-2). The total amount of the paper published in Iran has increased from 419 in 1995 to 34,669 in 2016, and its global ranking has jumped from No.53 in 1995 to No.16 in 2016. Iran is the fastest country in terms of the growth rate. Iran's rise is closely related to its national innovation and development strategy in recent years. Faced with harsh economic sanctions and the needs of alleviating excessive dependency on petroleum resources, the new Iranian government has initiated a "vision 2025" plan that focuses on improving national innovation capabilities through various instrumental policies and altering its resource-based economy towards a knowledge-based economy

In a word, the emerging East Asia is the most significant change of the landscape of the global scientific output in 1995-2016. First, at the global level, the scientific innovation is becoming a "global enterprise": on one hand, the total amount of global knowledge innovation continues to grow; on the other hand, an increasing number of countries are actively being engaged in the competition of global scientific innovation. Second, at the regional level, the spatial configuration of the global scientific innovation system has gradually evolved from a tripod structure underpinned by "North America-Western Europe-Japan" towards a multi-polarized structure with the rapid growth of emerging economies. Third, at the national level, although the US-centered hierarchical structure has not been fundamentally changed, the eye-catching rise of China is gradually challenging the monopoly of the US.

Table 4-3 Total amount and global share of the scientific output of countries classified by income level, regions and trade alliances (1995-2016)

	Total amount			Global share			1995-2016 growth rate	1995-2016 Percentage change
	1995	2005	2016	1995	2005	2016		
High income countries	613,691	903,968	1,497,984	89.02	82.45	69.24	1.44	-19.78
Middle income	52,449	149,746	519,089	7.61	13.66	23.99	8.90	16.38
Low income countries	1,318	2,500	9,395	0.19	0.23	0.43	6.13	0.24
East Asia and Pacific	100,972	224,075	571,351	14.65	20.44	26.41	4.66	11.76
Europe and Central Asia	281,992	453,706	804,723	40.91	41.38	37.19	1.85	-3.71
Latin America and the Caribbean	12,685	33,695	80,248	1.84	3.07	3.71	5.33	1.87
Middle East and North	13,404	24,905	98,394	1.94	2.27	4.55	6.34	2.60
North America	260,545	324,125	483,892	37.79	29.56	22.37	0.86	-15.43
South Asia	13,681	26,369	91,740	1.98	2.41	4.24	5.71	2.26
Sub-Saharan Africa	6,096	9,504	33,179	0.88	0.87	1.53	4.44	0.65
BRICS	52,744	131,584	454,220	7.65	12.00	20.99	7.61	13.34

EU	244,727	386,755	672,812	35.50	35.28	31.10	1.75	-4.40
Asian Four Tigers	64,023	122,429	180,317	9.29	11.17	8.33	1.82	-0.95
NAFTA	263,055	330,616	496,477	38.16	30.16	22.95	0.89	-15.21
China, Japan and South Korea and ASEAN	75,173	176,796	467,732	10.90	16.13	21.62	5.22	10.71

Source: author

4.1.3 The hierarchical structure

With regard to the overall hierarchical structure and local regional pattern, the evolution of the landscape of the global scientific output stay relatively stable rather than radical and leapfrogging, which can be termed as "space dependency".

As shown in Figure 4-5, the rank-size distribution of the total output of global scientific publications in the three time sections is in line with the power-law distribution, and the degree of fitting is satisfactory (R^2 of all three time sections are higher than 0.85). This result indicates that the polarization of global scientific innovation output is obvious--most of the scientific innovation output is produced in a few countries. In addition, by comparison, the regression lines did not change widely during 1995-2016 (the difference among the coefficients of the three sections was very small). Figure 4-6 is the K-means clustering result of national scientific innovation output. It is not difficult to find that the distribution of national scientific innovation output shows a clear-cut hierarchical structure. However, this hierarchical structure is not a well-proportioned "pyramid" pattern: the hierarchical structure almost presents an inverted "T-shaped" distribution since most of the publications are concentrated in a few cities.

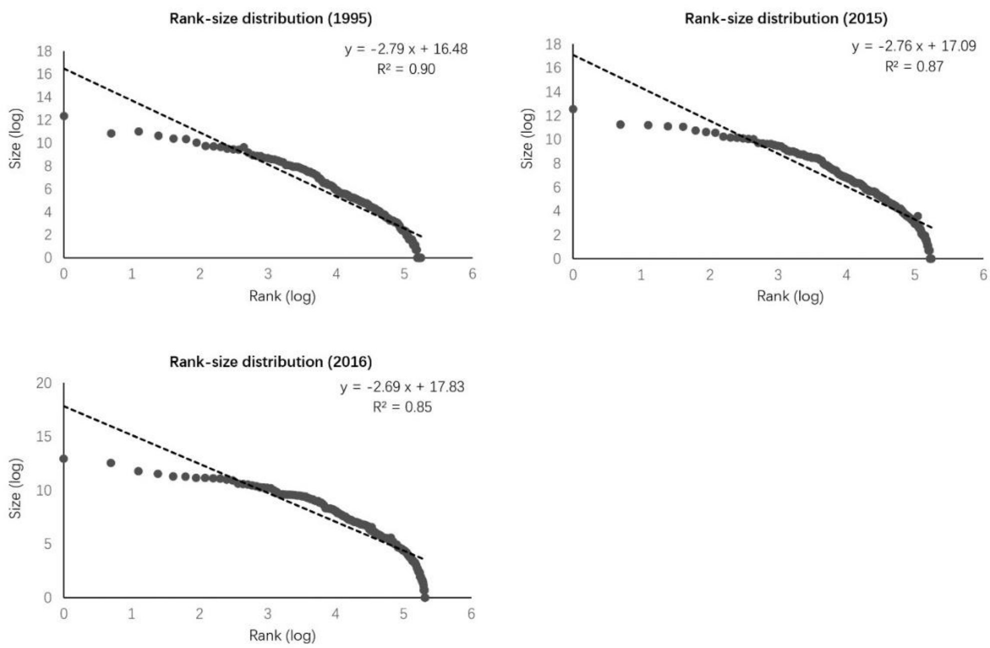


Figure 4-5 Rank-size distribution of the global scientific output (1995-2016)
Source: author

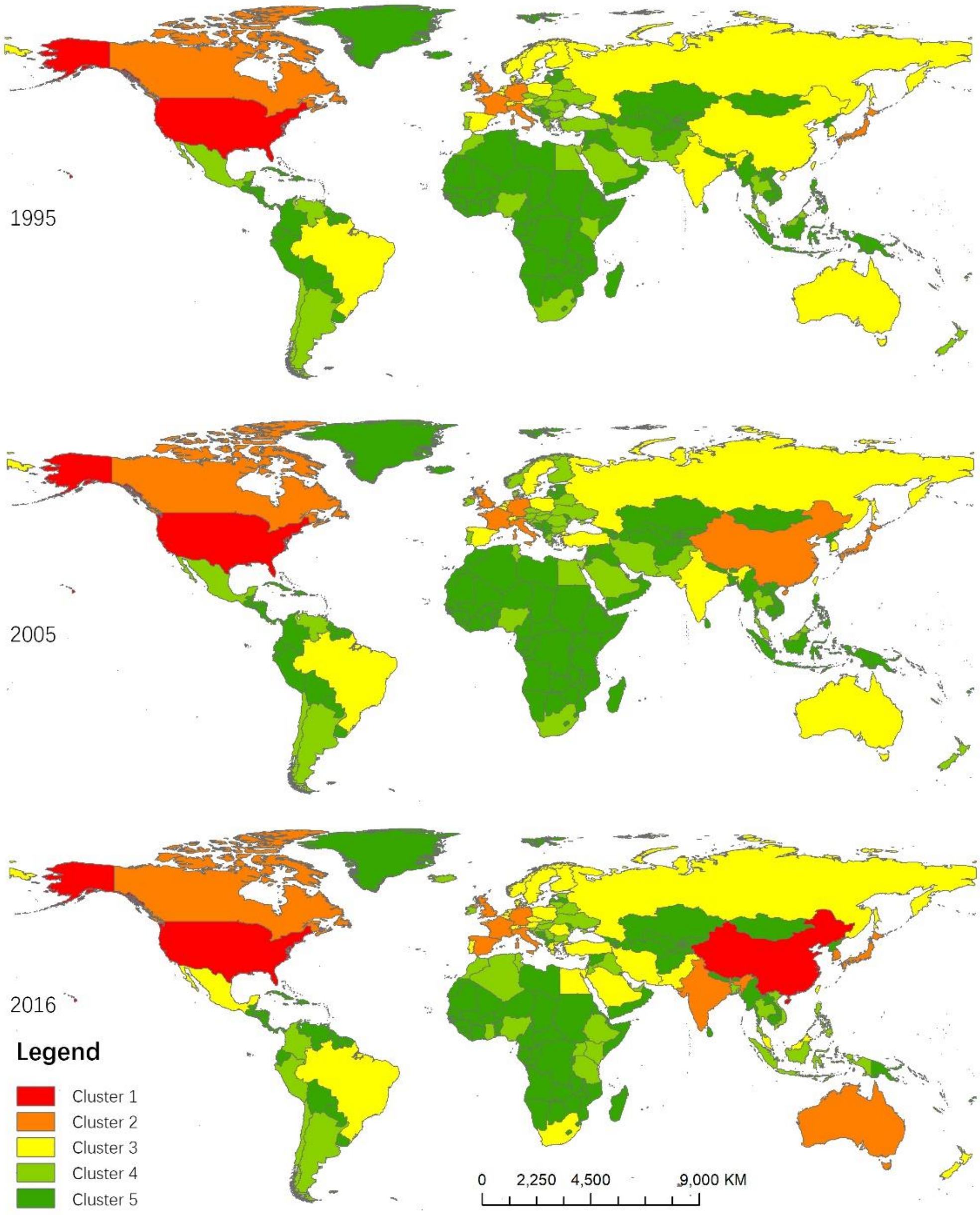


Figure 4-6 K-means clustering of the global scientific output (1995-2016)
Source: author

In addition to the stability of the overall hierarchical structure, the spatial patterns of the global scientific innovation output at regional scale also present relatively steady trajectories. Figure 4-7 shows the result of the spatial autocorrelation analysis. In general, the spatial patterns of the three cross-sections did not change too much, but presented a gradual development trend. Among them, North America and West Europe have maintained high-high correlation and show a certain degree of spatial spillover respectively. For example, in 2016, Mexico and some Eastern European countries also were infused into these two clusters of high-high correlation type respectively. The spatial patterns of Latin America and Africa are similar. Brazil and South

Africa, as emerging economies, are far outperformed than their surrounding countries in terms of the scientific innovation output, presenting a mixed pattern of high-low correlation type in the center and low-low correlation type in peripheral area. This echoes in the regions in East Asia and the Oceania-Southeast Asia. In comparison, the spatial pattern of the West Asia, Middle East and North Africa regions has changed most evidently. During the study period, Iran, Saudi Arabia, Turkey and Egypt have emerged rapidly in the previous contiguous areas of low-low correlation type and constituted an "undulating" structure along the Persian Gulf and the eastern coast of the Mediterranean. In general, the evolution of the regional spatial patterns of the scientific innovation output follows the rule of "space dependency". This finding is consistent with the conclusions of Heimeriks and Boschma (2013) in the study of the evolution of global biotechnology: the processes of knowledge learning and production tend to be stuck in specific place, and the cumulative cycles of knowledge production processes will be constantly strengthened.

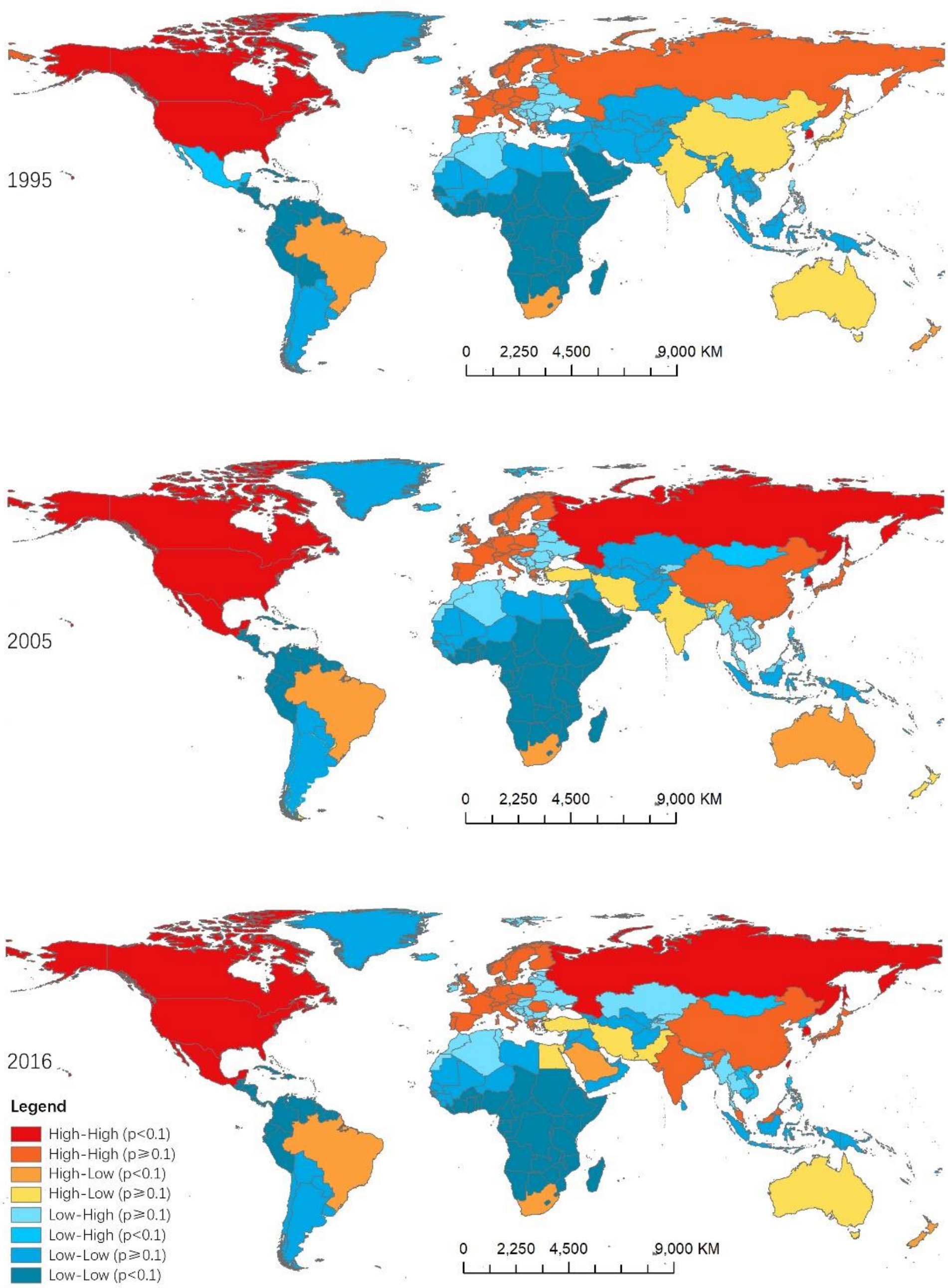


Figure 4-7 Local spatial autocorrelation analysis (1995-2016)

Note: When the significance level p is set to 0.1, the spatial autocorrelation of most regions is not significant and presents a random distribution. Thus, in order to make the results more interpretable, the autocorrelation results for all spatial units are all presented in the image by significant and non-significant categories.

4.2 The evolution of the spatial configurations of the transnational KCNs

In the context of the globalized knowledge economy, countries' innovation competitiveness not only depends on their own national innovation systems, but also increasingly relies on the interactions with other countries' innovation systems (Li and Pi, 2012). Seeking advantageous network positions in global KCNs is critical to enhance the global competitiveness of countries (Carlsson, 2006; Herstad et al., 2010). Many studies have shown that in the processes of scientific innovation, transnational collaboration is becoming more and more common. The same trend can be found in the growing frequency, the expanding spatial range and the broadening interdisciplinarity (Leydesdorff and Wagner, 2008; Wagner and Leydesdorff, 2005b; Wagner et al., 2019). The positive and fundamental role of transnational collaboration in improving the national innovation capability has been widely acknowledged. The following sections will focus on the characteristics of transnational KCNs and the global innovation system they form.

Table 4-5 reflects the increase of transnational scientific collaboration worldwide from 2000 to 2015 (Ribeiro et al., 2018). The table shows that the total amount, global share and spatial range of transnational collaboration have witnessed a significant growth. Compared with 2000, the total output of transnational collaboration publications has been tripled in 2015, and the global share has also increased from 10.7% to 21.3%. At the same time, the number of countries involving in transnational collaboration has increased from 174 to 200.

Table 4-5 Growth trends of the transnational scientific collaboration (2000-2015)

Year	Total amount of publications	Total amount of transnational collaboration publications	Share of transnational collaboration publications	Number of countries involving in transnational collaboration
2000	1,274,329	136,483	10.7%	174
2003	1,360,275	166,672	12.3%	184
2006	1,517,189	197,940	13.0%	189
2009	1,885,092	265,460	14.1%	190
2012	2,019,563	329,190	16.3%	189
2015	1,964,747	418,866	21.3%	200

Source: Ribeiro et al. (2018)

Table 4-6 lists the top 20 countries in terms of total scientific innovation output in 2016. The total amount, global share and number of partners of these countries have all increased in the period of 1995-2016 with the exception of Poland. By comparison, it is easy to find that the transnational collaboration growth in the European and American developed countries is faster than those in developing countries. China's transnational collaboration ratio had increased only by 5.2% during the study period, implying that China's rapid growth in scientific innovation output relies more on the country's endogenous capacity. Besides, it can be seen that the countries' shares of transnational collaboration and their total amount of scientific innovation are not obviously correlated, but they exhibit an evident regional heterogeneity. For example, in 2016, the total amount of transnational collaboration in the United States far exceeded that of other countries, but its domestic share was only 34.1%. The shares are even lower in some

Asian-Pacific countries, such as China, Japan and South Korea (less than 30%). In contrast, the shares of transnational collaboration among Western European countries are generally higher, most of the shares are above 50% with Switzerland being the highest (72%). These results suggest that in terms of the level of transnational collaboration, countries in Western Europe are more active than that in North America and East Asia

Table 4-6 Transnational collaboration of the top 20 countries in scientific publications (1995-2016)

	1995			2005			2016			Change in share
	Total amount	Number of partners	Share	Total amount	Number of partners	Share	Total amount	Number of partners	Share	
United States	46,463	149	13.07	94,695	166	21.98	204,538	194	34.06	20.99
China	2,923	73	21.14	16,761	105	21.97	89,416	171	26.49	5.35
United Kingdom	19,760	127	22.42	41,378	154	38.17	95,536	195	56.57	34.15
Germany	17,871	110	28.05	39,767	136	42.02	77,347	177	55.23	27.18
Japan	9,169	85	13.65	19,447	117	21.36	30,574	165	29.70	16.05
India	1,901	68	11.58	5,342	97	19.00	18,945	161	24.81	13.23
France	14,479	117	29.24	28,603	138	45.01	55,791	148	59.23	30.00
Canada	10,884	103	25.46	22,629	131	39.82	48,473	170	53.33	27.87
Italy	8,932	88	29.31	19,266	113	37.35	44,845	174	49.54	20.23
Australia	4,982	91	22.45	13,268	120	37.53	45,047	181	53.00	30.54
Korea	1,662	40	25.19	7,401	79	24.62	20,166	138	29.07	3.88
Spain	4,788	82	25.61	13,559	116	36.34	38,654	172	51.83	26.22
Brazil	2,281	64	33.41	5,990	94	29.61	20,305	165	37.78	4.37
Netherlands	6,468	90	31.33	13,916	115	44.82	33,380	174	62.31	30.98
Russia	6,165	69	21.98	9,903	93	36.67	14,376	149	35.46	13.48
Iran	144	11	29.51	1,276	54	22.47	8,506	140	23.64	-5.87
Turkey	598	36	19.42	2,698	79	15.99	8,661	141	22.40	2.98
Switzerland	5,905	90	43.97	11,999	121	56.93	29,374	168	71.97	28.00
Poland	3,237	63	39.68	6,194	79	37.47	12,223	139	37.11	-2.58
Sweden	5,308	80	35.12	10,017	105	48.36	23,094	164	66.05	30.94

Source: author

Ribeiro et al. (2018) analyze the distribution of the shares of transnational collaboration of 200 countries in 2015. Figure 4-8 is a histogram that shows the number of countries in each range of percentage of transnational scientific collaboration. The first peak, (around 30%, with 20 countries) is composed basically by "middle income" countries, i.e., countries whose national systems of innovation are not completely formed: the examples are Mexico, Philippines, South Africa and Thailand. In this peak, there are also large "high income" countries: Canada, England and Germany. The second peak, around 40%, is predominantly from "high income" small countries: Sweden and Netherlands are examples of this set of countries. There are also smaller "middle income" countries: Chile. Finally, the third peak (around 70%, with 21 countries) is composed only by "low income" countries, which might only have the beginnings of an innovation system: Uganda, Ecuador, and Kenya. It seems that beyond 60% of international co-authorship, there are only "low income" countries.

A preliminary analysis may suggest some patterns. First, least developed countries, namely countries with rudiments of national systems of innovation, depend strongly on international cooperation, therefore they display high levels of international co-authorship. Second, dynamic innovation systems of small countries are more internationalized than the average. Thirdly, larger countries with strong national scientific bases are proportionally less internationalized than the average, although they are leaders in absolute terms, like the USA and China.

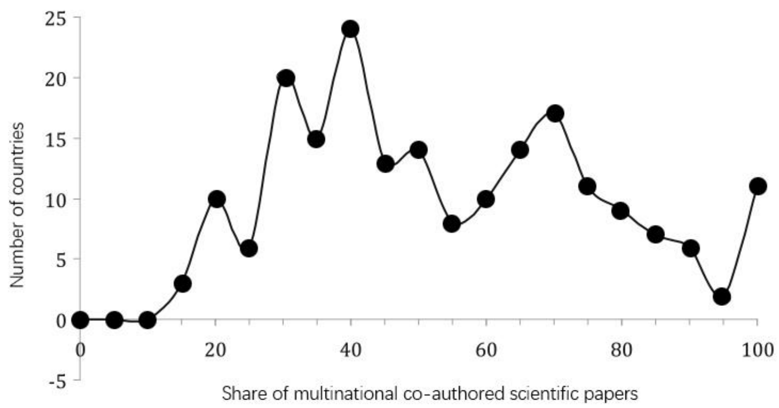


Figure 4-8 Frequency distribution of the proportion of transnational collaboration
Source: Ribeiro et al. (2018) (data source is also from WoS)

4.2.1 The overall spatial structures and regional spatial structures

The total number of scientific collaboration links between a focal country and all other countries represents the focal country's degree centrality, reflecting the country's "knowledge collaboration network connectivity" (KNC)[15, 16]. The larger the KNC, the more the importance of the country in the network. Figure 4-9 shows the Gastner-Newman cartogram of the spatial distribution of countries' KNC worldwide. Generally speaking, during1995-2016, the overall spatial configuration of the transnational collaboration network presents a multipolar structure that underpinned by the United States as the center of the network, along with Canada, Australia, Japan and some major developed countries in Western Europe. The evolution of this structure during 2005-2016 remained stable and steady, although emerging economies such as China, Brazil, and India have grown significantly in terms of the total amount of knowledge output, they have not yet greatly reshaped the hierarchical order in terms of network connectivity. The evolution of the spatial configuration of the transnational knowledge collaboration network is not completely consistent with the landscape of the global scientific innovation production.

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15 In the study of global urban networks, GaWC named the connectivity of cities in the network as "Global Network Connectivity" (GNC). Through analogy, this thesis terms "knowledge collaboration network connectivity" as "KNC" .

16 For the KNC ranking of all countries, see Appendix I.

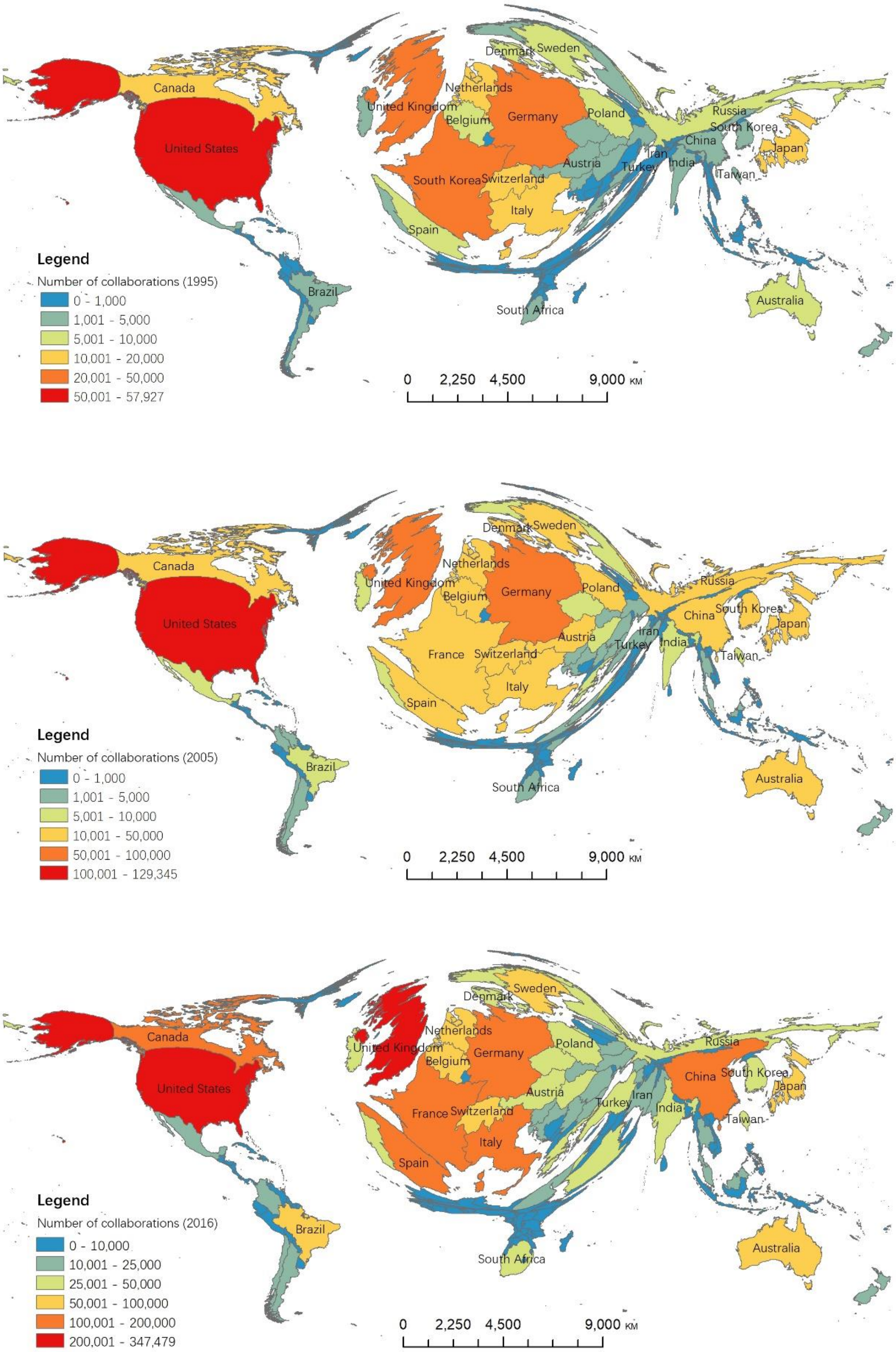

Figure 4-9 Spatial distribution of the KNC of countries(1995-2016)

Source: author

Table 4-7 is the descriptive statistics of the spatial distribution characteristics of the KNC from 1995 to 2016. First of all, there was a substantial increase in the maximum value and the average value of the KNC, indicating the overall growth of the number of transnational collaborations at global scale. The coefficient of variance decreased from 3.14 in 1995 to 2.23 in 2016, suggesting the gap of the KNC of countries had narrowed. At the same time, the Gini coefficient had gradually decreased but still registered 0.78 in 2016, which means that although the degree of polarization of the KNC was weakened, there was still large proportion of transnational collaboration dominated by a small number of countries. The stable Moran's I index further confirms this conclusion that the spatial distribution pattern of the countries' KNC remained stable and no structural changes occurred.

Table 4-7 Descriptive statistics of the spatial distribution of the KNC (1995-2016)

	1995	2005	2016
Observations	165	165	165
Max	57927.00	129345.00	347479.00
Min	0.00	0.00	6.00
Mean	1911.33	4810.43	18711.66
Coefficient of variance	3.14	2.92	2.23
Gini coefficient	0.87	0.85	0.78
Moran's I	0.23	0.23	0.23

Source: author

Table 4-8 shows the top 20 countries in terms of the KNC from 1995 to 2016. The United States, the United Kingdom and Germany were the top three, while the KNC of the US was much higher than all other countries, almost respectively 40% and 50% higher than the other two. The rest of countries were Canada, Australia, Western European countries and some Nordic countries. In 1995, only Japan, Israel, Russia and China came from other regions. In 2005 and 2016, Brazil and South Korea surpassed Israel and Finland and entered the top 20. The standardized changes of the KNC have been calculated[17]. The results show that China's KNC

[17] The standardized changes calculation is proposed by Derudder et al. (2018). It is designed to avoid the "saturation effect". The specification is as follows:

had changed most enormously (6.5%), reflecting China's rapid rise in the transnational KCNs. That of the United States, Japan and Russia have dropped greatly, with the standardized change of -3.1%, -1.7% and -1.5%, respectively. These changes do not indicate that the network connectivity of these countries decreased in absolute terms, However, it owes to the rapid emergence of some developing countries in the transnational KCN, such as China and Brazil in the network. The active participation of these emerging economies had squeezed part of the share of the former developed countries.

$$SKNCC_a = \frac{n(SKNC_{a2016} - SKNC_{a1995}) - \sum_i (SKNC_{i2016} - SKNC_{i1995})}{\sqrt{n\sum_i \left[(SKNC_{i2016} - SKNC_{i1995}) - \frac{1}{n}\sum_i (SKNC_{i2016} - SKNC_{i1995}) \right]^2}}$$

$$SKNC_a = \frac{nKNC_a - \sum_i KNC}{\sqrt{n\sum_i (KNC_i - \frac{1}{n}\sum_i KNC_i)^2}}$$

The main idea is to standardize data through two steps of Z-scores standardization. The standardized changes of countries' KNC_a is calculated through examining the regression residual of $SKNCC_a$ and GNC_a. If $RESID_a \geq 2$, it indicates a significant increase of the network connectivity; If $RESID_a \leq -2$, it indicates a significant drop of the network connectivity.

Table 4-8 Top 20 countries of the KNC（1995-2016）

Ranking	1995			2005			2016			Standardization change% (1995-2016)
	Country	KNC	KNC%	Country	KNC	KNC%	Country	KNC	KNC%	
1	United States	57,927	100.00	United States	129,345	100.00	United States	347,479	100.00	-3.09
2	United Kingdom	27,444	47.38	United Kingdom	66,956	51.77	United Kingdom	210,745	60.65	1.11
3	Germany	26,011	44.90	Germany	65,721	50.81	Germany	180,865	52.05	-0.17
4	France	21,563	37.22	France	49,002	37.88	China	140,028	40.30	-0.95
5	Italy	14,416	24.89	Italy	35,292	27.29	France	138,910	39.98	0.88
6	Canada	14,107	24.35	Canada	34,059	26.33	Italy	120,345	34.63	-0.23
7	Japan	11,921	20.58	Japan	27,863	21.54	Spain	104,563	30.09	-1.47
8	Netherlands	10,797	18.64	Netherlands	26,271	20.31	Canada	100,638	28.96	0.64
9	Switzerland	10,363	17.89	Spain	24,994	19.32	Australia	96,300	27.71	0.29
10	Russia	9,373	16.18	China	23,057	17.83	Netherlands	92,285	26.56	-1.74
11	Sweden	8,620	14.88	Switzerland	22,915	17.72	Switzerland	83,973	24.17	-0.13
12	Spain	7,956	13.73	Australia	20,495	15.85	Japan	66,456	19.13	2.61
13	Belgium	6,745	11.64	Sweden	18,964	14.66	Sweden	65,611	18.88	0.19
14	Australia	6,587	11.37	Russia	18,378	14.21	Belgium	58,185	16.74	2.66
15	Poland	5,499	9.49	Belgium	17,105	13.22	Brazil	53,206	15.31	-0.05
16	Denmark	5,370	9.27	Poland	12,101	9.36	Denmark	49,141	14.14	0.20
17	Israel	4,686	8.09	Austria	11,523	8.91	Austria	47,859	13.77	-0.85
18	Finland	4,120	7.11	Denmark	11,477	8.87	Poland	46,038	13.25	-0.15
19	Austria	4,067	7.02	Korea	11,305	8.74	Russia	45,189	13.00	0.66
20	China	4,030	6.96	Brazil	9,870	7.63	Korea	43,767	12.60	6.50

Source: author

Table 4-9 shows the top 20 country-dyads in terms of the number of transnational collaborations from 1995 to 2016. First of all, the most obvious feature is the "US center" pattern, that is, the United States was the primate partner country for each country, besides, the top 5 country-dyads all included the United States. The second feature is China's rapid rise. In 1995, China was not even on the list. By 2016, Sino-US transnational collaboration ranked the first with 43,255 collaboration links, which was much higher than the following UK-US collaboration (30,530). The third major feature is the role of geographical distance in transnational collaboration: on one hand, there is a positive interrelationship between geographical proximity and collaboration intensity: intense collaborations always occurred between neighboring countries, such as US-Canada, UK-Germany, UK-Ireland, UK-France collaboration; on the other hand, the existence of distant collaboration suggests that transnational collaboration is not always constrained by geographical distance, that is to say, geographical proximity is not the only factor that shapes the transnational KCNs.

Table 4-9 Top 20 country-dyads (1995-2016)

	1995		2005		2016	
Ranking	Collaboration countries	Amount of collaboration	Collaboration countries	Amount of collaboration	Collaboration countries	Amount of collaboration
1	United States-England	5,943	United States-England	12,604	United States-China	43,255
2	United States-Canada	5,937	United States-Germany	12,342	United States-England	30,530
3	United States-Germany	5,606	United States-Canada	11,880	United States-Germany	24,402
4	United States-Japan	4,559	United States-Japan	7,882	United States-Canada	23,218
5	United States-France	4,019	United States-France	7,415	United States-France	16,264
6	United States-Italy	3,066	United States-China	6,628	United Kingdom-Germany	15,805
7	United Kingdom-Germany	2,200	United States-Italy	6,479	United States-Italy	14,333
8	United States-Netherlands	2,039	United Kingdom-Germany	5,853	United States-Australia	14,065
9	United Kingdom-Ireland	1,980	Germany-France	4,705	United States-Japan	11,388
10	Germany-France	1,968	United States-Australia	4,557	United Kingdom-France	11,275
11	United States-Switzerland	1,936	United Kingdom-France	4,424	United Kingdom-Italy	11,080
12	United States-Israel	1,928	United States-Netherlands	4,289	United States-Spain	10,909
13	United States-Australia	1,881	United States-South Korea	4,104	Germany-France	10,875
14	United Kingdom-France	1,875	United States-Switzerland	3,714	United States-Netherlands	10,787
15	United States-Sweden	1,681	United States-Spain	3,706	United Kingdom-Australia	10,401
16	Switzerland-Germany	1,530	Switzerland-Germany	3,552	United States-South Korea	10,172
17	United States-Russia	1,513	United Kingdom-Italy	3,529	United States-Switzerland	9,918
18	United Kingdom-Italy	1,467	Italy-Germany	3,420	UK-China	9,805
19	Italy-France	1,389	Italy-France	3,363	United Kingdom-Netherlands	9,420
20	Russia-Germany	1,373	Netherlands-Germany	3,143	Italy-Germany	9,390

Source: author

Figure 4-10 shows the results of the spatial autocorrelation analysis of the KNC distribution from 1995 to 2016. The four types of spatial partners are globally dispersed and locally clustered, more specifically:

(1) High-high correlation type: In 1995, the high-high correlation type areas were mainly in most countries of Western Europe and North America, and some countries in Eastern Europe and Northern Europe. In 2005, the high-high correlation type spread to Turkey and Russia. In 2016, this type further occurred around most of the countries in Europe, also China, South Korea, Thailand, Singapore, Malaysia in Asia-Pacific region, and Egypt in North Africa as well as Mexico in North America. In general, there is an obvious core to periphery spatial diffusion trend.

(2) Low-low correlation type: In 1995, the low-low correlation type areas are located mainly in most countries of Southern Africa, the Middle East, Central Asia, Southeast Asia, and South America; In 2016, except for Africa, most of the low-low agglomeration areas gradually split apart. Meanwhile, the remaining continuous low-low correlation type areas still concentrated in countries in Africa, Central Asia and Southeast Asia.

(3) High-low correlation type and low-high correlation type: In 1995, the high-low agglomeration areas were mainly embedded in or adjacent to the low-low correlation areas, including Brazil, India, South Africa, China, Russia and Australia. In 2016, Saudi Arabia, Iran and Pakistan in the Middle East, Colombia, Chile and Argentina in South America are gradually turned into high-low agglomeration areas. The low-high correlation areas are relatively stable, mainly adjacent to the high-high correlation areas or the high-low correlation areas.

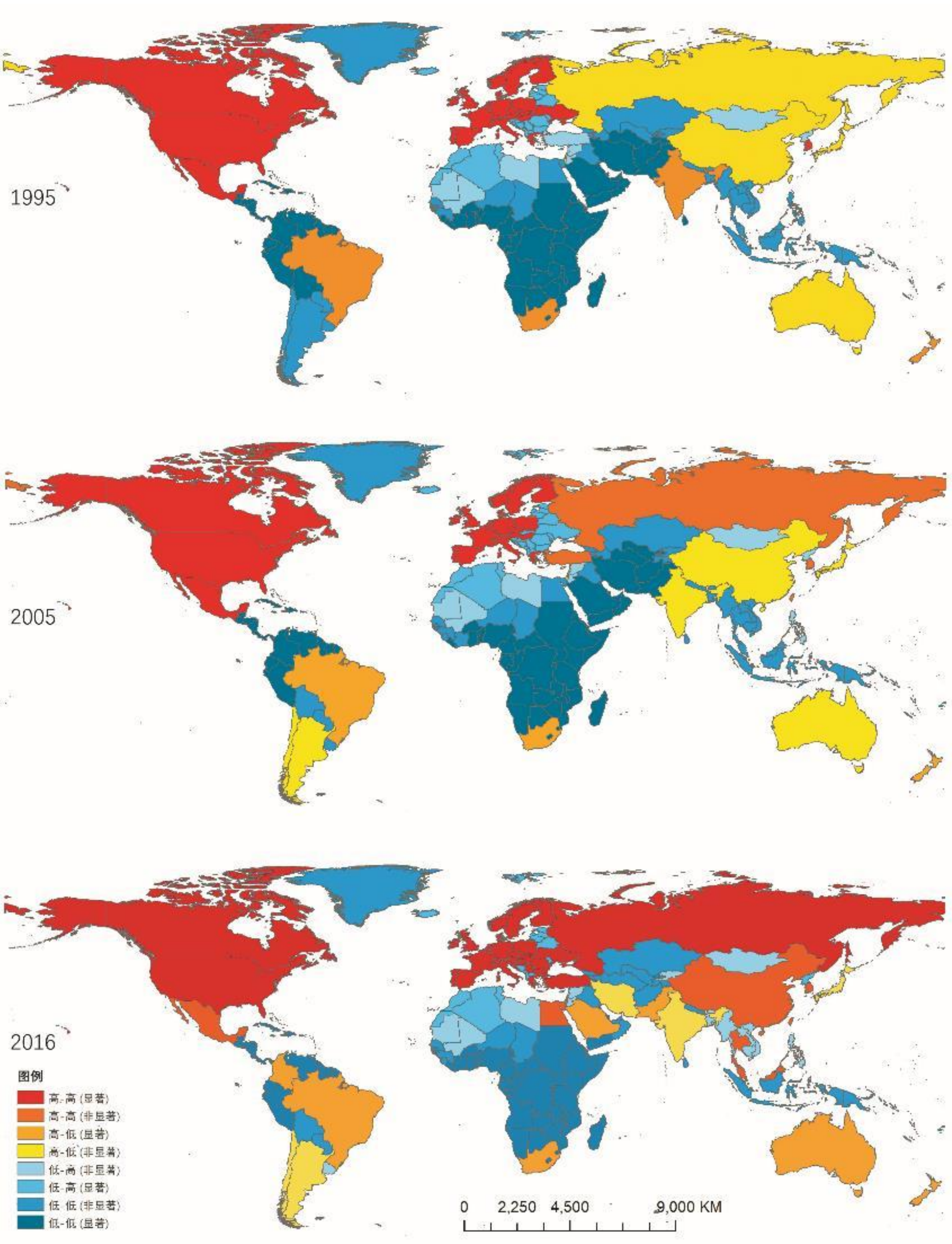

Figure 4-10 Spatial autocorrelation analysis of the KNC (1995-2016)

Source: author

4.2.2 Regional differences of the transnational KCNs

Figure 4-11 to 4-13 show the spatial organization of the transnational KCNs during 1995 to 2016[18]. The supra-regional KCNs and regional KCNs are separated so as to get clearer visualization results. Table 4-10 to 4-12 present the matrix composed of intra-regional and inter-regional collaboration links of the 7 regions. The numbers along the diagonal are the shares of intra-regional collaboration, while the other numbers represent the shares of inter-regional collaboration.

The figures show that in the period of 1995-2016, both the intra-regional and the inter-regional collaboration had witnessed great growth in terms of the intensity of collaboration, the number of countries involved and the spatial range worldwide. In addition, the spatial organization of the transnational KCNs of different regions presented both similarities and differences.

In 1995, the total number of collaboration links worldwide (more than 50 times) reached 230,763, within which the intra-regional collaboration intensity was 144,246, accounting for 62.5% of the total collaboration links. It indicates that the intra-regional collaboration was generally more intensive than inter-regional collaboration. Most of the inter-regional collaborations took place among developed countries. Not all countries have participated in transnational collaboration. For example, most Central Asian countries in the Eurasian region had not been engaged in transnational collaboration, while in Latin America, only Brazil, Argentina and Chile are involved in the transnational collaboratoins. The Eurasian region is far ahead than different regions in terms of inter-regional collaborations. On one hand, the Eurasian region is the primate collaborator for all the other regions, accounting for over 45% inter-regional collaborations of each region. On the other hand, the transnational collaboration within the Eurasian region was 66.2%, far exceeding that within other regions, which is nearly 50% higher than that within North America. By contrast, the intra-regional collaboration network in other regions was so weaker that it almost shows no connections on the map (the intensity of collaboration was generally less than 50 times). Plus, the figure also shows that there were loose connections among China, Japan, South Korea, Singapore, Australia and New Zealand in the Asia Pacific region.

In 2005, the total number of transnational collaborations was 578,432, 62% of which was intra-regional collaboration. The share did not seem to change much compared with 1995. Nonetheless, there was a significant growth in terms of the number of the countries involved and the spatial range they covered. Besides, the bipolar configuration underpinned by the North

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[18] In order to ensure the readability of the cartogram, but remain the backbones of the networks, the country dyads threshold is set to 50, that is, only the collaboration links that exceeds 50 times is retained. Although it is somewhat arbitrary, in comparison with 10, 20, 100, setting the threshold as 50 leads the most satisfactory.

America region and the Eurasia region remained stable: although the inter-regional collaborations of the other regions were less dependent on these two core regions, they were still the “hubs” in the transnational KCNs. Compared with 1995, the proportion of the intra-regional collaboration in all regions has increased to varying degrees with the exception of the North America, reflecting the overall improvement of knowledge innovation activities. Among them, the intra-regional collaboration networks in Asia-Pacific and Latin America have significantly expanded and intensified, the shares had increased from 16.9% and 12.8% in 1995 to 25.7% and 17.4% in 2005, respectively. By contrast, the intra-regional collaborations in Middle East, Sub-Sahara Africa and South Asia have shown no pronounced increase.

In 2016, the overall intensity and the spatial range of the transnational collaboration network tremendously increased with the total number of transnational collaborations worldwide had reached 2,202,562, which was nearly 10 times than that of 1995. The intra-regional collaboration totaled 1,298,988, accounting for 59% of the total amount. Compared with the prior time sections, the share decreased in 2016, which implies that inter-regional collaboration had gradually deepened. Notably, the Sino-US collaboration has exceeded the US-British and US-German collaboration, thereby had become the backbone of inter-regional collaboration network. At the same time, the Asia-Pacific region as a whole has also risen significantly in the global KCNs. For all other regions, the shares of the inter-regional collaboration with the Asia-Pacific region were over 10%, which made the Asia-Pacific region the third collaboration partner after North America and Eurasian. In terms of intra-regional collaboration, the transnational collaborations have gradually taken place in previous innovation deserts, such as Sub-Sahara Africa, the Middle East and South Asia. For example, in Sub-Sahara Africa, a “tripods” structure of the KCN formed with South Africa as the core, Nigeria, Kenya in East Africa and Cameroon in West Africa as the secondary cores. And in the Middle East, a “hub and spokes” structure of the KCN was formed by countries like Saudi Arabia, Israel, Iran, Egypt, etc.

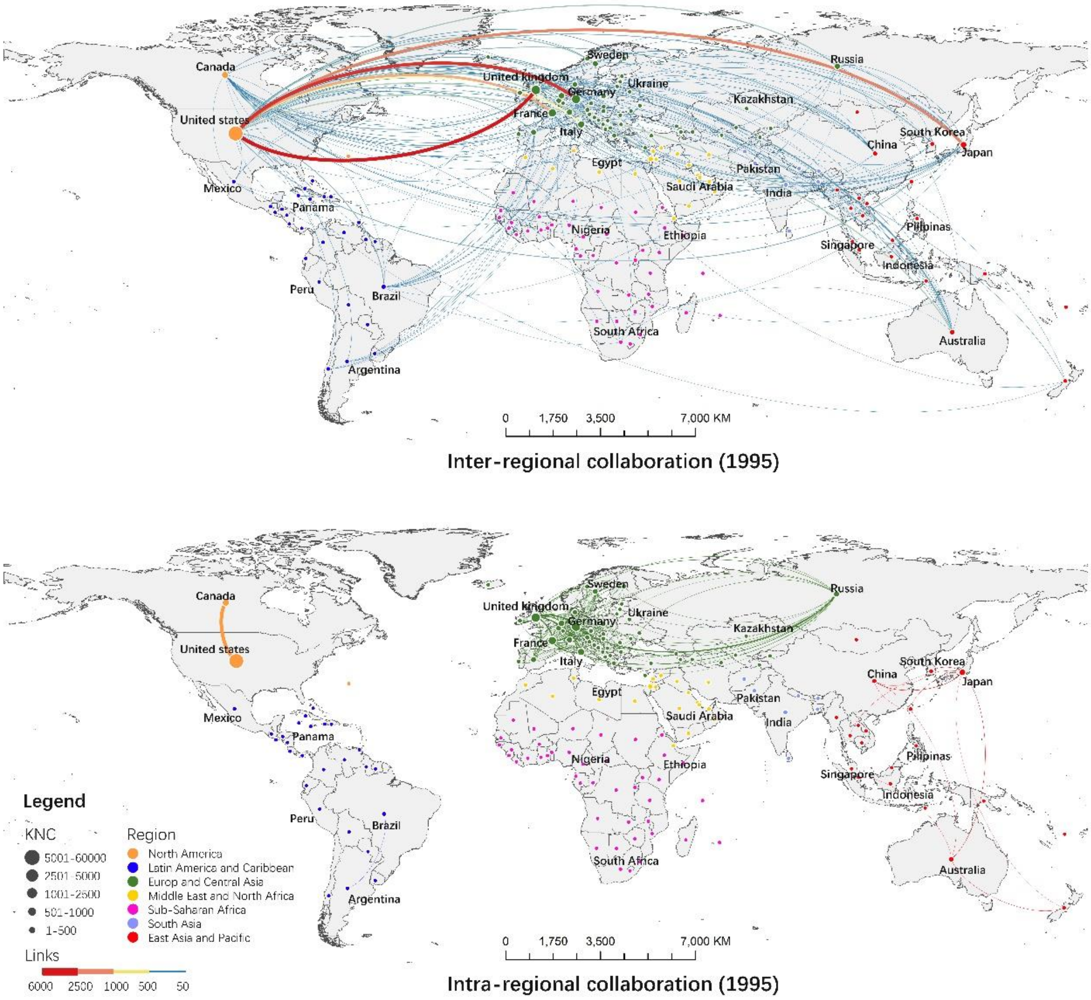


Figure 4- 1 The inter-regional and intra-regional collaboration networks（1995）

Source: author

Table 4- 1 The shares of inter-regional and intra-regional collaboration networks[19]（1995）

	NA	SA	EAPO	LAC	ECA	SSA	MENA	Total
NA	16.51	1.49	16.75	4.29	55.64	1.32	4.00	100.00
SA	32.12	1.79	14.22	2.84	45.53	1.49	2.00	100.00
EAPO	38.58	1.52	16.88	1.67	38.45	1.38	1.52	100.00
LAC	31.47	0.97	5.32	12.83	46.53	1.61	1.27	100.00
ECA	21.22	0.81	6.37	2.42	66.15	1.15	1.89	100.00
SSA	22.24	1.17	10.11	3.71	51.03	9.48	2.25	100.00
MENA	37.94	0.88	6.26	1.64	46.98	1.26	5.03	100.00

Source: author

[19] NA: North America, SA: South Asia, EAPO: East Asia and the Pacific Ocean, LAC: Latin America and the Caribbean, ECA: Europe and Central Asia, SSA: Sub-Saharan Africa, MENA: Middle East and North Africa.

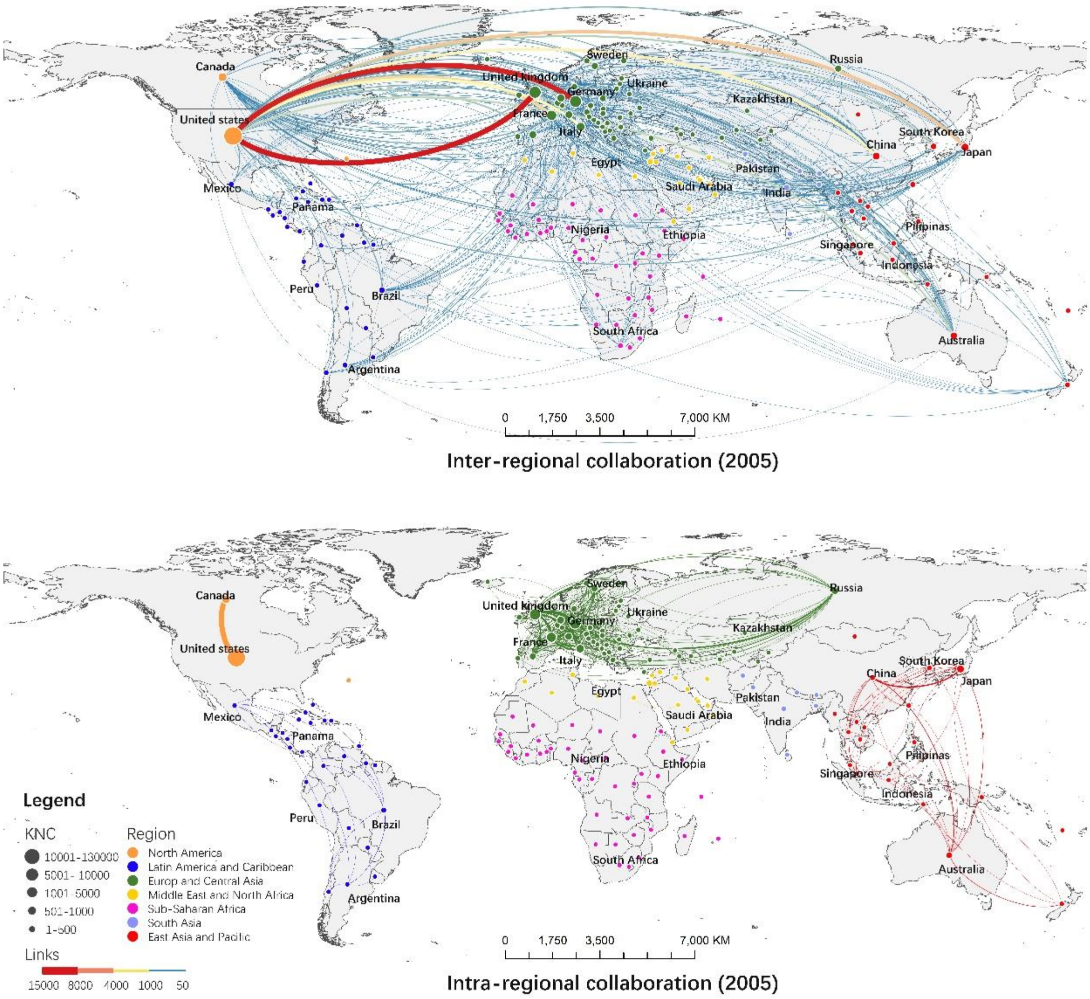


Figure 4- 2 The inter-regional and intra-regional collaboration networks（2005）

Source: author

Table 4- 2 The shares of inter-regional and intra-regional collaboration networks（2005）

	NA	SA	EAPO	LAC	ECA	SSA	MENA	Total
NA	14.56	1.61	20.15	5.13	53.84	1.64	3.07	100.00
SA	24.26	2.01	22.76	3.96	42.36	1.86	2.79	100.00
EAPO	31.39	2.35	25.65	1.91	36.26	1.06	1.38	100.00
LAC	27.46	1.41	6.57	17.35	45.07	1.13	1.01	100.00
ECA	19.21	1.00	8.30	3.00	65.16	1.31	2.01	100.00
SSA	20.98	1.58	8.71	2.70	47.02	17.32	1.69	100.00
MENA	28.11	1.70	8.09	1.73	51.55	1.21	7.61	100.00

Source：author

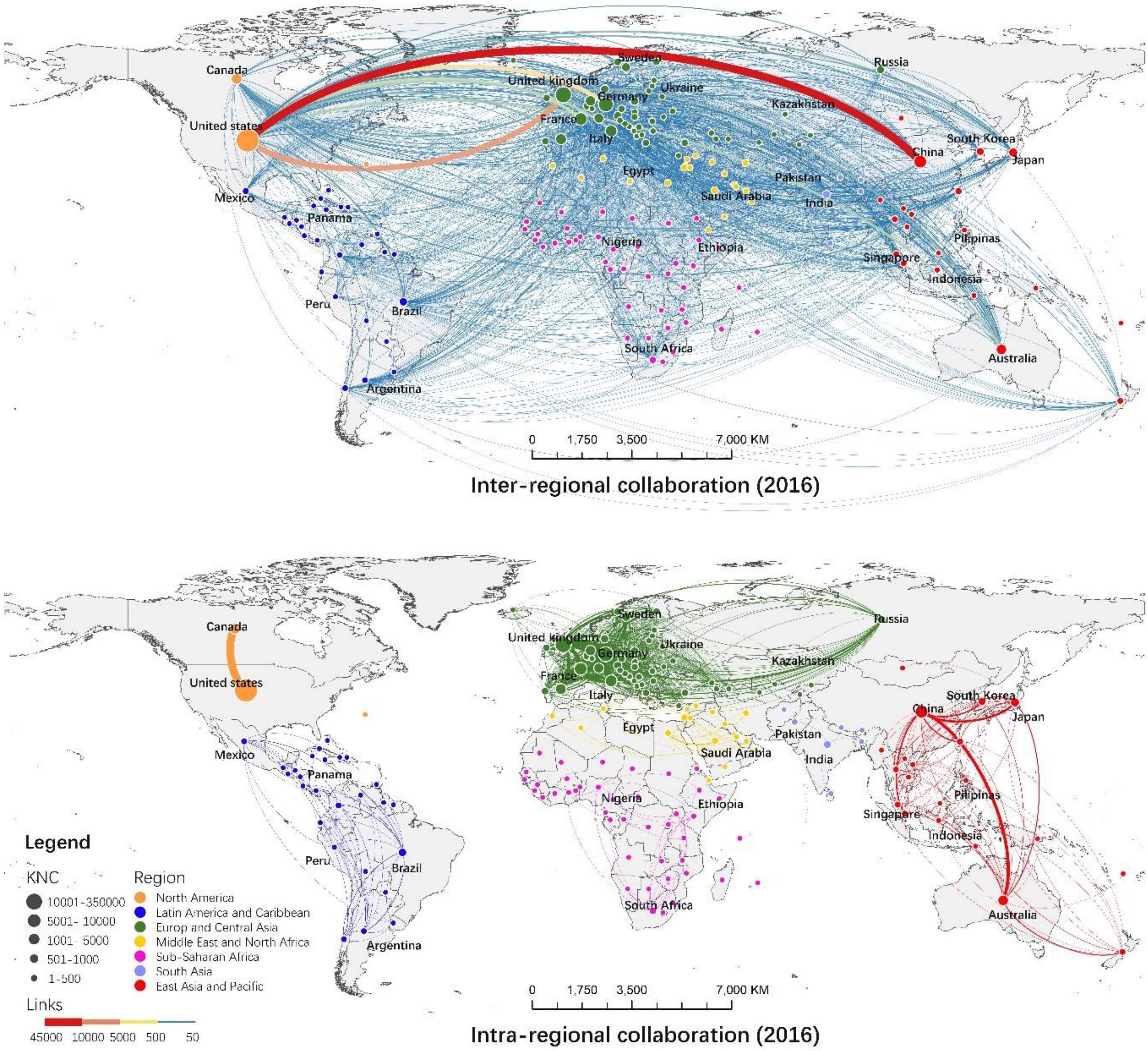


Figure 4- 3 The inter-regional and intra-regional collaboration networks（2016）

Source：author

Table 4- 3 The shares of inter-regional and intra-regional collaboration networks（2016）

	NA	SA	EAPO	LAC	ECA	SSA	MENA	Total
NA	10.38	2.29	24.87	5.68	49.59	2.66	4.52	100.00
SA	13.93	3.29	22.38	5.41	41.17	4.60	9.22	100.00
EAPO	23.03	3.40	23.90	3.71	39.53	2.22	4.21	100.00
LAC	15.06	2.36	10.62	15.75	49.35	3.09	3.77	100.00
ECA	13.09	1.79	11.27	4.91	63.00	2.10	3.85	100.00
SSA	13.28	3.77	11.95	5.82	39.64	20.48	5.05	100.00
MENA	14.15	4.74	14.23	4.45	45.59	3.17	13.68	100.00

Source：author

4.2.3 Spatial reach of countries in the transnational KNCs

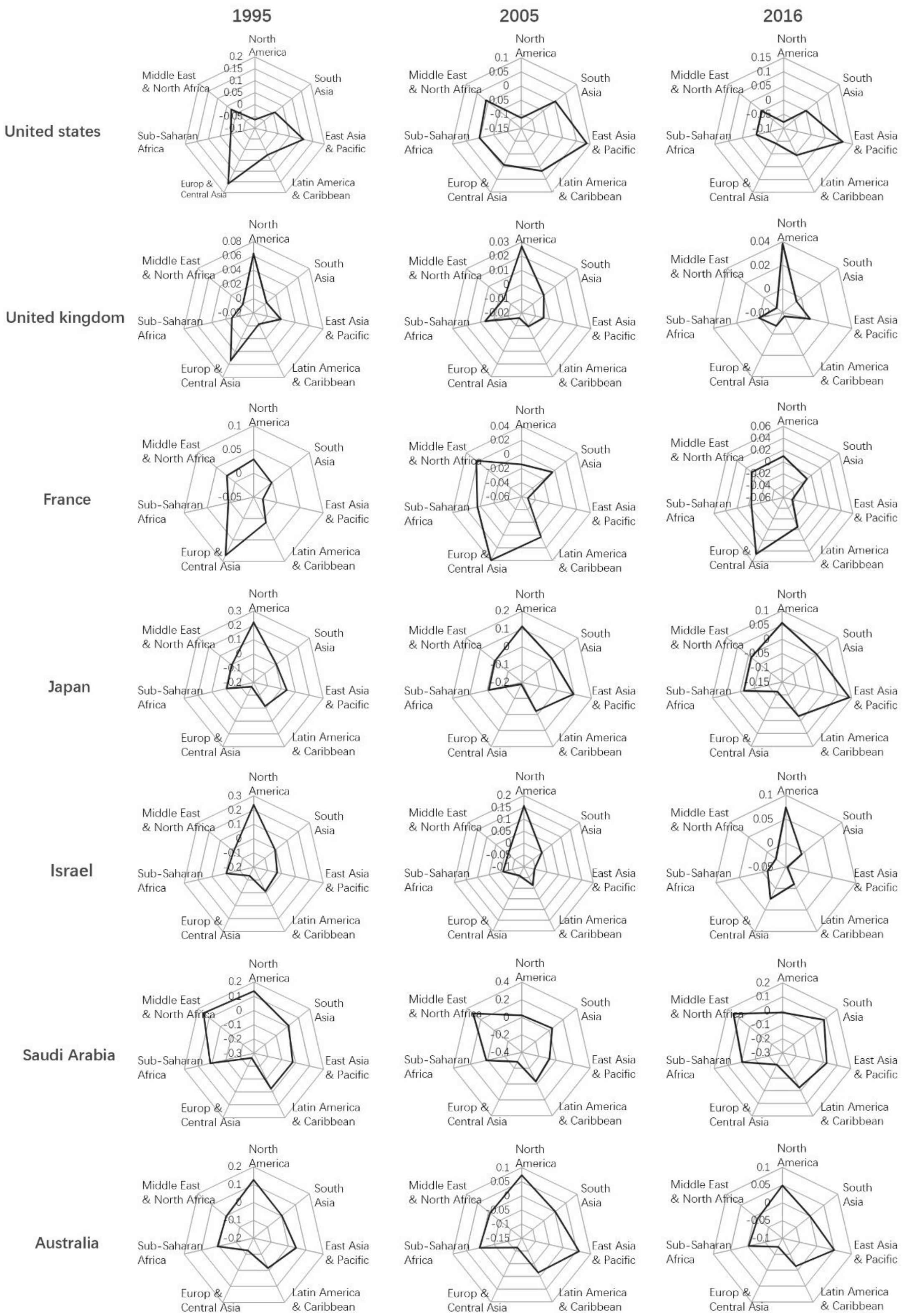
Drawing on the technique of GaWC in the measures of the city "regionalism" of world cities (Taylor and Derudder, 2015), we further examine the spatial reach of some major countries in the transnational KCNs. The expression is:

$$Regionalism_{a,m} = \frac{\sum_{i=1}^{Region_m} CDC_{a-i}}{\sum_{i=1}^{165} CDC_{a-i}} - \frac{\sum_{i=1}^{Region_m} KNC_i}{\sum_{i=1}^{165} KNC_i} \qquad (4\text{- }1)$$

Where, $Regionalism_{a,m}$ is the spatial reach of country a in region m, and CDC_{a-i} is the collaboration intensity between country a and country i in the region m. The function at the left side of the minus calculates the proportion of the sum of the collaboration links between country a and all the countries in region m to the total links that the country a have. The function at the right side of the minus calculates the proportion of the sum of the KNC of all the countries in region m to the total KNC of all countries worldwide. Lager $Regionalism_{a,m}$ indicates higher relative collaboration intensity between country a and countries in region m, and vice versa.

Figure 4-14 lists a series radar diagrams of the spatial reaches of some major countries. Between 1995 and 2016, the United States, the United Kingdom, Israel, and Taiwan (China) were less connected with the other countries within the same region, but were more connected with countries in other regions, which presented higher level of "globalization". Because of the considerable collaboration links between the United States and the United Kingdom, their spatial reaches were towards Eurasia and North America respectively. Due to the frequent political and diplomatic contacts with the United States, the spatial reaches of Israel and Taiwan (China) were towards to North America.

The second type of countries is more localized, including France, Saudi Arabia, Russia and Malaysia. They tended to collaborate with countries in their regions and showed pronounced "localization" characteristic. Except for European countries, other countries were weakly connected with European countries. One possible reason is that despite the collaboration linkages connected to European countries were very high in absolute terms, the connections between the countries within Europe were even higher, which led to relatively small values of the spatial reach indexes.


1995
2005
2016
United states
United kingdom
France
Japan
Israel
Saudi Arabia
Australia
North America
South Asia
East Asia & Pacific
Latin America & Caribbean
Europ & Central Asia
Sub-Saharan Africa
Middle East & North Africa

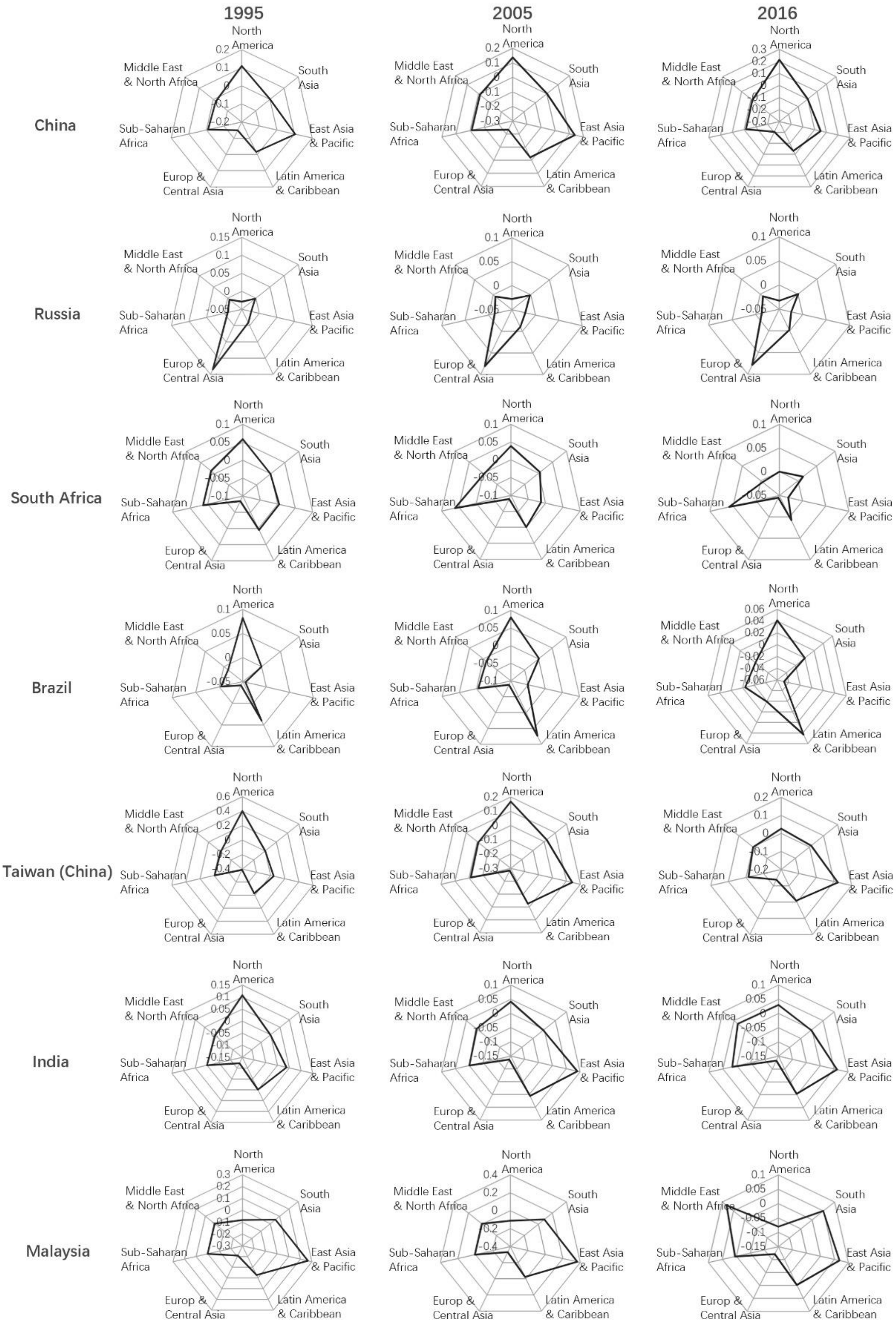


Figure4- 4 The spatial reach of countries（1995-2016）

4.3 Evolution of the topological structures of the transnational KNCs

4.3.1 Basic topological structures

4.3.1.1 Overall network topological properties

Table 4-13 shows the results of the measurements of the topological properties of the transnational KCNs from 1995 to 2016, including basic topological indicators, small-world property and scale-free property. Firstly, the increase of the average degree, the maximum and the minimum degree indicate the rising trend of the collaboration partners of countries worldwide. The increase of network density and overall efficiency implies the overall connectivity of the transnational KCN is also enhanced. The negative value of the degree-degree correlation indicates that there is "disassortativity" in the transnational KCNs, which means that countries with small connectivity tended to collaborate with countries with large degrees. In other words, the late-comer countries tended to collaborate with superpowers when accessing in the transnational KCNs, which also follows the general rule of knowledge spillovers, by which the knowledge often diffuses from developed regions to developing or underdeveloped regions. However, the disassortativity had been weakened (the correlation coefficient increased from -0.35 in 1995 to -0.17 in 2016), which partly shows the choice of partner countries tended to be diversified.

The results of the examination of the small-world property show that the characteristic path lengths of the transnational KNCs were smaller than that of the random networks in three time sections, which indicates the existence of "shortcuts" that connect different communities in the transnational KCNs. They acted as the bridges in the networks, which facilitated the effective knowledge spillovers and diffusion. Meanwhile, the clustering coefficients of the transnational KCNs were larger than that of the random networks, indicating that there were communities the networks within which countries tightly interconnected with their own community members while loosely connected to the members in other communities. The small-world quotients of the three networks were all bigger than 1, which implies that the transnational KCNs were small networks.

The results of the cumulative degree-degree distributions show that the power-law exponents were 1.31 in 1995 and 1.16 in 2005, respectively. Thus the cumulative power-law exponents were 2.31 (1.31 plus 1) and 2.16 (1.16+1), which fell into the range between 2 and 3, implying the existence of "scale-free" property. Such results imply that the transnational KCNs were significantly polarized: only a few countries like the USA and the UK possessed considerable transnational collaboration links, while most of the countries only had a small number of collaboration links. These results also suggest that the evolution of the network followed were governed by "preferential attachment". In 2016, the transnational KCN was no longer a scale-free network, which indicates that the polarization had been weakened. In summary, the transnational KCNs in this research exhibited the small-world and scale-free property and they can be considered as complex networks, which is in line with many research on KCNs (Barabâsi et al., 2002; Carayol and Roux, 2009; Dangalchev, 2004). Gay and Dousset, 2005; Moody, 2004; Uzzi and Spiro, 2005; Yu, 2018).

Table 4-13 Basic topological structures of the transnational KCNs

Network topological structure index		1995	2005	2016
Basic topological properties	Average degree	38.64	57.02	117.11
	Max	1.00	1.00	3.00
	Min	147.00	159.00	164.00
	Network density	0.24	0.35	0.71
	Global efficiency	0.62	0.68	0.85
	Degree-degree correlation	-0.35	-0.29	-0.17
Small-world property	Characteristic path length	1.73	1.62	1.27
	Characteristic path length of the same-size random networks	1.76	1.65	1.29
	Clustering coefficient	0.56	0.63	0.85
	Clustering coefficient of the same-size random networks	0.24	0.36	0.71
	Small-world quotient	2.27	1.76	1.20
Scale-free property	Cumulative power-law exponent	2.31	2.16	1.48
	R2	0.68	0.59	0.25

Source：author

Table 4-14 is the QAP correlation analysis of the transnational KCNs. First, the similarity coefficient of the networks between 1995 and 2016 was 0.838, which indicates that the topological structures of the transnational KCNs in 1995 and 2016 generally remained stable, albeit there was a certain extent of change. Second, the network similarity between the two adjacent time sections from 1995 to 2005 and from 2005 to 2016 exceeded 0.9, which was higher than that between 1995 and 2016. This confirms that, the evolution of the transnational KCNs during the research period is rather steady. Third, the network similarity coefficient between 1995 and 2005 (0.976) was slightly higher than that between 2005 and 2016 (0.924), that is, the evolution of transnational KCNs was not linear, but the speed of differentiation had been accelerated. In general, the evolution of the topological structures during 1995 to 2016 of the transnational KCNs presented a feature of "path dependency".

Table 4-4 The QAP regressions of the transnational KCNs（1995-2016）

	1995	2005	2016
1995	-	-	-
2005	0.976***	-	-
2016	0.838***	0.924***	-

Significant levels：***p<0.01, **p<0.05, *p<0.1;

Source：author

4.3.1.2 Individual network topological properties

Table 4-15 lists the top 10 countries in the transnational KCNs in terms of the weighted betweenness centrality. First, the traditional western innovation superpowers had always been in the club, including the USA, France, the UK, Russia, Germany, Canada and Australia. They not only were the leading countries in terms of scientific innovation output but also functioned as the "intermediaries" and "bridges" in the transnational KCNs and occupied many "structural holes", thus were able to access more resources and controlled the flow of knowledge. As the most powerful country in the transnational KCNs, the USA was the primate collaboration partner for most countries, and therefore it had the highest weighted betweenness centrality in the transnational KCNs across the period. As the main colonial countries during the maritime navigation era, Britain and France had many overseas territories, with which they still maintained close relationships, in turn it had been keeping connections in terms of knowledge collaboration. Therefore, it is reasonable that they acted as brokers between their former colonies and other countries. The high betweenness centrality of Russia and Germany is closely related to the post-war European geopolitical changes. Russia and Germany had been core countries in the former Soviet Union and the Warsaw Treaty bloc respectively, thus they had acted as the intermediaries between their allies and other countries. Japan, South Africa, Brazil and China were the leading powers of their respective regions in terms of network connectivity. They played as gateways or hubs connecting the countries in their own regions with the countries outside their regions.

Table 4-15 Top 10 countries in weighted betweenness centrality (1995-2016)

Rank	1995		2005		2016	
	Country	Weighted betweenness centrality	Country	Weighted betweenness centrality	Country	Weighted betweenness centrality
1	America	11,867.00	America	12,050.00	America	12,236.00
2	France	2,547.50	France	3,143.00	France	2,489.00
3	British	2,515.50	German	1,698.00	German	1,283.00
4	Russia	1,534.00	British	1,397.00	British	1,264.00

5	German	944.00	Russia	634.00	Russia	807.00
6	Japan	779.00	Japan	634.00	South Africa	650.00
7	Switzerland	158.00	South Africa	320.00	China	646.00
8	Canada	154.00	Turkey	319.00	Australia	644.00
9	Australia	132.00	Australia	319.00	Italy	613.00
10	Brazil	125.00	Switzerland	160.00	Brazil	485.00

Source：author

Table 4-16 shows the top 10 countries in terms of the weighted closeness centrality in the transnational KCNs, which reflects the country's capability in independent innovation. They were acknowledged as the global leaders with regard to knowledge innovation capabilities, which most countries would like to collaborate with. The rise of China was eye-catching: in 1995, China was not even on the list, but it ranked the second place in 2016. This reflects that its overall independent innovation capability had been improved and meanwhile, its prestige and influence in the KCNs worldwide had also significantly gained during the study period.

Table 4-5 Top 10 countries in weighted closeness centrality（1995-2016）

Rank	1995		2005		2016	
	Countries	Weighted closeness centrality	Countries	Weighted closeness centrality	Countries	Weighted closeness centrality
1	America	1,180.69	America	1,549.69	America	2,229.41
2	British	904.32	German	1,192.41	China	1,849.00
3	Canada	888.21	British	1,190.36	British	1,739.89
4	German	882.66	Canada	1,157.24	German	1,631.29
5	Japan	816.83	Japan	1,013.76	Canada	1,545.39
6	France	787.59	France	998.24	France	1,401.22
7	Italy	710.39	China	953.20	Italy	1,337.86
8	Holland	604.08	Italy	945.15	Australia	1,311.34
9	Switzerland	592.99	Australia	824.16	Japan	1,204.59
10	Israel	589.91	Holland	804.59	Spanish	1,201.76

Source：author

4.3.2 "Core-periphery" structure

Figure 4-15 shows the "core-periphery" structure of the transnational KCNs from 1995 to 2016 generated by the hierarchical clustering algorithm based on the block models. During the research period, the transnational KCNs have maintained a stable layer structure with the US as the core country. In 1995-2005, the countries in the second layer were mainly traditional innovation powers mostly located in West Europe. In 2016, China, Brazil, South Africa and India entered the second layer club. Evident changes occurred in the third layer. In 1995, there are 39 countries in this layer, the national innovation systems of these countries were still in development stage, including most European countries, China, South Korea, Brazil and other developing economies. While in 2005 and 2016, countries in the third layer have witnessed evident drops with the numbers falling to 22 and 27 respectively. Countries like Estonia, Bulgaria, Slovakia, Ukraine, Slovenia and many others in Eastern European fell into the forth or even the fifth layer, this is because after the political upheavals during the 1990s, their economy, science and technology had been relentlessly shocked and destroyed, while some emerging economics took their place instead. Finally, the countries in the fourth and fifth layers situated in semi-periphery or periphery of the transnational KCNs were mainly low-income or medium-income countries. With weak economic bases or long-term unstable political environment, these countries had rather limited innovation incentives and insufficient innovation input, thus they were locked in the peripheral layer and could hardly get out.

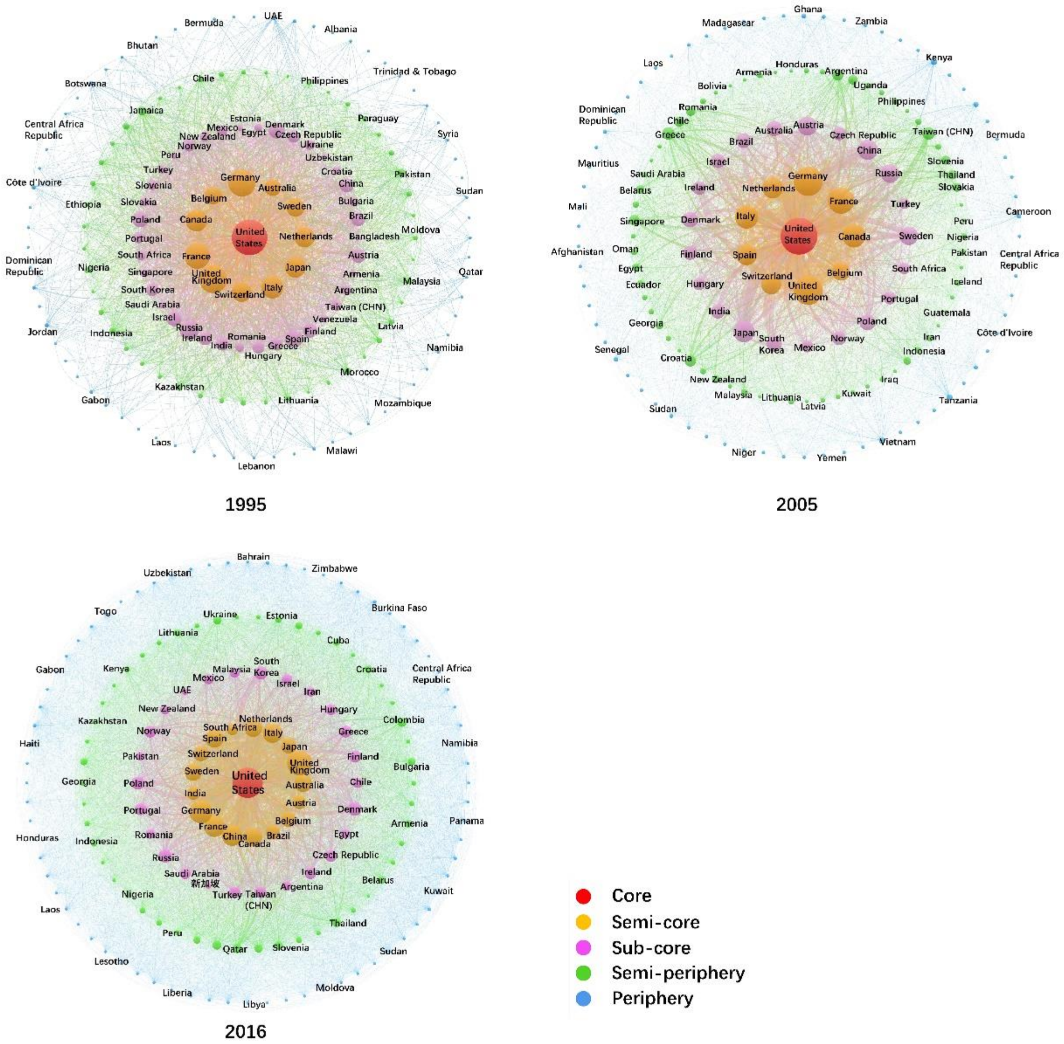


Figure4- 5 diagram of “core-periphery” structure of the transnational KCNs

Source：author

4.3.3 “Center-hinterlands” structure

Figure 4-16 to 4-18 are the diagrams of the “center-hinterland” structure of the KCNs in 1995, 2005 and 2016. In a bid to ensure the clarity and readability of the visualizations, the threshold of the collaboration dyads between countries is set as 50. The findings are as follows:

In the three cross-sections, the “center-hinterland” structure of the transnational KCNs present “hub-spoke” structure with additional “branches”. More specifically, the United States, as the primary core in the transnational KCNs, shows strong centripetal attraction to other countries. Most countries worldwide have become the direct hinterlands of the United States, resembling a “hub-spoke” structure. This structure was underpinned as the backbone of the transnational KCNs and strengthened over time.

In addition to the United States, some traditional innovation powers, such as Germany, British, France, had developed their own hinterlands as a secondary “center-hinterland” structures attached to the United States core. These sub-structures are characterized as: first, branches connected by ex-colonial relations were the main forms of some sub “center-hinterland” structures (Boshoff, 2009; Nagtegaal and de Bruin, 1994; Wagner and Leydesdorff, 2005a). For example, African countries like South Africa, Nigeria, Egypt, Kenya and Asian countries like Singapore, Malaysia and India were the direct hinterland for the United Kingdom. As “the empire on which the sun never sets”, British dominated the world in the era of great navigation and had numerous colonies worldwide. During its colonial history, British actively exported capital, technology, culture, language and infrastructure to colonies, thereby helping to maintain stable relationships with its former colonies even in the post-colonial era. Similar cases can be found in the sub “center-hinterland” structure of France and Spain. It is noticeable that the “center-hinterland” structure formed by the British and its former colonies has collapsed and been rebuilt. In 2005 and 2016, most of the British colonies had become the direct hinterlands of the US. In contrast, the ex-colonial relations have sustained in the French sub “center-hinterland”. This finding is consistent with Boshoff’s (2009) research. He believes that what causes such differentiation in development paths is resulted from language difference. With English as the official language, the former British colonial countries had more flexibility than its French counterparts in choosing collaborators worldwide in the transnational KCNs.

Apart from colonial ties, geopolitics is also an important factor in shaping the sub “center-hinterland” relations. The evolution of the “center-hinterland” structure of Germany and Russia are good examples. With the establishment of the Yalta system after World War II, the Western capitalist countries led by the United States and the socialist countries led by the Soviet Union began a long-term confrontation. During the cold war, the United States, Canada and several Western European countries established the North Atlantic, and absorbed West Germany as the member by the Paris Agreement. This move met strong opposition from the Soviet Union and Eastern European countries (including East Germany, Poland, Czechoslovakia, Hungary, Romania, Bulgaria and Albania), which immediately caused the Warsaw to fight back. However, along with a series of political events such as the drastic changes in Eastern Europe, the merger of the West Germany and East Germany and the disintegration of the Soviet Union, the Warsaw Treaty Organization also disintegrated afterwards. These geopolitical events are also reflected in the “center-hinterland” structure in the KCNs, that is, the secondary “center-hinterland” structure formed by (East) Germany and the countries previously affiliated with the Warsaw Treaty Organization.

Finally, geographical proximity is another important factor in shaping the secondary "center-hinterland" landscape. In addition to colonial relations and geopolitics, other secondary "center-hinterland" groups were organized by geographical proximity. For example, the secondary "center-hinterland" formed by Italy and countries from Balkans in the Apennine peninsula, Southern Africa group with South Africa as the core and etc.

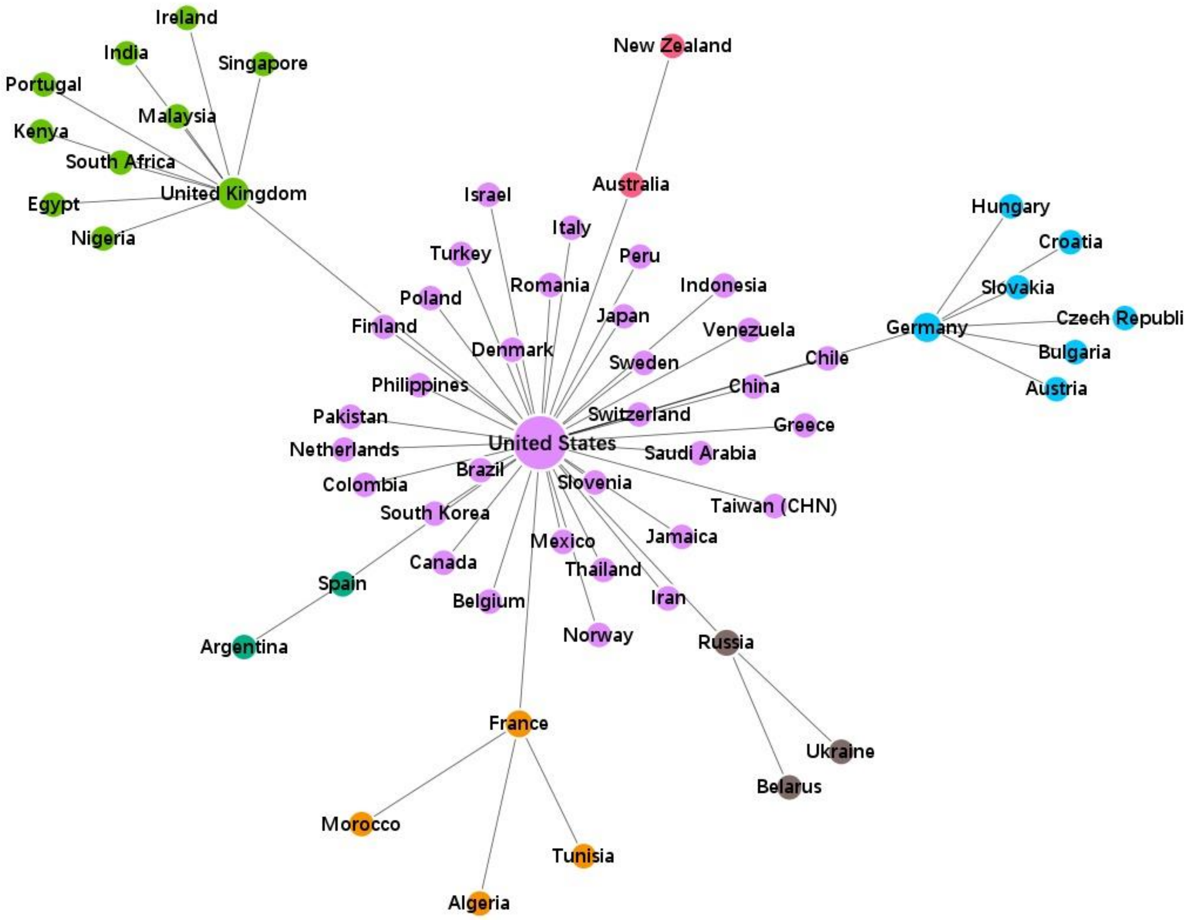


Figure4- 6 "Center-hinterlands" structure of the transnational KCNs（1995）
Source: author

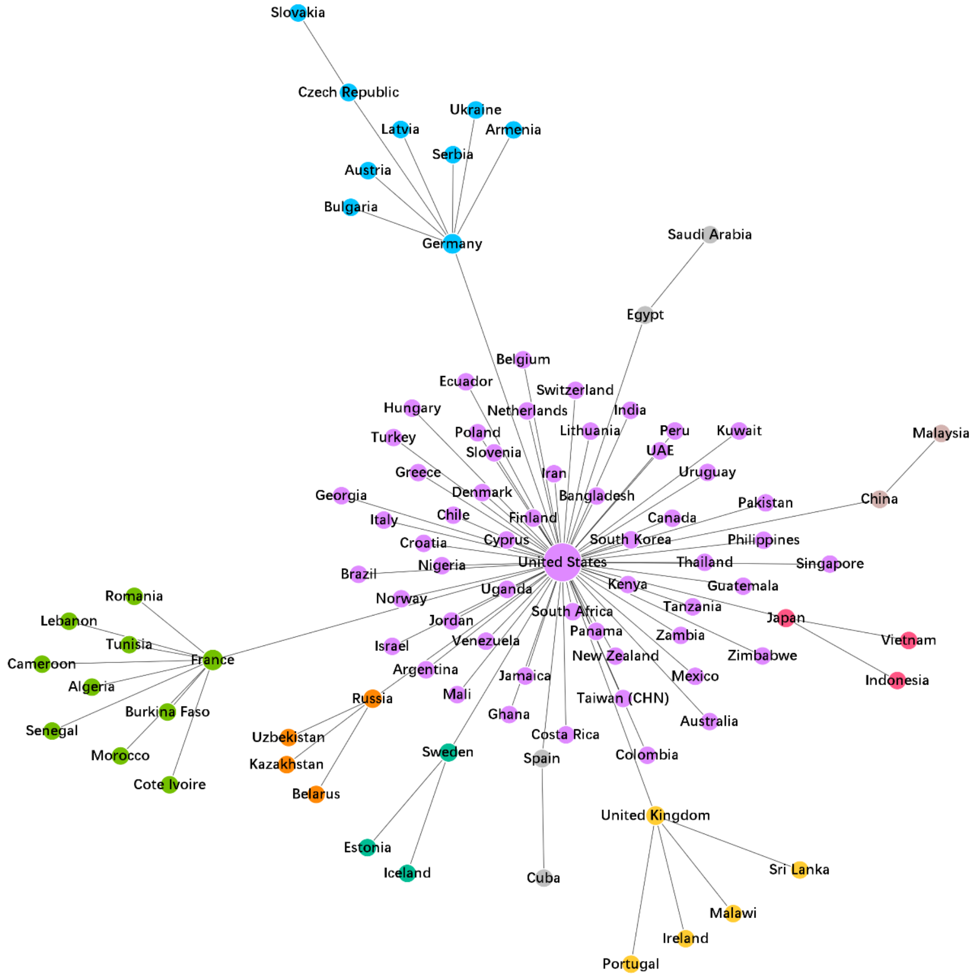


Figure4- 7 “Center-hinterlands” structure of the transnational KCNs（2005）

Source: author

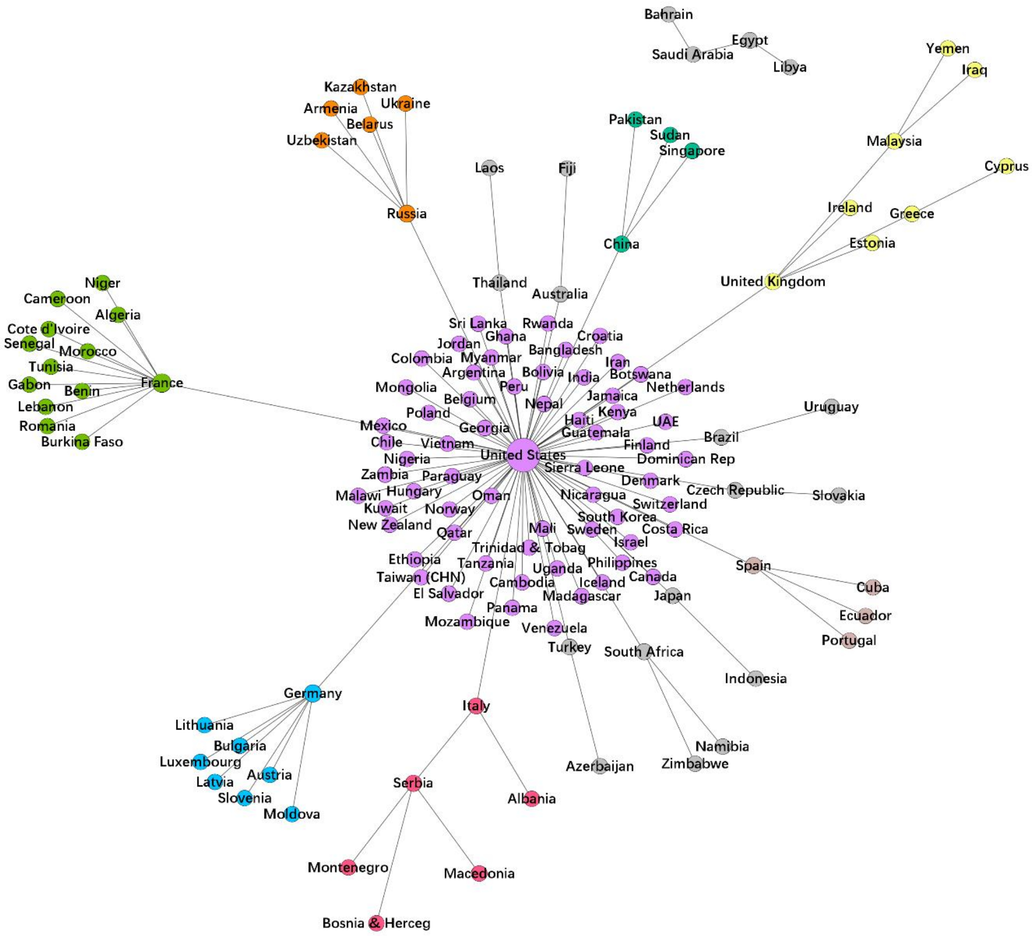


Figure4- 8 “center-hinterlands” structure of the transnational KCNs（2016）

Source：author

4.4 Summary

In a nutshell, during the research period from 1995 to 2016, scientific innovation and collaboration have increasingly become a “global enterprise”, but the spatial distribution is rather uneven across countries in terms of scientific output and connectivity in the transnational KCNs. In this chapter, the evolution of the transnational KCNs is examined and the highlight is shed on China’s role and its evolutionary path in the transnational KCNs. The main findings are as follows:

Firstly, the evolution of the landscape of the global scientific innovation output from 1995 to 2016 is examined. During the period, as the total output significantly increased, the spatial range of the countries engaged also expended. Drastic changes and stability coexisted in the evolution of the landscape of the global scientific output. On one hand, the former tripod structure of “American-Western Europe-Japan” had been challenged by the rise of emerging economies such as China, India, Brazil. The East Asia region with China and India as the core has gradually become the fourth pole. On the other hand, the overall hierarchical structure and the regional spatial pattern of the global scientific innovation have remained stable. First, most of the scientific output concentrated in a small number of countries, showing an inverted "T-shaped" hierarchy. Second, the dynamic spatial configuration of the scientific output at regional level remained stable overall and evolve gradually.

