Urban Innovation and Intercity Patent Collaboration: A Network Analysis Approach Using China's National Innovation System

Abstract

This research investigates the impact of extralocal interactions in intercity coinvention networks on innovation in cities. Adopting a social network lens, we argue that the innovation performance of a city hinges on its centrality in intercity coinvention networks, its ability to fill structural holes in these networks, and its node cohesiveness and transitivity within ego networks. Using a unique longitudinal data set of patents granted from 2001 to 2016 in China, we construct two types of networks—those involving collaborations among universities as well as research institutes (URI) and those involving industry actors only (II)—and identify six major stylized facts in regards to the formation of a complex intercity innovation network within China's national innovation system. A random-effects negative binomial regression model reveals positive effects of the degree centrality and structural holes variables on urban innovation in both URI and II networks, while a fixed-effects model suggests that the effects are only significant for II networks. Our study confirms that city innovation not only is determined by local innovative activities but also is enhanced when cities are deeply embedded in intercity innovative networks.

Keywords: Extralocal Interactions, Intercity Innovation Network, Coinvention, Urban Innovation, Network Embeddedness

1 Introduction

Cities are conducive to innovation processes (Hall, 1998; Glaeser, 2011; Shearmur, 2012) and are important hubs in national innovation systems (Lundvall et al., 2002). As key organizing units in localities, cities bring together firms, talent, and other institutions necessary for innovative activities (Florida et al., 2017). Two dominant theories seek to explain the innovation mechanisms at work in cities. Agglomeration theory posits that the scale and specialization of activities that are clustered and concentrated in the city stimulate innovation. Firms in an agglomeration setting benefit primarily from knowledge spillovers between proximate firms in the same industry in addition to access to a thicker and more specialized labor market and access to more specialized services (Shearmur, 2012). In contrast, diversity theory contends that it is the scope and diversity of activities in the city that drive innovation (Jacobs, 1969; Florida, 2002). Cities provide a diverse ideational milieu, i.e., a variety of economic actors and a dense ethnic, cultural and social fabric, that allows the creative mind to better overcome blocks in the creative process (Niebuhr, 2010; Simonton, 2011). Despite their differences, both theories nonetheless unanimously see innovation as endogenous to cities; in other words, cities draw upon their own resources to innovate (Bathelt, 2011).

Another stream of research challenges this view of cities and endogenous innovation. This literature argues that cities are in fact elements of an interdependent system (Pred, 1977; Simmie, 2003). First, cities are connected to each other by means of information pipelines, privileged communication and transport channels, which enable cities to share in each others dynamics (Bathelt, 2011). Second, cities are connected nodes in a space of flows, so they are not isolated entities but are part of a wider system of interdependent and functionally differentiated entities (Castells, 1996). Third, innovation-enhancing exchanges are fostered not only by interactions between proximate economic agents but also by social proximity (e.g., being part of a social network), organizational proximity (e.g., being part of a strategic alliance), cognitive proximity (e.g., working in the same knowledge domain) and institutional proximity (e.g., working for the same type of organization, such as a university)(Shaw and Gilly, 2000; Boschma, 2005; Carrincazeaux and Coris, 2011). This intertwined web of cities and its development plays a pivotal role in innovation in cities and the evolution of the national innovation system.

This systematic view of cities and innovation suggests that research on cities and innovation needs to go beyond local interactions in stand-alone innovation hubs to investigate extralocal interactions in the interdependent system of cities. More recently, research has started investigating extralocal interactions and their effects on innovation in cities in the context of city-region (Martin and Simmie, 2008; Cao et al., 2018; Clark et al., 2018; Ma and Xue, 2019) and global intercity networks (Simmie, 2003; Guan et al., 2015). Surprisingly, there is a dearth of research investigating extralocal interactions in intercity innovation networks within a single country and the impact of such interactions on city innovation. Guan et al.'s (2015) and Lee's (2018) research works are an exception. Guan et al. (2015) explored the impact of multilevel inventor collaboration networks on innovation using a sample of 41,007 patents in the field of alternative energy from the USPTO database. Their findings confirmed the importance of extralocal interactions in that there are positive effects of city-level network centrality and structural holes on the innovation performance of cities in China. The authors also found that this positive relationship is enhanced by country-level network centrality and the structural holes in China's international networks of collaboration. Lee (2018) examined the relative importance of extralocal interactions (network proximity) as opposed to local interactions (spatial proximity) in biotechnology copatenting in 150 American cities from 1983 to 2013. The results showed that extralocal interactions illustrate the biotechnology copatenting relationships among the U.S. cities better than local interactions. Overall, in the literature on cities and national innovation systems, little attention has been paid to intercity innovation networks, and few empirical studies have been conducted so far. We still know very little about the structure and dynamics of intercity networks and innovation. Without such knowledge, our understanding of cities and innovation in general and national innovation systems in particular is incomplete. Shearmur (2012) thus called for more research on how one locality connects to others to form city networks that facilitate innovation.

This research responds to this research gap and investigates extralocal interactions as manifested in intercity networks of coinvention and the impact of such interactions on innovation in cities. We pose two research questions: what are the patterns of intercity innovation networks and their evolving trajectories in China? How do extralocal interactions in the form of intercity innovation networks affect innovation in cities? Using a unique longitudinal data set on intercity copatenting, we identify six characteristics of interorganizational and intercity networks of coinvention in China. Adopting a social network lens, we particularly focus on the impact of structural embeddedness displayed in intercity coinvention networks on innovation in cities. We argue that the innovation performance of a city hinges on its centrality in intercity coinvention networks, its ability to fill structural holes in the networks, and its node cohesiveness and transitivity within ego networks. China is an intriguing case for the study of cities and the national innovation system. When China started to reform and open up to the outside world in the late 1970s, innovation in its cities was significantly underdeveloped; the countrys innovation system was rudimentary and fragmented. Forty years later, China had transformed itself from a backwater of global innovation into the world's hub of science and innovation (Ding and Li, 2015). Cities such as Beijing, Shanghai, and Shenzhen have emerged as truly innovative national hubs. Other cities across China have also gradually integrated into the national system of innovation. In this paper, we use China as a research context to test and confirm our arguments.