Second, in this chapter, the evolution of the spatial structures of the KCNs is analyzed , and the main results are as follows: (1) during the research period, the scientific superpower of the US remained unchallenged, to put it more specific, the United States had the highest network connectivity and is the primate collaboration partner for most countries. The other traditional scientific innovation powers like Canada, Australia, Japan and some countries in Western Europe also occupied central positions in the networks. The coexistence of the US and many other major countries has generally remained stable. Although emerging economies such as China, Brazil and India have witnessed evident rise in the networks, they still could not structurally change the hierarchy. (2) The spatial correlation of the network connectivity was "globally dispersed and locally concentrated". The evolution of the spatial correlation follows the general rule of geographical proximity in the process of knowledge spillovers. (3) Different countries in the transnational KCNs were significantly heterogeneous, complex and diverse in terms of their network organizational patterns and the spatial reaches. In general, the evolution of the spatial configuration of the transnational KCNs presents a feature of "space dependency".

Third, in this chapter, the evolution of the topological structures of the transnational KCNs is investigated, and the main results are as follows (1) in all three time sections, the transnational KCNs all showed "small-world" property, indicating that the existence of sub-communities in the network and the existence of "shortcuts" that connect them. The transnational KCNs also presented scale-free property in 2005 and 2015, which means the networks were evidently polarized, that is, a few countries had a large number of transnational collaboration ties while the majority of the countries merely had a small number of collaborative connections. However, the absence of "scale-free" in 2016 implied that the network polarization tended to decrease. (2) By examining the "core-periphery" structures, it can be found that the transnational KCNs stably maintained the multi-layer structure of "core, semi-core, subcore, semi-periphery, and periphery". Among them, the United States had always been the center, and emerging countries such as China, Brazil, South Africa and India have caught up and entered the semi-core layer. (3) By investigating the "center-hinterland" structures in the transnational KCNs, it is clear that the networks were underpinned by a "hub-spoke" centered on the US and several "sub-branches" organized by some developed economies. Geographical proximity, ex-colonial relations and geopolitics are the main influencing factors in shaping the "center-hinterland" structures of the networks. In summary, the evolution of the topological structures of transnational KCNs presents the feature of "path dependency".

Chapter 5 The evolution of global interurban knowledge collaboration networks

Cities, particularly those regional, national and global hubs in terms of innovation capability, serve not only as the centers of knowledge production (Florida et al., 2017; Matthiessen and Schwarz, 2006), but also as the hinges underpinning the regional, national and global IKCNs (Matthiessen and Schwarz, 2006; Matthiessen et al., 2010). Duranton and Puga (2001), Florida et al. (2017) emphasize that cities are not merely the containers for innovation, but innovation require cities. The production of new knowledge hinges on the spatial concentration of knowledge, talents, capitals and the innovation milieu surrounding the actors. The agglomeration economies and “local buzz” are, indeed, crucial to innovation, but accessing to external knowledge pools by “global pipelines” and possessing advantageous positions in knowledge collaboration are even more critical (Bathelt, 2007; Bathelt et al., 2004). This chapter will project on 500 major cities around the world and analyze the evolution of the global IKCNs with particular highlight shed on Chinese cities.

5.1 The evolution of the landscape of the innovation output of the global cities

Based on the database, there were 6,331,122 scientific publications worldwide in the period of 2002-2006, where 3,770,530 were produced from the 500 cities, accounting for 59.6%. When the total number of the publications worldwide raised to 9,967,552 by the period of 2012-2016, in which 6,748,313 were from the 500 cities, accounting for 67.7%. Table 5-1 demonstrates the national shares of the city-produced scientific publications. Although the number of cities among different countries selected varies, major cities such as the capitals and economic centers of each country have been encompassed. The statistics in this table can basically outline the importance of cities in their national innovation systems in terms of the total output: the national shares of the city-produced publications all exceed 50%. Notably, the national share of Chinese cities has reached as high as 90% in both time sections, followed by Russia, Brazil and India. This figure, to some extent, reflects a common feature in the innovation systems of these emerging economies, that is, the state plays a decisive role in allocating innovation resources and issuing innovation policies that are often preferentially towards large cities like the capital and economic centers (Li and Zhang, 2003; Zhong, 2011). In general, the results indicate that cities are not only the “incubators” of innovation, but particularly the mega cities are the main players of the national and global innovation.

Table5-1 The national shares of the city-produced scientific publications of major countries (2002-2006, 2012-2016)

Country	2002-2006 Total national output	2002-2006 Total city output	2002-2006 National share (%)	2012-2016 Total national output	2012-2016 Total city output	2012-2016 National share (%)
USA	2,081,643	1,114,424	53.54	2,846,298	1,633,903	57.40
CHN	328,249	296,794	90.42	1,354,946	1,238,739	91.42
UK	550,737	374,446	67.99	860,456	527,576	61.31
DEU	452,429	227,742	50.34	664,573	354,854	53.40
JPN	455,271	288,488	63.37	495,338	324,871	65.59
FRA	307,579	164,888	53.61	449,365	261,379	58.17
CAN	264,277	193,362	73.17	427,052	334,828	78.40
ITA	243,962	149,800	61.40	415,799	261,586	62.91
AUS	165,311	99,410	60.14	371,575	251,976	67.81
ESP	173,716	100,153	57.65	354,926	213,842	60.25
IND	129,433	90,390	69.84	332,574	214,010	64.35
KOR	133,838	76,798	57.38	319,120	205,065	64.26
BRA	95,834	71,726	74.84	244,694	173,012	70.71
RUS	135,024	106,186	78.64	178,138	142,081	79.76

Source: author

5.1.1 Rapid growth with uneven spatial distribution

Figure 5-1 is the geographical distribution of the scientific innovation output of global cities during the period of 2002-2006 and of 2012-2016, respectively. Figure 5-2 lists the corresponding descriptive statistics. It is apparent that all cities have experienced significant growth in terms of total output. The values of maximum, minimum and mean during the period of 2002-2006 were respectively 145,030, 0, and 9,765.45, and have risen to 327,000, 98, and 19,772.55 during the period of 2012-2016. In addition, the spatial range of the scientific output have expanded. There are 445 cities have produced more than 500 publications during the period of 2012-2016, while this figure was 376 during the period of 2002-2006.

The spatial distribution of the global scientific output could be marked by being rather uneven. First, there is a clear-cut gap between the "Global South" cities and the "Global North" cities. Second, among the "Global North", cities in North America, Europe and East Asian constitute three poles of knowledge output, followed by Indian cities. Third, the scientific output within one country is also uneven. For example, high-yielding cities in North America are mainly in urbanized areas along the northeast and western coasts. In China, most of the scientific output is in east coastal cities. Furthermore, such uneven spatial structures have been generally strengthening over time. In addition, Table 5-2 shows that the coefficient of variance has slightly reduced from 1.63 to 1.59, which indicates that the gap between cities has been gradually narrowed; the Gini coefficient also has reduced from 0.68 to 0.65, indicating that the polarization has been decreased to some extent; the Moran's I has fell from 0.095 to 0,056, implying a spatially dispersed trend of the scientific output at global scale.

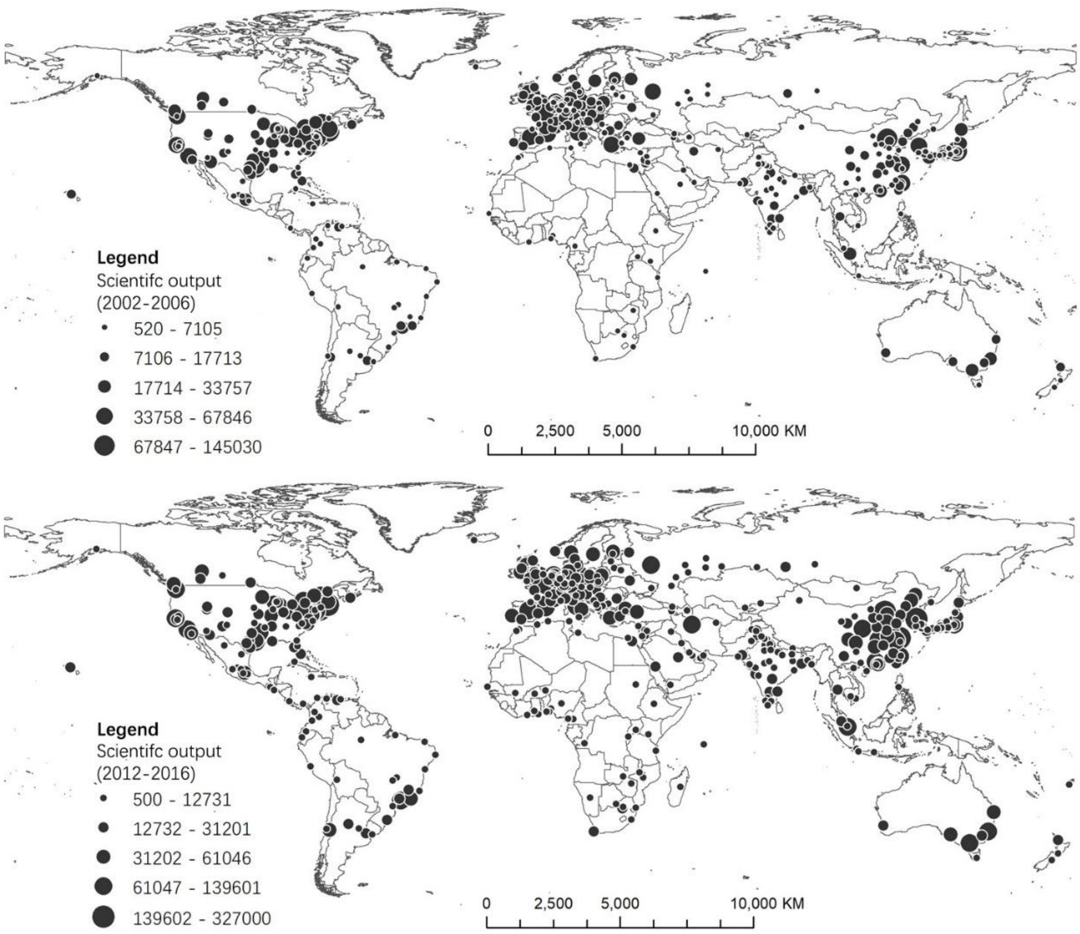


Figure 5-1 Scientific output of the global cities (2002-2006, 2012-2016)

Note: For a clearer visualization, cities with less than 500 and 1000 output are eliminated excluded

Source: author

Table 5-2 Descriptive statistics of the spatial distribution of the scientific output of the global cities (2002-2006, 2012-2016)

	2002-2006	2012-2016
Observations	500	500
Max	145,030	327,000
Min	0	98
Mean	9,765.45	19,772.55

Coefficient of variance	1.63	1.59
Gini Coefficient	0.68	0.65
Moran's I	0.095	0.056

Source: author

5.1.2 Differentiation in growth rates

Figure 5-2 shows the growth rates of the cites in terms of scientific output. Generally speaking, cities in Europe and North America are more productive than other regions but less competitive in terms of increase rate, while cities in Asia, Africa and South America have enjoyed faster growth. These fast-growing cities can be broadly divided into two categories: the cities in developing countries like China, India, and Brazil exhibit great momentum thanks to their burgeoning economy and open-up policies regardless of their relatively weak base of science and technology; and the cities in underdeveloped countries located in Africa, the Middle East, South America and Southeast Asia also display significant growth since they have started up innovation from scratch.

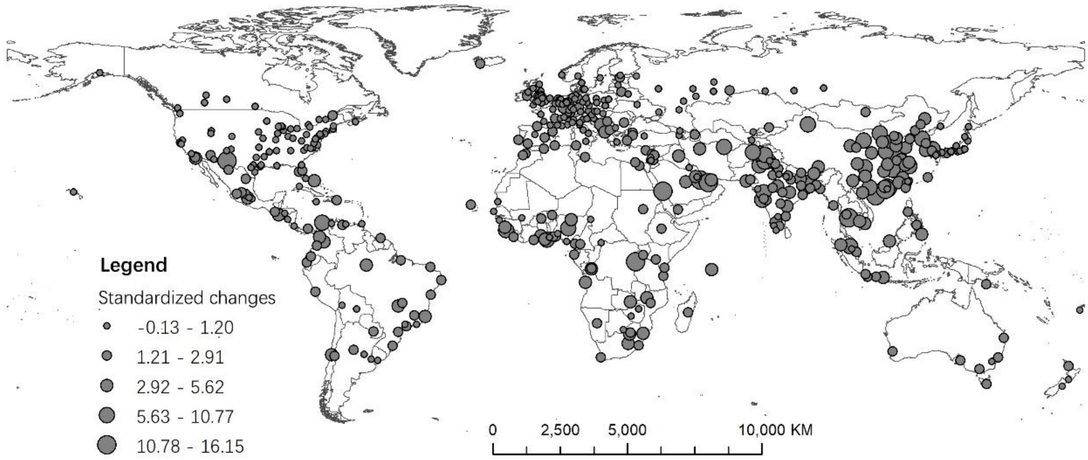


Figure 5-2 Standardized changes of the scientific output of global cities (2002-2006, 2012-2016)

Source: author

Figure 5-6 lists the top 50 cities in terms of scientific output. During the period of 2002-2006, 70% of these cities were in North America and Europe, including 19 cities in USA and 16 in Europe. Only Beijing, Shanghai and Taipei were on the list, ranking respectively 5th, 22nd and 29th. During the period of 2012-2016, the number of European and American cities in the top 50 shrank to 30, and there were 9 Chinese cities on the list, including Beijing, Shanghai, Nanjing, Guangzhou, Wuhan, Taipei, Xi'an, Hangzhou, Chengdu, and Tianjin. Among them, Beijing surpassed London to become the most productive city and meanwhile, Shanghai and Nanjing jumped into the top 10. Moreover, the scientific output of Chinese cities have grown considerably with the average growth rate of 11.01%, 6.26% higher than the global average. These cities not only have sound foundations in science and technology, but also enjoy more favorable policy and capital investment from the state and local governments.

Table 5-3 Top 50 cities in scientific output (2002-2006, 2012-2016)

Rank	city	2002-2006	city	2012-2016	Rank	city	2002-2006	city	2012-2016
1	London	145,030	Beijing	327,000	26	Athens	36,693	Atlanta	75,474
2	Tokyo	112,869	London	250,998	27	Kyoto	36,661	Milan	75,446
3	New York	101,523	New York	178,677	28	Amsterdam	36,603	Singapore	74,159
4	Boston	94,568	Boston	169,670	29	Taipei	36,501	Seattle	73,231
5	Beijing	89,458	Seoul	167,371	30	Barcelona	36,062	Montreal	71,027
6	Paris	78,696	Shanghai	163,737	31	San Francisco	35,836	Amsterdam	70,346
7	Seoul	67,846	Tokyo	139,601	32	Munich	33,757	Washington	70,328
8	Moscow	66,240	Paris	129,694	33	Stockholm	33,197	Melbourne	70,111
9	Los Angeles	62,326	Nanjing	104,915	34	Sydney	32,754	Sao Paulo	68,000
10	Philadelphia	60,641	Madrid	97,444	35	Singapore	32,425	Xi’an	66,184
11	Baltimore	57,858	Philadelphia	96,093	36	Vienna	31,832	Hangzhou	64,542
12	Chicago	57,109	Chicago	95,566	37	Cleveland	30,876	San Francisco	63,598
13	Houston	54,165	Los Angeles	95,239	38	Madison	30,627	Pittsburgh	61,046
14	Toronto	50,271	Toronto	94,278	39	St. Louis	29,894	Stockholm	59,581
15	Berlin	49,664	Baltimore	93,629	40	Zurich	29,789	Rochester	59,167
16	Washington	49,071	Houston	88,651	41	Minneapolis	28,553	Zurich	58,998
17	Madrid	46,894	Barcelona	85,954	42	Sao Paulo	28,400	Chengdu	57,359
18	Seattle	45,786	Sydney	85,361	43	Vancouver	27,174	Munich	55,897
19	Atlanta	44,917	Moscow	85,333	44	Manchester	26,166	Athens	55,819
20	Rome	44,176	Guangzhou	84,387	45	Osaka	25,503	Vienna	54,476
21	Montreal	41,659	Rome	82,027	46	Columbus	25,018	Tianjin	49,750
22	Shanghai	41,399	Tehran	79,732	47	Heidelberg	24,878	Vancouver	48,941
23	Pittsburgh	40,017	Berlin	79,478	48	Sendai	24,740	Istanbul	48,299

24	Milan	38,554	Wuhan	78,011	49	Nagoya	24,673	Copenhagen	47,439
25	Rochester	37,087	Taipei	77,217	50	San Diego	24,568	Ankara	47,035

Source: author

5.1.3 Convergence of the hierarchical structure

Figure 5-3 is the scatter plot of the rank-size of countries' scientific output. They are consistent with the power-law distribution and the goodness fit is satisfactory, which indicates that the scientific output of the global cities is significantly polarized, that is, the minority of cities enjoy considerable output while the majority of cities are much less productive. However, the slope of the linear fitting can be found to be flatter, suggesting that the distribution of the scientific output tends to be balanced over time.

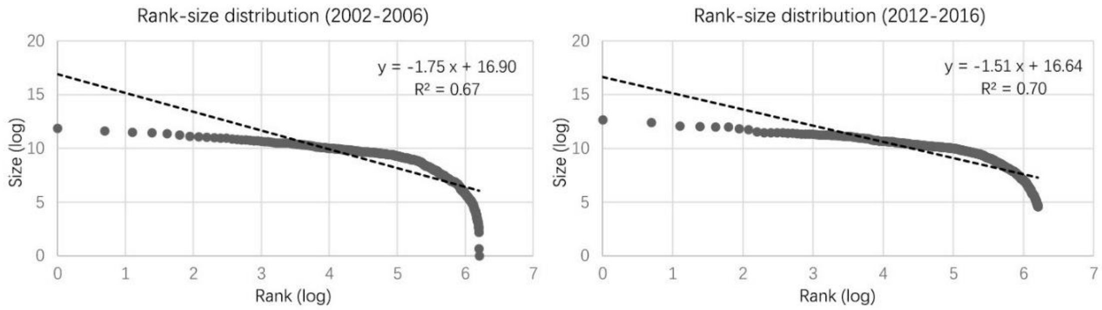


Figure 5-3 The rank-size distribution of the scientific output of global cities (2002-2006, 2012-2016)

Figure 5-4 is the K-means clustering analysis of the scientific output of the global cities. During the period of 2002-2006, only five cities were in the first layer, namely London, New York, Boston, Tokyo and Beijing. There were 11 cities in the second layer, 26 in the third, 128 in the fourth, and 316 in the fifth. The number of cities in the first three layers only accounted for 10.2% of the total, showing an inverted "T" hierarchical structure. During the period of 2012-2016, only Beijing and London stayed in the first layer. The numbers of cities in the second and fifth layer decreased to 6 and 280 respectively as the number of cities in the third and fourth layer increased to 33 and 174. In another word, in the hierarchy of the scientific output of the global cities, it has shown a convergence trend with a decrease in the number of the cities at both the top and bottom layers.

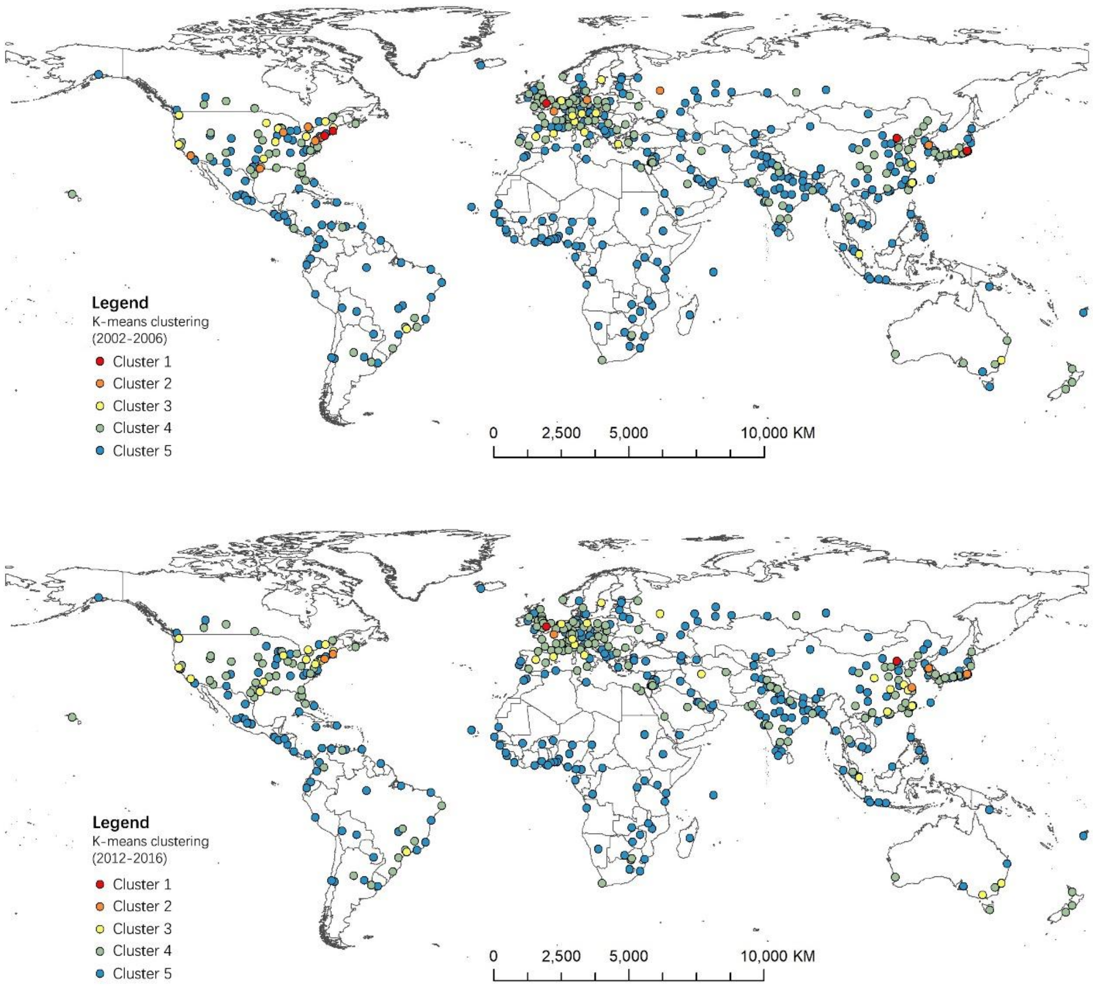


Figure 5-4 K-means clustering of the scientific output of global cities (2002-2006, 2012-2016)
Source: author

Figure 5-5 is the result of spatial autocorrelation analysis on the scientific output of the global cities. During the period of 2002-2006, significant high-high correlation type cities were mainly in North America and Western Europe. There were also high-high correlation type cities in the coastal areas of eastern China and in the east coast of Japan, but the correlation was not significant. A typical core-periphery structure was presented with large number of low-high correlation type cities surrounding around these high-high correlation cities, implying the existence of the processes of knowledge spillovers. Most cities in South America, Africa and South Asia were significant low-low correlation type. Till the period of 2012-2016, most obvious change, i.e., the high-high correlation type of the cities in eastern China, Japan and South Korea have become significant, was largely due to the rapid growth of knowledge production of Chinese cities. At the same time, the spatial correlation model in other parts of the world remained stable.

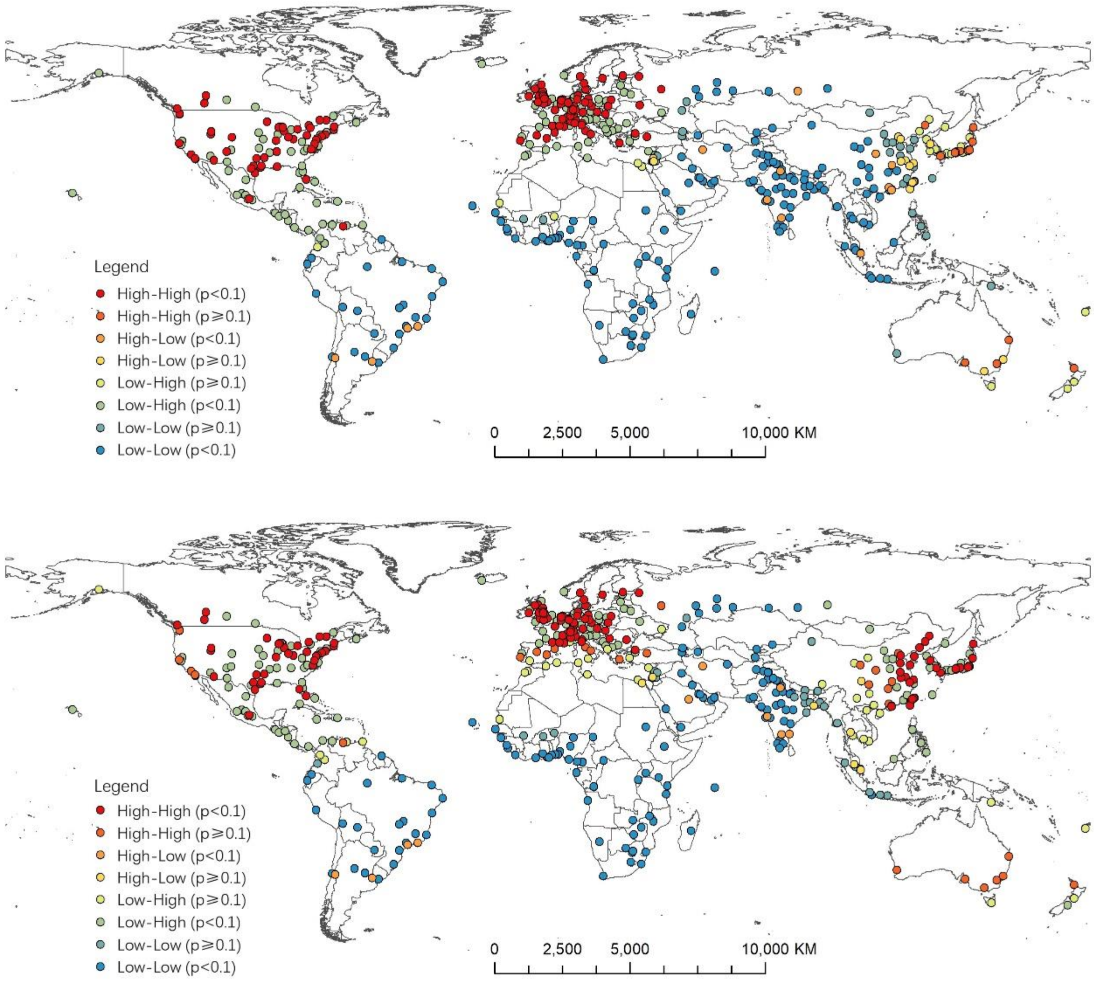


Figure 5-5 Spatial autocorrelation analysis of the scientific output of the global cities (2002-2006, 2012-2016)

Source: author

Combined with the analysis results in Chapter 4, it can be seen that the spatial configuration of scientific innovation of the global cities is in line with that of the countries, suggesting that the national context and innovation systems is crucial in shaping the scientific innovation landscape of the global cites, that is, cities as the main body of the innovation activities are embedded in the dynamic process of the national innovation systems.

5.2 Evolution of the spatial configurations of the global IKCNs

5.2.1 The uneven distributions across different geographical scales

The regression analysis between city scientific output and their network connectivity show that they are highly correlated (the Pearson correlation coefficient is 0.96 and 0.86 in the two time periods with significant level at 0.01 (Figure 5-6). Undoubtedly, a city's KNC is closely related to its innovation capacity. However, the output is only a reflection of the quantity of the scientific production, while the KNC can, to some extent, reflect the quality of the scientific activities. To be more specific, cities with higher KNC usually are more advanced in cutting-edge science and technology and in turn have more collaborators (Matthiessen et al., 2002, 2010).

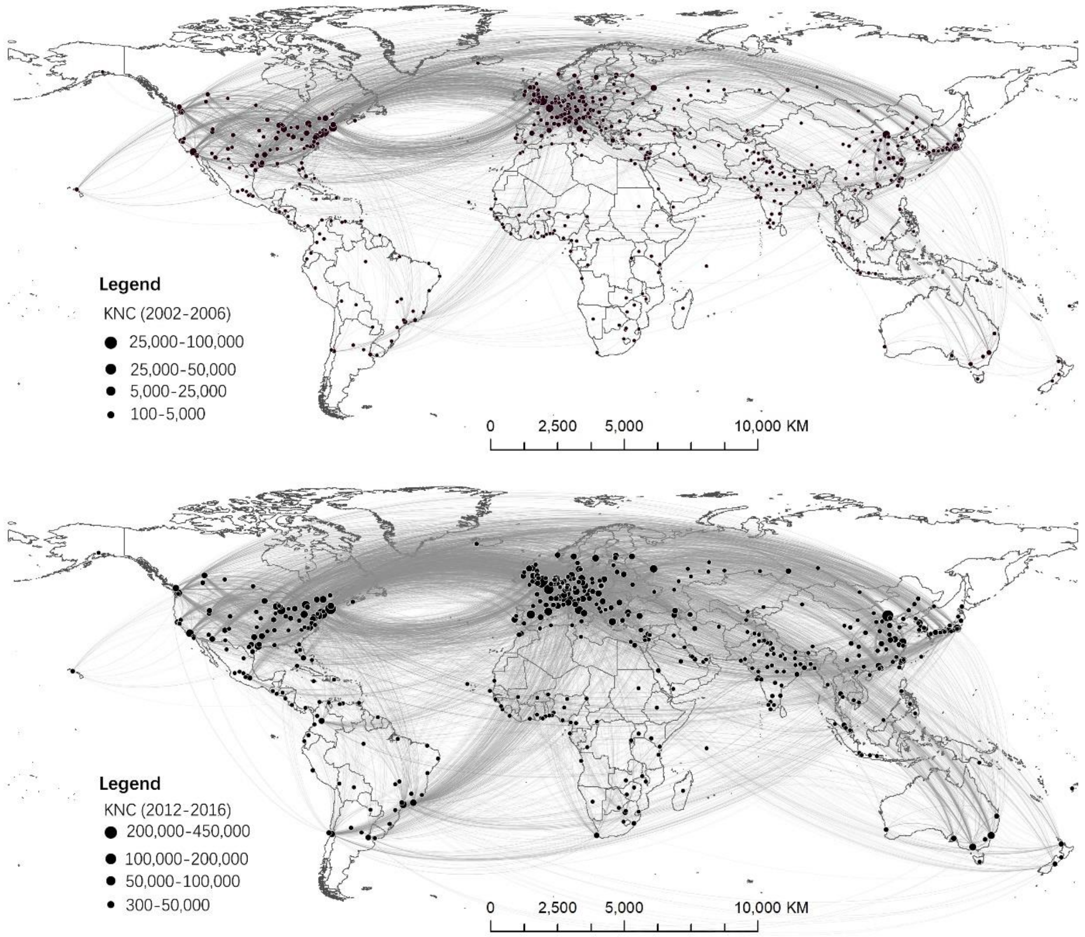


Figure 5-5 The global IKCNs (2002-2006, 2012-2016)

Table 5-4 lists the top 20 cities in terms of the KNC and total scientific innovation output. First of all, albeit the existence of up and downs of some cites, most cities have remained stable, with the exception of Montreal and Berlin that have been replaced by Madrid and Barcelona respectively. Second, London and New York have always been the leading “twins” in terms of the scientific output as well the network connectivity. Recalling the seminal studies on global cities such as Sassen’s and GaWC’s, it can be referred that the “NY-LON” axis also exist in the global IKCNs, that is to say, New York and London are not only the global centers of finance, business and culture, but also the centers of innovation.

Another salient feature is the "monopoly" of the US cities almost occupying half of the list both in overall output and network connectivity. These US cities indeed are at the frontier of knowledge innovation and science and technology. For example, Boston, the cradle of the US higher education, not only houses some of the renowned private universities such as Harvard University, MIT, Tufts University, Boston College and Brandeis University. Meanwhile it is also prized as the "US Athens" for the long-history public education system. With regard to scientific innovation, Boston wins the reputation of "science and technology steering wheel" for its outstanding contribution in the fields of bioengineering, health care, electronic information, mechanical engineering, etc. Another good example is the San Francisco Bay Area on the West Coast of the US that is acknowledged as a world-class knowledge innovation center. It is the home to some world-renowned institutions including UC Berkeley, Stanford, UCSF and also has incubated the "Silicon Valley" which is known as the hub of the ICT.

Except for the US cities, most of the remaining cities on the list are from European countries, then Canada in North America, and Beijing and Tokyo from Asia. Beijing's rapid take-off is eye-catching, with the ranking in network connectivity soaring from the 6th during 2002-2006 to the 2nd during 2012-2016. In terms of the total knowledge innovation output, it ascended from the 5th to the 1st, 30.3% higher than London in the second place. Beijing's soaring is not surprising. As the capital of China, Beijing boasts a solid foundation of science and technology, sound education and research facilities and sufficient human capital and financial resources. More importantly, this city has always enjoyed the national policies and resource input. For example, *"General Plan for Strengthening the Construction of Beijing as the National Science and Technology Innovation Centers"*, issued in 2016 by the State Council, proposes the important role of Beijing in the national innovation system. It also emphasizes that it is imperative for Beijing to take the lead in the implementation of innovation-driven and synergized development of the BTH city-region. Similarly, the rapid rise of Madrid and Barcelona also attributes to the Spanish government's unprecedented investment and policy support for technology and education in recent years (Afcha Chávez, 2011).

Table 5-4 Top 20 cities in KNC and scientific output (2002-2006, 2012-2016)

	2002-2006					2012-2016				
Rank	City	KNC	KNC%	City	Output	City	KNC	KNC%	City	Output
1	London	101,142	100.00	London	145,030	London	424,182	100.00	Beijing	327,000
2	New York	78,649	77.76	Tokyo	112,869	Beijing	371,252	87.52	London	250,998
3	Boston	75,005	74.16	New York	101,523	Boston	348,770	82.22	New York	178,677
4	Tokyo	69,989	69.20	Boston	94,568	New York	338,967	79.91	Boston	169,670
5	Paris	69,186	68.40	Beijing	89,458	Paris	293,350	69.16	Seoul	167,371
6	Beijing	63,483	62.77	Paris	78,696	Chicago	239,196	56.39	Shanghai	163,737
7	Los Angeles	57,097	56.45	Seoul	67,846	Rome	226,594	53.42	Tokyo	139,601
8	Baltimore	52,741	52.15	Moscow	66,240	Madrid	226,335	53.36	Paris	129,694
9	Philadelphia	52,422	51.83	Los Angeles	62,326	Milan	221,480	52.21	Nanjing	104,915
10	Chicago	49,319	48.76	Philadelphia	60,641	Barcelona	205,229	48.38	Madrid	97,444
11	Houston	45,346	44.83	Baltimore	57,858	Toronto	201,916	47.60	Philadelphia	96,093
12	Rome	45,334	44.82	Chicago	57,109	Tokyo	195,669	46.13	Chicago	95,566
13	Moscow	43,556	43.06	Houston	54,165	Baltimore	190,859	44.99	Los Angeles	95,239
14	Seattle	42,808	42.32	Toronto	50,271	Philadelphia	190,592	44.93	Toronto	94,278
15	Toronto	41,596	41.13	Berlin	49,664	Los Angeles	189,991	44.79	Baltimore	93,629
16	Milan	41,167	40.70	Washington	49,071	Seattle	188,810	44.51	Houston	88,651
17	Amsterdam	40,720	40.26	Madrid	46,894	Amsterdam	188,703	44.49	Barcelona	85,954
18	Montreal	38,944	38.50	Seattle	45,786	Moscow	185,325	43.69	Sydney	85,361
19	Pittsburgh	36,191	35.78	Atlanta	44,917	Houston	182,344	42.99	Moscow	85,333
20	Berlin	35,778	35.37	Rome	44,176	Pittsburgh	176,888	41.70	Guangzhou	84,387

Source: author

Table 5-5 presents the descriptive statistics of the spatial features of the global IKCNs. On one hand, the surge in the max, min and mean values shows that the global interurban knowledge collaborations tend to be more intensive and frequent. On the other hand, high Gini coefficient indicates the KNC distribution of the global IKCNs is obviously polarized and imbalanced, that is, a large amount of knowledge collaboration activities among a handful of cities. However, the decreasing Gini coefficient and coefficient of variance also reflect such polarization has been gradually weakened. The decreasing Moran's I index suggests a dispersed tendency of the spatial distribution of the global IKNC.

Table 5-5 Descriptive statistics of the spatial configurations of the global IKCNs (2002-2006, 2012-2016)

	2002-2006	2012-2016
Observations	500	500
Max	101,142.00	424,182.00
Min	0.00	31.00
Mean	7,823.51	43,511.99
Standard deviation	12,637.29	60,497.68
Gini Coefficient	0.69	0.65
Coefficient of variation	1.62	1.59
Moran's I	0.13	0.11

Source: author

Figure 5-7 and Figure 5-8 are the cartograms of the spatial configurations of the cities with the KNC greater than 10% during the period of 2002-2006 and 2012-2016, respectively. It is obvious that the geographical distributions of the KNC worldwide are uneven in different geographical dimensions and spatial scales.

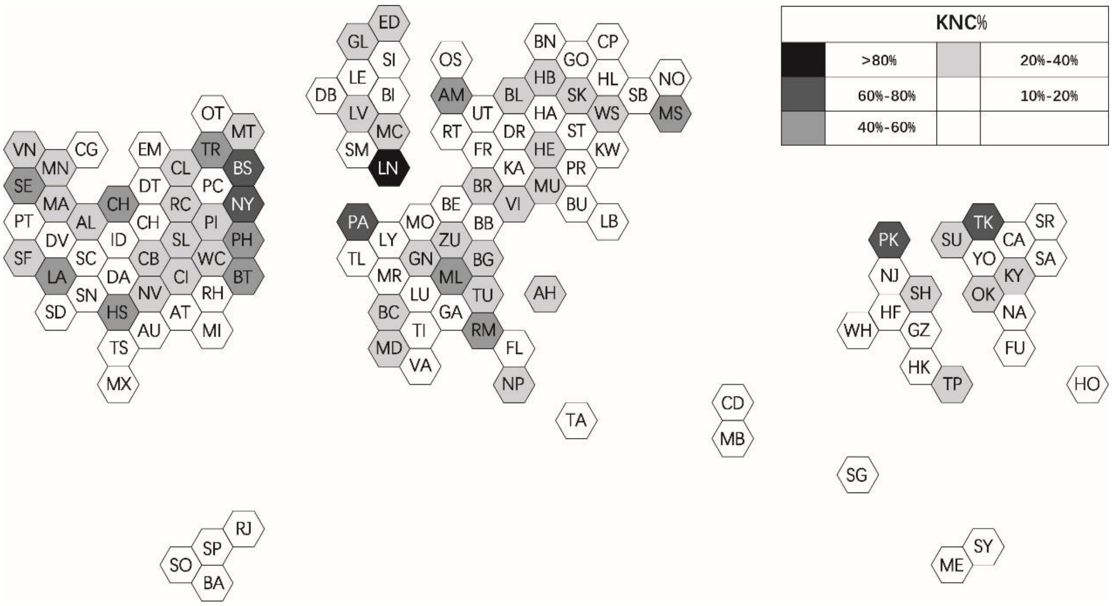


Figure 5-7 The spatial distribution of global cities' KNC (≥10%) (2002-2006)

LN: London, PK: Beijing, BS: Boston, NY: New York, PA: Paris, CH: Chicago, RM: Rome, MD: Madrid, ML: Milan, BC: Barcelona,TR: Toronto, TK: Tokyo, BT : Baltimore, PH: Philadelphia, LA: Los Angeles, SE: Seattle, AM: Amsterdam, MS: Moscow, HS: Houston, PI: Pittsburgh, GN: Geneva, SH: Shanghai, CB: Columbus, AH: Athens, SP : Sao Paulo, SY: Sydney, BG: Bologna, HE: Heidelberg, BL: Berlin, MU: Munich, TP: Taipei, MT: Montreal, ME: Melbourne, HB: Hamburg, PR: Prague, SK: Stockholm, SU: Seoul, RC: Rochester, CP: Copenhagen, NP: Naples, MA: Madison, GA: Genoa, RJ: Rio de Janeiro, VN: Vancouver, MC: Manchester, BU: Budapest, NJ: Nanjing, TI : Treviso, ED: Edinburgh, ZU: Zurich, GZ: Guangzhou, SO: Santiago (Chile), VI: Vienna, LS: Lisbon, IS: Istanbul, LV: Liverpool, OS: Oss , AK: Ankara, SF: San Francisco, MR: Marseille, GL: Glasgow, BB: Bern, WS: Warsaw, AT: Atlanta, OG: Bogota, BD: Belgrade, DA: Dallas, HL: Helsinki, SB: St. Petersburg, KW Krakow, MN: Minneapolis, VA: Valencia (Spain), TU: Turin, BH: Bucharest, OT: Ottawa, WC: Washington, KY: Kyoto, BR: Brussels, YE: EY Rive, NV: Nashville, EM: Edmonton, FL: Florence, OK: Osaka, NA: Nagoya, TS: Tucson, TB: Tbilisi, MK: Minsk, DT: Detroit , HF: Hefei, BI: Bristol, DR: Dresden, NO: Novosibirsk, AD: Adelaide, SI: Sheffield, BA: Buenos Aires, BN: Humble Ergen, MX: Mexico City, DB: Dublin, HK: Hong Kong, CT: Cape Town, UT: Utrecht, TA: Tel Aviv, SM: Southampton, AL: Albuquerque, WH: Wuhan , AU: Austin, ST: Strasbourg, MB: Mumbai, JB: Johannesburg, LB: Lu Burjana, JN: Jinan City, SG: Singapore, MI: Miami, CF: Clermont Ferrand, BV: Bratislava, CL: Cleveland, HR: Hiroshima, DO: Dortmund, SL: St. Louis, KB: Kobe, FU: Fukuoka, PC: Providence, HI: Haifa, BF: Buffalo, AC: Auckland, KL: Kuala Lumpur, LY: Lyon, ZG: Zagreb, RT: Rotterdam, BO : Brisbane, LU: Lausanne, SD: San Diego (USA), CI: Cincinnati, KA: Karlsruhe, TH: Tehran, VP: Valparaiso, FA: Sofia, AW: Antwerp, CD: Chandi Gar, KO: Kolkata, BE: Basel, TL: Toulouse, CR: Cairo, IM: Islamabad, RA: Rabat, BK: Bangkok, BW: Bhubaneshwar, HZ: Hangzhou, CS: Casablanca, BQ : Baku, KR: Kharkov, SC: Salt Lake City, FR: Frankfurt, CU: Christchurch, PB: Puebla, MO: Montpellier, CM: Campinas, CE: Chengdu, PT: Portland, IZ: Izmir, VL: Vilnius, NE: Newcastle, HA: Novi, NI: Nicosia, XA: Xi'an, TN: Tallinn, CG: Calgary, TJ: Tianjin, ID: Indianapolis, DN: Durban, JD:

Jeddah, LE: Leeds, YO :Yokohama, GO: Gothenburg, DH: Doha, DV: Denver, SA: Sendai, HO: Honolulu, SN: San Antonio, RH: Richmond, SR: Sapporo, CA: Chiba

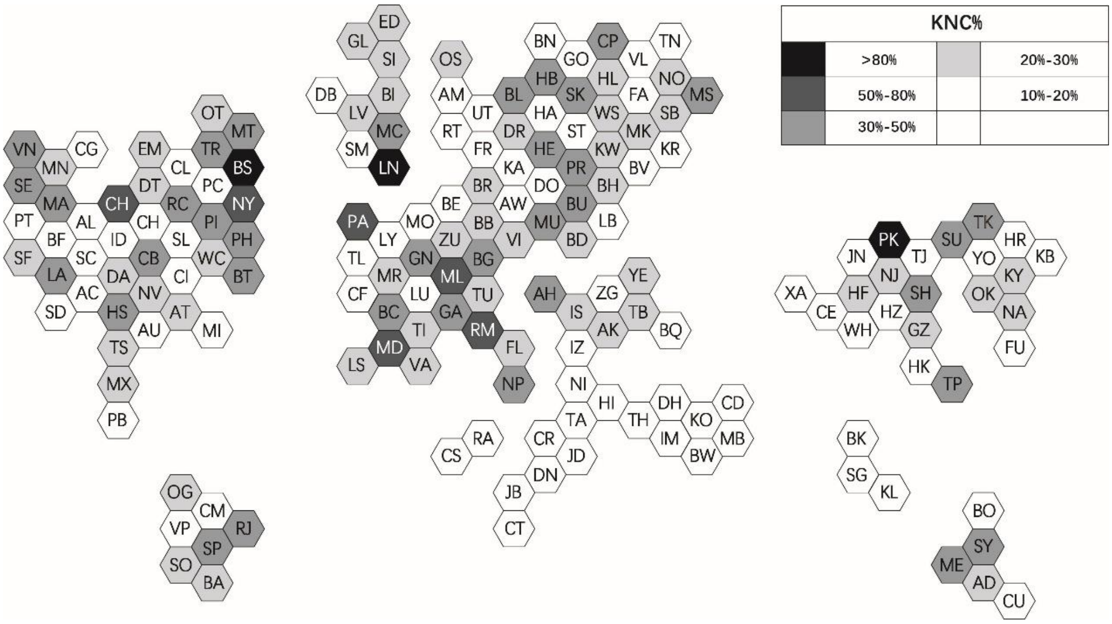


Figure 5-8 The spatial distribution of global cities' KNC (≥10%) (2012-2016)

First, at the global scale, cities with higher KNC are generally situated in the "Global North", while the cities with lower KNC are mostly located in the "Global South" and meanwhile a significant number of cities are off the map because of the less than 10% KNC.

Specifically, in the "Global North", major cities in Western Europe, North America and Asia Pacific constitute the "three main pillars in the global IKNC. In the period of 2002-2006, the number of cities from these three regions respectively reached 61, 41 and 20, accounting for 93.8% of all cities. However, in the "Global South", only six cities' KNC have been above 10%, namely Mumbai and Chandigarh in India, São Paulo and Rio de Janeiro in Brazil, and Mexico City and Buenos Aires. During the period of 2012-2016, 43 cities' KNC were above 10% with the share of cities of the three core regions falling to 72.1%, suggesting the gap between the "Global North" and the "Global South" has been narrowed. More specifically: first, most cities in three core regions have maintained their network positions, within which only a few cities have fell off the map, including Leeds (UK), Yokohama (JPN), Denver (USA), Sendai (JPN), Sapporo (JPN), Chiba (JPN), Honolulu (USA), San Antonio (USA), Richmond (USA). Second, newcomers have been gradually forming new layers around the three core layers. For example, the emergence of capital cities (20 cities) of many countries in Eastern Europe and Southern Europe has further strengthened the core position of the European cities. Similarly, cities in the Asia-Pacific region have also expanded to a certain degree, particularly with the rise of 6 Chinese cities, 64 cities in Southeast Asia and Oceania. Third, some cities emerged in the blank areas of the "Global South" are mostly better-developed capital cities, including 4 cities in Latin America, 6 in Middle East and North Africa and 3 in South Asia.

Secondly, at regional scale, the unbalanced configuration of city KNC take different forms in different regions. Cities in Western Europe have presented a mixed spatial distributions pattern, that is the mixture of high connectivity cities and low connectivity cities. "Innovation highlands" such as London, Paris, Amsterdam, Milan and Rome are surrounded by a large number of cities with low-and medium-connectivity. Such spatial configuration can be summarized as "multi-cores" structure with "locally concentration and globally dispersion", which has been strengthening over time. Similarly, cities in the North America also have presented such spatial pattern of a mixture of high, medium and low connectivity. Nonetheless, the differences are also evident: cities with higher KNC have predominantly distributed along the east coast urban corridor with core cities like Montreal, Toronto, Boston, New York, Philadelphia, and Baltimore, as well as an urban belt with core cities like "Vancouver, Seattle, San Francisco, and Los Angeles on the west coast. In addition, cities located in the Great Lakes region in the north and cities sit along the Mexico Bay in the south also have higher KNC. In comparison, cities in the central United States, central and northern Canada are less connected, presenting a "basin-like" structure as a whole. Unlike that of Western Europe and North America, the spatial distribution of city KNC in the Asia-Pacific region presents an increasingly obvious "unipolar" structure. In the period of 2002-2006, Beijing and Tokyo constituted the network core, while in 2012-2016 Beijing stood out to become the unchallengeable "network core" in the Asia-Pacific region, with cities like Tokyo, Seoul, Shanghai, Taipei, Sydney and Melbourne constituting the sub-core layer. Another worth noting change is the collective emergence of Chinese cities: there were only 8 cities with the KNC bigger than 10% in the period of 2002-2006, including the first-tiered cities like Beijing, Shanghai, Guangzhou, Hong Kong and Taipei as well as some cities with relatively rich education and research resources such as Nanjing, Hefei and Wuhan. By the period of 2012-2016, another 5 cities joined in the club including Tianjin, Hangzhou, Jinan, Chengdu and Xi'an. By the end of the study period, the total number of Chinese cities with KNC greater than 10% has reached 13, surpassing the UK (9 cities) and Japan (8 cities) to become the second place after USA (33 cities).

During the period of 2012-2016, cities in other regions came on the map outside three core regions, whose KNC were pretty low except Brazil and Rio de Janeiro and Sao

Paulo, Russia. Among these cities, 17 cities were from the Eastern Europe, 6 cities from the Middle East and North Africa, 3 cities from the South Asia, 4 cities from the Latin America, and 3 cities from Sub-Saharan Africa. The commonality of these cities is that their countries have witnessed a significant growth in terms of innovation capability in recent years. For example, countries like China, Brazil, India and South Africa have more than one city that come up to map, which reflects these emerging countries have been actively involving global scientific collaboration and accessing into the core of the global KCNs. However, the majority of these newly-joined cities are either the capitals or the economically-advanced cities. This reconfirms that the distribution of the cities' KCN is significantly uneven at national scale.

5.2.2 The up and downs of cities in the global interurban knowledge collaboration networks

Figure 5-9 and Figure 5-10 show the spatial distribution of the standardization change[20] of the KNC in the global IKCNs. Figure 5-9 shows cities with increased KNC and Figure 5-10 shows cities with reduced KNC. Without taking the absolute changes into consideration, two graphs are "symmetric" in terms of the positive and negative changes, and both present a clear-cut divide between the "Global South" and "Global North", as well as that between the "East" and the "West": the gravitational center of the global IKCN has gradually shifted from the North to the South and also from the West to the East. Specifically, cities with increasing connectivity can be broadly divided into two groups. The first group mainly includes cities newly joined the network during the period of 2012-2016. The second group include cities have been on the map the period of 2002-2006. Firstly, the most prominent increases in terms of the KNC belong to Chinese cities, especially to Beijing whose standardized change of the KNC was 2.86 during the two time periods as the fastest among all cities. Nanjing, Shanghai, Guangzhou, Wuhan and Hefei also enjoyed considerable growth. This reflects the great momentum of Chinese cities accessing into the global IKCNs. Secondly, some cities in the fringe of Europe also have witnessed significant increase in the KNC, including Madrid, Barcelona and some Italian cities in Southern Europe, Prague and Budapest in Eastern Europe, as well as Oslo, Copenhagen, Gothenburg in Northern Europe, etc. This implies that the spatial range of the scientific collaboration activities in European cities has gradually expanded from the core to periphery regions. Thirdly, the KNC of most cities in Western European has declined. Yet, some cities in Germany like Hamburg, Heidelberg, Düsseldorf and Munich have shown rapid growth thanks to the

[20] The algorithm can be found in the footnote in 6.2.2.1.

implementation of a series of innovation related policies that centered on the “Industry 4.0” strategy“ .

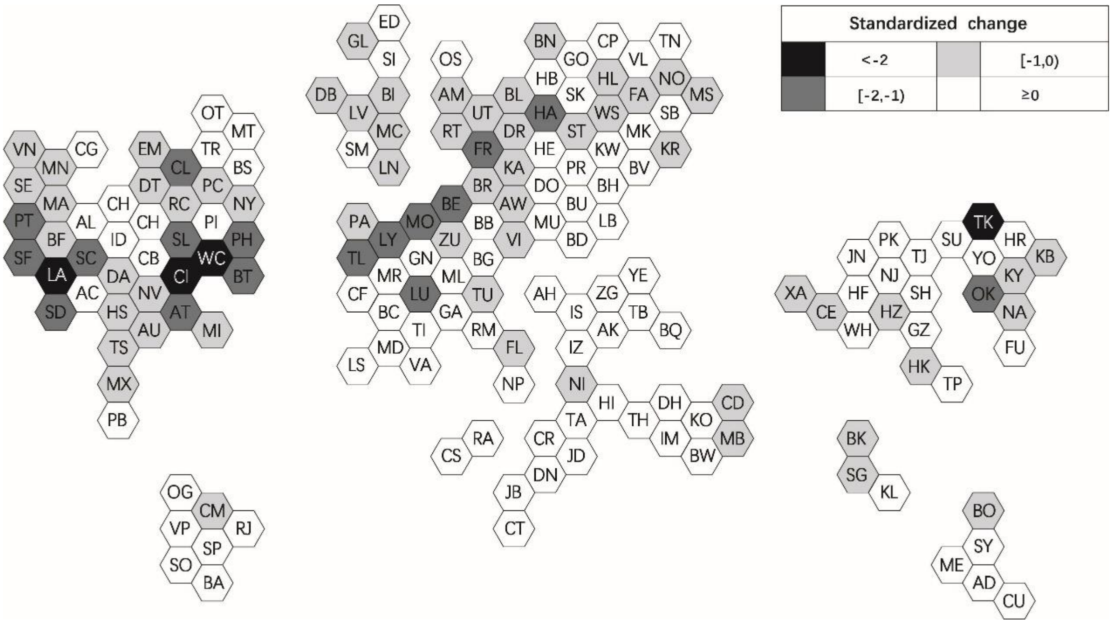


Figure 5-9 The spatial distribution of standardization KNC change (KNC⩾10%) (2002-2006, 2012-2016)

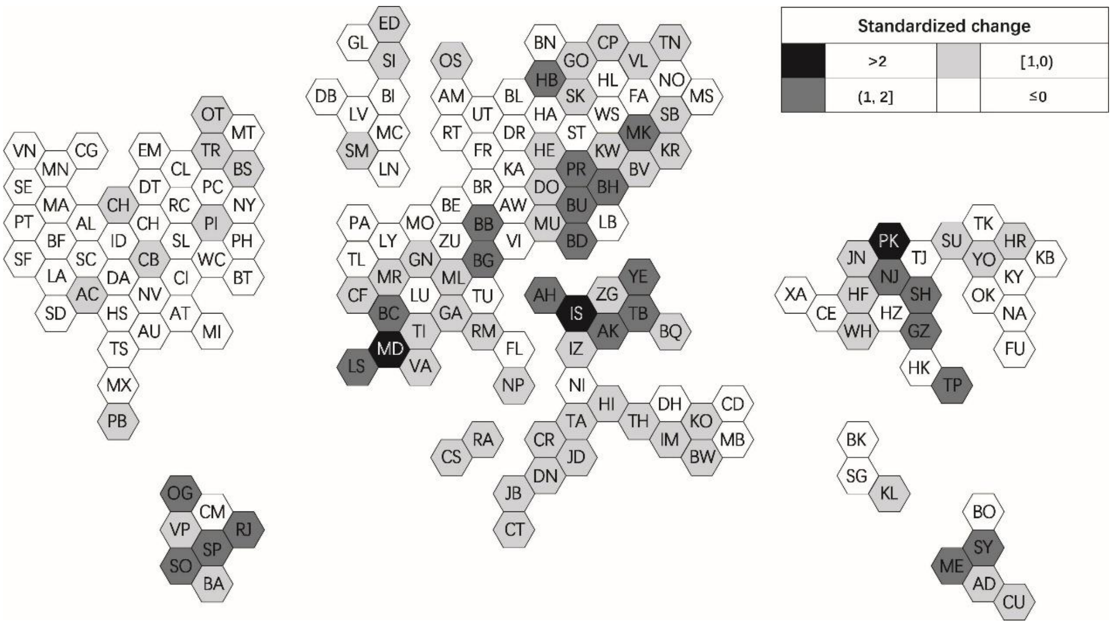


Figure 5-10 The spatial distribution of the standardization KNC change worldwide (KNC ⩾ 10%) (2002-2006, 2012-2016)

With regard to the cities with declined KNC, the majority are from North America, Western Europe, and Japan. However, cautiousness is required when explaining and interpreting this result: the relative decline of KNC neither equals to the claim that these cities are less likely to participate in interurban scientific collaborations nor that their innovation capabilities are weakening. On the contrary, the absolute KNC of almost all cities have increased to different degrees. The rise and fall of the standardized KNC changes are, to a large extent, a reflection of the relative speed of the KNC growth. The difference in growth rate, on one hand, stems from the micro-process of knowledge collaboration and on the other hand, from the mechanism of the innovation process itself. For the former, the actors (researchers or organizations) in the KCNs are not able to infinitely collaborate with new partners due to the time, money and energy-consuming process of collaboration and maintaining collaborative relations. In this sense, new partners will lead to more marginal costs for those who already have many collaborators. By contrast, newly-joined actors will have more space and greater freedom in building new collaborative relations (Wagner and Leydesdorff, 2005b). For the latter, the growth of the KCNs is non-linear but presents a "S-shaped" curve with "starting stage, growth stage, mature stage, bottleneck stage". As for the changing KNC, cities that have newly joined or yet to join the KCNs are mostly in the starting stage of knowledge innovation, so their KNC growth is relatively slow (such as most cities in the "Global South"). Cities in emerging economies are accelerating their pace and soaring in the KCNs. They have gained certain degrees of innovation capabilities after learning, absorbing and accumulating knowledge in the early stage, and they have more space for growth and development, in turn have showed great momentum in growing the KCNs. As for those cities that have reached the mature stage, their status quo is the possession of the most advanced science and technology and the further efforts in seeking the most cutting-edge research and frontier breakthroughs. Such processes are, inevitably, relatively slow with relatively small collaboration communities. Thus they present a relatively low growth rate in the IKCNs (Liu et al., 2017). (Fig. 5-11)

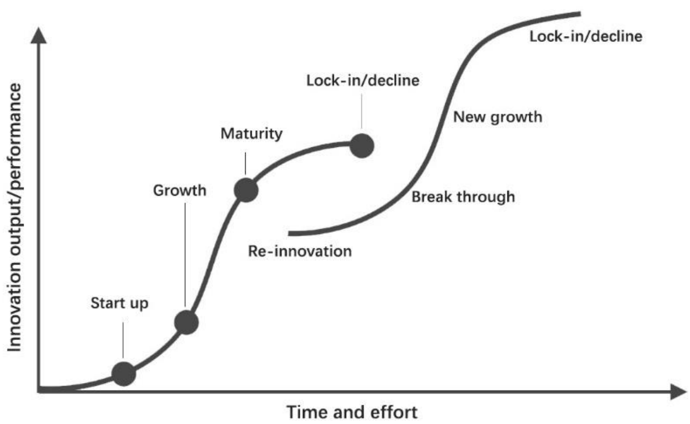


Figure 5-11 Innovation curve
Source: author

5.2.3 The spatial reach of cities in the global IKCNs

Figure 5-12 shows the spatial reach of the collaborative relations of some cities. The calculation is consistent with the method used in Section 4.2.3. The results show: first, all cities are more likely to collaborate with the cities in their own regions. This once again confirms that geographical proximity is an important factor in the formation of the IKCNs. Second, with the passage of time, the spatial reach of most cities still has remained steady without any structural changes. This again can be characterized as "space dependency". Third, for the cities outside Europe and North America, their collaborative connections with the European and the North American cities are relatively lower. This points to that there is still a lot of room for knowledge collaboration with cities in these two regions since their actual collaborations are far lower than expected.

Table 5-6 lists the relative collaboration intensity of Chinese cities in the global IKCNs. In the period of 2002-2006, among the 11 Chinese cities examined, the top 3 cities that had the highest collaboration strength with the Asia-Pacific cities were Xi'an, Chengdu and Lanzhou, indicating that the spatial reach of these cities was relatively "local". In contrast, Taipei, Hefei and Hong Kong were the top 3 cities that had the lowest collaboration strength with Asia-Pacific cities, which implies that their spatial reach of them was relatively "global". For Hong Kong and Taipei, their globalism can be attributed to their historical and political trajectories. As for Hefei, more than 80% of Hefei's co-authored papers during 2002-2006, according to the WoS data, were from the University of Science and Technology of China, 65% of which were co-authored with universities or institute in other countries. Therefore, Hefei relatively showed higher degree of "globalism".

The change of Beijing was prominent. During the period of 2002-2006, the relative intensity of collaboration between Beijing and other regions outside the Asia-Pacific region was relatively low. By the time of 2012-2016, Beijing's relative intensity of collaboration with North America, Latin America, Europe and Central Asia, the Middle East and North Africa all ranked in the top three. This change reflects that Beijing is going forward in playing the role as the "knowledge gatekeeper" at the national level. Similarly, Shanghai, Nanjing and Wuhan have also become more "global" during this period.

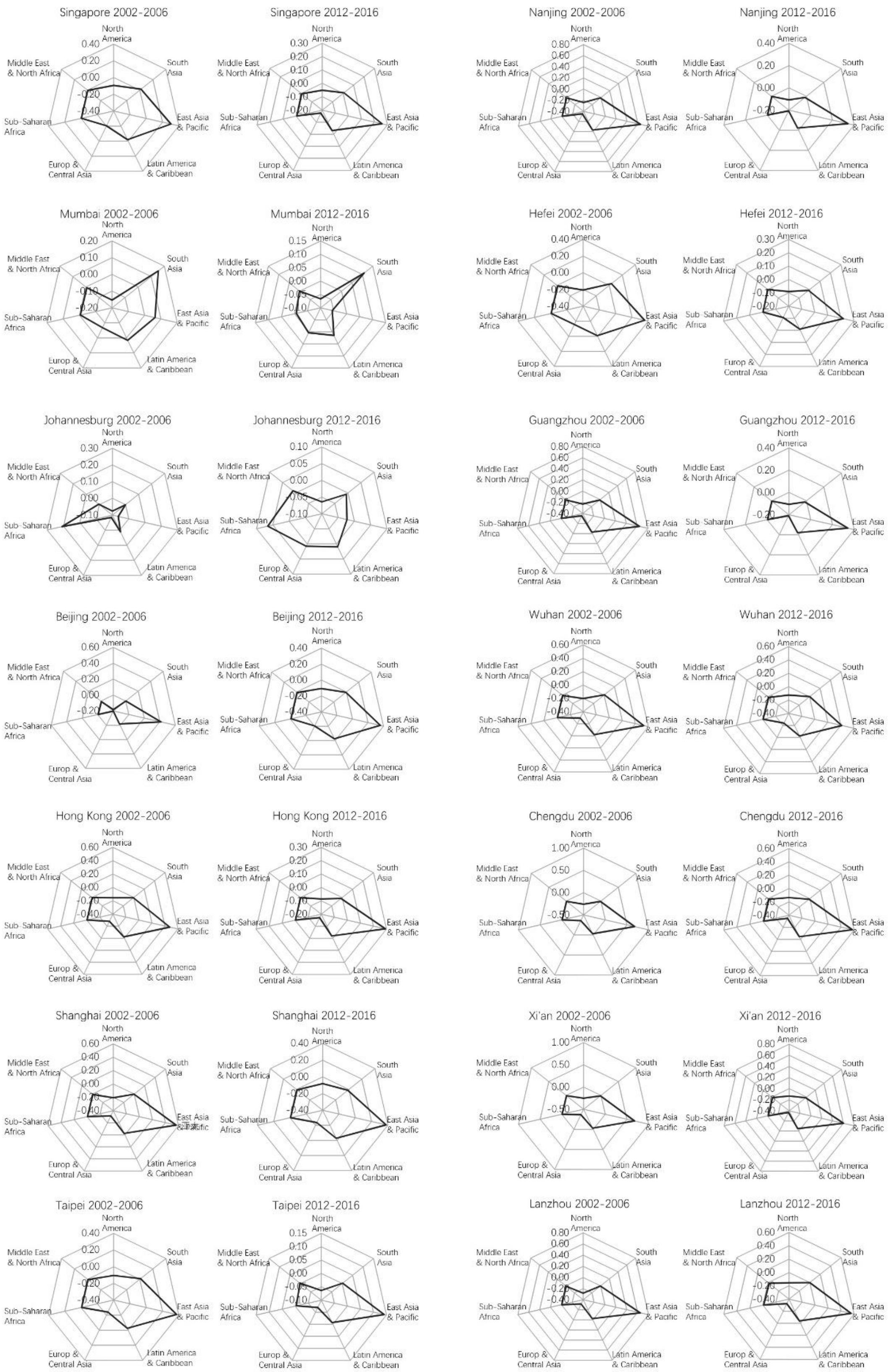
Table 5-6 Strength of connection of global collaboration relations of Chinese cities

	North America		South Asia		East Asia and Pacific		Latin America	
	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016

Beijing	-0.107	-0.183	-0.006	0.001	0.359	0.415	-0.025	-0.019
Shanghai	-0.081	-0.207	-0.016	-0.003	0.378	0.564	-0.029	-0.023
Taipei	-0.064	-0.105	0.002	0.012	0.141	0.373	-0.007	-0.025
Nanjing	-0.107	-0.241	-0.017	-0.013	0.344	0.650	-0.022	-0.027
Guangzhou	-0.106	-0.232	-0.017	-0.012	0.341	0.644	-0.021	-0.029
Heifei	-0.090	-0.206	-0.010	0.034	0.218	0.355	-0.009	-0.008
Hong Kong	-0.086	-0.155	-0.012	-0.006	0.292	0.473	-0.019	-0.022
Wuhan	-0.126	-0.202	0.002	0.007	0.414	0.529	-0.025	-0.019
Chengdu	-0.135	-0.258	-0.015	-0.014	0.573	0.676	-0.044	-0.031
Xi’an	-0.132	-0.251	-0.020	-0.015	0.602	0.676	-0.047	-0.030
Lanzhou	-0.154	-0.282	-0.002	-0.005	0.553	0.647	-0.039	-0.026

	Europe and Central Asia		Black Africa		Middle East and North Africa	
	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Beijing	-0.203	-0.199	-0.009	-0.006	-0.010	-0.009
Shanghai	-0.238	-0.315	-0.007	-0.006	-0.008	-0.010
Taipei	-0.069	-0.241	-0.004	-0.007	0.002	-0.008
Nanjing	-0.193	-0.350	-0.003	-0.007	-0.003	-0.010
Guangzhou	-0.190	-0.354	-0.003	-0.007	-0.004	-0.011
Heifei	-0.105	-0.157	-0.003	-0.008	0.000	-0.010
Hong Kong	-0.171	-0.281	-0.002	-0.004	-0.002	-0.005
Wuhan	-0.239	-0.297	-0.009	-0.007	-0.017	-0.011
Chengdu	-0.351	-0.358	-0.012	-0.006	-0.016	-0.010
Xi’an	-0.369	-0.364	-0.015	-0.007	-0.018	-0.010
Lanzhou	-0.326	-0.317	-0.012	-0.006	-0.021	-0.011

Source: author



Singapore 2002-2006
Singapore 2012-2016
Nanjing 2002-2006
Nanjing 2012-2016
Mumbai 2002-2006
Mumbai 2012-2016
Hefei 2002-2006
Hefei 2012-2016
Johannesburg 2002-2006
Johannesburg 2012-2016
Guangzhou 2002-2006
Guangzhou 2012-2016
Beijing 2002-2006
Beijing 2012-2016
Wuhan 2002-2006
Wuhan 2012-2016
Hong Kong 2002-2006
Hong Kong 2012-2016
Chengdu 2002-2006
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Xi'an 2002-2006
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Taipei 2002-2006
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South Asia
East Asia & Pacific
Latin America & Caribbean
Europ & Central Asia
Sub-Saharan Africa
Middle East & North Africa

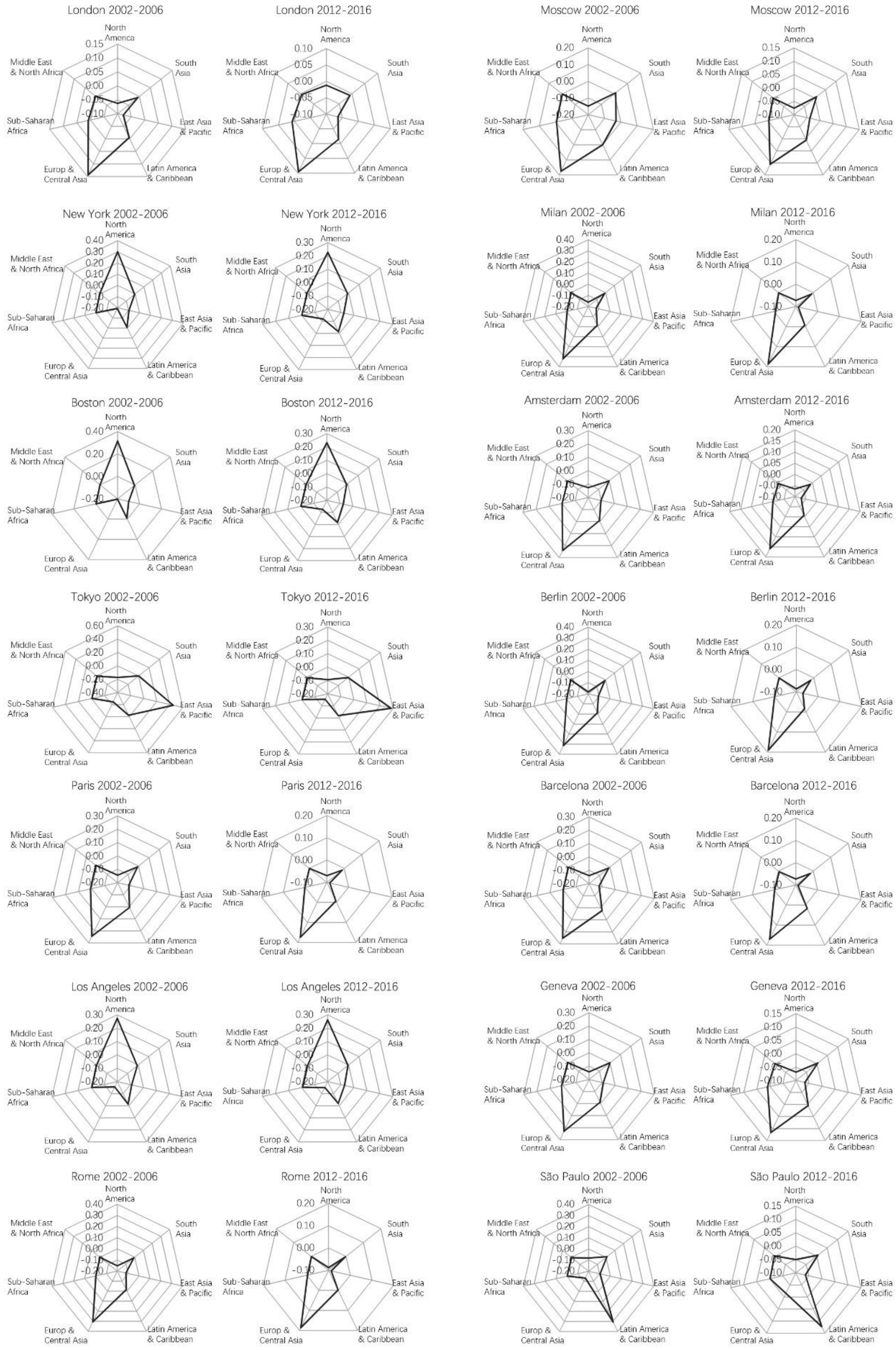


Figure 5-12 Spatial dimension of knowledge collaboration of some cities

Source: author

5.2.4 Cities in the global "knowledge collaboration networks" and the "advanced producer service networks"

Chapter 2 discusses in detail the origin and development of the concept of "global city" and reviews the related empirical research. The most influential one is the GaWC's global urban network research centered on the "advanced producer services networks" (APSNs). Figure 5-13 is a diagram of the geographical distribution of cities with connectivity greater than 20% in the APSN of 2016 (Derudder et al., 2018). This resembles and meanwhile differs from that of the KCNs. The two types of global urban network share the commonality of the "Global South" and "Global North" gap, that is, the number of the "Global North" cities is far greater than that of the "Global South" in both networks. Second, the spatial distribution of cities' network connectivity at different scales of the two networks can all be characterized as "multi-scalar unbalance". Despite the similarities, the obvious difference between them is that cities with higher connectivity in the producer service network are more widely distributed, while cities with higher connectivity are mainly distributed in North America, Western Europe and Asia Pacific in the KCNs.

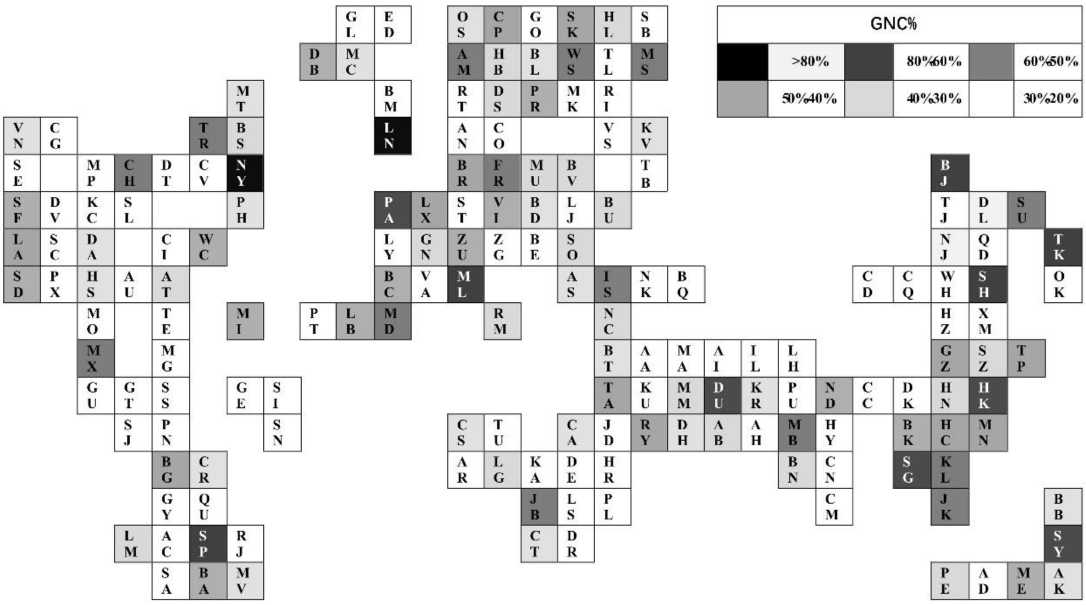


Figure 5-13 The spatial distribution of global urban network connectivity of the "advanced producers service network" (2016)
Source: Derudder et al. (2018)

Table 5-7 compares the top 20 cities in the KCN (2012-2016) and APSN (2016). At the global level (left half of the table), it is not difficult to see that the co-existence of overlaps and differences: the overlapping cities in the both networks include London, New York, Paris, Beijing, Tokyo, and Chicago, indicating that these cities are the dominant hubs in global innovation competition and global capital control. In fact, these cities are also core cities in many other aspects, such as economy, culture and transportation. By examining the remaining cities, it can be seen that the top global APS centers are more widely distributed and dispersed than the "global innovation centers. Specifically, the latter are mostly located in North America and Europe with the exception of Beijing and Tokyo from the Asia-Pacific. In contrast, the top APS centers are relatively more evenly distributed in all seven world regions. In addition to North America, Europe and Asia Pacific, Dubai in the Middle East and North Africa, São Paulo and Mexico City in Latin America, Mumbai in South Asia and Johannesburg in Sub-Saharan Africa are among the top APS centers.

Table 5-7 also lists the network connectivity of major Chinese cities both in global IKCNs and APSNs, which shows the variance of the network status of cities in different types of networks. Some cities like Hefei, Nanjing and Wuhan are more important in the global IKCNs than in the APSNs. Similar to the global-level analysis, "top city dominance" is also evident at national level, that is, top cities like Beijing, Shanghai, Taipei, and Guangzhou have high centrality and control in both network systems. In addition, it can be found from the comparison that the connectivity of cities in the APSN is highly correlated with the cities' economy: cities' network connectivity is significantly correlated with their GDP (Pearson coefficient is 0.91, $p<0.01$). Meanwhile, cities' connectivity in the IKCN is weakly correlated with their total GDP (Pearson coefficient is 0.49, $p<0.1$)[21].

[21] The city GDP data derives from the China Urban Statistical Yearbook. Among them, in the regression analysis of the correlation between production service network connectivity and GDP, the data of 2016 is used; in the regression analysis of knowledge cooperation network connectivity and GDP, the average value of urban GDP of 2008-2012 is adopted.

Table 5-7 Comparison of global cities and Chinese cities in the "IKCN (2012-2016) and "APSN" (2016)

Global city						Chinese city					
IKCN			APSN			IKCN			APSN		
Rank	City	KNC%	Rank	City	KNC%	Rank	City	KNC%	Rank	city	CNG%
1	London	100.00	1	London	100.00	2	Beijing	87.52	4	Hong Kong	74.89
2	Beijing	87.52	2	New York	95.65	22	Shanghai	39.41	6	Beijing	69.18
3	Boston	82.22	3	Singapore	75.40	31	Taipei	36.71	9	Shanghai	66.96
4	New York	79.91	4	Hong Kong	74.89	47	Nanjing	29.92	36	Taipei	45.64
5	Paris	69.16	5	Paris	70.39	51	Guangzhou	29.11	40	Guangzhou	43.27
6	Chicago	56.39	6	Beijing	69.18	89	Hefei	20.86	85	Shenzhen	32.18
7	Rome	53.42	7	Tokyo	68.38	99	Hong Kong	18.89	100	Chengdu	28.25
8	Madrid	53.36	8	Dubai	67.70	105	Wuhan	18.40	113	Tianjin	27.02
9	Milan	52.21	9	Shanghai	66.96	111	Jinan	17.40	139	Nanjing	22.87
10	Barcelona	48.38	10	Sydney	61.28	148	Hangzhou	12.09	140	Hangzhou	22.81
11	Toronto	47.60	11	Sao Paulo	59.70	158	Chengdu	10.91	143	Qingdao	22.57
12	Tokyo	46.13	12	Milan	59.67	165	Xi'an	10.05	160	Dalian	21.19
13	Baltimore	44.99	13	Chicago	58.12	168	Tianjin	9.79	163	Chongqing	20.95
14	Philadelphia	44.93	14	Mexico City	57.48	179	Hsinchu	8.42	171	Xiamen	20.14
15	Los Angeles	44.79	15	Mumbai	57.28	184	Changsha	8.04	190	Wuhan	18.84
16	Seattle	44.51	16	Moscow	56.47	195	Shenzhen	6.93	198	Suzhou	18.25
17	Amsterdam	44.49	17	Frankfurt	55.89	202	Chongqing	6.35	201	Changsha	18.05
18	Moscow	43.69	18	Madrid	53.24	205	Changchun	6.18	209	Xi'an	17.50
19	Houston	42.99	19	Warsaw	52.96	206	Shenyang	6.05	213	Shenyang	17.32
20	Pittsburgh	41.70	20	Johannesburg	52.85	211	Lanzhou	5.87	221	Jinan	16.79

Source: The results of the KCNs are from Web of Science data. The results APS network are from Derudder et al. (2018).

Such difference is not surprising, as the organizational logic of the IKCNs and the APSNs are not exactly the same. For the former, the “networking” process is the necessary way for the actors to generate knowledge innovation. Specifically, innovation relies on the integration of different know-how (Strambach and Klement, 2012) that is unevenly distributed in space at different scales (Asheim and Isaksen, 2002). Therefore, in terms of spatial structure, the organization of the KCNs directly reflects the geographical distribution of knowledge and the spatial trend of knowledge spillover, diffusion and dissemination. For the latter, “networking” by establishing overseas spinoffs in global hubs and economic centers is the most effective strategy for APS companies to occupy market niches, allocate global resources and maximize their interests. Therefore, the spatial range of the hub cities in the global APSN is relatively wider.

As the development in theories, empirical research and normative policies, the concept of “global cities” has been deepened and expanded. In broad sense, global cities are neither limited to the global producer service centers defined by Sassen nor not limited to the global production centers emphasized by Friedmann. In fact, any socioeconomic process of cities can be taken into consideration in the global city discussions. For example, some business consulting organizations or think tanks have conducted many multidimensional global city studies (Chen et al., 2017; Tang and Li, 2015). There are also institutions that focus on the innovation capability. For example, 2thinknow, an Australian think tank, has been publishing the *Innovation cities Analysis Report* annually since 2007 and dedicated itself to evaluating the innovation capabilities of major cities around the world. As Matthiessen et al (2010) put out the global IKCNs cannot be interpreted as the sub-system of the global city networks, but as a combination of such a sub-system and a system in its own right.

5.2.5 The variance of cities’ “national role” and “global role”

The above analysis mainly focuses on the “nodality” of cities in the networks, that is, the total amount of collaboration links of one city reflects its centrality and connectivity in the network. Besides the “nodality”, another important component of the network is the “edge” - the dyadic feature of the links among nodes. For the IKCNs, merely focusing on the centrality of cities falls short of fully describing the statuses and roles of the cities in the network. For example, during the period of 2012-2016, Moscow’s KNC was 185,325, followed by Houston of 182,344, both of which were comparable in terms of network connectivity. However, Moscow is the national capital while Houston is just a state capital. Clearly, their position and power in the IKCNs are different. It is difficult to distinguish only by comparing node connectivity. Therefore, the examination on the "dyadic feature between nodes can expand the understanding of the various functions and roles of cities in the IKCNs.

Figure 5-14 and Figure 5-15 show the simplified global IKCNs in two time periods. The networks are constructed as follows: first, the city-dyads are arranged in descending order by the strength of collaboration. Then, all city-dyads' strength of collaboration are standardized (divided by the largest strength of collaboration). Finally, the city-dyads with more than 20% collaboration are retained[22].

The most prominent is that the national borders have a significant impact on the global IKCNs, that is, the collaboration intensity between cities within the same country is generally larger than their transnational links. Table 5-9 lists the top 20 domestic city-dyads and transnational collaboration city-dyads in terms of the collaboration intensity, which confirms the influential role of the national borders. Meanwhile, the network is discontinuous with tightly interconnected communities of countries and loose transnational links. More specifically, in the period of 2002-2006, in addition to the "mega" IKCNs system positioned in the center, there were 10 rather independent and closed national IKCNs systems and this number reduced to 6 by the period of 2012-2016, reflecting the fact that more countries/cities became more active in participating in the transnational knowledge collaboration.

Focusing on individual cities, it can be clearly seen that a large number of transnational interurban collaborations occurred only among a few cities. These cities can be broadly divided into three categories: the first can be term as the "super centers" that are the dominant core in the global KCNs system. It is easy to notice in Figure 5-14 and Table 5-9 that, in 2002-2006, London were the city with the most extensive transnational collaboration links and the largest spatial range in all cities (visually say, in the figure, it has various transnational partners from the same world regions and more than two partners from other world regions). It connected to major cities in Europe (Paris, Berlin, Barcelona and Amsterdam), to major cities in North America (such as New York, Boston, Toronto, etc.) and that in the Asia-Pacific (Beijing, Melbourne, etc.), as well as other major cities in other parts of the world. At the same time, London was also the primate city in the UK in terms of collaboration intensity. During the period of 2012-2016, the spatial range of transnational connections of Paris, Boston and New York also

[22] Although it is arbitrary to take 20% as the threshold, its network refining results can better meet the analysis needs. To ensure comparability, both time periods are screened with the same threshold. In addition, thresholds of 10% and 30% respectively are also applied, and the networks either lost too much information or contain too much redundant information.

expanded significantly, showing trend of being “super centers”. In nutshell, London, Paris, New York, and Boston play a key role as “knowledge gatekeepers” at global, regional and national levels—not only are able to receive external knowledge and spread to other cities within the region or country, but also can diffuse the internal knowledge to the outside. These results are consistent with the findings of Matthiessen et al. (2010) and Maisonobe et al. (2016).

The second type of cities are “sub-centers”. Compared with the “super centers”, this type of cities with less transnational collaborations and smaller spatial range play the role as “knowledge gatekeeper” at the regional and national levels (visually say, in the figure, they have various transnational partners from the same world region and one partner from another world regions). In the period of 2002-2006, Paris in Europe, as well as New York, Boston, Toronto, and Montreal in North America could be categorized as the “sub-centers”. By the period of 2012-2016, cities such as Beijing, Amsterdam, Los Angeles, Madrid, and Rome also showed their power as “sub-centers” in the global IKCNs.

The third type of cities are the “knowledge gatekeepers” at the national level. Such cities are often the primate cities in domestic IKCNs and meanwhile, they have the most transnational collaboration links compared with other domestic cities (visually say, in the figure, they have various transnational partners from domestic regions and at least one partner from the same region). These cities are mainly national capitals or economically advanced cities.