By investigating extralocal interactions and their impact on innovation in cities, our study extends past research on extralocal interactions, which primarily focused on city-regions, and is one of the first to test properties of structural embeddedness to explain the effect of intercity networks of coinvention on innovation performance in cities. Our research also contributes to the literature on cities and innovation by delineating the effects of network properties of different types of interorganizational collaboration on innovation in cities. Finally, our work offers a better understanding of the distinct features of intercity networks of coinvention in China.

The remainder of the article is organized as follows: Section 2 lays out the theoretical framework and proposes testable hypotheses. Section 3 describes the data, the construction of the networks, and some stylized facts about network evolution in cities. Section 4 details the empirical method and construction of variables. Section 5 discusses the results. Section 6 concludes and discusses the theoretical implications.

2 Theoretical Background and Hypothesis Development

Social network theory

In this research, social network theory (SNT) underpins our conceptualization of the impact of the network structure in extralocal interactions on innovation in cities. SNT is concerned with the attributes and consequences of social relations and social structure (Coleman, 1988). A social network consists of a set of social actors and a set of relational ties connecting pairs of these actors. SNT postulates that the relational ties among interdependent social actors have important consequences for each social actor as well as for the larger social groupings that they comprise (Knoke and Kuklinski, 1982).

An important feature of social networks is the embeddedness of individual and collective actors in social relations and social structures, which generates trust and discourages malfeasance (Granovetter, 1985). Embeddedness can be defined as economic behavior that is closely integrated within networks of social relations (Granovetter, 1985). Embedded relationships are advantageous because they can generate social capital and a greater level of trust between embedded peers in webs of social relations (Uzzi, 1996), enable the development of cooperative norms that facilitate greater cooperation (Coleman, 1988), and create opportunities for finer-grained information flows between peers (Uzzi, 1996). Granovetter (1992) referred to all this as relational embeddedness and argued that the effect of relational embeddedness depends on the quality of dyadic relations between actors.

Equally important is the network structure of relationships between a number of actors. Granovetter (1985) described this as structural embeddedness. Network structure manifests itself in density, centrality, prestige, mutuality, and role at different levels: individual, organizational and territorial (Uzzi, 1996). Accordingly, structural embeddedness indicates that social actors who are situated within different network structures face different sets of resources and constraints (Granovetter, 1985). Evidence confirms that the network structure of social relationships impacts innovation (e.g., Lyu et al., 2019; Schillebeeckx et al., 2020). Therefore, from the innovation perspective, SNT predicts that a city will become more innovative if it displays greater strengths of social relations and a better network structure of social relationships. In this research, we primarily focus on structural embeddedness in intercity coinvention networks and its impact on innovation in cities. We nonetheless acknowledge that while structural embeddedness indicates the extent to which social actors benefit from their network structures, underneath it is the web of personal relations, or relational embeddedness, that binds social actors together through the development of social capital and trust.

In the system of innovation, innovators are ultimately embedded in localized economic systems in which the scale and specialization of activities, as emphasized in agglomeration theory, or the scope and diversity of activities, as referred to in diversity theory, stimulate innovation. The local embeddedness of actors also leads to institutional thickness, namely, the existence of local cultures and local institutional fabrics (Amin and Thrift, 1992). As a result, structural embeddedness may favor local interactions. In other words, actors within the same bounded geographical space benefit from trust-enabled, costless knowledge externalities, and thus information flows and knowledge diffusion through social networks require colocation of actors (Breschi and Lissoni, 2001). However, as argued by Anthony Giddens (1990; 1992), there are disembedding forces at work. Disembeddedness is described as a state in which social relations are detached from their localized context of interaction (Giddens, 1990). While disembedding does not mean that personal relations have lost all their importance in local embeddedness, it suggests that personal trust can be delocalized (Hess, 2004). Disembedding also results from the fact that knowledge flows between colocated actors in one locality might quickly become redundant if not complemented by flows of new external knowledge (Boschma, 2005). Evidence from transnational ethnic networks (e.g., Saxenian, 1999; Hsu and Saxenian, 2000) and regional innovation networks (e.g., Coffano et al., 2017) supports the importance of nonlocal forms of embeddedness. Overall, an important insight from SNT underpinning our research is that disembedding is a process of extralocal network building or embedding that creates and maintains personal relationships of trust at various, interrelated geographical scales (Hess, 2004). We therefore draw insights from the structural embeddedness of SNT to investigate the impact of network structure in intercity coinvention networks on innovation in cities.

Hypothesis Development

Traditionally, social network studies treated nodes as individuals and organizations, while more recent studies applied social network analysis to administrative spaces such as cities, provinces, regions, and countries (Fleming et al., 2007a; Sebestyén and Varga, 2013; Guan et al., 2015, 2016; Sun, 2016; Lyu et al., 2019). Different kinds of nodes have different types of capabilities. For example, when the nodes are firms, they can integrate information more efficiently than a city, where organizations are loosely connected within an administrative boundary. Cities, however, are capable of information integration to some degree due to intracity information exchange (local interaction) (Hutton, 2004; Bathelt, 2011). As cities are compact and densely populated entities, each city assumes a position as an innovation node within all interorganizational collaboration connections in the city. The position of a city embedded in an intercity collaboration network hence affects the innovation performance of the city through information flow. Because cities tend to be specialized in certain industries (Cuadrado-Roura and Rubalcaba-Bermejo, 1998; Kemeny and Storper, 2015), access to a flow of diverse information and knowledge is conducive to better innovation performance.

As cities form and maintain collaborations with each other, they create ties that evolve into an intercity patent collaboration network. Consistent with SNT, the position of a city in a network determines the information flow it receives, sends, or channels. A central position of a city enables the city to gain access to a variety of information and specialized knowledge from its network neighbors. Previous studies, most of which used individuals (He et al., 2009; Abbasi et al., 2011), organizations (Schilling and Phelps, 2007; Karamanos, 2012; Vasudeva et al., 2013), regions, and country-level nodes (Sebestyén and Varga, 2013; Guan et al., 2015; Sun, 2016), confirmed a close relationship between network structure embeddedness and an actor's innovation performance. Less is known about the effect of the network structure of a city as a node in intercity networks.