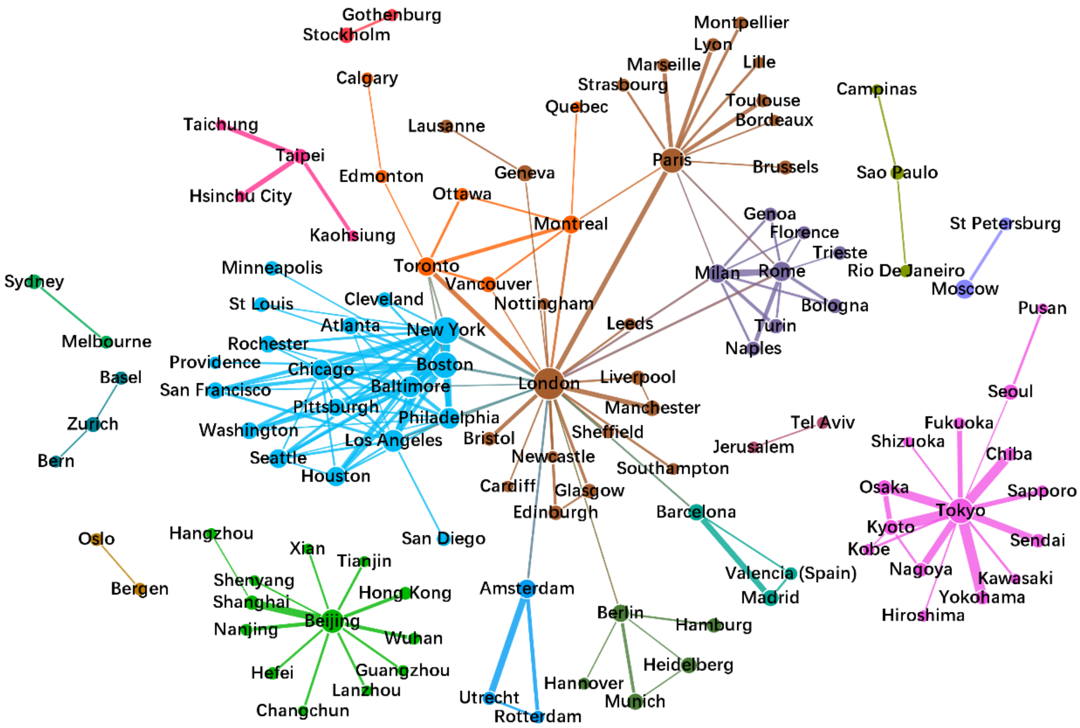


Figure 5-14 The global IKCNs of top 20% city-dyads in terms of collaboration intensity (2002-2006)

Note: The node size is proportional to the cities' KNC, and the lines thickness is proportional to the strength of collaboration between cities. Cities in different countries are distinguished by different colors.

Source: author

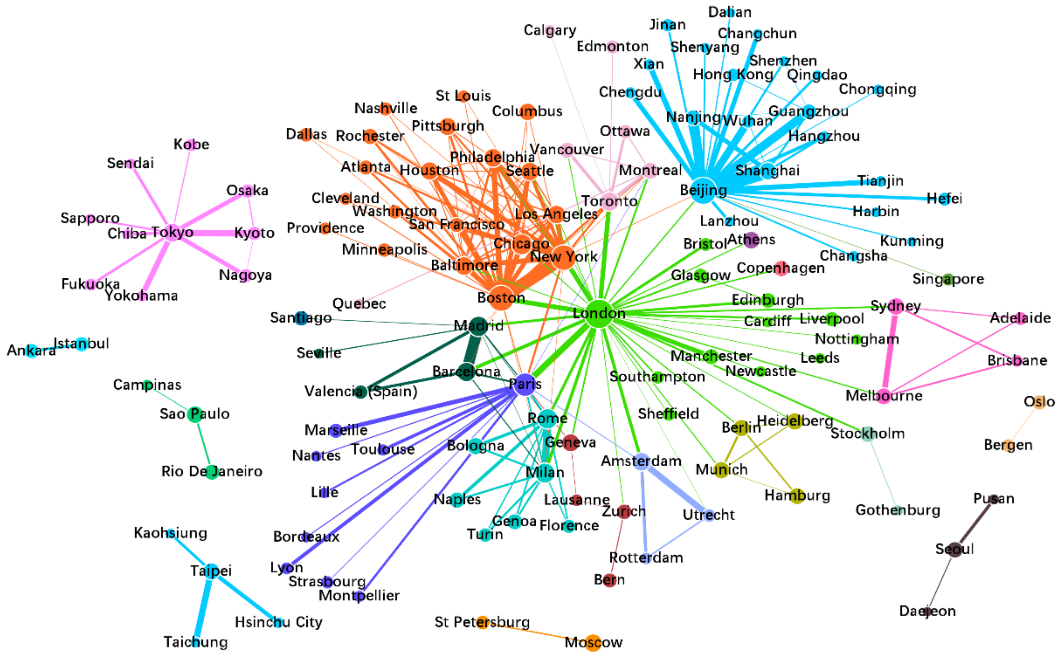


Figure 5-15 The global IKCNs of top 20% city-dyads in terms of collaboration intensity (2012-2016)

Note: The node size is proportional to the cities' KNC, and the lines thickness is proportional to the strength of collaboration between cities. Cities in different countries are distinguished by different colors.

Source: author

Table 5-9 The top 20 city-dyads of domestic and transnational collaboration

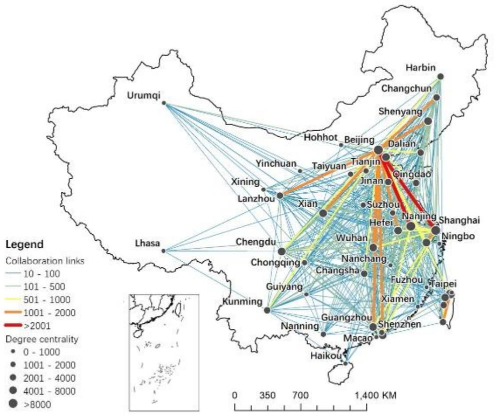
2002-2006				2012-2016			
Domestic city-dyads	Collaboration intensity	Transnational city-dyads	The amount of collaboration	Domestic city-dyads	Collaboration intensity	Transnational city-dyads	Collaboration intensity
Tokyo-Yokohama	4,692	London-Paris	2,437	Beijing-Shanghai	17,449	London-Paris	8,933
Kyoto-Tokyo	4,626	London-Toronto	2,336	New York-Boston	15,327	London-Boston	7,406
Boston-New York	4,394	London-New York	1,734	Madrid-Barcelona	13,723	London-New York	7,276
Chiba-Tokyo	4,390	London-Boston	1,526	Nanjing-Beijing	12,220	London-Toronto	7,228
Osaka-Tokyo	3,900	London-Montreal	1,489	Guangzhou-Beijing	11,264	London-Barcelona	6,212
Shanghai-Beijing	3,514	London-Rome	1,464	Wuhan-Beijing	10,100	London-Milan	5,900
Sendai-Tokyo	3,429	London-Amsterdam	1,389	Rome-Milan	9,939	London-Amsterdam	5,860
Nagoya-Tokyo	3,387	London-Milan	1,361	Tokyo-Kyoto	9,055	London-Rome	5,450
Amsterdam-Utrecht	3,183	London-Barcelona	1,233	Taichung-Taipei	9,015	London-Madrid	5,290
Milan-Rome	3,166	Rome-Paris	1,233	London-Paris	8,933	Boston-Toronto	4,775
New York-Philadelphia	3,089	New York-Toronto	1,196	Utrecht-Amsterdam	8,821	New York-Paris	4,718
Barcelona-Madrid	2,885	Boston-Toronto	1,185	Philadelphia-New York	8,500	New York-Toronto	4,713
Baltimore-New York	2,871	London-Philadelphia	1,171	Sydney-Melbourne	8,299	Barcelona-Paris	4,558
Chicago-New York	2,578	London-Los Angeles	1,145	Yokohama-Tokyo	8,202	London-Montreal	4,513
Kyoto-Osaka	2,569	Paris-Brussels	1,102	Philadelphia-Boston	8,199	London-Stockholm	4,493
Boston-Philadelphia	2,568	Paris-Montreal	1,096	Xi’an-Beijing	8,088	London-Sydney	4,361
Taipei-Hsinchu	2,472	London-Geneva	1,050	New York-Chicago	7,984	Rome-Paris	4,293
London-Manchester	2,469	Milan-Paris	1,041	Chicago-bus	7,824	Milan-Paris	4,272
Los Angeles-New York	2,461	London-berlin	1,037	Tianjin-Beijing	7,769	London-Geneva	4,268
Sapporo-Tokyo	2,454	London-Vancouver	1,016	Boston-Baltimore	7,756	London-Copenhagen	4,054

Source: author

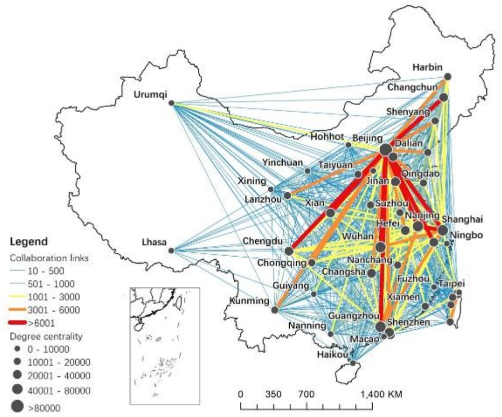
To sum up, it can be seen from examining the dyadic features of the IKCNs that the roles and functions played by different cities in the global IKCNs are different and that the organization of IKCNs follows a hierarchical and multi-layered structural logic: a few super centers have multiple roles, and they serve as vertical pivots for the entire network and hinges interconnecting the IKCNs at different geographical scales. Most of the cities have relatively simple functions, positioning around the core cities and forming subsystems nesting in the IKCNs of different scales. In addition, the dynamics of urban functions can be found to show an obvious "Matthew effect", that is, the hinge role of the core cities have strengthened and upgraded over time.

5.2.6 The spatial differences of different countries

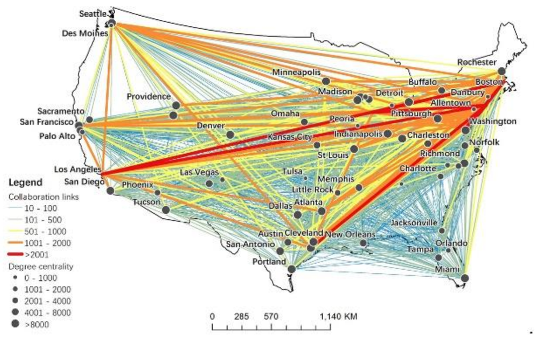
The above section discusses the functions and roles of individual cities in the IKCNs from the perspective of the dyadic features. At the same time, it can be seen that the states and their specific institutions and territorial contexts play the decisive role in forming the global IKCNs. As shown in Figure 5-16: first, the differences of the network structures of different countries are evident, such as "hub-spoke" structures (France and the United Kingdom), "networked" structures (the United States, Italy and Germany) and hybrid structures (China and Japan). Second, the structural constitutions of the "knowledge gatekeepers" are different in different countries: such as monocentric structures (UK, France, and China) and polycentric structures (US, Germany, and Italy). The following sections will focus on the differences in national IKCNs and further explore their relations to the network roles and functions of cities.



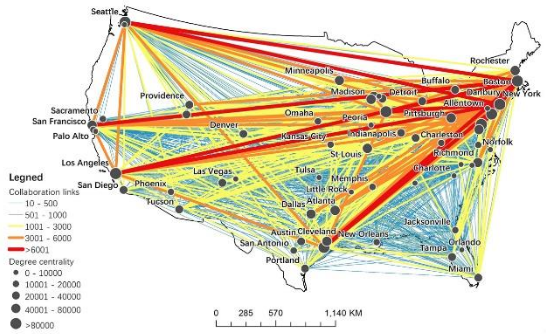
China 2002-2006



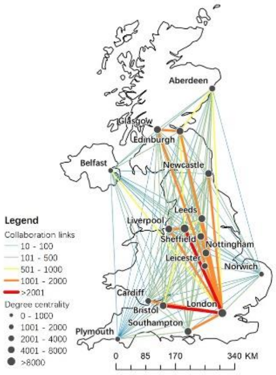
China 2012-2016



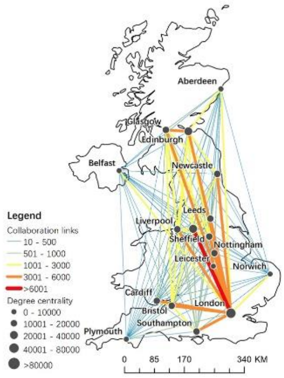
USA 2002-2006



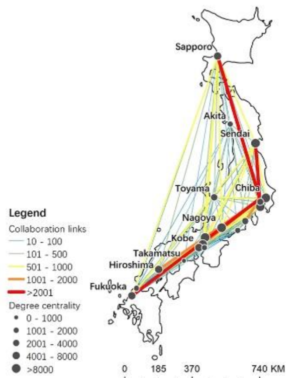
USA 2012-2016



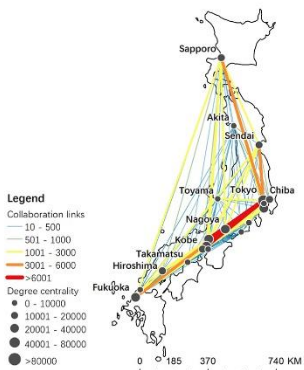
UK 2002-2006



UK 2012-2016



Japan 2002-2016



Japan 2012-2016

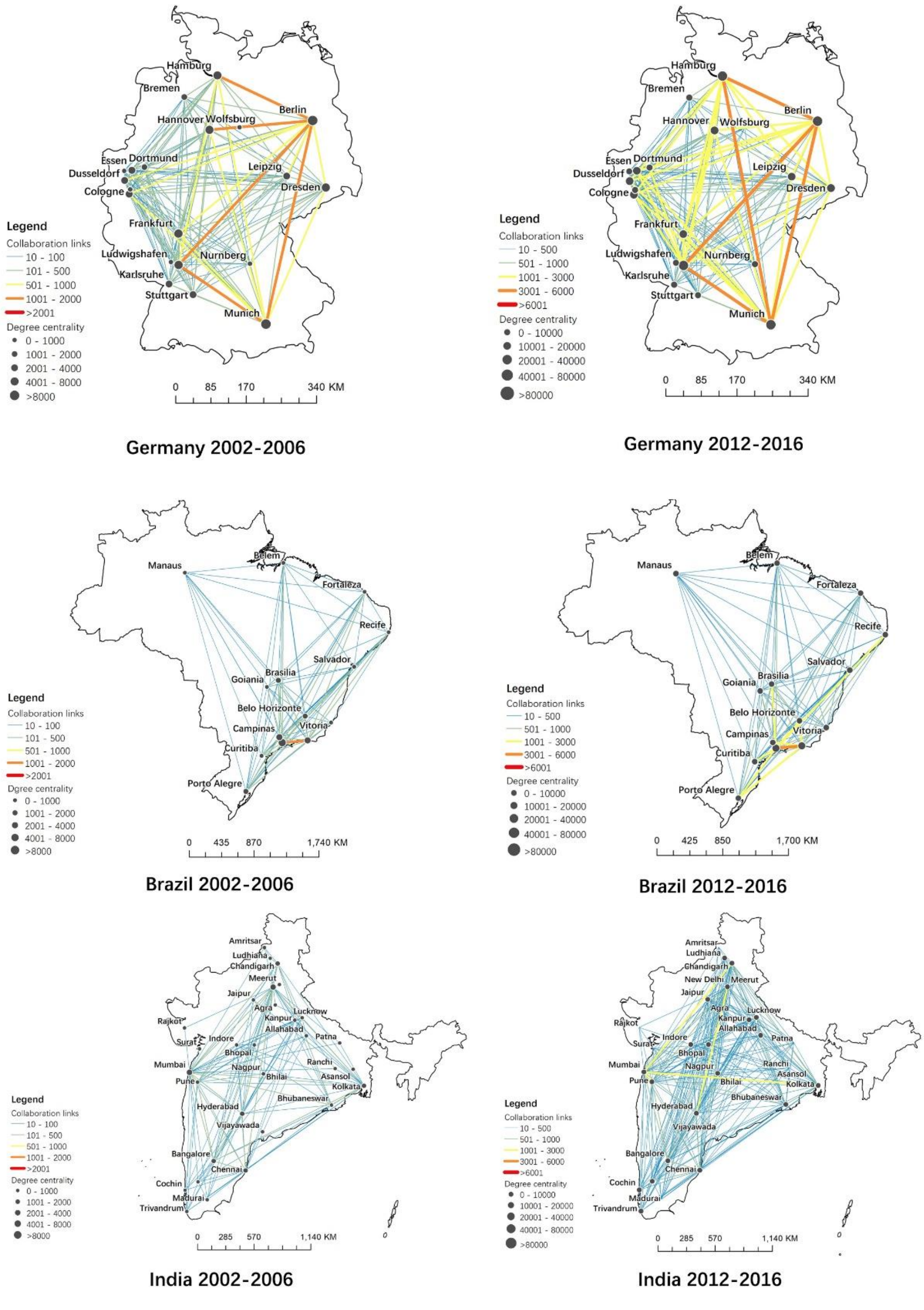


Figure 5-16 Structure of IKCNs of different countries

Source: author

Figure 5-17 and Figure 5-18 show the consist of the intranational/transnational collaboration links of the top 5 cities (in terms of the KNC) of 8 countries in the two time sections. First, the turning point of the line is the ratio of the transnational links of the city to its intranational connections. In 2002-2006, the values of the cities in the United States and Japan were less than 1 while by 2012-2016, the values of all cities were greater than 1, reflecting the deepening trend of the cities' participation in the international collaborations. Second, the spatial differences of the national IKCNs are also prominent: China, Russia, India, the United Kingdom, Brazil and Japan show obvious polarization characteristics, that is, the collaboration intensity in the primate cities far exceed that in other cities. Germany and the United States, by contrast, present a "polycentric pattern".

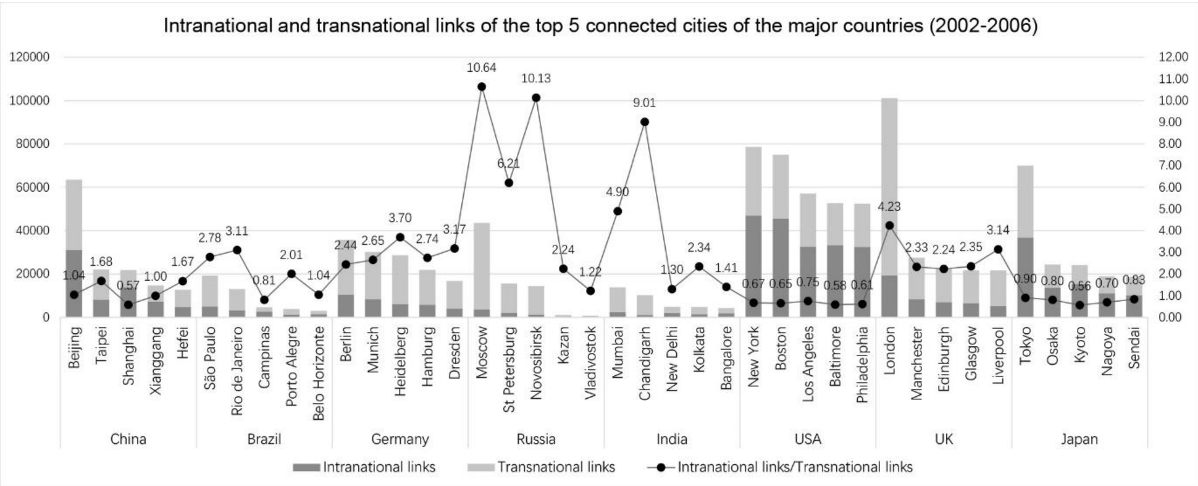


Figure 5-17 Comparison of the intensity of the intranational and transnational collaboration in major cities (2002-2006)

Source: author

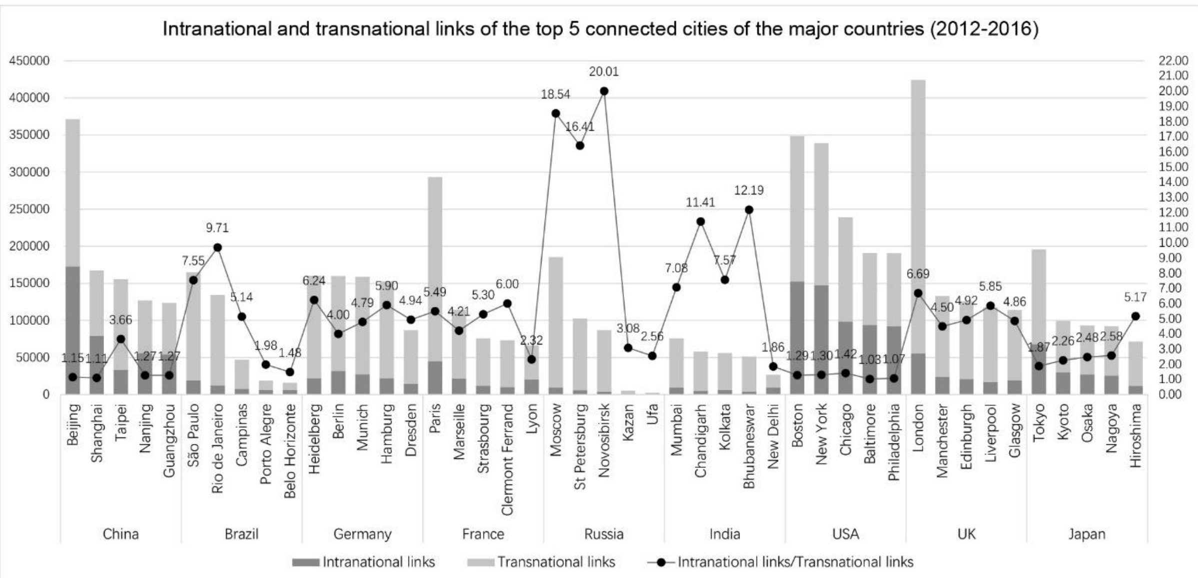


Figure 5-18 Comparison of the intensity of the intranational and transnational collaboration in major cities (2012-2016)

Source: author

Table 5-10 lists the Gini coefficients of the total amount of collaboration links of the top 10 cities of 9 different countries and also lists the Gini coefficients of the intranational and transnational collaboration links. This index can be used to compare the “polycentricity” of different countries in terms of their connection patterns. Figure 5-19 is the visualization results, in which, the dotted line is the average value of the Gini coefficients. These 9 countries can be divided into four quadrants: in the period of 2002-2006, the countries in the upper right quadrant were Russia, Brazil and China whose total Gini coefficient, intranational and transnational collaboration connections were relatively high. This indicates that spatial configurations of the IKCNs of these countries presented significant polarization characteristics. This might be explained by their socio-economic development trajectories that as governments of these developing countries play the decisive role in making innovation policies and allocating resource, the capitals and economically-developed cities therefore often receive more favorable policies and resources (Li and Pi, 2012; Zhong, 2011). By the period of 2012-2016, China has exited from this category and entered the lower right quadrant, which was characterized by a monocentric pattern of the intranational connections and a polycentric pattern of the transnational connections. This is full of the implication that China’s transnational interurban collaborations have developed in a more even way and that the Chinese cities have become more active engaging in the global scientific collaborations.

The countries in the lower left quadrant are characterized by a polycentric pattern of both the transnational collaboration and the intranational collaboration. In the period of 2002-2006, countries in this quadrant included the United Kingdom, Germany and the United States, while Japan and India also have joined in 2012-2016. Among them, the United States was the most polycentric country (closest to the origin point), which once again reflects the balanced development of the US cities in terms of knowledge collaboration. Meanwhile, the polycentric development of Germany and India might be attributed to their certain historical-political trajectories, socio-economic systems and the decentralization of state power (Growe and Volgmann, 2016; Kratke and Brandt, 2009; Rubinoff, 2006). Japan and the United Kingdom share some similarity: although their primate cities are much higher than other cities in terms of KNC, other cities are generally comparative, which offsets the polarization of the primate cities to some extent.

Table 5-10 Gini coefficients of the KNC of different countries (Top 10 Cities) (2002-2006, 2012-2016)

Country	2002-2006			2012-2016		
	Total	Intranational	Transnational	Total	Intranational	Transnational
CHN	0.46	0.40	0.57	0.35	0.39	0.36
USA	0.18	0.18	0.18	0.15	0.18	0.16
GBR	0.44	0.29	0.51	0.40	0.28	0.42
DEU	0.31	0.31	0.31	0.31	0.31	0.33

FRA	0.43	0.30	0.51	0.43	0.25	0.51
JPN	0.40	0.37	0.45	0.33	0.30	0.37
RUS	0.82	0.66	0.84	0.80	0.64	0.81
IND	0.40	0.28	0.48	0.35	0.22	0.40
BRA	0.56	0.41	0.65	0.66	0.36	0.72

Source: author

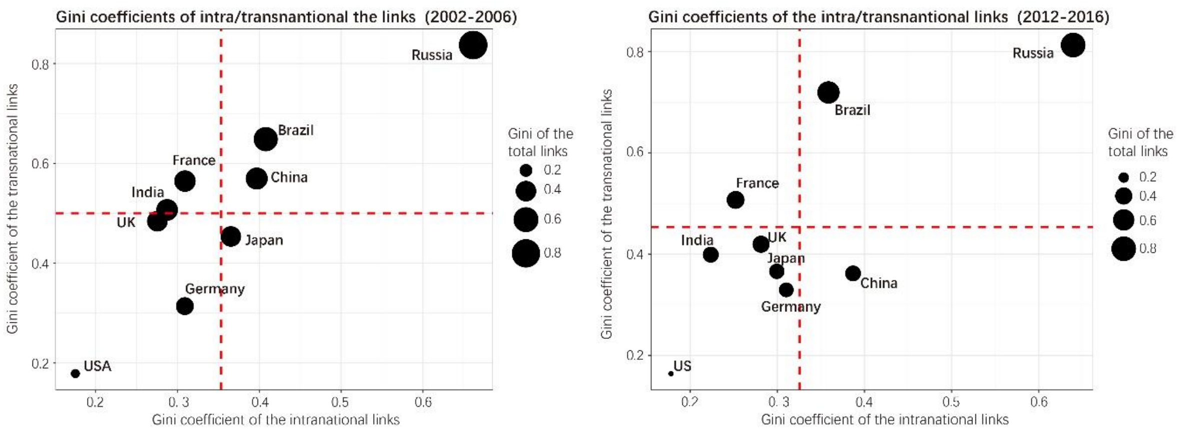


Figure 5-19 Comparison of the Gini coefficients of the intranational/transnational connections of different countries (Top 10 Cities in terms of the KNC) (2002-2006, 2012-2016)

Source: author

Based on the above analysis, the conclude can be drawn that the evolution of the statuses and functions of cities in the global IKCNs is closely related to the evolution of the political and economic development of their countries. Cities are the organic components of national innovation systems. Different countries have different urban spatial-functional systems, within which cities play different roles. One question that has to be put forward is that will different spatial-functional structure affect the performance of the IKCNs? An explicit answer can hardly be drawn standing upon the above analysis, yet, one can at least conclude that there probably do not exist an optimal spatial-functional model: for the countries with high level of innovation performance, the IKCNs could be a polarized monocentric structure or a polycentric structure at the same time. This needs to be analyzed under specific context and certain cases.

5.3 Evolution of topological structures of the global IKCNss

5.3.1 The Basic topological structures

5.3.1.1 **Overall network topological properties**

Table 5-11 is the results of the overall topological structures of the global KCNs in the periods of 2002-2006 and of 2012-2016, including several basic topological indicators, small-world property, scale-free and topological similarity. First, the evident increase of the average, maximum and minimum values indicates that the intensity of collaboration between the global cities have been reinforcing. Second, the network density and overall efficiency have also shown significant increase, suggesting the overall connectivity and efficiency of the global KCNs have enhanced. Third, the degree-degree correlation is negative, showing the existence of “disassortativity” of the global IKCNs, that is, cities with lower KNC tend to collaborate with that with higher KNC. It means that in the position of those cities with weaker innovation bases or newly involved in the IKCNs, collaboration with cities with high innovation performance turn out to be an effective way to acquire new knowledge. At the same time, for cities with higher innovation capability, disseminating and diffusing their advanced knowledge to cities with lower innovation performance is also a channel to expand its network influence and competitiveness.

In the two periods, the small-world quotients were all greater than 1, suggesting the global IKCNs could be termed as small-world network, although it tended to become less evident. The degree distribution of the IKCNs fit a power-law function with exponents of 1.20 and 1.09 in the two periods, thus the corresponding exponents for cumulative degree distribution are 2.20 and 2.09, respectively. Given that they are in the range between 2 and 3, the IKCNs thus could be characterized as scale-free networks. This indicates that the global IKCNs is polarized--a few cities have a large number of collaboration links, while most of the cities only have a small number of collaboration links. In addition, the scale-free property also indicates that the evolution of the IKCNs follows the rule of “preference attachment” and “Matthew effect”.

The topological similarities between the global IKCNs of the two time sections are examined by QAP correlation. The correlation coefficient is 0.87 and is significant at the 0.01 level. This shows that the topological structures of the global IKCNs have not structurally changed over time, suggesting the existence of the “path dependency”.

Table 5-11 Topological structures of the global IKCNs (2002-2006, 2012-2016)

	Topological structures index of networks	2002-2006	2012-2016
Basic topological properties	Average degree	205.97	346.11
	Max	1.00	14.00
	Min	468.00	491.00
	Network density	0.42	0.70
	Global efficiency	0.71	0.85
	Degree-degree correlation	-0.16	-0.15
Small-world property	Characteristic path length	1.56	1.28
	Characteristic path length of the same-size random networks	1.58	1.30

	Clustering coefficient	0.70	0.84
	Clustering coefficient of the same-size random networks	0.42	0.70
	Small-world quotient	1.67	1.19
Scale-free property	Cumulative power-law exponent	1.20	1.09
	R^2	0.70	0.68
Similarities of topological structures	QAP correlation	0.87 (p<0.01)	

Source: author

5.3.1.2 Individual network topological properties

Table 5-12 lists the top 20 cities in terms of betweenness centrality and closeness centrality in the two time periods. Most of the cities with higher betweenness centrality were national capitals or cities with higher innovation capabilities. These cities, mainly positioned in the intersections of the information flows in the KCNs, controll many resources and function as the “hub” and “intermediary” in networks. In most cases, these cities are the hinging points for domestic cities to connect with foreign cities, playing the roles of the national “knowledge gatekeepers”.

The closeness centrality reflects the degree of dependency of the cities on other cities in networks. Thus, it reflects cities’ capabilities in independent innovation. The rapid rise of cities in China is noteworthy. Only Beijing entered the list during the period of 2002-2006 while Shanghai, Nanjing, Guangzhou and Wuhan also entered the top 20 club by 2012-2016. This is suffice to demonstrate the rapid improvement of the innovation capabilities of Chinese cities.

Table 5-1 Top 20 cities in terms of the betweenness centrality and closeness centrality (2002-2006,2012-2016)

Rank	2002-2006				2012-2016			
	City	Betweenness centrality	City	Closeness centrality	City	Betweenness centrality	City	Closeness centrality
1	London	80,652	London	4,140	London	76,987	London	4,849
2	New York	26,028	New York	3,830	Beijing	21,854	New York	4,439
3	Moscow	21,360	Boston	3,715	Boston	20,525	Boston	4,428
4	Paris	21,342	Paris	3,572	New York	16,575	Beijing	4,299
5	Beijing	21,201	Tokyo	3,572	Paris	15,445	Paris	4,128
6	Tokyo	15,744	Toronto	3,390	Tokyo	9,647	Toronto	3,855
7	Mumbai	12,356	Manchester	3,260	Sao Paulo	8,923	Shanghai	3,767
8	Boston	7,869	Philadelphia	3,244	Moscow	8,670	Barcelona	3,708
9	Berlin	7,622	Los Angeles	3,226	Berlin	6,303	Milan	3,683
10	Sao Paulo	6,490	Baltimore	3,198	New Delhi	6,114	Rome	3,663
11	Toronto	6,149	Rome	3,164	Mumbai	5,902	Manchester	3,615
12	Madrid	4,892	Beijing	3,142	Mexico City	5,112	Madrid	3,598
13	Washington	4,831	Bristol	3,121	Madrid	4,612	Chicago	3,566
14	Rome	4,498	Chicago	3,118	Seoul	4,004	Philadelphia	3,564
15	Baltimore	4,321	Kyoto	3,063	Rome	3,770	Nanjing	3,563
16	Mexico City	3,433	Yokohama	3,057	Toronto	3,503	Amsterdam	3,547
17	Sydney	2,668	Milan	3,049	Montpellier	3,418	Baltimore	3,520
18	Seoul	2,539	Montreal	3,042	Singapore	2,861	Guangzhou	3,514
19	Los Angeles	2,521	Chiba	3,027	Islamabad	2,507	Los Angeles	3,465
20	Warsaw	2,451	Osaka	2,984	Riyadh	2,491	Wuhan	3,444

Source: author

5.3.2 “Globalization” and “Localization”

Table 5-13 lists the top 20 cities in terms of the globalization index and the localization index of the two time periods. These two indicators are calculated based on the weighted shortest path, which can measure the strength of a focal city’s collaboration on one hand, and can measure the accessibility and connectivity between the focal city and other cities. First, the localization index is examined. In the period of 2002-2006, among the top 20 cities, 3 out 4 cities were from the United States, indicating that the intranational IKCNs of the US was much more intensive than other countries. By the time of 2012-2016, among the top 20 cities, the numbers of the US cities and Chinese cities can be found to nearly comparative, suggesting the intranational IKCNs of China have witnessed a significant growth.

Then focus on the cities’ globalization index. Most of the top 20 cities are from Western Europe. This result is not surprising, given that the long history of regional integration both in policies and practices and that cities from Europe in general and Western Europe in particular have been actively engaging multidimensional transnational interactions including various types of scientific collaboration projects. In addition, it can be found that the high globalization index and localization index of New York and Boston once again confirm their roles as “knowledge gatekeepers” in the global IKCNs.

Table 5-13 Top 20 cities in terms of "localization" and "globalization" (2002-2006, 2012-2016)

Rank	2002-2006				2012-2016			
	City	Localization index	City	Globalization index	City	Localization index	City	Globalization index
1	New York	100.00	London	100.00	Beijing	100.00	London	100.00
2	Boston	96.92	Paris	87.92	Boston	86.71	Paris	85.45
3	Baltimore	77.63	Toronto	86.83	New York	84.20	Toronto	81.76
4	Philadelphia	77.51	Manchester	79.80	Shanghai	78.08	Barcelona	79.83
5	Tokyo	75.45	Montreal	77.86	Nanjing	69.51	Amsterdam	77.44
6	Los Angeles	74.75	Rome	77.71	Guangzhou	67.62	Madrid	77.07
7	Chicago	74.10	Amsterdam	77.08	Wuhan	64.93	Milan	76.85
8	Houston	67.33	Bristol	76.86	Chicago	62.06	Rome	75.93
9	Beijing	65.85	Milan	75.21	Philadelphia	61.36	Manchester	75.02
10	San Francisco	65.23	Barcelona	74.59	Baltimore	60.79	New York	73.56
11	Seattle	65.00	Moscow	73.78	Xi'an	59.54	Stockholm	72.54
12	Washington	61.65	Glasgow	73.47	Los Angeles	59.05	Boston	72.50
13	Pittsburgh	59.41	Edinburgh	72.89	Tianjin	58.56	Sydney	71.73
14	Rochester	59.33	Tokyo	71.66	Chengdu	57.63	Geneva	71.28
15	Atlanta	59.14	Geneva	71.47	Houston	57.42	Montreal	71.21
16	Cleveland	53.40	Marseille	71.46	Seattle	57.22	Bristol	70.52
17	Shanghai	52.56	Lyon	71.01	Changchun	57.09	Copenhagen	70.42
• 18	Kyoto	51.31	Southampton	70.68	San Francisco	55.06	Edinburgh	69.82
19	Yokohama	50.68	Toulouse	70.54	Hangzhou	53.38	Athens	69.10
20	Providence	50.13	New York	70.07	Hefei	52.10	Melbourne	68.05

Source: author

By taking the average of the sum of the globalization and localization indices of all cities in a country, one can examine and compare the globalization and localization degree of different countries. Figure 5-20 shows the results. The horizontal and vertical dotted lines in the figure are the mean values of the globalization and localization indices respectively, and thus the countries are divided into four quadrants.

In the period of 2002-2006, the countries in the upper right quadrant had high levels of globalization and localization, including the United Kingdom, France, Italy and Japan. The intensive collaborative relations built by these countries with cities in other countries enable them easier to access to diverse external knowledge. At the same time, the developments of their internal collaboration networks are relatively mature.

In the lower right quadrant, the globalization indexes of countries are relatively higher and the localization index of countries are relatively lower, that is, the intranational IKCNs of the countries are much denser than their transnational IKCNs. In the period of 2002-2006, Germany and the United States in this quadrant show a rather “localized” feature. By the period of 2012-2016, Japan has also entered into the quadrant. One common feature of these countries share is that with quite high level of independent innovation capabilities they do not necessarily rely much on external knowledge. Therefore, relatively speaking, their intranational collaboration activities are more intense.

In the upper left quadrant, the globalization indexes of countries are relatively higher and the localization index of countries are relatively lower, thus the countries fall into this quadrant are more “globalized”. Only Canada showed the characteristics in both time periods, which means that cities in Canada are more likely to participate in global knowledge collaboration than intranational collaboration.

In the lower left quadrant, both of the globalization index and localization index of the countries are relatively low. In the period of 2002-2006, China, Russia, Brazil and India were in this quadrant, which have lot of room for improvement in the national innovation system. They, as emerging economies, still have gaps with developed countries in terms of innovation capabilities to different degrees. It is not unexpected that the intranational and transnational collaboration of the countries are relatively low. In the period of 2012-2016, China entered the upper right quadrant with a significant increase in both its globalization and localization index, which once again reflects the rapid growth of its connectivity in the KCNs and the fast improvement of its overall innovation capability.

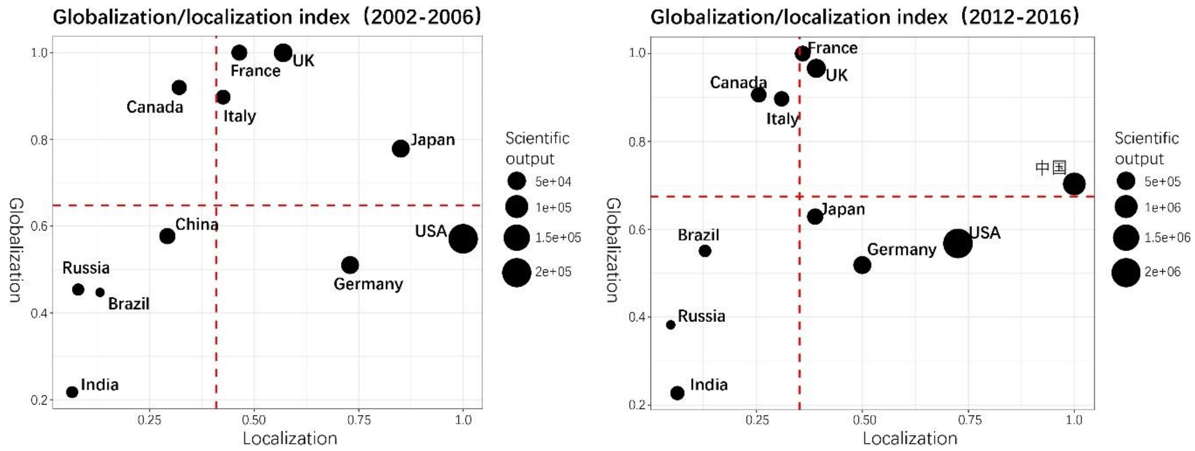


Figure 5-20 Globalization index and localization index of major countries

Source: author

5.3.2 "Core-periphery" structure

Figure 5-21 shows the "core-periphery" structures of the global IKCNs in the period of 2002-2006 and 2012-2016. The original networks are simplified to ensure clearer visualization results: the screening threshold of the city-dyad collaboration intensity is set as 100 for network of the period of 2002-2006 and as 300 for network of the period of 2012-2016. The number of cities in the simplified IKCNs are 324 and 349 respectively. Based on the block model with hierarchical clustering algorithm, the networks are divided into five layers, i.e., core, semi-core, sub-core, semi-periphery and periphery.

In general, the result is consistent with the result in Section 4.3.2 which takes countries as the research basic units. That is, the cities situated in the core layers are mainly from Europe and the United States, while cities in other regions are mostly in the peripheral layers of the networks. During the 2002-2006 period, London was the absolute core of the network. There were 15 cities in the semi-core layer, including 13 American cities and 2 Canadian cities, which has emphasized as the leading cities around the world in terms of innovation capability and network power in previous sections. Most of the cities in the third layer are also from the North America and Europe with the exception of Beijing and Tokyo. The sum of the KNC of the cities in these three core layers accounts for nearly 85% of the total. The fourth and fifth layers are the periphery of the network. The cities located in these two layers scattered in all regions of the world. Besides, the hierarchical distribution of these cities in peripheral layers also showed a mixed feature: there were small, medium and large-sized cities. During this period, except for Beijing, all other Chinese cities located at the peripheral layers of the network (the fifth layer).

In the period of 2012-2016, the changes of the "core-periphery" structure of the IKCN can be summarized as: first, the core cities (which located in the first, second and third layers) and the periphery cities (which located in the fourth and fifth layers) have clear-cut boundaries and the overall structure has remained stable. That is, cities in peripheral layers can hardly ascend into core layers, showing a "periphery lock-in" effect. Specifically, the total number of the cities in the core layers has increased from 63 in 2002-2006 to 65 in 2012-2016 while that in the peripheral layers has increased by 23, albeit this is partly because the number of samples has increased from 324 to 349. Second, the changes mostly occurred within the core layers or the peripheral layers. There are no such cities that directly promoted from the peripheral layers into the core layers. Within the core layers, New York, Boston and Beijing joined London and constituted the core layers of the network. At the same time, 8 cities originally located in the third layer entered into the second layer. Generally, the cities in the three core layers show an upward trend. Compared with the core layers, the cross-layer replacements of cities in the peripheral layers were more frequent: 65 cities changed their positions. During the period of 2012-2016, 7 Chinese cities rose from the fifth to the fourth layer, including Shanghai, Taipei, Nanjing, Guangzhou, Hefei, Hong Kong and Jinan.

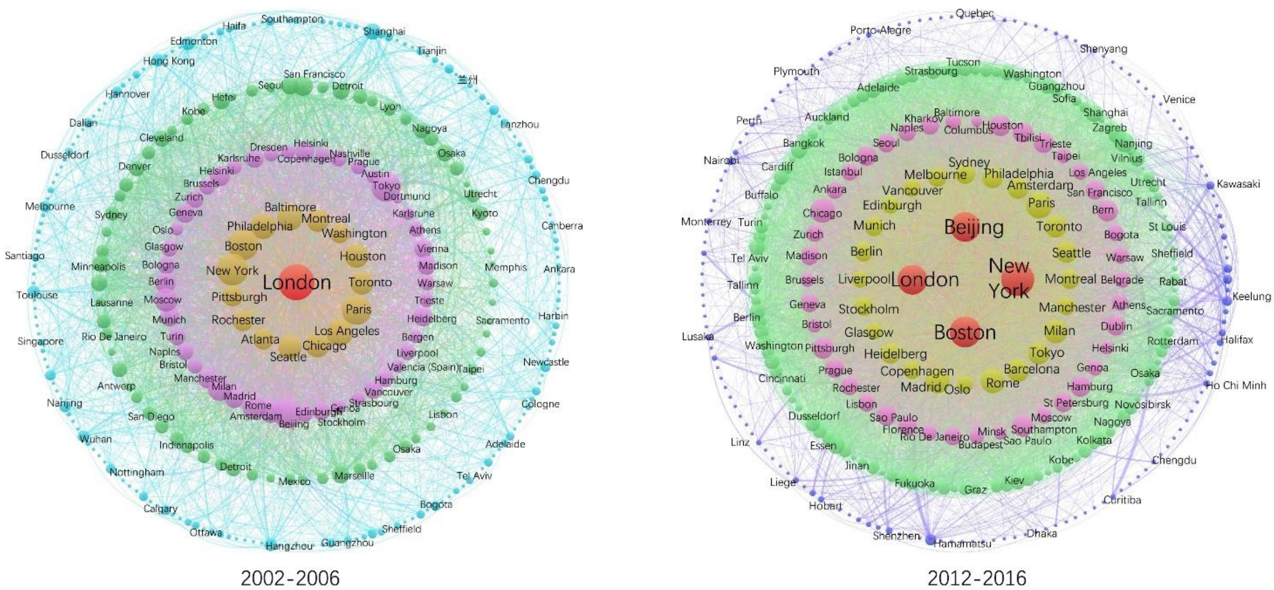


Figure 5-21 "Core-periphery" structures of global IKCNs (2002-2006,2012-2016)

Source: author

5.3.3 "Community" structure

Figure 5-22 shows the results of "community detection" of the global IKCNs. Cities with the same color belong to the same "community". The cities in the same community generally have close and intense collaboration relations with each other, while the collaboration links between different communities are relatively sparse. Based on this, it is not difficult to find that the formation and differentiation of network communities are significantly affected by geographical factors, including geographical distance, national boundaries, colonial ties, which is broadly consistent with the results of Chapter 4.

During the period of 2002-2006, the global IKCNs was divided into 10 different communities, and the number dropped to 8 in the period of 2012-2016 because of the merger of the United States and Canada as well as the merger of some countries in Western Europe. To some extent, this reflects the integration trend of the IKCNs within the two regions. In addition, the community structure of the global IKCNs has remained generally stable.

During the period of 2012-2016, the largest community covered the United Kingdom, France and many countries Africa, as well as some countries in the Middle East and Southeast Asia. The intense interurban collaboration between Britain and France is largely due to geographical proximity. In the process of knowledge collaboration, geographical proximity can facilitate face-to-face communication, promote the spillovers and diffusion of knowledge, in turn can encourage innovation. This can also be applied in the Dutch-Belgian-German-Swiss community and some other communities in Europe.

The second factor that has a significant impact on the formation of network communities is the national boundaries. Countries like the United States, China, Canada and Japan are examples. The roles of national boundaries actually overlap with the influencing mechanism of geographical proximity, but in many cases, the impact of national boundaries is more divisive than the geographical distance. For example, cities in south Canada and north America, though spatially adjacent, still belong to two different clusters because the existence of the national boundaries. It is noteworthy that cities from mainland China are separated with cities of Taiwan due to the long-term historical and political conflict regardless of the fact that they are within the same national boundary.

Third, knowledge collaboration is not always confined by geographical distances and national boundaries. The communities maintained by previous colonial ties are the typical cases: many countries in Africa and many island countries in Southeast Asia had been the colonies of some European countries. The colonial ties can be inferred to play important roles in the formation of the global IKCNs even in the post-colonial era. This is also the case in the “Spain-Portugal-Latin America” cluster.

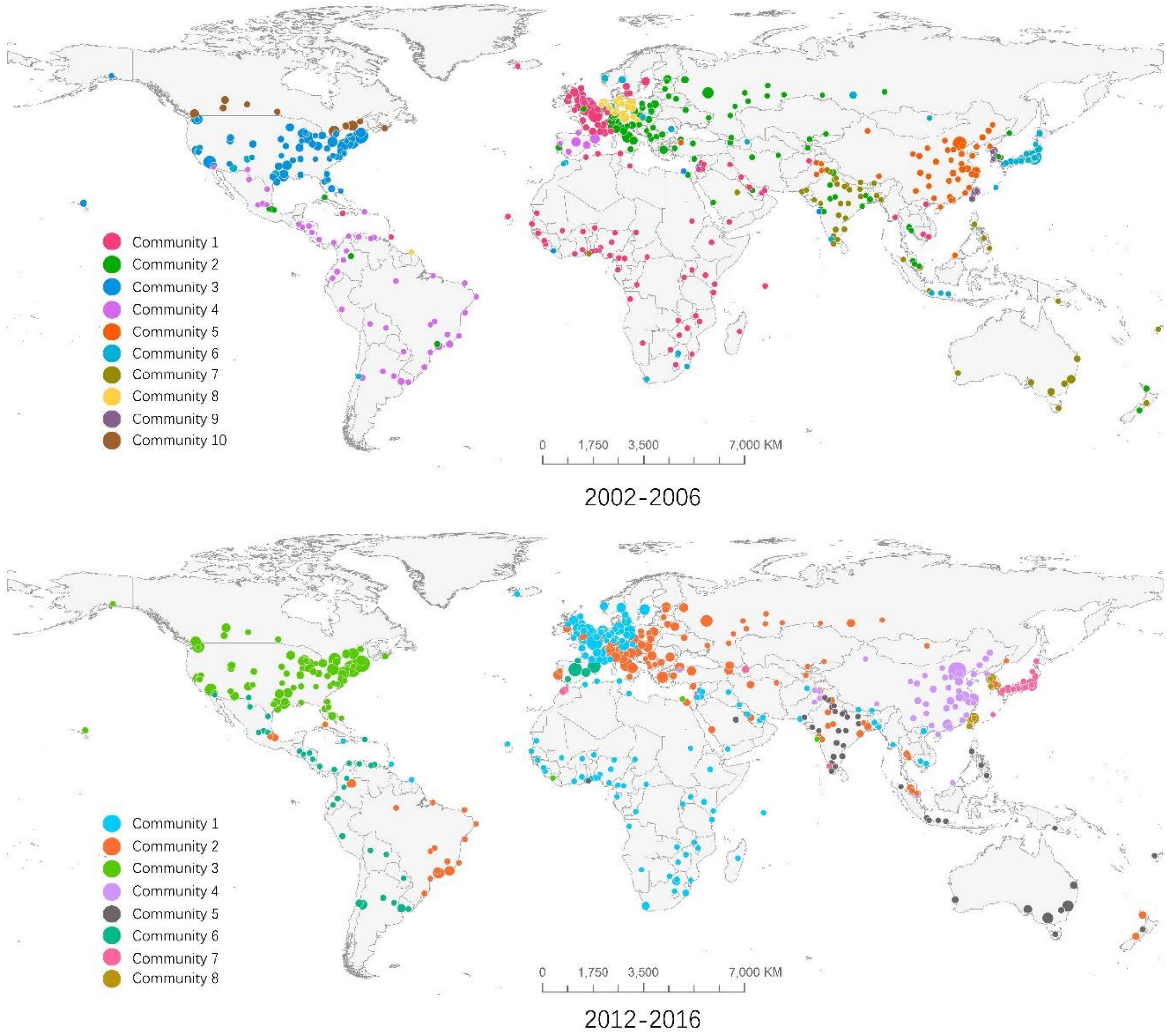


Figure 5-22 The “community” structure of global IKCNs (2002-2006,2012-2016)
Source: author

5.3.5 “Center-hinterland” structure

Figure 5-23 and Figure 5-24 are the results of the “center-hinterland” structures of the global IKCNs in the period of 2002-2006 and 2012-2016, respectively. It can be found that the global IKCNs are composed of many “sub-center-hinterland” systems in different sizes, resemble many discrete “archipelago-like” configurations. In the period 2002-2006, there were 36 independent “islands” and this number fell to 30 by the period of 2012-2016, indicating a trend of integration of the global IKCNs.

Focusing on single “island”, it is clear that their sizes and structural forms are quite different. In the period of 2002-2006, the largest “island” consisted 114 cities pivoting around London and Paris, while the smallest consisted only one city (Karachi). During the period of 2012-2016, the number of cities composed the largest “island” raised to 118, and the smallest one is Accra.

The structures of these "island" can be broadly divided into two categories: the first type is the "hierarchical multi-core" structure, such as the United States community, the London-Paris community, the India community, the Germany community and the South America-Spain community. Their common feature is that there are more than two major centers act as the pivots underpinning the entire network structure of the community, while several sub-center-hinterlands attached to the main body of the community also exist, showing a hierarchically nested organization mode. The second type is the "unipolar" structure, such as China community, Japan community, Brazil community and Russia community.

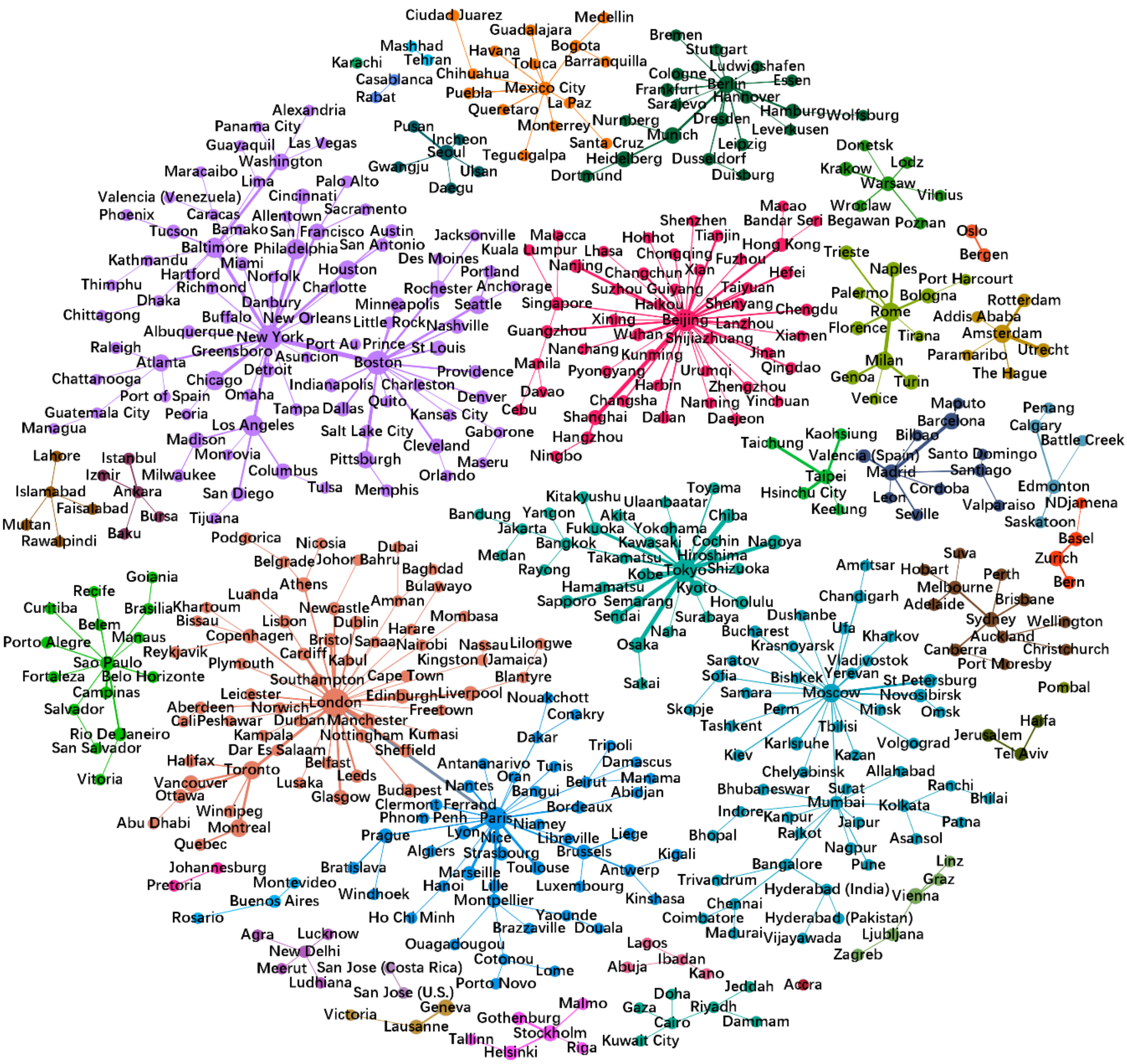


Figure 5-23 The "center-hinterlands" structures of global IKCNs (2002-2006)

Source: author

In addition, the "center-hinterland" structures are consistent with many of the previous findings. For example, the influence of geographical distance, national boundaries, geopolitics, and precolonial ties on the structure of the global IKCNs is also evident in the "center-hinterland" structures. Secondly, the "center-hinterland" structures of the global IKCNs also reflects, to some extent, the "core-periphery" characteristics. Thirdly, different "center-hinterland" systems also partly depict the "community" of cities in the global IKCNs.

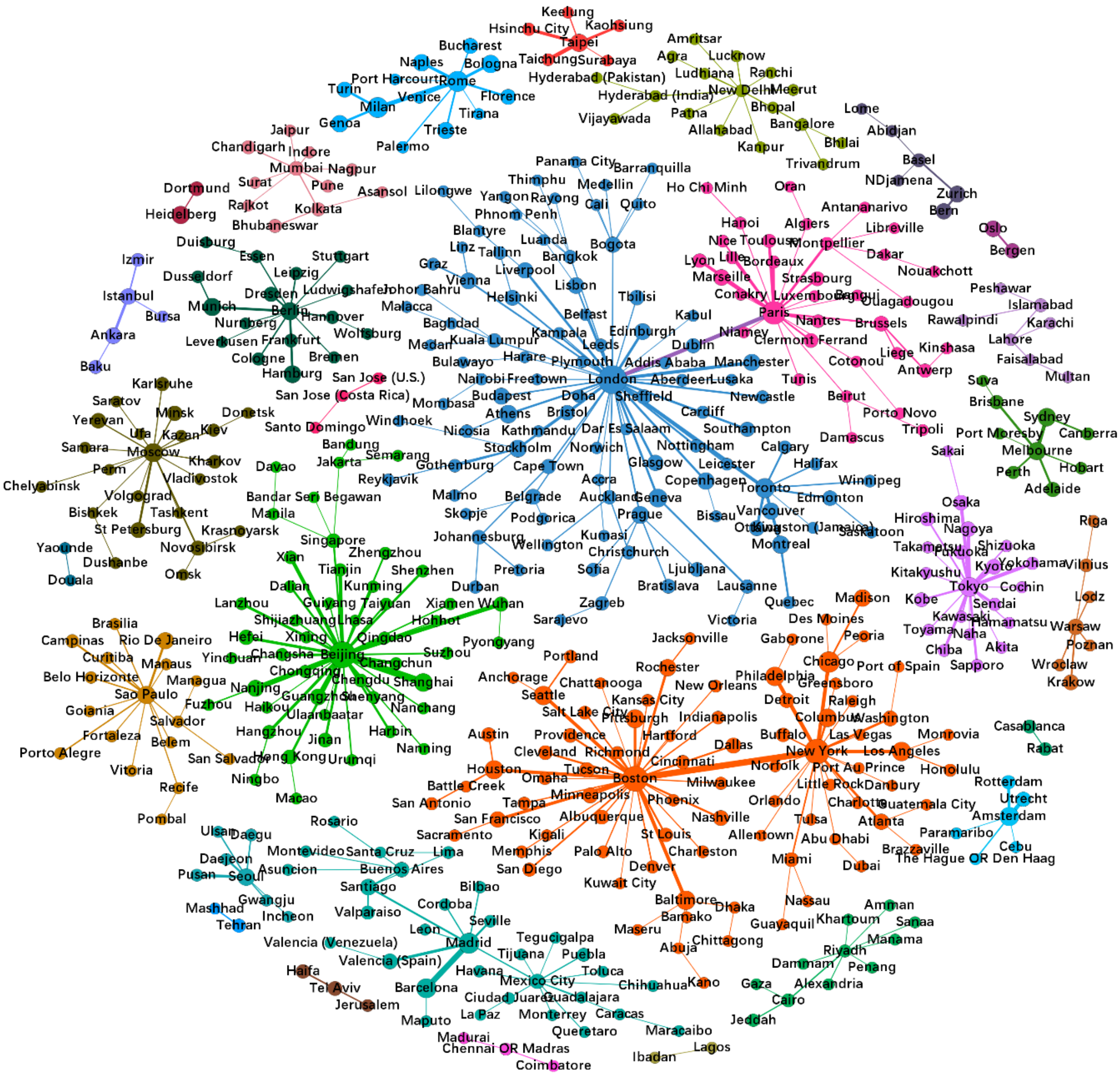


Figure 5-24 "center-hinterlands" structures of global IKCNs (2012-2016)

Source: author

5.4 Summary

This chapter examines the evolution of the global IKCNs and particularly focuses on the roles and evolutionary paths of Chinese cities in the global IKCNs. The main findings are as follows:

First, the overall pattern of the global scientific output is examined. The results show that: (1) during the research period, the total amount of knowledge output of the cities has increased to varying degrees, but has been unevenly distributed across different geographical scales. Compared with the initial stage of research, the distribution of urban innovation output shows a trend of balanced development. (2) From the perspective of the growth rate, the output of cities in the East Asia have been growing faster than that in the Western European and North American. Among them, the rapid rise of Chinese cities is the most eye-catching. (3) Through spatial clustering analysis, it is clear that in the hierarchy of the global scientific output, the number of cities at the top end have been gradually decreasing while that at the bottom-end have also been gradually decreasing, showing a balanced and convergent development trend. Through spatial autocorrelation analysis, it can be seen that the spatial clustering trend of the East Asia cities in general and Chinese cities in particular has strengthened over time.

Secondly, the evolution of the spatial configurations of the global IKCNs in the period of 2002-2006 and of 2012-2016 are studied. The main findings are as follows: (1) the spatial configurations of the global IKCNs are, to a large extent, consistent with the transnational KCNs. Among them, the most notable feature is the “monopoly” of the European and the US cities. Among the top 20 cities, in terms of network connectivity, only Beijing and Tokyo are from Asia. Beijing’s rapid growth is particularly remarkable. Its network connectivity ranking has risen from the 6th in the 2002-2006 period to the 2nd in the 2012-2016 period, and has risen from 5th to the 1st in terms of total scientific output.（2）The spatial pattern of the global IKCNs are imbalanced across different geographical scales. Specifically, at global scale, the imbalance is embodied as a clear-up gap between “Global North” and “Global South”. At regional scale, cities in Western Europe presents a “globally dispersed and locally concentrated “polycentric” structure. Cities in North America form a “basin” with highly connected cities circling around the edge of the region and less connected cities sitting in the central area. In the Asia-Pacific has a “bipolar” structure with Beijing and Tokyo as the apex. In addition, more and more Chinese cities have emerged in the global IKCNs and present a trend of regionalization. (3) The similarities and differences between the global IKCNs and the global APSNs are compared, the two different types of urban networks reflect the differentiation of functions and statuses of the cities as global innovation centers and global capital service centers. The most apparent difference between these is that the top global APS centers are more widely distributed and more dispersed than the global innovation centers. New York, London, Paris, Beijing, and Tokyo all have considerable powers and influences in both of the global interurban networks. The results demonstrate that the global IKCNs cannot be interpreted as the sub-system of the global city networks, but as a combination of such a sub-system and a system in its own right. （4）By calculating the relative strengths of connections of the cities to different regions, the spatial reach of the cities are investigated. Regional heterogeneity can be found for different cities in terms of the spatial range and the introverted and extroverted degrees in the global IKCNs.（5）Through the analysis of the dyadic features between cities, the differences between "national roles" and "global roles" of the cities are identified. Specifically, cities with higher network connectivity can be divided into three categories: the first category is the "super center", which are the "unchallengeable cores" in the global IKCNs. London, Paris, New York and Boston are the "super centers" that play the role as "knowledge gatekeepers" at global, regional and national scales. The second category is the "sub-centers" in the global IKCNs. Compared with the "super centers", this type of cities has lower degree of network connectivity and smaller spatial range. They play as the "knowledge gatekeepers" at the regional and national scales, such as Beijing, Amsterdam, Los Angeles, Madrid, Rome and other cities. The third type of cities are the "knowledge gatekeepers" at the national scale, which mainly are the primate cities in their intranational IKCNs.（6）The IKCNs in different countries show different spatial organization characteristics, which are closely related to their different development history paths, institutional backgrounds and regional contexts. In general, the evolution of global IKCNs is a gradual and stable process with a feature of "space dependency".

Third, the evolution of the topological structures of the global IKCNs are investigated. The main findings are: (1) the global IKCNs present both "small-world property" and "scale-free property". (2) The degrees of "globalization" and "localization" of cities and countries are examined respectively. the results suggest that the differences in the development stages of cities and countries the main factor that determine their "globalization" and "localization" features. (3)The "core-periphery" structures of the global IKCNs are examined. The results show that cities in developed countries in Europe and America have occupied the core layer of the network, while most of the cities in other countries are located in the peripheral layers of the network. The layers structure is quite stable within which peripheral cities find it hard to enter into the core layer, thereby showing an "periphery lock-in" effect. It is noteworthy that by the end of the study period, Beijing have entered the core layer and been transformed as the center of the global IKCNs together with New York, London and Boston. (4) By analyzing the "community" structure of the network, it is found that multiple factors such as geographical distances, national boundaries and colonial histories are the main forces in shaping the "community structures" of the global IKCNs. (5) Finally, the research on the "center-hinterland" structures of the global IKCNs networks shows that the global IKCNs consist of many "sub-center-hinterland" systems, which generally present a discontinuous "archipelago-like" mode. But the degree of integration of the global IKCNs has strengthened over time. The influences of geographical distances, national boundaries, geopolitics and previous colonial ties on the structure of KCNs are also evident in the "center-hinterland" relations. In general, the evolution of the topological structures of the global IKCNs also exhibits a gradual trend of being strengthened over time, which can be summarized as "path dependency".

Chapter 6 The evolution of the interurban knowledge collaboration networks in China

Based on a comprehensive analysis of massive publications data on transnational collaboration, Maisonobe et al. (2016) and Hennemann et al. (2012) point out that although the transnational collaboration activities have become increasingly obvious, most of the collaboration activities are still intranational oneenos, which can also be found in the conclusions of Chapter 5. This chapter will examine the structural characteristics of China's IKCNs at national scale.

By the end of 2018, there were 297 prefectural-level or above cities in China (excluding Hong Kong, Macao and Taiwan cities). To ensure the territorial integrity, 10 cities[23], including Hong Kong, Macao and other 8 in Taiwan, are included in the research. Therefore, there are a total of 307 cities involved. Yet, this is adopted only in the study of the landscape of the scientific output of Chinese cities, but not in the study of the IKCNs. This is because that not all cities in mainland China have scientific output or have participated in knowledge collaboration during the research period so they can be excluded from the study of the IKCNs. Other than that, in order to ensure the consistency of the analysis objects and the coherence of the empirical frameworks, the cities selected in the study of the IKCNs of chapter are also cross-referenced and in line with Chapter 7. By doing so, 217 prefectural-level or above cities are included in the construction and analysis of the national IKCNs[24].

6.1 The evolution of the landscape of the scientific output of Chinese cities

6.1.1 The eastern - western gap

In 1990, the number of China's R&D personnel were only 681,700, and R&D expenditure were 34.87 billion yuan, accounting for 0.58% of the total domestic GDP. By 2016, the number of R&D personnel reached 3,878,100, and R&D expenditure rose to 1,576,675 million yuan, accounting for 2.12%[25] of GDP. In 1990, the total number of the WoS scientific publications was 8,002, and by 2016 this number hit 337,679 (Figure 6-1), with an average annual growth rate of 15.63%.

[23] Including Taiwan cities of Taipei, New Taipei City, Kaohsiung, Hsinchu, Taichung, Taoyuan, Hsinchu, Tainan, and Keelung. The city selection refers to the screening and selection of cities in Taiwan in GaWC.

[24] See appendix III for a list of the selected cities.

[25] Source：China Statistical Yearbook

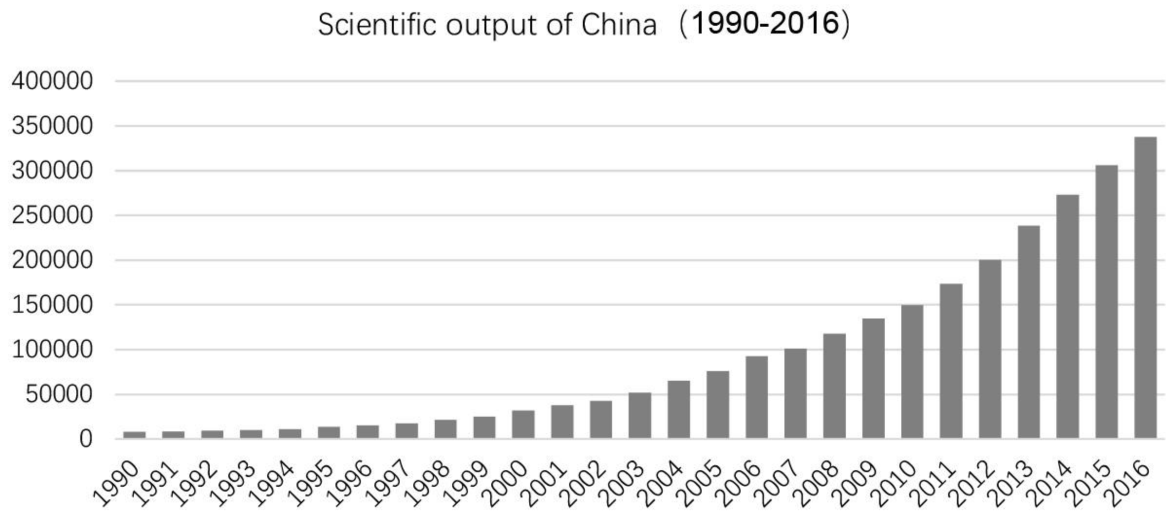


Figure 6-1 The scientific output of China (1990-2016)
Source: author

In terms of the spatial range, the number of cities actively participating in scientific innovation increased significantly. In the period of 2002-2006, there were 137 cities with more than 50 scientific publications. By 2012-2016, this number nearly doubled with an increase of 126. Figure 6-2 maps the cities with more than 50 scientific publications. It can be seen that there is a clear gap between eastern and western China. Particularly, the cut-off is in line with the "Hu Huanyong line" (black dotted lines in the graphs) which is originally introduced by geographer Hu Huanyong to describe the differences of regional population of China. To a certain degree, this result shows that the spatial distribution of urban scientific output in China is closely related to the population and socio-economic development.

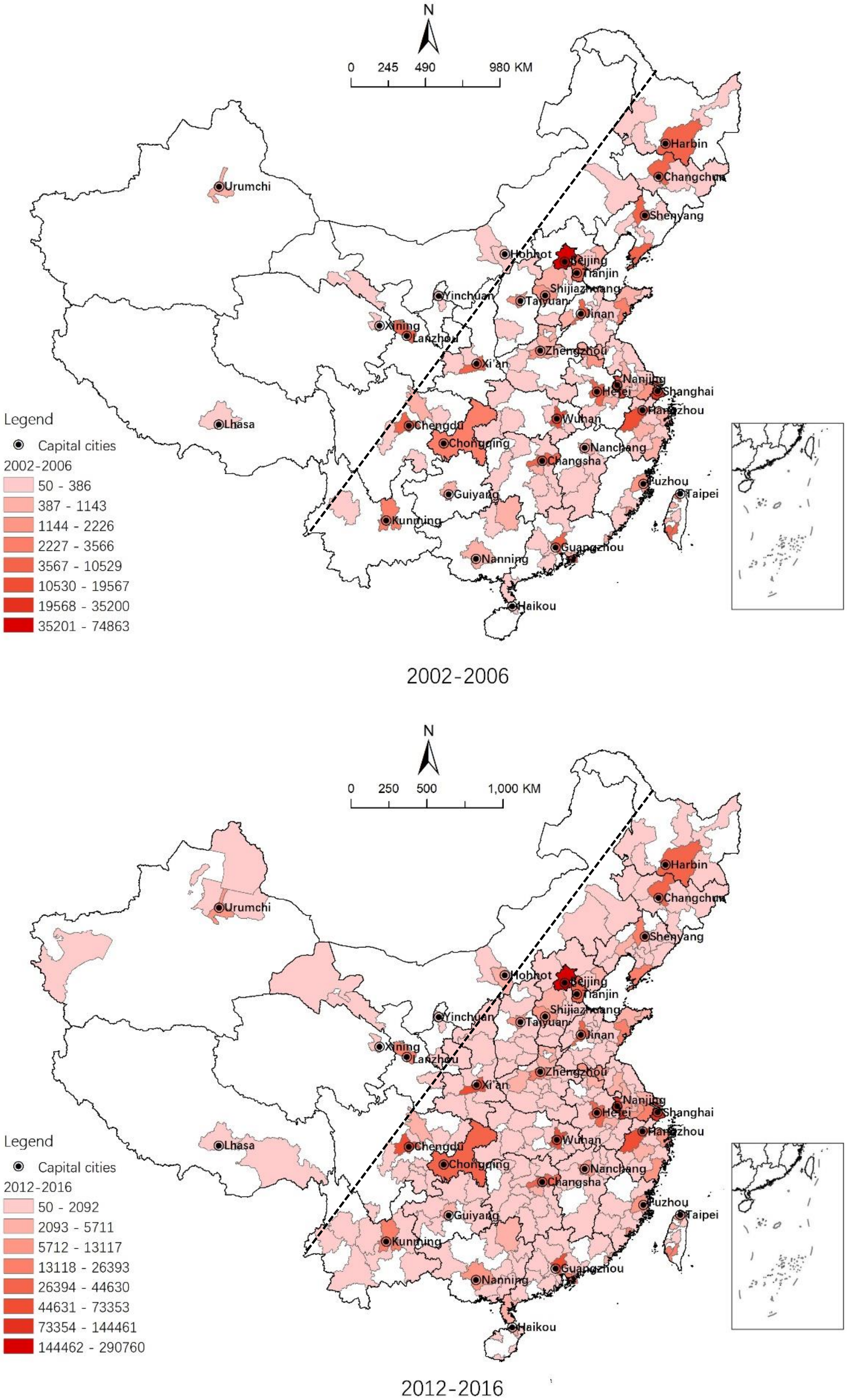


Figure 6-2 Cities with more than 50 scientific publications (2002-2006, 2012-2016)
Source: author

Table 6-1 lists the descriptive statistics of China's scientific innovation output. Among them, the increase in the maximum, minimum and the mean values reflects the overall improvement of the innovation capability of the urban China. The coefficient of variance and the Gini coefficient gradually decreased from 5.014 and 0.935 in the period of 2002-2006 to 4.263 and 0.901 in the period of 2012-2016, respectively. This shows that the gap between cities has been narrowed over time in terms of the scientific output. The overall Moran's I rose from 0.004 to 0.006, which indicates that cities with higher levels of scientific output tend to concentrate in space.

Table 6-1 Descriptive statistics of China's scientific output (2002-2006, 2012-2016)

	2002-2006	2012-2016
Observations	384	384
Max	74863	290760
Min	0	0
Mean	1000.706	4613.174
Coefficient of variance	5.014	4.263
Gini coefficient	0.935	0.901
Moran's I	0.004	0.006

Source: author

6.1.2 The "capital monopoly" and the inverted "T-shaped" hierarchy

Figure 6-3 shows the rank-size distributions of the urban scientific publications output in China during two time periods. The results fit the power-law distribution, indicating that there is an obvious polarization in terms of the scientific innovation output of Chinese cities. That is, a large amount of output is concentrated in a small number of cities. Figure 6-2 is the K-means clustering map of the scientific publications output, while Table 6-2 shows 20 most productive cities. In general, the "capital monopoly" effect is significantly evident, that is the national capitals, provincial or autonomous prefectural capitals are the main players in the processes of knowledge production in China. Specifically, in the two time periods, the total output of knowledge innovation in the 34 capital cities accounted for 95.65% and 89.83% of the national total output. This is closely related to China's top-down administrative systems and the resource allocation in practices: strategic resources, preferential policies and human capitals are often bias toward these high-level cities.

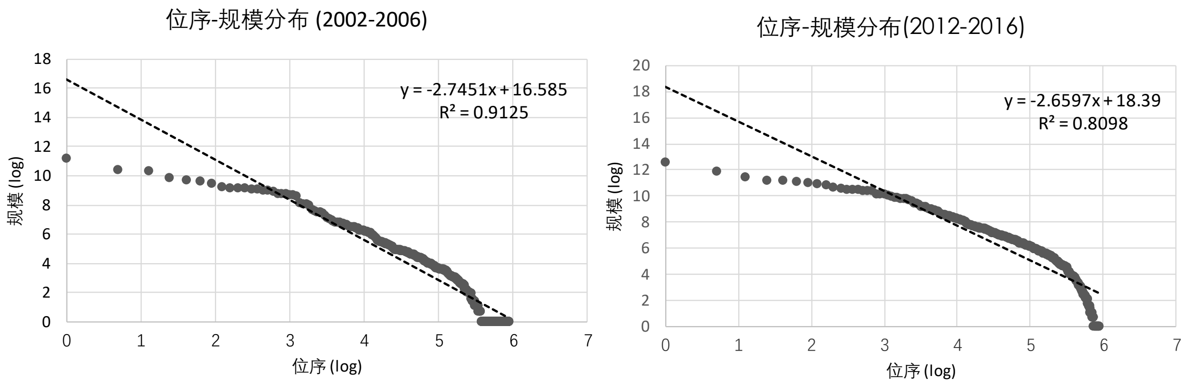
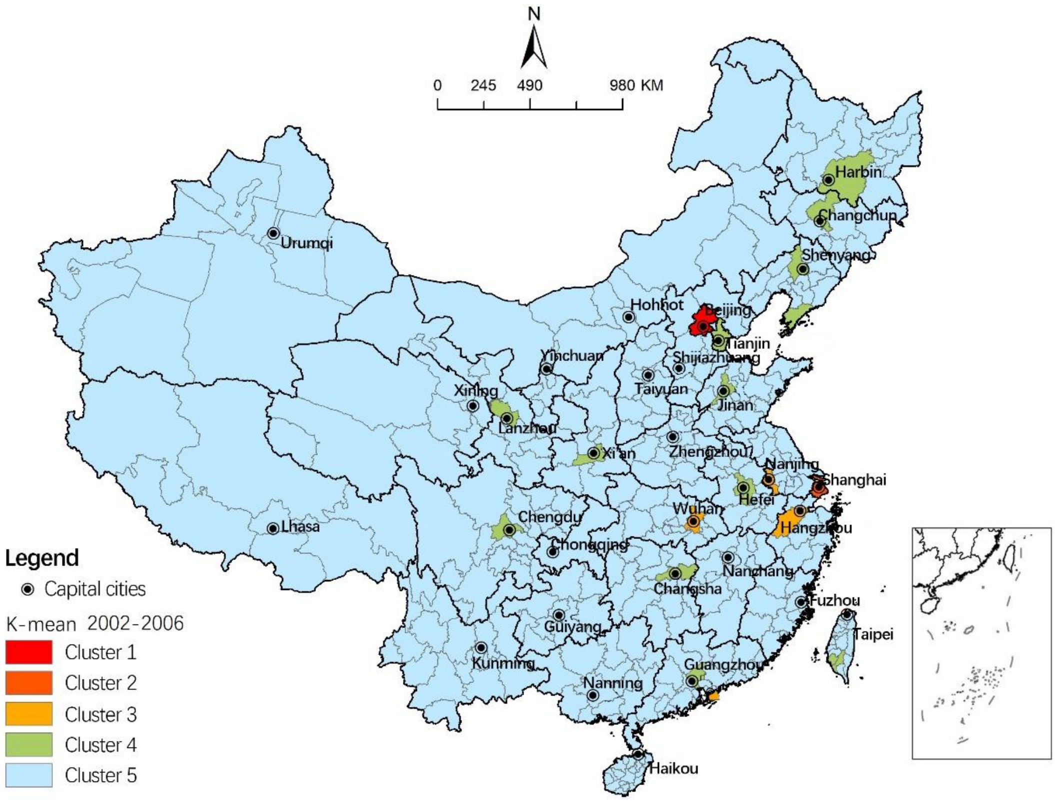


Figure 6-3 Rank-size distribution of China's scientific output (2002-2006, 2012-2016)
Source: author

As can be seen from Figure 6-4, Beijing and Shanghai are first-level cities with most scientific innovation output. During the period of 2002-2006, Nanjing, Hangzhou and Wuhan were the second-level cities. By the period of 2012-2016, Xi'an, Chengdu and Guangzhou also entered the second layer. Besides, cities in the third and fourth layers are also capital cities with the only exception of Dalian. The rest cities are located in the fourth and mainly in the fifth layer. This hierarchical structure exhibits almost an inverted "T-shaped" pattern.



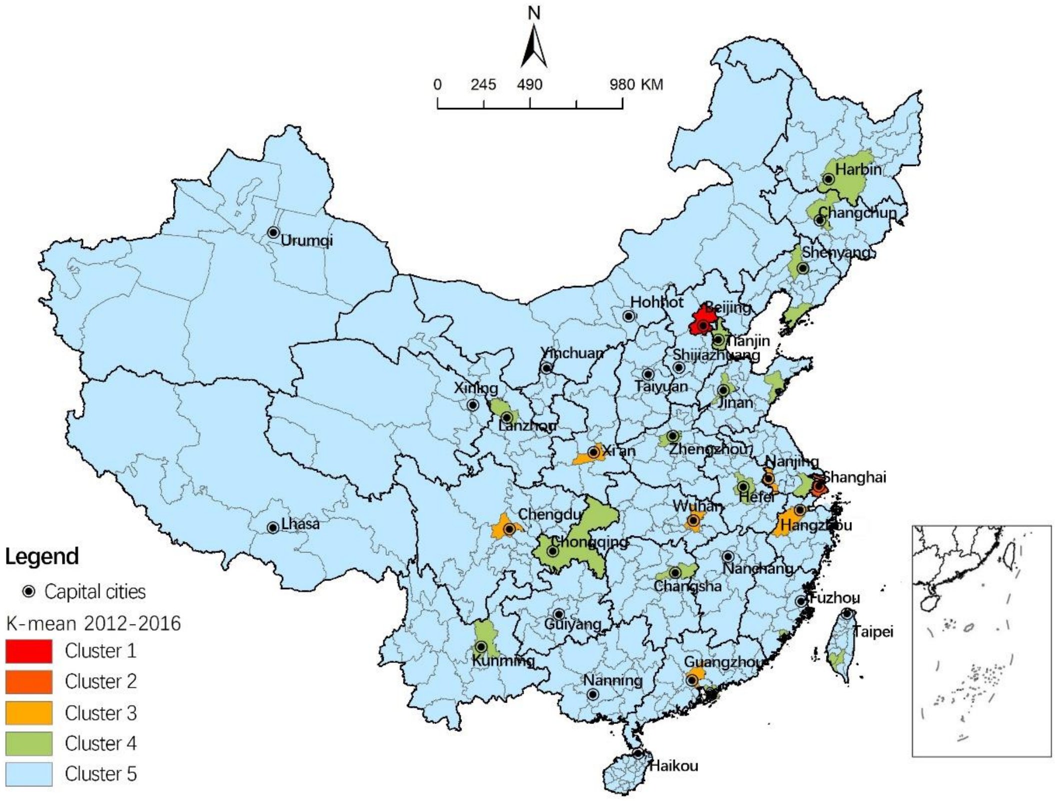


Figure 6-4 K-means map of the scientific output of Chinese cities

Source: author

Table 6-2 The 20 most productive cities (2002-2006, 2012-2016)

Rank	2002-2006			2012-2016		
	City	Total amount	Share	City	Total amount	Share
1	Beijing	74,863	18.40	Beijing	290,760	19.40
2	Shanghai	35,200	8.65	Shanghai	144,461	9.64
3	Taipei	31,876	7.83	Nanjing	96,636	6.45
4	Hong Kong	19,567	4.81	Guangzhou	73,353	4.89
5	Nanjing	17,223	4.23	Wuhan	71,437	4.77
6	Wuhan	15,262	3.75	Taipei	64,644	4.31
7	Hangzhou	13,152	3.23	Xi'an	59,916	4.00
8	Guangzhou	10,529	2.59	Hangzhou	57,610	3.84
9	Xi'an	9,875	2.43	Chengdu	50,875	3.39
10	Tainan	9,872	2.43	Tianjin	44,630	2.98
11	Tianjin	9,445	2.32	Changsha	39,435	2.63
12	Kaohsiung	9,300	2.29	Harbin	35,692	2.38
13	Hefei	8,938	2.20	Hefei	35,550	2.37
14	Taichung	8,558	2.10	Hong Kong	34,892	2.33
15	Changchun	8,369	2.06	Changchun	33,776	2.25
16	Chengdu	7,506	1.84	Jinan	32,298	2.15
17	Changsha	6,727	1.65	Chongqing	32,005	2.14
18	Shenyang	6,680	1.64	Shenyang	26,393	1.76
19	Lanzhou	6,451	1.59	Dalian	25,342	1.69
20	Dalian	6,209	1.53	Qingdao	24,594	1.64

Source: author

6.1.3 The archipelago-like regional formation

Figure 6-5 shows the spatial autocorrelation analysis of the scientific innovation output of Chinese cities in the two periods of 2002-2006 and of 2012-2016. There is a clear-cut difference between coastal and inland provinces. Specifically, most of the cities exhibiting significant spatial clustering with high-high and high-low correlation are located in the eastern coastal provinces, while most of the cities in inland regions are scattered in the form of low-low correlation. At national scale, this structure remains stable and presents a trend of self-reinforcement over time.

At regional level, it is worth noting that most of the high-high correlation type cities during the 2002-2006 period were not spatially contiguous, only Shanghai and Suzhou were adjacent to each other. By the time of 2012-2016, only cities in the YRD region with high-high correlation presented recognizable spatial clustering. One possible explanation is that most cities with high-high correlation are high-level with higher innovation capacities and better innovation bases, such as the capital cities or municipalities with independent planning status. Yet, their neighboring cities are much weaker by contrast. This disparity creates a “spatial compression” effect that the intense spatial interaction and spillovers between those high-level cities, to some degree, offset the friction cost of the geographical distance, which can be considered as another dimension of the “capital monopoly” effect. At the same time, small and medium size cities around these high-level cities show a spatially continuous low-high correlation mode, exhibiting “core-periphery” spatial organizations along with the high-level cities as the cores. The “core-periphery” organizations are quite different in terms of spatial configurations in different regions: in the advanced east coast regions, the “core-periphery” groups are more concentrated due to the denser distribution of high-level cities, while in inland and western China, the distribution of “core-periphery” organizations are relatively sparse and scattered.

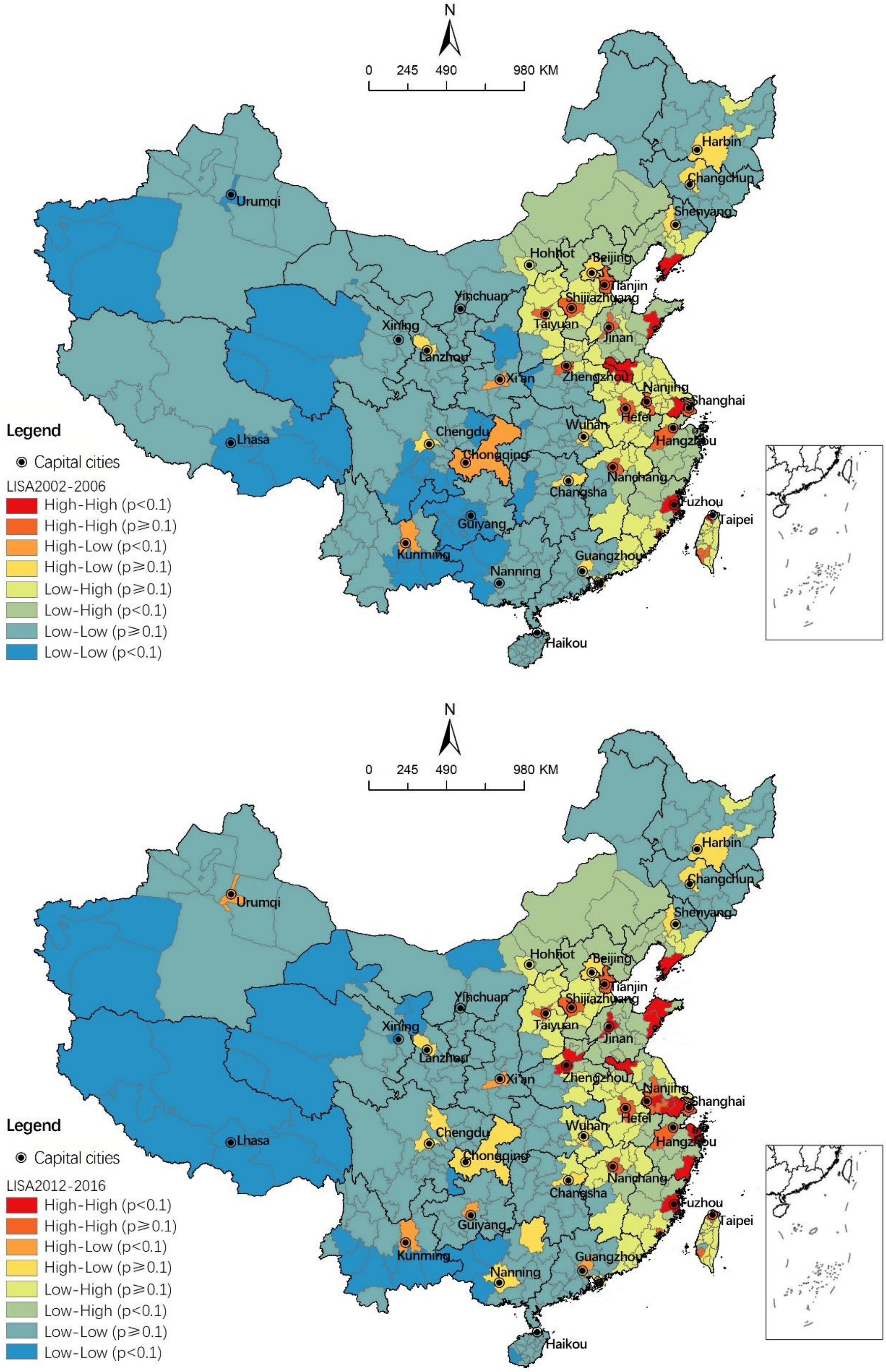


Figure 6-5 Spatial autocorrelation analysis (2002-2006, 2012-2016)

Source: author

In this section, the evolution process of knowledge innovation output of China's cities in 2002-2006 and 2012-2016 is discussed. First, the knowledge innovation output of China's cities has not only increased significantly in terms of the scientific production, but also significantly expanded in terms of the spatial range. However, the spatial distribution of the scientific output with a clear-cut gap between the eastern and western China is far from balance. Second, the effect of "capital monopoly" is evident, that is, the knowledge innovation output of the national capital, provincial capitals and autonomous prefectural capitals are far more higher than other cities presenting an inverted "T-shaped" hierarchical structure. At the same time, the gravity between capitals is prominent, and to some extent, it can overcome the friction costs of the geographical distances. Third, the spatial correlation modes of urban scientific innovation output of China show structural differentiation at both national and regional scales. At the national scale, the spatial destitution of high-high correlation type cities is mainly concentrated in coastal region, while the low-low correlation type cities are mostly located in inland China. At the regional scale, the "core-periphery" archipelago organizations with capital cities as cores are densely distributed in eastern provinces but much more sparse in western provinces.