Centrality is an important feature of network structure that reflects the power and prominent status of an actor (Burkhardt and Brass, 1990; Jackson, 2008). High centrality of a city reflects its intermediary role and degree of access to resources and information from other cities. Integrating and exploiting complementary, specialized, and heterogeneous information and technology is essential to innovation (Borgatti, 2005; Nieto and Santamaría, 2007). The argument of structural embeddedness suggests that intercity collaboration ties facilitate information flows and that different collaboration ties have different abilities to deliver such flows, leading to the integration of different types of knowledge. Two key features of centrality that are essential to information flows in networks are degree centrality and closeness centrality (Jackson, 2008).[1] Degree centrality (DC) describes how a node is connected with other adjacent nodes, reflecting the width of connections a focal node has in the network. Since DC refers to immediate effects of all parallel duplication information flows from other connected nodes, a high DC means that a node is more likely to acquire information with ease from a number of adjacent nodes when the information is channeled simultaneously through many neighboring nodes (Borgatti, 2005). Therefore, a city with high DC in an intercity innovation network can likely access information and knowledge easily from many other cities it has a direct connection with. Hence, a greater breadth of connection of a focal city in an intercity innovation network means that the city should perform well in innovation as a result of its capacity to obtain and recombine emerging information and knowledge to engage in innovation.

In contrast, closeness centrality (CNC) indicates how quickly a node can reach other nodes, reflecting its depth of connection. The CNC of a node refers to the sum of the shortest distance over which information travels from all other nodes. Since a node with a high CNC lies at a short distance from other nodes, it tends to receive information flows sooner (Borgatti, 2005). If DC represents the scale of connections, CNC depicts the communication efficiency of each edge (Lu and Feng, 2009; Abbasi et al., 2011; Guan et al., 2016). With regard to information flows in social networks, a high CNC suggest that a node is better positioned to obtain novel information early, when such information has the most value (Borgatti, 2005). Thus, cities with high CNC in an intercity innovation network are able to develop new ideas sooner than others and therefore perform better in innovation. Based on the reasoning above, we propose the following hypotheses:

Hypothesis 1a *The degree centrality of a city in a collaboration network positively affects its innovation performance.*

Hypothesis 1b *The closeness centrality of a city in a collaboration network positively affects its innovation performance.*

While centrality refers to the position of a node in the whole network, structural holes exist in the ego network[2] for each node. When two of the ego's contacts are not connected, a structural hole exists between them (Burt, 1992). A node that fills a structural hole tends to have

[1]Numerous measures of centrality have been proposed in the literature, including degree centrality, closeness, betweenness, eigenvector centrality, information centrality, flow betweenness, and the rush index (Borgatti, 2005). However, there is no consensus so far on the measurement of network centrality. Papers on innovation and social network analysis often considered one or a few selected measures (e.g., Ferriani et al., 2009; Guan et al., 2015, 2016; Guan and Liu, 2016; Zhang et al., 2014) for reasons of research relevance and/or the correlation of measures. Since our research is concerned with intercity innovation collaboration, which assumes the importance of information flows, we follow Borgatti (2005) in considering DC and CNC as the two most relevant features of network centrality in this paper.

[2]An ego network refers to all the nodes surrounding a given node with all the ties among them.

more nonredundant ties, through which more fresh ideas are channeled. Consistent with Burt's (1992) pioneering social network studies, nodes (cities) that fill greater structural holes in intercity networks can achieve better performance in innovation as a result of greater access to novel information, minimized information redundancy and control over who benefits from exchange of information when the focal nodes facilitate connections between nonredundant contacts. Burt's theory has been confirmed by numerous studies (Burt, 1992, 1997, 2004; Fleming et al., 2007b).

Based on this overall reasoning, we propose the following hypothesis:

Hypothesis 2 *The structural holes filled by a city in an innovation network positively affect its innovation performance.*

In addition to degree centrality, closeness centrality and structural holes, the clustering coefficient (CC) is another important feature of the egocentric network of each node. It indicates a network's transitivity, that is, the likelihood that the connected nodes in the ego network also connect to each other (Watts and Strogatz, 1998). A networks transitivity has considerable consequences. If focal city a is connected to city b and cities b and c are connected to each other, resulting in cities a and c also being connected, city a in the highly clustered intercity networks will benefit from the density and cohesiveness of the networks. According to Coleman (1990), dense and cohesive networks reduce information search costs, promote trust, and facilitate the emergence of norms. All this suggests that a higher CC should enhance higher-level local cooperation and information transmission (Uzzi and Spiro, 2005), thereby enhancing cities' innovation performance. Thus, we posit the following hypothesis:

Hypothesis 3 *The clustering coefficient of a city in an innovation network positively affects its innovation performance.*

3 Data and Network Evolution

3.1 Patent Data

In this study, we use a comprehensive data set of coinvention patents from the Chinese Patent Office (SIPO) to investigate the structure and dynamics of intercity innovation collaboration in China and the effect of network structure on city innovation performance. SIPO maintains a patent database with complete information on every patent granted since 1985, the year China enacted its patent law (Hong, 2008). The database includes information on titles of patents, dates of application, names, and address of the first assignee and has been extensively used in studies of Chinese innovation (e.g., Hong and Su, 2013; Sun and Cao, 2015). The SIPO database is preferred to USPTO data for Chinese studies because its patent collection is more representative and comprehensive and does not just cover overseas patents (Sun and Cao, 2015). We limit the time window to 2001 to 2016 due to a limited number of copatenting events before 2001 and incomplete information after 2016. In addition, recent data are more informative than older data about Chinas current innovation dynamics and are better for charting innovation trends.

SIPO grants three types of patents, namely, invention, utility and design patents. Since patent values vary across types, we only include granted invention patents because it is generally acknowledged that invention patents are of consistently higher value than utility and design patents (Dang and Motohashi, 2015). Coinvention patents are those registered with more than two organizations or individuals. We include patents filed by firms, universities, and research institutions, but we exclude patents registered with individuals because of their lack of location information.

The original patent data include only the addresses of the first assignees. To compile a data set for the purposes of this research, we use registration information to locate the second assignee. Specifically, for firms, we match firm names with the official firm registration information from the State Administration of Industry and Commerce (SAIC), where all firms are legally required to register with an address. Since our study only considers intercity collaboration networks (extralocal interactions), in the empirical section, we exclude intracity collaboration observations (local interactions).