It is worth noting that, in the analysis of spatial autocorrelation, cities with high-high correlation are not continuous in space, which means that the spatial interactions between these cities are not limited by geographical spaces. This probably can be attributed to the effect of the IKCNs which will be discussed in following sections.

6.2 The evolution of the spatial configurations of China's IKCNs

6.2.1 The emergence of the "diamond-shaped" structure

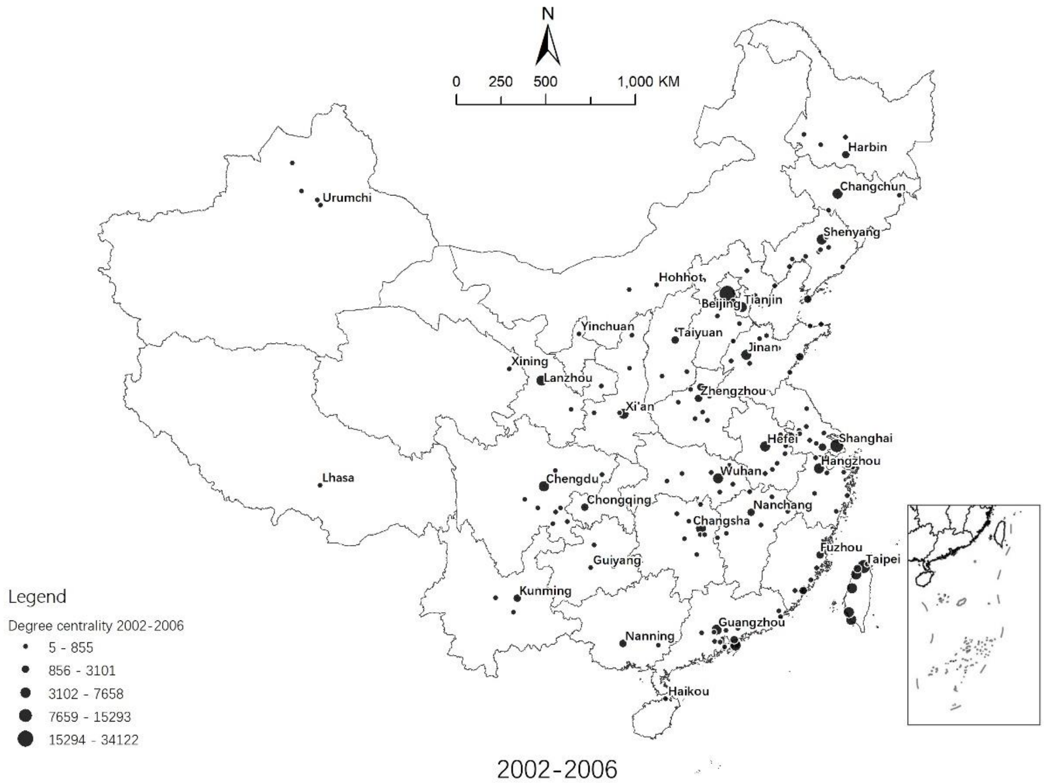
Table 6-3 is the descriptive statistics of the spatial distribution of KNC of Chinese cities. In the period of 2002-2006, 192 of the 217 cities surveyed participated in the IKCN. By the time of 2012-2016, 217 cities were all involved in the collaboration. The maximum, minimum and mean values of the KNC have increased significantly, indicating a considerable growth of the overall connectivity of the IKCNs. Figure 6-6 shows the spatial distribution of cities with the KNC greater than 50. During the period of 2002-2006, the number of cities with the KNC greater than 50 was 113. By 2012-2016, the number increased to 185. In both time periods, the Gini coefficients were higher than 0.8, indicating that the distribution of the KNC was quite polarized. However, over time, both the Gini coefficients and the coefficient of variance have reduced, reflecting that the polarization of the KNC have been weakened. While the Moran's I results tell another story: the index was close to 0 in both time periods and the p values were greater than 0.1, indicating that was no obvious significant polarization or concentration in terms of spatial agglomeration patterns. This seemingly contradictory conclusion explains exactly the "spatial compression" effect caused by the "capital monopoly" mentioned in the previous section.

Table 6-3 Descriptive statistics of the spatial distribution of the KNC (2002-2006, 2012-2016)

	2002-2006	2012-2016
Observations	192	217
Max	34,122	194,096
Min	0	1
Mean	935.57	6,279.22
Coefficient of variance	3,006.65	17,656.16
Gini coefficient	0.87	0.83
Moran's I	3.21	2.81
Observations	0.054	0.052

Source: author

It can be seen from Figure 6-6 that during the period of 2002-2006, the spatial distribution of the KNC was evenly scattered. Only the BTH, the YRD, the GBA and the EST city-regions presented noticeable trend of regionalization, exhibiting a "bow-shaped" structure at national scale. This can also the explain the low Moran's I. In general, the cities with relatively higher KNC are mostly located in the eastern provinces. During the period of 2012-2016, increasing number of cities began to participate in knowledge collaborations. Among them, the CHC city-region and the MRY city-region were remarkable with the rapid development, along with the BTH city-region, the YRD city-region and the GBA city-region, thus a "diamond-shaped" structure has been formed at national scale. Other regions have also developed to varying degrees, within which small- and medium-sized cities have gradually emerged around their regional core cities.



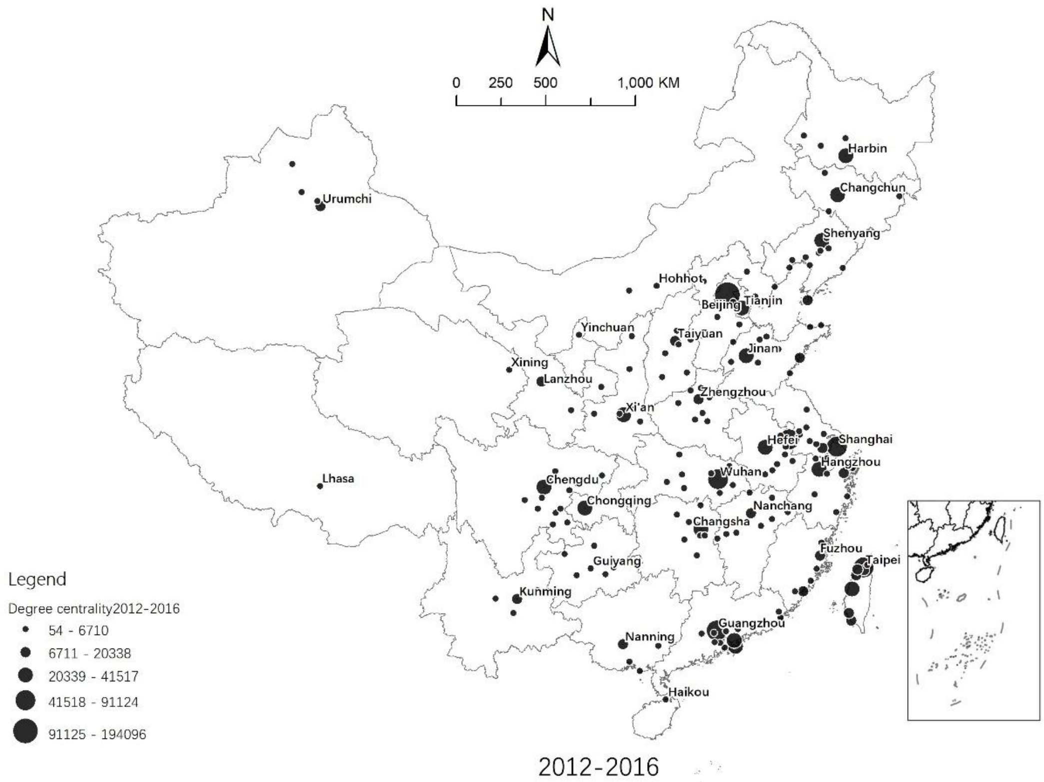


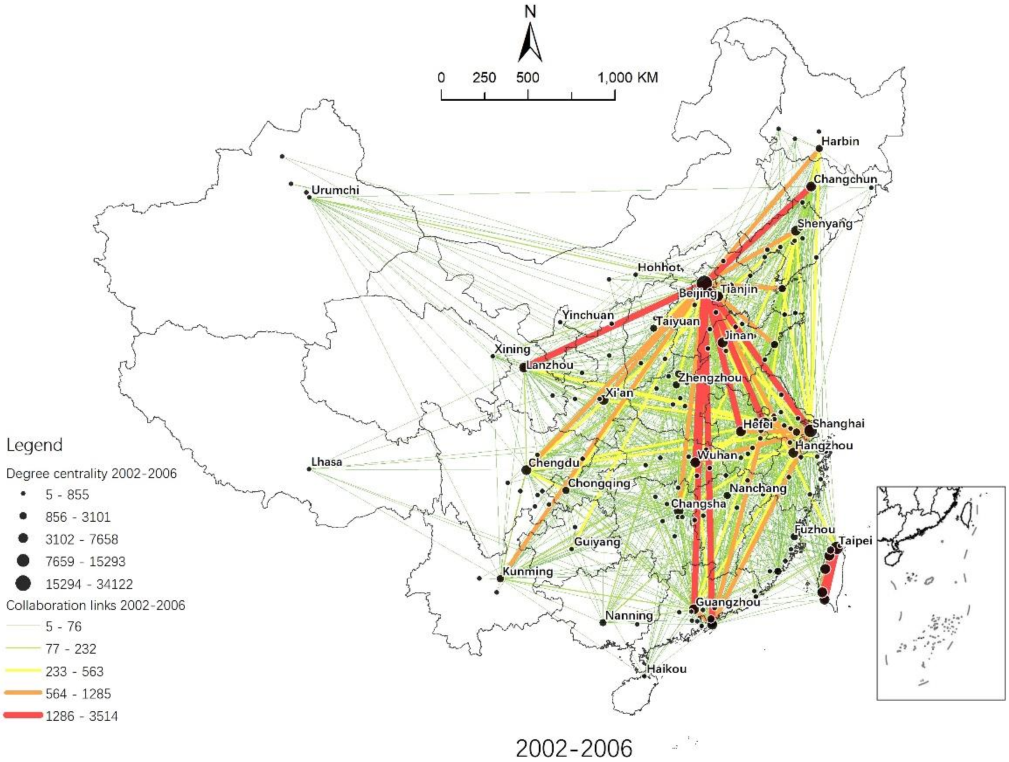
Figure 6-6 Spatial distribution of cities with the KNC greater than 50 (2001-2006, 2012-2016)

Source: author

6.2.2 The “Capital monopoly” effect and the “hub-spoke” structure

Figure 6-7 presents the spatial structure of the IKCNs of China in the two time periods. Table 6-4 is the top 20 cities in terms of the KNC. At the first glimpse, the “capital monopoly” are evident: the capitals, municipalities and provincial capitals are the hubs and hinges of the IKCNs. These capital cities have aggregated a large number of collaborative connections. In the period of 2002-2006, the KNC of all cities totaled 203,018, 76.3% of which are concentrated on the 34 capital cities whose totals were 154,955. Although this number has slightly declined in the period of 2012-2016, the “capital monopoly” embodied by the national share of 73.6% remained unchallenged.

Further, the result of the K-means clustering analysis of urban KNC shows that these capital cities can be divided into three categories. The first category is the national capital--Beijing, which is the dominant center in the IKCNs with the strongest gravitation. It is the primate collaboration city for all other capitals. Table 6-4 shows that Beijing’s KNC far exceed than other cities, almost 50% higher than Shanghai in the second place. The second category of cities include Shanghai, Nanjing, Taipei, Hong Kong, and Guangzhou. Compared with Beijing, such cities have relatively lower connectivity and smaller spatial range. For example, although Shanghai has a quite wider spatial range in the IKCNs, its KNC are much lower than that of Beijing. Unlike Shanghai, Nanjing and Guangzhou with relatively smaller spatial ranges yet function as the regional centers in East China and South China respectively, also have lower KNCs. Taipei has a relatively larger KNC, however, its collaboration connections with cities in mainland China is relatively weak and the spatial range is confined in Taiwan due to the political and historical issues. The last category is the rest of capital cities that are weaker in terms of gravitational intensity and radiation range but mostly are the network centers of their provinces or cities.



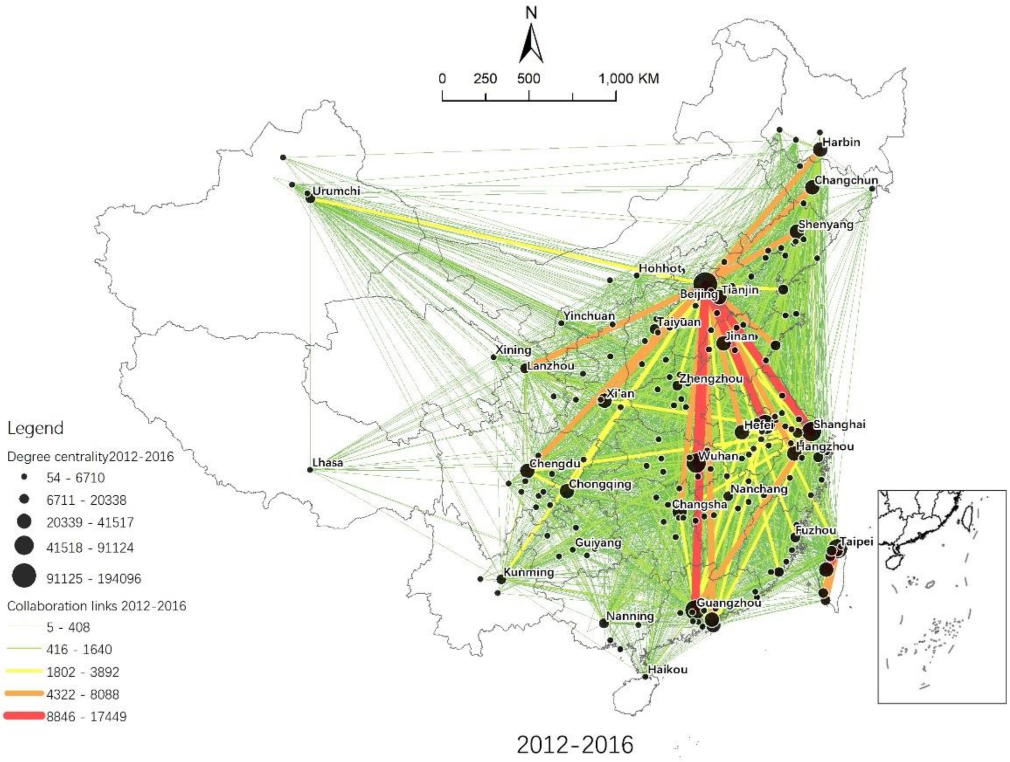


Figure 6-7 Spatial structure of China's IKCNs (2002-2006, 2012-2016)

Note: for clearer visualizations, the threshold of the KNC of cities is set as 50.

Source: author

Table 6-4 Top 20 cities in terms of the KNC (2002-2006, 2012-2016)

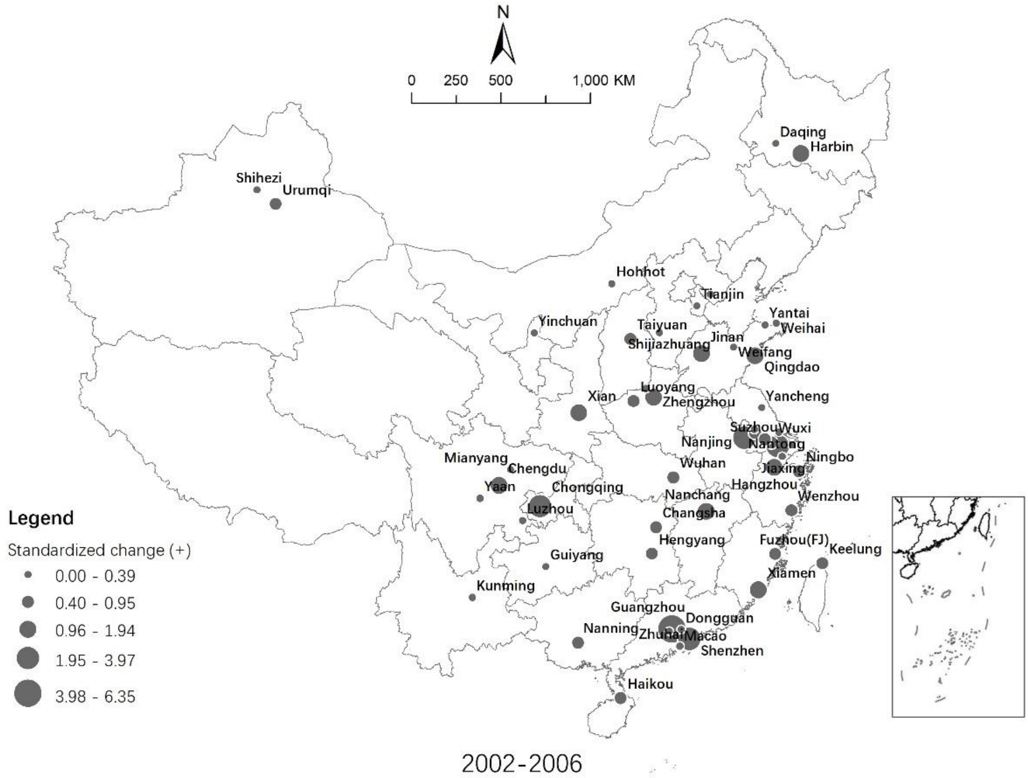
Ran	2002-2006			2012-2016		
k	City	KNC	KNC%	City	KNC	KNC%
1	Beijing	34,122	100.00	Beijing	194,096	100.00
2	Shanghai	15,293	44.82	Shanghai	91,124	46.95
3	Taipei	10,773	31.57	Nanjing	67,894	34.98
4	Hong Kong	9,583	28.08	Guangzhou	62,574	32.24
5	Nanjing	7,658	22.44	Taipei	51,212	26.38
6	Wuhan	7,595	22.26	Hong Kong	48,002	24.73
7	Guangzhou	6,117	17.93	Wuhan	41,517	21.39
8	Hangzhou	6,061	17.76	Hangzhou	38,811	20.00
9	Hsinchu	5,350	15.68	Chengdu	35,277	18.18
10	Tianjin	5,249	15.38	Xi’an	31,973	16.47
11	Kaohsiung	5,200	15.24	Tianjin	30,872	15.91
12	Hefei	5,166	15.14	Hefei	28,991	14.94
13	Chengdu	5,131	15.04	Jinan	28,422	14.64
14	Shenyang	5,074	14.87	Changsha	28,152	14.50
15	Taichung	4,760	13.95	Changchun	24,525	12.64
16	Xi’an	4,692	13.75	Shenzhen	23,929	12.33
17	Tainan	4,638	13.59	Shenyang	22,365	11.52
18	Changchun	4,157	12.18	Chongqing	21,720	11.19
19	Changsha	4,002	11.73	Harbin	21,263	10.95
20	Lanzhou	3,896	11.42	Taichung	21,258	10.95

Source: author

The three types of capital cities have jointly formed as the backbone of the national IKCNs: a “hub-spoke” structure with Beijing as the core, and Shanghai, Guangzhou and Beijing interlinked as a “triangle” in the east, within which, Nanjing, Hangzhou, Wuhan and Hefei have stand out and structured dense secondary networks. In the west, Chongqing, Chengdu, and Xi’an have gradually emerged as regional hubs and become the hinging axis that interconnects the cities in the east and west. It is clear that the structure of the IKCN is coupled with the well-recognized national urban-region system: high intensity of collaborations occur within and between the five major city-regions—the BTH, the YRD, the GBA, the CHC and the MRY city-regions. Among them, the collaboration between the BTH and the YDR, as well as between the BTH and the GBA are most intense, while the collaboration between the CHC and the GBA is relatively lower. In summary, with combined forces generated by different types/sizes of the capitals in the networking processed, the IKCNs of China present a mixed spatial organization of a “hub-spoke” backbone attached by several “triangular” subsystems. More specific, Beijing is at the center of the “hub-spoke” backbone, while capitals of the five major city-regions consist the secondary hub and are attached to the backbone. In addition, it also can be seen that the spatial organization of the "hub-spoke + triangles" structure is constantly self-reinforcing.

The "capital monopoly" is also reflected in the changes of the KNC. Compared with the 2002-2006 period, the total KNCs of all cities in the 2012-2016 have increased by 1,159,572, 73.12% of which were from the capital cities, registering 847,865. Figure 6-8 maps the spatial distribution of the standardized KNC changes. It is clear that capitals have been growing much faster than other cities. As shown in Table 6-5, 25 among the 34 capital cities are positive in terms of the standardized changes. In terms of the growth rate, there are 13 capitals in the top 20. In contrast, 120 of the 129 cities whose standardized KNC changes are negative are non-capital cities. This indicates that the growth of connectivity of the capital cities is generally faster than that of the non-capital cities.

It is noteworthy that there are also capitals whose standardized KNC changes decreased significantly, including Taipei, Shenyang, Beijing, and Lanzhou. First of all, the decrease of the network connectivity in Taipei is no exception but is accompanied by all Taiwanese cities. This indicates that the speed of the development of the IKCNs and the innovation capability is much faster than that of Taiwan. The decrease of network connectivity of Beijing indicates that the degree of monocentricity of the IKCN of China has weakened. Both Shenyang and Lanzhou are former industrial centers. At the founding of China, they had received more resources and policies under the regime of planned economy, during which they had developed and accumulated solid industrial technology. However, due to some reasons such as their location disadvantages and the shifting national development strategies, they have gradually lagged behind in the new round of competition, thus experiencing huge decline in terms of the standardized KNC changes.



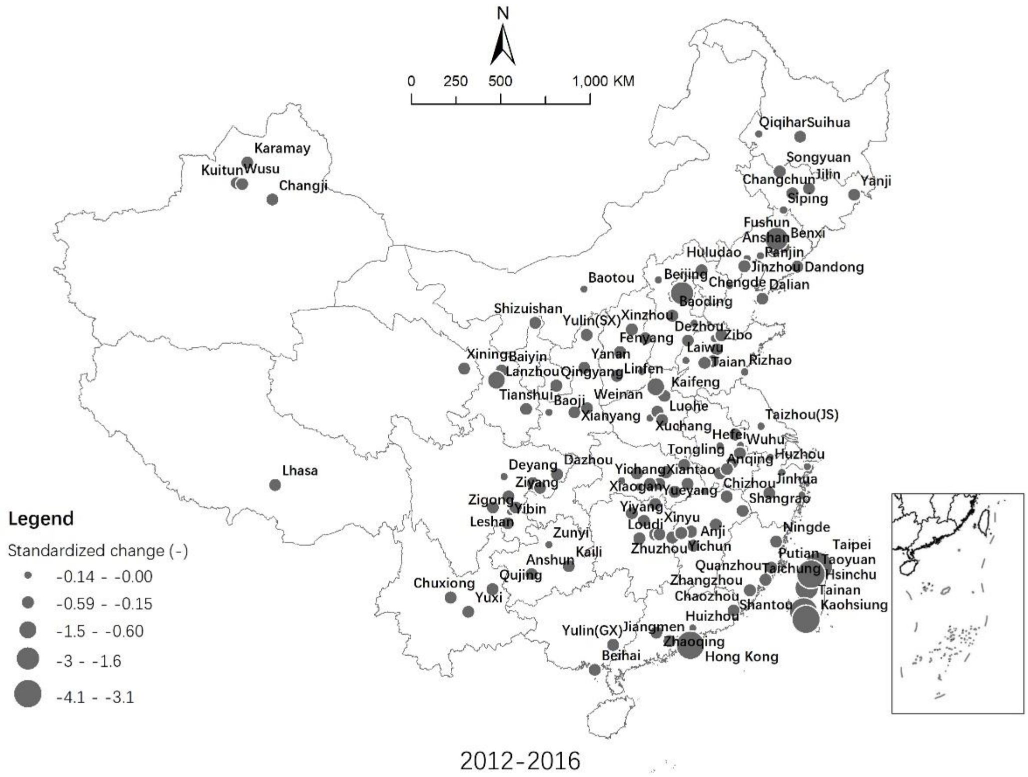


Figure 6-8 The spatial distribution of the standardized KNC changes

The upper one shows cities with positive changes, the lower shows the cities with negative changes.

Source: author

Table 6-5 Top 20 cities in terms of the standardized KNC changes

City	standardization changes (+)	City	standardization changes (-)
Guangzhou	6.35	Hong Kong	-4.11
Shenzhen	3.97	Hsinchu	-3.68
Nanjing	2.67	Kaohsiung	-3.35
Suzhou	2.64	Taipei	-3.13
Chongqing	2.51	Tainan	-3.11
Chengdu	1.94	Shenyang	-2.02
Zhengzhou	1.92	Taichung	-1.84
Xi'an	1.70	Beijing	-1.63
Qingdao	1.56	Lanzhou	-1.02
Harbin	1.33	Xinxiang	-0.67
Nanchang	1.30	Taoyuan	-0.60
Jinan	1.27	Linyi	-0.43
Hangzhou	1.26	Dalian	-0.32
Xiamen	1.08	Dongying	-0.32
Taiyuan	0.95	Fuzhou	-0.31
Changsha	0.94	Zhuzhou	-0.30
Urumqi	0.85	Wuhu	-0.26
Zhenjiang	0.77	Zhangzhou	-0.25
Wenzhou	0.72	Yellowstone	-0.25
Wuxi	0.71	Yibin	-0.25

Source: author

6.2.3 The coexistence of spatial agglomeration and diffusion

Figure 6-9 shows the results of local spatial autocorrelation analysis of the KNC. On the national scale, the high-high correlation type cities are mainly located in North China, East China, and Northeast China. It should be pointed out that there are two different types of high-high correlation. The first one is the "detached" spatial agglomeration in Chinese mainland, that is, the high-high correlation mainly occurs in the capital cities or the cities with higher socio-economic development. On account of the existence of the "capital monopoly", the physical distances between these cities are actually "shortened", in turn, the capitals present a spatially "discontinuous" high-high correlation form. The second is the east strait city-region in Taiwan, which corresponds with spatial spillovers based on geographical proximity. That is, the co-located cities have stronger interactions and closer connections.

At the regional scale, there are also two different spatial autocorrelation processes. The first pattern is the spatial diffusion and spillovers from the core cities to the periphery cities. This type of spatial correlation is mainly distributed in the eastern provinces and part of the central provinces. Specifically, this spatial correlation type is characterized by an organization logic of the central place and generally present a core-periphery configuration, where the core cities mostly are high-high correlation or high-low correlation, while the surrounding small and medium-sized cities exhibit low-high correlation. The second type of spatial correlation is mainly in the western provinces. Although the core cities show high-low correlation, the surrounding small and medium-sized cities are of low-low correlation. It is largely because that within these regions, the interactions and collaboration intensity are much lower. At the same time, the core cities themselves are not so strong as their eastern counterpart to succeed in driving or leading the regional development.

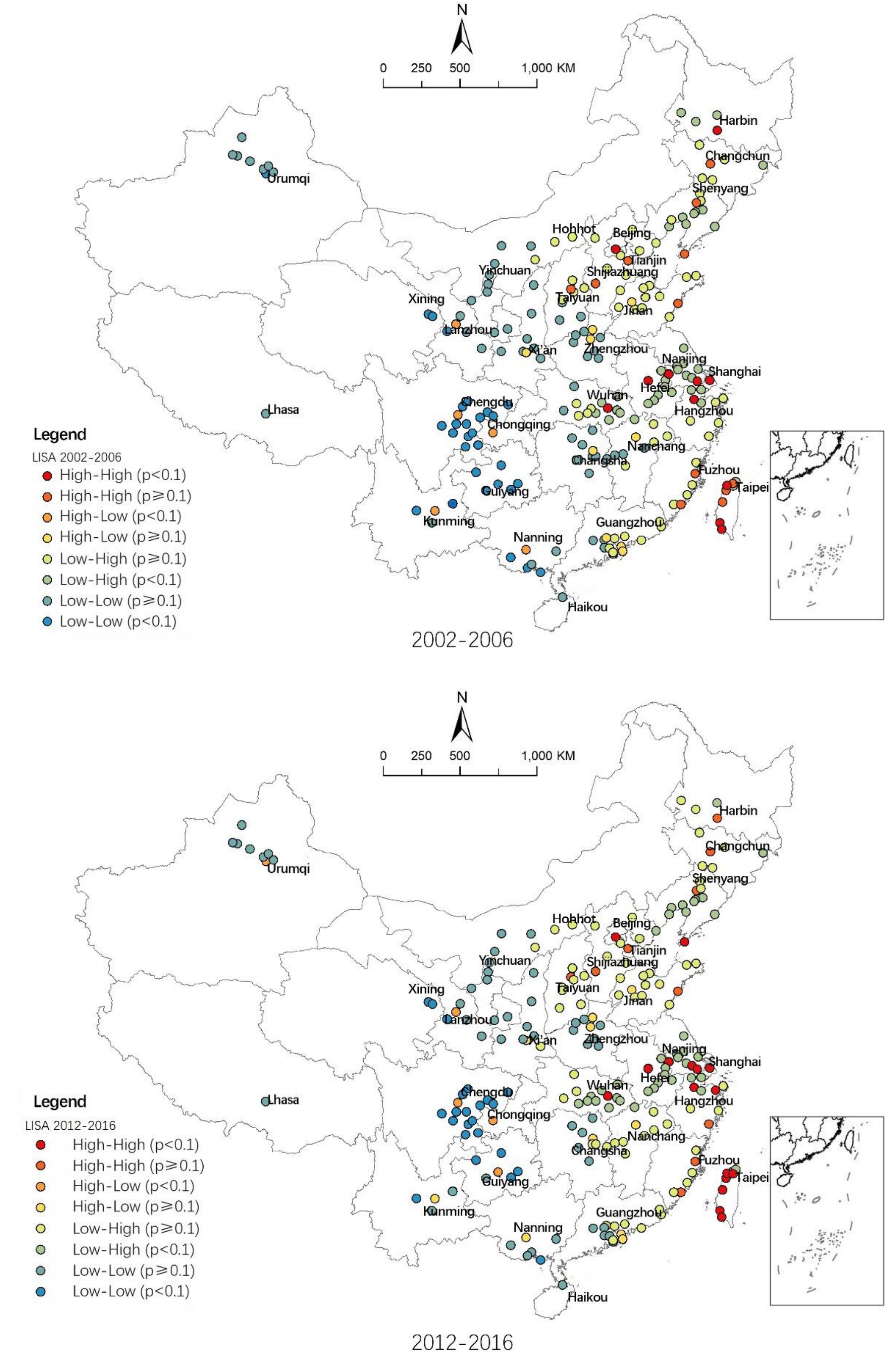


Figure 6-9 Spatial autocorrelation of cities' KNC (2002-2006, 2012-2016)

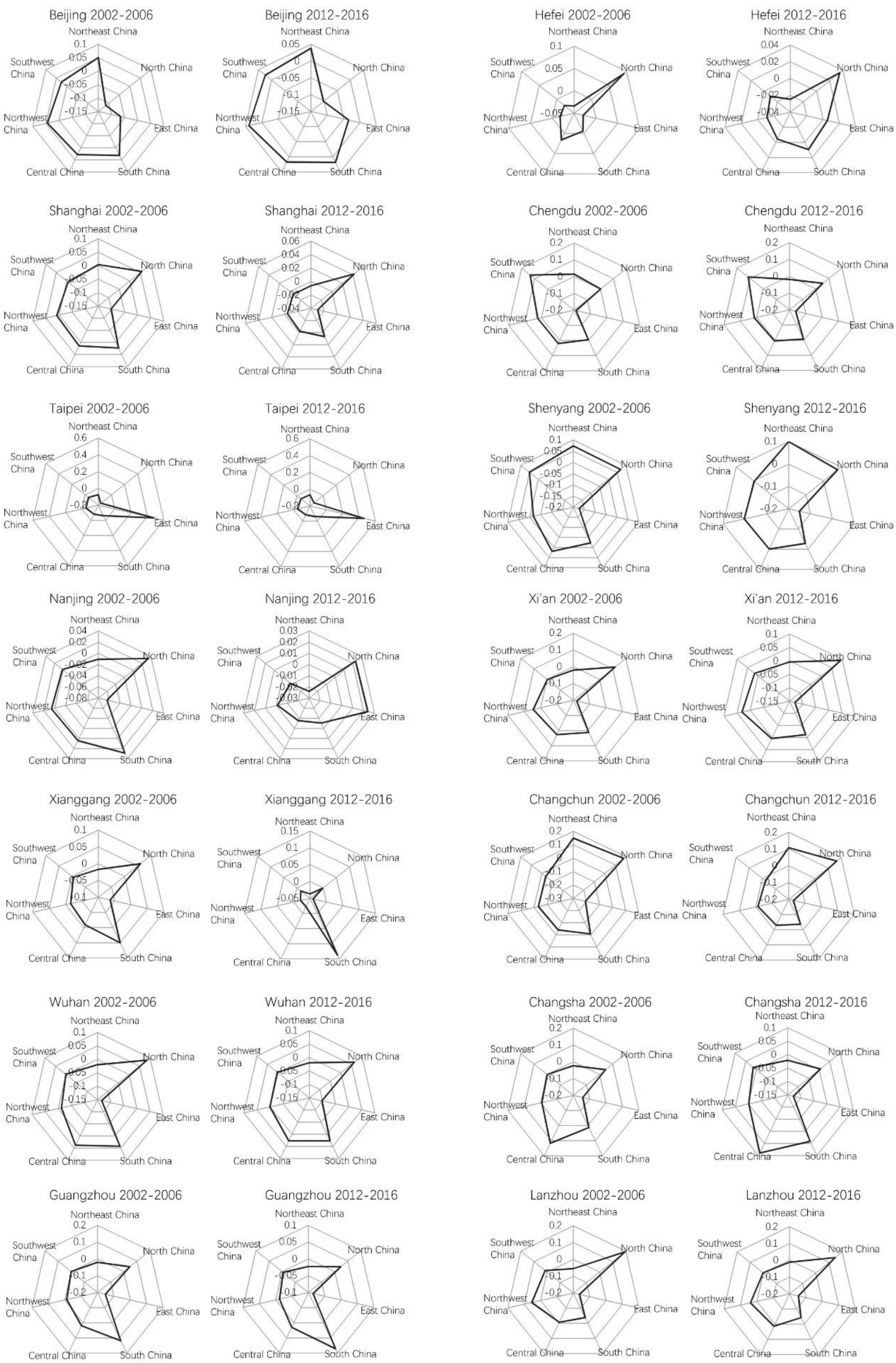
Source: author

6.2.4 The spatial reach of cities in the national IKCNs

Figure 6-10 shows the spatial reach of the domestic collaboration of some cities. The results suggest there exist both common and different features among these cities. First of all, it can be found that the relative collaboration intensity between most capital cities and the cities in East China in the two periods were relatively low. One possible explanation is that there are quite large number of cities in East China. Due to the "capital monopoly", most of collaborative connections are concentrated among the capital cities, so the actual number of collaborative connections in the region is much smaller than expected. However, non-capital cities such as Ningbo, Suzhou and Xiamen have higher relative collaboration intensity with cities in East China. This result suggest that the spatial reach of the capital cities are more outward, while the spatial reach of the non-capital cities are more inward.

Secondly, chances are that most cities tend to collaborate with cities within their own regions, but not for all. For example, the relative collaboration strength between Beijing and cities in North China where it situated is significantly lower than that of other regions. This suggest that Beijing's role as a national hub in the IKCNs is more prominent than that as a regional hub. Fuzhou and Xiamen are also interesting examples. It is obvious that Fuzhou are more likely to collaborate with cities in North China rather than where it locates, which is largely due to its large amount of collaboration with Beijing. In contrast, the spatial reach of Xiamen is wider than Fuzhou. Its relative collaboration intensity with South China, Central China and East China are much higher than that of Fuzhou. This shows that Xiamen's role as regional hub is more prominent than Fuzhou, albeit it is not the provincial capital.

Finally, the spatial reach of most city remains stable over time, with the exception of Hong Kong, Nanjing and Hefei, mainly due to their specific development trajectories in their regional KCNs. These will be further discussed in Chapter 7.


Beijing 2002-2006
Beijing 2012-2016
Hefei 2002-2006
Hefei 2012-2016
Shanghai 2002-2006
Shanghai 2012-2016
Chengdu 2002-2006
Chengdu 2012-2016
Taipei 2002-2006
Taipei 2012-2016
Shenyang 2002-2006
Shenyang 2012-2016
Nanjing 2002-2006
Nanjing 2012-2016
Xi'an 2002-2006
Xi'an 2012-2016
Xianggang 2002-2006
Xianggang 2012-2016
Changchun 2002-2006
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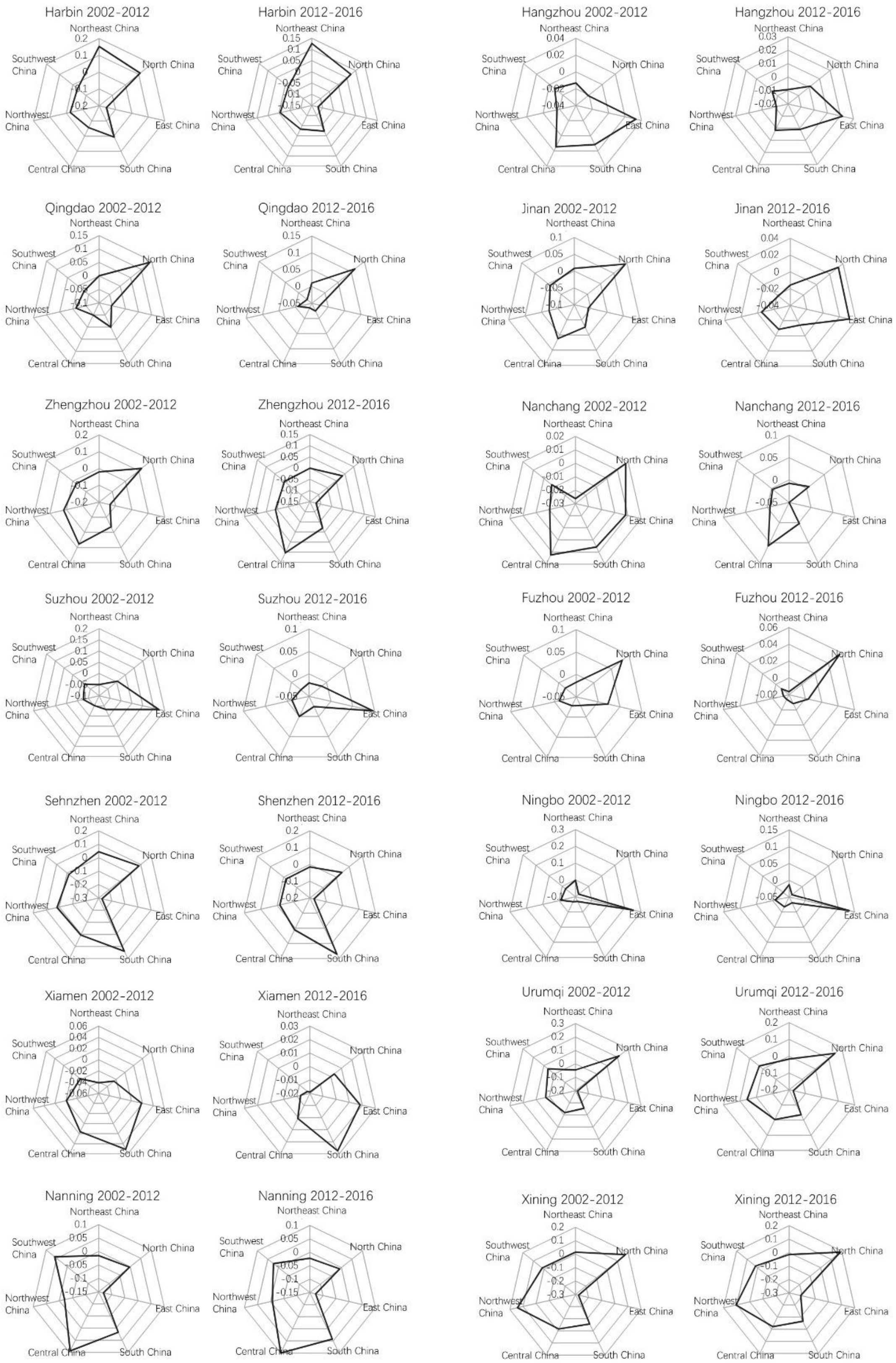


Figure 6-10 The spatial reach of major cities in the national IKCNs
Source: author

6.2.5 Integrated network: the "central place model" and the "urban network model"

6.2.5.1 **Conception**

"Polycentric urban systems" is an important conceptual model used to describe the organizational structure of "networked" urban systems, which differs from the traditional "central place" model. Similar size of cities is an important criteria for judging if the urban systems are polycentric, but what it reflects and explains is only part of the concept of polycentric urban systems. More importantly, the interactions between cities - the exchange of people, goods, capital and information - are the fundamental mechanism of polycentric urban system (Burger et al., 2014; Kloosterman and Musterd, 2001; Lambregts et al., 2005; Liu et al., 2016; Meijers, 2005). The balanced distribution of urban sizes only reflects polycentricity in morphological term, while the functional polycentricity implies the complementarity and integration of functions between different cities, which is also the key of the conception of "urban network". In an urban system of functional polycentricity, the inter-city flows are multi-directional (Meijers, 2007). Camagni and Capello (2004) point out that ideal-typically, regional integration entails that the intensity of the inter-city flows should be determined by the size of cities and the physical distance between them rather than by hierarchical spatial ordering and visible factors like the administrative forms of spatial organization.

Figure 6-11 shows three typical urban system models. The left one is the central place model, in which the spatial organization has a distinct hierarchical structure, and the interaction between cities is unidirectional and vertical with inter-city flows only pumping from the central cities to their hinterland (Meijers, 2007). In the context of China, this would reflect hierarchical orderings between the capitals and their prefectural cities. The second model is the urban network model, within which the interactions between cities are diverse. There are both vertical connections between different size of cities and horizontal connections between the cities of the same size. At the same time, the interactions between cities are multidirectional (Camagni and Capello, 2004; Camagni, 1993). In the third model, the network is regarded as an open system. The interurban network connections are not limited within regions, and the spatial interaction may thus increasingly stretch across regions and/or administrative areas, producing functional interdependencies across wider areas.

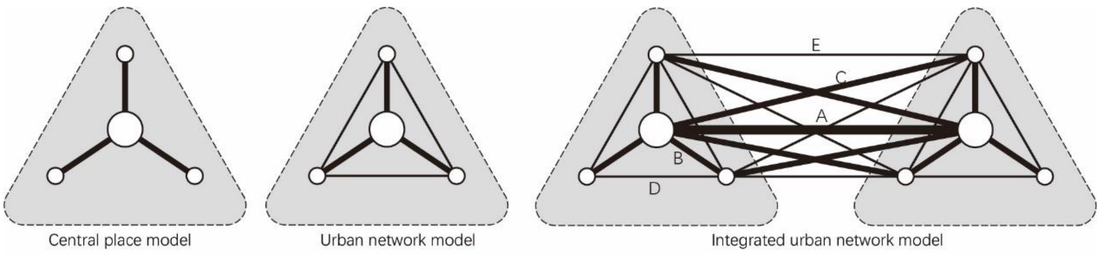


Figure 6-11 “Central place model”, “urban network model” and “integrated urban network model”
Source: author

As mentioned above, in a fully integrated network, the strength of connection between cities solely depends upon their economic mass and the distance between them. Other impeding factors producing spatial hierarchies in a city-pair should be either unimportant, random, or very minor at best. In China’s political-economic context, the pyramidal administrative system is, to a large extent, responsible for the existence of the spatial hierarchies among cities (Andersson et al., 2014; Cao et al., 2018; Zhao et al. 2017).

In Figure 6-11, the connections between cities can be divided into five types: type A is the connection between the two capitals from different provinces; type B is the connection between a capital city and a prefectural city in a same province; Type C is the connection between the capital city and a prefectural city from other province; Type D is the connection between two different prefectural cities in the same province; Type E is the connection between two prefectural cities from different provinces. The diagram represents an idea integrated urban network: the thickness of the lines indicates the strength of interdependencies between cities, that is, the amount of interurban knowledge collaboration links. Within the network, the administrative boundaries will not impede the IKCN. So, the strengths of type B and type C connections, type D and type E connections should be identical when the physical distances are controlled. Based on this logic, the examination the degree of the integration of the national IKCNs can be conducted by examining whether the actual strength of interurban collaboration is as same as expected strength in the ideal model.

Table 6-6 shows the details of different types of interurban collaboration connections of two time periods. The results show that type A, type B and type C connections are relatively stronger than the others, which, once again, confirms the significant impact of the “capital monopoly” effect in shaping the IKCNs. By contrast, type D and type E connections are much weaker. The results of the mean value explicitly reflect the hierarchical orderings among different types of inter-city collaboration links. In the next section, a statistical model will be introduced to see if this hierarchy is determined only by masses of cities and physical distances between them and further to test if the IKCN can be considered as a fully integrated network.

Table 6-6 Different types of interurban collaboration links (2002-2006, 2012-2016)

Type	Description	2002-2006				2012-2016			
		The total amount	Share	The number of city-dyads	Mean	The total amount	share	The number of city-dyads	Mean
	All connections	83,912	100.00	21,736	3.86	596,183	100.00	21,736	27.43
A	Links between capital city-capital city	59,690	71.13	528	113.05	363,787	61.02	528	688.99
B	Links between capital cities and prefectural cities in a same province	4,696	5.60	176	26.68	41,887	7.03	176	237.99
C	Links between capital cities and prefectural cities from other provinces	17,646	21.03	5,632	3.13	163,091	27.36	5,632	28.96
D	Links between prefectural-level cities in a same province	733	0.87	653	1.12	10,124	1.70	653	15.50
E	Links between prefectural-level cities from different provinces	1,147	1.37	14,747	0.08	17,249	2.89	14,747	1.17

Source: author

6.2.5.2 **Model specification**

In line with the research of De Goei et al. (2010), Hanssens et al. (2014) and van Oort et al. (2010), this section adopts the gravity model as a baseline for measuring the degree of network integration. The “gravity model”, widely used in examining spatial interactions, derived from Newton’s law of gravity—the interaction intensity between any two objects is proportional to their masses and is inversely proportional to the distance between them. In this case, the intensity of scientific collaboration between two cities is hypothesized to be positively correlated with their size and inversely correlated with the physical distance between them. More specifically:

$$I_{ij} = K \frac{(M_i \times M_j)^{\beta_1}}{d_{ij}^{\beta_2}} \qquad (6\text{-}1)$$

Among them, I_{ij} is the total amount of collaboration between city i and city j, which is also the dependent variable in the regression model; K is a constant; M_i and M_j represent the size of city i and city j respectively, and both are defineed by their KNCs in this case; d_{ij} is the Euclidian distance between city i and city j. and are the parameters to be estimated.

The other independent variables examine the impact of non-spatial factors on the strength of interurban connection. At least two spatial conditions should be met before the IKCN of China can be qualified as fully integrated: (1) intra-provincial connections should not be stronger than inter-provincial connections; and (2) there should be no significant differences among the five types of inter-city links when the masses and distances are controlled. Based on this, the other independent variables are set as binaries to indicate if the link is a certain type of inter-city collaboration. Since the dependent variable in this section is the counts, Poisson regression, zero-inflated Poisson regression, negative binomial regression, or zero-inflated negative binomial regression should be used. In order to select the best-fitting model, a likelihood ratio test for over-dispersion and a Vuong statistic test for excessive zero counts are conducted.

6.2.5.3 **Regression results**

Table 6-7 is the report of the regression results. In all models, the dispersive coefficient Alpha is significant at the 1% level, indicating that the negative binomial regression is better than Poisson regression. At the same time, the Vuong test is also significant at the 1% level, indicating that the zero-inflated negative binomial regression works better than the negative binomial regression. In addition, the coefficients of the variables across different models are stable, suggesting the robustness of the results.

First, Model 1 and Model 4 are the baseline models that only include the gravity-type factors. As expected, city size has a strong positive correlation with the collaboration intensity between cities, while physical distance has a sizable opposite effect. By comparison, the coefficient of variable *Mass* increased from 1.18 in 2002-2006 period to 1.23 in 2012-2016 period, while the coefficient of the variable *Distance* increased from-0.81 to-0.71. This suggests the impeding effect of physical distance on the formation of the IKCN tend to decline and further the IKCN of China has become more and more integrated.

In Model 2 and Model 5, the dummy variable *Intra-provincial links* is introduced to test the condition of spatial integration, which states that the interaction between cities in the same province should not be significantly stronger than that between cities from different provinces. The coefficients of both periods are significantly positive. This suggests, when controlling the size of the cities and the distance between them, the intensity of intra-provincial links is stronger than inter-provincial links. These results indicate that the administrative boundaries in China act as invisible walls circumscribing inter-city scientific collaborations. According to this, the IKCN of China cannot be qualified as an integrated network. However, the coefficient has decreased from 1.52 in the 2002-2006 period to 1.33 in the 2012-2016 period, indicating that the negative effect of administrative boundaries had gradually reduced.

Model 3 and Model 6 examine the second condition of network integration, which states that there should be no identifiable differences between different types of interurban collaboration links. Relations between prefectural-level cities from different provinces, which are conceptually the weakest types of interurban collaborations, have been taken as the reference category (marked as ※ in the table). Among them, type B and type D connections have higher possibilities to form than type A and type C, indicating that the second spatial condition is not met either. Interestingly, it can be seen that the probability of the occurrence of the type A connections is not the highest and even lower than the type D connections. This result seems to run counter to the law of “capital monopoly” verified in the previous sections. However, it is reasonable that in the two time periods, the total number of collaboration connections between capital cities are 59,690 and 363,787 respectively, among them, the number of collaboration connections with Beijing involved is 27,921 and 149,648 respectively, accounting almost half of the total links. This implies that the actual connections between capitals are lower than expected. On contrary, the coefficient of type B connections, which between capitals and the prefecture cities within a same region, is much higher, suggesting the prevalence of “central place” organizational logic in the IKCN of China.

Table 6-2 Zero-inflated and negative binomial regression of the IKCNs of China

Variable	2002-2006			2012-2016		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Negative binomial part						
Constant	9.93(0.33)***	5.00(0.41)***	5.36(0.42)***	9.92(0.16)***	5.56(0.21)***	5.66(0.21)***
Mass (log)	1.18(0.02)***	1.22(0.02)***	1.15(0.02)***	1.23(0.01)***	1.25(0.01)***	1.19(0.01)***
Distance (log)	-0.81(0.03)***	-0.47(0.03)***	-0.49(0.03)***	-0.71(0.01)***	-0.41(0.02)***	-0.41(0.02)***
Intra-provincial links		1.52(0.09)***			1.31(0.05)***	
Type A			0.26(0.09)**			0.37(0.05)***
Type B			1.75(0.13)***			1.88(0.07)***
Type C			0.08 (0.08)			0.12(0.03)***
Type D			0.97(0.14)***			0.95(0.05)***
Type E			※			※
Zero-inflated part						
Constant	-6.46(0.93)***	-0.31(1.54)	0.25(1.43)	-9.28(0.56)***	-4.06(0.77)***	-4.48(0.75)***
Mass (log)	-7.93(0.71)***	-9.25(0.83)***	-7.11(0.92)***	-8.81(0.37)***	-8.87(0.38)***	-7.67(0.34)***
Distance (log)	0.74(0.07)***	0.30(0.11)**	0.26(0.1)*	0.86(0.04)***	0.49(0.06)***	0.52(0.06)***
Intra-provincial links		-1.3(0.26)***			-1.64(0.15)***	
Type A			-0.98(1.19)			-7.49(67.71)
Type B			-2.48(0.36)***			-9.05(0.06)
Type C			-0.70(0.2)***			-0.63(0.09)***
Type D			-1.52(0.27)***			-1.63(0.15)***

Type E			※			※
Observations	21736	21736	21736	21736	21736	21736
Alpha	2.90***	2.11***	2.39***	11.73***	7.80***	7.86***
Vuong-statistic	-24.35***	-24.54***	-18.39***	-21.39***	-23.17***	-36.75***
Log likelihood	-10390.97	-10206.78	-10167.97	-29776.79	-29267.58	-29121.63
McFadden's Adjusted R2	0.30	0.31	0.33	0.29	0.31	0.33
AIC	20795.95	20431.55	20365.95	59567.58	58553.16	58273.26

Significance level: ***p<0.01, **p<0.05, *p<0.1; standard error between brackets. ※ Benchmark

Source: autho

In summary, the IKCN of China currently cannot be qualified as a fully integrated network. Taken together, these results suggest that the organization of China's IKCN could, to a certain degree be described as an evolving "networked system" given the existence of sizable interurban interactions. However, the hierarchical impact of the administrative organization imposed by the spatial organization of Chinese state still stand out.

6.3 The evolution of the topological structures of China's IKCNs

6.3.1 Basic topological structures

6.3.1.1 **Overall network topological properties**

Table 6-8 shows the results of the overall network's topological properties of China's IKCNs during the period of 2002-2006 and of 2012-2016. First, the mean, maximum and minimum values of the KNC have increased significantly during the research periods, indicating that the intensity of collaboration between Chinese cities shows a remarkable momentum in growth. Second, the network density and global efficiency also have sizable growth, indicating the overall connectivity of China's knowledge collaboration network has also been greatly enhanced. Third, the negative degree-degree correlation shows "disassortativity", that is, cities have smaller KNC tend to collaborate with cities with higher KNC. This result is consistent with the network properties of the national IKCNs and the global IKCNs, confirming the general law of knowledge acquisition, diffusion and transfer. That is, collaboration with hub cities is the most effective way for cities with weak innovation bases or newly entered knowledge innovation networks to acquire new knowledge and improve their importance in the networks. For hub cities, disseminating and diffusing to cities with low levels of innovation are the main ways to expand their network influence.

In both time sections, the networks have shorter characteristic path lengths and higher clustering coefficients with the small-world quotients greater than 1, exhibiting a typical small-world property. The power-law exponents of the cumulative distribution are respectively 1.47 and 1.44 in two time periods, And the corresponding actual power-law exponents are 2.47 and 2.44, respectively. Given that they are in the range of 2-3, these characterize the national IKCNs as scale-free networks. This shows that China's IKCNse are quite polarized, that is, only a few cities have a large number of collaborative connections, and most cities have limited number of collaborative connections.

The topological similarities of the networks in the two time periods are examined by QAP correlation. The coefficient reaches 0.91 and is significant at 0.01 level, which shows that the topological structures of the national IKCN has not structurally changed, indicating the evolution of the national IKCNs follow the "path dependency" property.

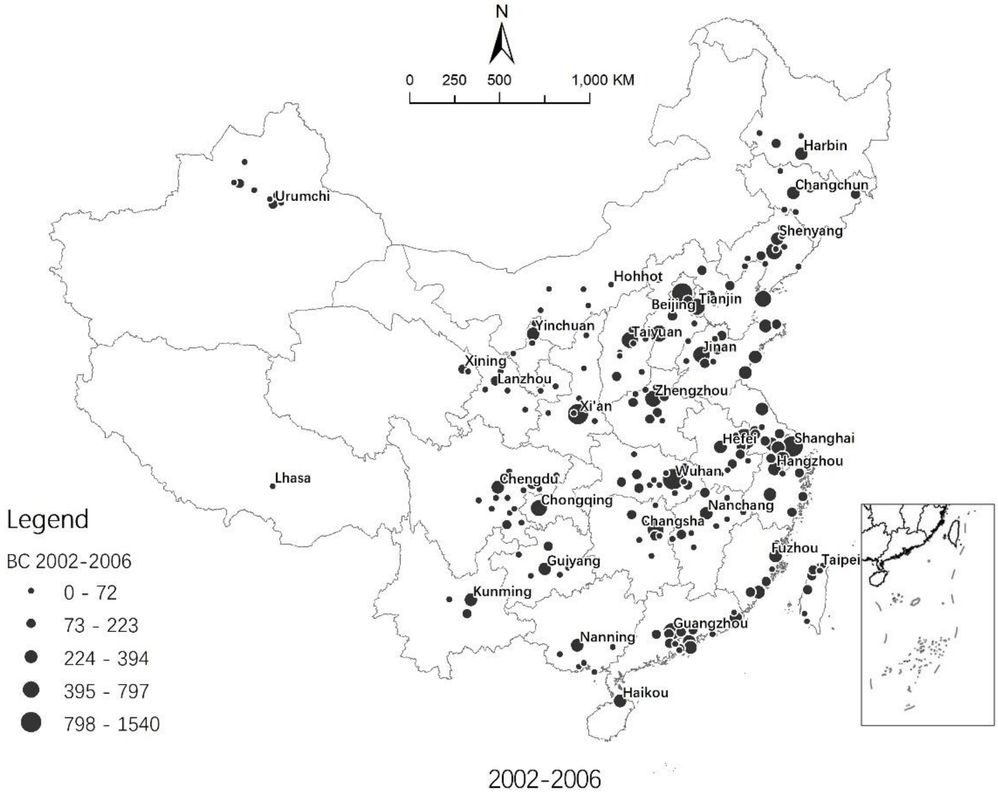
Table 6-3 Topological structures of China's IKCNs (2002-2006, 2012-2016)

	Topological structures index of networks	2002-2006	2012-2016
Basic topological properties	Average degree	28.00	72.41
	Min	1.00	2.00
	Max	169.00	210.00
	Network density	0.15	0.34
	Global efficiency	0.56	0.67
	Degree-degree correlation	-0.44	-0.38
Small-world property	Characteristic path length	1.92	1.67
	Characteristic path length of the same-size random networks	1.87	1.66
	Clustering coefficient	0.45	0.60
	Clustering coefficient of the same-size random networks	0.14	0.34
	Small-world quotient	3.01	1.77
Scale-free property	Cumulative power-law exponent	1.47	1.14
	R2	0.76	0.54
Similarities of topological structures		0.91(p<0.01)	

Source: author

6.3.1.2 **Individual network topological properties**

Figure 6-12 shows the spatial distribution of the betweenness centrality of the cities in the national IKCNs during the two sections. The cities with higher betweenness centrality are often located at the intersections of information flow in the IKCNs, in turn, control strategic resources and play the roles of "hubs" and "bridges" in the networks. It can be seen from the figure that the distribution of betweenness centrality also comply with "capital monopoly", that is, the betweenness centrality of the capital cities is much higher. However, compared with the period of 2002-2006, the distribution of betweenness centrality in the period of 2012-2016 was more balanced with the coefficient of variance reducing from 1.59 to 0.76. This indicates that the roles of small and medium-sized cities as "bridges" have improved to varying degrees.



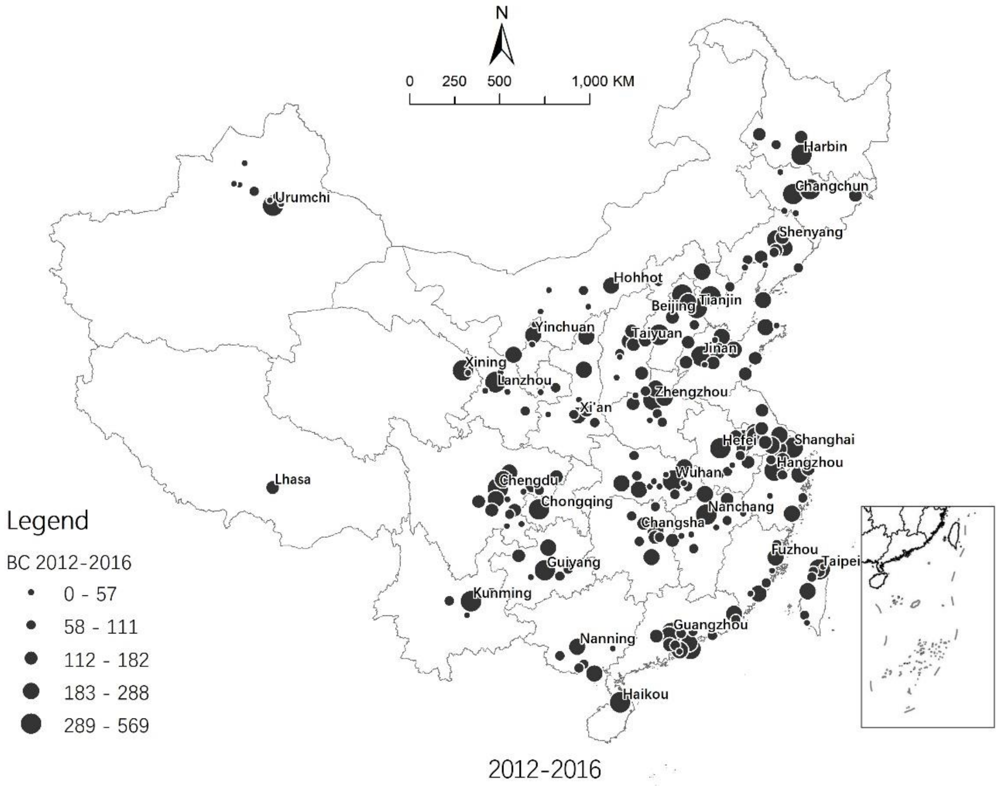
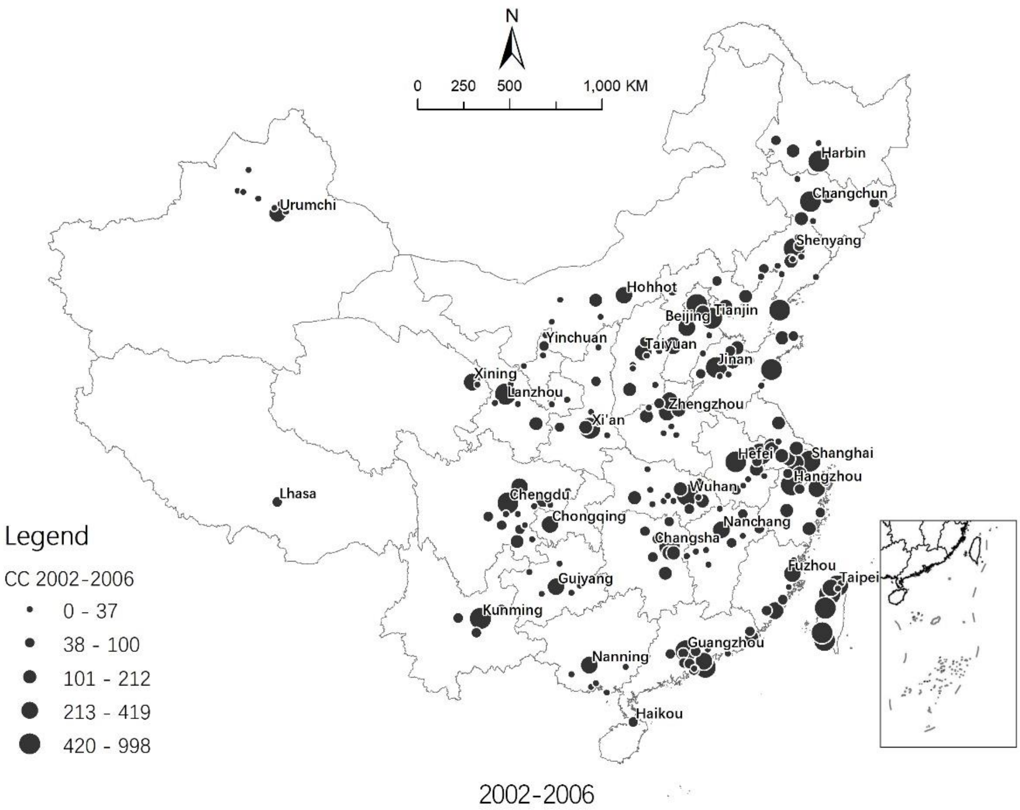


Figure 6-12 Distribution of cities' betweenness centrality

Source: author

Figure 6-13 presents the spatial distribution of closeness centrality of the cities in the KCNs in two time periods. The closeness centrality reflects the extent to which a city is not subject to other cities in the network, and thus it can reflect the city's capability of independent innovation. In addition to the obvious "capital monopoly", the overall spatial configuration have not structurally changed. However, the gap between the capital cities and other cities has been gradually widened. The coefficient of variation increased from 1.41 in 2002-2006 to 1.76 in 2012-2016, indicating there is "accumulative advantage effects" in the development of the independent innovation of the cities. That is, the cities with stronger capabilities of independent innovation will self-reinforce over time and grow faster.



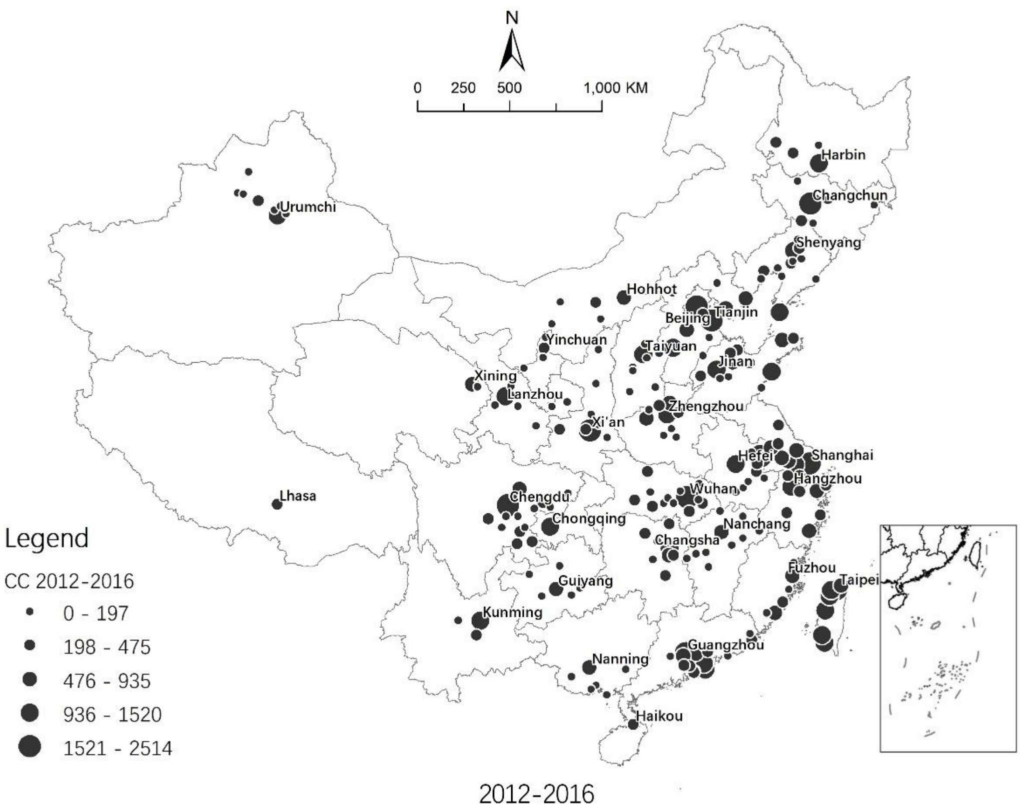


Figure 6-3 Distribution map of closeness centrality
Source: author

6.3.2 “Core-periphery” structure

Figure 6-14 shows the “core-periphery” structure of the China’s IKCNs for the period of 2002-2006 and 2012-2016. The network is divided into five levels: “core, semi-core, sub-core, semi-periphery and periphery”.

During the period of 2002-2006, Beijing was the unchallenged strong core city in the network, with Shanghai, Nanjing, Hangzhou, Wuhan and Guangzhou in the semi-core layer and 17 cities in the sub-core layer. Among those core layer cities, only Dalian and Qingdao were non-capital cities. There were 88 cities in the semi-periphery layer, including capital cities such as Shijiazhuang, Urumqi, Nanning and Hohhot in relatively lagging behind provinces, as well as prefectural-level cities like Shenzhen, Zhuhai, Suzhou, Ningbo, Changzhou, etc. In general, 88.63% of the cities in the semi-preiphery layer are located in the relatively developed provinces of East China and South China. Finally, among 81 cities in the periphery layer, the majority were smaller cities, 79.01% of which are located in the remote provinces in Southwest, Northwest and Northeast China[26].

It is noteworthy that cities in Taiwan were located in the semi-periphery layer (Taipei, Taichung, Tainan, Kaohsiung and Hsinchu) and the periphery layer (Taoyuan and Keelung), albeit they were highly connected in terms of the KNC. This is because most of the collaboration links of the Taiwanese cities were confined within the island so that their interactions with other cities in China mainland were much weaker and thus were “isolated” from the other cities in the network.

During the period of 2012-2016, most changes occurred in the core, semi-core and sub-core layers. Shanghai and Nanjing have climbed into the core layer. The number of cities in the semi-core and sub-core layers increased to 10 and 22, respectively. Among 25 core-layer cities, 17 were capital cities, and the remaining 8 were advanced cities in terms of socio-economic development and innovation capabilities, namely Ningbo, Qingdao, Dalian, Shenzhen, Wuxi, Xiamen and Wenzhou. Compared with the period of 2002-2006, the composition of two peripheral layers have remained stable with 16 cities promoted from the periphery layer to the semi-periphery layer, including Taoyuan, Xiaogan, Siping, Xianning, Zigong and Xuchang, etc.

[26] Northeast China (Heilongjiang Province, Jilin Province, Liaoning Province, Inner Mongolia Autonomous Region), East China (Shanghai, Jiangsu Province, Zhejiang Province, Anhui Province, Fujian Province, Jiangxi Province, Shandong Province, Taiwan) Province), North China (Beijing, Tianjin, Shanxi, Hebei, Inner Mongolia Autonomous Region), South China (Henan Province, Hubei Province, Hunan Province, Guangxi Zhuang Autonomous Region, Guangdong Province, Hong Kong Special Administrative Region, Macao Special Administrative Region, Hainan Province) , Southwest (Chongqing, Sichuan, Guizhou, Yunnan, Tibet Autonomous Region), Northwest (Shaanxi, Gansu, Qinghai, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region)

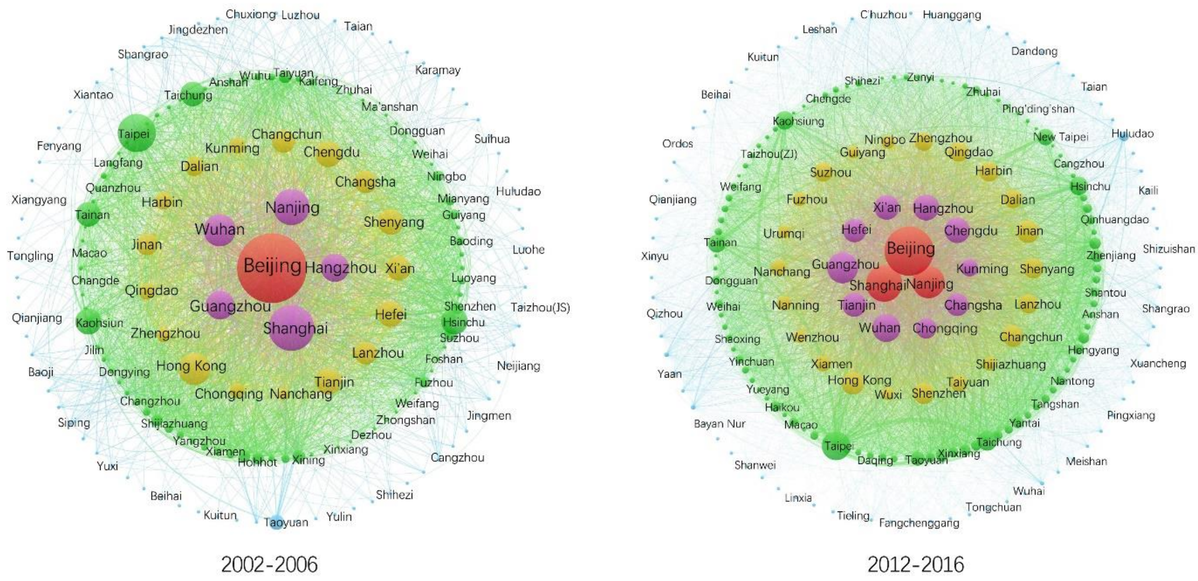


Figure 6-14 Core-periphery structure of China's IKCNs (2002-2006, 2012-2016)

Source: author

Note: The size of the city node is proportional to its KNC

6.3.3 "External reach" and "internal reach"

Table 6-9 lists the top 20 cities in terms of the "external reach" and "internal reach" during the two time periods. In the 2002-2006 period, the five most outward cities were Taiwanese cities. However, their index of external reach were not even on the list. This again confirms their isolation, that is cities in Taiwan collaborate with each other more intensively and frequently than with cities in mainland China. The following cities are mostly core cities in the major city-regions, such as Shanghai, Nanjing, Hefei and Hangzhou in the YRD city-region, Beijing, Tianjin and Shijiazhuang in the BTH city-region; Guangzhou and Hong Kong in the GBA city-region. This indicates that these city-regions are relatively mature in the development of collaborative networks. During the period of 2012-2016, the top 20 cities did not change much, yet particularly some Taiwanese cities have been replaced by cities in the YRD city-region.

In the period of 2002-2006, 19 among the most outward 20 cities were capital cities. This number was 18 in the period of 2012-2016. First, Beijing and Shanghai have always been the top 2 cities in terms of external reach, indicating their roles as hub cities in the IKCNs at national scale. Second, from the perspective of spatial distribution, cities with higher external reach in the period of 2002-2006 were traditional industrial centers such as Wuhan, Lanzhou, Changchun and Xi'an. By the period of 2012-2016, cities that have been possessing the location advantages and the preferential policies since opening-up become more outward such as Nanjing, Guangzhou, and Chengdu. Third, the external reach of Hong Kong significantly declined, from the 4th in the period of 2002-2006 to the 15th in the period of 2012-2016. This, however, does not imply that the network connectivity and the innovation capability of Hong Kong decreased in absolute term but can be attributed to the rapid improvement of the overall innovation capacity and network connectivity of the cities in mainland China.

Table 6-9 Top 20 cities in terms of the "internal reach" and the "external reach" (2002-2006, 2012-2016)

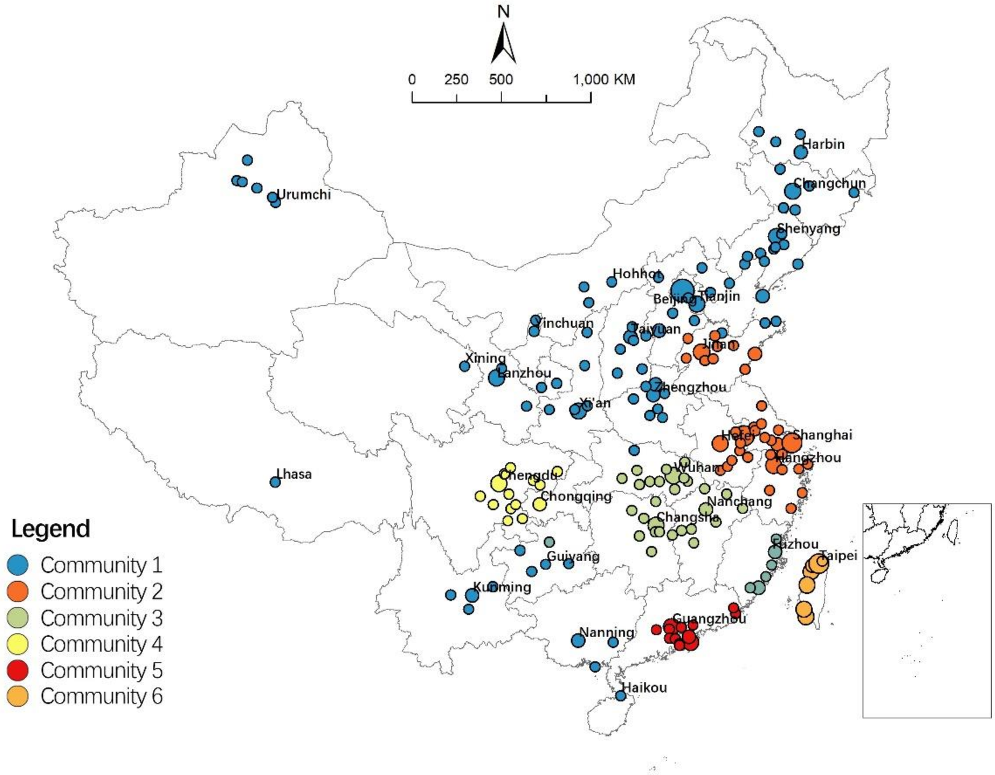
Rank	2002-2006 （%）				2012-2016（%）			
	City	Internal reach	City	External reach	City	Internal reach	City	External reach
1	Taipei	100.00	Beijing	100.00	Taipei	100.00	Beijing	100.00
2	Hsinchu	68.96	Shanghai	75.09	Taichung	69.29	Shanghai	73.28
3	Taichung	67.39	Wuhan	69.95	Shanghai	69.09	Guangzhou	72.40
4	Kaohsiung	67.39	Hong Kong	69.76	New Taipei	68.63	Nanjing	70.51
5	Tainan	59.10	Lanzhou	66.96	Nanjing	67.35	Wuhan	69.34
6	Shanghai	50.26	Changchun	65.39	Hsinchu	59.56	Xi'an	66.27
7	Nanjing	44.11	Xi'an	63.94	Hangzhou	56.30	Chengdu	65.46
8	Hefei	39.52	Nanjing	63.40	Kaohsiung	56.05	Changchun City	65.44
9	Hangzhou	38.58	Guangzhou	63.17	Hefei	53.66	Tianjin	62.89
10	Taoyuan	38.55	Tianjin	61.03	Tainan	51.90	Lanzhou	61.01
11	Beijing	28.03	Shenyang	60.34	Taoyuan	42.91	Qingdao	57.27
12	Tianjin	25.77	Kunming	56.62	Suzhou	38.78	Jinan	55.22
13	Suzhou	18.72	Hefei	56.11	Beijing	33.11	Shenyang	54.35
14	Ningbo	16.96	Chengdu	55.37	Tianjin	31.19	Harbin	54.01
15	Wuhan	15.89	Jinan	54.64	Zhenjiang	25.97	Hong Kong	53.98
16	Changsha	15.76	Dalian	51.66	Guangzhou	25.73	Shenzhen	53.88
17	Shijiazhuang	14.77	Changsha	51.45	Ningbo	24.84	Hangzhou	53.37
18	Zhenjiang	13.37	Harbin	50.08	Wuxi	24.44	Kunming	53.28
19	Hong Kong	13.13	Hangzhou	49.30	Changzhou	24.02	Hefei	52.50
20	Guangzhou	13.02	Qingdao	47.64	Hong Kong	22.90	Dalian	52.05

Source：author

6.3.4 "Community" structure

Figure 6-15 shows the community structure of the national KCNs for the two time periods. There were 6 communities in the period of 2002-2006. Being the largest in terms of the spatial range and the number of cities included, the "community 1" covered most of the provinces in North China, Northeast China, and Northwest China, as well as remote cities in Fujian, Guangxi, Guizhou, and Yunnan provinces. This resonances with the discussion of Castells (2002) on the dynamic of the "space of flow" and "space of place", in which the friction costs of the physical distance can be compensated by networks. In contrast, the other 5 communities are more “localized”, such as the YRD city-region, the MRY city-region, the CHC city-region, the GBA city-region and the EST city-region, indicating that “space of flow” is , to a large extent, confined within “space of place”.

During the period of 2012-2016, the community structure of the national IKCN have witnessed both “splitting” and “merging” in some communities. First, the former largest cluster split into three different communities, namely the northeast community, the central plains community and the Shandong peninsula cluster. While the cities of Hubei split from the middle reaches of the Yangtze River community and merged into the northern community. The Yangtze River Delta community split the Jiangsu-Anhui cluster and meanwhile merged the west coast strait community and the Hunan community. Guizhou and Guangxi once belonged to the northern community merged into Chengdu-Chongqing community and split a one independent community, respectively. The coexistence of “splitting” and “merging” in the evolution of the national IKCN actually reflects the interactive mechanism between the spatial configuration and the networking processes of the national IKCN. To put it simple, this dynamic process can be summarized as the dual effects of “geographical proximity” in shaping and influencing on the formation of the IKCNs: on one hand, geographical proximity can facilitate the formation of collaborative networks and on the other hand, it is not the only determinant since networking processes can, to some extent, diminish the friction cost generated by physical distance and thus facilitate the establishment and maintenance of the long-distance collaborations. That is to say, certain factors can replace the role of geographical proximity in the formation of knowledge networks.



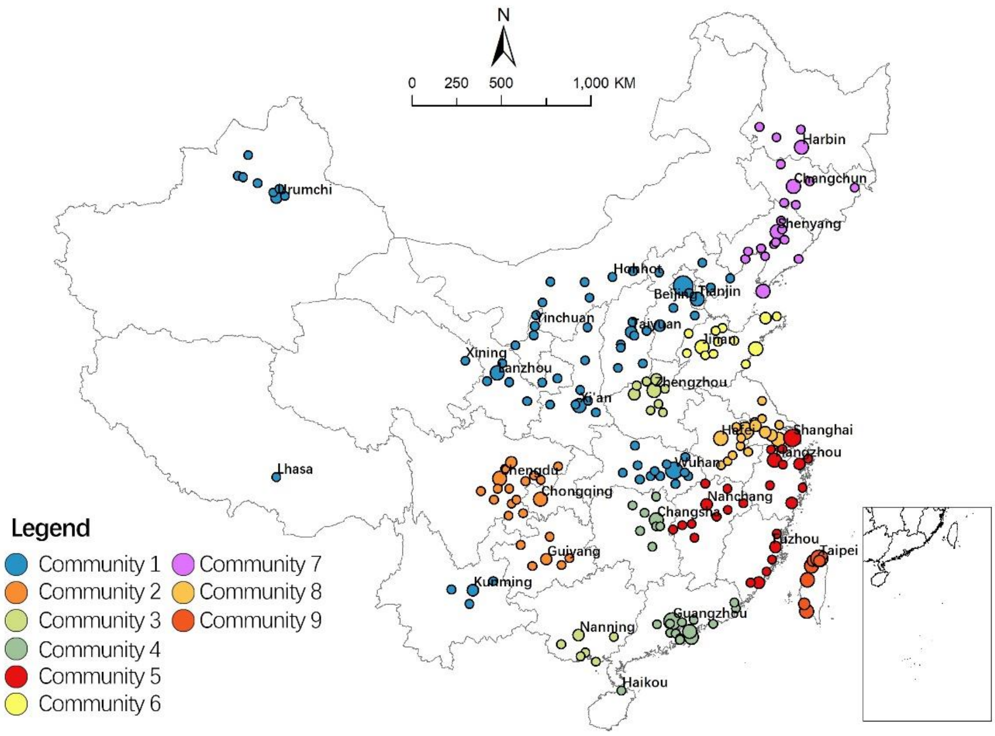


Figure 6-15 The community structure of China's IKCNs (2002-2006, 2012-2016)
Source: author

6.3.5 “Center-hinterlands” structure

Figure 6-16 and figure 6-17 show the “central-hinterland” structure of China’s IKCNS for the period of 2002-2006 and of 2012-2016, respectively. In general, the “central-hinterland” structure of the national IKCN has remained stable over time. It consists of two different sizes of “hub-spoke” components. The larger one is centered on Beijing while the smaller one is centered on Taipei. For the former, the direct hinterland cities of Beijing include capitals on one hand, and lots of northern cities of different size, which also explains the constitution of the northern community mentioned in previous section. In addition, several sub-branches are formed around Beijing and hinged by provincial capitals.

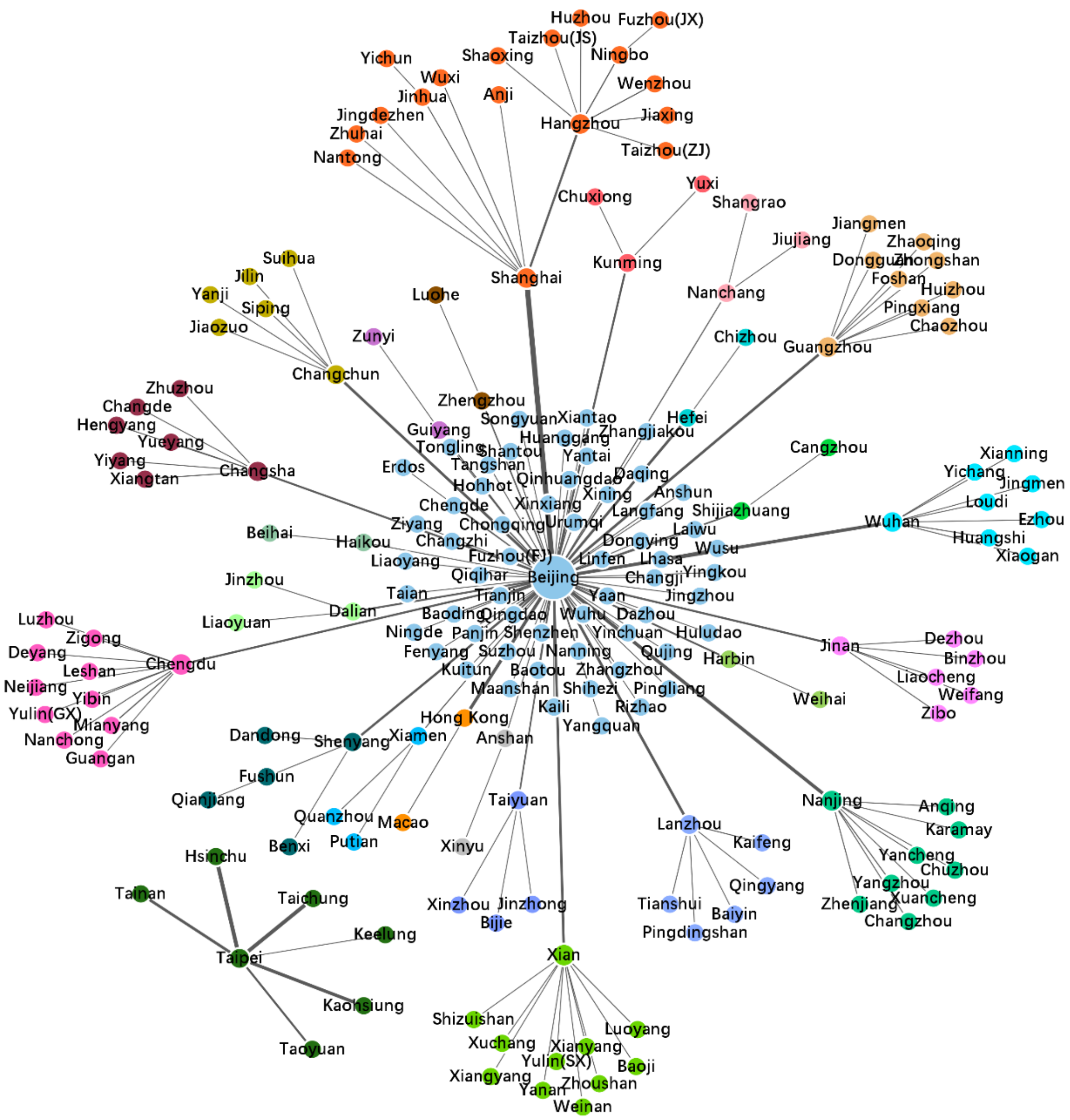


Figure 6-16 “Center-hinterlands“ structure of China’s KCNs (2002-2006)

Source: author

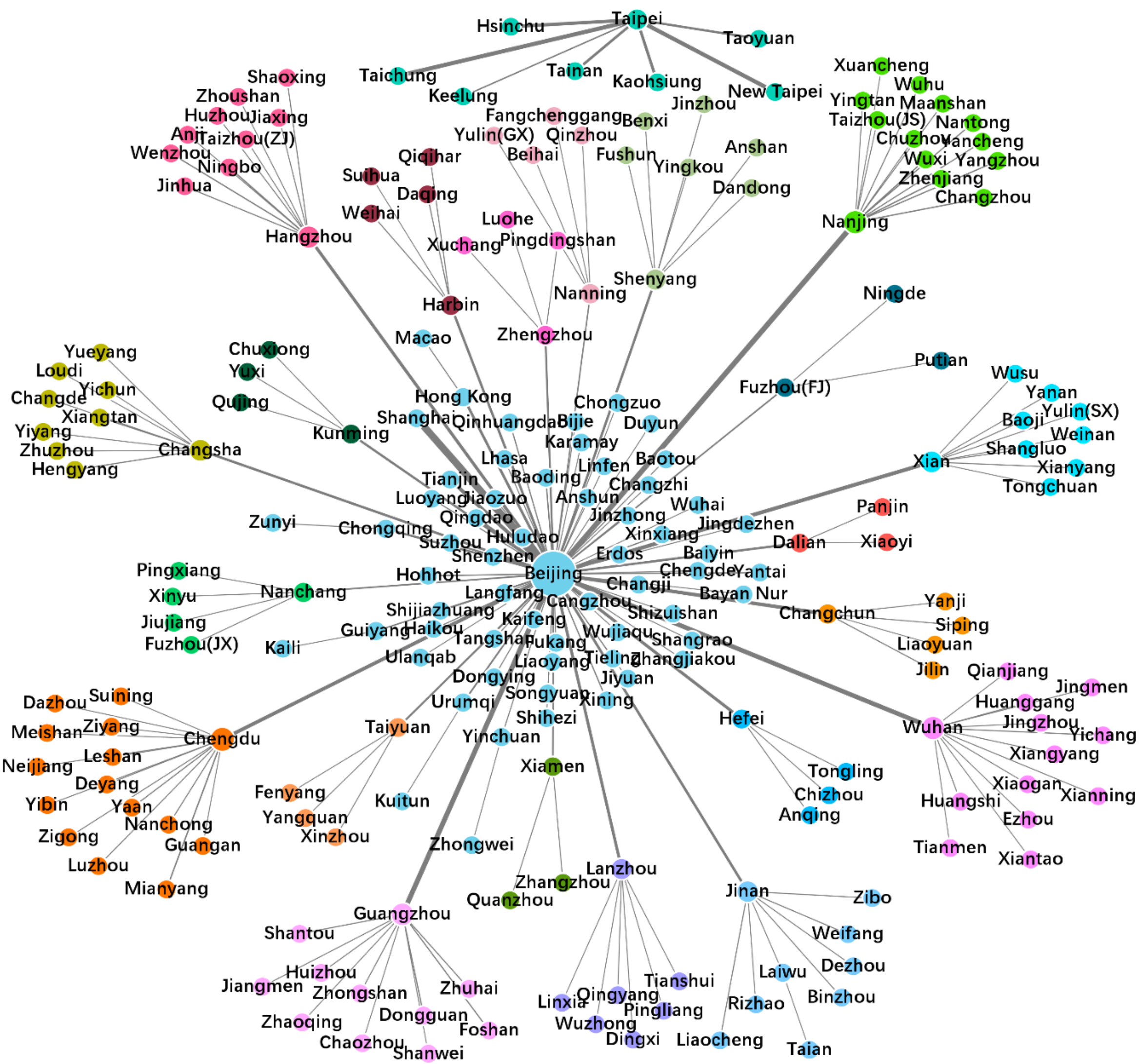


Figure 6-17 “Center-hinterlands” structure of China KCNs (2012-2016)

Source: author

In spite of the stable overall structure of the national IKCNs over time, changes can also be found, especially in the YRD city-region. In the period of 2002-2006, Hangzhou was the direct hinterland of Shanghai and acted as the hub city for the other cities in Zhejiang Province. By the period of 2012-2016, Hangzhou was detached from Shanghai and became the direct hinterland of Beijing, suggesting the improvement of the importance of Hangzhou in the national IKCN.