To assess coinvention, we construct our data by using copatents filed by interorganizational collaborators and then aggregating them to the prefecture city level. In total, we examine 137,098 coinvention patents[3], 69,347 intercity collaborations, and 293 prefecture-level cities in our study.

3.2 Constructing Networks

Collaborative innovation actors are deeply embedded in network structures. We use a group of research organizations and firms within a city as a node, and an urban collaboration network is formed by aggregating the collaborative ties of innovative actors into cities. The edges that connect cities come from intercity organizational collaborations (extralocation interactions), which represent information flows between cities. Borgatti and Halgin (2016) categorized network models as *choice* or *success* models based on the outcome variable and *flow* or *bond* models based on the connection types. Our analysis is of the *choice* type because we use city-level patents, and it is a *flow* model because the underlying mechanism is that information and knowledge flow from city to city through intercity collaboration ties (extralocation interactions).

[3]From 2001 to 2016, a total of 243,264 coinvention patents were granted. After excluding foreign applicants, we are left with 201,586 patents. Then, in the process of locating the second applicant, we eliminate those patents applied for by individuals and firms that cannot be matched with registration information. After data cleaning, we use a data set containing 137,098 patents, which account for 68% of the total domestic coinvention patents granted in the sample period.

Interorganizational patent collaborations come in different types based on cooperation among different innovative actors. The triple helix (TH) theory, developed by Etzkowitz and Leydesdorff (2000), explains the interactive dynamics and mechanisms among universities, industries, and governments. This theory emphasizes the achievement of the optimal level of interaction among the three sectors to produce a highly efficient innovation system (Ivanova and Leydesdorff, 2014; Etzkowitz and Zhou, 2017). Some literature focuses on industry, university, and research institute (IUR) research collaborations, stressing their positive influence and importance (Cohen et al., 2002; Perkmann and Walsh, 2010; Dutrénit and Arza, 2010; Laursen et al., 2011; Chen et al., 2017). However, most of those studies underline the effect on each type of organization, and few have explored the influence of interorganizational collaborations on organizations within the administrative boundaries of a city. We distinguish between two types of interorganizational collaboration networks, i.e., collaborations involving universities as well as research institutes (URI) and intra-industry collaboration (II). Since most universities and research institutes are publicly funded in China, their URI network position reflects the degree to which each city can access publicly funded knowledge, while the II network property indicates the innovative capacity of the commercial and private sectors. The two types of innovation capacity may overlap with each other to varying degrees. For example, Beijing hosts the best research institutes and universities in China, while the private sector remains strong as well. In contrast, Shenzhen has stronger private (II) than public (URI) innovation capacity. By examining both, we can uncover which interorganizational networks are more relevant for determining innovation performance in cities. Therefore, we analyze two types of intercity collaboration (extralocal interaction) networks and their respective impacts on city innovation performance in China's national innovation system.

3.3 Stylized Facts on Intercity Coinvention Networks in China

The analysis of Chinese patents over the period 2001-2016 highlights six stylized facts on intercity coinvention networks in China.

First, the number of coinvention patents in China increased rapidly from 2001 to 2016, as shown in the left panel of Figure 1. The country experienced a surge of innovation as manifested in the number of granted patents primarily due to rapid economic growth and government support (Li, 2012; Gao, 2015). The total granted patent count peaked in 2015 and stagnated thereafter. The reason for this trend may be that the patenting process, from application to the grant of the patent, typically takes three years or even longer. Therefore, many patent applications may simply not yet have been processed and published by the time of our data collection. Other factors may also explain this change, for example, the petering out of funding from the government patent subsidy program, closer scrutiny of patent applications, and a new normal inaugurated by the

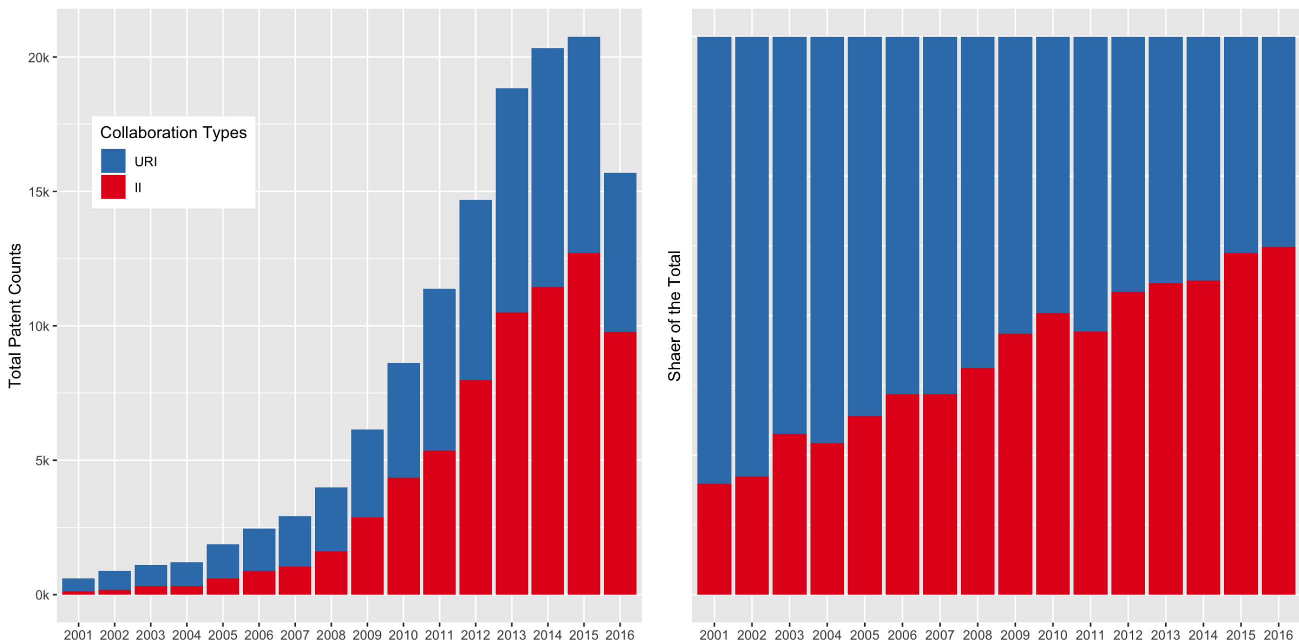

Figure 1: Total Patenting and Organization Types in Patent Collaborations over Time