6.4 Extended discussion: the impacts of network positions on the innovation performance of cities

In endogenous growth theory, technological progress and knowledge innovation are considered as endogenous variables of national, regional or urban economic growth. How to improve the innovation performance has become the focus of economic geography. In literature, the "knowledge production function" is commonly used to explore the influencing factors for the innovation performance of the countries, regions or cities (Autant-Bernard, 2012; Basile and Mínguez, 2018; Jaffe, 1989). Under this regime, regional knowledge inputs such as R&D expenditure, human capitals and technology bases are considered to be the determinant factors for improving knowledge output. In addition, geographic factors (spatial proximity in particular) are also recognized to play an important role in influencing the process of knowledge spillovers, thus the econometric estimations based on distance weight matrixes are widely used in such research.

In recent years, some scholars have also pointed out that rather than solely depending on local investment and endowments, the regional innovation performance also hinges on network factors. For regions do not occupy advantageous locations and sufficient local input, being in advantageous positions in trans-local networks can, to some extent, compensate for these disadvantages (Araújo et al., 2018; Autant-Bernard et al., 2007b; Boschma and Ter Wal, 2007; Maggioni and Uberti, 2011; Wanzenbock et al., 2014). Taking China's IKCN as the study case, the remainder of this section will investigate the roles of individual network topological properties, i.e. "centrality", "closure", "structural hole" and "internal /external reach" in improving cities' innovation performance.

6.4.1 Theoretical basis

6.4.1.1 **The impact of "centrality" on innovation performance**

"Centrality" is the most basic indicator to measure the importance and role of network members in networks. Broadly speaking, in the KCNs, high centrality not only refers to that the innovation actor is at the core of the network, but also that the actor tends to have stronger innovation capability (Lee and Kim, 2011; Powell Et al, 1996; Qian et al, 2010a). Among them, degree centrality (DC), designed to measure the number of direct partners of a focal innovation actor in the KCNs, reflects their importance in the networks. On one hand, higher degree centrality means more new information can be directly and effectively obtained by the actor. On the other hand, it indicates higher power, prestige and visibility in the network that enable it easier to attract potential collaborators (Granovetter, 1983), which eventually has a positive effect on the innovation performance of the actors. This has been confirmed by many scholars (Cassi and Plunket, 2015; Gui et al., 2018 Fan et al., 2010; Qian et al., 2010b; Wang and Kang, 2018; Zhou et al., 2017). However, some scholars point out that the innovation actors cannot collaborate infinitely. Having excessive collaborations will lead higher costs and the risk of opportunism (Hou et al., 2019).

6.4.1.2 **The impact of "closure" on innovation output**

Closure is used to measure the cohesiveness and embeddedness of nodes in the networks—whether a node and its direct neighbors forms a triadic closure. In social sciences, the "social capital" and the social networks that underpinning are considered to be influential to the sustained development and performance of the economy (Granovetter, 2005; Guo et al., 2003; Qi and Li, 2018). Coleman (1988) points out that the more Tertius iungens actors possesses, the more they embeds in the social network, in turn they can utilize more capital and benefit more. Ma (2017) investigates the petroleum equipment manufacturing industry in Dongying (China) and finds out that the closure is specifically favorable for innovation in this industry and that members who are more embedded in the network have more innovation output. Zhang and Hu (2013) explore how closure affects different types of technological innovation activities in enterprises. Their finding is that closure is only beneficial for explorative innovation activities.

6.4.1.3 **Impact of "structural holes" on innovation output**

The "structural hole", originally developed by Burt (1992), is understood as a gap between two individuals who have complementary information sources. The individual who acts as a mediator between two or more closely connected groups of people occupies the "structural hole" of the network, and could gain important comparative advantages. In particular, the position of a bridge between distinct groups allows him or her to transfer or gatekeep valuable information from one group to another. (Burt, 1992; Liang, 2011; Zhu, et al. 2018). Fleming et al. (2007) study the careers of 35,400 inventors from 1975 to 2002 and find that inventors occupying more structural holes are more creative, but excessive structure hole is not conducive to the diffusion of new knowledge. Similar results can be found in the study of the collaborative networks of high-tech enterprises by Podolny and Baron (1997) that though beneficial for individuals' innovation performance, structural holes do have negative effects on the innovation performance and knowledge spillovers of the overall network. After investigating the Canadian inter-organizational collaboration networks, Zaheer and Bell (2005) find that the structural holes can only improve innovation performance when the companies themselves already are innovative to a certain degree. Using co-patent data in the field of new energy, Guan et al. (2015) examine the impact of closure and structural holes on the innovation performance of American cities both at the national and urban scales. Their finding is that cities occupying more structural holes are more productive and that closure significantly inhibits the innovation performance.

However, according to some empirical research, the relationship of closure/structure holes and innovation performance is not linear but rather an inverted U-shaped curve. That is to say, closure may provide advantages for actors at the early stages of the innovation process, but the reciprocal obligation followed renders it difficult to get rid of the lock-in and in turn restrain their ability to find new opportunities afterwards (Lee and Kim, 2011). Although openness encourages innovation performance, occupying too much structural holes brings actors unnecessary costs, including the direct cost of obtaining non-redundant information and the indirect cost of processing, handling and integrating too much redundant information (Luo and Han, 2018; Ma et al., 2018; Yu et al., 2018).

In recent years, more and more scholars propose that “closure” and “structural holes” are not the opposites and that there might be complementarity and substitution between them under different conditions (Gargiulo and Benassi, 2000; She et al., 2018). For example, Latora et al. (2013) demonstrate “closure” and “structural holes” are consistent in logic through mathematical modeling and emphasize that they are essentially “two sides of a coin”. After investigating the innovation collaboration networks of 276 R&D personnel, Tortoriello and Krackhardt (2010) find that neither structural hole nor closure solely affect the innovation performance of individuals. Only when actors and their neighbors have formed closures, occupying structural hole can be positive for innovation performance. Wei and Dang (2017) examine the industry alliances and co-authored patent collaboration networks and conclude that open networks are more beneficial for innovation of specialized knowledge while closed networks are more favorable for innovation of diverse knowledge.

6.4.1.4 **Impact of “intra-regional collaboration” and “supra-regional collaboration” on innovation performance**

According to Marshall’s industrial district theory, opportunities of face-to-face communication and trust-based collaborative network supported by geographical proximity are important for the long-term development for innovation clusters. Since then, a series of concepts and discussions about regional innovation have emerged, such as the “buzz” (Storper and Venables, 2004b), the “noise” (Grabher, 2002) and the “local broadcasting” (Owen-Smith and Powell, 2004). Though more or less different, the local innovation mechanisms they emphasize are fairly similar: the sustained success of innovative regions can be, to a large extent, attributed to the close collaborative relations, the rich social capital and the intense knowledge exchange among innovation actors. The processes take place among actors embedded in a community by just “being there”: spontaneous learning, unplanned meetings, shared culture and traditions are beneficial for the formation of favorable innovation milieus and in turn foster the generation of new knowledge. The cost of participating in such process is low, and you just need “being there” to get constantly updated information and knowledge.

In the context of globalization, traditional industrial regions and clusters face more challenges. Self-sufficient endogenous growth is no longer sustainable (Asheim and Isaksen, 2002; Markusen, 1996). Maintaining competitive advantage needs extra-local interactions, external resources and markets which can be achieved by trans-local collaborations. A good example is the Swiss watch industry and the crises it experienced. The regional crises that took place in the 1970s and 1980s was due to a collective underestimation of new technological trajectories (quartz and digital technologies) that had been developed in other countries and that created new market opportunities for the producers in these countries (Glasmeir 2000). It was only due to the opening up of the Swiss production system, the integration of external patterners into regional networks and the development of new institutional settings, many producers were able to jointly overcome this crisis eventually.

Bathelt et al. (2004) establish a conceptual model of "local buzz" and "global pipelines", in which they emphasize that local collaborations and trans-local collaborations are equally important for regional innovation performance. They believe that innovative regions or clusters that attain sustained development and high competitiveness not only have frequent face-to-face communication, close local collaboration and active local innovation milieu, but also have efficient, long-term, stable trans-local collaborations. High-quality cross-regional collaboration brings new knowledge and technologies that are spread and absorbed within the region through efficient local collaboration networks. However, Bathet et al. (2004) emphasize the intrinsic trade-off exist between an excessively inward-looking and an excessively outward-looking organizational structure. For the former, knowledge is easily transmitted throughout the cluster, but new external knowledge would be difficult to comprehend. For the later, the external information can be understood and translated by the gatekeepers while the internal communication gaps may prevent it from reaching the actors by whom it could be transformed into commercially useful knowledge.

Based on the above analysis, the next section will formally examine the impact of centrality, closure, structural holes and internal/external reach on the innovation performance of cities in the IKCN of China.

6.4.2 Variable construction and model selection

6.4.2.1 **Variable construction**

（1） Dependent variable

The total scientific output of cities is set as the dependent variable of measuring innovation performance.

（2） Independent variable

a) Degree centrality

Degree centrality is the number of connections a node has in network. In the IKCNs, the degree centrality is the total number of direct collaborations of a focal city, reflecting its importance in the network.

b) Closure

Local clustering coefficient, widely used in measuring the closure of nodes in networks, quantifies how close its neighbors are to be a triadic closure. The algorithm is as follows:

$$LC_{Gi} = \sum_{i=1}^{N} \frac{2E_{Gi}}{k_i(k_i - 1)} \qquad (6\text{-}2)$$

where LC_{Gi} is the local clustering coefficient of city i in the IKCN G, and E_{Gi} indicates the actual number of edges between the neighbors of node i. LC_{Gi} values between 0 and 1. If LC_{Gi} =0, it means that the city i does not have a triadic closure. If LC_{Gi} =1, it means that the city i and its neighboring cities are all in the triadic closure structure.

c) Structural holes

“Constraint” proposed by Burt is used as the indicator of the “structural holes”. This indicator measures the extent to which time and energy is concentrated within a single cluster. It consists of two components: direct, when a contact consumes a large proportion of a network’s time and energy, and indirect, when a contact controls other individuals, who consume a large proportion of a network’s time and energy. The algorithm is as follows:

$$C_{ij} = \left(p_{ij} + \sum_{q} p_{iq} p_{qj} \right)^2 \qquad (6\text{-}3)$$

Where, q is the number of third-party nodes to which both city i and city j are connected and p_{ij} is the number of the focal city i’s network contacting with j（p_{iq} and p_{qj} are defined analogously）. Then, the constraint of city i is:

$$Ci = \sum_{j} C_{ij} \qquad (6\text{-}4)$$

Cities with smaller constraint have more structural holes and have more opportunities in accessing non-redundant information. To estimate structural holes subtract C_i from 2 to represent the extent to which cities tied to a focal city I are disconnected:

$$SH_i = 2 - C_i \qquad (6\text{-}5)$$

d) "Intra-regional collaboration" and "supra-regional collaboration"

Intra-regional collaboration and extra-regional collaboration refer to the "internal reach" and "external reach" of cities in the IKCNs. Breschi and Lenzi (2013) and Araújo et al. (2018) introduce a measurement of the "internal reach" and "external reach" of cities in the IKCNs. This method has been used in previous sections and will not be detailed here.

e) Control variables

Control variables include "resource endowments", "resource input" and "institutional context". The proxy for "resource endowments" is cities' GDP that directly reflects their socio-economic development. The data is drawn from the *City Statistical Yearbook of China*. Given the time lag effect the GDP is calculated as averages of the preceding periods of 1998-2002 and of 2008-2012 respectively.

Another proxy variable that measures the cities' resource endowments is the "Herfindahl-Hirschman Index". According to Jacobs' theory of urbanization economies, the diversed industries and knowledge are beneficial for cities' innovation performance. Although originally designed for examine the degree of diversity of regional or urban industries, the Herfindahl-Hirschman Index can also be applied to measure the variety of the knowledge that cities possess:

$$HHI_m = \sum_{i=1}^{n} (X_i / X)^2 \qquad (6\text{-}6)$$

where n is the total number of scientific research fields, X_i is the total output of the city m in the i research field, and X is the total output of the country in all research fields. *HHIm* range between 1/n and 1, cities with higher *HHIm* are more diverse in terms of knowledge base.

Every journal and book covered by WoS database is assigned to at least one of the following subject categories. Every publication record in WoS core collection contains the subject category of its source publication in the 252 Categories field[27]. In order to facilitate bibliometric analysis or scientific development research, different countries and institutions have proposed different subject category schemes based on how similar the disciplines are. For example, the Organization for Economic Co-operation and Development (OECD) divides it into 6 major subjects and 42 minor subjects; Essential Science Indicators (ESI) of Thomson Reuters divides

[27] Because a research often involves multiple fields and belongs to interdisciplinary research, it can be attributed to multiple disciplines at the same time.

it into 22 subject categories; the Academic Degrees Committee of the State Council divides it into 13 major subjects and 110 minor subjects; the Research Excellence Framework (REF) divides it into 35 subject categories; Japan KAKEN divides it into 3 major subjects and 66 minor subjects[28]. In this chapter and all the content related to the subject classification in following sections, the OECD categorization is adopted[29].

The third control variable is the share of R&D expenditure in GDP, which represents the intensity of the "resource input" of different cities. The data sources from the *City Statistical Yearbook of China*. Similar to the processing of GDP, share of R&D expenditure of a city is taking the average value of the period of 1998-2002 and of 2008-2012 respectively.

The fourth control variable is the "administrative level", which is used to reflect the "capital monopoly" effect in China's unique top-down administrative system. It is set as a binary variable that values 1 If the city is a (provincial) capital, otherwise values 0.

f) Squared variable

Based on the literature review, being in a key position in the IKCNs does not necessarily improve actors' innovation performance. Embedding too much in the network, in some cases, may be detrimental. So the squared variables of the topological characteristics are introduced to test this. If the estimation results of the squared variables are negative, then there exists an inverted U-shaped relationship between the topological properties and the innovation performance of actors. In order to avoid the possibility of multivariate collinearity, the input variables are centered before those squares (subtracting the mean).

g) Time fixed effect

A binary variable is introduced to control the time fixed effect, which set as 1 for the period of 2002-2006 and as 0 for the period of 2012-2016.

6.4.2.2 **Model selection**

Since the dependent variable in this case is the count data, Poisson regression, zero-inflated Poisson regression, negative binomial regression or zero-inflated negative binomial regression should be used. In order to select the best-fitting model, a likelihood ratio test for over-dispersion and a Vuong statistic test for excessive zero counts are conducted.

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[28] http://help.prod-incites.com/inCites2Live/filterValuesGroup/researchAreaSchema.html。

[29] Refer to Appendix Ⅳ

Figure 6-10 Descriptive statistics

	Sample size	Minimum value	Maximum	Mean	Standard deviation	1	2	3	4	5	6	7	8	9
Centrality	359	2.000	194096.000	6239.862	18377.125	1.000								
Closed	359	0.345	1.000	0.779	0.164	-0.631	1.000							
Structural hole	359	1.364	1.898	1.739	0.081	0.294	-0.456	1.000						
Introversion	359	0.000	318.155	30.057	49.446	0.644	-0.636	0.280	1.000					
Extroversion	359	2.255	2361.887	386.293	449.769	0.778	-0.933	0.358	0.653	1.000				
GDP	359	2.233E + 06	2.018E+08	2.512E + 07	2.981E + 07	0.780	-0.723	0.333	0.739	0.789	1.000			
R&D ratio	359	0.017	1.578	0.246	0.202	0.481	-0.352	0.191	0.510	0.391	0.474	1.000		
Capital effect	359	0.000	1.000	0.164	0.371	0.566	-0.737	0.273	0.408	0.778	0.483	0.291	1.000	
Herfindahl Index	359	0.066	0.418	0.118	0.050	-0.254	0.499	-0.310	-0.321	-0.427	-0.376	-0.237	-0.289	1.000

Source：author

Table 6-11 Estimation results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Constant	-1.334 (0.001)***	-1.234 (0.091)***	-1.667 (0.021)***	-1.221 (0.002)***	-0.993 (0.001)***	-1.893 (0.003)***	-1.600 (0.023)***	-2.345 (0.632)*
Control variable								
GDP (ln)	0.798 (0.002)***	0.843 (0.212)***	0.801 (0.098)***	0.589 (0.432)***	0.724 (0.024)**	0.692 (0.625)**	0.490 (0.003)**	0.341 (0.023)**
R&D expenditure	0.192 (0.201)***	0.166 (0.122)***	0.167 (0.021)***	0.073 (0.097)**	0.198 (0.227)***	0.153 (0.034)***	0.302 (0.048)**	0.202 (0.057)*
Administrative level	0.402 (0.004)***	0.372 (0.056)***	0.399 (0.012)***	0.456 (0.012)***	0.393 (0.036)**	0.214 (0.004)***	0.312 (0.003)***	0.109 (0.991)**
Herfindahl index	-0.581 (0.120)***	-0.677 (0.012)**	-0.592 (0.600)***	-0.791 (0.446)**	-0.602 (0.203)***	-0.563 (0.012)*	-0.209 (0.421)**	-0.278 (0.083)
Topological characteristic variable								
Centrality		0.300 (0.240)***						0.012 (0.021)
Centrality^2		0.010 (0.019)						
Closure			-0.890 (0.230)**					-0.502 (0.260)***
Closure^2			0.288 (0.116)*					
Structural holes				0.677 (0.012)***				0.012 (0.400)*
Structural holes^2				-0.143 (0.190)**				
Internal reach					0.320 (0.090)***		0.445 (0.003)***	0.089 (0.002)***
Internal reach^2					0.001 (0.234)			
External reach						0.891 (0.002)***	0.709 (0.034)***	0.977 (0.087)**
External reach^2						-0.101 (0.056)		

Internal reach* external reach						0.024 (0.060)**	
Over-dispersion (α)	6.000***	5.563***	7.903**	6.302**	6.003***	6.032***	5.022***
Log likelyhood	-1541.168	-1582.984	-1599.003	-1634.024	-1734.001	-1688.002	-1677.301
Pseudo R2	0.231	0.221	0.322	0.234	0.201	0.256	0.266
Sample quantity	359	359	359	359	359	359	359
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Significance level: ***p<0.01, **p<0.05, *p<0.1; standard error in parentheses

Source: author

6.4.3 Results and discussions

Table 6-10 shows the descriptive statistics for the independent variables with no sign of multicollinearity. There are positive correlations between most of the variables, while the variable "local clustering coefficient" and the variable "Herfindahl index" are negatively correlated with all other variables.

Table 6-11 shows the estimation results of the fixed-effect negative binomial regression. The over-dispersion test of all models was significant at the 0.01 level, indicating that the negative binomial regression results were superior to the Poisson regression. In addition, the passage on the Wald test of all model indicates that they have a satisfactory goodness of fit and strong explanatory power. Model 1 is the baseline model with only four control variables. As expected, first, the variables "GDP" and "R&D expenditure" are significantly positive, which indicate that the higher level of urban socio-economic development and larger resource input increase the innovation performance of the cities. Second, the "administrative level" is also significantly positive, indicating that the innovation performance of the capital cities is higher than that of the non-capital cities. Third, the significantly negative variable "Herfindahl Index" implys that more diversified knowledge structure of the cities will lead to higher innovation performance, while specialized knowledge base may be detrimental to cities' innovation performance. This is consistent with the theory of "urbanization economies" developed by Jacobs.

Model 2 examines the impact of the degree centrality. The coefficient of the variable "centrality" is significantly positive while the "$centrality^2$" is not significant, suggesting a monotone linear relationship between cities' degree centrality in the IKCNs and their innovation performance. Higher degree centrality of a city means more collaborators in the IKCNs, in turn the city may have more opportunities to access to diverse external knowledge. During this process of integrating the external knowledge with the existing knowledge, the probability of generating new knowledge will significantly increase. These enable cities to continuously innovate and maintain high innovation performance. Some scholars put forward that maintaining too much collaborative ties will cost more time and resources as the unnecessary costs on filtering redundant information and knowledge surge, thus are not beneficial for innovation performance. However, this is not the case in this study. It is mainly because cities, other than individuals or institutions, have much higher margins.

In Model 3, the impact of closure on innovation performance of cities is examined. The coefficient of variable "closure" is significantly negative, indicating that high closure is not beneficial for cities' innovation performance. However, the variable "$closure^2$"is significantly positive, which indicates that as the closure of a city exceed a certain criterion, its innovation performance will increase correspondingly. One possible explanation is that higher degree of exclusivity, specificity and confidentiality is needed particularly in some high-tech or specialized fields. That is to say, for cities focusing on cutting-edge sciences and technologies and at the frontier of sophisticate innovation, higher network closure secures better innovation performance. This result is in line with the findings of Ter Wal (2014) on the biotechnology collaboration networks of Germany.

Model 4 examines the impact of structural holes on innovation performance of cities. The variable "structural holes" is significantly positive while the variable "Structure hole^2" is significantly negative, which indicates an inverted U-shaped relationship between structural holes and innovation performance. By occupying more structural holes in the IKCNs, cities are more capable of controlling resources and information. They are often the intersections for knowledge exchange as the brokers or hubs in the IKCNs, thus having higher possibilities of creating new knowledge. However, occupying too much structural holes means the cities have to deal with more redundant information and higher probability of opportunism.

Model 5 and Model 6 examine the influence of intra-regional links and extra-regional links on innovation performance of cities, respectively. The results show that both of them can significantly promote the innovation performance of cities, but there is no sign of inverted U-shaped relationships. Model 7 further examines the interaction between these two variables. The results are significantly positive, indicating that the combination of intra-regional and extra-regional collaborations will enhance the innovation performance of cities. This is consistent with the conception of the dynamics of "local buzz" and "global pipelines" (Bathett et al., 2004).

It is clear that accessing into the IKCNs and occupying an advantageous position is beneficial for cities' innovation performance. At the same, it should be emphasized that the impact of the networks on innovation is not monotone linear. Under certain conditions, the network will also has a negative effect: being too embedded or open in the network may bring redundant information and knowledge, as well as risks and opportunism. Therefore, while emphasizing integrating, accessing into the IKCNs and searching the advantageous positions in the networks, it is also imperative to pay attention to the cities' innovation capability, development stage, advantages and disadvantages, so as to develop appropriate collaboration modes and networking strategies to avoid excessive embeddedness or exposure.

6.5 Summary

This chapter studies the evolution of the IKCNs of 217 Chinese cities. The main findings are as follows:

First, the evolution of the innovation output landscape of Chinese cities is examined. The results show that: (1) In terms of spatial range, increasing number of cities are actively participating in knowledge innovation, but the spatial distribution of knowledge output between the eastern and the western China is rather uneven, albeit such gap is gradually narrowing. (2) The hierarchical structure of the scientific output is characterized by noticeable "capital monopoly". Specifically, the national capital and provincial capitals are main producers of scientific output. (3) According to the results of spatial autocorrelation analysis, most of the high-high correlation type cities are concentrated in the east coast provinces while they are spatially separated. This is mainly due to the existence of "capital monopoly", that is the sizable masses of capitals create enormous "gravitational force" that compress the physical distance.

Second, the evolution of the spatial configurations of the IKCNs of China are analyzed. The main findings are: (1) The spatial distribution of cities' KNC was sparse in the period of 2002-2006 with only the BTH, the YRD, the GHM city-regions and Taiwanese cities showing obvious spatial agglomeration. In the period of 2012-2016, the development of the CHC city-region and the CPL city-region were remarkable, that together with the BTH, the YRD and the GBA city-regions gradually formed a "diamond-shaped" spatial structure. Other regions also have experienced varying degrees of growth and development, embodied mainly by the spatial clustering of small cities around regional centers. (2) "Capital monopoly" effect is evident in the evolution of the IKCNs of China, that is, the national capitals and provincial capitals act as the hubs underpinning the IKCNs. More specifically, these capitals possess considerable collaboration links. The "capital monopoly" effect is directly related to China's top-down administrative system and hierarchical institutional arrangement. (3) The spatial reach of different cities are different, and the roles of the cities play in the network are also different. (4) the spatial organization of China's IKCNs show both characteristics of the "central place model" and the "city network model". The top-down administrative hierarchy and the uneven resource allocation are important factors in shaping this spatial configuration.

Third, the evolution of the topological structures of China's IKCNs are studied. The results show that: (1) the networks showed "small-world" and "scale-free" property. (2) The "core-periphery" structure of the IKCNs is evident and stable. In the period of 2002-2006, Beijing was the unchallenged center city in the network, while in the period of 2012-2016, Shanghai and Nanjing joined in the club. (3) by analyzing the "internal reach" and the "external reach" of the cities in the IKCNs, the dynamics of "local buzz" and "global pipelines" are discussed. The cities' inward and outward status are highly related to the development stages and the regional contexts. (4) In the "community" structure of the IKCNs, the "geographical proximity" plays an important role in shaping and influencing the formation of the IKCNs. However, geographical proximity is not the only determinant. The network can, in some cases, produce the "compression" effect on the space and hence offset the friction costs caused by the physical distance, in which long-distance collaborations are established and maintained. (5) The "center-hinterland” structure of the IKCNs is analyzed. It be summarized as a “hub-spoke” structure centered on Beijing attached by sub-branches hinged by provincial capitals.

In addition, this chapter discusses the impact of individual network topology on cities innovation performance. The research results show: (1) the degree centrality plays a positive role in promoting innovation performance of cities. There is a U-shaped relationship between closure and innovation performance of cities. (2) The relationship between structural holes and cities’ innovation performance is inverted U-shaped. (3) intra-regional collaborations and extra-regional collaborations have positive impacts on the innovation performance of cities, both separately and conjunctionally.

Chapter 7 The evolution of regional interurban knowledge collaboration networks

City-regions are highly integrated urban groups in terms of spatial continuity and functional synergy (Fang, 2014). In 2013, for the first time, the Central Committee of the Communist Party of China (CPC) held an central working conference on urban and rural development, in which the regional integration and optimizing the development city-regions are designated as the key spatial coordination and policy strategies of China's rapid urbanization. Since then, a series of official documents have highlighted the importance and necessity of city-regions as the main embodiment of the socio-economic development of the state, such as the "*National New Urbanization Plan (2014-2020)*" and the "*National Thirteenth Five-Year Plan*" all. City-regions or megalopolis, proposed by Gottmann (1957), are incubators for innovation production, and are hinges of the diffusion of knowledge. In the era of knowledge-based economy, city-regions are the main players and spatial-economic entities in the global, national and regional competition of innovation. Therefore, it is imperative to carry out research on the IKCNs at the regional scale with the city-regions as the basic units.

7.1 Research objects

7.1.1 Designations of China's city-regions

City-region related research and practice in China started rather late. However, recent years have witnessed burgeoning literature or normative practices about the designation, identification and classification of the national urban system through the lens city-regions. Table 7-1 lists the key researches and plans on the topic of city-region designation since 2000. In this chapter, the designation of the national city-region system is based on the "5+9+6" scheme proposed by Fang et al. (2005). The fundamental spatial structure of their scheme is based on the "*The National Plan for Functional Zones*" the *"National Urban System Planning"* , in which the the national urban system is divided into 20 main city-regions, including 5 national level city-regions, 9 regional level city-regions and 6 local level city-regions.

Table 7-1 Main schemes of the designation of national urban system since 2000

Scholars or institutions	Publications or plans	Scheme	City-regions
Fang et al. (2016)	City-regions Development Report of China (2016)	“5+9+6”	5 national level city-regions
			9 regional level city-regions
			6 local level city-regions
State council	The National Plan for Functional Zones	“3+18”	3 optimizing development zones
（2011）			18 key development zones
Fang et al.	City-regions Development Report of China (2010)	“15+8”	15 developed city-regions
（2010）			8 under-developed city-regions
State council	National Urban System planning	“3+8”	3 major city-regions
（2007）			8 key city-regions
Yao et al.（1992）	Urban Agglomeration Development of China	“6+7”	6 mega city-regions
			7 megapolitan areas
Gu et al.（2008）	Structures, processed and mechanisms of China’s urbanization	“3+3+7+17”	3 mega city-regions
			3 major city-regions
			7 medium city-regions
			17 small city-regions
Ning et al.（2015）	Several issues of the development of China’s urban agglomerations	“10+3”	10 developed city-regions
			3 developing city-regions

Source：author

7.1.2 “5+8+6+1” national city-regions system

In this chapter, the designation scheme is based on the “5+9+6” scheme proposed by Fang et al. (2005). According to the “*Development Plan of the Yangtze River Delta urban agglomeration (2016)*” issued by the State Council , the Jianghuai city region (in the scheme of Fang et al.) is merged into the YRD city-region. In addition, according to the “*Development Plan of the Guangdong-Hong Kong-Macao Great Bay Area*” issued by the State Council in 2019, Hong Kong and Macao are merge into the PRD city-region (in Fang et al.’s scheme) and renamed as the GBA city-region. In addition, this thesis also incorporates Taiwanese cities located along the East-Strait in the study and termed as East-Strait city-region (EST). The designation scheme of city-regions in this chapter is thus the “5+8+6+1” national urban system, including 5 national level city-regions, 8 sub-national level city-regions, 6 regional level city-regions and one Taiwanese city-region(Figure 7-1, Table 7-2).

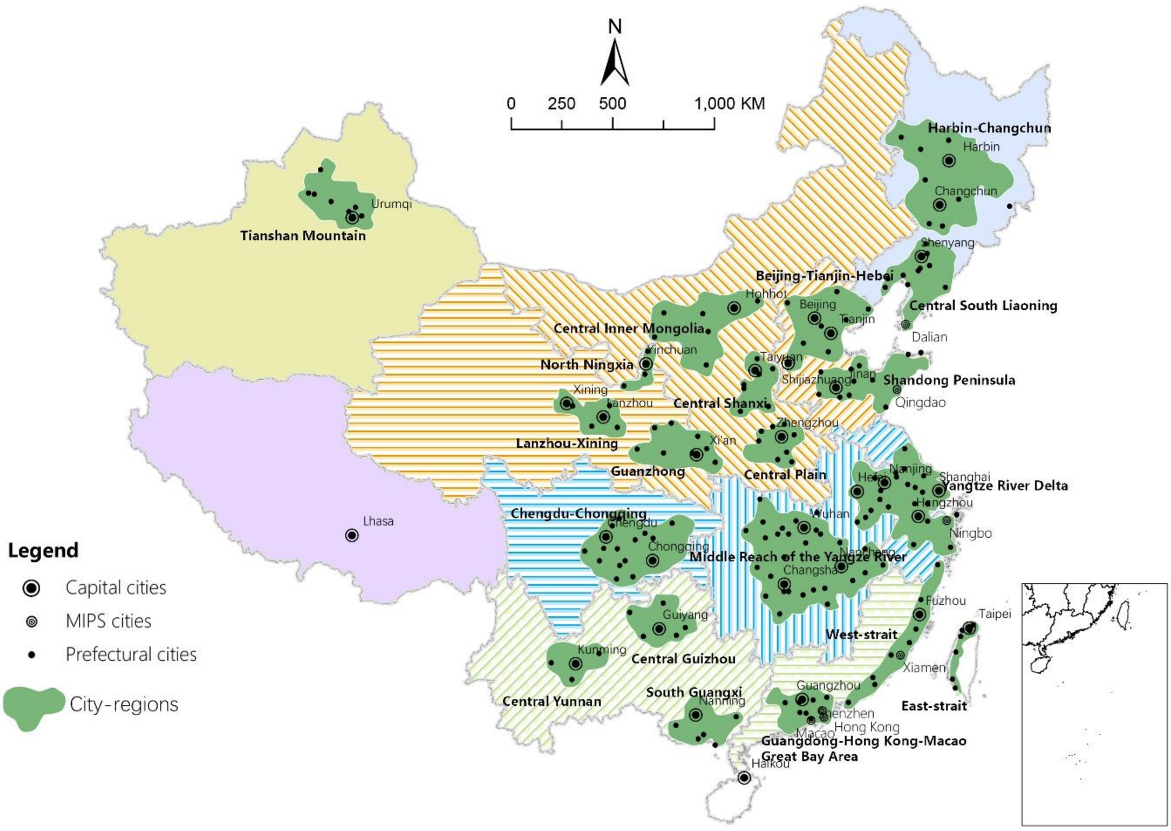


Table 7-1 The “5+8+6+1” city-region designation scheme of China’s urban system
Source: author

Figure 7-2 The designation scheme of China's city-regions

Serial number	Categorization	city-region	Spatial range
1	5 national level city-regions	The Yangtze River Delta city-region (YRD)	Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, Taizhou, Yancheng, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Zhoushan, Taizhou, Jinhua, Hefei, Wuhu, Anqing, Chizhou, Tongling, Xuancheng, Maanshan, Zhangzhou
2		The Great Bay Area city-region (GBA)	Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, Zhongshan, Hong Kong, Macau
3		The Beijing-Tianjin-Hebei city-region (BTH)	Beijing, Tianjin, Tangshan, Langfang, Baoding, Qinhuangdao, Shijiazhuang, Zhangzhou, Chengde, Zhangjiakou
4		The Middle Reach of Yangtze River city-region (MRY)	Wuhan, Huangshi, Ezhou, Xiaogan, Huanggang, Xianning, Xiantao, Qianjiang, Tianmen, Xiangyang, Yichang, Jingzhou, Jingmen, Changsha, Zhuzhou, Xiangtan, Hengyang, Yueyang, Yiyang, Changde, Loudi, Nanchang, Jiujiang, Jingdezhen, Yingtan , Xinyu, Fuzhou, Yichun, Pingxiang, Shangrao, Ji'an
5		The Chengdu-Chongqing city-region (CHC)	Chongqing, Chengdu, Deyang, Mianyang, Meishan, Ziyang, Suining, Leshan, Ya'an, Zigong, Zhangzhou, Neijiang, Nanchong, Yibin, Dazhou, Guang'an
6	8 sub-national level city-regions	The Central South Liaoning city-region (CSL)	Shenyang, Dalian, Dandong, Jinzhou, Yingkou, Panjin, Huludao, Anshan, Fushun, Benxi, Liaoning, Tieling
7		The Shandong Peninsula city-region (SDP)	Jinan, Qingdao, Yantai, Weihai, Rizhao, Dongying, Weifang, Zibo, Tai'an, Laiwu, Binzhou, Dezhou, Liaocheng
8		The West-Strait city-region (WST)	Fuzhou, Xiamen, Quanzhou, Wenzhou, Shantou, Zhangzhou, Putian, Ningde, Chaozhou, Jieyang, Shanwei
9		The Harbin-Changchun city-region (HAC)	Harbin, Daqing, Qiqihar, Suihua, Mudanjiang, Changchun, Jilin, Songyuan, Siping, Liaoyuan, Yanji
10		The Central Plain city-region (CPL)	Zhengzhou, Luoyang, Kaifeng, Xinxiang, Jiaozuo, Xuchang, Jiyuan, Pingdingshan, Weihe
11		The Guangzhong city-region (GZP)	Xi'an, Xianyang, Baoji, Tongchuan, Weinan, Shangluo, Tianshui, Yan'an, Qingyang, Pingliang
12		The South Guangxi city-region (SGX)	Nanning, Beihai, Fangchenggang, Qinzhou, Yulin, Chongzuo
13		The Tianshan Mountain city-region (TSM)	Urumqi, Shihezi, Changji, Jikang, Kuitun, Wusu, Wujiaqu, Karamay
14	6 regional city-regions	The Central Shanxi city-region	Taiyuan, Jinzhong, Quanyang, Zhangzhou, Linyi, Changzhi, Fuyang, Xiaoyi

15		The Central Inner Mongolia city-region (CIM)	Hohhot, Baotou, Erdos, Wulanchabu, Bayannaoer, Wuhai, Yulin
16		The Central Yunnan city-region (CYN)	Kunming, Qujing, Yuxi, Chuxiong
17		The Central Guizhou city-region (CGZ)	Guiyang, Zunyi, Anshun, Bijie, Kaili, Duyun
18		The Lanzhou-Xining city-region (LAX)	Lanzhou, Baiyin, Xining, Haidong, Dingxi, Linxia
19		The North Ningxia city-region (NNX)	Yinchuan, Wuzhong, Shizuishan, Zhongwei
20	1 Taiwanese city-region	The East-Strait city-region (EST)	Taipei, New Taipei, Hsinchu, Kaohsiung, Keelung, Taichung, Tainan, Taoyuan

Source: author

By the end of 2016, China's city-regions[30] accounted for 29.18% of the urbanized area of the world and 70.13% of the nation. It accounted for 76.22% of the total population, 87.99% of the GDP, 55.11% of the national added value of the primary industry, 95.11% of the national added value of the second industry, 79.82% of the national added value of the tertiary industry, 85.11% of China's total retail sales of consumer goods, 77.89% of the society fixed assets, 92.38% of the foreign direct investments, 93.22% of the total import and export volume and 85.12% of the local revenue[31].

7.1.3 The evolution of the landscape of the scientific output of China's city-regions

In terms of innovation output, it can be seen from Table 7-3 that these 20 city-regions produced more than 90% of the scientific output in China in both period of 2002-2006 and of 2012-2016. During the period of 2002-2006, the BTH city-region was the most productive city-region, accounting for 31.12% of the country's total output, followed by the YRD city-region that accounts for 27.37% and the EST city-region that accounts for 18.77%. The MRY city-region (8.70%) and the HAC city-region (5.39%) were in the fourth and fifth place, respectively. The national share of the CHC city-region was 4.23% who fell behind the HAC city-region, this is largely due to the fact that the HAC city-region, once an important region of the northeast traditional industrial bases, still have industrial advantages and technological accumulation over the CHC city-region prior to the state-led regional rebalance strategy of the West-

[30] Taiwan province is not included in these statistics.

[31] Cited from the China City Statistical Yearbook 2017.

Development. In general, these 20 city-regions' landscape of the scientific output is consistent with the "5+8+6+1" national urban system in terms of size and socio-economic development.

During the period of 2012-2016, the five national level city-regions accounted for 68.82% of the national scientific output. The YRD city-region has surpassed the BTH city-region to become the most productive city-regions, while the scientific output of the CHC also has surpassed that of the HAC city-region. However, there has been a sharp decrease of the EST city-region, which directly reflects the rapid rise of Chinese mainland cities as a whole.

Table 7 -3 The scientific output of city-regions and their national shares (2002-2006, 2012-2016)

	2002-2006		2012-2016	
city-region	Scientific output	National share	Scientific output	National share
YRD	89,850	27.37	406,854	30.03
BTH	102,154	31.12	384,331	28.36
GBA	38,158	11.62	146,371	10.80
MRY	28,558	8.70	144,282	10.65
EST	70,272	18.77	140,093	9.35
CHC	13,873	4.23	98,323	7.26
HAC	17,690	5.39	79,258	5.85
SDP	13,071	3.98	73,936	5.46
GZP	12,387	3.77	67,703	5.00
CSL	15,765	4.80	59,439	4.39
WST	6,732	2.05	42,444	3.13
CPL	4,333	1.32	33,343	2.46
LAX	8,047	2.45	26,158	1.93
CYN	3,541	1.08	17,506	1.29
CSX	3,153	0.96	14,774	1.09
TSM	900	0.27	9,352	0.69
SGX	900	0.27	9,186	0.68
CGZ	1,066	0.32	7,297	0.54
CIM	653	0.20	5,672	0.42
NNX	181	0.06	1,927	0.14
Total	374,351	0.92	1,435,668	0.96
The national output	406,949	100.00	1,498,762	100.00

Source: author

Figure 7-2 shows the spatial distribution of scientific output of the 20 city-regions. In general, five national level city-regions in the mainland and the EST city-region in Taiwan have always been the poles in the landscape of the national scientific output, and such structure appears to be reinforcedover time. In contrast, the knowledge production from other city-regions is much lower. Broadly speaking, the geographical pattern of the evolution of regional knowledge output in China has basically remained stable, showing the characteristics of "space dependence”. It is noteworthy that the HAC city-region and the CSL city-region were comparable with 17,690 and 15,765 respectively in terms of scientific output during the period of 2002-2006. By the period of 2012-2016, the former has witnessed a more significant growth than the latter, with the output of 79,258 and 59,439, respectively, reflecting the trend of imbalanced development within the Northeast China.

The following section will focus on the evolution of the IKCNs of the 20 city-regions. First, the evolution of the spatial configurations and topological structures of the IKCNs of the 20 city-regions are discussed. Second, a comparative analysis focusing on the spatial configurations and the topological structures of the YRD city-region, the BTH city-region, the GBA city-region are conducted, and further the regional-specific factors and the underlying mechanisms that determine their different structures and evolution trajectories are examined.

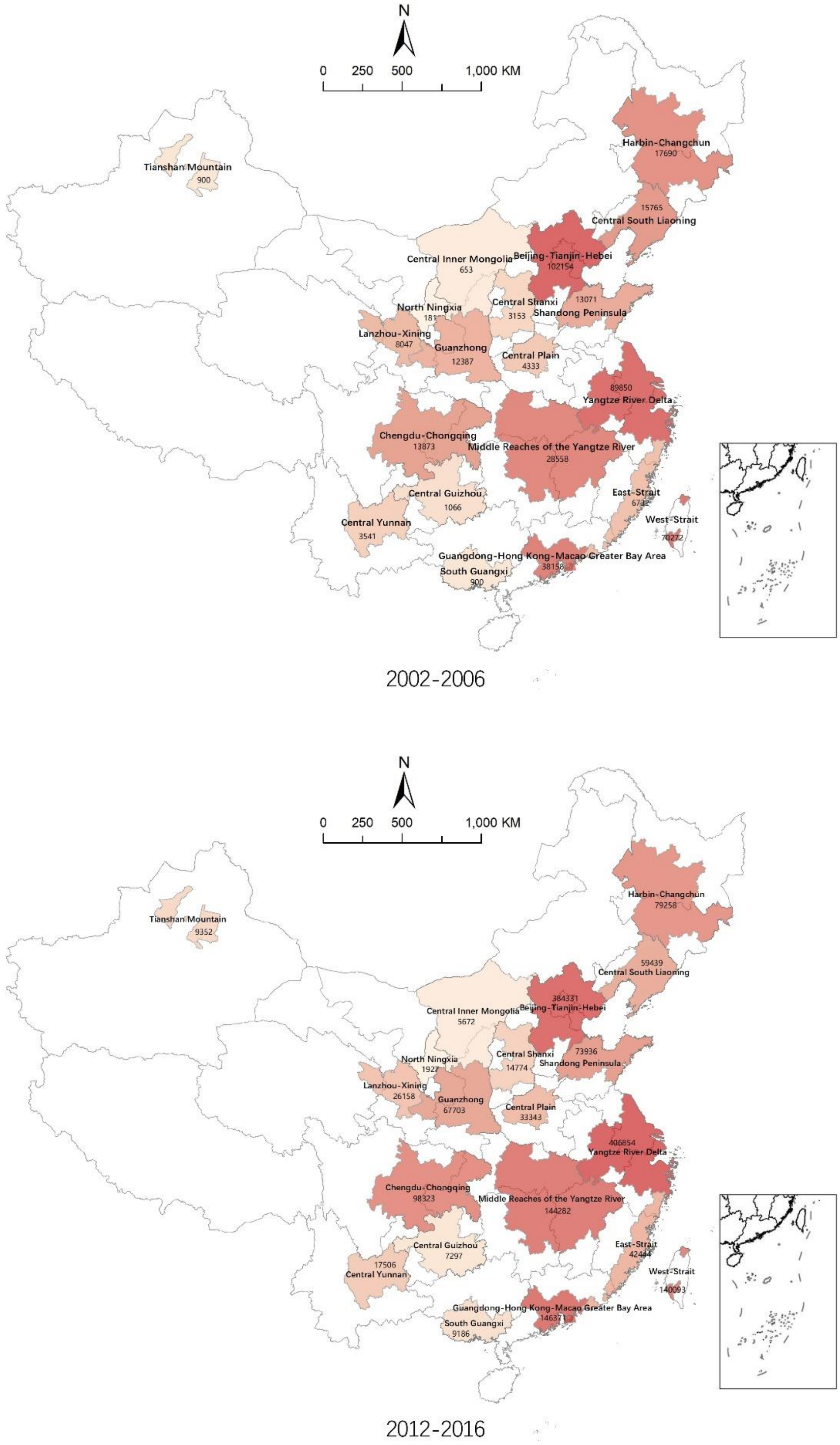


Figure 7-2 Spatial distribution of the scientific output of China’s 20 city-regions (2002-2006, 2012-2016)
Source: author

7.2 7.2 The evolution of the spatial configurations of the IKCNs of Chinese city-regions

7.2.1 The uneven distribution and imbalanced development

Figure 7-3 shows the spatial configurations of the IKCNs of thses 20 city-regions. During the period of 2002-2006, the intra-regional IKCNs of the city-regions in eastern China were much denser and more intense than that in western China, of which the IKCN of the EST city-region was the most dynamic and vigorous one, followed by the YRD, the BTH and the DBA city-regions. While the IKCNs of the city-regions in central and western China were relatively under-developed with the exception of the MRY city-region and the CHC city-region.

The "capital monopoly" effect are evident in the IKCNs of the city-regions. For city-regions include multiple provinces, the provincial capitals are the hubs and hinges that organize the backbones of the intra-regional IKCNs, such as the "Shanghai-Nanjing-Hangzhou-Hefei" in the YRD city-region, the "Beijing-Tianjin-Shijiazhuang" in the BTH city-region, "Guangzhou-Hong Kong" in the DBA city-region, "Chengdu-Chongqing" in the CHC city-region, "Wuhan-Changsha" in the MRY city-region, "Jinan-Qingdao" in the SDP city-region, "Shenyang-Dalian" in the CSL city-region and "Harbin-Changchun" in the HAC city-region.

Base on the discussion of the "integration" of city networks in Chapter 6, the examination of connection types can also reflect the development of the IKCNs of city-regions. In an "integrated" city-region , collaborative connections exist not only among larger cities but also among small or medium-sized cities. The city-regions that meet this condition include the YRD city-region, the BTH city-region, the DBA city-region, the MRY city-region, the CHC city-region, the HAC city-region, the CSL city-region, the SDP city-region, the WST city-region, the EST city-region, the CSX city-region. In the remaining cities, the collaboration ties cannot be found between non-capital cities, which correspond with a typical "central place" spatial organization mode.

During the period of 2012-2016, the IKCNs of all city-regions have developed to varying degrees, and the gravity has gradually shifted from eastern china to central and western China. For the developed city-regions in the eastern China, on one hand, the collaborations between core cities have reinforced. For example, the network backbone underpinned by the four capital cities in the YRD city-region have gradually evolved from the "open triangle-shaped" to "closed square-shaped" structure. Meanwhile, the well-developed non-capital cities such as Ningbo and Suzhou have emerged in the core layer of the network. Similarly, the three capital cities in the MRY city-region have also gradually evolved from the "Wuhan-Changsha" dual-core structure to the "Wuhan-Changsha-Nanchang" triangular structure. On the other hand, in most of the city-regions, connections between small and medium-sized cities have become increasingly frequent and dense, suggesting the trend of regional integration. The only exception is the NNX city-region that still exhibits a star-shaped configuration and the organization logic of the “central place” model.

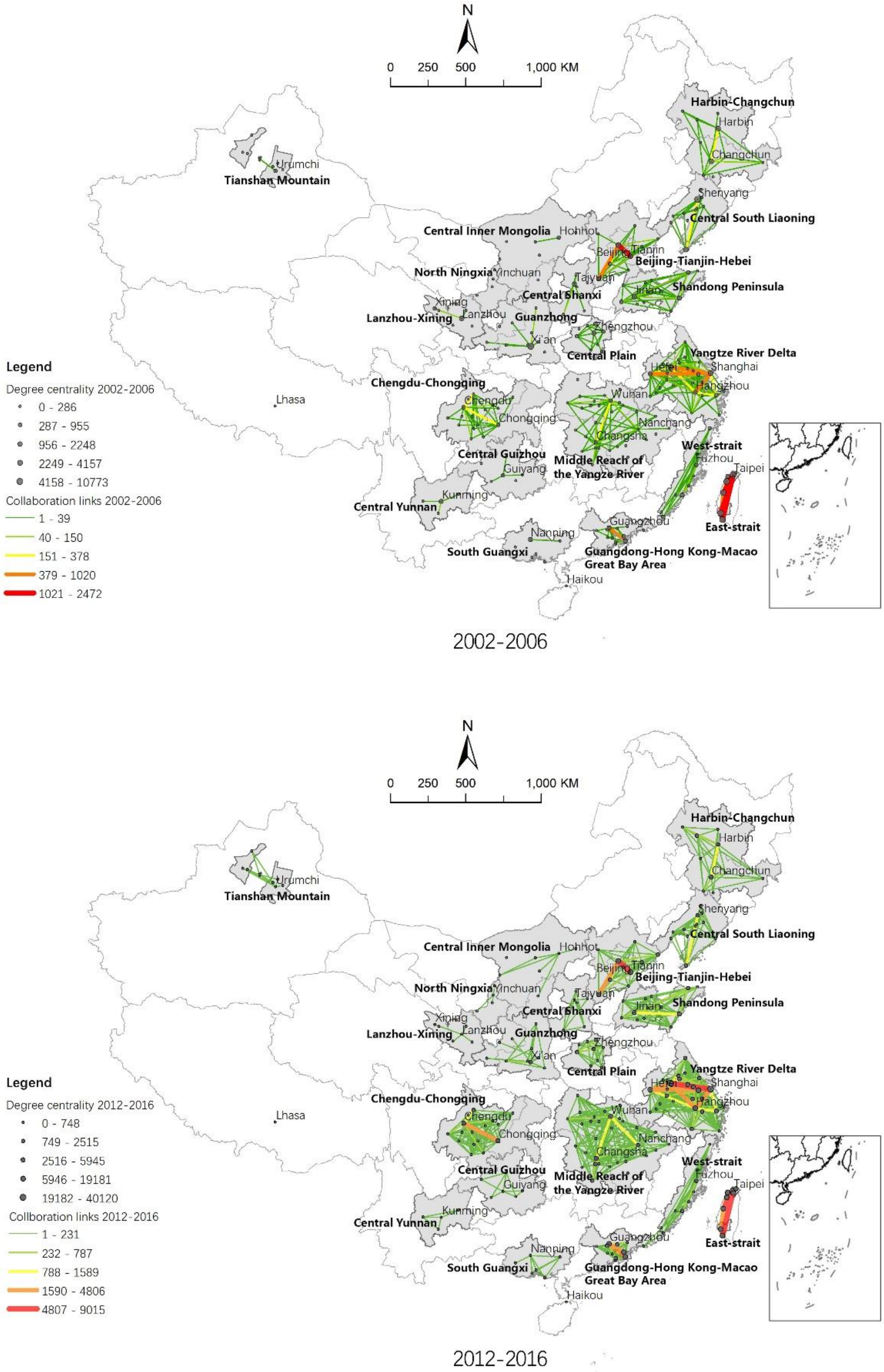


Figure 7-3 The intra-regional IKCNs of China’s city-regions (2002-2006, 2012-2016)

Source: author

Table 7-4 shows the descriptive statistics of the spatial distribution of the IKNCs of each city-region. First of all, during the study period, the maximum, minimum and mean values of the KNC of all city-regions have increased to varying degrees, indicating the growth of the intra-regional IKCNs. In the period of 2002-2006, the average KNC of all city-regions was 103.3 and has increased to 775.60 during the period of 2012-2016, with a growth rate of 650.82%. Among them, the city-regions with higher than the average growth rate are mostly located in the central and western China, including the GBA city-region, the CHC city-region, the GZP city-region, the SGX city-region, the WST city-region, the CIM city-region, the CGZ city-region, the SDP city-region, the TSM city-region and the CPL city-region: First, for those developed city-regions, their network growth rates are relatively small because the actors in the networks cannot build new collaborations indefinitely due to the marginal cost. In comparison, the city-regions with under-developed IKCNs have more room for growth. Second, the advance of the scientific activity itself presents an “S-shaped” curve. For the city-regions entered the mature stage of innovation, they often have possessed the most advanced science and technology and devoted themselves to the most cutting-edge research and frontier breakthroughs. These processes are relatively slow and the collaboration communities are relatively small, thus presenting a relatively low growth rate of the IKCNs. For those formerly underdeveloped city-regions, they have gained certain degrees of innovation capabilities after learning, absorbing and accumulating science and technology in the early stage. They have more space for growth and development, in turn show great momentum in terms of the development of the IKCNs .

The coefficient of variance and the Gini coefficient of the cities’ KNC of all city-regions have decreased to different degrees. This shows that first, the gap between different cities within the city-regions is gradually narrowing. In those city-regions, The collaboration links between small and medium-sized cities have become more intense and stronger. Second, the polarization of primate cities in the IKCNs has decreased and the networks tend to be more balanced.

The Moran’s I indexes of the KNC of cities in these city-regions are all negative, which indicates that spatial distributions of the IKCNs of the city-regions are quite dispersed. However, by the period of 2012-2016, the Moran’s I indexes of most of the city-regions have increased to varying degrees, suggesting a general trend of spatial concentration.

Figure 7-4 shows the spatial configuration of the extra-regional collaboration networks between different city-regions. In the period of 2002-2006, the most notable feature is the “hub-spoke” structure centered on the BTH city-region. The most intense extra-regional collaboration links occurred among the “BTH - YRD -DBA” and “BTH -YRD - MRY” triangles. During the period of 2012-2016, the two “triangles” were further strengthened, while a new “triangle” formed by “BTH -YRD - CHC” has emerged.

Generally speaking, at the regional scale, the evolution of the spatial configuration of the IKCNs shows the gradual and steady trend of self-reinforcement, which basically comply with the law of “space dependence”.

Table 7-4 Descriptive statistics of the spatial distribution characteristics of the IKNCs of Chinese city-regions

	YRD		GBA		BTH		MRY		CHC		CSL		SDP	
	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Number of cities	26	26	11	11	10	10	31	31	16	16	12	12	13	13
Max	3,698	23,223	1,056	10,113	2,609	13,284	740	4,949	827	5,945	417	2,062	367	4,262
Min	1	53	9	160	10	218	0	0	0	10	0	11	0	2
mean	507.85	4,000.92	224.73	2,575.09	588.40	3,112.20	80.06	578.26	109.88	892.38	87.50	459.50	86.00	976.77
Coefficient of variance	1.82	1.60	1.76	1.34	1.50	1.43	2.23	2.08	2.01	1.79	1.68	1.54	1.29	1.29
Gini Coefficient	0.76	0.71	0.80	0.67	0.75	0.71	0.80	0.76	0.83	0.76	0.78	0.72	0.65	0.62
Moran's I	-0.096	-0.051	-0.12	-0.059	-0.142	-0.168	-0.027	-0.075	-0.057	-0.011	-0.135	-0.177	-0.366	-0.459

	WST		HAC		CPL		GZP		SGX		TSM		CSX	
	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Number of cities	10	10	10	10	9	9	10	10	6	6	8	8	8	8
Max	131	1,179	523	2,607	118	1,809	136	1,075	1	143	3	225	72	225
Min	0	3	0	8	0	13	0	1	0	7	0	2	0	1
mean	39.20	332.00	120.00	781.00	36.44	536.22	27.20	222.20	0.33	49.67	0.75	58.00	19.50	60.00
Coefficient of variance	1.20	1.19	1.49	1.25	1.14	1.13	1.58	1.48	1.55	1.07	1.85	1.51	1.47	1.18
Gini Coefficient	0.66	0.63	0.73	0.65	0.64	0.62	0.77	0.72	0.80	0.61	0.88	0.86	0.78	0.59
Moran's I	-0.364	-0.135	-0.015	-0.026	0.059	-0.071	-0.117	0.014	-0.171	-0.301	-0.158	-0.311	-0.275	-0.278

	CIM		CYN		CGZ		LAX		NNX		EST	
	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Number of cities	7	7	4	4	6	6	6	6	4	4	31	31
Max	4	118	67	275	11	106	59	256	0	9	740	4,949
Min	0	0	5	34	0	11	0	0	0	2	0	0
mean	1.14	34.29	33.50	138.50	3.67	37.00	19.67	85.33	0.00	4.50	80.06	578.26
Coefficient of variance	1.71	1.53	0.87	0.76	1.28	1.00	1.51	1.44	0.00	0.69	2.23	2.08
Gini Coefficient	0.83	0.78	0.95	0.94	0.73	0.53	0.79	0.77	0.00	0.41	0.47	0.36
Moran's I	-0.318	-0.203	-0.891	-0.742	-0.471	-0.111	-0.727	-0.685	-0.263	-0.193	-0.171	-0.288

Source: author

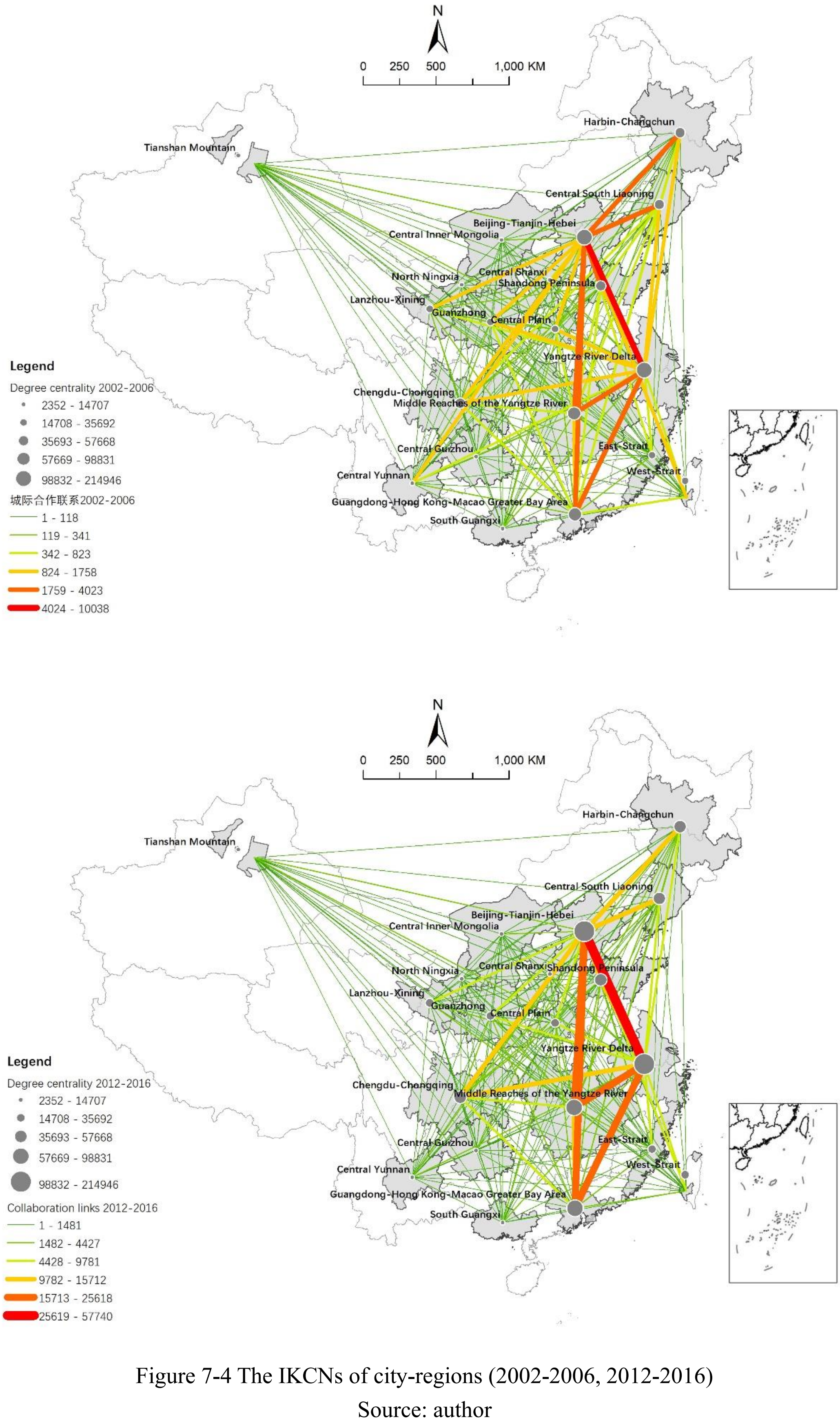


Figure 7-4 The IKCNs of city-regions (2002-2006, 2012-2016)

Source: author

7.2.2 Polycentricity of the IKCNs of Chinese city-regions

7.2.2.1 **Concepts**

Recent research has highlighted that, with continued globalization and informatization, a new urban form seems to be emerging: polycentric city-region (Hall, 2009). In a broad sense, polycentric city-region materializes when formerly adjacent but distinct cities become integrated into a wider urban region. As a result, regions are increasingly found to be characterized by similar sizes, interdependent economies, joint labor markets and common infrastructures, binding different settlements together into an integrated geographical entity (Burger and Meijers, 2012). Nonetheless, the the concept of polycentricity can be applied to describe the multicentered spatial-functional organizations at metropolitan level, (Greater London, Greater Paris, Tokyo, etc.) regional level, (Randstad, Flemish, the YRD city-region, etc.) national and transnational level (EU) (Brezzi and Veneri, 2015; Champion, 2001; Halbert et al., 2006). Moreover, "polycentricity" has also been advocated as normative policies for spatial development by many countries or local governments. For example, polycentric urban region development has been set as a main spatial instrument in *European Spatial Development Perspective*. The EU-funded European Spatial Planning Observation Network (ESPON) also has dedicated to promoting polycentric development in Europe. 18 out of the 29 ESPON member countries have highlighted the polycentric development as their primary strategy of national spatial coordination. Table 7-5 summarizes some propositions that related to polycentric development. This chapter mainly focuses on the regional level of polycentricity, in another word, the polycentric city-regions.

Table 7-5 Polycentric development and related propositions

Spatial scale	Related propositions	Policy goals	Measurements
National level	National urban system; Hierarchy of cities; Growth pole	Agglomeration economies and scale economies; Balanced development (income, infrastructure, services, etc.)	Primate cities Rank-size
Regional level	Functional synergy and complementarity; Hierarchy of cities	Regional agglomeration economies and network economies; Functional integration	Primate cities Rank-size City network
Metropolitan level	Urban sprawl and concentration; Commuting mode; Work-job balance	Urban efficiency and land use; Environmental issues (air quality, landscape ecology, etc.);	Spatial concentration/dispersion mode Commuting mode

Source: author

Harrison and Hoyler (2015) claim that there are two mainstreams in the research of polycentric city-regions: the first is the North American approach that focuses on the spatial distribution and the geographical configurations of city systems; and the second is the Western Europe approach that focuses on the functional interdependency and integration of cities in city systems. For the former, the polycentricity of city-regions is examined in morphological term, i.e., morphological polycentricity. The most commonly employed measurement is to examine the rank-size distribution of cities' importance in terms of their sizes, such as population or GDP (Meijers, 2005; Meijers and Burger, 2017). As polycentricity highlights an even spatial distribution of geographical entities within a region, the rank-size method provides an instrumental benchmark. In many empirical studies, the most straightforward indicator for measuring polycentricity is the slope of the best-fitting regression lines (Batty, 2013; Meijers, 2008).

With the rise of city network paradigm and network thinking, increasing number of scholars have been trying to incorporate social network analysis and relational data to explore the underlying organizational processes of the polycentric city-regions in functional term (Hall and Pain, 2006; Green, 2007; Hoyler et al., 2008). They believe that the functional interdependencies between cities are fundamental for the synergy and complementarity, i.e., "functional polycentricity". Partly pioneered by the Sustainable Management of European Polycentric Mega-City Region (POLYNET) (Hall and Pain, 2006), this approach exploits the analogies between network logic of city systems and social networks to gauge the polycentricity of city-regions through different network statistics.

Burger and Meijers (2012) combine the morphological polycentricity and functional polycentricity of the city-regions in an unified analytical framework. In their conception, the importance of a city is composed by "internal centrality" (connections with all other cities within the region) and "external centrality" (connections with cities outside the region). The internal centrality of a city is defined as the part of its importance of the provision of goods, services and jobs for its own inhabitants, while the external centrality is defined as a central place that providing goods, services and jobs to surrounding cities. The total centrality of a city can be used to establish morphological polycentricity (MP). Meanwhile, functional polycentricity (FP) is defined on the premise of integration at the regional level, and thus entails the focus on the balance of intraregional flows. In short, from the network perspective, the measurement of morphological polycentricity is based on an analysis of the relative intraregional balance of total centrality (internal and external centrality), and functional polycentricity is assessed based on analysis of the relative intraregional balance of internal centrality. (Burger and Meijers, 2012; Liu et al., 2016; Zhang and Derudder, 2019). (Figure 7-5)

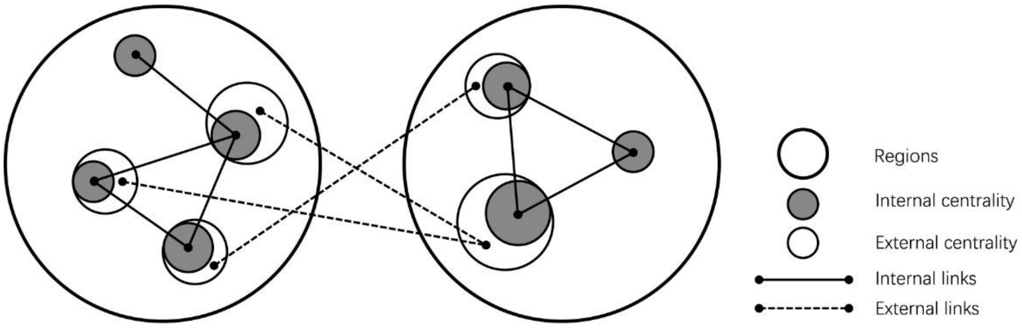


Figure 7-5 Conceptual diagram of morphological polycentric and functional polycentric based on internal and external network relations
Source: author

In existing city network studies, the empirical examination of the polycentric city-regions are mostly base on corporate networks or commuting networks, relatively little is known about the polycentricity of city-regions' knowledge system. Li and Phelps (2016) argue that through the discussions of the polycentricity of knowledge networks, especially the comparative studies on the polycentric IKCNs at different spatial scales, one can reveal the different roles of cities in the IKCNs. In view of this, the following sections will compare and discuss the polycentricity of Chinese city-regions in the IKCNs.

7.2.2.2 **Measurements**

Based on Burger and Meijers' (2012) definitions of morphological polycentricity and functional polycentricity , combined with Green's (2007) mathematical method, Liu et al. (2016) propose an approach of measuring both morphological and functional polycentricity of city-regions in a single analytical framework with a consistent manner.

First, morphological polycentricity can be measured by:

$$P_M = 1 - \frac{\sigma_M}{\sigma_{M\max}} \tag{7-1}$$

where P_M represents the morphological polycentricity of an urban region, ranging from 0 (total absence of polycentricity) to 1 (absolute polycentricity). σ_M represents the standard deviation of total (i.e. external and internal) centrality measured for the cities in the region. σ_{Mmax} is the standard deviation of nodal centrality in a two-node network where one node has zero total centrality and the other's external centrality equals the maximum observed value.

Functional polycentricity, in turn, can be measured by:

$$P_F = (1 - \frac{\sigma_F}{\sigma_{F\max}}) \times \Delta \quad (7\text{-}2)$$

where P_F represents the functional polycentricity of an urban region, ranging from 0 (total absence of polycentricity) to 1 (absolute polycentricity); σ_F and σ_{Fmax} are calculated in a similar way as σ_M and σ_{Mmax}, albeit using internal centrality; and Δ represents the network density of regional networks to ensure that functional polycentricity falls to zero when there is no linkage/flow between cities.

7.2.2.3 **Results**

Table 7-6 shows the results of the scores of MP and FP of different city-regions. Compared with the period of 2002-2006, the FP of most cities in the period of 2012-2016 has increased to varying degrees, indicating that the IKCNs within the city-regions have become more balanced, and the interdependencies among cities have also become more diverse. In terms of MP, only a few city-regions have witnessed growth, i.e., the YRD city-region, the DBA city-region, the WST city-region, the CPL city-region, the SGX city-region, the CGZ city-region and the CIM city-region. This suggests that both intra-regional and inter-regional collaborations of these city-regions have developed to be more balanced. For the YRD city-region and the GBA city-region, there are two possible reasons for their growth in MP. First, both have more than one core city (such as Shanghai, Nanjing, and Hangzhou in the YRD city-region, Hong Kong, Shenzhen and Guangzhou in the DBA city-region), these cities are not only provincial hubs, but also regional even national hubs, thus their external centrality grow faster than small and medium-sized cities. Second, the spatial spillovers of the hub cities are evident in these two city-regions,, which have significantly enhanced the connectivity of their surrounding small and medium-sized cities. The IKCNs of the other city-regions are mostly underdeveloped, thus with relatively smaller growth of the marginal effect they have more space to grow in both internal and external centrality. The city-regions have showed decline in MP include the MRY city-region, the CHC city-region, the HAC city-region, the SDP city-region and the CSL city-region. One common feature of these city-regions is that there exist clear gaps between core cities and other smaller cities in terms of internal and external centrality. The growth rate of the core cities are much faster than that of smaller cities, thus the scores of the MP have declined.

Table 7-6 Morphological polycentricity and functional polycentricity index of different city-regions

city-regions	2002-2006		2012-2016	
	Morphological polycentricity	Functional polycentricity	Morphological polycentricity	Functional polycentricity
YRD	0.59	0.27	0.65	0.47
BTH	0.56	0.32	0.56	0.48

GBA	0.49	0.18	0.55	0.50
MRY	0.72	0.08	0.71	0.24
CHC	0.64	0.14	0.61	0.42
HAC	0.51	0.19	0.46	0.30
SDP	0.58	0.28	0.56	0.50
GZP	0.56	0.07	0.56	0.25
CSL	0.55	0.16	0.51	0.37
WST	0.48	0.20	0.50	0.34
CPL	0.44	0.24	0.54	0.42
LAX	0.43	0.04	0.43	0.09
CYN	0.31	0.19	0.31	0.38
CSX	0.51	0.08	0.51	0.24
TSM	0.51	0.01	0.51	0.19
SGX	0.42	0.02	0.43	0.28
CGZ	0.43	0.08	0.44	0.30
CIM	0.46	0.01	0.47	0.11
NNX	0.30	0.00	0.30	0.26

Source: author

The results are visualized in Figure 7-6. The individual city-regions are plotted with their scores on the MP and FP measures respectively as longitudes and latitudes. By centering on the point with mean values of the two indicators, the figure is thus divided into four quadrants.

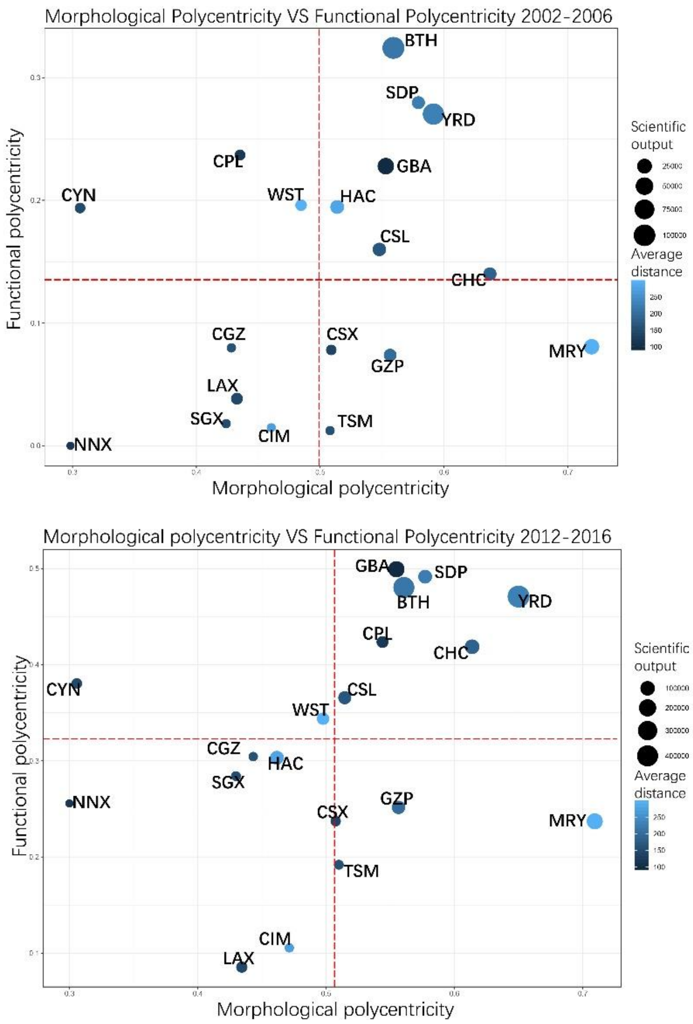


Figure 7-6 Morphological polycentricity and functional polycentricity of different city-regions
Source: author

City-regions in the upper right quadrant show both higher MP and FP. In the period of 2002-2006, the BTH city-region, the SDP city-region, the YRD city-region, the DBA city-region, the HAC city-region, the CSL city-region and the CHC city-region were in this category. During the period of 2012-2016, the CSL city-region has replaced with the HAC city-region. These city-regions boast relatively higher socio-economic development and innovation capability and have enjoyed more preferential policies. Among them, the BTH city-region, the YRD city-region, the DBA city-region and the CHC city-region, as the most mature city-regions in China, have sufficient innovation infrastructure, human capitals, resource input and generate more scientific output. One thing in common is that they have more than one hub cities, such as Beijing and Tianjin in the BTH city-region; Shanghai, Nanjing and Hangzhou in the YRD city-region; Guangzhou, Shenzhen and Hong Kong in the DBA city-region, as well as Chongqing and Chengdu in the CHC city-region. These cities constitute the dual- or triple-core structure in their respective regions, which not only have formed intense internal relations with each other, but also have built external connections beyond the local regional boundaries. In addition, the polycentric characteristic of a city-region is determined by a few core cities. Therefore, the MP and FP of these city-regions are higher.

In addition to the four national-level city-regions, the CSL city-region and the SDP city-region also have show higher MP and FP. Although they are not comparable to the four giants in terms of innovation input, output and network connectivity, they have typical dual-cores spatial structures, i.e., the “Shenyang-Dalian” and “Jinan-Qingdao”. It is worth mentioning that in the sense of spatial configuration, the BTH city-region, the SDP city-region and the CSL city-region have the potential to form a continuous corridor of polycentric city-regions along the Bohai Bay. Under appropriate policies and guidance, this region could be build as a cross-regional innovation corridor.

City-regions in the upper left quadrant have higher FP but lower MP. During the period of 2002-2006, the CYN city-region, the WST city-region and the CPL city-region were in this category. First, these city-regions have showed a high degree of FP because the internal network connections are relatively balanced, butrather weak and sparse at the same time, which is different from the high FP of the city-regions in the upper right quadrant (high-density and high-intensity internal collaboration networks). The power of the core cities in these city-regions are dominant, and most of their power comes from external centrality. For example, in the CPL city-region, Zhengzhou’s total centrality was 1554 and the external centrality 1459 while the sum of the external centralities of all other cities totaled only 305, showing a significant monocentricity in morphological term. Although the WST city-region exhibit a “dual-cores” spatial structure composed by Xiamen and Fuzhou in terms of economic scale and population, Xiamen’s external centrality was much higher than that of Fuzhou in terms of connectivity in the IKCNs, which also presented a pattern of monocentricity. By the time of 2012-2016, the MP of the CPL city-region has significantly increased and entered the upper right quadrant, which attributes to the rapid rise of Xinxiang and Luoyang in education and science.

City-regions in the lower right quadrant exhibits higher MP and lower FP. The MYR city-region is a typical example, within which Wuhan, Changsha and Nanchang as core cities not only have high external centrality but also have many collaborations with each other, thereby presenting higher MP. Although composed of cities from three different provinces, this city-region has less supra-provincial collaborations than that of the YRD city-region. In the period of 2002-2006, the internal collaboration network density of the MYR city-region was only 0.12 while that of the YRD city-region was 0.42. By the period of 2012-2016, the two figures are 0.36 and 0.77 respectively. Therefore, the FP of the MYR city-region is lower.

The city-regions located in lower left quadrant are mostly located in the underdeveloped provinces in western China. Among these city-regions, except for the capital cities, all other small and medium-sized cities are rather weak in terms of internal and external centrality. Therefore, such city-regions exhibit monocentricity in both morphological and functional terms.

7.3 The evolution of topological structures of regional IKCNs

7.3.1 Basic topological structures

Table 7-7 shows the basic topological characteristics of the IKCNs within each city-region. First, among the five national-level city-regions, the intensity and density of the interurban knowledge collaborations of the YRD city-region, the BTH city-region and the GBA city-region are higher than that of the MRY city-region and the CHC city-region by looking at the scores mean, minimum, maximum and network density. In the period of 2002-2006, the city-region with the highest average degree (23) and degree maximum degree (10.46) is the YRD city-region. The city-region with the highest network density (0.62) is the BTH city-region that also has the highest global efficiency (0.18) among the five city-regions. The results of the degree-degree correlation, the small world quotient and the degree distribution of networks show that the five city-regions have exhibited significant “disassortativity” and “small-world” property, but presented no “scale-free” property. Over time, all indicators show that the regional IKCNs of five city-regions have achieved significant growth in the period of 2012-2016. Finally, by examining the QAP correlation coefficient, it can be found that the IKCNs of the five city-regions in two time periods have presented higher similarity, which indicates that the evolution of the topology of these city-regions follows the general law of “path dependence”.

Secondly, based on the results, the eight sub-national level city-regions are divided into three categories that reflect different development stages of the regional IKCNs. The first-class city-regions are the SDP city-region and the HAC city-region. The second-class city-regions include the CSL city-region, the WST city-region and the CPL city-region. The third-class city-regions are the GZP city-region, the SGX city-region and the TSM city-region. The IKCNs of these eight city-regions show significant “dissimilarity” and “small world” property with no “scale-free” property. The result of QAP correlation shows that the evolutionary processes of the topology of the regional IKCNs are consistent with the law of “path dependence”.

Because of the fact that smaller sizes and fewer cities involved, the results of the topology of the six regional level are somehow not interpretable. However, it can be partly seen as the results that the IKCNs of these city-regions have come increasingly complex and intense to varying degrees.

Finally, the IKCNs of the EST city-region is the most mature. In the period of 2002-2006, the density and the global efficiency of the IKCNs of this city-region had reached 0.9 and 0.95, respectively. By the period of 2012-2016, both indicators were 1, implying that any two cities within the city-region have established collaboration ties with each other and formed an interconnected closure network.

Table 7-7 Topological structures of the intra-regional IKCNs of China's city-regions

Network topological characteristic index		The YRD city-region		The GBA city-region		The BTH city-region		The MRY city-region		The CHC city-region	
		2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Basic topological properties	Average degree	10.46	19.31	3.82	9.64	5.60	8.20	4.38	11.20	4.15	10.13
	Max	1.00	8.00	1.00	8.00	2.00	6.00	1.00	1.00	1.00	4.00
	Min	23.00	25.00	10.00	10.00	9.00	9.00	23.00	28.00	11.00	15.00
	Network density	0.42	0.77	0.38	0.96	0.62	0.91	0.18	0.39	0.35	0.68
	Global efficiency	0.71	0.89	0.69	0.98	0.81	0.96	0.58	0.69	0.67	0.84
	Degree-degree correlation	-0.44	-0.22	-0.64	-0.23	-0.59	-0.33	-0.57	-0.33	-0.64	-0.38
Small world property	Characteristic path length	1.60	1.23	1.62	1.04	1.38	1.09	1.89	1.62	1.67	1.33
	Characteristic path length of the same-size random networks	1.58	1.23	1.75	1.04	1.38	1.09	2.29	1.62	1.81	1.33
	Clustering coefficient	0.61	0.83	0.43	0.97	0.69	0.92	0.29	0.60	0.42	0.78
	Clustering coefficient of the same-size random networks	0.39	0.77	0.31	0.96	0.57	0.91	0.19	0.40	0.33	0.63
	Small world quotient	1.53	1.09	1.48	1.00	1.22	1.01	1.87	1.50	1.38	1.23
Scale-free property	Cumulative power-law exponent	0.90	0.41	1.13	0.07	0.70	0.17	1.22	1.14	1.11	0.63
	R2	0.73	0.37	0.91	0.22	0.76	0.39	0.96	0.72	0.88	0.51
Similarities of topological structures		0.96		0.77		0.99		0.92		0.96	

Network topological characteristic index		The CSL city-region		The SDP city-region		The WST city-region		The HAC city-region		The CPL city-region	
		2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Basic topological properties	Average degree	4.20	7.83	6.33	10.31	4.00	6.20	4.25	3.00	0.61	6.44
	Max	2.00	4.00	1.00	2.00	2.00	2.00	1.00	2.00	4.25	4.00
	Min	9.00	11.00	11.00	12.00	7.00	8.00	7.00	9.00	1.00	8.00
	Network density	0.47	0.71	0.58	0.86	0.50	0.69	0.61	0.64	0.46	0.81
	Global efficiency	0.73	0.86	0.79	0.93	0.74	0.84	0.80	0.82	0.80	0.90
	Degree-degree correlation	-0.65	-0.43	-0.52	-0.12	-0.31	-0.13	-0.49	-0.49	-0.43	-0.45
Small-world property	Characteristic path length	1.53	1.29	1.42	1.14	1.56	1.36	1.39	1.36	1.43	1.19
	Characteristic path length of the same-size random networks	1.60	1.29	1.42	1.14	1.50	1.31	1.39	1.36	1.39	1.19
	Clustering coefficient	0.52	0.76	0.70	0.96	0.59	0.80	0.72	0.72	0.75	0.82
	Clustering coefficient of the same-size random networks	0.55	0.70	0.54	0.84	0.40	0.72	0.66	0.66	0.49	0.77
	Small-world quotient	0.98	1.08	1.30	1.13	1.42	1.06	1.09	1.09	1.49	1.07
Scale-free property	Cumulative power-law exponent	0.94	0.55	0.84	0.37	1.05	0.44	0.94	0.71	0.94	0.39
	R2	0.84	0.61	0.65	0.15	0.75	0.53	0.67	0.70	0.67	0.56

Similarities of topological structures		0.99		0.93		0.81		0.92		0.94	

Network topology characteristic index		The GZP city-region		The SGX city-region		The TSM city-region		The CSX city-region		The CIM city-region	
		2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Basic topological properties	Average degree	1.71	4.00	4.25	3.00	3.38	3.00	2.00	3.00	2.00	2.00
	Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Min	6.00	8.00	7.00	8.00	5.00	7.00	4.00	6.00	4.00	5.00
	Network density	0.29	0.44	0.41	0.60	0.18	0.43	0.30	0.43	0.50	0.40
	Global efficiency	0.64	0.70	0.80	1.40	0.58	0.71	0.75	0.69	0.75	0.70
	Degree-degree correlation	-1.00	-0.41	-0.49	-0.64	-0.57	-0.84	-0.81	-0.40	-0.81	-0.83
Small-world property	Characteristic path length	1.71	1.69	1.39	0.65	1.89	1.57	1.50	1.71	1.50	1.60
	Characteristic path length of the same-size random networks	2.67	1.58	1.39	0.47	2.20	1.68	1.50	1.43	1.60	1.50
	Clustering coefficient	0.00	0.64	0.72	1.38	0.29	0.37	0.38	0.45	0.38	0.25
	Clustering coefficient of the same-size random networks	0.00	0.28	0.53	0.80	0.17	0.39	0.38	0.47	0.43	0.60
	Small-world quotient	NA	2.14	1.36	1.27	1.96	1.01	1.00	0.81	0.93	0.39
Scale-free property	Cumulative power-law exponent	0.97	1.03	0.97	0.44	0.97	1.01	1.28	1.25	1.28	1.24
	R2	0.66	0.78	0.66	0.53	0.66	0.84	0.91	0.82	0.91	0.91
Similarities of topological structures		0.93		0.91		0.97		0.61		1.00	

Network topology characteristic index		The CYN city-region		The CGZ city-region		The LAX city-region		The NNX city-region		The EST city-region	
		2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016	2002-2006	2012-2016
Basic topological properties	Average degree	1.50	2.50	1.50	3.00	1.33	1.60	0.00	1.50	5.43	7.00
	Max	1.00	2.00	1.00	2.00	1.00	1.00	0.00	1.00	4.00	7.00
	Min	3.00	3.00	3.00	5.00	2.00	4.00	0.00	3.00	6.00	7.00
	Network density	0.50	0.83	0.50	0.60	0.67	0.70	0.00	0.50	0.90	1.00
	Global efficiency	0.75	0.92	0.75	0.80	0.83	-1.00	0.00	0.75	0.95	1.00
	Degree-degree correlation	-1.00	-0.67	-1.00	-0.59	-1.00	1.60	NA	-1.00	-0.37	NA
Small-world property	Characteristic path length	1.50	1.17	1.50	1.40	1.33	1.33	0.00	1.50	1.10	1.00
	Characteristic path length of the same-size random networks	1.67	1.17	1.50	1.40	1.33	0.00	0.00	1.67	1.10	1.00
	Clustering coefficient	0.00	0.75	0.00	0.55	0.00	0.60	0.00	0.00	0.91	1.00
	Clustering coefficient of the same-size random networks	0.00	0.75	0.00	0.47	0.00	0.00	0.00	0.00	0.88	1.00
	Small-world quotient	NA	1.00	NA	1.15	NA	0.00	NA	NA	1.03	1.00
Scale-free property	Cumulative power-law exponent	1.34	0.56	1.34	1.08	1.59	1.18	NA	1.34	0.21	NA
	R2	0.87	0.61	0.87	0.80	1.00	0.78	NA	0.87	0.40	NA

Similarities of topological structures	0.91	0.94	1.00	NA	0.75

Source：author

7.3.2 “Internal reach” and “external reach”

Table 7-8 lists the scores of the internal reach and external reach index of all city-regions of mainland China in the two time periods. The internal reach index reflects the intensity and connectivity of the collaboration links between cities within the city-region. The external reach index reflects the strength and connectivity of the collaboration links between cities within the city-regions and other supra-regional cities. The results show that the internal and external reach of all city-regions have increased to varying degrees.

Table 7-8 Internal reach and external reach indexes of city-regions (2002-2006, 2012-2016)

City-regions	2002-2006		2012-2016	
	internal reach index	external reach index	internal reach index	external reach index
BTH	11.61	121.5	27.55	331.4
GBA	4.88	80.5	25.26	290.62
YRD	15.3	73.12	49.13	225.31
HAC	3.18	71.53	9.54	208.42
SDP	3.31	58.67	12.52	193.92
CYN	0.77	82.71	1.09	187.02
CPL	1.85	52.73	5.94	163.79
LAX	0.69	65.06	1.72	163.13
CHC	2.74	44.43	10.31	157.65
WST	2.2	48.62	5.92	153.33
CSL	2.17	54.63	5.29	143.68
GZP	1.01	46.97	2.99	136.93
MRY	4.5	35.79	13.54	118.19
CSX	0.37	34.95	0.91	93.32
TSM	0.12	19.19	0.83	86.74
CGZ	0.08	26.22	0.57	84.6
CIM	0.24	25.83	0.94	82.26
SGX	0.02	19.43	0.45	75.15
NNX	0.01	11.24	0.05	45.38

Source：author

Figure 7-7 visualizes the scores of the external reach and internal reach of these city-regions. The horizontal and vertical red dotted lines in the diagram are the means of the external reach and internal reach indexes respectively, thereby dividing the figure into four quadrants. The city-regions in the upper right quadrant have both high external reach and high internal reach, that is, the collaborations are intense between cities within the city-region as well as between the cities within and the cities outside the region a. In other word, the “local buzz” and more “global pipelines” of these city-regions are well-developed. During the period of 2002-2006, the city-regions located in this quadrant included the YRD city-region, the BTH city-region, the DBA city-region, the HAC city-region and the SDP city-region. By the period of 2012-

2016, the CHC city-region also presented such feature. What they have in common are being relatively more developed in terms of socio-economic bases, innovation performance and spatial coordination.

In the lower right quadrant is only the MRY city-region, which is marked by high internal reach and low external reach. Although the number of cities of these region are the biggest across the nation, most of their external links occur in the three capitals, namely, Wuhan, Changsha and Nanchang. While the collaboration links of other cities are mostly confined within their own provinces, thus the region presents high internal reach and low external reach.

In the upper left quadrant, there are three city-regions: the CYN city-region, the LAX city-region and the CPL city-region. The feature they share in common is the monocentric structure. In these city-regions, there exist clear-cut gaps between capital cities and their smaller surrounding neighbors in terms of socio-economic development, innovation capability and network status. The intra-regional KCNs are rather weak and sparse, while the capital cities—Lanzhou, Zhengzhou and Kunming—have a higher status in the national KCNs, thus, these city-regions exhibit high external reach and low internal reach.

The rest of the city-regions, namely the GZP city-region, the CGZ city-region, the TSM city-region, the CIM city-region, the SGX city-region and the NNX city-region, are in the lower left quadrant, showing low external reach and low internal reach. Most of these city-regions are located in the under-developed areas of the Northwest and Southwest China. The intra-regional collaboration links and extra-regional collaboration links of these region are rather weak and sparse, locked in the periphery of the IKCNs.

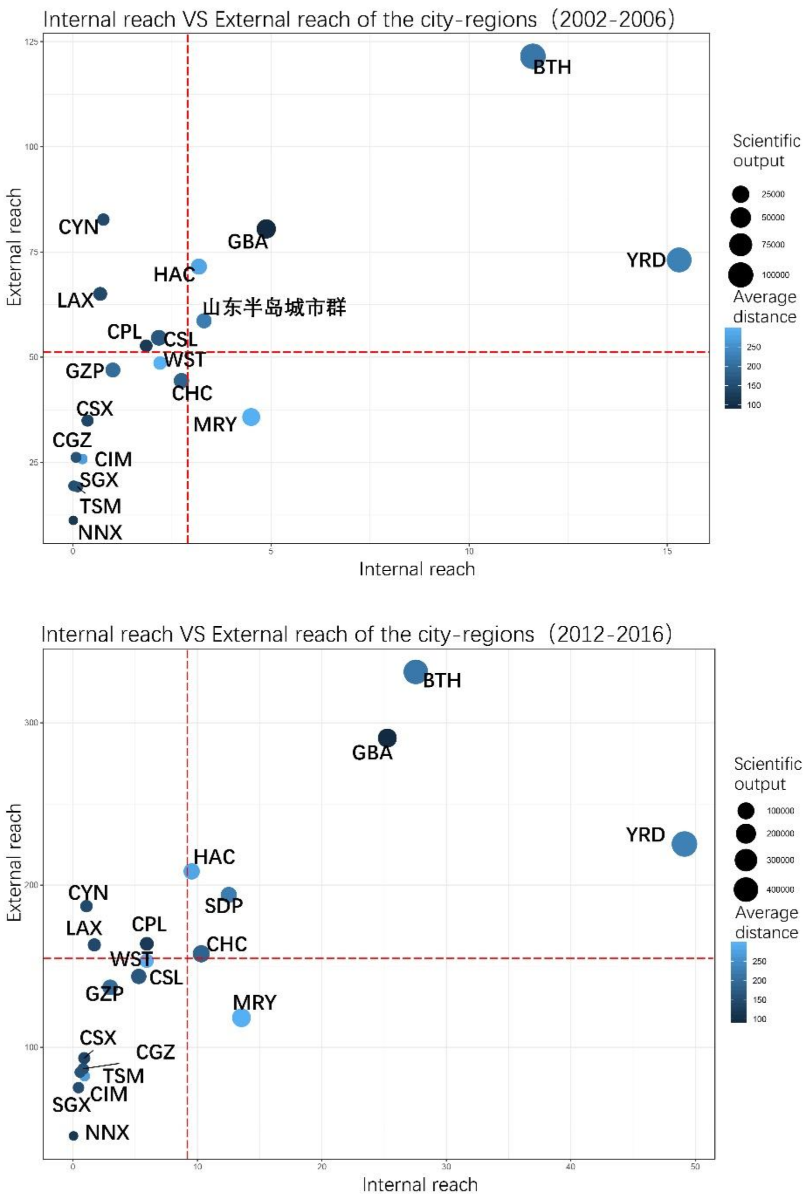


Figure 7-7 external reach and internal reach index of city-regions
Source: author

Based on the analysis above, it is not difficult to find that there is a positive correlation between external/internal reach of the regional IKCNs and their regional innovation performance. This finding corroborates the theory of Bathelt et al. (2004) that the combination and interaction of “local buzz” and “global pipelines” are crucial for regional innovation.

7.4 Comparing the evolution of the IKCNs of China's three major city-regions

7.4.1 The evolution of the IKCNs of the three major city-regions

This section compares the different evolutionary paths of the IKCNs of the YRD city-region, the BTH city-region and the GBA city-region, as well as discusses the contextual and region-specific factors that determine the differences between the three regional IKCNs.

7.4.2 The evolution of the IKCNs of the Yangtze River Delta city-region

7.4.2.1 **Overview**

The YRD city-region is one of the most dynamic and innovative region in terms of socio-economic development, urbanization progress, openness, innovative human capital and innovation resource input . After 40 years of reform and opening up, the YRD city-region has formed a relatively well-developed and complementary industrial system, as well as a competitive triple-helix-based regional innovation system. In terms of the innovation infrastructure, the YRD city-region houses more than 300 colleges and universities, including 8 world-class building universities like Fudan University, Shanghai Jiaotong University, Nanjing University, Zhejiang University and China University of Science and Technology etc. Beside, many world-famous universities have set oversea campus or colleges in this city-region, such as Shanghai-New York University, Ningbo-Nottingham University, Kunshan-Duke University, Xi'an Jiaotong-Liverpool University and Wenzhou Keen University. There are numerous national key laboratories and more than 320 innovation platforms such as the National Engineering Research Centers, the National Synchrotron Radiation Laboratory and the National Laboratory for Magnetically Constrained Nuclear Fusion etc. As for promoting the industry-university research collaboration, the establishments have been saw like Shanghai Zhangjiang National Innovation Demonstration Zone, South Jiangsu National Innovation Demonstration Zone, Hangzhou National Innovation Demonstration Zone, and Ningbo - Wenzhou NationalInnovation Demonstration Zone.

With regard to the scientific and technological innovation history and basis, the YRD city-region has been receiving a large amount of foreign investment by virtue of its preferential policies, location advantages and sufficient human resources since the reform and opening up, in turn, has introduced, absorbed and accumulated considerable advanced science and technology. The YRD city-region has been participating in the global division of production via joint ventures and the "exchange market for technology" approach, during which its innovation capability has witnessed a significant increase. At present, this city-region has formed an innovation-driven development model featured by "FDI driven + Industry-university collaboration + Government support" (Yan and Li , 2019).

In terms of collaborative innovation and construction of KCNs, the YRD city-region has formed dense collaboration networks due to geographical proximity, cultural proximity, industrial synergy and complementarity, interconnected infrastructures, which to a large extent facilitate frequent exchange of talents and technological factors. This innovative collaboration network has laid a good foundation for building the YRD city-region as one of the world-class innovation city-regions. The earliest knowledge exchange and collaborations in the YRD city-region can be traced back to the technology export practice named "Sunday Engineers" from Shanghai to township enterprises in Jiangsu and Zhejiang in the early stage of reform and opening up (Li et al., 2018). Since reform and opening-up, the YRD city-region's has gradually transformed from "spontaneous" to "self-conscious" innovation collaboration, during which it has been proactively exploring and developing multidimensional paths for regional collaborative innovations (Chen, 2018; Gao, 2018). In 2003, the *"Suzhou-Zhejiang-Shanghai Joint Agreement of Promotion of the Yangtze River Delta Innovation System"* was signed and the YRD collaborative innovation and knowledge collaboration entered the fast lane. In 2008, Anhui joined the agreement, together with Jiangsu, Zhejiang and Shanghai, they jointly promulgated the *"Three-Year Action Plan for Science and Technology collaborations in the Yangtze River Delta (2008-2010)"* and established a joint conference system for the support of the regional innovation system. In 2016, the State Council approved and issued the *"Development Plan for the Yangtze River Delta city-region"*, which highlights the role of regional innovation and collaboration network as one of the important pillars underpinning the development of the YRD city-region. In the same year, the three provinces and one city jointly signed the "*Shanghai-Jiangsu- Zhejiang-Anhui provinceJoint Agreement Framework of the Promotion ofRegional Innovation Collaboration of the YRD Region"*. In 2017, the three provinces and one city jointly formulated the *"Three-Year Action Plan for the Construction of Collaborative Innovation Network in the YRD city-region (2018-2020)"*. In 2018, the *"Collaboration Agreement on the Joint Promotion of Technology Transfer System in the YRD region"* was successively signed.

With regard to the spatial coordination of the regional innovation and collaboration, in 2017, Songjiang district (Shanghai) , Jiaxing (Zhejiang) and Hzhou (Zhejiang) jointly signed the *"Strategic collaboration Agreement of the construction of G60 Science and Technology Corridor"*. In 2018, another 6 cities joined in the G60 plan, including, Suzhou, Huzhou, Jinhua, Xuancheng, Wuhu and Hefei. The G60 Science and Technology Corridor is built to improve the industrial agglomeration, infrastructure connectivity, institution reform, innovation activities as well as the industry-university collaboration. In addition, the G60 Science and Technology Corridor is designed to play the role as the "engine" for regional integration and further develop into the main frontier of the transformation from "Made in China" towards "Created in China" . The G60 project is one of the best exmaple that the governments in the

YRD city-region has achieved a strategic consensus on innovation synergy and collaboration. Secondly, many cities nearby Shanghai have been actively seeking to carry out innovative collaboration with Shanghai. For example, Nantong has issued the *"Action Plan for Nantong as a Service Center for Docking Shanghai's Science and Technology"* with the goal of accessing to Shanghai's innovation resources. Similarly, Jiading district (Shanghai), Kunshan county (Suzhou) and Taicang county (Suzhou) have reached the consensus on the development and construction of "Jiading-Kunshang-Taicang Innovation Zone" aiming for deep collaborations in automobile electronics industry. Finally, the construction of the "enclave colleges and universities" is also one of the main modes for the YRD city-region to promoting the collaboration of the industry-university collaboration in the YRD city-region. For example, Jiangsu have jointly established collaborative research and development institutions like Nanjing Advanced Laser Technology Research Institute, Zhejiang University Suzhou Industrial Technology Research Institute together with Fudan University, Shanghai Jiaotong University, Zhejiang University, University of Science and Technology and other famous universities.

In terms of innovation service support, the YRD city-region takes the lead in establishing the "Scientific Instruments Sharing and Co-construction System". In 2007, the "Sophisticated Scientific Instrument and Equipment Sharing Public Network of the Yangtze River Delta region" was launched. By 2017, 27,479 large-scale scientific instruments and facilities from 2192 institutes in the YRD city-region have been registered and open for researchers. In addition, a financial support in the form of the "innovation vouchers" has been invented in the region, which is designed to encourage the innovation activities and collaborations among SMEs. At present, Suzhou, Wuxi, Suqian, Huzhou, Jiaxing and other places have already started the "innovation voucher" program.

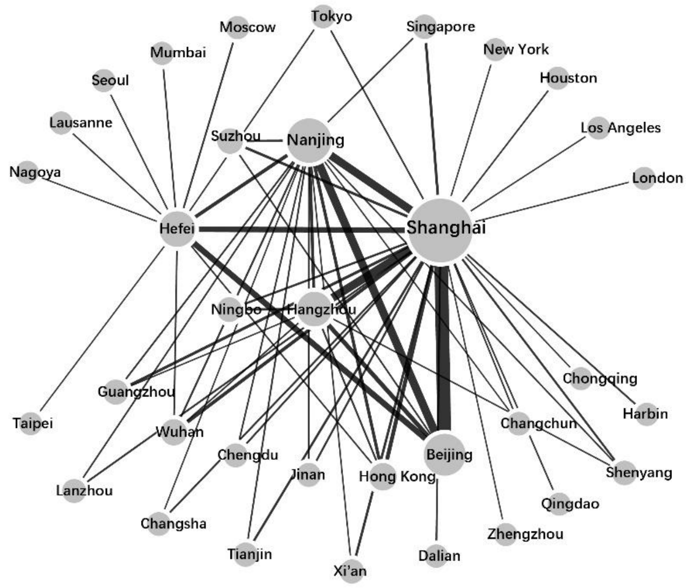
In general, the efforts for the promotion the innovation and the construction of collaboration networks in the YRD city-region have laid a solid foundation for achieving the goal as a world-class innovation city region. First, with multidimensional policies, institutional reforms, financial support and spatial plans, the YRD city-region has transformed from a passive learning region to an active innovative oneo. Second, with Shanghai as the core and Nanjing, Hangzhou and Hefei as the secondary core, the spillovers effect appear to be more obvious. The processed of integration and synergy between the core cities as well as the peripheral cities are moving towards a new stage of high-quality development. In particular, cross-border collaboration intensity between spatially adjacent cities is also significantly increasing. Third, the homogeneous competition between cities in the region is gradually replaced by integrated collaboration, while the expansionary development modes such as competing for foreign investment with lower price and interests are also gradually replaced by a multidirectional collaborative development model.

7.4.2.2 **The evolution of the extra-regional IKCNs of the YRD city-region**

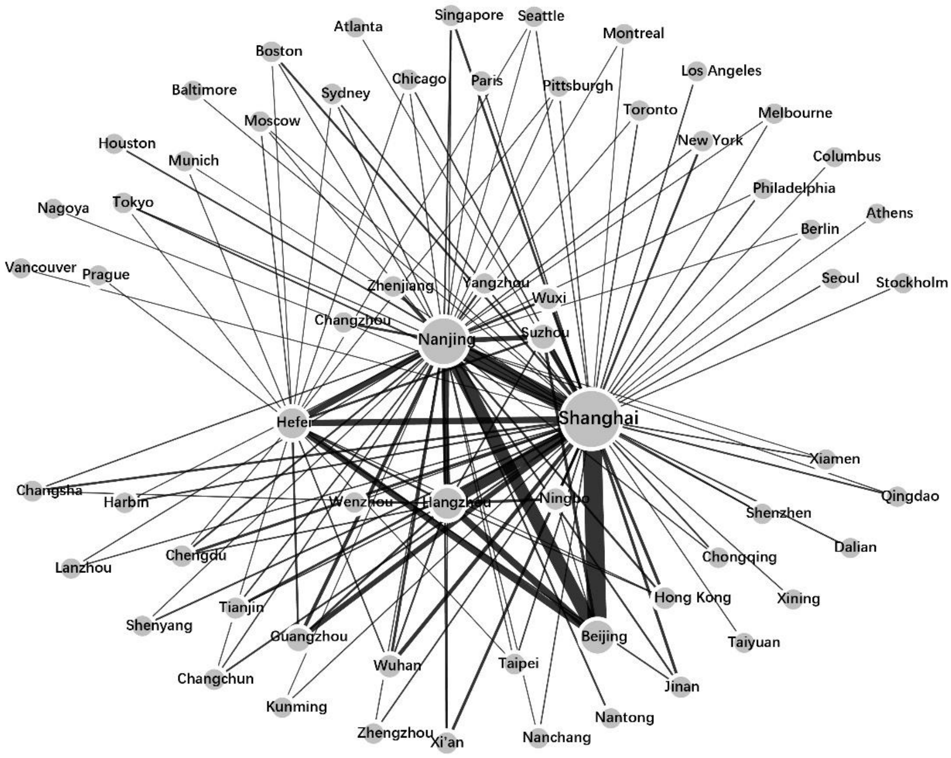
Combined with Figure 7-8 and Table 7- 9, it is not difficult to find that Shanghai is the unchallengeable core of the IKCNs of the YRD city-region, while Nanjing, Hangzhou and Hefei are the sub-cores. During the period of 2002-2006, the total collaboration links of the four cities was 53,506, accounting for 89.42% of all connections of the city-region. In the period of 2012-2016, this ratio, although decreasing, still reached 84.25%. Plus, the four core cities are much more powerful than other cities at different spatial scales of the IKCNs. First, at global scale, during the period of 2002-2006, the supranational connections of Shanghai, Nanjing, Hangzhou and Hefei accounted for 37.59%, 13.85%, 36.19% and 9.15% of the supranational connections of all cities, respectively, with a total of 96.78%. By the time of 2012-2016, the proportions were 34.62%, 23.10%, 11.06% and 14.44%, respectively, and the total was 94.18%. Among them, Hefei's centrality in the transnational KCNs has dropped from second place to third place. This is related to the different science and technology development strategies during different periods in China. In the early stage of participating in transnational knowledge collaboration, the state had paid more attention to basic subjects. For example, the Ministry of Science and Technology points out in *"The Tenth Five-Year Plan"* that "breakthroughs should be made in the basic disciplines such as theoretical physics, basic chemistry, life sciences and nuclear energy science and technology." Based on the WoS data, it can be found that China University of Science and Technology, located in Hefei, participated in 87.51% of Hefei's 6507 multinational coauthored publications in the period of 2002-2006. It has traditional cumulative advantages in basic sciences. More specifically, according to ESI statistical analysis of the data from 2002 to 2012, materials science, earth science, engineering science, mathematics, physics, chemistry, clinical medicine and environment/ecology of China University of Science and Technology have exceeded the world average. With the fast growth of transnational collaboration and the improvement of the country's innovation capability, the disciplines of international collaborations have been largely broadened. For example, the major projects are specified in the "The twelfth Five-Year Plan" involve subjects like core electronic devices, high-end general-purpose chips, large-scale integrated circuit manufacturing, wireless mobile communication technology, high-end CNC machine tools, advanced pressurized water reactors and pollution control and governance of waters, etc. With stronger industrial bases, more mature industrial system as well as a large number of universities, Jiangsu, Zhejiang and Shanghai have experienced a more significant improve in transnational innovation collaboration than Anhui. It can be seen from the figures that during the period of 2002-2006, Shanghai and Hefei performed comparatively in terms of cross-border collaborations. Hefei's foreign partners are mostly located in the Asia-Pacific region while Shanghai's foreign partners are often concentrated in North America and Europe. By the time of 2012-2016, Nanjing has surpassed Hefei to be the second largest city in terms of the amount of transnational collaborations in the region. Compared with other three core cities, Hangzhou started relatively late in transnational collaboration, thereby relatively low in its centrality transnational collaboration.

On national scale, during the period of 2002-2006, the domestic connections of Shanghai, Nanjing, Hangzhou and Hefei accounted for 40.47%, 24.31%, 13.79% and 13.09% of the domestic connections of all cities, respectively, with a total of 91.67%. In the the period of 2012-2016, the proportions were 34.62%, 23.10%, 11.06% and 14.44%, respectively, and the total was 83.22%. In figure 7-8, among the four cities, Shanghai has the widest range of high-intensity domestic trans-regional collaboration, followed by Nanjing and Hefei and Hangzhou. In addition to the four core cities, most of the other prefectural-level cities in the region have rather lower network centrality. In the period 2002-2006, only Suzhou in Jiangsu province and Ningbo in Zhejiang province have higher network centrality and presented on the graph; During the the period of 2012-2016, Changzhou, Zhenjiang, Wuxi, Yangzhou in Jiangsu province, and Huzhou City in Zhejiang province also have been emerging rapidly, while prefectural-level cities in Anhui province were weaker. As shown in the figure, the visible collaboration links of these prefectural cities mainly occur between themselves and their capitals, with the exception of Suzhou and Ningbo. These two cities not only have strong collaborative connections with Nanjing and Hangzhou, but also with other capital cities, indicating that the two cities are more important than other prefectural cities in the KCNs of the YRD city region, especially on the national level.

The coefficients of variance and the Gini coefficients of the cities in the IKNCs at different spatial scales are also listed in Table 7-9. First of all, the coefficients of variance and the Gini coefficients of collaborative connections at different scales have dropped over time to varying degrees, indicating that the degree of polarization of the IKCN of this region has weakened. Interestingly, the two indicators drop with the descending of spatial scales. More specifically , on the global scale, the distribution of the collaborative connections of cities in the region is the most polarized, while on the regional scale, the degree of polarization is the smallest. These results indicate that cities in regional KCNs have different functional levels at different spatial scales. On the global scale, only a few cities play as hubs, so the overall network tend to be rather monocentric. On the national scale, in addition to the core cities, some second-tiered cities may also play as national hubs, thus the IKCN network as a whole are more evenly distributed than that on global scale. In this vein, it is not surprising that the distribution of the IKCN on regional scale is most balanced and polycentric. This result is consistent with many scholars' finding that polycentricity is "scalar sensitive" by nature, and the polycentricity of a certain group of cities decrease with the ascending geographical scales (Hall and Pain, 2006; Li and Phelps, 2016; Ma et al., 2018). Other city-regions studied below also show similar results.



2002-2006



2012-2016

Figure 7-1 Structural features of the YRD city-region in global-national KCNs (2002-2006, 2012-2016)
Note: for clearer visualizations, the thresholds of collaboration links for the two time periods are set to 180 and 700 respectively; the node size is proportional to cities' KNC, and the thickness of lines is proportional to the collaboration links between the cities.

Source: author

Table 7-1 The KNC of cities in the YRD city-region of different spatial scales (2002-2006, 2012-2016)

City	2002-2006				2012-2016			
	Transnational	Domestic	Regional	Total	Transnational	Domestic	Regional	Total
Shanghai	6,760	11,595	3,698	22,053	75,937	67,901	23,223	167,061
Nanjing	2,491	6,966	2,617	12,074	61,136	45,318	22,576	129,030
Hefei	6,507	3,752	1,414	11,673	52,785	21,701	9,171	83,657
Hangzhou	1,645	3,952	2,109	7,706	13,885	28,323	13,194	55,402
Suzhou	187	630	673	1,490	5,784	10,788	8,469	25,041
Ningbo	56	330	525	911	1,456	4,542	3,524	9,522
Wuxi	73	201	281	555	1,354	2,891	3,698	7,943
Zhenjiang	61	180	201	442	863	3,060	3,183	7,106
Changzhou	6	74	169	249	463	1995	2,936	5,394
Yangzhou	95	264	275	634	550	1892	2,210	4,652
Nantong	21	67	159	247	401	1045	2,385	3,831
Jinhua	18	145	235	398	414	1125	1,242	2,781
Wuhu	12	156	246	414	191	696	1,472	2,359
Yancheng	9	43	115	167	127	533	1,400	2,060
Huzhou	8	57	121	186	233	882	821	1,936
Jiaxing	3	31	84	118	246	701	882	1,829
Shaoxing	4	77	76	157	106	537	876	1,519
MaanShan	6	54	58	118	91	559	658	1,308
Zhoushan	1	33	13	47	95	587	361	1,043
Taizhou	4	14	19	37	38	468	417	923
Taizhou	0	3	8	11	35	158	420	613
Anqing	12	18	55	85	30	208	336	574
Zhangzhou	2	8	31	41	97	115	226	438
Tongling	1	3	3	7	10	47	146	203
Chizhou	0	0	18	18	6	43	145	194
Xuancheng	0	0	1	1	8	37	53	98
Total amount	17,982	28,653	13,204	59,839	216,341	196,152	104,024	516,517
Mean	691.62	1,102.04	507.85	2,301.50	8,320.81	7,544.31	4,000.92	19,866.04
Coefficient of variance	2.66	2.45	1.82	2.29	2.49	2.16	1.60	2.14

Gini coefficient	0.91	0.88	0.76	0.85	0.89	0.83	0.71	0.83

Source: author

Table 7-10 lists the share of the collaboration links at different geographical scales of the cities in the IKCNs of the YRD city-region. Among the four capitals, in the period of 2002-2006, Shanghai's share of domestic extra-regional collaboration links was the highest (52.58%), the share of transnational collaborative connections was the second (30.65%), and the share of intra-regional collaborative connections was smallest (16.77%). Nanjing and Hangzhou showed similar characteristics, that is, the shares of domestic extra-regional collaboration links were relatively higher (57.69% and 51.28%, respectively), the shares of intra-regional collaborative connections were second (21.67% and 27.37% respectively), while the shares of transnational collaborative connections were the smallest (20.63% and 21.35%), respectively. These results directly show that Shanghai is more globalized than Nanjing and Hangzhou. Compared with Shanghai, Nanjing and Hangzhou, Hefei was more globalized with its share of transnational collaboration links atta 55.74%, which was much higher than the other three cities. However, its shares of the collaboration links on national and regional scales were relatively small (32.14% and 12.11%, respectively), suggesting that Hefei's collaboration with the cities in the region is relatively weaker. Except for these four core cities, the shares of regional collaborative connections in other cities are the highest, showing rather "localized" features.

In the the period of 2012-2016, 21 of the 26 cities have increased in the shares of the transnational links, indicating that these cities have become more and more "globalized". Among the four core cities, the shares of transnational links of Shanghai and Nanjing have exceedede that of their domestic collaboration connections. Among other non-capital cities, the shares of domestic extra-regional links of Suzhou and Ningbo have exceeded the that within the region, indicating that the importance of these two cities in the national knowledge network have significantly improved. In addition, the share of transnational collaborative connections in Hefei increased to 63.10%, while the shares of its domestic connections decreased, indicating that Hefei, although as a capital city, has neither effectively driven the development of its surrounding neighbors and nor showed any significant effect of spatial spillovers.

Table 7-2 The shares of cities in the YRD city-region in terms of the KNC on different scales (2002-2006, 2012-2016)

City	2002-2006			2012-2016		
	Transnational %	Domestic %	Regional %	Transnational %	Domestic %	Regional %
Shanghai	30.65	52.58	16.77	45.45	40.64	13.90
Nanjing	20.63	57.69	21.67	47.38	35.12	17.50
Hefei	55.74	32.14	12.11	63.10	25.94	10.96
Hangzhou	21.35	51.28	27.37	25.06	51.12	23.82

Suzhou	12.55	42.28	45.17	23.10	43.08	33.82
Ningbo	6.15	36.22	57.63	15.29	47.70	37.01
Wuxi	13.15	36.22	50.63	17.05	36.40	46.56
Zhenjiang	13.80	40.72	45.48	12.14	43.06	44.79
Changzhou	2.41	29.72	67.87	8.58	36.99	54.43
Yangzhou	14.98	41.64	43.38	11.82	40.67	47.51
Nantong	8.50	27.13	64.37	10.47	27.28	62.26
Jinhua	4.52	36.43	59.05	14.89	40.45	44.66
Wuhu	2.90	37.68	59.42	8.10	29.50	62.40
Yancheng	5.39	25.75	68.86	6.17	25.87	67.96
Huzhou	4.30	30.65	65.05	12.04	45.56	42.41
Jiaxing	2.54	26.27	71.19	13.45	38.33	48.22
Shaoxing	2.55	49.04	48.41	6.98	35.35	57.67
MaanShan	5.08	45.76	49.15	6.96	42.74	50.31
Zhoushan	2.13	70.21	27.66	9.11	56.28	34.61
Taizhou	10.81	37.84	51.35	4.12	50.70	45.18
Taizhou	0.00	27.27	72.73	5.71	25.77	68.52
Anqing	14.12	21.18	64.71	5.23	36.24	58.54
Zhangzhou	4.88	19.51	75.61	2.15	36.26	61.60
Tongling	14.29	42.86	42.86	4.93	23.15	71.92
Chizhou	0.00	0.00	100.00	3.09	22.16	74.74
Xuancheng	0.00	0.00	100.00	8.16	37.76	54.08

Source: author

7.4.2.3 **The evolution of the intra-regional IKCNs of the YRD city-region**

Figure 7-9 and Table 7-11 show the spatial and topological characteristics of the IKCNs within of the YRD city-region. In terms of spatial structure, the region's IKCNs —are centered on the four capitals of Shanghai, Nanjing, Hangzhou and Hefei, with two second-tier cities of Ningbo and Suzhou, together they have weaved a "Z-shaped" corridor that pillaring as the backbone of the regional IKCNs. Other cities sparsely attached to this backbone and have formed a multilayer-periphery areas scattered along the corridor. The increase of the mean, maximum, minimum values, and the network density suggests the rapid development of the IKCNs of the YRD city-region. The degree-degree correlation increased from -0.44 to -0.22, indicating that the connections between cities of different levels or of the same level were increasingly balanced and diversified. The spatial and topological structures of the regional IKCN remained stable over time, indicating that the evolution of the IKCNs of the the YRD city-region comply with the general role of "spatial dependency" and "path dependency". In addition, the IKCNs of the region showed small world property, but no scale-free property.

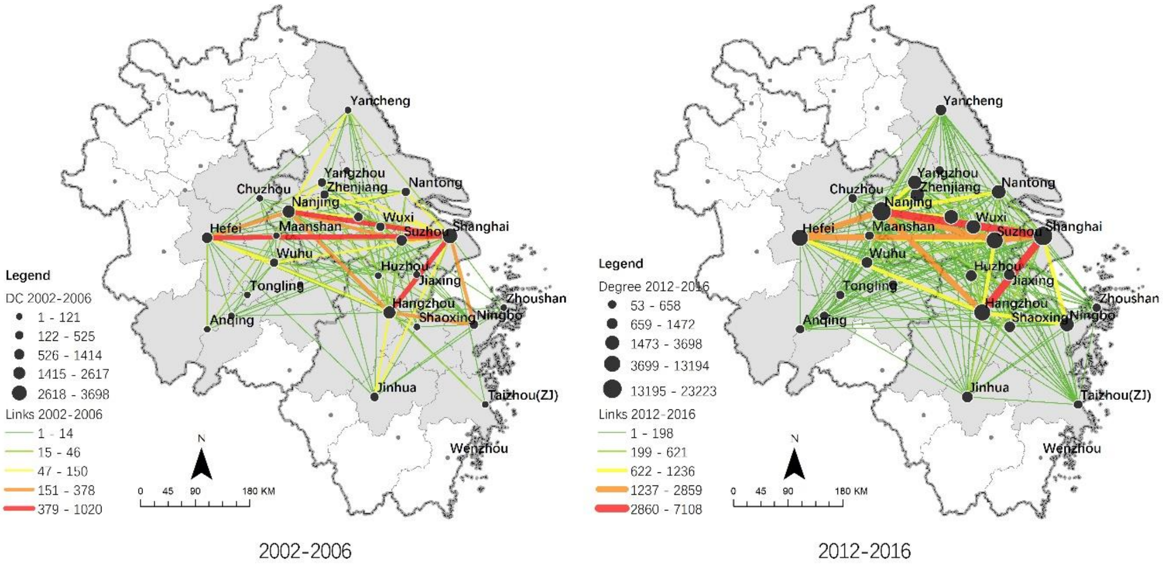


Figure 7-2 The structure of the IKCNs of the YRD city-region (2002-2006, 2012-2016)
Source: author

In terms of degree centrality, the four capital cities--Shanghai, Nanjing, Hangzhou and Hefei are far ahead of other cities in the region. In the period of 2002-2006, Shanghai was the dominant core of the regional IKCNs its degree centrality was 41.31% higher than Nanjing at the second place. By the period of 2012-2016, Nanjing's position in the regional IKCNs has rapidly increased. Its degree centrality has been almost comparable to that of Shanghai, only slightly lower by 2.87%. Beside, distinct differences between cities can be found in different provinces. More specifically, The degree centrality of the cities in Jiangsu pprovince is significantly higher than that of the cities in Zhejiang and Anhui pprovince. In the the period of 2012-2016, in addition to the four capital cities, 7 of the top 10 prefectural cities in terms of degree centrality were from Jiangsu provinces, including Suzhou, Wuxi, Zhenjiang, Changzhou, Nantong, Yangzhou and Yancheng. The other three cities are Ningbo and Jinhua in Zhejiang province as well as Wuhu in Anhui province. Compared with Zhejiang province,the importance of prefectural cities in Anhui province as a whole in the regional KCNs is relatively lower. Among the 7 prefectural cities in Anhui, 5 of them were in bottom 5, including Xuancheng , Chizhou, Tongling, Zhangzhou and Anqing. This is in line with the socio-economic development status of the four municipalities.

In terms of betweenness centrality, only the four capital cities were greater than 0 in both time periods, indicating that these four cities have strong power in controlling resources and play as brokerages in the IKCNs. In terms of the changes of betweenness centrality, it can be seen once again that Nanjing has grown rapidly in the KCNs, and its role as a knowledge gatekeeper and knowledge hub has been more pronounced.

The closeness centrality can indirectly reflect the independent innovation ability of a city. It can be found that the closeness centrality is highly correlated with the degree centrality of the cities. The Pearson coefficients between them are all above 0.95 with significance at the 0.01 level in both time periods. This reflects that cities' independent innovation capability is closely related to their importance in the IKCNs.

Table 7-3 The topological structures of the IKCNs of the YRD city region (2002-2006, 2012-2016)

	City	2002-2006			2012-2016		
		DC	BC	CC	DC	BC	CC
Topological features of nodes	Shanghai	3698	202	3.30	23223	140	5.03
	Nanjing	2617	176	2.61	22576	209	4.69
	Hangzhou	2109	129	2.65	13194	129	3.76
	Hefei	1414	46	2.14	9171	69	3.13
	Suzhou	673	0	1.40	8469	0	2.84
	Wuxi	281	0	0.82	3698	0	1.85
	Ningbo	525	0	1.26	3524	0	1.86
	Zhenjiang	201	0	0.77	3183	0	1.96
	Changzhou	169	0	0.66	2936	0	1.82
	Nantong	159	0	0.61	2385	0	1.52
	Yangzhou	275	0	0.99	2210	0	1.70
	Wuhu	246	0	0.65	1472	0	1.09
	Yancheng	115	0	0.56	1400	0	1.28
	Jinhua	235	0	0.82	1242	0	1.17
	Jiaxing	84	0	0.57	882	0	0.81
	Shaoxing	76	0	0.37	876	0	0.94
	Huzhou	121	0	0.48	821	0	0.81
	Maanshan	58	0	0.26	658	0	0.78
	Taizhou	8	0	0.05	420	0	0.53
	Taizhou	19	0	0.22	417	0	0.60
	Zhoushan	13	0	0.10	361	0	0.53
	Anqing	55	0	0.30	336	0	0.39
	Chuzhou	31	0	0.16	226	0	0.32
	Tongling	3	0	0.02	146	0	0.22
	Chizhou	18	0	0.10	145	0	0.23
	Xuancheng	1	0	0.02	53	0	0.09
Basic topological properties	Average degree	10.46			19.31		
	Max	1.00			8.00		
	Min	23.00			25.00		
	Network density	0.42			0.77		
	Global efficiency	0.71			0.89		
	Degree-degree correlation	-0.44			-0.22		

Small world property	Characteristic path length	1.60	1.23
	Characteristic path length of the same-size random networks	1.59	1.23
	Clustering coefficient	0.61	0.83
	Clustering coefficient of the same-size random networks	0.43	0.76
	small world quotient	1.42	1.10
Scale-free property	Cumulative power-law exponent	0.90	0.41
	R^2	0.73	0.37
Similarities of topological structures	QAP correlation	0.96 (p<0.01)	

Source: author

From the above analysis, it can be concluded that the roles of different cities show both differences and similarities at global and national scales. This is also the case at regional scale. Figure 7-10 shows the "center-hinerland" topological relations of the IKCNs of the YRD city-region. Shanghai is the dominant regional hub, the other three capitals and Suzhou from Jiangsu province constitute the direct hinterlands of Shanghai. The direct hinterland of Nanjing includes not only most prefectural cities in Jiangsu province, but also includes four prefectural cities from Anhui province, i.e. Wuhu, Zhangzhou, Xuancheng and Maanshan. The direct hinterlands of Hangzhou are made up of the prefectural cities in Zhejiang province. The direct hinterlands of Hefei include only part of the prefectural cities in Anhui province, i.e., Anqing, Tongling and Chizhou. Combining with the results of the previous section on the cities' functions and roles in the global-national KCNs, one can conclude: first, Shanghai is the most important but not the only "knowledge gatekeeper" in the YRD city-region. Together with Nanjing, Hangzhou and Hefei, they play the roles as brokers in the multiscalar IKCNs. On one hand, they absorb and digest the external knowledge, further diffuse it to other cities within the region, acting as the terminal valves for "global pipelines"; on the other hand, they collect and integrate local knowledge, then spread it outside the region, functioning as the concentrators for "local buzz". Second, although the functions of the four core cities overlap to some extent, the differences are also evident. With regard to the compositions of different types of the collaboration links, Shanghai, Nanjing and Hefei have more transnational collaboration links suggesting they are more globalized, that is to say, for themselves, they are more powerful as global or national hubs than that as regional hubs.

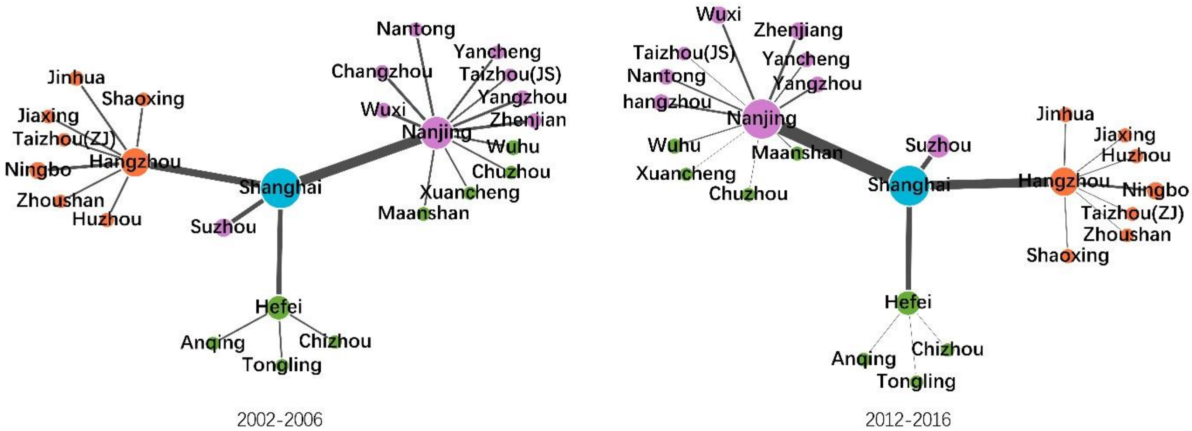


Figure 7-3 “Center-hinterlands” structure of the IKCNs of the YRD city-region (2002-2006, 2012-2016)

Source: author

To sum up, as the first mover in social and economic development, as well as the growth pole of the national innovation progress, the IKCN of the YRD city-region has formed with a distinct hierarchical and diverse feature. The “Z-shaped” corridor with Shanghai, Nanjing, Hangzhou and Hefei as the cores and with Suzhou and Ningbo as the sub-cores as the backbone of the regional IKCN has strengthened over time. From the analysis results, Bathelt’s et al. (2004) theoretical models of “global pipeline” and “local buzz” is once again confirmed: the combination and interaction of high-quality external links and intensive internal links is both important for regional innovation systems. More importantly, the positive effects of “local buzz” and “global pipelines” only emerge as catalyst when the two achieve a certain degree of balance. In line with this logic, it can be preliminarily claimed that for further enhancing the overall innovative capability of the region, balanced development of the IKCNs is crucial. Related policies could be implemented that targeting the optimization of Hangzhou and Hefei in the regional IKCN: Hangzhou should devote more efforts to establish high-quality “global pipelines”, while Hefei needs to strengthen its “local buzz”.

7.4.3 The evolution of the IKCNs of the Beijing-Tianjin-Hebei city-region

7.4.3.1 **overview**

Since the reform and opening up, the BTH city-region has accomplished great achievements in terms of socio-economic development as well as scientific and technological innovation. It has become one of the most dynamic city-regions in terms of innovation resources, innovation output, openness and innovative capabilities in China, which is considered as a ready world-class innovative region (Bo et al., 2019; Li, 2014). From the perspective of innovative resources, in 2014, the BTH city-region houses more than a quarter of the country’s key universities, one-third of the national key laboratories and research institutes, and two-thirds of the academicians of the Chinese Academy of Sciences and Chinese Academy of Engineering. The number of R&D personnel reached 664,000 (accounting for 11.8% of the country), R&D expenditure reached 188.6 billion yuan (accounting for 15.8% of the country), and it had 14 national high-tech zones and economic and technological development zone led by Zhongguancun National Independent Innovation Demonstration Zone. In the region, Beijing has the most outstanding innovation capability. It has huge advantages in basic research, applied technology and advanced cutting-edge technology as well as the knowledge-based and service-oriented industries. Tianjin's technological innovation capability takes the second place in the region. It has distinctive advantages in some knowledge intensive industries such as high-tech manufacturing, new energies and bio-pharmaceutical medicine. The innovation capabilities of cities in Hebei province are weaker, its industries are mostly in the lower value chain, and the independent innovation capability is limited.

Different from the YRD and the GBA city-regions, there exist prominent gaps of the three municipalities in the BTH city-region. A large number of superior innovation resources are excessively and exclusively concentrated in Beijing. The IKCNs of the region are also weak. These issues are the nonnegligible barriers for the long-term development of the BTH city-region in scientific and technological innovation (Qi and Liu, 2019; Xing and Zhang, 2018; Zhao and Zhao, 2015). Despite this, lot of the efforts have been made to promote the regional integration, such as interconnection of infrastructures, attracting talents, encouraging scientific and technological collaborations, mainly in the forms of trans-local collaborative agreements. Since 2013, the three municipalities have signed the "*Beijing-Hebei Collaboration Framework Agreement (2013-2015)*" and the "*Beijing-Tianjin Collaboration Agreement on Economic and Social Development*". It has been emphasized in the National Twelfth Five-Year Plan that "it is important to promote the regional economic integration of Beijing, Tianjin and Hebei". The coordinated development of the BTH city-region have been emphasized as a national strategy. In April 2015, the Political Bureau of the CPC Central Committee deliberated and approved the "*Outlines of the Beijing-Tianjin-Hebei Collaborative Development Plan"*. The outline points out that the establishment of a coordinated regional innovation system and the promotion of innovative collaborations are crucial for realizing innovation-driven development.

Zhongguancun National Independent Innovation Demonstration Zone is a flagship of China's innovation-driven development strategy. It is known as China's "Silicon Valley" and has gathered a large number of high-quality innovation resources, including 14 high-level research institutes such as the Chinese Academy of Engineering, and 17 national university science parks. More than quarter of the national key laboratories, national engineering (technological) research centers, and national enterprise technological research and development centers are located in Zhongguancun park. Drawing on the development experience of Silicon Valley innovation corridor, utilizing the huge influence and energy of the Zhongguancun park have become one of the instrumental ways for the BTH city-region to move toward an integrated innovative center. (Bo et al., 2019). In 2014, the Zhongguancun National Independent Innovation Demonstration Zone established a working group and established action outline with institutes such as the central Ministry of Science, the Science and Technology Commissions of the three municipalities, together dedicate to provide financial and institutional support for building regional collaboration networks. By the end of 2018, there were 11 innovative collaborative communities jointly established by Zhongguancun and institutions from Tianjin and Hebei.

In addition, the industry-university collaborations have increasingly become the main plyers in the regional innovation collaboration networks. For example, Peking University and Tianjin Binhai new district jointly built a new generation of information technology research academy, and a R&D center with Hebei Chengde High-tech Zone. Tsinghua University and Hebei jointly established the Tsinghua Development Research Institute, and successively established four high-tech research centers such as the Intelligent Transportation Experimental Research Center. The Chinese Academy of Sciences and Tianjin jointly established the Tianjin Electronic Information Industrial Park, at the same time, jointly established the Tangshan High-tech Research and Technology Transfer Center with Tangshan, Hebei.

Although the BTH city-region has accomplished some achievements in the development of innovative collaboration networks, there are still a series of problems and challenges. For example, factors like (1) the market segmentation, the regional development gaps and the homogenous competition led by administrative boundaries (Guo, 2016; He and Liu, 2015; Zhao and Zhao, 2015); (2) uneven distribution of resources and human capital created by the top-down administrative (Deng et al., 2007; and (3) the lack of institutional and policy support (Chen et al., 2015)are barriers for the integration of the BTH city-region and its development of collaborative networks.

7.4.3.2 **The evolution of the extra-regional IKCNs of the BTH city-region**

From Table 7-12 and Figure 7-11, it can be seen that the Beijing is the unchallengeable core of the IKCNs in the BTH city-region. First, in the period 2002-2006, the number of Beijing's number of the transnational collaboration was 26,956, accounting for 94.62% of the total of the BTH city-region. The amount of Tianjin's transnational collaboration was 1,271, accounting for 4.46% of the total, indicating its importance in the transnational IKCNs was much lower than that of Beijing. In comparison, the share of the transnational links of the cities in Hebei is much lower with only 0.92% of the total. Among 8 cities of Hebei province, only Shijiazhuang's number of transnational collaborations exceeded 100, Zhangjiakou and

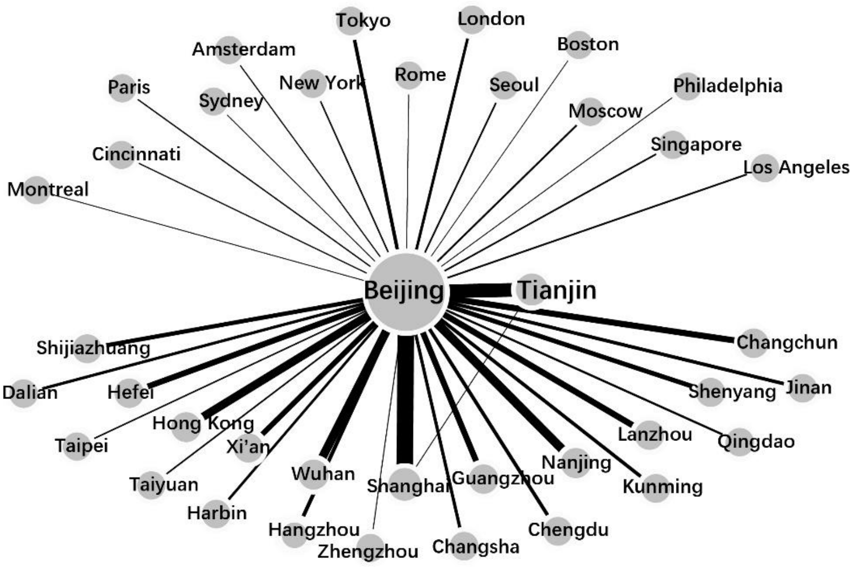
Langfang did not even participate in the transnational collaboration networks. By the time of 2012-2016, the amount of transnational collaboration of all cities in the city-region has increased to varying degrees. At the same time, the dropping of coefficients of variance and the Gini coefficients reflect that the polarization of the transnational collaboration in the city-region has weakened. Beijing's transnational collaboration ratio was 92.12%, which was 2.5% lower than that of the 2002-2006 period, but its core position in the network had not been shaken. Correspondingly, the proportion of transnational collaboration of Tianjin and 8 cities in Hebei have increased by 1.81% and 0.96% respectively.

In the national KCNs, Beijing has been still at the very top in the IKCNs. In the period 2002-2006, the number of collaborative connections of Beijing with other domestic cities outside the city-region were 31,513, accounting for 87.68% of the region total. The transnational collaboration of Tianjin and Hebei accounted for 9.88% and 2.44% respectively. What is more prominent is the rapid rise of Shijiazhuang. The proportion of its domestic collaboration has increased by 1.27% during the 2012-2016 period, ranking the first among the BHD city-region. It can also be seen from Figure 7-11 that in the period of 2012-2016, the importance of Shijiazhuang in the national-scale KCNs has been greatly enhanced, and has reconstructed the configuration of the IKCNs of the BTH city-region from a "Beijing-Tianjin" dual-core structure to a "Beijing-Tianjin-Shijiazhuang" triple-cores structure.

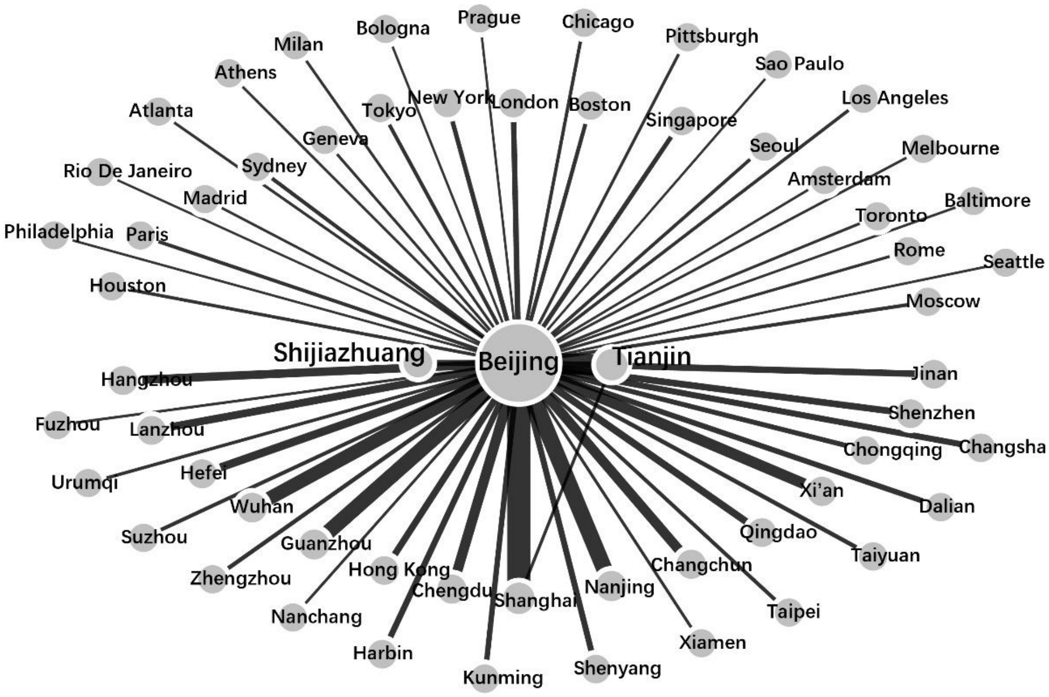
Table 7-12 The KNC of cities in the BTH city-region of different spatial scales (2002-2006, 2012-2016)

City	2002-2006				2012-2016			
	Transnational	Domestic	Regional	Total	Transnational	Domestic	Regional	Total
Beijing	26,956	31,513	2,609	61,078	170,707	180,812	13,284	364,803
Tianjin	1,271	3,550	1,699	6,520	11,624	23,032	8,941	43,597
Shijiazhuang	145	386	746	1,277	1,420	5,030	3,373	9,823
Baoding	50	173	435	658	373	1,911	1,756	4,040
Tangshan	17	40	105	162	652	1,427	1,206	3,285
Qinhuangdao	43	205	166	414	392	1,594	1,254	3,240
Langfang	7	47	77	131	66	494	587	1,147
Zhangzhou	0	1	10	11	31	254	240	525
Zhangjiakou	0	12	18	30	24	224	263	511
Chengde	1	14	19	34	27	168	218	413
Total amount	28,490	35,941	5,884	70,315	185,316	214,946	31,122	431,384
Mean	2,849.00	3,594.10	588.40	7,031.50	18,531.60	21,494.60	3,112.20	43,138.40
Coefficient of variation	2.98	2.75	1.50	2.72	2.89	2.62	1.43	2.64
Gini Coefficient	0.98	0.96	0.75	0.95	0.97	0.94	0.71	0.94

Source: author



2002-2006



2012-2016

Figure 7-11 Structural features of the BTH city-region in global-national KCNs (2002-2006, 2012-2016)

Note: Structural features of the BTH city-region in global-national KCNs (2002-2006, 2012-2016) Note: for clearer visualizations, the thresholds of collaboration links for the two time periods are set to 400 and 1200 respectively; the node size is proportional to cities' KNC, and the thickness of lines is proportional to the collaboration links between the cities.

Source: author

Table 7-13 lists the shares of collaboration links of cities in the BTH city-region at different geographical scales. It is clear that most of Beijing's collaboration links are transnational links and domestic extra-regional links. In contrast, the share of its intra-regional links is much smaller, indicating that compared with other cities in the region. Beijing has more prominent influences in the IKCNs at the global and national scales, which, once again, confirms its important role as a national "knowledge gatekeeper". For Tianjin, in the period of 2002-2006, its domestic extra-regional collaboration accounted the most, indicating that for Tianjin, its relatively high importance in the IKCNs at national scale. By 2012-2016, the share of Tianjin's transnational collaboration has increased significantly, reflecting Tianjin has become more and more important in the KCNs. Compared with Beijing and Tianjin, Shijiazhuang's role as a hub in the IKCNs was functioning at national and regional scale. For the rest cities, their collaborative connections mostly occurred within the region, presenting a more "localized" feature.

Table 7-4 The shares of cities in the BTH city-region in terms of the KNC on different scales (2002-2006, 2012-2016)

City	2002-2006			2012-2016		
	Transnational %	Domestic %	Regional %	Transnational %	Domestic %	Regional %
Beijing	44.13	51.59	4.27	46.79	49.56	3.64
Tianjin	19.49	54.45	26.06	26.66	52.83	20.51
Shijiazhuang	11.35	30.23	58.42	14.46	51.21	34.34
Baoding	7.60	26.29	66.11	9.23	47.30	43.47
Tangshan	10.49	24.69	64.81	19.85	43.44	36.71
Qinhuangdao	10.39	49.52	40.10	12.10	49.20	38.70
Langfang	5.34	35.88	58.78	5.75	43.07	51.18
Zhangzhou	0.00	9.09	90.91	5.90	48.38	45.71
Zhangjiakou	0.00	40.00	60.00	4.70	43.84	51.47
Chengde	2.94	41.18	55.88	6.54	40.68	52.78

Source: author

7.4.3.3 **The evolution of the intra-regional IKCNs of the BTH city-region**

Figure 7-12 and Table 7-14 show the spatial and topological characteristics of the IKCNs within the BTH city-region. In general, the evolution of the IKCNs of the region shows spatial dependency and path dependency. That is, the evolution of the IKCNs of the city-region has been stable and self-reinforcing (QAP correlation coefficient is 0.99), the intensity of collaboration has significantly increased (the mean, the maximum and minimum values have increased), the overall connectivity of the network was continuously strengthened (the global efficiency has increased from 0.81 to 0.96, while the network density has grew from 0.62 to

0.91). The ways of formation of the collaboration links have also become more and more diverse (degree-degree correlation increased from -0.95 to -0.33). In addition, the internal IKCNs of the BTH city-region also exhibited the small world property (small world quotient was greater than 1), but did not show scale-free property (cumulative power-law exponent was less than 2), which was largely because of the small size and the high density of the network (there were only 10 nodes).

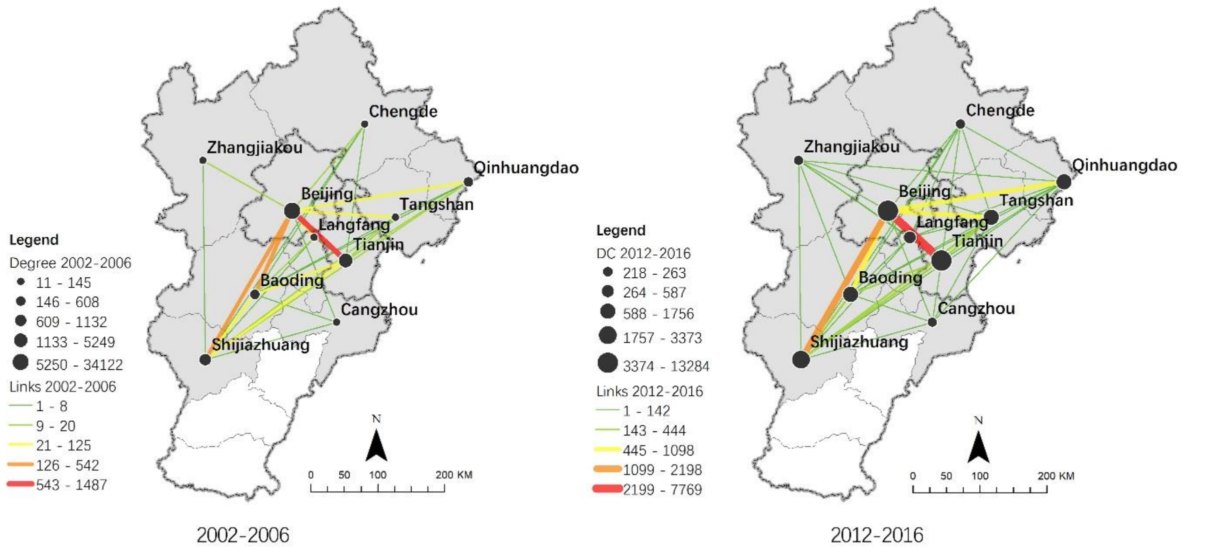


Figure 7-4 The structure of the IKCNs of the BTH city-region (2002-2006, 2012-2016)
Source: author

Figure 7-14 lists the individual network topological property of the cities in the regional IKCNs. The distribution of degree centrality shows a significant hierarchical structure. A tripe-cores structure of Beijing, Tianjin and Shijiazhuang has been formed. The second-tier cities include Baoding, Tangshan, Langfang and Qinhuangdao, while Chengde, Zhangjiakou and Zhangzhou are located in the periphery layer. In terms of betweenness centrality, Beijing has the strongest power and act as the "knowledge gatekeeper" in the regional IKCNs. In term of closeness centrality, Beijing and Tianjin were higher than other cities, indicating that Beijing and Tianjin had far more advanced in independent innovation than other cities.

The collaboration intensity between Beijing and Tianjin have always been far ahead. In the period of 2002-2006, the collaboration intensity between the two cities was 1,487, accounting for 50.54% of the regional total. By the time of 2012-2016, this ratio was still as high as 49.92%. Besides, in the two time periods, Beijing was also the primate city for all other cities in the region to collaborate with, while Tianjin was the secondary city for most cities in the region. Among the cities of Hebei province, only Cangzhou, Chengde and Zhangjiakou took Shijiazhuang--their capital as the secondary city to collaborate with. This indicates that in the

BTH city-region, the administrative hierarchy have greater influences on the evolution of the IKCNs than the administrative boundaries.

Table 7-5 The topological structures of the IKCNs of the BTH city region (2002-2006, 2012-2016)

	City	2002-2006			2012-2016		
		DC	BC	CC	DC	BC	CC
Topological features of nodes	Beijing	2,609	35	2.76	13,284	36	3.89
	Tianjin	1,699	10	2.54	8,941	9	3.66
	Shijiazhuang	746	8	1.45	3,373	6	1.88
	Baoding	435	0	1.03	1,756	0	1.26
	Qinhuangdao	166	0	0.57	1,254	0	1.02
	Tangshan	105	0	0.36	1,206	0	0.88
	Langfang	77	0	0.31	587	0	0.70
	Zhangjiakou	18	0	0.11	263	0	0.28
	Cangzhou	10	0	0.04	240	0	0.23
	Chengde	19	0	0.11	218	0	0.25
Basic topological properties	Average degree	5.60			8.20		
	Max	2.00			6.00		
	Min	9.00			9.00		
	Network density	0.62			0.91		
	Global efficiency	0.81			0.96		
	Degree-degree correlation	-0.95			-0.33		
Small world property	Characteristic path length	1.38			1.09		
	Characteristic path length of the same-size random networks	1.38			1.09		
	Clustering coefficient	0.69			0.92		
	Clustering coefficient of the same-size random networks	0.63			0.90		
	small world quotient	1.10			1.02		
Scale-free property	Cumulative power-law exponent	0.70			0.14		
	R2	0.76			0.35		
QAP correlation		0.99 (p<0.01)					

Source: author

To sum up, the development of the IKCNs of the BTH city-region present a prominent polarization feature with Beijing as the absolute core at global, national and regional scales. However, its power in the knowledge network have not effectively boost the growth of its surrounding cities in its own region, especially the cities of Hebei province. On one hand, this imbalanced development can be attributed to the long-existing gap in the region with respect to industrial bases and resource endowments. Comparing with Beijing and Tianjin, the industries in Hebei province have been locked in lower levels along the value chain, and can hardly meet the needs of the advanced industries in Beijing and Tianjin. For example, in certain fields of advanced technologies such as electronic information, automobile manufacturing and biomedicine, the supply chains and technological collaboration of Beijing and Tianjin's high-tech firms are mostly connected with enterprises in the GBA and the YRD city-regions (Li, 2014). On the other hand, Hebei's innovative resource base is far weaker than that of Beijing and Tianjin. Beijing and Tianjin show strong "siphon effects" to Hebei's resources and talents, while Beijing and Tianjin's high-level innovation resources rarely flow to Hebei. A recent the plan of building Xiong'an new district has been considered an effective spatial coordination aiming at promoting the regional integration of the BTH city-region as well as strengthening the radiant effect and spillovers of Beijing. This may provide new opportunities for the balanced development of KCNs in the BTH city-region.

7.4.4 The evolution of the IKCNs collaboration networks in the GBA city-region

7.4.4.1 **overview**

In January 2014, the concept of "Bay Area Economy" was first proposed by Shenzhen government in the annual work report. In 2015, the strategic concept of building a "Greater Bay Area" around Guangdong, Hong Kong and Macao was first proposed in the "*Vision and Actions on Jointly Building the Silk Road Economic Belt and the 21st-Century Maritime Silk Road*". In 2016, the establishment of Guangdong-Hong Kong-Macao Greater Bay Area was highlighted in the "13th Five-Year Plan". In 2017, the National Development and Reform Commission, Guangdong provincial government province, the Hong Kong SAR Government, and the Macao SAR Government jointly signed the *The Agreement Framework of Strengthening Guangdong-Hong Kong-Macao Collaboration and Promoting the Construction for the Greater Bay Area*. The agreement clearly states that the Greater Bay Area should be built as an international center for technology and innovation. In 2019, the State Council issued *The outlines of Guangdong-Hong Kong-Macao Greater Bay Area Development Plan*, emphasizing that the development goal of the Greater Bay Area is to build a "dynamic world-class city-region" and an "world-class international technology and innovation center". In particular, establishing the "Guangzhou-Shenzhen-Hong Kong-Macao" scientific and technological corridor is the key spatial coordination in this strategic plan, which will be exemplified as powerful engine for the implementation of the innovation-driven development strategy of the region and the nation.

The GBA city-region includes 11 cities, i.e. Guangzhou, Shenzhen, Foshan, Dongguan, Huizhou, Zhaoqing, Zhuhai, Zhongshan, Jiangmen, and Hong Kong and Macao. *The Ouelines of Development Plan in Guangdong-Hong Kong-Macao Greater Bay Area* states that "Guangdong, Hong Kong and Macao have solid bases of scientific research and development as well as better capability of technology transfer. There are a number of universities, research institutes, high-tech enterprises and national scientific facilities that have important influence in China and the world located in the GBA city-region. All these endowments have built a solid foundation for the GBA city-region to achieve the goal of being the world-class innovation center. As the most important experimental field for reform and opening up, in the process of receiving the direct investment, attracting enterprises and outsourcing production from Hong Kong and Macao, the GBA city-region has formed a closely linked collaboration community as well as an open and tolerant innovation environment. Hong Kong and Macao have a high degree of internationalization and openness, which has attracted innovation resources from all over the world. At the same time, Guangdong has also formed a tolerant "immigration culture" in the practice of reform and opening-up, particularly exemplified by Shenzhen: in 2017, the number of migrants in Shenzhen was 8.06 million, accounting for 67% of the total population. It has formed an immigration culture that purses for innovation, fairness and competitiveness, as well as innovative spirits of taking risks, pursuing success, advocating innovation and being tolerable for failures. Within this favorable environment, a number of scientific and technological giants have emerged and actively participated in global innovation competitions e.g. Huawei, ZTE, BYD, Beijing Genomics Institution, Tencent (Gu, et al., 2018; Yan and Cao, 2019).

However, due to some historical and political reasons, the unique administrative mode of "one country, two systems, and three customs jurisdictions" is a barrier for the GBA city-region to achieve fully integration, resulting in a fragmentation of cross-boundary governance, which in turn increases cost of innovation collaboration (Gu, et al., 2018). Although the business collaboration between Guangdong, Hong Kong and Macao has a long history, the institutional support for collaboration in general and innovation collaboration in particular is mostly in the form of "joint summit meeting" without legal effects or regulation power (Ye and Song, 2019). At present, a leading group of the construction of the Guangdong-Hong Kong-Macao Greater Bay Area has been established by central and local governments, but an effective, unified and coordinated mechanism has not yet been set.

7.4.4.2 **The evolution of the extra-regional IKCNs of the GBA city-region**

From Figure 7-13 and Table 7-15, it is not difficult to see that Guangzhou, Shenzhen and Hong Kong are the core cities of the GBA city-region, forming a "tripolar" structure. In the period of 2002-2006, Hong Kong was the dominant core in the IKCN of the GBA city region. The amount of its transnational collaboration was 6,743, accounting for 75.38% of the regional total. It can be inferred that Hong Kong is the most important gateway city for transnational collaboration in the GBA city-region. Most of the transnational collaboration of other cities should be done inevitably through Hong Kong. In addition, most of the domestic extra-regional collaboration is mainly concentrated in Hong Kong and Guangzhou, accounting for 51.41% and 38.91% of the total respectively, indicating that the two cities together act as "knowledge gatekeepers" for the region at national level. In comparison, during this period, Shenzhen's centrality in the IKCNs at both global and national scales was much lower than that of Hong Kong and Guangzhou.

During the the period of 2012-2016, the structure of the IKCN in the GBA city-region has experienced significant changes. Compared with the early years since Hong Kong's return, the amount of collaboration between Hong Kong, Guangzhou and Shenzhen has increased rapidly. In particular, Shenzhen's centrality in the network has been greatly improved, further strengthening the "tripolar" structure of "Hong Kong-Guangzhou-Shenzhen" as the centers. During this period, the total amount of Guangzhou's collaborative connection was 122,790, which was 6.81% higher than that of Hong Kong. It has shaken Hong Kong's unipolar position in the regional IKCN. The total number of transnational collaborative connections in Hong Kong was still 49.42% higher than that in Guangzhou, but its domestic extra-regional collaborative connections have been surpassed by Guangzhou. Although Shenzhen has a short history of urbanization development, in recent years, its overall innovation capability has been continuously enhanced. For example, Shenzhen has attracted six internationally renowned universities in Hong Kong to set up new campuses in Shenzhen. In 1996, Shenzhen government and Tsinghua University jointly established the Shenzhen Research Institute of Tsinghua University. Since then, more than 30 well-known domestic universities and research institutions have collaborated with Shenzhen and set up co-research establishments in Shenzhen. As it can be seen from Figure 7-13, Hong Kong has the widest spatial range and largest amount of transnational collaborative connections, while Guangzhou has the widest spatial range and largest amount of connections with other domestic cities outside the region. This suggests that in the IKCN of the GBA city-region, Hong Kong and Guangzhou have formed a certain degree of specialization. That is, Hong Kong is the "knowledge gatekeeper" for the GBA city-region at global scale, and Guangzhou is the "knowledge gatekeeper" at national scale. This result is consistent with the findings of Ma et al. (2018). The specialization between Hong Kong and Guangzhou is largely attributed to the historical and institutional differences between Hong Kong and Guanghzou: the history of Hong Kong as an outgoing city, also a colony, makes it highly international, while Guangzhou has been strategized as national level city since the reform and opening-up. After the return of Hong Kong, the historical and institutional differences between two cities have continued, thus they formed a specialization not only in knowledge collaboration but also in many different aspects.

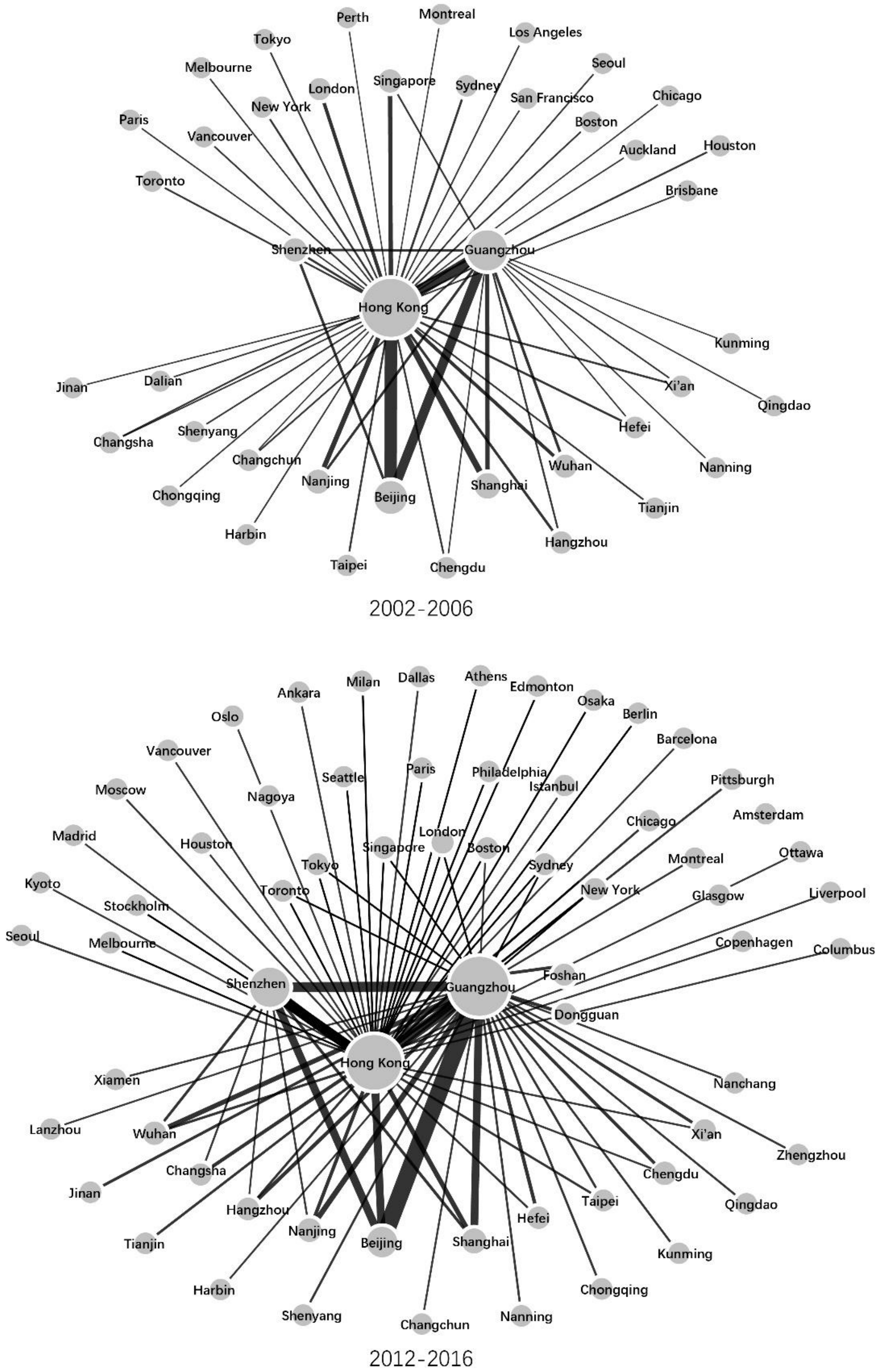


Figure 7-13 Structural features of the GBA city-region in global-national KCNs (2002-2006, 2012-2016)

Note: for clearer visualizations, the thresholds of collaboration links for the two time periods are set to 80 and 600 respectively; the node size is proportional to cities' KNC, and the thickness of lines is proportional to the collaboration links between the cities.

Source: author

Table 7-6 The KNC of cities in the GBA city-region of different spatial scales (2002-2006, 2012-2016)

City	2002-2006				2012-2016			
	Transnational	Domestic	Regional	Total	Transnational	Domestic	Regional	Total
Guangzhou	1,917	5,061	1,056	8,034	60,216	52,461	10,113	122,790
Hong Kong	6,743	6,686	972	14,401	89,975	18,213	6,778	114,966
Shenzhen	168	926	250	1,344	6,490	17,675	6,254	30,419
Macao	39	72	49	160	1,041	1,793	1,007	3,841
Dongguan	3	29	25	57	401	1421	1,184	3,006
Foshan	10	85	30	125	288	852	950	2,090
Zhuhai	3	45	10	58	190	1011	770	1,971
Zhongshan	49	21	21	91	111	585	478	1,174
Jiangmen	9	48	21	78	77	350	285	712
Huizhou	2	11	9	22	35	288	347	670
Zhaoqing	2	22	29	53	66	182	160	408
Total amount	8,945	13,006	2,472	24,423	14,444.55	8,621.00	2,575.09	25,640.64
Mean	813.18	1,182.36	224.73	2,220.27	2.13	1.87	1.34	1.83
Coefficient of variation	2.52	2.00	1.76	2.11	0.88	0.82	0.67	0.83
Gini Coefficient	0.94	0.87	0.80	0.88	0.90	0.84	0.84	122,790

Source: author

Table 7-16 lists the shares of the collaboration links of cities in the GBA city-region at different scales. Comparing the results of the two time periods, the shares of transnational collaboration in most cities have increased to varying degrees, indicating that the cities in the GBA city-region have become increasingly “globalized”. Another interesting finding is that, except for Huizhou and Foshan, the shares of the domestic extra-regional collaboration connections in other prefectural cities were higher than their shares of the intra-regional collaboration connections. This feature is opposite to that of the YRD city-region and the BTH city-region, indicating that the overall openness of the GBA city-region on the national scale is relatively higher.

Table 7-7 The shares of cities in the GBA city-region in terms of the KNC on different scales (2002-2006, 2012-2016)

City	2002-2006	2012-2016

	Transnational	Domestic	Regional	Transnational	Domestic	Regional
Guangzhou	23.86	62.99	13.14	49.04	42.72	8.24
Hong Kong	46.82	46.43	6.75	78.26	15.84	5.90
Shenzhen	12.50	68.90	18.60	21.34	58.11	20.56
Macao	24.38	45.00	30.63	27.10	46.68	26.22
Dongguan	5.26	50.88	43.86	13.34	47.27	39.39
Foshan	8.00	68.00	24.00	13.78	40.77	45.45
Zhuhai	5.17	77.59	17.24	9.64	51.29	39.07
Zhongshan	13.85	33.08	23.08	19.45	49.83	30.72
Jiangmen	11.54	61.54	26.92	10.81	49.16	40.03
Huizhou	9.09	50.00	40.91	5.22	42.99	51.79
Zhaoqing	3.77	41.51	54.72	16.18	44.61	39.22

Source: author

7.4.4.3 **The evolution of the intra-regional IKCNs of the GBA city-region**

Figure 7-14 and Table 7-17 show the spatial structures and topological structures of the IKCN in the GBA city-region, respectively. It can be seen from the figure that the connections among Hong Kong, Guangzhou, Shenzhen, Macao and Zhuhai are relatively more intensive, which have formed a “diamond-shaped” structure. At the same time, the “triangle” core, which is composed of Hong Kong, Guangzhou and Shenzhen, is becoming more and more prominent in underpinning the regional IKCN. At the same time, it can be clearly seen that the intensity of collaboration of Guangzhou-Dongguan and, Guangzhou-Foshan has become stronger, not only suggesting the rapid improvement of the centrality of the two cities in the KCN, but also reflecting the fact that Guangzhou, as a hub in the regional IKCN, its spillover effects and radiation effects to neighboring cities have become more and more significant.

It can be seen from Table 7-17 that the values of average, maximum, minimum KNC, the network density and the global efficiency all have increased, showing a rapid development trend of the IKCNs of the GBA city-region. The degree-degree correlation has increased from -0.64 to -0.23, indicating that the connections among cities have become increasingly balanced and diverse. During the two periods, the spatial and topological structures of the network in the two time periods remained basically stable with the QAP correlation coefficient reaching 0.77, which was significant at the 0.01 level. This indicated that the evolution of the IKCN in the GBA city-region has shown spatial dependency and path dependency. In addition, in two time periods, the IKCNs of the region showed obvious small-world property (small-world quotients were all greater than 1); in the period 2002-2006, the regional IKCN presented scale-free property (cumulative power-law exponent was 2.13), but in the 2012-2016 time period, the scale-free property disappeared (cumulative power-law exponent was 1.66).

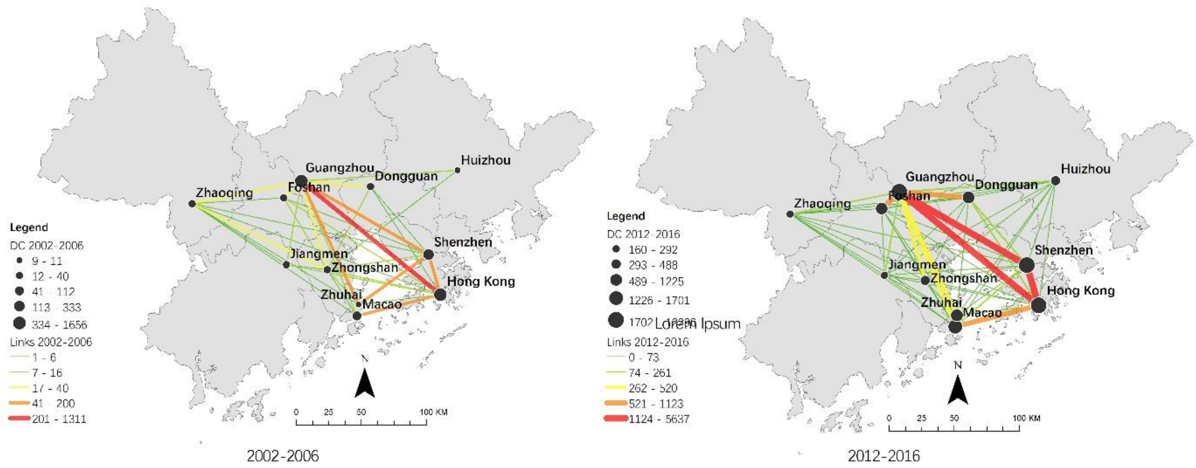


Figure 7-5 The structure of the IKCNs of the GBA city-region (2002-2006, 2012-2016)
Source: author

Table 7-17 The topological characteristics of the internal KCN in the GBA city-region (2002-2006, 2012-2016)

	City	2002-2006			2012-2016		
		DC	BC	CC	DC	BC	CC
Topological structures of the nodes	Guangzhou	1056	39	1.85	10113	43	3.78
	Hong Kong	1272	17	1.82	6778	33	3.44
	Shenzhen	250	0	1.65	6254	0	3.29
	Macao	25	0	0.22	1184	0	1.47
	Dongguan	49	0	0.32	1007	0	0.97
	Foshan	30	0	0.26	950	0	1.38
	Zhuhai	10	0	0.07	770	0	1.09
	Zhongshan	21	0	0.16	478	0	0.85
	Jiangmen	9	0	0.12	347	0	0.68
	Huizhou	21	0	0.18	285	0	0.58
	Zhaoqing	29	0	0.26	160	0	0.40
Basic topological properties	Average degree		3.82			9.64	
	Max		1.00			8.00	
	Min		10.00			10.00	
	Network density		0.38			0.96	
	Global efficiency		0.69			0.98	
	Degree-degree correlation		-0.64			-0.23	
small world property	Characteristic path length		1.62			1.04	

	Characteristic path length of the same-size random networks	1.73	1.04
	Clustering coefficient	0.43	0.97
	Clustering coefficient of the same-size random networks	0.31	0.96
	small world quotient	1.48	1.00
Scale-free property	累计度分布幂律指数	1.13	0.66
	R^2	0.90	0.45
QAP correlation		0.77 (p<0.01)	

Source: author

Table 7-17 lists the individual network topological properties of the cities in the regional IKCNs. In the period of 2002-2006, Hong Kong was the core of the regional IKCN with its degree centrality reaching 1,272, which was 20.45% higher than Guangzhou and five times higher than Shenzhen. The intra-regional collaboration links of these three core cities accounted for 93.01% of the entire region. In 2012-2016, Guangzhou and Shenzhen's positions in the regional KCN increased rapidly, Guangzhou had surpassed Hong Kong and become the primate city, and Shenzhen's amount of internal collaborative connection was almost equal to that of Hong Kong. The results of betweenness centrality show that only Guangzhou and Hong Kong have noticeable capabilities of controlling information and resources in the regional IKCN, which play the roles of "brokers". Finally, the closeness centrality of Hong Kong, Guangzhou and Shenzhen was much higher than that of other cities, indicating that these three cities had stronger capabilities of independent innovation.

To sum up, as one of the most dynamic city-region in terms of innovation, the evolution of its regional IKCN is characterized by diversification and complexity. In general, it evolves from a "bipolar" structure centered on Guangzhou and Hong Kong to a "tripolar" structure that consists of Guangzhou, Hong Kong and Shenzhen". Among them, Shenzhen, as the "third pole" in the IKCN of the GBA city-region, has showed a great momentum in the regional IKCNs. By taking the advantage of the spillovers effect of Guangzhou, the network centrality of Foshan and Dongguan has also increased rapidly, together they have the potentials to form an innovative metropolitan area. In terms of network functions, at global scale, Hong Kong's status as the primate city in the region for global collaboration has been gradually challenged by Guangzhou and Shenzhen. At national scale, Guangzhou has surpassed Hong Kong and become the primate city for other domestic cities outside the region. At the regional scale, more and more cities have rapidly emerged and manifested their places in the regional IKCN. It is noteworthy that, in the KCN of the GBA city-region, Guangzhou and Hong Kong have gradually formed functional complementarity and differentiation. Guangzhou plays the role of "knowledge gatekeeper" at national scale, while Hong Kong plays the role of "knowledge gatekeeper" at global scale.

For the GBA city-region, it has already built a solid foundation and a good "hard environment" for developing innovative economy. In the future, it is necessary to further optimize and strengthen the "soft environment" such as eliminating institutional barriers, utilizing institutional differences and legalizing collaborative agreements (Cao, 2019; Cao, 2018).

7.4.5 The impact of regional factors on the formations of the IKCNs of the three major city-regions

The analysis in previous sections shows that the IKCNs of different city-regions present different spatial structures, topological features and evolutionary paths. The formation and evolution of the urban network are affected and influenced by many factors. As Zhang et al. (2019) point out that the formation of urban networks is determined by multiple factors such as the masses of cities, geographical distances, administrative boundaries, landform features, cultural differences, regional alliances etc. Through a comparative study of the commuting network, corporate network and infrastructure network of the YRD city-region, they find that the same regional factor has different effects on different types of urban networks of a same region. Conversely, it can be assumed that a same regional factor might have different effects on the same type of urban network of different regions. This section introduces a series regional factors that would potentially influence the formation of the IKCNs, and further builds an econometric model with the aid of QAP regression to formally test this hypothesis.

7.4.5.1 **The construction of variables and model specification**

First, the dependent variable is the amount of collaborated publications between any two cities in 2012-2016. There are eight independent variables as the proxies of regional factors, i.e. geographical distance, GDP, the share of R&D expenditure, the number of colleges and universities, trains, technical similarities, administrative boundaries and capital monopoly.

（1） Geographical distances

Knowledge diffusion and spillovers by nature follows the rule of distance decay. Therefore, co-located cities are more likely to collaborate with each other. (Katz, 1994). In this section, the geographical distance is the Euclidean distance between two cities.

（2） GDP

GDP is a direct reflection of the economic masses of the city. According to the gravitational model, the intensity and frequency of flows between two cities are positively correlated with the sizes of the two cities. In addition, many studies have proved that the economic sizes of the cities are highly related with their innovation capabilities. Based on the gravitational model, this section uses the product of two cities' GDP as the proxy for sizes of the cities. The urban GDP is the average of the data from 2007 to 2011, which is sourced from the 2008-2012 China City Statistical Yearbook. The data of Hong Kong is sourced from the official website of the Census and Statistics Department of the Hong Kong Special Administrative Region[32]. The data of Macao is from the official website of the Statistics and Census Bureau of the Macao Special Administrative Region[33].

（3） Share of R&D expenditure

The share of R&D expenditure in total GDP is obviously highly related with urban innovation capability, reflecting the support and investment from the government in scientific and technological research and development activities. The same as GDP, the share of R&D expenditure of a city is the average of the data from 2007 to 2011, drawn from the 2008-2012 China City Statistical Yearbook. The data of Hong Kong comes from the official website of the Statistics Department of the Hong Kong Special Administrative Region. The data of Macao is sourced from the official website of the Statistics and Census Bureau of the Macao Special Administrative Region.

（4） The number of colleges and universities

Colleges and universities are the main producers of scientific paper output. The more colleges and universities a city have, the more advanced knowledge it process, and in turn, more collaborations will occur. The number of universities is also the average of the data in 2007-2011, drawn from the 2008-2012 China City Statistical Yearbook. The data of Hong Kong and Macau data is from Wikipedia.

（5） Trains

Many studies have pointed out that the interconnectedness of transportation infrastructure has a positive effect on innovation cooperation, because efficient and convenient transportation can facilitate face-to-face communication and reduce the cost of distance frictions. This section uses the number of trains between the two cities to reflect the connectivity of the transportation infrastructure. The data is sourced from the official website of China Railway. The data was collected in February 2016[34].

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32 https://www.censtatd.gov.hk/

33 https:// www.economia.gov.mo/

34 https://www.12306.cn/index/

（6） Technological similarities

Sharing a similarities or dissimilarities knowledge background and structure is considered to be a precondition for innovation collaboration. In the process of seeking knowledge collaboration, the innovation actors may choose actors that are similar to their own knowledge and technology to ensure efficient communication and learning. They may also choose the actors that differ from their own knowledge and technology to achieve complementarity. By using the OECD category scheme of the WoS disciplines, the Pearson coefficients of the distribution of different disciplines between any two cities are calculated. Higher value means higher similarities between two cities and vice versa. The discipline classification method is described in detail in section 6.4.

（7） Administrative boundaries

From the previous analysis, it can be seen that the administrative boundaries have negative effects on the formation of the IKCNs, that is, the probability of urban collaboration between different cities in the same province is higher than that of trans-provincial collaboration. This section sets the administrative boundaries factor as a binary variable: 1 if the two cities are in the same province, otherwise 0.

（8） Capital monopoly

In the previous sections, the "capital monopoly" has been frequently proved as an important factor in forming the IKCNs. Due to the particularity of China's administrative system, capital cities often enjoy more innovation resources and more preferential policies, which are more likely to attract collaborations. Two binary variables are used in this section to reflect the effect of "capital monopoly". Capital 1: If both cities are capital cities, set as 1; otherwise, set as 0. Capital 2: Set as 1 if only one of the two cities is the capital city; otherwise, set it as 0.

（9） Cultural similarities

Culture is a direct manifestation of territorial embeddedness and local embeddedness. Cultural proximity can promote mutual trust between actors and reduce costs and uncertainties in the process of interactive practice. However, culture is difficult to quantify. Dialects, languages, and ethnics are often used as proxies. This section uses dialects as a proxy: 1 if the two cities belong to the same dialect zone, otherwise, 0. The data is drawn from the *Language Atlas of China* (Xiong and Zhang, 2012).

Thus, the econometric models can be constructed and the QAP regression is used for parameter estimation:

$\mathrm{Ln}(\textit{collaboration intensity})=a_1\mathrm{Ln}(\textit{Geographical distance})+a_2\mathrm{Ln}(GDP_1*GDP_2)+a_3\mathrm{Ln}(R\&D_1*R\&D_1)+a_4\mathrm{Ln}(\textit{Universities}_1*\textit{Universities}_2)+a_5\mathrm{Ln}(\textit{Trians})+a_6\mathrm{T}\textit{echnological}$

similarity)+a_7*(Administrative boundaries)*+a_8(*Capital monopoly1*)+a_9(*Capital monopoly2*)+ a_{10} (*Cultural similarity*)

7.4.5.2 **Regression results**

Table 7-18 shows the QAP regression results. For the three city-regions, most of the variables are statistically significant with the only exception of "Cultural similarity". One possible explanation is that the dialect, which serves as a proxy for cultural similarity , is only a reflection of informal vernacular culture of daily life. The culture of scientific research is more strictly and formally structured, and it provides common rules for scientists to follow. This is consistent with the research results of Cao et al. (2019).

Comparing the three different city-regions, most of the variables have significant positive impacts on the formation of the knowledge networks with the exception of "Geographical distance". Only the variable "Technological similarity" of the BTH city-region and the variable "Administrative boundary" of the GBA city-region show significant negative effects. From the results, one can tell that the effects of different factors on the IKCNs in different regions differ.

Table 7-8 Results of the QAP regressions

	The YRD city-region	The GBA city-region	The BTH city-region
Geographical distance (Log)	-0.10 (0.12)***	-0.19 (0.23)*	-0.08 (0.32)*
GDP (Log)	0.43 (0.09)***	0.42 (0.12)***	0.06 (0.22)*
R&D (Log)	0.08 (0.06)***	0.08 (0.61)*	0.15 (0.21)*
Universities	0.30 (0.12)***	0.60 (0.49)**	0.72 (0.23)***
Trains	0.05 (0.01)**	0.01 (0.01)*	0.23 (0.01)**
Technological similarity	0.07 (0.23)***	5.18 (6.97)***	-0.22 (1.20)**
Administrative boundaries	0.24 (0.13)***	-5.07 (7.55)***	0.23 (0.58)*
Capital 1	0.15 (0.48)***	0.22 (3.11)*	0.09 (1.35)*
Capital 2	0.19 (0.20)***	0.33 (1.27)*	0.01 (0.61)*
Cultural similarity	0.04 (0.12)	-0.01 (0.25)	0.08 (0.32)
R2	0.87	0.94	0.90
AIC	796.28	88.70	113.88
Observations	325	45	45

Significance level: ***p<0.01, **p<0.05, *p<0.1; standard error in parentheses

Source: author

Based on the above regression results, a series of stepwise QAP regression procedures are conducted to further select the most significant factors. Figure 7-15 visualized the regression results, showing both similarities and dissimilarities. For the three different city-regions, the common feature they share is that the variables "GDP" and "Universities" all have a sizable positive impact on the formation of the regional IKCNs. This shows that the urban economic masses and the innovation facilities/resources are crucial for interurban knowledge collaboration: the larger the cities, the more innovative human capitals, the higher the possibility of interurban collaboration occurs.