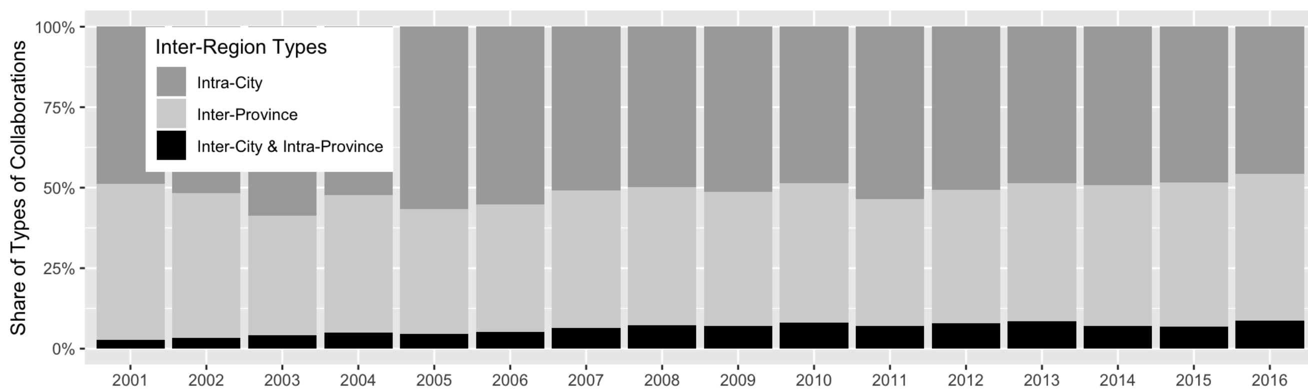

Figure 2: Share of Interregional Patent Collaborations over Time

economic slowdown.

Second, interfirm collaboration has grown to become the dominant form of coinvention. In the right panel of Figure 1, the colors indicate the share of different types of interorganizational coinvention, namely, URI and II collaborations. In the early 2000s, the majority of coinvention patents involved either universities or research institutes. However, the share of interfirm collaboration has grown steadily, and by the end of the sample period, coinvention involving interfirm collaboration had become dominant.[4]

Third, intercity collaborations have become more important over time. While interorgani-

[4]A similar pattern was documented by Sun and Cao (2015) for the post-2001 period.

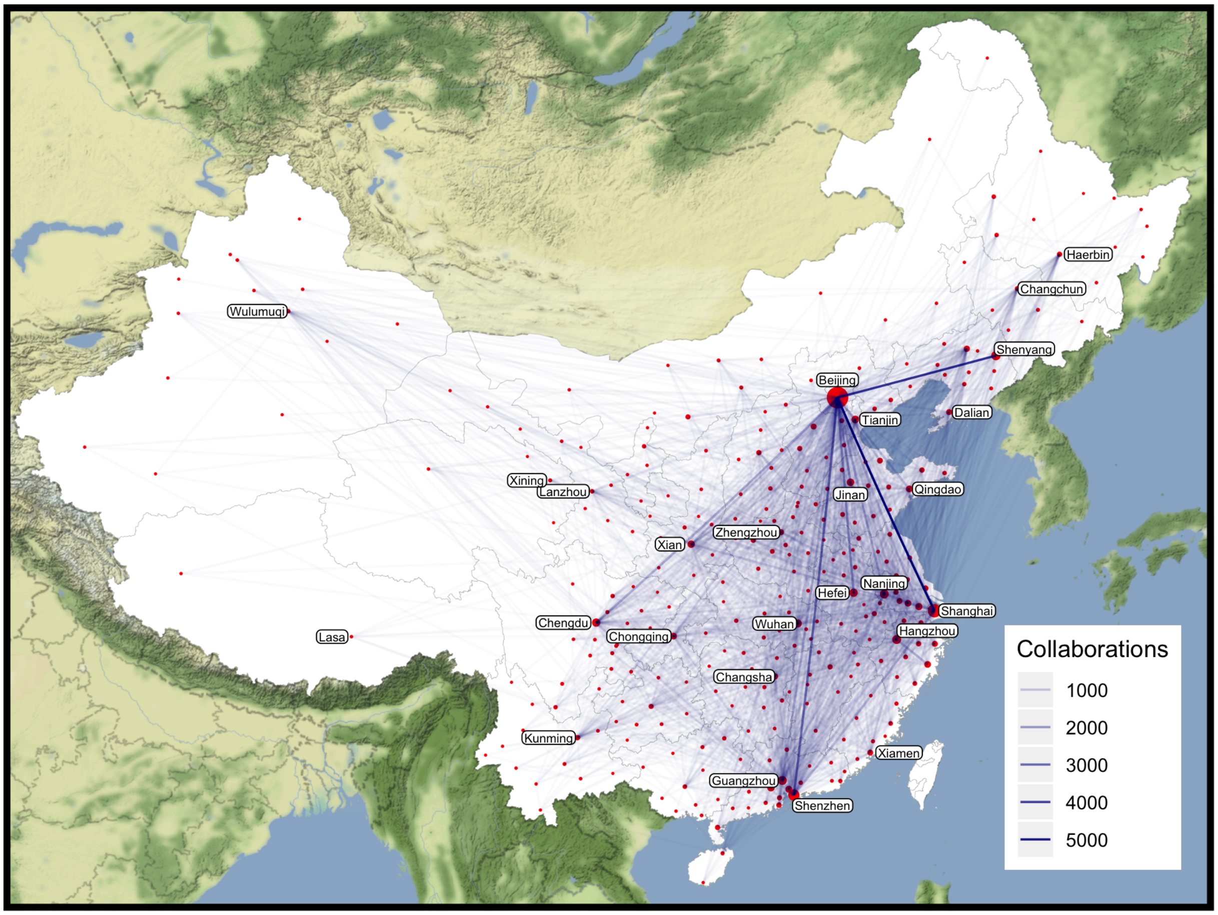

Figure 3: Graphical Representation of Intercity Patent Collaboration

zational coinvention patterns have evolved over time, interregional collaboration patterns have remained stable over the same period. Figure 2 shows that approximately half of interorganizational patent collaborations were within the same cities, suggesting that local interactions remained influential in coinvention and that intracity patent collaboration has an important function for city innovation performance (Marrocu et al., 2013). However, there was an increase in intercity collaborations (both within and across provinces) after 2011, indicating the growing importance of extralocal interactions, thanks in part to the rapid development of transport infrastructure, which potentially facilitates collaboration among high-skilled knowledge workers (Dong et al., 2019).

Fourth, the cities that were most deeply embedded in invention collaboration networks were located in the eastern regions of China with the highest population density and most dynamic economic activities, as shown in Figure 3. Cities in the periphery, including the northeastern, southwestern, and northwestern regions, tended to collaborate with cities in central China. A glance at the map suggests that Beijing, Shanghai, and Shenzhen were the three most influential innovation hubs in China in terms of network embeddedness. Beijing was the dominant force in the entire country, and Shanghai and Shenzhen held the second and third positions.

Fifth, intercity coinvention networks have evolved from being relatively sparse and fragmented to being the fabric of the national innovation system.[5] As illustrated in Figure 4, from 2001 to 2004, the intercity network of innovation was relatively sparse, with few nodes and edges. The two largest innovation hubs were clearly Beijing and Shanghai, and yet they were only connected through one third city, Wenzhou. Some cities were disconnected from the largest component of the network. During that period, collaborations were largely bounded by the geographical distance separating the cities. For example, Shanghai formed a close collaboration with the cities of Suzhou, Wenzhou, and Taizhou, two of the cities within the Yangtze River city cluster, while Beijing was connected with Baoding and Nanjing. The thick edges between Beijing and Nanjing indicate the intensity of their collaboration, while Shanghai maintained a relatively weak connection with its partners. Several cities were disconnected from the nationwide network. The sparse collaboration suggests that during the period, a nationwide intercity collaboration network had yet to be formed.

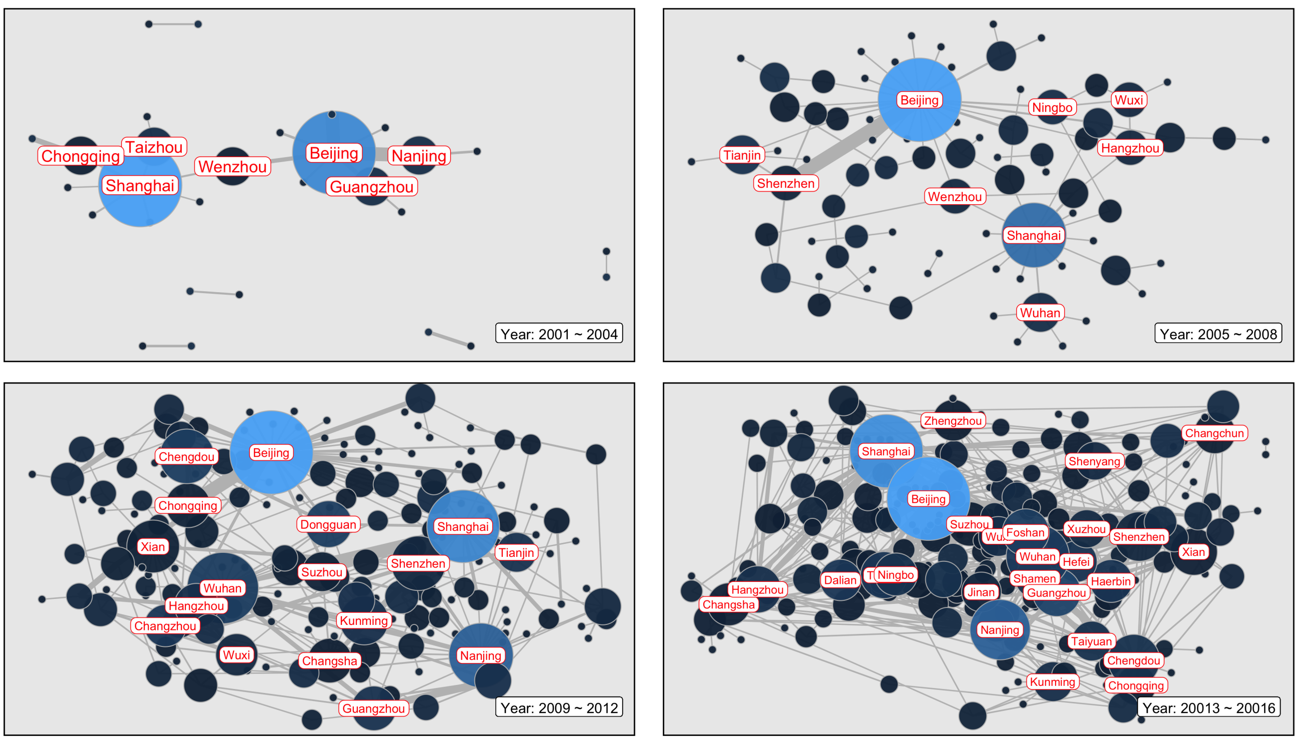

Figure 4: Intercity Invention Collaboration Network Evolution from 2001 to 2017

[5]While Figure 3 shows the overall innovation performance and innovation connectedness of Chinese cities, we next demonstrate the network evolution of intercity invention collaborations in Figure 4. Figure 4 shows the network evolution in China using four periods with four-year, nonoverlapping time windows from 2001 to 2016. A larger size and lighter color of the nodes represent high centrality of the city, and the edges represent the invention collaboration between each pair of cities. We use the number five as the minimum for connections, so a pair of cities is only connected when they created more than five coinventions during that period.

From 2005 to 2008, many more cities took part in nationwide invention collaborations, with Shanghai and Beijing still being in the dominant position. Some cities, for example, Hangzhou, Shenzhen, Wuhan, and Tianjin, moved to a more central position. However, parts of the network were still characterized by geographical regions. For example, Shanghai and Wuhan formed local collaboration networks that were distinct and distant from those of Beijing.