The impact of geographical distance on the IKCNs is only significant for the YRD city-region, and it is negative. This result indicates that for the YRD city-region, geographical proximity can facilitate the formation of IKCNs. However, for the the BTH and the GBA city-regions, the impact of geographical distances is not significant. This is largely because, compared to the YRD city-region, the distances between the cities within the BTH or the GBA city-regions are relatively small, and the cost of spatial friction caused by geographical distances is not enough to become the main obstacle for interurban collaboration. Specifically, the average distance between cities in the YRD city-region is 228.68 km (Euclidean distance), while the average distances between cities within the BTH and the GBA city-regions are 114.75 km and 95.14 km respectively. Based on this, it can be assumed that 100 kilometers may be a threshold distance for interurban knowledge collaboration. If it is more than 100 kilometers, the marginal cost of interurban collaboration will increase significantly.

Variable “Trains” has significant positive impact on the formation of IKCNs of the BTH and the YRD city-regions, while the impact on the GBA city-region is not significant. In 2016, the railway network density in the BTH and the YRD city -region was 0.95 and 0.67, respectively, while that in the GBA city-region was only 0.43.

The variable “Technological similarity” has positive impacts on the formation of the IKCNS of the YRD and the GBA city-regions, but has a negative effect on the BTH city-region. On one hand, this shows that there is significant homogenization of the science and technology among the cities in the BTH city-region, and it is not conducive to interurban collaboration. Therefore, the complementary and diversified development is the key to strengthen the IKCNs for this region. On the other hand, for the YRD and the GBA city-region, similar technological structure has a positive effect on the formation of interurban collaboration networks, reflecting that “specialization” or “localization economies” is governing the development of the IKCNs in the YRD and the GBA city-regions.

The variable “Administrative boundaries” has positive impacts on the formation of the IKCNs in the YRD and the BTH city-regions, indicating that the possibility of building collaboration connections between cities located in the same municipality is higher than that of cities belonging to different municipalities. For the GBA city-region, the impact of administrative boundaries is not significant. Despite the institutional differences between Hong Kong and mainland cities, its shares of collaborative connections with Guangzhou and Shenzhen are rather high, thus, to some extent, the negative effect of administrative boundaries has been offset in a statistical term.

Finally, two variables reflecting the “capital monopoly” effect (the capital 1 and the capital 2) only have significant positive impacts on the IKCN of the YRD city-region. This may be because the number of cities in the YRD city-region is larger than that of the other two city-regions, the types of collaborative connections are more complex and diverse (for example, there is no collaboration link between different prefectural-level cities from different provinces in the other two city-regions), so the “capital monopoly” effect is more significant.

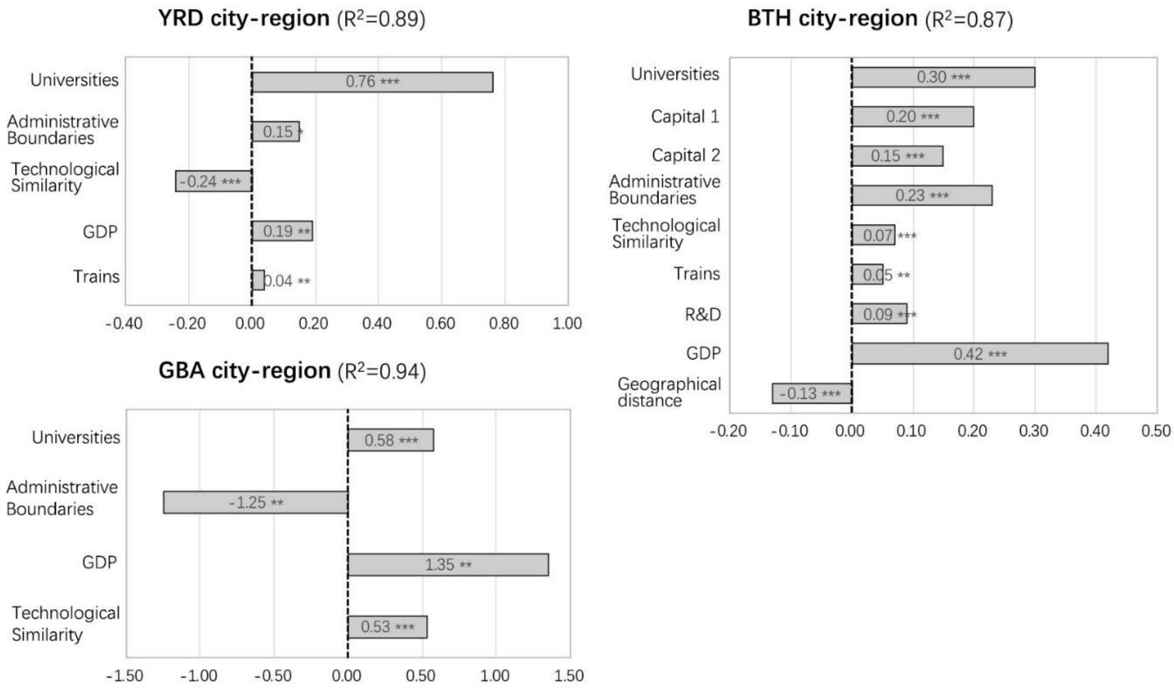

Figure 7-6 Influencing factors on the regional IKCNs’ of the three city-regions based on stepwise QAP regressions

Source: author

To sum up, the structures of the intra-regional IKCNs are affected by different regional factors. In addition to the above-mentioned factors, there are many other possible factors that also influence the formation of the IKCNs, such as innovative alliance agreements between cities, etc. Importantly, a same factor may affect differently on the IKCNs of different city-regions. This is mainly because that different regions have different historical development trajectories and different regional contexts. These regional differences are the key factors in determining the different structural models and evolutionary paths of the IKCNs of different city-regions.

7.5 Summary

This chapter studies the evolution of the IKCNs of 20 city-regions in China, and particularly compares the evolution of the IKCNs of the three major city-regions. The main research conclusions are as follows:

First, the evolution of the spatial structure of the IKCNs of the 20 city-regions is analyzed and compared. The main findings are: (1) there is a clear-cut regional gap between eastern and western China, that is, city-regions located in eastern China are generally more developed than that in western China in terms of the overall connectedness and cohesiveness of the IKCNs. (2) Compared with the period of 2002-2006, in the period of 2012-2016, almost all the city-regions have witnessed growth to varying degrees. The growing speed of city-regions in western China is generally faster than that in eastern China. (3) Within most of the city-regions, the gap between different cities is gradually narrowed in terms of KNC. On one hand, the participation of small and medium-sized cities into the IKCNs has increased and intensified. On the other hand, the polarization of the primate city in terms of KNC has decreased in all city-gions, showing an evident trend of balanced development. (4) Different city-regions show different polycentricity in both morphological and functional terms. The degree of polycentricity of a certain region is closely related to its overall development status, spatial configuration and hierarchical organization.

Secondly, the evolution of the topological structures of the IKCNs of 20 city-regions is studied and compared. The main findings are: (1) Among the five national-level city-regions, in terms of connectivity and intensity, the IKCNs of the YRD, the BTH and the GBA city-regions are more developed than those of the MRY and the CHC city-regions. At the same time, the five city-regions showed significant "disassortativity" and "small-world" property, but show no sign of "scale-free" property. (2) According to their development status of the IKCNs, the eight city-regions of sub-national level can be divided into three different groups. The first-level city-regions are the SDP city-region and the HAC city-region. And the second-level city-regions are the CSL city-region, the WST city-region and CPL city-region. The third-level city-regions are the GZP city-region, the SGX city-region and the TSM city-region. The IKCNs of these eight city-regions mostly show significant "disassortativity" and "small world property", but show no sign of "scale-free" property. (3) Among the six regional-level city-regions, the sizes of networks are small, so there is no significant complex network topological property. (4) Compared with all other city-regions, the IKCN of the EST city-region is most mature. The collaboration links exist between any two cities within the city-region, forming an internally closed and fully connected network. (5) Through the analysis of "internal reach" and "external reach" of city-regions, it is found that "local buzz" and "global pipelines" are equally important for regional innovation.

Thirdly, the evolution of the IKCNs in the YRD city-region, the BTH city-region and the Guangdong-Hong Kong-Macao GBA city-region is compared. The main findings are: (1) Cities in regional IKCNs show different degrees of network importance at different geographical scales: at global scale, only a few cities play as hubs, and the hierarchy of the IKCNs is most polarized. At national level, some second-teir cities may also act as hubs in the IKCNs. At regional scale, small and mediumn-sized cities may also emerge, while the degree of polycentricity of the IKCNs is the highest. (2) The differences of the IKCNs in different city-regions are mainly caused by the different regional factors. And a same type regional factor may have different impacts on the IKCNs of different city-regions. (3) In the YRD city-region, Shanghai, Nanjing, Hangzhou and Hefei constitute the backbone underpinning the regional IKCN. Shanghai is the “knowledge gatekeeper” at global, national and regional levels. Nanjing is the “knowledge gatekeepers” at national and regional level. Hangzhou is abundant in “local buzz” but lack of “global pipeline”, while Hefei is abundant in “global pipelines” but lack of “local buzz”. In the BTH city-region, the development of regional KCN is extremely uneven with Beijing being the dominant core city. At the same time, Beijing and Tianjin have significant “siphon effect” and negatively affect cities in Hebei province. In the GBA city-region, Guangzhou, Hong Kong and Shenzhen have formed a “tripolar” structure of the regional IKCN. Guangzhou and Hong Kong have achieved a certain degree of specialization in terms of network function: Guangzhou is a “knowledge gatekeeper” at national scale, while Hong Kong is the “knowledge gatekeeper” at global scale.

Chapter 8 The mechanisms of the evolution and formation of the interurban knowledge collaboration networks

The previous chapters have comprehensively investigated the structures of the IKCNs of different geographical scales. Then, how do these IKCNs form? What kind of factors shape, influence and determine the formation and evolution of the IKCNs? Thus, the internal mechanisms of knowledge networks' formation and the key determinant factors need to be explored. On one hand, knowledge collaboration as a social practice is socially embedded in a broader institutional context and also spatially embedded in territorial-specific places, so its evolution and formation process are influenced and restricted by certain macro- structural factors. On the other hand, the processes of selecting, establishing and maintaining collaboration relationships are essentially processes that rational actors' tradeoff between the benefits and costs of the collaboration practices, during which their individual behavioral logic is influenced and shaped by certain micro-initiative factors. With the aid both qualitative and quantitative approaches, this chapter first takes the "Sino-Belgium joint laboratory for geo-information" program as the study case to explore the macro-structural factors that influence the formation of the IKCNs. Second, based on a set of fine-grained WoS data, an inter-organizational knowledge collaboration network of the medical sciences of the "Jiangsu-Zhejiang-Shanghai" region (JZS region) has been constructed, as well as interviews with three PhD candidates of Tongji University Medical School are conducted, which together are used as cases to further explore the micro-initiative factors in the formation of IKCNs .

8.1 The macro-structural factors

During 2016-2018, the author studied in the Geography department of Ghent University in Belgium, and conducted a series of in-depth interviews with the participants of the "Sino-Belgium joint laboratory for geo-information", which was established by the Xinjiang Institute of Ecology and Geography of Chinese Academy of Sciences (IEG) and the Department of Geography of Ghent University, Belgium (DGG). The interviews focus on the topic of the macro mechanisms of the formation of inter-city knowledge collaboration. Based on the results, three macro-structural factors that influence the formation of the IKCNs are identified, i.e. "scientific paradigm", "innovation resources" and "collaboration environment".

8.1.1 Research objects and research design

8.1.1.1 Semi-structured interviews

The semi-structured interviews are the main research instrument of this section. A semi-structured interview is a method of research used most often in the social sciences. Before the interview, the interviewer generally has a framework of themes to be explores, yet the response of a interviewee is open-ended, allowing new ideas to be brought up during the interview as a result of what the interviewee says . During the interview, interviewers can flexibly make the necessary adjustments depend on the actual situations. More specifically, the time and places, the forms and orders of the questions and answers are not rigorously restricted.

In this section, the questions of the interview start with interviewees' descriptions of their current collaboration projects, followed by a series of investigations on their cognitions and feelings about the collaboration experiences, as well as their incentives and reasons of conducting collaborations.

In addition, because the interviewees often have different education backgrounds, occupations, research interests, collaboration incentives, etc., the interview outlines are then set as two parts: basic information on one hand and target questions on the other hand. The basic information is designed to attain the personal information of the interviewees based on which the target questions are then customized and adjusted to fit for particular cases. By doing so, the interviews could be more efficient and explicit. The target questions are regard to three aspects: "scientific paradigm", "innovation resource" and "collaborative environment". The questions about "scientific paradigm" are designed to investigate the impact of the shifting scientific research paradigm on collaboration incentives. The questions about "knowledge resources" are brought up to examine the complementation and synergy of the two institutions involved in the project in terms of human capital, funding, technology and instruments. The main purpose of the questions about "collaborative environment" is to explore the roles of certain supportive factors like policies, culture and institutions in the process of knowledge collaboration. (Appendix V).

8.1.1.2 **Interviewees**

The interviewees are some of the participants from the "Sino-Belgium Joint Laboratory for geo-information" program. This program is not only a transnational scientific collaboration project, but also a interurban scientific collaboration project. After years of development, the two institutions have established a mutual trust, produced fruitful payoffs and drawn many attentions from officials. Therefore, empirically, the case is fit for the purpose of this chapter.

In 1998, the Xinjiang Institute of Biological Soil Desert Research, CAS (established in 1961) and the Xinjiang Institute of Geography, CAS (established in 1965) merged and established the Xinjiang Institute of Ecology and Geography, CAS (IEG). The IEG devotes to exploring the frontier in the fields of ecology, environment and resource of the arid zone worldwide, and focuses on supporting "The Silk Road Economic Belt" initiative, maintaining social security and long-term stability of Xinjiang and exploring key issues of national resource exploitation, ecological rehabilitation, environment management, biodiversity protection and regional sustainability. Since the establishment, the IEG have conducted a series of studies on major issues such as the environmental monitoring and assessment of "The Silk Road Economic Belt", mineral exploration and environmental management in Xinjiang and Central Asia, sustainable use of biological resources in arid areas, and improvement in the well-being of Xinjiang farmers and herdsmen. (Figure 8-1) The Geography department of Ghent University (GGU), established in 1900, is well known around the world. The department has five different teaching/research groups, i.e. 3D Data Acquisition, Cartography & GIS, Physical Geography, Landscape Research, and Social and Economic Geography

The "Sino-Belgium joint laboratory for geo-information" devotes to the application of geo-information technology in studies of climate change, sustainable development, archaeology, environment, ecology and geology. The collaboration between the IEG and the GGU originated from an unexpected meeting between the heads of the two institutions in an international conference in 2005. Since then, they have established frequent informal interpersonal collaborations and also began to discuss the possibility of carrying out formal inter-organizational collaborations. In November 2007, the IEG and the GGU signed up a first 5-year bilateral collaboration agreement. In April 2012, the two institutions signed a second 5-year collaboration agreement. In October 2014, the IEG and the GGU carried out a series of field research on the protection of the cultural heritages of the Jiaohe Old City, the Gaochang Old City, the Toksun Panjier Rock Painting Area and the ancient water conservancy system of Kaner. In addition, the two institutions have jointly conducted many academic conferences and academic forums in different forms and scales.

With the expansion and deepening of the collaboration, in 2014, the two institutions launched the "joint PhD training program". In 2016, the first joint doctoral student graduated and was awarded a double degree by both of the institutions. In the same year, the IEG and the GGU formally established the "Sino-Belgium Joint Laboratory for geo-information". At the same time, the "joint PhD training program" also received a special funding from the China Scholarship Council. By the end of 2018, more than 20 Chinese doctoral students have successfully applied the funding and participated in the joint training program, and 5 of them have graduated. In addition, the two institutions have jointly published 48 scientific papers, including 32 SCI papers.

Interviewees in the study includes the program coordinators, key researchers as well as doctoral students from both sides of the joint program. Table 8-1 lists the detailed information of interviewees, including 2 researchers and 6 doctoral students on Chinese side and also 2 professors and 6 doctoral students on Belgian side.

Table 8-1 Detailed information of the interviewees

No.	Institution	Positions	Nationality	Time	Duration
A1	IEG	Project coordinator, senior researcher	China	2019.8.25	30min
A2	IEG	Assistant researcher	China	2019.8.26	30min
A3	IEG	Doctoral student	China	2019.8.28	30min

A4	IEG	Doctoral student	China	2019.9.29	35min
A5	IEG	Doctoral student	China	2019.9.1	40min
A6	IEG	Doctoral student	China	2019.9.2	30min
B1	GGU	Project coordinator, dean, professor	Belgium	2019.9.2	30min
B2	GGU	Professor	Netherlands	2019.9.3	35min
B3	GGU	Doctoral student	Belgium	2019.9.4	30min
B4	GGU	Doctoral student	Belgium	2019.9.4	30min
B5	GGU	Doctoral student	Ethiopia	2019.9.5	30min
B6	GGU	Doctoral student	Belgium	2019.9.6	30min

Source: author

In each interview, the research purposes of the interviewer are first introduced with a brief statement on confidentiality and privacy. Interview duration ranges from 30 minutes to 45 minutes. After the interview, the recordings are transcribed within 24 hours. The raw materials are then systematically sorted, refined and further analyzed. By doing so, the macro-structural factors that influence the formation of the IKCN can be extracted[35].

8.1.2 The triangle model of the macro-structural factors

Based on a systematic analysis of the interview documentations, a triangle model of macro-structural elements that affects the formation of the IKCNs is established: first, the shifting scientific paradigm is the external force that drives formation of the IKCNs. With the end of the "scientific genius" era and the arrival of the "big science" era, the needs for collaboration in scientific research have become more and more urgent, including the needs of knowledge combination, the needs of specialization, the needs of interdisciplinary integration and the needs of satisfying the interests of different subjects. Secondly, the complementation of innovation resources is a prerequisite for the formation of the IKCNs. Due to the uneven distribution of innovation resources across space, innovation actors in different cities are thus driven to achieve complementary resources in the form of interurban collaborations, including complementary human resources, complementary financial resources, complementary facility resources and complementary knowledge resources. Finally, the support of collaborative environment is an important guarantee for the formation of the IKCNs, including the support of policy environment, support of cultural environment and support of institutional environment. These three macro-structural factors, separately and conjunctionally, facilitate and influence the formation and maintenance of the IKCNs. (Figure 8-1)

[35] See the Appendix V and Appendix VI for the interview outline.

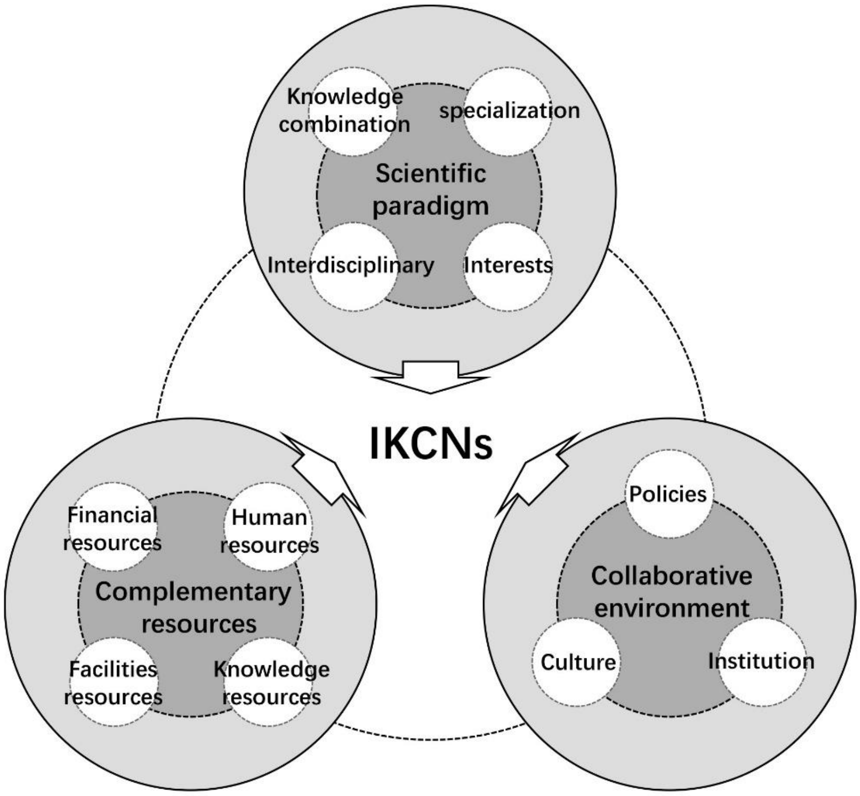

Figure 8-1 The triangle model of macro-structural factors

Source: author

8.1.3 Shifting scientific research paradigm

Today's cutting-edge scientific research is characterized by more significant systematic complexity, deeper and broader interdisciplinarity, higher risks and uncertainty, and unprecedented long-term and high-input. These changes have put forward new requirements for scientific research. Based on the interview results, four of the requirements are identified, i.e., the needs of knowledge combination, the needs of specialization, the needs of interdisciplinary integration and the needs of satisfying the interests of different subjects. Together, they play as the external forces of the formation of the IKCNs.

8.1.1.3 The needs for knowledge combination

In contemporary science, the space for great leap-forward progress is getting smaller and smaller, while most of the breakthrough innovation and discoveries are based on existing knowledge rather than "starting from scratch". This requires the researchers have ever wider and deeper knowledge reserves. However, the individual's knowledge pool is rather limited. Through collaboration, the knowledge pool could be expanded, thus to provide sufficient knowledge and intelligence for innovation breakthroughs.

In the case of Sino-Belgium collaboration program, the IEG have more experiences, data, specialties and techniques in the ecology and geology of the arid areas in Xinjiang. The GGU has more experiences in the study of marine climates and lowland geological features in Western Europe. In recent years, the two institutions have jointly conducted scientific research on the ecological environment, climate and geological evolution of the across Eurasia area. In the process of research, the differentiated knowledge bases of the two institutions can be combined and complemented.

> *A1: "The main focus of our institution (IEG) is the arid regions in Xinjiang and the five Central Asian countries (Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, Turkmenistan). In these regions, we have rich data, mature technology and fruitful research results. Their (GGU) focus mainly in Western Europe region, they have a lot of data and related results about the ecology and climate of Western Europe. Through cooperation, we can expand the scope of our research"*

> *B1: "We know relatively little about the arid regions because climate here is humid and rainy. But we are interested in arid regions. In fact, we do have very successful collaborations with some countries in Africa, such as Ethiopia and Kenya. The arid climate there is quite similar to Central Asia, and there are also some differences. I think comparing the arid climate in different regions is an interesting topic. I have learned a lot by working with researchers from different countries."*

8.1.3.2 The needs for specialization

The scale of contemporary science has become ever larger, within which each task and step requires different types of professionals and specialists. An individual's capability, energy and time are limited, and can hardly master all professional skills. Therefore, for certain fields, the specialization and division of labor through collaboration can significantly improve efficiency of scientific research.

In the projects of the protection and rehabilitation of some ancient towns in Xinjiang, the division of labor is evident. More specifically, during the field surveys phases, Chinese side were particularly responsible for logistics assistance such as administrative stuff, accommodations, transportations, personnel coordination and funds raising etc. During research phases, each research has a specific task based on their specialties and know-how.

> *B4: "My main research interest is the impact of climate change on hydrological processes which is a very sophisticate topic and needs different professionals. Every person in my team has a specific job: some do remote sensing data collection, some build and analyse 3D models, some work on software and programming, others do algorithms optimization and so on . I am the leader of the team, the main task is to keep things going".*

8.1.3.3 The needs for interdiscipline

In the second half of the 20th century, various interdisciplinary subjects emerged rapidly. Some unresolved scientific issues have been successfully tackled by interdisciplinary collaborations. Undoubtedly, the advancement and development of interdisciplinary research must be achieved through the collaboration of researchers from different disciplines.

> *In the Sino-Belgium collaborated project, the research fields of IEG are relatively limited, while the research fields of the GGU are more diverse. In addition to geographic information or geography-related subjects, there are professors, researchers and students with a variety of research backgrounds, e.g. mathematics, agronomy and biology. A key incentive of the IEG to seek cooperation with the GGU is to take advantages of the interdisciplinary resources.*
>
> *A4: "One of the most important reasons of seeking for collaboration with the GGU is because the needs of interdisciplines. The researchers and students on our side (IEG) mostly major in physical geography-related subjects since bachelor. In comparison, researchers in the GGU are more diverse. There are professors or PhD students with different education backgrounds, like mathematics, agriculture and biology."*
>
> *B3: "I have got my bachelor's degree in mathematics and my master's degree in hydromechanics. I am an environmentalist, so I chose physical geography as my PhD to do research on climate change. At first, I didn't have too much confidence because I don't have much geography knowledge. But my supervisor supported me a lot. He thinks it is meaningful and necessary to collaborate with people from different disciplines with different education backgrounds.*

8.1.3.4 The needs of satisfying interests

Collaboration can bring both tangible and intangible benefits to the participants at different levels. For countries, encouraging transnational collaboration is not just a channel for knowledge import/export, but also a way of building and maintaining good diplomatic relations with other countries. Encouraging domestic interurban and inter-regional collaborations can promote balanced regional development and enhance the overall efficiency of the national innovation system. For cities and research institutions, seeking for trans-local collaboration can enhance/compensate their advantages/disadvantages. For the individual researcher, collaboration is an effective way to access into the academic center, build and expand their academic reputation.

In the Sino-Belgium program, collaboration is a win-win for both sides at different levels. At national level, in addition to scientific collaboration, the collaborated project has drawn many attentions by the officials of the two countries and has been valued as an successful example for Sino-Belgium friendship in diplomatic term. At city level, a complementary development of urban innovation can be achieved through formal scientific collaboration. At the same time, the interurban collaboration can also enhance cites' influence. At organizational level, the IEG and the the GGU have accomplished remarkable achievements in terms of scientific output through collaboration, enhanced their international academic influences and established an attractive band of internationalization. At individual level, for the teachers and students from the IEG, through collaboration, they have obtained new knowledge and produced more and better academic publications. More importantly, the experiences of studying abroad are beneficial for job hunting. For professors, supervising more international students can also be helpful to their annual assessments

A1: "The central government really appreciated and valued this Sino-Belgium collaboration program. On one hand, the China Scholarship Council has have given us lot of financial support for the joint PhD training program, and they will continue to do so. On the other hand, our collaboration is an good example of the friendship between China and Belgium I have been invited to participate several diplomatic meetings between China and Belgium, and our research results and collaboration achievements have been displayed and exemplified in these diplomatic occasions. This shows that both the Chinese government and the Belgian government prefer to encourage and support such international collaboration."

A6: "Through collaboration, we can not only learn advanced science and technology from developed countries, but also can export our (IEG) science and technology to underdeveloped countries."

A2: "Our city (Urumqi) does not have location advantage, it sits in the remote northwest. The transport facilities are not as good as eastern China. A big problem that always disturb us is that our city is much less attractive to the best students. But now, many students are looking forward to going abroad through our collaboration program. After years of development, our collaboration with Ghent University has already established an attractive brand that helps us to recruit better students"

A3: "The students who have joined the program and gone abroad normally will have more opportunity and more room to improve themselves in many aspects, such as language ability, experiences, knowledge and so on. The most important is that their ability and experience as a scholar have been improved a lot. I feel that there is a big difference of participating in this (joint PhD training program) or not. Specifically, the quality and quantity of the publications of the participants are generally better than those who have not participated in the program. What's more, as a student or a young scholar, working with the best is a shortcut to quickly enter the top academic club in the field. For most of professors, they are willing to have more PhD students. The more doctoral students mean the more publications and more chances for promotion"

8.1.4 Complementation of innovation resources

8.1.4.1 Complementary human resources

Collaboration requires different kinds of talents to jointly support the development and operation of the IKCNs through the coordination, exchange and matching of human resources. The interactive exchange of diversified human resources in the collaboration network can significantly accelerate the rate of the combination of knowledge, improve the efficiency of specialization and promote the innovation performance.

In terms of the complementation of human resources, the Sino-Belgium program has achieved a win-win collaboration mode. Through employing professors of the GGU as foreign experts or honorary professors, the researching/teaching staff construction and the academic reputation of the IEG have been strengthened and improved. For the GGU, the number of teachers and students is relatively smaller. When conducting large-scale scientific research projects, there will sometimes be a shortage of human resources. Collaboration with the IEG will greatly increase its human resources pool.

> *A5: "I think that in terms of talents, our institution (IEG) and theirs (GGU) have mutually achieved a 'win-win' collaboration mode. Their department head has been granted as our foreign expert. He will spend some time to do research and teach in Xinjiang. It is not only good for our collaboration, but also good for our international academic reputation. There are also students from Ghent University coming to our institution, although few in number, but at least it shows that our institution has been internationally recognized ."*

8.1.4.2 Complementary financial resources

Financial support is a fundamental lifeline for scientific collaboration. Due to the risks of knowledge innovation, the uncertainty of future benefits or profits, the demands of multi-channel scientific funds have become increasingly higher. Specifically, it normally takes long time for the results of basic scientific research to directly transfer into commercial profits. Thus, most of the funding for these research come only from governments other than market, which are often quite limited. However, through collaboration, different financial resources held by different partners could complement to each other in various ways, which in turn is important for sharing risks, balancing interests and promoting innovation.

In the Sino-Belgium collaboration program, in terms of financial resources, both sides have obtained considerable financial support through various channels which complement each other. The research funding of both parties includes (1) the funding for the early stage of the joint PhD training program provided by Chinese Academy of Sciences, the IEG and the China platform of Ghent University. (2) the funding provided by China Scholarship Council for the current Joint PhD training program and the funding provided by Fonds Wetenschappelijk

Onderzoek for post doctors. In comparison, China's financial support is higher than Belgium's, which is one of the important reasons for the UUG to seek collaboration with the IEG.

A6: "During early years, this project (joint PhD training program) is funded by our institute (IEG), but the funding is quite limited. The cost of living for a PhD student was about 5,000 RMB per month. The tuition or the bench fee of Ghent University are exempted. Then, part of the accommodation costs of the PhD students are covered by the UUG. But for students, the cost of living is still relatively high. Since recently, the China Scholarship Council has begun to pay attention to our program and started to fund us through the Special Fund for International Talents, which is about 1,200 Euros a month per person."

B2: "In our collaboration program, there are diverse sources of funding, including not only funding from the IEG and the UUG, as well as governments' public R&D funding from both sides, but also donations from some non-governmental organizations.

In comparison, they (IEG) have more research funding than us (GGU), that is one of the important reasons why we are willing to cooperate with them."

8.1.4.3 Complementary facilities resources

Facilities resources refer to research instruments, equipment, materials, laboratories, experimental bases and other kinds of research-related infrastructure. On one hand, the lack of necessary research facilities will hinder the efficiency of innovation. On the other hand, if the research facilities are not fully utilized or efficiently functioned, it will increase unnecessary costs and reduce innovation performance. Therefore, it is imperative to share and make full use of research facilities especially in the form of collaboration.

In the Sino-Belgium collaboration program, both sides have their own advantages and disadvantages in scientific research facilities. Through collaboration, they could achieve positive externalities of "1+1>2". For example, both of the IEG and the GGU have advanced Unmanned Aerial Vehicle (UAV) remote sensing equipment. In comparison, the UAV of the IEG is more advanced in flight height and battery life. The remote sensing equipment and supporting software of the GGU are more advanced. Currently, the two institutions have been trying to assemble the remote sending equipments and software of the GGU to the UVA of the IEG, in order to take full advantages of both institutions advanced technology .

B2: "Our institution (GGU) and their institution (IEG) both have relatively advanced UAV remote sensing equipment. Our UAVs are equipped with advanced remote sensing devices. And our software system is also more advanced. However, their UAVs are better than ours, which have longer battery life and higher flying heights. So what we are doing now is to use their drones to carry our remote sensing detection device.

A4: "They (GGU) and the Royal Meteorological Institute of Belgium have jointly developed a highly advanced 'earth-surface system', which was mainly used to simulate *the surficial geology process. When they visited our institution before(IEG), they had presented this system to us. It is a very powerful system, and we have been trying to learn how to operation. At present, several excellent doctoral students in our institute have mastered this system.”*

B3: “We (GGU) do not think that this system (the ‘earth surface system’) needs to be kept confidential. This is a good research tool that can be shared. When we collaborate with them (IEG), we can also test whether the system can be applied to other regions.”

8.1.4.4 Complementary knowledge resources

Knowledge resources here refer to tacit knowledge in particular. Tacit knowledge can be defined as skills, ideas and experiences that people have but are not codified and may not necessarily be easily expressed through language, words, diagrams or symbols. It is the result of human non-verbal intellectual activities, mainly embodied in an imperceptible habit, technique, attitudes and preferences. And they are indispensable foundations for the success. The acquisition, exchange and transmission of such knowledge requires extensive personal contact, regular integration and trust, in other word, in-depth collaboration.

In the Sino-Belgium collaboration project, especially for Chinese teachers and students, it is often impossible to comprehensively and profoundly understand and capture the authors’ thinking processes and their inspiration only by reading papers and books. The in-depth cooperation of joint training for doctoral students can provide them with lot of opportunities for face-to-face communication, which in turn contributes to the acquisition of the tacit knowledge.

A4: “I think it is necessary to stay in the UUG for at least one year, because some knowledge cannot be learned merely by watching videos or reading articles. For example, I have read articles written by Belgian professors and colleagues before I came. I felt that I had basically understood and they were not difficult at all. After arriving in Belgium, when discussing with the authors in person, I finally realized that although I thought I had understood them, I didn’t grasp the ways they think. Therefore, the depth of cooperation has a great impact on the effectiveness of cooperation.”

B6: “For me, when doing research, collecting data, building models and calculations are relatively simple. They can be learned if spending enough time. However, the ‘intuition’ or ‘inspiration’ is hard to learn. These two things are very crucial for innovation. My supervisor has great sense of intuition and can always find interesting questions. Therefore, to gain this kind of ’intuition’, frequent face-to-face interactions and in-depth collaborations are needed.”

8.1.5 Support of collaborative environment

The collaborative environment includes the policy environment, cultural environment and institutional environment. Establishing collaboration networks and maintaining collaborative relationships between different cities requires the partners to work together to create a favorable collaborative environment. These factors have significant impacts on the Sino-Belgium collaboration.

8.1.5.1 Policy environment support

Policies, laws and regulations are the means by which the state and the government encourage and guide knowledge collaboration. On one hand, favorable policies can effectively encourage collaboration activities, cultivate innovation incentives, coordinate the allocation of innovation resources and mobilize the exchange of talents. On the other hand, laws and regulations, especially those on intellectual property protection, are guarantees for the interests and incentives of all patterners involved.

In the Sino-Belgium collaboration program, both sides have been enjoying different levels of preferential policies and legal support. For example, the IEG has received not only the special financial support from China Scholarship Council, but also from Chinese Academy of Sciences and University of Chinese Academy of Sciences. Ghent University has always supported and encouraged international collaboration and has in particular established the "China Platform" to promote and expand scientific and technological cooperation with Chinese scholars. At national level, both in China and Belgium, in the process of applying for national scientific research funding, whether it is inter-organizational, inter-city or even international collaboration has become an important issue to be considered in the examinations. Lastly, in terms of legal support, both countries have well-developed intellectual property protection laws, providing important legal support for knowledge exchange and innovation production.

> *A3: "The collaboration program has been supported by different levels of policies. At the national level, China Scholarship Council has provided us with sufficient funding and it will continue to do so. At institutional level, Chinese Academy of Sciences and University of Chinese Academy of Sciences also have introduced a series of policies to support us. For example, the students who failed in applying for the China Scholarship Council funding still can give a shot for the funding provided by the University of Chinese Academy of Sciences, which is as same as CSC's amount"*

> *A4: "It is an unspoken rule that if you want to successfully apply for some national major scientific funding such as '973' (National Key Basic Research Development Program), '863' (National High Technology R&D Program), and 'Key Natural Science projects' (major projects of National Natural Science Foundation of China), the number of institutions involved in is an important indicator needs to be evaluated."*

> *B1: "Legal support, especially the laws of intellectual property protection, is very important for us to carry out in-depth scientific and technological cooperation. Some of my colleagues think that China's intellectual property protection is not very good, but in the processes of working with them, we (the GGU) found that this is not the case.*

The confidentiality of our cooperation is under clear agreements, which is beneficial to both of us. We have jointly applied for several patents, including application in the EU and in China. I believe that our collaboration and innovation results will be well protected."

8.1.5.2 Cultural environment support

The cultural environment will profoundly affect people's values and behaviors, particularly their the attitudes and perceptions of knowledge collaboration. In a rigid, closed and repressed culture, the attitude of actors towards collaboration are negative to a large extent, while in a dynamic, open and free culture, actors tend to be positive and active on collaboration.

In the Sino-Belgium collaboration program, on China side, Xinjiang province is relatively closed in term of the cultural environment due to its remote location, and partly due to some political issues, which is not conducive to the flow of talents and the diffusion of knowledge. Consequently, it may negatively influence trans-local collaborations. In comparison, Ghent city and Ghent University have a culture of freedom and openness, which has a positive impact on scientific and technological cooperation.

A5: "Xinjiang's political and cultural environment is quite complicated, it does have a negative impact on talents and knowledge exchange. For example, there are quite a lot political censorship procedures before going abroad, although in most cases there will be no big problems, but it is still troublesome."

A1: "Ghent University is a very open university. We welcome different forms of cooperation. We have established a 'China Platform', and its main purpose is to promote cooperation between Chinese institutions and Ghent University, and to serve Chinese students and scholars at the same time. I am also one of the chairs of the 'China Platform'. Our openness and inclusiveness have attracted many Chinese students and scholars."

8.1.5.3 Institutional environment support

There are differences in institutional structures, operational systems, and incentives for innovation in different organizations. This differences in organizational environment have a significant impact on the purposes and forms of knowledge cooperation. For example, the institutional environment of universities and enterprises is distinct. Compared with enterprises, the institutional environment of universities is more flexible and open. The purpose of innovation of universities focus more on exploring and discovering new knowledge. Enterprises, however, focus more on commercialization and marketization their knowledge, thus their attitude towards collaboration may be more rigid. These institutional differences determine the processes, forms, depth of knowledge collaboration.

In the Sino-Belgium collaboration program, the impact of institutional environment on collaboration is mainly embodied in administrative systems. The administrative system of Ghent University is relatively simple and efficient. In the process of joint PhD training program, for Chinese students, the administrative procedures of registration, application for funding and reimbursement are very easy and efficient, so that students can devote more time and energy to research. The administrative system of the IEG is rather complex. Foreign professors and students need to spend a lot of time to handle various paperwork in accordance with the administrative procedures, which has certain negative impacts on collaboration.

A6: "When I arrived Ghent University, what surprises me most is that the administrative procedures in Ghent University are very simple and is completely different from China. Registering, applying for funding and reimbursement are easy and very friendly to our international students. This is very beneficial for collaboration."

B2: "When I was working there (IEG) as a visiting scholar, I was very disappointed with the complicated administrative staff there. In order to get the reimbursement of my transportation and accommodation, I needed to fill lots of complicated forms. Without the help from my Chinese colleagues, I would go crazy. As a scholar, I don't want to waste a lot of time on these trivial things. It's not good for collaboration."

8.2 The micro-initiative factors

The aggregation of innovation actors' behaviors of selecting, building and maintaining collaboration relationships are the micro-dynamics of the evolution and formation of the IKCNs. It is believed that the different dimensions of proximity are the main micro-initiative factors that determine the behavioral logics and decision making of innovation actors in the processes of collaboration (Boschma, 2005; Knoben and Oerlemans, 2006; Torre and Labelt, 2005). Taking the inter-organizational KCN of the medical sciences of the "Jiangsu-Zhejiang-Shanghai" region (JZS region) as the study case, this chapter quantitatively examines the impact of the multidimensional proximity, i.e. geographical proximity, institutional proximity, social proximity, cognitive proximity and cultural proximity on the evolution and formation of IKCNs. In addition, some complementary qualitative references are provided by in-depth interviews with several PhD candidates of the medical school of Tongji University.

8.2.1 Multidimensional proximity

Collaboration rarely takes place spontaneously: the decision of who to work with comes at a high cost in terms of time, resources and trust building. In the economic geography and regional science research literature on this topic, it has been emphasized that physical proximity can reduce this cost and thus positively affect collaborative activities: easy face-to-face contact stimulated and maintained by co-location creates a favorable atmosphere for knowledge learning and sharing among agents (Maskell and Malmberg, 1999). Scientific collaboration, one of the main forms of learning and sharing, is highly sensitive to geographical distance (Katz, 1994, Andersson et al., 2014). Nevertheless, simply being co-located is neither a prerequisite nor a sufficient condition for collaboration (Boschma, 2005, Knoben and Oerlemans, 2006).

Recent discussions have indeed highlighted that geographical proximity is not the only determinant of interactive learning and knowledge exchange. It has been shown that non-geographical forms of proximity can support the formation of collaborative networks by reducing coordination costs, particularly in scientific research networks (Cassi et al., 2015, Hoekman et al., 2010, Ponds et al., 2009). Boschma (2005) argues that knowledge interactions emerge from cumulative and combined processes of geographical proximity and non-geographical proximities such as institutional, social, cognitive and organizational proximity.

8.2.1.1 Geographical proximity

Geographical proximity, which is denoted as territorial, spatial, local or physical proximity as well, is the most frequently used dimension of proximity in the literature. The importance of geographical proximity in the formation of collaboration networks lies in the fact that small geographical distances facilitate face-to-face interactions (both planned and serendipitous) and, therefore, fosters knowledge transfer and innovation. The main reasoning behind these effects is that short geographical distances bring organizations together, favor interaction with a high level of information richness and facilitate the exchange of, especially tacit, knowledge between actors (Torre and Gilly, 2000).

8.2.2.2 Institutional proximity

Institutional proximity can be defined as the extent to which the operations of different actors or groups are similar in terms of habits, routines, established practices and incentive structures (Boschma, 2005). It is believed to be beneficial to knowledge collaboration by allowing free knowledge transfer among agents based on a common institutional regime, Institutional differences at the inter-organizational level (e.g. universities, companies, and public research centers) are often thought to be barriers for knowledge exchange and collaborative activities (Frenken et al., 2005, Ponds et al., 2007).

8.2.1.3 Social proximity

Social proximity refers to the relational embeddedness of agents in terms of partnership, kinship and friendship (Boschma, 2005; Granovetter, 1985). Any form of knowledge exchange, including scientific collaboration, is a process of social construction through interpersonal networks. As a consequence, strong and trust-based social linkages are believed to facilitate knowledge exchange among individuals (Gertler & Wolfe, 2004) and institutions alike (Knoben & Oerlemans, 2006).

8.2.1.4 Cognitive proximity

Cognitive proximity is commonly defined as the extent to which two actors share the same perception, interpretation and evaluation of the world (Boschma, 2005). It is argued that actors can better understand, absorb and implement external knowledge when it is 'close' to their own knowledge base (Cohen & Levinthal, 1990). In a narrow sense, in the field of scientific research collaboration, cognitive proximity is almost equivalent to 'technological proximity' (Knoben & Oerlemans, 2006) or 'technological relatedness' (Boschma, Frenken, Bathelt, Feldman, & Kogler, 2012), which refers to the degree of overlap between two actors when considering their technological experiences, communication language and knowledge bases. In short, similarities in the knowledge backgrounds of agents facilitate effective and efficient collaboration.

8.2.1.5 Cultural proximity

Cultural/linguistic proximity is, according to Knoben and Oerlemans (2006), broadly similar to institutional proximity when studying inter-organizational knowledge collaboration. Teixeira, Santos, and Brochado (2008) distinguish between both notions by defining cultural proximity as informal institutional proximity: a common language, the same ethnic community, shared habits and a coherent manner of interpretation and articulation that binds members together and separates one group from other groups. This form of proximity can increase trust and lower transactions costs, assisting in the generation and diffusion of collaborative ideas.

8.2.2 The interactions between geographical proximity and non-geographical proximity

Except of the recognition on the important role of geographical and non-geographical proximity, Boschma (2005) also stresses the possible co-existence of both substitutional and complementary relationships between geographical and non-geographical forms of proximity in facilitating interactive learning and knowledge collaboration: on the one hand, physical distance can, to some extent, be overcome and compensated for by different forms of non-geographical proximity; on the other hand, geographical proximity can accrue and reinforce non-geographical proximity.

8.2.2.3 **Geographical proximity and institutional proximity**

In the literature on regional innovation systems, interactive collaboration between local universities, companies and governments-also known as the "triple helix"-is considered to be a crucial driving force for the long-term development of innovative regions (Leydesdorff, 2000). This puts forward a vision where geographical proximity can, to some extent, offset institutional differences in inter- -organizational collaboration. Conversely, it has also been argued that institutional proximity can facilitate long-distance knowledge collaboration (Ponds et al., 2007). This suggests possible existence of substitutional relations between geographical and institutional proximity.

Rallet and Torre (1999) report that in the biological and medical poles of Aquitaine and the Rhone-Alps Region, there are intensive scientific collaborations and technological competencies among research institutions, but fewer interactions can be observed between research institutions and industrial companies. The authors conclude that the positive effect of geographical proximity on inter-organizational collaboration can only be activated based on a similar institutional setting of group members. Meanwhile, Ponds et al. (2009), investigating the geography of the university-industry research collaborate on network in the Netherlands, found that scientific collaboration can occur over large physical distances, and this in spite of the institutional differences among partners. These examples suggest that geographical and institutional proximity may complement and reinforce one another.

8.2.2.4 **Geographical proximity and social proximity**

Saxenian and Hsu (2001) found that the transnational collaborations between information technology corporations from Silicon Valley and Hsinchu-Taipei region are attributable to the strong inter-institutional social relations connecting a community of US-educated Taiwanese specialists. Similarly, Huber’s (2012) investigation of R&D collaboration activities among innovation-based firms and research institutions in the Cambridge IT clusters showed that local contacts are not socially closer than non-local contacts. This suggests possible existence of substitutional relations between geographical and social proximity.

In the traditional view of localized learning, geographical proximity plays a crucial role in facilitating and sustaining the formation of trust-based social networks, within which co-located agents can benefit from local social assets and are able to exchange knowledge (particularly tacit knowledge) at low costs (Malmberg & Maskell, 2006). Autant-Bernard, Billand, Frachisse, and Massard (2007) investigated the inter-organizational collaborations in the micro-and nanotechnologies of European countries. The results show that more collaborative projects could be found within socially closer and spatially more concentrated firms. Thus, a complementary relationship between geographical and social proximity can be expected.

8.2.2.5 **Geographical proximity and cognitive proximity**

It has been argued that geographical and cognitive proximity can be substitutes for one another. On the one hand, cognitive proximity can overcome the lack of geographical proximity— long-distance collaborations can occur within a scientific community because of participation in conferences, conventions, exhibitions and other kinds of gathering creating “temporary spatial proximity” for researchers with similar knowledge backgrounds (Malmberg & Maskell, 2006). On the other hand, specialized clusters can be detrimental for knowledge collaboration if members’ technological bases are too similar because similar knowledge bases will lead to technological lock-in (Boschma,2005). Thus, a certain degree of technology diversification among agents is necessary for the long-term development of clusters and organizations therein.

Many studies on regional innovation systems (Cooke, 2001), learning regions (Morgan, 1997) and localized knowledge economy(Maskell &Malmberg,1999) are built around the argument that collaboration is prevalent within specialized clusters in which people share a similar, sometimes exclusive knowledge base, as different clusters possess distinct subsets of knowledge as their main competitive advantage. Investigating the fuel cell patenting within EU regions, Tanner (2016) reports that regions where intensive inter-institutional knowledge spillovers occur share specific technologically-related knowledge fields and are geographically proximate, which implies that the relationship between geographical and cognitive proximity is complementary in facilitating knowledge interactions.

8.2.2.6 **Geographical proximity and cultural proximity**

Some scholars have suggested that geographical and cultural proximity can be substitutes in their influence on knowledge diffusion. For instance, by investigating the role of socio-cultural factors in knowledge spillover processes among Indian software companies over long geographical distance, Taube (2005) found that the necessity of spatial proximity for the exchange of tacit knowledge could be substituted by cultural proximity found in ethnic networks. Kerr (2008) claims that knowledge diffusion between entrepreneurial research firms in which researchers share the same cultural background and a common language is not geographically constrained so that those communities can serve as a main channel for international knowledge spillovers.

Hansen (2014) studied the innovative collaborations among the Danish cleantech firms and found that the positive benefits from co-location of firms could only emerge if they share a high degree of cultural similarity. Meanwhile, Teixeira et al. (2008) found that successful international R&D collaborations between SMEs with similar cultural backgrounds that are also located relatively closer to each other are primarily found in low-tech fields, whereas actors involved in technologically advanced collaborative projects are often geographically distant and culturally diversified. This points to the possible existence of a complementary relationship between geographical and cultural proximity in facilitating inter-institutional knowledge collaboration.

8.2.3 Case study: the inter-organizational collaboration network of medical sciences of the Jiangsu-Zhejiang-Shanghai region

8.2.3.1 **Research objects**

Composed of three municipalities (i.e., Shanghai, Jiangsu and Zhejiang), with three provincial-level cities, 22 prefecture-level cities and 96 county-level cities, the SJZ region houses 11.6% of China's population, but generated nearly one-fifth of its GDP and produced approximately one-quarter of the nation's scientific publications in 2016. Notably, in terms of its national share, the medical sciences are the most competitive and productive scientific field in the region: it produced 28.5% of the nation's total number of medical sciences publications between 2012 and 2016 (Table 8-2). Meanwhile, 98.1% of these medical sciences papers were co-authored and 55.6% were inter-organizational co-publications (i.e. involving more than one research institution). The statistics also reveal that universities and hospitals have been the most active contributors, with 79.8% and 84.8% total publication shares, respectively (Table 8-3). Therefore, this section focuses on the collaborative research networks in the JZH medical sciences particularly among universities and hospitals. Note, the basic spatial units in this section are at institutional scale, thus the network construction approach is more intricate than that of previous chapters. The details of the method are elaborated in Section 3.3.

Table 8-2 Statistics of the scientific output of China and its main regions (aggregated counts from 2012-2016)

	Scientific output				share		
Disciplines	China	JZH	Beijing-Tianjin	PRD	JZH	Beijing-Tianjin	PRD
Medical science	326,491	92,918	70,312	54,185	28.46%	21.54%	16.60%
Natural science	859,598	221,502	243,304	82,249	25.77%	28.30%	9.57%
Agriculture	34,577	8,488	10,647	3,316	24.55%	30.79%	9.59%
Engineering	905,902	204,997	250,819	76,324	22.63%	27.69%	8.43%
Literature	5,962	1,235	1,071	1,767	20.71%	17.96%	29.64%
Philosophy	1,766	338	461	601	19.14%	26.10%	34.03%
Economics	18,382	3,464	4,834	2,680	18.84%	26.30%	14.58%
History	1,062	192	350	323	18.08%	32.96%	30.41%
Management science	66,019	11,916	14,618	8,733	18.05%	22.14%	13.23%
Art	826	137	151	223	16.59%	18.28%	27.00%
Education	38,211	5,422	6,715	6,368	14.19%	17.57%	16.67%
Law	33,218	4,098	5,015	4,018	12.34%	15.10%	12.10%
Total	2,292,014	554,707	608,297	240,787	24.20%	26.54%	10.51%

Source: author

Table 8-3 Numbers of publications produced by different types of institutions in medical science of the JZH region (aggregated counts from 2012-2016)

Institution type	Number of publications	Share

Universities	74,167	79.88%
Hospitals	78,751	84.81%
Companies	14,495	15.62%
Governmental agencies	10,220	11.03%
Others	13,826	14.91%

Source: author

In addition, we excluded publications from institutions that produced only one paper during the time period. In doing so, we can reduce potential opportunists and free riders, such as ghost and guest/gift authors, who have limited scientific productivity and credibility (da Silva and Dobranszki, 2016, Ross et al., 2008). The final dataset contains 11,699 publications involving 573 institutions, including 111 universities and 462 hospitals (including 249 university-affiliated hospitals). As the nodes of the network, organizations are geo-located into the county-level jurisdictions of the JZH region, and this based on their addresses. The collaboration frequencies of organization pairs are the edges of the network.

Figure 8-4 shows the spatial configuration of scientific collaboration in the medical sciences in the YRD between 2012 and 2016. It is clear that the spatial distribution of inter-organizational scientific collaboration is highly uneven: intensive collaborations primarily take place in the central parts of the YRD, particularly in the Shanghai-Nanjing-Hangzhou triangle and its surrounding cities. Most of the peripheral cities are loosely connected in the collaborative research network, with the exceptions of Xuzhou and Wenzhou.

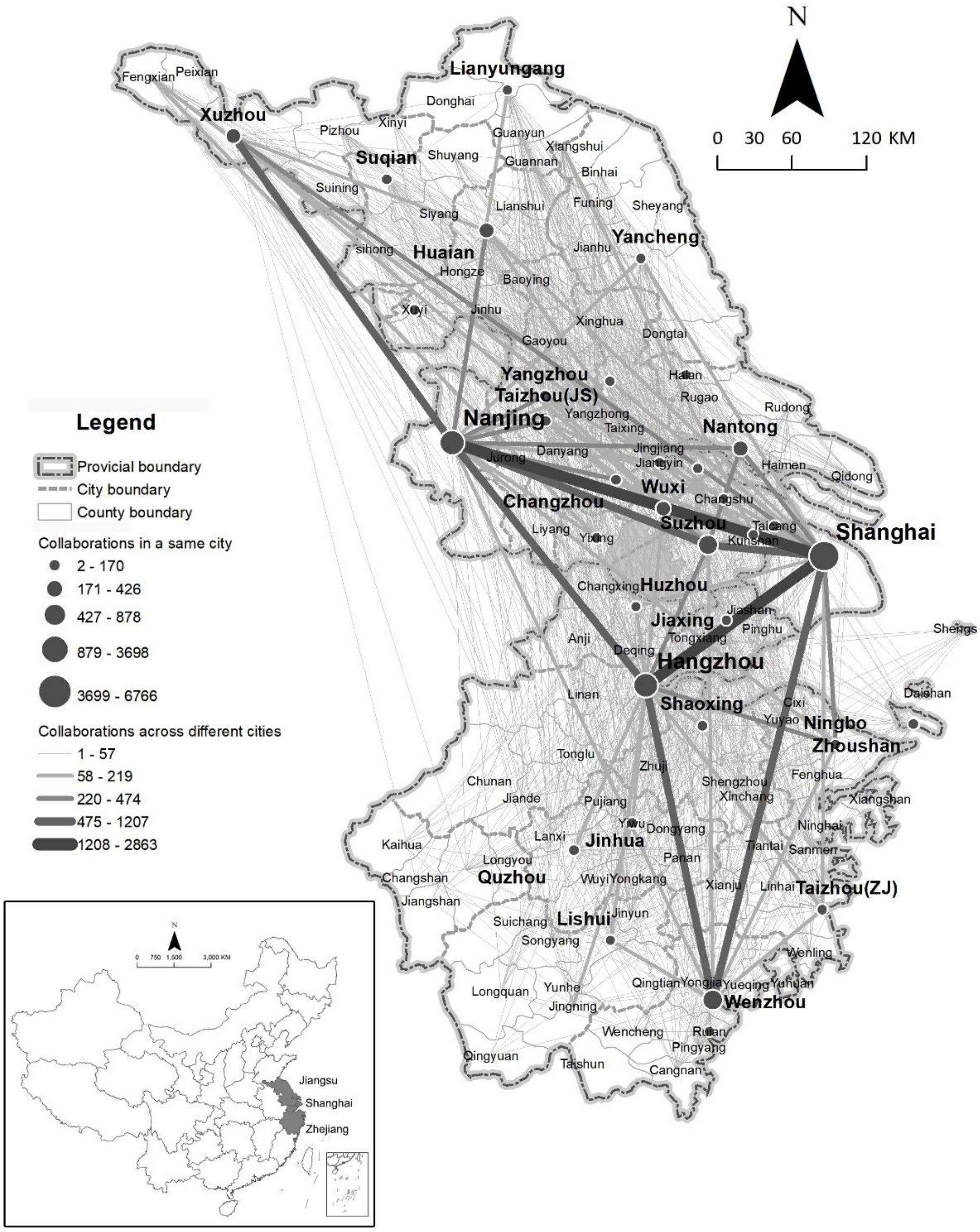

Figure 8-3 Spatial structure of the medical science KCNs in JZH region(2012-2016)
Source: author

Table 4 shows that a city's publication productivity is positively associated with its frequency of collaborative linkages. Interestingly, the intensity of cities' inter-city collaborations is much greater than their intra-city collaborations, which indicates that the knowledge exchanges and spillovers of the JZH' medical science are not locally confined.

Table 8-4 The statistics of medical scientific papers output and collaborative connections (Top 15, 2012-2016)

City	Output	City	Collaboration within the city	City	Inter-city collaboration	City-dyad	The amount of collaboration
Shanghai	7,557	Shanghai	6,766	shanghai	17,049	Shanghai-Nanjing	2,863
Nanjing	5,755	Nanjing	3,698	Nanjing	12,675	Shanghai-Hangzhou	2,398
Hangzhou	4,134	Hangzhou	2,496	Hangzhou	8,791	Suzhou-Shanghai	1,207
Suzhou	2,385	Suzhou	878	Suzhou	4,695	Hangzhou-Nanjing	849
Wenzhou	1,696	Wenzhou	810	Wenzhou	3,196	Suzhou-Hangzhou	730
Nantong	1,019	Nantong	426	Nantong	1,999	Wenzhou-Suzhou	654
Wuxi	919	Huaian	358	Wuxi	1,919	Wenzhou-Nanjing	631
Xuzhou	859	Xuzhou	298	Xuzhou	1,712	Xuzhou-Nanjing	594
Changzhou	704	Wuxi	270	Huaian	1,620	Nantong-Nanjing	474
Huaian	685	zhenjiang	170	Zhenjiang	1,333	Huaian-Nanjing	468
Ningbo	680	Ningbo	126	Changzhou	1,329	Changzhou-Nanjing	456
Zhenjiang	602	Changzhou	102	Ningbo	1,266	Wuxi-Nanjing	447
Yangzhou	503	Taizhou	98	Yangzhou	969	Wuxi-Shanghai	405
Yancheng	251	Yangzhou	96	Yancheng	511	Ningbo-Hangzhou	403
Taizhou	225	Yancheng	34	Lishui	486	Nantong-Shanghai	383

Source: author

Table 8-5 provides some organizational level details. First, the 15 most productive institutions are all key hospitals, leading medical universities or high-ranking universities with reputable medical schools. Second, similar to the city level pattern, the inter-organizational collaborations are also much higher than their intra-organizational collaborations (collaborations between different departments within a same institution). Lastly, in terms of organization pairs, it is clear that intensive collaborations are more likely to take place between universities and their affiliated hospitals.

Table 8-5 The statistics of medical scientific papers output and collaborative connections (Top 15, 2012-2016)

Institutions	Publications	Institutions	Intra-organizational collaborations	Institutions	Inter-organizational collaborations	Institution pairs	Collaborations
Nanjing Medical University First Affiliated Hospital	1126	Fudan University	922	Nanjing Medical University First Affiliated Hospital	2405	Nanjing Medical University First Affiliated Hospital – Nanjing Medical University	219
Fudan University	863	Nanjing Medical University	372	Nanjing Medical University	1802	Nantong University – Nantong University Affiliated Hospital	123
Nanjing Medical University	850	Soochow University	336	Soochow University First Affiliated Hospital	1782	Wenzhou Medical University – Wenzhou Medical University First Affiliated Hospital	118
Soochow University First Affiliated Hospital	842	Nanjing Medical University First Affiliated Hospital	265	Fudan University	1774	Soochow University First Affiliated Hospital – Soochow University	113
Zhejiang University	749	Soochow University First Affiliated Hospitals	237	Zhejiang University First Affiliated Hospital	1601	Wenzhou Medical University Second Affiliated Hospital – Wenzhou Medical University	111
Soochow University	714	Zhejiang University	204	Zhejiang University	1235	Nanjing Medical University First Affiliated Hospital – Nanjing Medical University Huaian First Affiliated Hospital	104
Zhejiang University First Affiliated Hospital	702	Wenzhou Medical University	180	Soochow University	1161	Nanjing Medical University – Shanghai 10th Hospital	97
Wenzhou Medical University	627	Wenzhou Medical University First Affiliated Hospital	177	Shanghai Jiao Tong University Ruijin Hospital	1147	Fudan University – Fudan Univisity Affiliated Zhongshan hospital	96

Zhejiang University Second Affiliated Hospital	545	Zhejiang University First Affiliated Hospital	169	Zhejiang University Second Affiliated Hospital	1143	Fudan University – Fudan University Huashan Hospital	91
Wenzhou Medical University First Affiliated Hospital	519	Wenzhou Medical University Second Affiliated Hospital	162	Second Military Medical University Affiliated Changhai Hospital	1127	Zhejiang University First Affiliated Hospital – Shanghai Jiao Tong University Ruijin Hospital	82
Shanghai Jiao Tong University	489	China Pharmaceutical University	151	Wenzhou Medical University	1085	Nanjing Medical University First Affiliated Hospital – Soochow University First Affiliated Hospital	77
Shanghai Jiao Tong University Ruijin Hospital	449	Nanjing Medical University Huaian First Affiliated Hospital	148	Fudan University Affiliated Huashan Hospital	1080	Zhejiang University First Affiliated Hospital – Zhejiang University	74
Nanjing University Affiliated Jinling Hospital	442	Nantong University Affiliated Hospital	143	Wenzhou Medical University First Affiliated Hospital	1053	Zhejiang University Second Affiliated Hospital – Zhejiang University	73
Second Military Medical University Affiliated Changhai Hospital	427	Shanghai Jiao Tong University	142	Shanghai Jiao Tong University	1004	Nanjing Medical University – Nanjing Medical University Huaian First Affiliated Hospital	68
Fudan University Affiliated Zhongshan Hospital	426	Fudan University Affiliated Zhongshan Hospital	140	Fudan University Affiliated Zhongshan Hospital	985	Nanjing Medical University Huaian First Affiliated Hospital – Xuzhou Medical University Huaian Second People's Hospital	66

Source: author

8.2.3.2 **Construction of variables**

The collaboration intensity is measured as the total number of co-occurrences of two institutions in publications and is the dependent variable in our empirical framework. The explanatory variables consist of two groups of indicators: (1) a series of vector sets functioning as proxies for the different dimensions of proximity, and (2) interaction variables created by the products of the variables of geographical proximity on the one hand and the different forms of non-geographical proximity on the other hand. In addition, a number of control variables concerning the absorptive capacity of institutions and local institutional context are introduced. First, the five basic variables of proximity are constructed as follows:

（1） Geographical proximity

Geographical proximity is calculated as the Euclidian distance between the city centers in which institutions are located. For institutions that are located in the same city, the geographical proximity between them is calculated by taking two-third of the radius of the circle equaling the area of the city's built-up urban area (Frost and Spence, 1995). Values are log-transformed.

（2） Institutional proximity

Institutional proximity is captured through dummy variables, which equal 1 if the institution types are the same and 0 otherwise. There are three basic types of collaboration, i.e., university-university collaboration, university-hospital collaboration, hospital-hospital collaboration. In addition, as can be seen from the analysis of the previous section, the strength of collaboration between universities and their affiliated hospitals is also quite high. In fact, in China, universities and their affiliated hospitals have close links in terms of institutional institution, personnel transfer and internships. In view of this, the university-affiliated hospital collaboration is considered to be the same type of institution, so the variable is also set to 1.

（3） Social proximity

Social proximity is measured as the inverse weighted shortest path between two institutions in the KCN. Breschi and Lissoni (2009) point out that research collaboration is likely to lead to future spillovers among researchers who have collaborated in the past. Thus, a direct linkage between two researchers implies the existence of past collaboration and a social relationship between them. Singh (2005) uses the shortest path as a measure for social proximity and finds that the path length between two researchers is negatively associated with the probability of collaboration. Except for the existence of past collaboration between two actors, the frequency of past collaborations between them (edge weight) and their total collaborations with all other network actors (degree centrality) also have a positive impact on the probability of further collaborations. Thus, the weighted shortest path is more accurate in the measurement of social distance. Following Opsahl et al. (2010), this reaserch calculated the weighted shortest path that incorporates both edge weight and degree centrality as our proxy for social proximity. The values are log-transformed.

（4） Cognitive proximity

Cognitive proximity is computed based on institutions' technology profiles. Following Gilsing et al. (2008), the technology profile is constructed as a vector of an institution' s stock of publications for the 56 subcategories of medical sciences[36]. In doing so, each institution is then assigned a (56, 1) 'technology 9 vector'. The cognitive proximity between two institutions is obtained by calculating the Pearsons correlation coefficients between their technology vectors, after which the values are min-max scaled. Two institutions with the highest similarity in technology profiles have a value equal to 1, while the two institutions with the most different technology profiles have a value equal to 0.

（5） Cultural proximity

The operationalization of cultural proximity is based on an examination of linguistic similarity in space. Although culture is a complex and multi-layered concept that is difficult to measure quantitatively, empirical studies have provided evidence that the formation of cultural identity of a certain social community coincides with the evolution of languages and dialects (Falck et al., 2012). Therefore, the variation of dialects can be used as a proxy to measure cultural differences (Wu et al.2018). The variables for cultural proximity are set to 1 when two institutions are located in the same dialect area and otherwise 0. The partition of dialect areas is indexed from the 2010 Atlas of Chinese Dialects. The accuracy of dialect classification is medium.

（6） Interaction variable

The second set of independent variables mainly examines the interaction between geographical and non-geographical forms of proximity. The interaction variables are simply calculated as the products of the variable geographical proximity and the different variables capturing non-geographical proximity, respectively. The input variables are centred (i.e. subtracting the mean) before these multiplications to mitigate multicollinearity.

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[36] Referred to Appendix Ⅳ.

（7） Control variable

Cohen and Levinthal (1990) point out that absorptive capacity, which refers to organization's ability to identify, assimilate and use external knowledge, is believed to greatly influence the collaboration activities of organizations. This capacity has been approximated by three variables: size, trans-regional links, and trans-national links. Size is calculated by the product of the total number of scientific publications of each institution in a collaboration pair in a given time period. Trans-regional links and trans-national links, which refer to organizations' openness to external knowledge resources and are defined by the products of the number of trans-regional and trans-national collaboration links of each institution in a collaboration pair, respectively. These three variables are log-transformed.

The previous chapters have highlighted the impact of "capital monopoly" on the formation of IKCNs, which corroborates the study of Andersson et al. (2014) and Cao et al. (2018): the top-down administrative system of China is a crucial factor affecting the formation of scientific collaboration: the geography of co-publications at the national and regional levels shows two types of 'spatial political bias': (1) more scientific collaborations are found at the intra-provincial level than at the inter-provincial level; and (2) inter-city co-authorship involving provincial capitals is more intense than those not involving provincial capitals. Therefore, we introduced two dummy variables concerning such border effects. For the former, we assign the value 1 if the two institutions of a collaboration pair are located in the same province and 0 if the two institutions are located in different provinces (variable 'same province'). For the latter, the value of collaboration pairs with at least one of their institutions located in a provincial capital city is assigned as 1. Meanwhile, if both institutions in a collaboration pair are located in non-provincial capitals, the value is equal to 0 (variable 'capitals'). Table 3 provides an overview of our variables and their mathematical specification. Table 4 summarizes the statistics and correlation matrices of the variables. We run a VIF test for all the variables. The results suggest that most of our variables of interest are free from multicollinearity problems with the exceptions of variables of 'size', 'trans-regional links' and 'trans-national links' (VIF values of the three variables are above 4.5). This can also be found in Table 4: high correlation coefficients are detected between them. This result aligns with Krätke's (2010) finding that the degree of a R&D organization's connectivity to the ensemble of inter-regional and international partners positively affects innovation output. Therefore, we decided to omit the variables 'trans-regional links' and 'trans-national links' to avoid potential multicollinearity.

Table 8-6 Descriptive statistics

	Min	Max	mean	S.D.	1	2	3	4	5	6	7	8	9	10
Geographical proximity	0.11	6.76	5.18	0.90	1.00									
institutional proximity	0.00	1.00	0.68	0.46	0.02	1.00								
Social proximity	1.36	10.23	3.29	1.17	-0.07	-0.02	1.00							
Cognitive proximity	0.21	1.00	0.33	0.28	-0.02	0.13	0.41	1.000						
Cultural proximity	0.00	1.00	0.36	0.48	-0.31	0.00	0.05	0.027	1.00					
Knowledge output	1.38	13.78	5.25	2.18	-0.09	-0.05	0.22	0.468	0.06	1.00				
Cross-regional relations	0.00	11.47	1.97	2.31	-0.08	-0.04	0.38	0.357	0.08	0.78	1.00			
Transnational relations	0.00	10.89	1.13	1.91	-0.10	-0.08	0.36	0.295	0.09	0.71	0.74	1.00		
Administrative boundary	0.00	1.00	0.38	0.48	-0.36	0.01	0.01	0.014	0.08	-0.02	-0.04	-0.03	1.00	
Administrative level	0.00	1.00	0.45	0.49	0.10	-0.05	0.036	0.013	0.04	0.09	0.08	0.06	-0.21	1.00

Source：author

8.2.3.3 **Model specification**

Since the dependent variable in this case is the count data, Poisson regression, zero-inflated Poisson regression, negative binomial regression or zero-inflated negative binomial regression should be used. In order to select the best-fitting model, a likelihood ratio test for over-dispersion and a Vuong statistic test for excessive zero counts are conducted.

To formally test the impact of multi-dimensional proximity on inter-organizational scientific collaboration, we use a gravity model as our baseline. Gravity models are widely applied in empirical studies that model spatial patterns of knowledge collaboration (Andersson et al., 2014, Scherngell and Barber, 2011, 2011, Ponds et al., 2007, Frenken et al., 2009) and/or models of interaction in polycentric urban regions (van Oort et al., 2010; Hanssens et al., 2014). The process of collaborative interaction, in which actors at different places make contacts, can be related with Newton's law of gravity (Roy and Thill, 2004). In our case, the intensity of scientific collaborations between two research institutions is hypothesized to be positively correlated with their size and inversely correlated with the physical distance between them. More specifically,

$$I_{ij} = K\frac{(M_i \times M_j)^{\beta_1}}{d_{ij}^{\beta_2}} \qquad (8\text{-}1)$$

where, I_{ij}, the dependent variable in the regression model, is the total amount of collaborations between city i and city j; K is a constant term; M_i and M_j respectively represent the masses of city i and city *j and defined by their total scientific output*; d_{ij} is the Euclidean distance between institution i and institution j.

The measurement model is as follows:

Ln (collaboration volume) = a_1Ln (knowledge output 1 * knowledge output 2) + a_2Ln (geographical proximity) + a_3 system proximity + a_4 social proximity + a_5 cognitive proximity + a_6 cultural proximity + a_7 administrative boundary + a_8 administrative level + a_9 (geographical proximity * institutional proximity) + a_{10} (geographical proximity * social proximity) + a_{11} (geographical proximity * cognitive proximity) + a_{12} (geographical proximity * cultural proximity +ε

Table 8-7 Detailed description and algorithm of variables

Variables	Type	Algorithm
Dependent variable		
Number of collaborations	Counts	$N_{a,b} = \sum_{i=1}^{n} N_{a,bi}$, where $N_{a,b}$ stands for the total number of collaborations between institution a and b. $N_{a,bi}$ is the co-authored paper i between institution a and b
Independent variables		
Geographic proximity	Numeric	For institutions located in different cities: $GP_{(i,j)different} = ln(CityDist_{i,j})$, where $GP_{(i,j)different}$ stands for the geographic proximity between institution i and j, located in different cities. $CityDist_{i,j}$ is the Euclidian distance between city i and j, within which institution i and j, respectively, are located For institutions located in a same city: $GP_{(i,j)same} = \frac{2}{3}\sqrt{\frac{S_{i,j}}{\pi}}$, where $GP_{(i,j)same}$ stands for the geographic proximity between institution i and j, located in the same city. $S_{i,j}$ is the area of the built-up area of the city where institution i and j located. The data of built-up area of cities is from the China City Statistical Year Book (2016)
Institutional proximity	Binary	$GP_{(i,j)} = 1$, if the institution pair is 'university – university', 'hospital – hospital' or 'university – university affiliated hospital', $GP_{(i,j)} = 0$, if the institution pair is 'university-hospital'
Social proximity	Numeric	$SP_{i,j} = ln(1/SD_{i,j})$, where $SD_{i,j} = \min\left(1/\left(CO_{i,h}\right)^{\alpha} + \cdots + 1/\left(CO_{h,j}\right)^{\alpha}\right)$, where $SP_{i,j}$ stands for the social proximity between organization i and j. $SD_{i,j}$ is the shortest social distance between organization i and j and is defined as the shortest path between two nodes in a network. $CO_{i,j}$ is the number of collaborations between i and j (edge weights), h is the intermediary organization on the path between i and j. α is the tuning parameter and is set as 1.5 in this research (see Opsahl et al. for more detailed descriptions of the algorithm)
Cognitive proximity	Numeric	$CP_{i,j} = Cov(CSC_i, CSC_j)$, where $CP_{i,j}$ stands for the cognitive proximity between organization i and j. CSC_i and CSC_j are vectors for organization i and j that contain their shares of publications in each of the research areas defined by CSC. Cov is the Pearson's correlation coefficient between CSC_i and CSC_j. The values are min-max scaled

Cultural/linguistic proximity	Binary	1 if members of a co-publishing pair are located in the same dialect zone. The dialect zones are defined by the 2010 Atlas of Chinese Dialects (Xiong and Zhang, 2012)
Size	Numeric	$S_{i,j} = ln(N_i \times N_j)$, where $S_{i,j}$ stands for variable Size. N is the total number of publications of an organization
Trans-regional links	Numeric	$TRL_{i,j} = ln(TRL_i \times TRL_j)$, where $TRL_{i,j}$ stands for variable Trans-regional links. TRL is the total number of the publications of an organization that co-authored with other domestic organizations outside the YRD
Trans-national links	Numeric	$TNL_{i,j} = ln(TNL_i \times TNL_j)$, where $TRL_{i,j}$ stands for variable Trans-national links. TNL is the total number of the publications of an organization that co-authored with other foreign organizations
Same province	Binary	1 if the members of a co-publishing pair are located in the same province, 0 if not
Capitals	Binary	1 if at least one organization in a co-publishing pair locates in a provincial level city (i.e., Shanghai, Nanjing and Hangzhou), 0 if not

Source: author

8.2.3.4 **Interviews**

In addition to quantitative analysis, this section also uses the qualitative analysis in the form of in-depth interviews to supplement the quantitative analysis. Three doctoral students from Tongji University School of Medicine who have participated in different forms of trans-regional knowledge collaborations are interviewed. The interviews start with their interurban collaboration experiences and focuses the topic that how “multidimensional proximity” affects the knowledge collaboration behaviors. The goal is to figure out: (1) the specific forms, incentives, contexts and achievements of the interviewees’ interurban collaborations (2) the impact of multidimensional proximity on the formation of collaboration networks (3) complementary and substitutional relations between geographical and non-geographical proximity. The basic information of the interviewees is as follows (Table 8-8):

Table 8-8 Related information of the interviewees

Number	Age and grade	Education background	Research field	Partner and location	Time	Duration
A	25, doctoral student of the first year	B.Sc. degree from Tongji University; M.Sc. degree from Tongji University	Relation between respiratory diseases and intestinal flora	China Pharmaceutical University (Nanjing)	2019.9.9	30 mins
B	27, doctoral student of the second year	B.Sc. degree from Soochow University, M.Sc. degree from the joint program of Soochow University- and Tongji University	Relation between lipid metabolism and respiratory infection	Soochow University (Suzhou)	2019.9.9	35 mins
C	27, doctoral student of the third year	B.Sc. degree from Wenzhou Medical University, M.Sc.degree from Tongji University	Application of nano-coated drugs in intestinal diseases	Zhejiang University (Hangzhou)	2019.9.11	25 mins

Source: author

Doctoral student A has established an informal collaboration relation with professor Z from China Pharmaceutical University (Nanjing), who specialize in big data analysis. The research team that doctoral student A works to holds small academic forums on a regular basis. The host professor X (the supervisor of doctoral student A) often invites experts who specialize in respiratory diseases to attend the forums and exchange their views. Once in a forum, doctoral student A met professor Y from China Pharmaceutical University who was a friend of Professor X. During the discussion, Professor Y introduced his colleague Professor Z of China Pharmaceutical University to doctoral student A. Since then, doctoral student A and professor

Z established a close collaboration relation. During the collaboration, doctoral student A is in charge of collecting and classifying samples and research design. Professor Z processes and analyzes the data. By now, the collaboration of them has been carried out very well.

Doctoral student B keeps a stable collaborative relation with Medical College of Soochow University. He got the B.Sc. degree from Soochow University and M.Sc. degree from the joint training program of Soochow University and Tongji University. After he got the mater degree, student B have been staying in Tongji University to pursue his PhD and meanwhile keeping close collaborations with his supervisor of Soochow University.

Doctoral student C has established a formal collaboration with a research team from the School of Materials Science and Engineering, Zhejiang University. The research interest of doctoral students C is rather interdisciplinary, more specifically, the application of nano-technology in pharmaceuticals.

Table 8-9 Estimation results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Negative binomial part								
Constant term	-4.499 (0.105)***	-4.738 (0.115)***	-5.239 (0.137)***	-5.226 (0.159)***	-5.537 (0.224)***	-5.905 (0.197)***	-5.405 (0.253)***	-6.209 (0.340)***
Knowledge output	0.638 (0.009)***	0.274 (0.014)***	0.281 (0.014)***	0.282 (0.014)***	0.281 (0.014)***	0.286 (0.014)***	0.280 (0.014)***	0.288 (0.014)***
Geographical proximity	-0.228 (0.012)***	-0.225 (0.014)***	-0.227 (0.019)***	-0.231 (0.026)***	-0.155 (0.047)***	-0.078 (0.037)**	-0.197 (0.043)***	-0.025 (0.067)*
Institutional proximity		0.394 (0.032)***	0.402 (0.031)***	0.370 (0.112)***	0.399 (0.031)***	0.403 (0.031)***	0.403 (0.031)***	0.294 (0.113)***
Social proximity		0.542 (0.020)***	0.540 (0.019)***	0.540 (0.019)***	0.596 (0.038)***	0.537 (0.019)***	0.541 (0.019)***	0.543 (0.042)***
Cognitive proximity		0.704 (0.071)***	0.675 (0.070)***	0.674 (0.070)***	0.683 (0.070)***	0.635 (0.224)***	0.677 (0.070)***	0.683 (0.241)***
Cultural proximity		-0.024 (0.034)	0.028 (0.036)	0.028 (0.036)	0.023 (0.036)	0.023 (0.036)	0.204 (0.227)	0.318 (0.227)
Administrative boundary			0.409 (0.035)***	0.409 (0.035)***	0.401 (0.035)***	0.406 (0.035)***	0.416 (0.036)***	0.415 (0.036)***
Administrative level			0.356 (0.041)***	0.354 (0.041)***	0.355 (0.041)***	0.349 (0.040)***	0.360 (0.041)***	0.351 (0.041)***
Geographical proximity × institutional proximity				0.006 (0.023)***				0.023 (0.024)*
Geographical proximity × social proximity					-0.013 (0.008)*			-0.001 (0.009)***
Geographical proximity × cognitive proximity						-0.221 (0.047)***		-0.233 (0.052)**
Geographical proximity × cultural proximity							-0.034 (0.043)	-0.058 (0.043)
Zero expansion								
Constant term	1.828 (0.196)***	1.405 (0.226)***	4.396 (0.241)***	4.831 (0.283)***	3.939 (0.481)***	4.664 (0.347)***	4.408 (0.450)***	4.447 (0.700)***
Knowledge output	-0.554 (0.013)***	-0.834 (0.023)***	-0.891 (0.025)***	-0.891 (0.025)***	-0.889 (0.025)***	-0.890 (0.025)***	-0.892 (0.025)***	-0.890 (0.025)***
Geographical proximity	0.597 (0.028)***	0.789 (0.033)***	0.417 (0.035)***	0.327 (0.047)***	0.520 (0.095)***	0.371 (0.063)***	0.416 (0.076)***	0.422 (0.134)***
Institutional proximity		-0.653 (0.054)***	-0.704 (0.055)***	-1.360 (0.240)***	-0.705 (0.055)***	-0.704 (0.055)***	-0.704 (0.055)***	-1.358 (0.260)***
Social proximity		0.599 (0.037)***	0.655 (0.039)***	0.655 (0.039)***	0.735 (0.095)***	0.650 (0.039)***	0.655 (0.039)***	0.880 (0.110)***

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive proximity		-1.421 (0.110)***	-1.425 (0.113)***	-1.429 (0.114)***	-1.408 (0.113)***	-2.512 (0.486)***	-1.424 (0.113)***	-2.939 (0.542)***
Cultural proximity		0.556 (0.057)	0.232 (0.063)	0.234 (0.063)	0.225 (0.062)*	0.242 (0.063)	0.204 (0.421)	-0.041 (0.431)
Administrative boundary			-1.229 (0.063)***	-1.228 (0.063)***	-1.234 (0.063)***	-1.217 (0.062)***	-1.231 (0.065)***	-1.235 (0.064)***
Administrative level			-0.361 (0.067)***	-0.359 (0.067)***	-0.359 (0.067)***	-0.340 (0.066)**	-0.364 (0.068)***	-0.355 (0.068)***
Geographical proximity × institutional proximity				0.133 (0.048)***				0.131 (0.051)**
Geographical proximity × social proximity					-0.019 (0.018)			-0.045 (0.021)**
Geographical proximity × cognitive proximity						0.199 (0.095)**		0.281 (0.107)***
Geographical proximity × cultural proximity							0.005 (0.079)	0.053 (0.081)
Statistics								
Over-dispersion (α)	1.000***	0.535***	0.515***	0.515***	0.516***	0.517***	0.517***	0.518***
Vuong-statistic	11.554***	16.057***	14.98***	15.051***	14.673***	15.221***	14.981***	15.067***
Log likelyhood	-38,237.273	-36,629.624	-35,893.130	-35,888.411	-35,891.708	-35,865.494	-35,892.573	-35,856.148
Pseudo R^2	0.296	0.326	0.340	0.340	0.340	0.340	0.340	0.340
AIC	76,488.554	73,289.251	71,824.272	71,818.834	71,825.403	71,772.971	71,827.155	71,766.276
Sample amount	163,878	163,878	163,878	163,878	163,878	163,878	163,878	163,878
Non-zero value sample amount	9,563	9,563	9,563	9,563	9,563	9,563	9,563	9,563

Significance level: ***p<0.01, **p<0.05, *p<0.1; standard error in the parentheses

8.2.3.5 **Results and discussion**

Table 8-9 shows the results of the ZNB. The model diagnostics for over-dispersion (α) and excessive zero counts (Vuong-statistic) are significant, indicating that the ZNB fits our data best. The coefficients of variables across different models are stable, suggesting the robustness of the results.

(1) The impact of multidimensional proximity on the formation of knowledge collaboration network

Model 1 presents the baseline model, which restricts the analysis to the sizes of the organizations and the physical distance between them, while Model 2 and Model 3 introduce different proximity and control variables. We first look at the results of the negative binomial part. As expected, the results of all three models show that both mass and geographical proximity are powerful indicators for predicting the collaboration intensity of the medical sciences research network in the JZH region. Positive values of the variable size indicate that inter-organizational collaboration increases if both partners have higher absorptive capacity. Physical distance has a significant negative impact on the intensity of inter-organizational collaboration, which implies collaborations are more likely to take place between geographically co-located institutions. This result confirms received knowledge about geographical proximity being relevant in the processes of knowledge exchange .

A: "As far as I am concerned, face-to-face communication is extremely necessary. Only through face-to-face communications partners can build mutual trust and collaboration afterwards. How is it possible for me to know who he/she really is and whether reliable or not if I have never met him/her?

..

Although making phone calls and texting WeChat message is quite convenient, the first time collaboration can only be successfully established after we have met each other. Still, it is not enough, we still need to meet on a regular basis during the collaboration."

B: "In my research, I will do a comparative study with samples from hospitals both in northern China and southern China, which means I need to collaborate with hospitals in both areas. Currently, I am collecting and analyzing the samples from southern China in general and the YRD region in particular. It is much easier because of the geographical proximity. In comparison, collaborating with hospitals in northern China costs more simply because the long distance."

C: "The collaboration activities we are doing now requires frequent face-to-face contacts. For example, each prototype sample they made will be transported to our laboratory for pilot tests or clinical trials The samples are fragile and cost a lot in transportation and storage. Normally, the samples are transported by arranged special vehicles and monitored by them all the way. It is not possible to collaborate with an institution in Beijing or Guangzhou .In a word,, distance matters."

In Model 2, four non-geographical proximity factors are incorporated. The results suggest that institutional, social and cognitive proximity are positively associated with the propensity to co-publish. Similar to Ponds et al.'s (2007) findings, the institutional proximity has a sizable impact on scientific collaboration, suggesting that scientific collaborations are more common between organizations sharing an institutional context, likely because in the medical sciences the research trajectories of universities and hospitals, to some extent, are different. According to Vandenbroucke (2008), medical researchers working in academic institutions focus more on discoveries and explanations of causes of disease, as well as in verifications and falsifications of existing experiments. In contrast, doctors who deal with specific clinical cases place more emphasis on the evaluation of interventions to determine whether the patients, clinical manifestations are truly improved by new therapies or diagnostics. Vandenbroucke (2008) also points out that these two trajectories in medical sciences also coexist, making the case for university–university–affiliated hospital collaborations.

A: "The medical sciences can be basically divided into two somewhat separated fields: basic research and clinical application. Professors in the universities mostly engage in basic research, while doctors in the hospitals focus more on clinical application. For example, although my supervisor is a professor in medical school, he spends most of his time in affiliated hospital and focus more on clinical application, and he only teaches two times a week in the medical school. What I am doing is basic research. In fact, my supervisor cannot solve all the problems that I encounter. He is more likely to play the role as a 'consultant' or 'intermediary' to me. When I encounter some difficulties that he is not able to handle, he will contact the professors he knows to help me."

B: "There are some common interests between basic research and clinical application, but not too many. The main purpose of the basic research is to explore the underlying mechanism of the disease, the nosogenesis of the certain bacteria or virus, which is quite forward-looking. But the research results, to a large extent, are difficult to convert into clinical application within a short time. The aim of clinical medicine is generally to examine whether certain therapies *and diagnostics have improved patients' clinical manifestations. Scholars in basic research do collaborate with doctors in clinical application, but the depth and range of the collaborations are rather limited.* Social proximity, estimated by the weighted shortest path between institutions in the research collaboration network, is also found to be important in the formation of scientific collaboration. The medical sciences researchers in the YRD more frequently collaborated with researchers in other institutions with whom they have already worked in the past. At the same time, for researchers who have never worked together before, the number of intermediaries between them is an influential factor for the possibility of future collaborations: the fewer intermediaries in between two researchers, the easier they can develop future collaborations.

A: "The collaborations cannot be built spontaneously. There are two intermediaries have helped me in the establishment of the collaboration between me and the China Pharmaceutical University. Without them, I will never know there is such a professor who specializes in big data application . ."

B: "My partners in Soochow University are my former colleagues when I was in Suzhou. Because we have the same supervisor, we have had many collaborations before I started my doctoral study."

Cognitive proximity, measured here by technological relatedness, is positively associated with the intensity of inter-organizational scientific collaboration, which indicates that institutions in the YRD medical sciences research network tend to collaborate more with technologically similar organizations, a result that corroborates Boschma's (2005) argument that although knowledge creation through collaboration is dependent on the combination of different and diverse knowledges, there are still certain technology gap criteria, under which actors are able to communicate efficiently.

A: "In terms of education background and knowledge structure, we are rather different to each other. Because of this difference, we can take advantage of other's specialties. However, the premise of our successful collaboration is that both of us had been a medical student. Sharing a common basic knowledge pool is very important."

B: "The similarity of knowledge structure is the precondition for collaboration. For example, it is impossible for the Tongji Pulmonary Hospital where I study to cooperate with an ophthalmological hospital."

Cultural proximity is not shown to be a driver of the formation of the KCN. This is consistent with the findings in the section 7.4.2. One possible explanation is that the dialects, which serve as a proxy for cultural proximity, is only a reflection of informal vernacular culture of daily life. The culture of scientific research is more strictly and formally structured, and it provides common rules for scientists to follow.

> *A: "Cultural differences do exist. For example, there are Shandong community, Sichuan community and Northeast community in our hospital, but this is only in extracurricular life. In terms of scientific research, the communities are based on units like departments, laboratories and research groups."*
>
> *B: "The differences in cultural backgrounds are not problems in scientific collaborations, because we speak Mandarin only rather than dialects."*
>
> *C: "Local culture may affect collaboration, but are not influential. Because the language of scientific research is strict and formalized."*

In Model 3, two control variables "administrative boundary" and "administrative level" are introduced. The coefficient of the variable same province is significantly positive, which corroborates Andersson et al. (2014)'s finding that a form of 'regional protectionism' in scientific research is still prevalent in the YRD. Meanwhile, the coefficient of the variable capitals is also significantly positive, which suggests that the organizations located in provincial capitals (i.e., Shanghai, Nanjing and Hangzhou) are more likely to be involved in collaborative scientific research. In China's top-down science and education system, the allocation of research-related resources is determined by the central government. Administratively higher-ranking cities always host a fair amount of highly educated individuals, leading universities, reputed hospitals. In addition, the national or provincial scientific funding is often preferentially granted to large-scale collaborative projects involving distinguished researchers and leading institutions (Cao et al. 2018). Together, these results show that, in the YRD, political decisions play a more important role than markets in the allocation of scientific resources, and further in shaping the spatial formation of its scientific collaboration network.