In the third period from 2009 to 2012, the network became denser. Notably, some of the second-tier cities came to rival those in the top tier. For example, Nanjing, Wuhan, Chengdu, Shenzhen, and Hangzhou began to catch up with Shanghai and became the dominant forces in their respective regional innovation systems. In the last period, a completely interwoven nationwide collaboration network emerged, featuring an even denser and more complex system. The four graphs depict the rapid formation of a full-blown intercity collaboration network within the Chinese national innovation system.

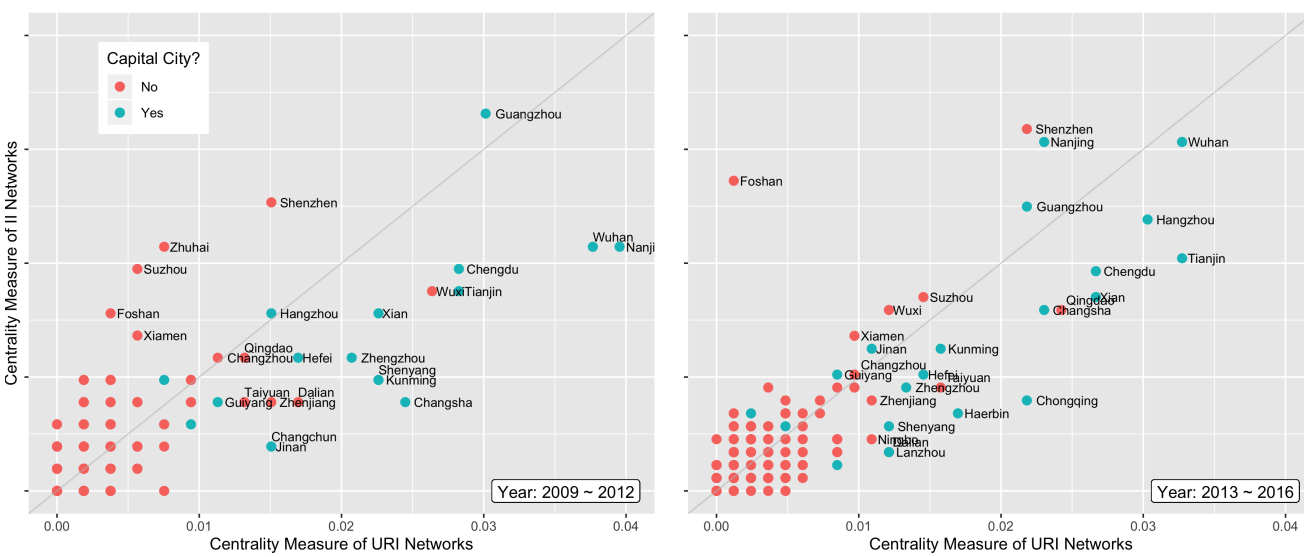

Figure 5: Comparison of Degree Centrality of URI and II Networks

Sixth, different types of interorganizational collaborations displayed varying centrality in the intercity networks of coinvention.[6] As shown in Figure 5, a salient pattern is that there exists a clear positive correlation between the two network types. Most of the cities are concentrated in the left lower corner because of their low centrality in both URI and II networks, and only a handful of cities stand out as achieving high centrality in terms of both measures. The 45-degree

[6] Figure 4 uses the number of total patents for cities, but it fails to capture the different types of collaborations between innovative organizations. To demonstrate a deeper dimension of the intercity collaboration network, Figure 5 compares the degree centrality of the URI and II networks in each city, with the y-axis representing the II networks and x-axis representing the URI networks. We use the normalized degree centrality measure, which is measured by node connections divided by total connections in the network. Therefore, the sum of all degrees equals one. By normalization, we can compare the two degree centrality types for the same city, and the value represents the relative degree among all cities. The figure excludes two outliers, Shanghai and Beijing.

line divides the sample into two halves: cities in the upper half achieve higher centrality in the II than the URI network, and the opposite is true for those in the lower half. We use blue to indicate provincial capital cities and municipalities[7] and red to denote the others. Most of the red cities are small or medium and less influential cities, except cities such as Shenzhen, Suzhou, Xiamen, and Qingdao[8]. Blue cities are important in terms of both their political and their economic roles. One interesting phenomenon is that for most of the blue cities, the relative centrality of their URI networks is higher than that of their II networks because cities with political significance tend to possess more public resources to fund academic and research institutes. Cities such as Shenzhen, Zhuhai, Suzhou, and Foshan perform better in terms of II than URI centrality.