The results of the zero-inflated part broadly tell the same story as the negative binomial results. However, estimates of social proximity in both the negative binomial and the zero-inflated part are positive, indicating that there is an inverted U-shaped relationship between the likelihood to cooperate and social proximity. Boschma (2005) argues that although social proximity may positively affect interactive learning due to common trust and commitment, too much social proximity may also be harmful to collaborative innovation because of the lock-in effect and risk of opportunism.

(2) Interaction between geographical and non-geographical proximity

Model 4 to model 8 introduce the pairwise interaction terms to test the interaction between the different forms of non-geographical proximity considered in relation to geographical proximity. In this section, only the results of the negative binomial part are examined, since the interpretations of interaction terms on zero count are meaningless. First, the interaction effect between geographical proximity and institutional proximity is significantly positive (Model 5). This can be interpreted as evidence that institutional and geographical proximity are substitutes in facilitating scientific collaboration. Medical sciences researchers in the JZH who are geographically distant from one another have a high probability to collaborate if they are working at the same type of institutions. On the other hand, collaboration between different kinds of organizations is more geographically localized .

> *A: "Generally speaking, university-university collaborations and hospital-hospital collaborations are not sensitive to distance. For the former, researchers can temporarily meet each other in conferences or meetings. For the later, one of the main purposes of hospital-hospital collaborations are statistical analysis of certain diseases or epidemic preventions, they could be nationwide."*

The estimated interaction effect between geographical and social proximity is negative and statistically significant (Model 5), indicating that there exists a complementary relation. More future collaborations among researchers who have already worked together in the past are more likely to take place if they are spatially close to one another. This finding corroborates the theories of localized learning and innovation milieus, in which it is argued that being co-located is a prerequisite for knowledge spillovers as it acts as a catalyst in building trust-based inter-personal relations through facilitating face-to-face contacts (Malmberg and Maskell, 2006,) .

> *B: "I received my M.Sc. degree from Soochow University. After graduation, some of my colleagues went to Beijing, Guangzhou or Wuhan for their PhD. Even though we have a good collaboration foundation during the master years, we rarely contact with each other now because of the distance. However, I still have close contact with those who stay in Soochow University, not only scientific collaborations but also hang out. "*

The interaction between geographical and cognitive proximity is also negative and statistically significant, implying that the positive impact of high technology relatedness on scientific collaboration is more important for geographically proximate organizations (Model 6). Thus, the spatial pattern of the medical sciences research network of the JZH is shaped by a degree of territorial specialization .

> *A: "In fact, in the field of nano-technology, Tsinghua University (Beijing), Huazhong University of Science and Technology(Wuhan) and Dalian University of Technology (Dalian) outperform Zhejiang University. So in the case that the technology of different universities are neck and neck, we tend to collaborate with Zhejiang University which is spatially closer to us."*

Finally, the interaction effect between geographical proximity and cultural proximity is not significant, indicating that there is neither substitution nor complementarity between the two.

Based on a combination of qualitative and quantitative analysis, this section explores the micro-mechanisms of the formation of the KCNs. The multidimensional proximity, i.e., geographical proximity, institutional proximity, social proximity, cognitive proximity and cultural proximity, are highlighted as the micro-initiative factors in shaping the formation of the KCNs.

The primary empirical findings confirm that both geographical and non-geographical proximity positively impact scientific collaboration, with the exception of cultural proximity. In addition, the analysis of the joint effect between geographical and non-geographical forms of proximity provides more in-depth details about the interaction dynamics among them and explains how they have been shaping the regional scientific collaboration network. The results point to the existence of a substitution effect between geographic and institutional proximity in promoting the interactive research activities. Conversely, geographical proximity is found to be a reinforcing factor, which, in combination with social and cognitive proximity, support the process of knowledge exchange. (Figure 8-2)

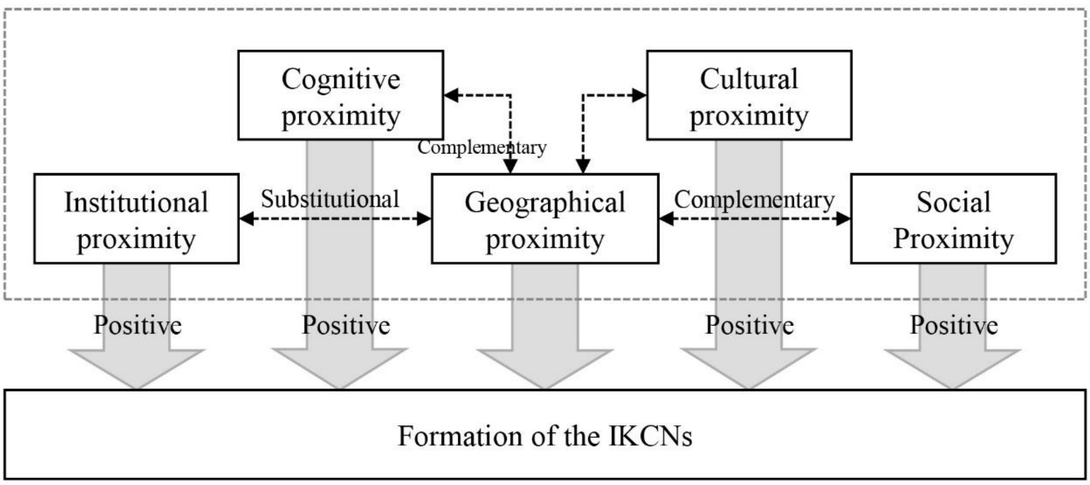

Figure 8-3 Impact of multidimensional proximity on the formation of the KCN
Source: author

Although the analysis focuses on a specific scientific field, the implications for innovation policies in the JZH are not necessarily restricted to that field. At the organization level, the innovation capacity of research institutions is closely associated with the quantity and diversity of their external linkages. Thus, the resource management of an institution should focus not only on its own knowledge base but also on fostering and encouraging to build external collaborative linkages outside their organizational boundaries. For a research institution, being in an advantageous position in a broader collaborative network could, to some extent, compensate for its location disadvantage. At the cluster level, the spatial coordination of clusters and the public resources to support them should not be overemphasized as being the only method of cultivating knowledge spillovers and (re)generation: the direct contribution of geographical proximity and its positive effect only emerge as a catalyst in combination with non-geographical proximity. Therefore, in addition to spatial clustering and large financial investments, more attention should be directed toward creating a favorable environment ensuring the effectiveness of building scientific collaboration networks.

8.3 Summary

This chapter explores the underlying mechanisms of the formation of the IKCNs. Firstly, this chapter takes the “Sino-Belgium Geographic Information Joint Laboratory” as an example, which is jointly organized by the Xinjiang Institute of Ecology and Geography of the Chinese Academy of Sciences and the Geography Department of the University of Ghent, Belgium. In-depth interviews with some participants are conducted. Based on the references of the interviews the macro-structural factors on the formation of the IKCNs are summarized. Second, based on the case of the inter-organizational medical sciences collaboration network of the Jiangsu-Zhejiang-Shanghai region, and in-depth interviews with three PhD candidates from Tongji University School of Medicine, this chapter quantitatively and qualitatively investigates the impact of micro-initiative factors, i.e. multidimensional proximity, in the formation of the IKCNs . The main findings are:

The macro-structural factors that influence the formation of the IKCNs are the “shifting scientific research paradigm”, the “complementation of innovation resources” and the “support of collaborative environment”. First, much more than in the past, sciences today require collaborations because of their need for knowledge combination, the need for specialization, the need for interdisciplinary and the need for satisfying interests.

Second, because innovation resources are evenly distributed across space, complementation of resources could be achieved through collaboration, more specifically, the complementation of human resources, the complementation of financial resources, complementation of facility resources and complementation of knowledge resources. Third, the crucial role of the support of collaborative environment in promoting innovation performance has been widely acknowledged, which include the support of policy environment, the support of cultural environment and institutional environment.

Multidimensional proximity is the micro-initiative factors that influence the formation of the IKCNs. Essentially, actors' behaviors of selecting, building and maintaining collaboration relations is processes of weighing the costs and benefits of collaborations. Geographical proximity is believed as a decisive factor that influences the formation of the KNCs. However, simply being co-located is neither a prerequisite nor a sufficient condition for collaboration. Non-geographical forms of proximity such as institutional proximity, social proximity, cognitive proximity and cultural proximity also facilitate the formation of the KCNs. The case of inter-organizational medical sciences collaboration network of the Jiangsu-Zhejiang-Shanghai region demonstrates that both geographical proximity and non-geographical proximity positively impact the formation of the KCNs, with the exception of cultural proximity. In addition, the analysis of the joint effect between geographical and non-geographical forms of proximity provides more in-depth details about the interaction dynamics among them and explains how they have been shaping the regional scientific collaboration network. The results point to the existence of a substitution effect between geographic and institutional proximity in promoting the interactive research activities. Conversely, geographical proximity is found to be a reinforcing factor, which, in combination with social and cognitive proximity, support the process of knowledge exchange.

Chapter 9 Conclusions and discussions

9.1 Main findings and explanations

Innovation is the primary force that drives development, the strategic support for China's modernization and also the key to improve China's status and overall competitiveness. Cities are innovation machines. However, cities' knowledge pool and innovation resources are limited. In the context of increasingly fierce global competition, endogenous development might lead to technological lock-in. It is imperative for cities to access in the trans-local IKCNs to acquire new knowledge and to avoid lock-in. In view of this, conducting research on the IKCNs has crucial theoretical and practical significance.

Using co-publication data drawn from the Web of Science database, this thesis investigate the evolution of the IKCNs across different geographical scales, i.e., a transnational knowledge collaboration network consists of 165 sovereign states and territories, a global IKCN consists of 500 world cities, a national IKCN consists of 217 Chinese cities, and regional IKCNs consists of 20 city-regions of China.. With the aid of various methods and techniques, such as spatial analysis, social network analysis and econometric analysis, this thesis tries to answer two interrelated questions: (1) What are the spatial and topological structures of the evolution of China's IKCNs at different geographical scales? (2) What are the underlying mechanisms of the formation of the IKCNs? The main findings are as follows:

9.1.1 Structures

9.1.1.1 "Space dependency" and "path dependency" in the evolution of the IKCNs

Based on multidimensional and multi-scalar empirical examinations, the first hypothesis is confirmed: in the evolution of the IKCNs, the spatial configuration and topological structure are interrelated and interactional, which follows the general rules of "space dependency" and "path dependency". That is, the evolution of the spatial configurations and topological structures of the IKCNs at different scales exhibits gradual, stable and self-reinforced development trajectories, which can be explained as:

Knowledge production is a spatially exclusive and contextually specified process, that is, different places possess different specialized knowledge and technological know-how because of different local contexts. Meanwhile, the diffusion and spillovers of knowledge are often confined to certain actors within certain regions. In the era of globalization and knowledge-based economy, trans-local collaboration has been proven to be an important way for countries, regions and cities to access to new external knowledge and avoid technological lock-in. Knowledge production and innovation depend on the integration of different kinds of knowledge. However, these processes are not random. Only the (re)combination of certain knowledge can lead to meaningful innovation. Although the rapid development of transportation and communication technologies has enlarged the spatial range of knowledge spillovers, the complex tacit knowledge, sophisticated know-how are still highly "sticky" to the certain places. Therefore, in the processes of collaboration networking, the spatial formations of the KCNs are constrained by the distribution of knowledge in space and certain knowledge combination logics, which can be termed as "space dependency".

The processes of knowledge collaboration are essentially the processes of the formation and maintenance of the social linkages among innovation actors, which are governed and regulated by the "network routines" – the norms, institutions and consensus accepted by most network members. Network routines are unique and non-replicable, which facilitate specific social practice and social capital accumulation. Further, the formation of the network routines are long-term accumulated assets including shared values and culture, common norms and technology paradigms as well as trust-based relations, which plays an important role in containing opportunism, maintaining local order and promoting knowledge spillovers. Therefore, in topological term, the formation and evolution of the IKCNs also follow specific network routines with cyclic accumulation and self-reinforcement. Based on this logic, in the evolution of the IKCNs topology, the topological characteristics show the pattern of "path dependency".

9.1.1.2 **The hierarchical structures and uneven distributions of the IKCNs**

This research constructs the knowledge networks of different spatial scales, i.e., a transnational IKCN consists of 165 sovereign states and regions, a global IKCN consists of 500 world cities, a national IKCN consists of 217 prefectural-level and above cities; an intra-regional IKCN consists of 20 city-regions in China. The results show that these networks all present "hierarchical" structures and "uneven" distribution patterns in both spatial and topological terms, albeit there are trends of balanced developments to varying degrees.

Specifically, in terms of spatial structure: (1) At global level, a clear-cut gap between the "Global South" cities and the "Global North" cities can be found in the global IKCN. Meanwhile, in the "Global North", cities in North America, Europe and East Asian constitute a tripolar structure that underpinning the whole network. (2) At national level, the evolution of China's IKCN has witnessed the emergence of a "diamond-shaped" structure with a "globally dispersed" and "locally concentrated" spatial configuration, in which "capital monopoly" effect plays a key role in shaping such spatial pattern. (3) At regional level, intra-regional IKCNs in eastern China are generally better developed than that in western China in terms of network connectedness and cohesiveness.

In terms of topological features: (1) "Scale-free" property universally exists in different scales of IKCNs, indicating the prevalence of polarized structures, that is, only a few cities have a large number of collaboration links while most cities only have a few collaboration links. (2)

The distribution of the IKCNs presents evident “core-periphery” structures, and it is difficult for peripheral cities to enter the core layers, showing a “periphery lock-in” effect. (3) There are clear-cut “central-hinterlands” relations among cities in the IKCNs.

In addition, “hierarchy” is also embodied in the cities’ network status and network functions: (1) different cities show different statuses and in turn play different roles in the IKCNs. For example, in the GBA city-region, Hong Kong is the “knowledge gatekeeper” that connects the region with the other part of the world, while Guangzhou is the “knowledge gatekeeper” that links the region with other part of the country. (2) The hierarchical status and functional role of a city varies in different scales of the IKCNs. For example, London and New York are not only the knowledge hubs at global level, but also the hubs at national and regional levels. Cities like Tokyo and Seoul are only the knowledge hubs in their countries and regions. (3) The external reach (globalization) and internal reach (localization) of cities in the IKCNs differ, reflecting the dynamics between “global pipelines” and “local buzz”.

9.1.1.3 **The explanations for the ups and downs of cities in the IKCNs**

The up and downs of cities in the evolution of the IKCNs can be attributed to their development status.

The innovation activities of cities are non-linear but present “S-shaped” curves with “starting stage, growth stage, mature stage, bottleneck stage”. This development trajectories are also embodied in the evolutionary paths of different cities in the IKCNs: cities that have newly joined or cities have not yet joined the KCNs are mostly in the starting stage of knowledge innovation, so their KNC growth is relatively slow (such as most cities in the “Global South”). Cities in emerging economies are accelerating their pace and soaring in the KCNs. Having gained certain degrees of innovation capabilities after learning, absorbing and accumulating knowledge in the early stage, they have more space for growth and development, and in turn show great momentum in the IKCNs. As for those cities that have entered the mature stage, they often have possessed the most advanced science and technology and have been devoting a lot to the most cutting-edge research and frontier breakthroughs. These processes are relatively slower and the collaboration communities are relatively smaller, thus they present a relatively low growth rate in the IKCNs. When sailing through the mature stage, the cities will experience the decline in innovation rate to a certain degree and even the “technological lock-in”, and their collaborative activities will, inevitably, decline. Under certain situations, the city can get out of the “technological lock-in” through “destructive innovation” and enter a new round of innovation stages.

9.1.1.4 The impacts of regional-specific factors in the evolution of the IKCNs.

Broadly speaking, knowledge collaborations are fundamentally social practice process governed by rational economic behaviors which are socially situated and institutionally restricted. Collaboration processes are “network embedded” and also “territorially embedded”. The IKCNs within different social backgrounds and territorial contexts thus present different structures and evolutionary trajectories.

For example, at national scale, the IKCNs of Russia, Brazil and China are significantly polarized, which is largely due to the fact that governments of these developing countries play decisive roles in making innovation policies and allocating resources so that the capitals and economic-advanced cities will benefit more. While the IKCNs of the United States, the UK, Germany, Japan and India show polycentricity to varying degree, which are also closely related to their socio-economic developments.

At regional scale, the research examines the structure configurations and evolutionary trajectories of different city-regions of China from the perspectives of morphological polycentric and functional polycentricity of the IKCNs. The results show that better developed city-regions tend to exhibit polycentric structures, while underdeveloped city-regions are more likely to show monocentric structures. In addition, the comparative analysis of the IKCNs of the three major city-regions suggests that the same regional factor has different effects on the structural configurations and evolutionary trajectories of the KCNs in different regions.

9.1.1.5 The two-sided effects of the network positions on the innovation performance of cities.

Being embedded in the IKCNs, cities can enjoy positive externalities generated by the networks. For cites, occupying advantageous positions in the IKCNs can, to some extent, compensate for their disadvantages in terms of geographical locations or endowments. The research on China’s IKCN points out that network topologies i.e., “centrality”, “closure”, “structural holes” and “internal /external reach” improve cities’ innovation performance.

However, the networks may also have negative externalities, that is, excessively embedded or exposed in network will lead to unnecessary competitions, opportunism and risks, which could be detrimental to cities’ innovation performance. The empirical results suggest that the impacts of closure on cities’ innovation performance present a positive U-shaped relation while that of structural holes present an inverse U-shaped relation.

9.1.2 Mechanisms

9.1.2.1 **Scientific paradigm, innovation resources and collaborative environment as the macro-structural factors**

Based on in-depth interviews with the participants of the “Sino-Belgium joint laboratory for geo-information” program, three macro-structural factors that influence the formation of the IKCN are identified, i.e. shifting scientific research paradigm, complementation of innovation resources and support of collaborative environment.

First, much more than in the past, sciences today require collaborations because of their needs for knowledge combination, the needs for specialization, the needs for interdisciplinary and the needs for satisfying interests. Second, because innovation resources are evenly distributed across space, complementation of resources could be achieved through collaboration, more specifically, the complementation of human resources, the complementation of financial resources, the complementation of facility resources and the complementation of knowledge resources. Third, the crucial role of the support of collaborative environment in promoting innovation performance has been widely acknowledged, which includes the support of policy environment, the support of cultural environment and institutional environment.

9.1.2.2 **Multidimensional proximity as the micro-initiative factors**

Different types of proximity are the micro-initiative factors that influence the formation of the IKCNs. Essentially, actors’ behaviors of selecting, building and maintaining collaboration relations are processes of weighing the costs and benefits of collaborations. Geographical proximity is believed as a decisive factor that influences the formation of the KNCs. However, simply being co-located is neither a prerequisite nor a sufficient condition for collaboration. Non-geographical forms of proximity such as institutional proximity, social proximity, cognitive proximity and cultural proximity also facilitate the formation of the KCNs. The case of inter-organizational medical sciences collaboration network of the Jiangsu-Zhejiang-Shanghai region demonstrates that both geographical proximity and non-geographical proximity positively impact the formation of the KCNs, with the exception of cultural proximity. In addition, the analysis of the joint effects between geographical and non-geographical forms of proximity provides more in-depth details about the interaction dynamics among them and explains how they have been shaping the regional scientific collaboration network. The results point out the existence of a substitution effect between geographical and institutional proximity in promoting the interactive research activities. Conversely, geographical proximity is found to be a reinforced factor, which is combined with social and cognitive proximity, supporting the process of knowledge exchange.

9.2 Policy implications

In addition to examining the structures and mechanisms of the evolution of China's IKCNs, this thesis may offer some general policy implications:

（1） Encourage participations in the IKCNs

Occupying advantageous or strategic positions in the network is an effective way to improve cities' innovation performance, especially for those cities that do not possess locational advantages and sufficient endowments. However, for most of the cities, it is not possible or necessary to pursue to be the "central city" or "hub city". More attention should be paid to promote the balanced development at regional, national as well as global levels. In addition, it should be noted that networks may also have negative externalities, that is, being overly embedded or exposed in network will lead to unnecessary competitions, opportunism and risks, which could be detrimental to cities' innovation performance.

（2） Balanced development of "local buzz" and "global pipelines"

This research has repeatedly emphasized the importance of "local buzz" and "global pipelines" for national and regional innovation: "local buzz" is the basis for the formation of local innovation milieu while "global pipelines" provide the channels for accessing external knowledge. The "local buzz" and "global pipelines" are not independent and cannot absolutely ensure sustainable innovation development. Only the balance of the two can stimulate regional vitality and sustain innovation. Specifically, overly dense "local buzz" will lead to information overload, which increases the cost of searching for effective information and undermines the establishment of "global pipelines". While too many strong "global pipelines" will weaken the flexibility and self-organizing of "local buzz" and they could be harmful for the formation of local innovation milieu.

（3） Pay attention to both "spatial coordination" and "milieus cultivation"

It can be seen from the results in Chapter 8 that geographical proximity is not the only factor that promotes the formation of the KCNs, its positive effect only emerge as a kind of catalyst in combination with non-geographical proximity. In other words, in addition to spatial coordination and construction, e.g., high-tech industrial parks, university parks, technology incubators, etc., more attention should be directed towards creating a favorable environment that ensures the effectiveness of building collaboration networks.

（4） Reduce the intervention of "top-down system" and "administrative boundaries"

Based on the investigation of the evolution of China's IKCNs, it can be concluded that the formation of the IKCNs is not only determined by "visible factors" like local endowments and locational advantages. Under the unique Chinese institutional context, the interventions by government is an “invisible factor” that significantly affects the formation of the IKCNs. The “top-down system” and the “administrative boundaries” are the current bottlenecks for the balanced development of China’s IKCNs. Therefore, to foster a balanced development of the IKCNs, it is necessary to improve the institutional arrangements to reduce the negative impact of “top-down system” and “administrative boundaries”.

9.3 Limitations and avenues for future research

This research inevitably has shortcomings, which may at the same time open some avenues for future research:

(1) The data in this research is mined from the Web of Science database, which has obvious advantages over others in terms of accuracy and reliability. However, the WoS is an English database, which cannot fully outline the whole picture of China’s IKCNs. Second, co-publication is just one type of knowledge collaboration activities and cannot represent all knowledge collaboration activities. In future research, it is necessary to expand the scope and incorporate more types of data sources into consideration.

(2) In the process of network construction-, considering the operability of data of such large scale, the measurement of the intensity of collaboration is simply calculated as co-authorship links, which means that there is no difference between these links. Weighting collaboration links based on citations and journal impact factors may enrich future research in this field

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Appendix

Appendix I KNC ranking for 165 countries (1995-2016)

Rank	Country	1995 (%)	Country	2005 (%)	Country	2016 (%)
1	USA	100.00	USA	100.00	USA	100.00
2	UK	47.38	UK	51.77	UK	60.65
3	Germany	44.90	Germany	50.81	Germany	52.05
4	France	37.22	France	37.88	China	40.30
5	Italy	24.89	Italy	27.29	France	39.98
6	Canada	24.35	Canada	26.33	Italy	34.63
7	Japan	20.58	Japan	21.54	Spain	30.09
8	Netherlands	18.64	Netherlands	20.31	Canada	28.96
9	Switzerland	17.89	Spain	19.32	Australia	27.71
10	Russia	16.18	China	17.83	Netherlands	26.56
11	Sweden	14.88	Switzerland	17.72	Switzerland	24.17
12	Spain	13.73	Australia	15.85	Japan	19.13
13	Belgium	11.64	Sweden	14.66	Sweden	18.88
14	Australia	11.37	Russia	14.21	Belgium	16.74
15	Poland	9.49	Belgium	13.22	Brazil	15.31
16	Denmark	9.27	Poland	9.36	Denmark	14.14
17	Israel	8.09	Austria	8.91	Austria	13.77
18	Finland	7.11	Denmark	8.87	Poland	13.25
19	Austria	7.02	South Korea	8.74	Russia	13.00
20	China	6.96	Brazil	7.63	South Korea	12.60
21	Brazil	6.36	Finland	6.97	India	12.48
22	Norway	5.66	India	6.91	Norway	10.60
23	Ireland	5.62	Israel	6.86	Finland	10.16
24	Czech Republic	4.73	Norway	6.47	Portugal	10.15
25	India	4.70	Ireland	6.30	Czech Republic	9.82
26	South Korea	4.51	Czech Republic	5.45	Greece	9.66
27	Greece	4.51	Greece	4.85	Ireland	9.04
28	Hungary	4.31	Hungary	4.64	South Africa	9.00
29	Portugal	3.31	Taiwan	4.51	Turkey	8.91
30	Mexico	3.02	Portugal	4.47	Taiwan	8.39
31	Taiwan	2.90	Mexico	4.32	Israel	8.08
32	Slovakia	2.73	New Zealand	3.73	Saudi Arabia	8.06
33	New Zealand	2.60	Argentina	3.48	Hungary	7.56
34	Ukraine	2.53	South Africa	3.45	Mexico	6.95
35	South Africa	2.29	Singapore	3.14	Malaysia	6.85
36	Argentina	2.06	Turkey	2.99	Chile	6.49
37	Slovenia	1.86	Chile	2.48	Singapore	6.20
38	Bulgaria	1.74	Ukraine	2.36	New Zealand	6.19

39	Romania	1.68	Thailand	2.19	Colombia	5.75
40	Chile	1.64	Romania	2.04	Argentina	5.54
41	Turkey	1.32	Slovenia	1.94	Iran	5.44
42	Egypt	1.26	Slovakia	1.85	Romania	5.39
43	Thailand	1.19	Bulgaria	1.65	Egypt	5.24
44	Singapore	1.18	Egypt	1.29	Thailand	5.08
45	Croatia	1.06	Colombia	1.26	Serbia	4.95
46	Morocco	0.88	Iran	1.22	Pakistan	4.89
47	Indonesia	0.74	Croatia	1.21	Ukraine	3.98
48	Colombia	0.74	Malaysia	1.01	Slovakia	3.96
49	Kenya	0.71	Kenya	0.87	Slovenia	3.90
50	Venezuela	0.70	Venezuela	0.84	Croatia	3.83
51	Belarus	0.69	Serbia	0.78	Bulgaria	3.73
52	Malaysia	0.58	Indonesia	0.76	Armenia	3.30
53	Saudi Arabia	0.58	Estonia	0.73	Belarus	3.27
54	Philippines	0.54	Lithuania	0.70	Georgia	3.15
55	Nigeria	0.52	Morocco	0.68	Estonia	3.02
56	Estonia	0.50	Vietnam	0.68	Qatar	2.84
57	Cyprus	0.50	Tunisia	0.68	Lithuania	2.63
58	Algeria	0.45	Iceland	0.66	Morocco	2.40
59	Guinea	0.44	Belarus	0.64	Cyprus	2.21
60	Armenia	0.42	Philippines	0.61	Vietnam	2.12
61	Pakistan	0.42	Saudi Arabia	0.60	Kenya	1.87
62	Iceland	0.42	Ecuador	0.60	Peru	1.85
63	Tanzania	0.40	Armenia	0.60	Sri Lanka	1.84
64	Cuba	0.40	Tanzania	0.59	Indonesia	1.73
65	Lithuania	0.39	Peru	0.57	Nigeria	1.67
66	Tunisia	0.37	Pakistan	0.53	UAE	1.64
67	Peru	0.37	Cuba	0.52	Tunisia	1.58
68	Bangladesh	0.36	Bangladesh	0.49	Azerbaijan	1.57
69	Papua N Guinea	0.35	Nigeria	0.49	Philippines	1.41
70	Vietnam	0.33	Algeria	0.45	Iceland	1.36
71	Latvia	0.32	Cyprus	0.43	Bangladesh	1.27
72	Uzbekistan	0.31	Uruguay	0.42	Ecuador	1.26
73	Iran	0.30	Costa Rica	0.40	Lebanon	1.21
74	Uruguay	0.30	Uganda	0.40	Algeria	1.21
75	Zimbabwe	0.30	UAE	0.39	Uganda	1.15
76	Kuwait	0.28	Latvia	0.37	Latvia	1.15
77	Senegal	0.27	Cameroon	0.37	Luxembourg	1.07
78	Georgia	0.25	Lebanon	0.35	Ghana	1.04
79	Jamaica	0.25	Ghana	0.33	Tanzania	1.03
80	Costa Rica	0.25	Georgia	0.32	Ethiopia	0.90

81	Kazakhstan	0.24	Jordan	0.32	Cuba	0.88
82	UAE	0.22	Kuwait	0.30	Cameroon	0.84
83	Cameroon	0.21	Senegal	0.30	Jordan	0.83
84	Uganda	0.21	Luxembourg	0.27	Uruguay	0.82
85	Luxembourg	0.21	Sri Lanka	0.27	Venezuela	0.74
86	Moldova	0.20	Ethiopia	0.26	Costa Rica	0.69
87	Ethiopia	0.19	Kazakhstan	0.25	Iraq	0.63
88	Cote Ivoire	0.19	Burkina Faso	0.25	Oman	0.63
89	Jordan	0.19	Uzbekistan	0.23	Malawi	0.62
90	Ghana	0.17	Zimbabwe	0.22	Zambia	0.60
91	Bolivia	0.17	Panama	0.21	Panama	0.59
92	Zambia	0.17	Moldova	0.21	Rep Congo	0.54
93	Sri Lanka	0.17	Guinea	0.20	Nepal	0.54
94	Panama	0.16	Bolivia	0.20	Kuwait	0.52
95	Ecuador	0.14	Malawi	0.20	Guinea	0.49
96	Azerbaijan	0.14	Oman	0.19	Kazakhstan	0.48
97	Nepal	0.13	Namibia	0.17	Mozambique	0.48
98	Malawi	0.13	Nepal	0.17	Cote Ivoire	0.47
99	Guatemala	0.12	Botswana	0.17	Bosnia & Herceg	0.47
100	Mali	0.11	Mali	0.16	Benin	0.46
101	Syria	0.11	Gabon	0.15	Zimbabwe	0.46
102	Gabon	0.10	Cote Ivoire	0.15	Rwanda	0.41
103	Rwanda	0.10	Syria	0.14	Macedonia	0.41
104	Lebanon	0.09	Azerbaijan	0.14	Dem Rep Congo	0.41
105	Sudan	0.09	Zambia	0.14	Burkina Faso	0.39
106	Burkina Faso	0.08	Papua N Guinea	0.13	Senegal	0.38
107	Benin	0.08	Guatemala	0.13	Sudan	0.36
108	Macedonia	0.07	Benin	0.13	Bahrain	0.33
109	Oman	0.07	Bosnia & Herceg	0.13	Myanmar	0.33
110	Paraguay	0.07	Madagascar	0.12	Cambodia	0.31
111	Niger	0.07	Sudan	0.12	Bolivia	0.29
112	Serbia	0.07	Cambodia	0.10	Guatemala	0.25
113	Guinea Bissau	0.06	Jamaica	0.10	Papua N Guinea	0.25
114	Trinid & Tobago	0.06	Rep Congo	0.10	Paraguay	0.25
115	Cent Afr Republ	0.06	Macedonia	0.09	Mali	0.24
116	Libya	0.06	Qatar	0.09	Madagascar	0.23
117	Mongol Peo Rep	0.06	Trinid & Tobago	0.08	Botswana	0.23
118	Bahrain	0.06	Mozambique	0.08	Mongol Peo Rep	0.22
119	Mozambique	0.05	Laos	0.08	Moldova	0.22
120	Albania	0.05	Nicaragua	0.08	Albania	0.22
121	Fiji	0.05	Honduras	0.08	Namibia	0.20
122	Sierra Leone	0.05	Mongol Peo Rep	0.08	Uzbekistan	0.20

123	Yemen	0.04	Bahrain	0.07	Togo	0.19
124	Nicaragua	0.04	Albania	0.07	Jamaica	0.19
125	Seychelles	0.04	Fiji	0.06	Brunei	0.19
126	Rep Congo	0.04	Myanmar	0.06	Montenegro	0.17
127	Dominican Rep	0.04	Niger	0.06	Laos	0.17
128	Botswana	0.03	Kyrgyzstan	0.05	Gabon	0.16
129	Namibia	0.03	Libya	0.05	Fiji	0.16
130	Qatar	0.03	Iraq	0.05	Kyrgyzstan	0.16
131	Honduras	0.03	Mauritius	0.05	Libya	0.16
132	Iraq	0.03	Dem Rep Congo	0.05	Angola	0.16
133	Mauritius	0.03	Guinea Bissau	0.05	Palestine	0.15
134	Kyrgyzstan	0.03	Paraguay	0.04	Dominican Rep	0.14
135	Myanmar	0.03	Dominican Rep	0.04	Niger	0.13
136	Brunei	0.02	El Salvador	0.04	El Salvador	0.13
137	Bermuda	0.02	Togo	0.04	Syria	0.13
138	Bosnia & Herceg	0.02	Yemen	0.04	Yemen	0.13
139	Togo	0.02	Mauritania	0.03	Sierra Leone	0.13
140	Angola	0.02	Angola	0.03	Seychelles	0.13
141	Mauritania	0.02	Eritrea	0.03	Afghanistan	0.12
142	Chad	0.02	Cent Afr Republ	0.03	Guinea Bissau	0.11
143	Cambodia	0.01	Haiti	0.03	Honduras	0.11
144	Laos	0.01	Brunei	0.03	Trinid & Tobago	0.11
145	Haiti	0.01	Chad	0.03	Nicaragua	0.11
146	Guyana	0.01	Swaziland	0.03	Haiti	0.09
147	Somalia	0.01	Tajikistan	0.03	Mauritius	0.08
148	Turkmenistan	0.01	Bermuda	0.03	Liberia	0.05
149	Dem Rep Congo	0.01	Seychelles	0.02	Surinam	0.05
150	Swaziland	0.01	Rwanda	0.02	Cent Afr Republ	0.05
151	Equat Guinea	0.01	Guyana	0.02	Swaziland	0.05
152	Djibouti	0.01	Surinam	0.02	Bhutan	0.05
153	El Salvador	0.01	Afghanistan	0.01	Tajikistan	0.04
154	Bahamas	0.01	Sierra Leone	0.01	Chad	0.03
155	Tajikistan	0.00	Lesotho	0.01	Guyana	0.03
156	Lesotho	0.00	Bhutan	0.01	Bermuda	0.03
157	Eritrea	0.00	Bahamas	0.01	Mauritania	0.03
158	Liberia	0.00	Montenegro	0.01	Bahamas	0.03
159	Surinam	0.00	Turkmenistan	0.01	Somalia	0.02
160	Bhutan	0.00	Liberia	0.00	Lesotho	0.02
161	Madagascar	0.00	Equat Guinea	0.00	Equat Guinea	0.01
162	Montenegro	0.00	Djibouti	0.00	Eritrea	0.01
163	Palestine	0.00	Somalia	0.00	Timor-Leste	0.01
164	Afghanistan	0.00	Palestine	0.00	Cayman Islands	0.01

165	Timor-Leste	0.00	Timor-Leste	0.00	Djibouti	0.01

Source: author

Appendix II KNC ranking for 500 world cities

Rank	2002-2006		2012-2016	
	City	KNC (%)	City	KNC (%)
1	London	100.00	London	100.00
2	New York	77.76	Beijing	87.52
3	Boston	74.16	Boston	82.22
4	Tokyo	69.20	New York	79.91
5	Paris	68.40	Paris	69.16
6	Beijing	62.77	Chicago	56.39
7	Los Angeles	56.45	Rome	53.42
8	Baltimore	52.15	Madrid	53.36
9	Philadelphia	51.83	Milan	52.21
10	Chicago	48.76	Barcelona	48.38
11	Houston	44.83	Toronto	47.60
12	Rome	44.82	Tokyo	46.13
13	Moscow	43.06	Baltimore	44.99
14	Seattle	42.32	Philadelphia	44.93
15	Toronto	41.13	Los Angeles	44.79
16	Milan	40.70	Seattle	44.51
17	Amsterdam	40.26	Amsterdam	44.49
18	Montreal	38.50	Moscow	43.69
19	Pittsburgh	35.78	Houston	42.99
20	Berlin	35.37	Pittsburgh	41.70
21	Atlanta	34.15	Geneva	41.35
22	Rochester	33.47	Shanghai	39.41
23	Washington	33.20	Columbus	39.38
24	San Francisco	31.74	Athens	39.13
25	Barcelona	31.11	Sao Paulo	38.84
26	Geneva	30.22	Sydney	38.70
27	Munich	29.87	Bologna	37.96
28	Madrid	29.41	Heidelberg	37.78
29	Madison	28.81	Berlin	37.66
30	Heidelberg	28.32	Munich	37.40
31	Columbus	28.00	Taipei	36.71
32	Vancouver	27.68	Montreal	36.20
33	Manchester	27.18	Melbourne	36.07
34	Vienna	27.11	Hamburg	35.98
35	Stockholm	26.96	Prague	35.65
36	Cincinnati	25.65	Stockholm	35.26
37	Seoul	25.56	Seoul	34.30
38	Zurich	25.07	Rochester	32.93

39	Cleveland	24.16	Copenhagen	32.67
40	Osaka	24.12	Naples	32.57
41	Kyoto	23.78	Madison	32.55
42	Sydney	23.14	Genoa	31.72
43	St Louis	22.73	Rio De Janeiro	31.65
44	Minneapolis	22.66	Vancouver	31.58
45	Turin	22.49	Manchester	31.39
46	Edinburgh	22.32	Budapest	30.26
47	Bologna	22.18	Nanjing	29.92
48	Taipei	21.81	Trieste	29.70
49	Hamburg	21.65	Edinburgh	29.58
50	Shanghai	21.58	Zurich	29.26
51	Nashville	21.40	Guangzhou	29.11
52	Glasgow	21.36	Santiago	29.00
53	Liverpool	21.36	Vienna	28.47
54	Athens	21.09	Lisbon	28.20
55	Naples	20.75	Istanbul	27.76
56	Brussels	20.23	Liverpool	27.68
57	Warsaw	20.09	Oslo	27.33
58	San Diego	19.87	Ankara	27.13
59	Dallas	19.49	San Francisco	26.97
60	Helsinki	19.27	Marseille	26.96
61	Sao Paulo	19.05	Glasgow	26.91
62	Prague	18.99	Bern	26.70
63	Bristol	18.74	Warsaw	26.55
64	Nagoya	18.69	Atlanta	26.52
65	Sendai	18.47	Bogota	25.53
66	Copenhagen	18.24	Belgrade	25.08
67	Yokohama	18.14	Dallas	25.07
68	Genoa	18.13	Helsinki	24.62
69	Trieste	18.08	St Petersburg	24.26
70	Lausanne	17.95	Krakow	24.18
71	Marseille	17.84	Minneapolis	24.06
72	Tucson	17.74	Valencia (Spain)	23.60
73	Detroit	16.87	Turin	23.59
74	Krakow	16.81	Bucharest	23.57
75	Basel	16.64	Ottawa	23.57
76	Edmonton	16.63	Washington	23.53
77	Lyon	16.61	Kyoto	23.42
78	Dresden	16.57	Brussels	23.22
79	Utrecht	16.56	Yerevan	22.86
80	Austin	16.50	Nashville	22.71

81	Ottawa	16.02	Edmonton	22.54
82	Florence	15.77	Florence	22.36
83	Strasbourg	15.69	Osaka	22.02
84	St Petersburg	15.44	Nagoya	21.77
85	Chiba	15.30	Tucson	21.47
86	Toulouse	15.07	Tbilisi	21.19
87	Melbourne	15.05	Minsk	21.19
88	Oslo	15.05	Detroit	20.98
89	Frankfurt	14.98	Hefei	20.86
90	Denver	14.73	Bristol	20.81
91	Valencia (Spain)	14.68	Dresden	20.51
92	Hong Kong	14.54	Novosibirsk	20.49
93	Budapest	14.41	Adelaide	20.27
94	Novosibirsk	14.20	Sheffield	20.25
95	Indianapolis	14.09	Buenos Aires	20.00
96	Bergen	13.88	Bergen	19.98
97	Portland	13.81	Mexico City	19.95
98	Karlsruhe	13.74	Dublin	19.23
99	Mumbai	13.73	Hong Kong	18.89
100	Rotterdam	13.69	Cape Town	18.87
101	Dublin	13.53	Utrecht	18.82
102	Montpellier	13.39	Tel Aviv	18.78
103	Mexico City	13.15	Southampton	18.62
104	Rio De Janeiro	12.91	Albuquerque	18.48
105	Singapore	12.62	Wuhan	18.40
106	Providence	12.61	Austin	18.24
107	Salt Lake City	12.59	Strasbourg	17.91
108	Hefei	12.51	Mumbai	17.87
109	San Antonio	12.24	Johannesburg	17.59
110	Albuquerque	12.10	Ljubljana	17.42
111	Honolulu	12.06	Jinan	17.40
112	Miami	12.01	Singapore	17.39
113	Leeds	11.52	Miami	17.29
114	Gothenburg	11.48	Clermont Ferrand	17.24
115	Nanjing	11.30	Bratislava	17.15
116	Sheffield	11.08	Cleveland	16.93
117	Fukuoka	10.90	Hiroshima	16.88
118	Tel Aviv	10.75	Dortmund	16.87
119	Santiago	10.50	St Louis	16.62
120	Newcastle	10.45	Kobe	16.58
121	Calgary	10.41	Fukuoka	16.49
122	Sapporo	10.39	Providence	16.35

123	Ljubljana	10.36	Haifa	16.02
124	Bern	10.32	Buffalo	15.95
125	Wuhan	10.24	Auckland	15.75
126	Southampton	10.15	Kuala Lumpur	15.64
127	Buenos Aires	10.15	Lyon	15.62
128	Chandigarh	10.11	Zagreb	15.45
129	Richmond	10.10	Rotterdam	14.46
130	Hannover	10.08	Brisbane	14.35
131	Lisbon	9.81	Lausanne	14.30
132	Nottingham	9.28	San Diego	14.18
133	Buffalo	9.05	Cincinnati	14.01
134	Brisbane	9.04	Karlsruhe	13.99
135	Kobe	8.87	Tehran	13.97
136	Cologne	8.86	Valparaiso	13.85
137	Milwaukee	8.84	Sofia	13.84
138	New Orleans	8.84	Antwerp	13.70
139	Jerusalem	8.63	Chandigarh	13.64
140	Antwerp	8.58	Kolkata	13.25
141	Nantes	8.41	Basel	13.25
142	Cardiff	8.36	Toulouse	12.88
143	Leipzig	8.26	Cairo	12.84
144	Omaha	8.22	Islamabad	12.83
145	Memphis	8.00	Rabat	12.48
146	Haifa	7.94	Bangkok	12.37
147	Lille	7.93	Bhubaneswar	12.09
148	Palo Alto	7.81	Hangzhou	12.09
149	Hiroshima	7.75	Casablanca	12.05
150	Canberra	7.71	Baku	11.98
151	Guangzhou	7.67	Kharkov	11.89
152	Clermont Ferrand	7.46	Salt Lake City	11.84
153	Dortmund	7.38	Frankfurt	11.68
154	Leicester	7.31	Christchurch	11.44
155	Dusseldorf	7.22	Puebla	11.40
156	Sofia	7.16	Montpellier	11.14
157	Adelaide	7.07	Campinas	11.09
158	Hangzhou	7.05	Chengdu	10.91
159	Aberdeen	7.01	Portland	10.77
160	Hsinchu City	6.97	Izmir	10.64
161	Bordeaux	6.76	Vilnius	10.45
162	Stuttgart	6.70	Newcastle	10.29
163	Halifax	6.49	Hannover	10.25
164	Bucharest	6.38	Nicosia	10.07

165	Charleston	6.38	Xian	10.05
166	Kansas City	6.34	Tallinn	10.04
167	Auckland	6.33	Calgary	9.96
168	Tampa	6.27	Tianjin	9.79
169	Graz	6.27	Indianapolis	9.48
170	Tianjin	6.11	Durban	9.33
171	Winnipeg	6.00	Jeddah	9.25
172	Kaohsiung	5.89	Cologne	9.23
173	Essen	5.87	Nantes	9.08
174	Shenyang	5.77	Leeds	8.98
175	Ankara	5.68	Perth	8.77
176	Chengdu	5.61	Yokohama	8.55
177	Perth	5.57	Gothenburg	8.54
178	Raleigh	5.45	Doha	8.43
179	Xian	5.43	Hsinchu City	8.42
180	Bratislava	5.42	Denver	8.32
181	Belfast	5.32	Tampa	8.11
182	Liege	5.32	Lille	8.09
183	Bangkok	5.26	Milwaukee	8.09
184	Zagreb	5.22	Changsha	8.04
185	Sacramento	5.03	Sendai	7.93
186	Nice	5.01	Kiev	7.77
187	Istanbul	4.92	Honolulu	7.73
188	Seville	4.88	Leipzig	7.69
189	Kiev	4.85	Cardiff	7.69
190	Palermo	4.84	Nottingham	7.63
191	Quebec	4.78	San Antonio	7.47
192	New Delhi	4.77	Canberra	7.44
193	Little Rock	4.75	Quebec	7.33
194	Kolkata	4.74	Bordeaux	7.21
195	Taichung	4.73	Shenzhen	6.93
196	Campinas	4.58	Richmond	6.93
197	Lanzhou	4.51	Riyadh	6.80
198	Changchun	4.48	Essen	6.79
199	Saskatoon	4.48	Pusan	6.71
200	Toyama	4.46	Dusseldorf	6.48
201	Changsha	4.30	Omaha	6.43
202	Bogota	4.29	Chongqing	6.35
203	Bangalore	4.22	New Delhi	6.29
204	Shizuoka	4.10	Pune	6.19
205	Jinan	4.10	Changchun	6.18
206	Jacksonville	4.08	Shenyang	6.05

207	Wroclaw	4.07	Palo Alto	5.99
208	Phoenix	4.05	Charleston	5.99
209	Lodz	3.94	Kansas City	5.98
210	Bremen	3.89	Leicester	5.96
211	Kawasaki	3.85	Lanzhou	5.87
212	Pusan	3.85	Harbin	5.86
213	Malmo	3.79	Sapporo	5.86
214	Porto Alegre	3.79	Winnipeg	5.85
215	Bhubaneswar	3.77	Halifax	5.77
216	Poznan	3.70	Graz	5.72
217	Norwich	3.67	Seville	5.68
218	Yerevan	3.57	Memphis	5.64
219	Cape Town	3.56	Lima	5.63
220	Dalian	3.47	Taichung	5.59
221	Norfolk	3.43	Chiba	5.57
222	Harbin	3.32	Suzhou	5.31
223	Cordoba	3.32	Jerusalem	5.28
224	San Jose (U.S.)	3.22	Nice	5.27
225	Quito	3.14	Qingdao	5.19
226	Johannesburg	2.91	Daegu	5.16
227	Belo Horizonte	2.89	Hanoi	4.98
228	Charlotte	2.79	Aberdeen	4.90
229	Kunming	2.77	New Orleans	4.90
230	Wellington	2.77	Chennai	4.82
231	Orlando	2.73	Phoenix	4.76
232	Chennai	2.72	Belfast	4.72
233	Nicosia	2.69	Dalian	4.70
234	Belgrade	2.61	Bangalore	4.68
235	Tehran	2.61	Stuttgart	4.54
236	Christchurch	2.58	Porto Alegre	4.50
237	Kitakyushu	2.57	Zhengzhou	4.45
238	Nairobi	2.53	Wroclaw	4.45
239	Qingdao	2.53	Lodz	4.37
240	Plymouth	2.42	Kunming	4.35
241	Cairo	2.39	Kaohsiung	4.21
242	Lima	2.38	Palermo	4.16
243	Reykjavik	2.36	Reykjavik	4.14
244	Valparaiso	2.34	Liege	3.98
245	Chongqing	2.33	Jacksonville	3.97
246	Pretoria	2.32	Sacramento	3.90
247	Minsk	2.28	Cordoba	3.73
248	The Hague	2.24	Belo Horizonte	3.72

249	Hyderabad (India)	2.22	Daejeon	3.64
250	Caracas	2.21	Nairobi	3.60
251	Pune	2.16	Bremen	3.58
252	Hobart	2.15	Malmo	3.54
253	Kharkov	2.15	Norwich	3.51
254	Hamamatsu	2.14	Bilbao	3.51
255	Hartford	2.13	Raleigh	3.49
256	Brasilia	2.12	Lahore	3.44
257	Vilnius	2.02	Taiyuan	3.43
258	Las Vegas	1.94	Xiamen	3.40
259	Kuala Lumpur	1.91	Wellington	3.37
260	Havana	1.89	Hobart	3.29
261	Alexandria	1.82	Jaipur	3.28
262	Izmir	1.81	Pretoria	3.18
263	Curitiba	1.81	Hyderabad (India)	3.11
264	Jaipur	1.80	Saskatoon	3.10
265	Salvador	1.79	Havana	3.09
266	Akita	1.75	Brasilia	3.09
267	Linz	1.74	Nanchang	3.01
268	Hanoi	1.74	Beirut	2.80
269	Bilbao	1.70	Poznan	2.78
270	Dhaka	1.66	Indore	2.76
271	San Jose (Costa Rica)	1.64	Nanning	2.73
272	Cochin	1.61	Orlando	2.69
273	Greensboro	1.61	Kampala	2.68
274	Riyadh	1.60	San Jose (U.S.)	2.64
275	Zhengzhou	1.58	Karachi	2.63
276	Ludwigshafen	1.57	Salvador	2.59
277	Sakai	1.55	The Hague	2.55
278	Puebla	1.53	Plymouth	2.51
279	Manila	1.50	Dhaka	2.47
280	Montevideo	1.49	Little Rock	2.46
281	Nurnberg	1.49	Curitiba	2.39
282	Durban	1.47	Riga	2.33
283	Beirut	1.45	Quito	2.27
284	Xiamen	1.43	Charlotte	2.26
285	Kampala	1.40	Norfolk	2.25
286	Recife	1.39	Fuzhou	2.21
287	Taiyuan	1.38	Shizuoka	2.15
288	Suzhou	1.36	Manila	2.14
289	Duisburg	1.34	Montevideo	2.10
290	Riga	1.34	Alexandria	2.06

291	Shenzhen	1.31	Shijiazhuang	2.03
292	Yaounde	1.29	Ningbo	2.02
293	Fortaleza	1.29	Urumqi	1.99
294	Venice	1.28	Jakarta	1.87
295	Jakarta	1.27	Kitakyushu	1.86
296	Nanning	1.26	Kawasaki	1.84
297	Tunis	1.21	Recife	1.83
298	Shijiazhuang	1.18	Medellin	1.74
299	Luxembourg	1.16	Tunis	1.72
300	Dar Es Salaam	1.16	Lucknow	1.69
301	Dakar	1.15	Guiyang	1.68
302	Karachi	1.12	Las Vegas	1.67
303	Peoria	1.09	Bhopal	1.65
304	Medellin	1.08	Dar Es Salaam	1.65
305	Tbilisi	1.08	Yaounde	1.64
306	Guadalajara	1.05	Abu Dhabi	1.62
307	Nanchang	1.05	Addis Ababa	1.61
308	Leon	1.04	Rosario	1.61
309	Kazan	1.03	Ho Chi Minh	1.60
310	Tulsa	1.02	Luxembourg	1.58
311	Harare	1.00	Caracas	1.54
312	Fuzhou	1.00	San Jose (Costa Rica)	1.51
313	Cali	0.99	Linz	1.50
314	Islamabad	0.99	Lusaka	1.43
315	Anchorage	0.98	Hartford	1.41
316	Kanpur	0.94	Ulsan	1.40
317	Tallinn	0.93	Nurnberg	1.37
318	Rabat	0.92	Cochin	1.35
319	Lucknow	0.92	Toyama	1.32
320	Guiyang	0.89	Mashhad	1.32
321	Rosario	0.88	Bursa	1.27
322	Belem	0.88	Fortaleza	1.24
323	Ningbo	0.86	Kazan	1.23
324	Tashkent	0.83	Vitoria	1.20
325	Ho Chi Minh	0.82	Trivandrum	1.16
326	Addis Ababa	0.80	Abidjan	1.16
327	Queretaro	0.80	Hamamatsu	1.16
328	Ibadan	0.78	Leon	1.14
329	La Paz	0.75	Gwangju	1.13
330	Des Moines	0.75	Goiania	1.12
331	Abidjan	0.74	Amman	1.12
332	Goiania	0.74	Ibadan	1.10

333	Urumqi	0.73	Dubai	1.09
334	Trivandrum	0.72	Cali	1.09
335	Vladivostok	0.71	Ludwigshafen	1.09
336	Monterrey	0.70	Belem	1.08
337	Ulsan	0.69	Tulsa	1.06
338	Leverkusen	0.67	Nagpur	1.06
339	Manaus	0.66	Haikou	1.06
340	Kathmandu	0.66	Guadalajara	1.04
341	Allentown	0.64	Harare	1.04
342	Indore	0.64	Dakar	1.02
343	Ufa	0.63	Kigali	1.01
344	Ouagadougou	0.63	Manaus	0.99
345	Bamako	0.62	Venice	0.99
346	Donetsk	0.59	Accra	0.98
347	Guatemala City	0.58	Hohhot	0.98
348	Krasnoyarsk	0.57	Anchorage	0.97
349	Algiers	0.57	Greensboro	0.96
350	Lahore	0.55	Faisalabad	0.93
351	Xining	0.54	Skopje	0.92
352	Blantyre	0.53	Kinshasa	0.91
353	Amman	0.53	Lagos	0.91
354	Lusaka	0.53	Kathmandu	0.90
355	Accra	0.53	Monterrey	0.89
356	Chattanooga	0.51	Macao	0.88
357	Casablanca	0.51	Cotonou	0.88
358	Jeddah	0.51	Kumasi	0.88
359	Vitoria	0.50	Abuja	0.86
360	Allahabad	0.50	Duisburg	0.85
361	Cotonou	0.49	Panama City	0.84
362	Gaborone	0.49	Maputo	0.82
363	Antananarivo	0.48	Keelung	0.79
364	Saratov	0.48	Sakai	0.78
365	Podgorica	0.47	Ludhiana	0.78
366	Takamatsu	0.47	Rawalpindi	0.77
367	Bandung	0.46	Coimbatore	0.77
368	Panama City	0.46	Blantyre	0.76
369	Bursa	0.45	Ouagadougou	0.76
370	Lagos	0.42	Kuwait City	0.76
371	Skopje	0.41	Akita	0.75
372	Maracaibo	0.41	Algiers	0.75
373	Madurai	0.40	Xining	0.75
374	Valencia (Venezuela)	0.40	Queretaro	0.74

375	Kuwait City	0.39	Manama	0.74
376	Windhoek	0.39	Guatemala City	0.70
377	Baku	0.38	Khartoum	0.68
378	Hohhot	0.38	Phnom Penh	0.68
379	Mashhad	0.37	Ulaanbaatar	0.67
380	Lilongwe	0.37	La Paz	0.67
381	Ulaanbaatar	0.36	Bamako	0.65
382	Khartoum	0.35	Allentown	0.65
383	San Salvador	0.35	Lilongwe	0.63
384	Coimbatore	0.35	Kanpur	0.61
385	Kingston (Jamaica)	0.35	Gaborone	0.60
386	Nagpur	0.34	Antananarivo	0.59
387	Phnom Penh	0.34	Windhoek	0.58
388	Sarajevo	0.33	San Salvador	0.57
389	Amritsar	0.33	Peoria	0.57
390	Kumasi	0.32	Yinchuan	0.56
391	Doha	0.32	Peshawar	0.55
392	Tegucigalpa	0.31	Sarajevo	0.53
393	Asuncion	0.30	Ufa	0.52
394	Tirana	0.30	Vladivostok	0.49
395	Maputo	0.29	Suva	0.48
396	Chihuahua	0.28	Multan	0.48
397	Guayaquil	0.28	Kingston (Jamaica)	0.48
398	Santo Domingo	0.27	Baghdad	0.47
399	Samara	0.27	Tashkent	0.47
400	Bhopal	0.26	Barranquilla	0.46
401	Ludhiana	0.25	Asuncion	0.43
402	Haikou	0.24	Kabul	0.42
403	Niamey	0.24	Chattanooga	0.41
404	Damascus	0.24	Valencia (Venezuela)	0.41
405	Tijuana	0.24	Allahabad	0.41
406	Toluca	0.23	Leverkusen	0.40
407	Gwangju	0.22	Madurai	0.38
408	Douala	0.22	Tripoli	0.38
409	Dubai	0.21	Krasnoyarsk	0.38
410	Perm	0.21	Bandung	0.37
411	Kinshasa	0.21	Podgorica	0.37
412	Faisalabad	0.20	Guayaquil	0.37
413	Brazzaville	0.20	Takamatsu	0.36
414	Suva	0.20	Niamey	0.36
415	Abu Dhabi	0.20	Bishkek	0.36
416	Managua	0.20	Des Moines	0.35

417	Surabaya	0.19	Tirana	0.35
418	Santa Cruz	0.19	Lome	0.35
419	Bangui	0.18	Brazzaville	0.35
420	Lome	0.18	Damascus	0.34
421	Lhasa	0.18	Monrovia	0.34
422	Omsk	0.18	Santo Domingo	0.34
423	Yangon	0.18	Santa Cruz	0.32
424	Manama	0.17	Saratov	0.32
425	Bissau	0.17	Tegucigalpa	0.30
426	Yinchuan	0.17	Dammam	0.30
427	Peshawar	0.16	Cebu	0.29
428	Macao	0.16	Incheon	0.28
429	Meerut	0.16	Douala	0.26
430	Bishkek	0.15	Samara	0.24
431	Danbury	0.15	Victoria	0.24
432	Mombasa	0.15	Donetsk	0.24
433	Libreville	0.15	Yangon	0.24
434	Multan	0.15	Port Harcourt	0.23
435	Tripoli	0.15	Chelyabinsk	0.23
436	Agra	0.15	Freetown	0.23
437	Rawalpindi	0.15	Maracaibo	0.23
438	Chelyabinsk	0.14	Ranchi	0.23
439	Oran	0.14	Sanaa	0.23
440	Conakry	0.14	Port Moresby	0.22
441	Volgograd	0.14	Toluca	0.22
442	Cebu	0.13	Lhasa	0.22
443	Port Au Prince	0.13	Surat	0.21
444	Ranchi	0.13	Conakry	0.21
445	Dammam	0.11	Port Au Prince	0.21
446	Gaza	0.11	Patna	0.21
447	Port Harcourt	0.11	Oran	0.20
448	Chittagong	0.11	Chihuahua	0.20
449	Patna	0.10	Managua	0.20
450	Rajkot	0.10	Libreville	0.19
451	Kigali	0.09	Surabaya	0.19
452	Nouakchott	0.09	Tijuana	0.18
453	Dushanbe	0.09	Kano	0.18
454	NDjamena	0.09	Bissau	0.17
455	Semarang	0.09	Bandar Seri Begawan	0.16
456	Hyderabad (Pakistan)	0.09	Perm	0.16
457	Barranquilla	0.09	Hyderabad (Pakistan)	0.15
458	Sanaa	0.08	Volgograd	0.15

459	Wolfsburg	0.08	Mombasa	0.14
460	Luanda	0.08	Amritsar	0.14
461	Baghdad	0.08	Chittagong	0.13
462	Rayong	0.08	Bangui	0.13
463	Victoria	0.07	Omsk	0.12
464	Abuja	0.07	Danbury	0.12
465	Battle Creek	0.07	Meerut	0.11
466	Malacca	0.07	Wolfsburg	0.11
467	Port Moresby	0.06	Agra	0.10
468	Port of Spain	0.06	Luanda	0.10
469	Bulawayo	0.06	Paramaribo	0.09
470	Naha	0.06	Bulawayo	0.08
471	Monrovia	0.05	NDjamena	0.08
472	Kano	0.05	Malacca	0.08
473	Porto Novo	0.05	Gaza	0.07
474	Medan	0.04	Dushanbe	0.07
475	Surat	0.04	Ciudad Juarez	0.07
476	Kabul	0.04	Medan	0.07
477	Nassau	0.03	Semarang	0.07
478	Paramaribo	0.03	Naha	0.06
479	Daejeon	0.03	Thimphu	0.06
480	Maseru	0.03	Davao	0.06
481	Thimphu	0.03	Nouakchott	0.06
482	Freetown	0.03	Nassau	0.05
483	Pyongyang	0.02	Johor Bahru	0.05
484	Bandar Seri Begawan	0.02	Pyongyang	0.05
485	Davao	0.02	Rajkot	0.04
486	Ciudad Juarez	0.02	Vijayawada	0.04
487	Vijayawada	0.02	Maseru	0.04
488	Daegu	0.01	Battle Creek	0.04
489	Incheon	0.01	Port of Spain	0.04
490	Asansol	0.01	Penang	0.03
491	Keelung	0.01	Porto Novo	0.03
492	Bhilai	0.00	Rayong	0.03
493	Penang	0.00	Bhilai	0.02
494	Johor Bahru	0.00	Asansol	0.01
495	Pombal	0.00	Pombal	0.01
496	Rayong	0.00	Rayong	0.00
497	Pombal	0.00	Pombal	0.00
498	Johor Bahru	0.00	Penang	0.00
499	Penang	0.00	Asansol	0.00
500	Asansol	0.00	Porto-Novo	0.00

Source: author

Appendix III KNC ranking for 217 Chinese cities

Rank	2002-2006		2012-2016	
	City	KNC	City	KNC
1	Beijing	100.00	Beijing	100.00
2	Shanghai	44.82	Shanghai	46.95
3	Taipei	31.57	Nanjing	34.98
4	Nanjing	28.08	Guangzhou	32.24
5	Hong Kong	22.44	Taipei	26.38
6	Wuhan	22.26	Wuhan	24.73
7	Guangzhou	17.93	Hangzhou	21.39
8	Hangzhou	17.76	Chengdu	20.00
9	Hsinchu	15.68	Xian	18.18
10	Tianjin	15.38	Tianjin	16.47
11	Kaohsiung	15.24	Hefei	15.91
12	Hefei	15.14	Hong Kong	14.94
13	Chengdu	15.04	Jinan	14.64
14	Shenyang	14.87	Changsha	14.50
15	Taichung	13.95	Changchun	12.64
16	Xian	13.75	Shenzhen	12.33
17	Tainan	13.59	Shenyang	11.52
18	Changchun	12.18	Chongqing	11.19
19	Changsha	11.73	Harbin	10.95
20	Lanzhou	11.42	Taichung	10.95
21	Jinan	11.19	Qingdao	10.48
22	Dalian	9.09	Lanzhou	10.07
23	Harbin	7.48	Suzhou	9.92
24	Kunming	6.59	Zhengzhou	9.17
25	Qingdao	6.56	Dalian	9.14
26	Taoyuan	5.37	Kaohsiung	9.10
27	Chongqing	5.31	Hsinchu	8.87
28	Zhengzhou	4.55	Tainan	7.90
29	Xinxiang	4.25	Kunming	7.46
30	Taiyuan	3.92	New Taipei	6.84
31	Suzhou	3.82	Taiyuan	6.48
32	Shenzhen	3.45	Nanchang	6.25
33	Xiamen	3.37	Xiamen	6.20
34	Nanning	3.34	Nanning	5.00
35	Shijiazhuang	3.32	Taoyuan	4.72
36	Nanchang	2.99	Fuzhou(FJ)	4.35
37	Fuzhou(FJ)	2.80	Shijiazhuang	4.33
38	Ningbo	2.51	Ningbo	4.16

39	Guiyang	2.31	Urumqi	3.99
40	Mianyang	2.08	Wenzhou	3.46
41	Baoding	1.78	Xinxiang	3.43
42	Urumqi	1.70	Wuxi	3.39
43	Yantai	1.61	Guiyang	3.37
44	Yangzhou	1.58	Zhenjiang	3.22
45	Xiangtan	1.49	Luoyang	3.01
46	Wenzhou	1.45	Yantai	2.92
47	Xining	1.42	Mianyang	2.59
48	Wuxi	1.41	Changzhou	2.54
49	Kaifeng	1.29	Yangzhou	2.11
50	Luoyang	1.27	Haikou	2.06
51	Shantou	1.24	Hohhot	2.01
52	Wuhu	1.18	Hengyang	1.99
53	Zhenjiang	1.12	Baoding	1.89
54	Jinhua	1.11	Keelung	1.81
55	Qinhuangdao	1.09	Nantong	1.77
56	Liaocheng	1.03	Xiangtan	1.62
57	Hohhot	0.93	Xining	1.54
58	Anshan	0.75	Shantou	1.53
59	Zibo	0.72	Qinhuangdao	1.47
60	Changzhou	0.71	Macao	1.44
61	Dongying	0.71	Weihai	1.38
62	Haikou	0.70	Tangshan	1.36
63	Linfen	0.69	Dongguan	1.34
64	Nantong	0.66	Daqing	1.30
65	Zhuzhou	0.66	Liaocheng	1.29
66	Jilin	0.63	Kaifeng	1.26
67	Hengyang	0.58	Jinhua	1.22
68	Daqing	0.57	Yinchuan	1.19
69	Nanchong	0.55	Wuhu	1.12
70	Quanzhou	0.55	Yancheng	1.00
71	Jinzhou	0.54	Foshan	0.93
72	Huzhou	0.52	Zhuhai	0.92
73	Huangshi	0.49	Weifang	0.90
74	Yinchuan	0.49	Huzhou	0.88
75	Yancheng	0.46	Anshan	0.87
76	Shaoxing	0.45	Jiaozuo	0.86
77	Yichang	0.44	Zibo	0.86
78	Tangshan	0.42	Jinzhou	0.84
79	Xianyang	0.39	Jiaxing	0.82
80	Yueyang	0.38	Siping	0.75

81	Baotou	0.38	Shihezi	0.74
82	Fushun	0.37	Yichang	0.74
83	Langfang	0.36	Shaoxing	0.73
84	Macao	0.35	Baotou	0.72
85	Jiaozuo	0.35	Jilin	0.70
86	Lhasa	0.34	Nanchong	0.68
87	Foshan	0.34	Yaan	0.66
88	Jiaxing	0.34	Maanshan	0.63
89	Maanshan	0.33	Binzhou	0.56
90	Yibin	0.33	Langfang	0.56
91	Weihai	0.33	Zhongshan	0.55
92	Yanji	0.32	Luzhou	0.54
93	Fuzhou(JX)	0.32	Qiqihar	0.52
94	Zhangzhou	0.30	Dongying	0.51
95	Siping	0.30	Quanzhou	0.50
96	Qiqihar	0.26	Zunyi	0.50
97	Weifang	0.23	Zhoushan	0.49
98	Xiaogan	0.22	Zhuzhou	0.48
99	Anqing	0.21	Taizhou(ZJ)	0.46
100	Changde	0.21	Zigong	0.44
101	Tianshui	0.21	Huangshi	0.42
102	Jiangmen	0.20	Zhangzhou	0.41
103	Yuxi	0.20	Xianyang	0.39
104	Yanan	0.20	Fushun	0.37
105	Baoji	0.18	Lhasa	0.36
106	Binzhou	0.18	Baoji	0.36
107	Jingdezhen	0.17	Yueyang	0.33
108	Dezhou	0.16	Pingdingshan	0.33
109	Zhuhai	0.16	Jiangmen	0.33
110	Dongguan	0.16	Huizhou	0.33
111	Yaan	0.16	Rizhao	0.33
112	Zhaoqing	0.15	Yanji	0.32
113	Yiyang	0.15	Taizhou(JS)	0.30
114	Xianning	0.14	Xiangyang	0.29
115	Zigong	0.14	Jiujiang	0.28
116	Xinzhou	0.14	Changzhi	0.28
117	Zhoushan	0.13	Anqing	0.28
118	Loudi	0.13	Panjin	0.28
119	Shihezi	0.12	Jingzhou	0.28
120	Zhongshan	0.12	Yibin	0.27
121	Jiujiang	0.12	Changde	0.27
122	Chuzhou	0.11	Jingdezhen	0.26

123	Yichun	0.11	Linfen	0.26
124	Pingdingshan	0.10	Cangzhou	0.25
125	Qujing	0.10	Dezhou	0.25
126	Taizhou(ZJ)	0.10	Zhangjiakou	0.25
127	Chengde	0.10	Xianning	0.24
128	Zunyi	0.09	Xuchang	0.20
129	Zhangjiakou	0.09	Chengde	0.20
130	Luzhou	0.08	Deyang	0.19
131	Xuchang	0.08	Yuxi	0.19
132	Panjin	0.08	Yiyang	0.19
133	Benxi	0.08	Xiaogan	0.19
134	Chaozhou	0.07	Zhaoqing	0.18
135	Chuxiong	0.07	Chuzhou	0.18
136	Huizhou	0.06	Leshan	0.18
137	Dandong	0.06	Yanan	0.17
138	Shangrao	0.06	Tianshui	0.16
139	Neijiang	0.06	Qujing	0.16
140	Leshan	0.05	Huanggang	0.16
141	Chizhou	0.05	Chaozhou	0.15
142	Taian	0.05	Putian	0.14
143	Rizhao	0.05	Neijiang	0.14
144	Pingxiang	0.05	Ningde	0.13
145	Changzhi	0.05	Yulin(GX)	0.13
146	Jingmen	0.05	Weinan	0.13
147	Weinan	0.04	Yichun	0.13
148	Huanggang	0.04	Karamay	0.13
149	Karamay	0.04	Fuzhou(JX)	0.13
150	Liaoyang	0.04	Laiwu	0.12
151	Changji	0.04	Benxi	0.11
152	Taizhou(JS)	0.03	Loudi	0.11
153	Cangzhou	0.03	Yulin(SX)	0.11
154	Yulin(GX)	0.03	Dandong	0.11
155	Putian	0.03	Jingmen	0.10
156	Huludao	0.03	Dazhou	0.10
157	Qingyang	0.03	Tongling	0.10
158	Yulin(SX)	0.02	Chizhou	0.10
159	Dazhou	0.02	Changji	0.09
160	Suihua	0.02	Liaoyang	0.09
161	Tongling	0.02	Shangrao	0.09
162	Kaili	0.02	Kaili	0.08
163	Keelung	0.01	Beihai	0.07
164	Luohe	0.01	Luohe	0.07

165	Deyang	0.01	Huludao	0.07
166	Laiwu	0.01	Shangluo	0.07
167	Songyuan	0.01	Pingxiang	0.07
168	Anji	0.01	Qinzhou	0.07
169	Shizuishan	0.01	Bijie	0.07
170	Qianjiang	0.01	Jinzhong	0.06
171	Kuitun	0.01	Chuxiong	0.06
172	Jingzhou	0.01	Songyuan	0.06
173	Ningde	0.01	Xinzhou	0.06
174	Beihai	0.01	Anshun	0.06
175	Anshun	0.01	Yingtan	0.06
176	Xinyu	0.01	Xinyu	0.06
177	Baiyin	0.01	Meishan	0.05
178	Ziyang	0.01	Xuancheng	0.05
179	Fenyang	0.01	Suihua	0.04
180	Yangquan	0.01	Yingkou	0.04
181	Wusu	0.01	Qingyang	0.04
182	Guangan	0.01	Duyun	0.04
183	Xiantao	0.01	Fenyang	0.03
184	Xiangyang	0.00	Yangquan	0.03
185	Bijie	0.00	Suining	0.03
186	Jinzhong	0.00	Ezhou	0.02
187	Xuancheng	0.00	Baiyin	0.02
188	Yingkou	0.00	Chongzuo	0.02
189	Ezhou	0.00	Jiyuan	0.02
190	Erdos	0.00	Dingxi	0.02
191	Pingliang	0.00	Tongchuan	0.02
192	Liaoyuan	0.00	Wuhai	0.02
193	New Taipei	0.00	Anji	0.02
194	Shangluo	0.00	Zhongwei	0.02
195	Qinzhou	0.00	Tieling	0.02
196	Yingtan	0.00	Wusu	0.01
197	Meishan	0.00	Erdos	0.01
198	Duyun	0.00	Tianmen	0.01
199	Suining	0.00	Shizuishan	0.01
200	Chongzuo	0.00	Pingliang	0.01
201	Jiyuan	0.00	Fangchenggang	0.01
202	Dingxi	0.00	Ziyang	0.01
203	Tongchuan	0.00	Guangan	0.01
204	Wuhai	0.00	Wujiaqu	0.01
205	Zhongwei	0.00	Qianjiang	0.01
206	Tieling	0.00	Shanwei	0.01

207	Tianmen	0.00	Xiantao	0.01
208	Fangchenggang	0.00	Liaoyuan	0.01
209	Wujiaqu	0.00	Kuitun	0.01
210	Shanwei	0.00	Wuzhong	0.01
211	Wuzhong	0.00	Ulanqab	0.00
212	Ulanqab	0.00	Taian	0.00
213	Linxia	0.00	Linxia	0.00
214	Fukang	0.00	Fukang	0.00
215	Xiaoyi	0.00	Xiaoyi	0.00
216	Bayan Nur	0.00	Bayan Nur	0.00
217	Haidong	0.00	Haidong	0.00

Source: author

Appendix IV WoS subjects and OECD category scheme

OECD category 1	OECD category 2	WoS subjects
Natural sciences	Mathematics	Logic
Natural sciences	Mathematics	Mathematics applied
Natural sciences	Mathematics	Mathematics interdisciplinary applications
Natural sciences	Mathematics	Mathematics
Natural sciences	Mathematics	Physics mathematical
Natural sciences	Mathematics	Statistics probability
Natural sciences	Computer and information sciences	Computer science artificial intelligence
Natural sciences	Computer and information sciences	Computer science cybernetics
Natural sciences	Computer and information sciences	Computer science information systems
Natural sciences	Computer and information sciences	Computer science interdisciplinary applications
Natural sciences	Computer and information sciences	Computer science software engineering
Natural sciences	Computer and information sciences	Computer science theory methods
Natural sciences	Physical sciences and astronomy	Acoustics
Natural sciences	Physical sciences and astronomy	Astronomy astrophysics
Natural sciences	Physical sciences and astronomy	Optics
Natural sciences	Physical sciences and astronomy	Physics applied
Natural sciences	Physical sciences and astronomy	Physics fluids plasmas
Natural sciences	Physical sciences and astronomy	Physics atomic molecular chemical
Natural sciences	Physical sciences and astronomy	Physics multidisciplinary
Natural sciences	Physical sciences and astronomy	Physics condensed matter
Natural sciences	Physical sciences and astronomy	Physics nuclear
Natural sciences	Physical sciences and astronomy	Physics particles fields
Natural sciences	Chemical sciences	Chemistry applied
Natural sciences	Chemical sciences	Chemistry multidisciplinary
Natural sciences	Chemical sciences	Chemistry analytical
Natural sciences	Chemical sciences	Chemistry inorganic nuclear
Natural sciences	Chemical sciences	Chemistry organic
Natural sciences	Chemical sciences	Chemistry physical
Natural sciences	Chemical sciences	Crystallography
Natural sciences	Chemical sciences	Electrochemistry
Natural sciences	Chemical sciences	Polymer science
Natural sciences	Earth and related environmental sciences	Geochemistry geophysics

Natural sciences	Earth and related environmental sciences	Environmental sciences
Natural sciences	Earth and related environmental sciences	Geography physical
Natural sciences	Earth and related environmental sciences	Geology
Natural sciences	Earth and related environmental sciences	Geosciences multidisciplinary
Natural sciences	Earth and related environmental sciences	Meteorology atmospheric sciences
Natural sciences	Earth and related environmental sciences	Mineralogy
Natural sciences	Earth and related environmental sciences	Oceanography
Natural sciences	Earth and related environmental sciences	Paleontology
Natural sciences	Earth and related environmental sciences	Water resources
Natural sciences	Biological sciences	Biodiversity conservation
Natural sciences	Biological sciences	Biochemical research methods
Natural sciences	Biological sciences	Biochemistry molecular biology
Natural sciences	Biological sciences	Biology
Natural sciences	Biological sciences	Biophysics
Natural sciences	Biological sciences	Plant sciences
Natural sciences	Biological sciences	Cell biology
Natural sciences	Biological sciences	Ecology
Natural sciences	Biological sciences	Evolutionary biology
Natural sciences	Biological sciences	Developmental biology
Natural sciences	Biological sciences	Entomology
Natural sciences	Biological sciences	Genetics heredity
Natural sciences	Biological sciences	Mathematical computational biology
Natural sciences	Biological sciences	Limnology
Natural sciences	Biological sciences	Marine freshwater biology
Natural sciences	Biological sciences	Microbiology
Natural sciences	Biological sciences	Mycology
Natural sciences	Biological sciences	Ornithology
Natural sciences	Biological sciences	Reproductive biology
Natural sciences	Biological sciences	Virology
Natural sciences	Biological sciences	Zoology
Natural sciences	Other natural sciences	Multidisciplinary sciences

Engineering and technology	Civil engineering	Construction building technology
Engineering and technology	Civil engineering	Engineering civil
Engineering and technology	Civil engineering	Transportation science technology
Engineering and technology	Electrical eng, electronic eng	Automation control systems
Engineering and technology	Electrical eng, electronic eng	Computer science hardware architecture
Engineering and technology	Electrical eng, electronic eng	Engineering electrical electronic
Engineering and technology	Electrical eng, electronic eng	Robotics
Engineering and technology	Electrical eng, electronic eng	Telecommunications
Engineering and technology	Mechanical engineering	Engineering aerospace
Engineering and technology	Mechanical engineering	Thermodynamics
Engineering and technology	Mechanical engineering	Engineering mechanical
Engineering and technology	Mechanical engineering	Mechanics
Engineering and technology	Mechanical engineering	Nuclear science technology
Engineering and technology	Chemical engineering	Engineering chemical
Engineering and technology	Materials engineering	Materials science paper wood
Engineering and technology	Materials engineering	Materials science ceramics
Engineering and technology	Materials engineering	Materials science multidisciplinary
Engineering and technology	Materials engineering	Metallurgy metallurgical engineering
Engineering and technology	Materials engineering	Materials science characterization testing
Engineering and technology	Materials engineering	Materials science coatings films
Engineering and technology	Materials engineering	Materials science composites

Engineering and technology	Materials engineering	Materials science textiles
Engineering and technology	Medical engineering	Engineering biomedical
Engineering and technology	Medical engineering	Medical laboratory technology
Engineering and technology	Medical engineering	Cell tissue engineering
Engineering and technology	Environmental engineering	Energy fuels
Engineering and technology	Environmental engineering	Engineering environmental
Engineering and technology	Environmental engineering	Engineering marine
Engineering and technology	Environmental engineering	Engineering ocean
Engineering and technology	Environmental engineering	Engineering petroleum
Engineering and technology	Environmental engineering	Engineering geological
Engineering and technology	Environmental engineering	Remote sensing
Engineering and technology	Environmental engineering	Mining mineral processing
Engineering and technology	Environmental biotechnology	Biotechnology applied microbiology
Engineering and technology	Industrial biotechnology	Materials science biomaterials
Engineering and technology	Nano-technology	Nanoscience nanotechnology
Engineering and technology	Other engineering and technologies	Engineering multidisciplinary
Engineering and technology	Other engineering and technologies	Engineering industrial
Engineering and technology	Other engineering and technologies	Engineering manufacturing
Agricultural sciences	Other agricultural science	Food science technology
Engineering and technology	Other engineering and technologies	Instruments instrumentation
Engineering and technology	Other engineering and technologies	Microscopy

Engineering and technology	Other engineering and technologies	Imaging science photographic technology
Engineering and technology	Other engineering and technologies	Spectroscopy
Medical and health sciences	Clinical medicine	Audiology speech language pathology
Medical and health sciences	Basic medical research	Anatomy morphology
Medical and health sciences	Basic medical research	Chemistry medicinal
Medical and health sciences	Basic medical research	Psychology clinical
Medical and health sciences	Basic medical research	Immunology
Medical and health sciences	Basic medical research	Medicine research experimental
Medical and health sciences	Basic medical research	Neurosciences
Medical and health sciences	Basic medical research	Pathology
Medical and health sciences	Basic medical research	Pharmacology pharmacy
Medical and health sciences	Basic medical research	Physiology
Medical and health sciences	Basic medical research	Toxicology
Medical and health sciences	Clinical medicine	Allergy
Medical and health sciences	Clinical medicine	Andrology
Medical and health sciences	Clinical medicine	Anesthesiology
Medical and health sciences	Clinical medicine	Oncology
Medical and health sciences	Clinical medicine	Cardiac cardiovascular systems
Medical and health sciences	Clinical medicine	Critical care medicine
Medical and health sciences	Clinical medicine	Emergency medicine
Medical and health sciences	Clinical medicine	Dentistry oral surgery medicine

Medical and health sciences	Clinical medicine	Dermatology
Medical and health sciences	Clinical medicine	Endocrinology metabolism
Medical and health sciences	Clinical medicine	Gastroenterology hepatology
Medical and health sciences	Clinical medicine	Geriatrics gerontology
Medical and health sciences	Clinical medicine	Gerontology
Medical and health sciences	Clinical medicine	Hematology
Medical and health sciences	Clinical medicine	Integrative complementary medicine
Medical and health sciences	Clinical medicine	Medicine general internal
Medical and health sciences	Clinical medicine	Clinical neurology
Medical and health sciences	Clinical medicine	Neuroimaging
Medical and health sciences	Clinical medicine	Obstetrics gynecology
Medical and health sciences	Clinical medicine	Ophthalmology
Medical and health sciences	Clinical medicine	Orthopedics
Medical and health sciences	Clinical medicine	Otorhinolaryngology
Medical and health sciences	Clinical medicine	Pediatrics
Medical and health sciences	Clinical medicine	Psychiatry
Medical and health sciences	Clinical medicine	Radiology nuclear medicine medical imaging
Medical and health sciences	Clinical medicine	Respiratory system
Medical and health sciences	Clinical medicine	Rheumatology
Medical and health sciences	Clinical medicine	Surgery
Medical and health sciences	Clinical medicine	Transplantation

Medical and health sciences	Clinical medicine	Urology nephrology
Medical and health sciences	Clinical medicine	Peripheral vascular disease
Medical and health sciences	Health sciences	Substance abuse
Medical and health sciences	Health sciences	Health care sciences services
Medical and health sciences	Health sciences	Health policy services
Medical and health sciences	Health sciences	Public environmental occupational health
Medical and health sciences	Health sciences	Infectious diseases
Medical and health sciences	Health sciences	Medical ethics
Medical and health sciences	Health sciences	Medicine legal
Medical and health sciences	Health sciences	Medical informatics
Medical and health sciences	Health sciences	Nursing
Medical and health sciences	Health sciences	Nutrition dietetics
Medical and health sciences	Health sciences	Parasitology
Medical and health sciences	Health sciences	Psychology psychoanalysis
Medical and health sciences	Health sciences	Rehabilitation
Medical and health sciences	Health sciences	Social sciences biomedical
Medical and health sciences	Health sciences	Sport sciences
Medical and health sciences	Health sciences	Tropical medicine
Medical and health sciences	Health sciences	Primary health care
Agricultural sciences	Agriculture, forestry, fisheries	Agriculture multidisciplinary
Agricultural sciences	Agriculture, forestry, fisheries	Agronomy
Agricultural sciences	Agriculture, forestry, fisheries	Fisheries
Agricultural sciences	Agriculture, forestry, fisheries	Forestry

Agricultural sciences	Agriculture, forestry, fisheries	Horticulture
Agricultural sciences	Agriculture, forestry, fisheries	Soil science
Agricultural sciences	Animal and dairy science	Agriculture dairy animal science
Agricultural sciences	Veterinary science	Veterinary sciences
Agricultural sciences	Other agricultural science	Agricultural engineering
Agricultural sciences	Other agricultural science	Agricultural economics policy
Social sciences	Psychology	Psychology biological
Social sciences	Psychology	Behavioral sciences
Social sciences	Psychology	Psychology educational
Social sciences	Psychology	Ergonomics
Social sciences	Psychology	Psychology developmental
Social sciences	Psychology	Psychology applied
Social sciences	Psychology	Psychology
Social sciences	Psychology	Psychology multidisciplinary
Social sciences	Psychology	Psychology mathematical
Social sciences	Psychology	Psychology experimental
Social sciences	Psychology	Psychology social
Social sciences	Economics and business	Business
Social sciences	Economics and business	Business finance
Social sciences	Economics and business	Economics
Social sciences	Economics and business	Industrial relations labor
Social sciences	Economics and business	Management
Social sciences	Economics and business	Operations research management science
Social sciences	Educational sciences	Education educational research
Social sciences	Educational sciences	Education scientific disciplines
Social sciences	Educational sciences	Education special
Social sciences	Sociology	Anthropology
Social sciences	Sociology	Demography
Social sciences	Sociology	Ethnic studies
Social sciences	Sociology	Family studies
Social sciences	Sociology	Social sciences mathematical methods
Social sciences	Sociology	Social issues
Social sciences	Sociology	Social work
Social sciences	Sociology	Sociology
Social sciences	Sociology	Women s studies
Social sciences	Law	Criminology penology
Social sciences	Law	Law
Social sciences	Political science	International relations
Social sciences	Political science	Political science
Social sciences	Political science	Public administration

Social sciences	Social and economic geography	Area studies
Social sciences	Social and economic geography	Environmental studies
Social sciences	Social and economic geography	Geography
Social sciences	Social and economic geography	Planning development
Social sciences	Social and economic geography	Transportation
Social sciences	Social and economic geography	Urban studies
Social sciences	Media and communication	Communication
Social sciences	Media and communication	Information science library science
Social sciences	Other social sciences	Hospitality leisure sport tourism
Social sciences	Other social sciences	Asian studies
Social sciences	Other social sciences	Cultural studies
Social sciences	Other social sciences	Social sciences interdisciplinary
Humanities	History and archaeology	Archaeology
Humanities	History and archaeology	History
Humanities	History and archaeology	History philosophy of science
Humanities	History and archaeology	History of social sciences
Humanities	History and archaeology	Medieval renaissance studies
Humanities	Languages and literature	Classics
Humanities	Languages and literature	Folklore
Humanities	Languages and literature	Linguistics
Humanities	Languages and literature	Literary theory criticism
Humanities	Languages and literature	Language linguistics
Humanities	Languages and literature	Literary reviews
Humanities	Languages and literature	Literature
Humanities	Languages and literature	Literature african australian canadian
Humanities	Languages and literature	Literature american
Humanities	Languages and literature	Literature british isles
Humanities	Languages and literature	Literature german dutch scandinavian
Humanities	Languages and literature	Literature romance
Humanities	Languages and literature	Literature slavic
Humanities	Languages and literature	Poetry
Humanities	Philosophy, ethics and religion	Ethics
Humanities	Philosophy, ethics and religion	Philosophy
Humanities	Philosophy, ethics and religion	Religion
Humanities	Art	Architecture
Humanities	Art	Art
Humanities	Art	Dance
Humanities	Art	Film radio television
Humanities	Art	Music

Humanities	Art	Theater
Humanities	Other humanities	Humanities multidisciplinary
Social sciences	Social and economic geography	Regional urban planning
Engineering and technology	Other engineering and technologies	Quantum science technology
Engineering and technology	Other engineering and technologies	Green sustainable science technology
Social sciences	Other social sciences	Development studies

Source: author

Appendix V Outline of the semi-structural interview (macro-structural factors)

All contents of this interview will be only used as research purpose. Any references that includes codified projects or personal information will be keep confidential and anonymous. not all the questions must be answered. Please inform the interviewer if you don't want to answer any at any point during the course of the interview.

Part 1: Basic information

- Please tell me the research field you are working on and the position or the role you play in this collaboration program.
- Please talk about your knowledge on the Sino-Belgium collaboration program, like establishment, development, outcomes and problems.

Part 2: About the 'shifting scientific research paradigm'

- Please tell me how you see the approaching era of 'Big science'? What are the differences between the 'Big science' era and the 'Scientific genius' era?
- Do you think scientific research today needs more collaborations than before? Why?
- What are your incentives to collaborate with other scholars?

Part 3: About the 'knowledge resources complementation'

- In your opinion, in the collaboration program, what are the advantages and disadvantages of U-gent geography department, and what are the advantages and disadvantages of the Chinese institution?
- Please talk about how you work with your Chinese counterparts.

Part 4: About the 'collaboration environment support'

- Please talk about the preferential policies that support the collaboration program.
- Please tell me the attitude and perception of each institution towards knowledge collaboration.
- Please tell me the differences of the administrative and institutional structures between the two institutions. And how they influence your collaboration?

Appendix VI Outline of the semi-structural interview (micro-initiative factors)

All contents of this interview will be only used as research purpose. Any references that includes codified projects or personal information will be keep confidential and anonymous. not all the questions must be answered. Please inform the interviewer if you don't want to answer any at any point during the course of the interview.

- Please introduce your major, job and position.
- Please define scientific collaboration.
- Please tell me about your attitude to collaboration.
- Please tell me your current collaboration activities. Where are your partners?
- How you and your partners built the collaboration relations?
- Does geographical distance influence your collaborations? How? Why?
- Please tell me the differences between hospital and medical school in terms of research paradigm and their influence on collaborations?
- Do you think sharing a similar knowledge background is beneficial for collaboration? How? Why?
- Do you think sharing a similar culture is beneficial for collaboration? How? Why?

This thesis reveals the structures and mechanisms of the evolution of China's interurban knowledge collaboration networks (IKCNs). First, by using various spatial analysis and social network analysis techniques, the study comprehensively examines the spatial configurations and topological structures of China's IKCNs at different geographical scales, i.e. a transnational network of 233 countries, a global network of 500 world cities (including 44 Chinese major cities), a national network of 217 Chinese cities and regional networks of 20 Chinese city-regions. The main results show that the evolutions of both spatial and topological structures of different scales of China's IKCNs all present gradual and steady trajectories which comply with the general patterns of "space dependency" and "path dependency" respectively.

Second, through the case studies of the "Sino-Belgium joint laboratory for geo-information" and the "inter-organizational knowledge collaboration network of the medical sciences in the Jiangsu-Zhejiang-Shanghai region", the thesis uncovers the macro and micro mechanisms of the evolution and formation of the IKCNs. Results of the former case show that three "macro-structural factors", i.e. scientific research paradigm, innovation resources and collaborative environment, have significant impacts on the formation of the IKCNs. Results of the latter case suggest that the different types of proximity act as the "micro-initiative factors" that play important roles in shaping the IKCNs.