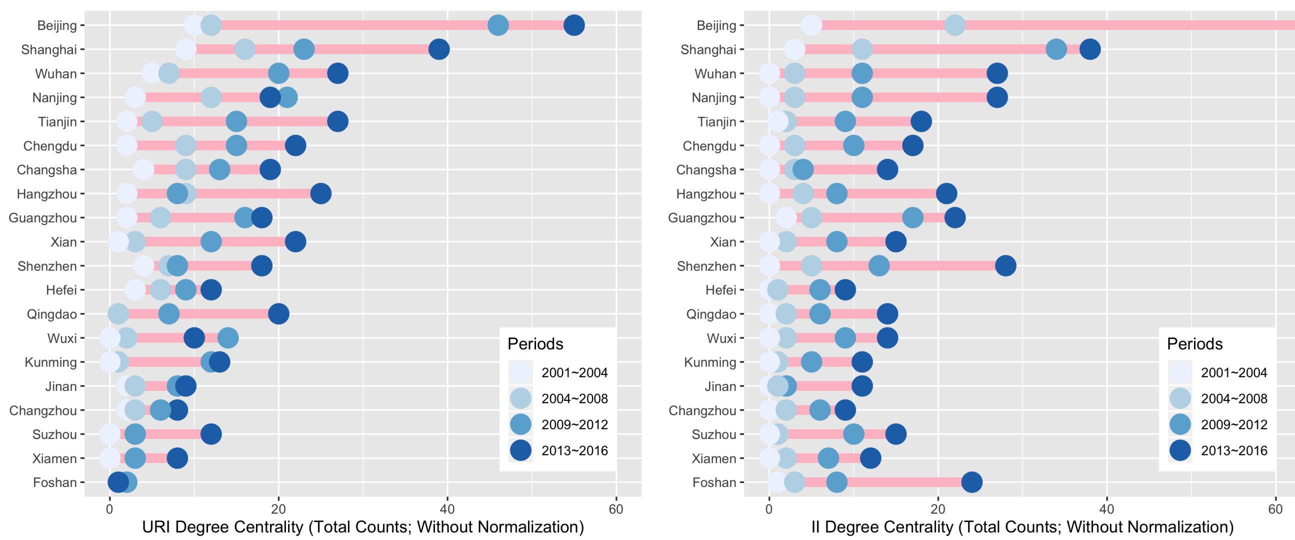

Figure 6: Change in Degree Centrality of URI and II Networks

Figure 6 demonstrates the evolution of degree centrality over the years. Beijing was relatively more dominant in II than URI degree centrality in the sample period because it hosts the headquarters of many state-owned enterprises (Hu and Jefferson, 2004). Among the first-tier cities, Shanghai maintained the second position over the years, and Guangzhou and Shenzhen had similar importance relative to the second-tier cities. Recent years saw the rise of second-tier cities (Bolshaw, 2014) such as Hangzhou, Xi'an, Qingdao, Tianjin, and Suzhou, which experienced a remarkable improvement in URI degree centrality, while Nanjing, Wuhan, Foshan, and Changsha made good progress in II degree centrality.

[7] There are a total of four municipality cities in China, including Shanghai, Chongqing, Tianjin, and Beijing
[8] Shenzhen, Suzhou, and Qingdao are each home to close to or more than 10 million people.

4 Method and Construction of Variables

4.1 Dependent Variables

This paper investigates the effects of the network structures of cities in intercity innovation networks on city innovation performance. We use the total invention patents granted for each city as the dependent variable. This is consistent with extant research using the city-level patent count of a specific field (Guan et al., 2015), country-level R&D efficiency (Guan et al., 2016), and total patent count in a region (Sebestyén and Varga, 2013; De Noni et al., 2017). We use invention patents because they are the most valuable type of patents compared to utility or design patents because normally the requirements to be granted an invention patent are the highest and the process takes more than four years on average (Tong et al., 2018).

4.2 Explanatory Variables

As discussed previously, we include degree centrality (DC), closeness centrality (CNC), structural holes (SH), and the clustering coefficient (CC) as our independent variables. DC and CNC represent the structural embeddedness of cities in the whole network, whereas SH and CC reflect the property of the ego network of each node.

Degree Centrality (DC)

DC refers to the number of connections that a node has (Freeman, 1978; Opsahl et al., 2010). It is calculated by the following formula:

$$DC_i = \frac{k_i}{N-1} = \frac{\sum\limits_{i \neq j} \alpha_{ij}}{N-1} \quad ,$$

where k_i indicates the number of connections of each node i, and N is the total number of nodes in the social network. An adjacency matrix describes the social network, in which α_{ij} is 1 if a tie exists between nodes i and j and 0 otherwise.

Closeness Centrality (CNC)

CNC measures how close a given node is to other nodes. The traditional closeness definition is restricted to nodes within the largest component of a network (Opsahl et al., 2010). Because numerous nodes are disconnected from the main component in our networks, we adopt another measure of closeness centrality, namely, decay centrality (Jackson, 2008),

$$CNC_i = \sum_{j \neq i} \delta^{l(i,j)} \quad ,$$

where $l(i,j)$ is set to infinity if i and j are not path-connected and $l(i,j)$ is the number of links on the shortest path between i and j. The decay parameter δ, where $0 < \delta < 1$, tunes the measurement of closeness centrality. As δ approaches one, decay centrality measures the sum of the number of links on the shortest paths a node lies on. As δ approaches 0, decay centrality gives infinitely more weight to closer nodes than to more distant nodes. At intermediate values of δ, a node is rewarded for how close it is to other nodes, but in such a way that very distant nodes are given less weight than closer nodes.

Structural Holes (SH)

We use a network constraint to measure structural holes (Burt, 1992; Wang et al., 2014; Guan et al., 2016). The formula for SH is

$$SH_i = 2 - \sum_j (P_{ij} + \sum_{q \neq i \neq j} p_{iq} p_{qj})^2 \quad ,$$

where the second term is the network constraint of node i and p_{ij} is the proportion of the connections of node i that are connected to node j. Hence, SH_i is the proportion of node i's relationships that are connected with node j through node i. Higher values on this measure imply that the node fills a greater structural hole, thereby brokering the network more extensively.

Clustering Coefficient (CC)

CC indicates the node cohesiveness and transitivity within the ego network, which is calculated for node i as the fraction of linked neighbors of i (Barrat et al., 2004).

The measure is computed on a node-by-node basis. We use the following formula,

$$CC_i(g) = \frac{\#\{jk \in g | k \neq j, j \in N_i(g), k \in N_i(g)\}}{d_i(g)(d_i(g) - 1)/2} \quad ,$$

where g denotes the whole network, $j \in N_i(g), k \in N_i(g)$[9] denotes that j and k are partners of node i, and $jk \in g$ denotes that j and k are also connected to each other. $d_i(g)(d_i(g)-1)/2$ shows the possible maximum number of links among i's total partners. Thus, CC_i considers all pairs of nodes that are linked to i and then considers how many of them are linked to one another.

4.3 Control Variables

The existing literature indicates that innovation performance is also a function of other socioeconomic factors. We include the following control variables.

City-level GDP: Overall city-level economic development is measured by GDP. It is widely recognized that innovation capacity tends to be positively correlated with income. This pattern holds not only at the national level but also at the city level.

[9] We borrow the notations from Jackson (2008).

City-level science & technology public expenditure: Government support is essential for local innovation (Li, 2012). We control for science and technology public expenditure by the local government, which indicates the level of government support. Higher public expenditure and support for science and technology research is expected to lead to stronger innovation performance.

Mobile phone users: We use the total number of mobile phone users as a proxy for the telecommunication infrastructure. Telecommunication infrastructure serves as the fundamental hardware for information flows. A better telecommunication framework enhances the efficiency of information flows for both local and extralocal interactions.

Share of manufacturing industry output: China is the worlds workshop, and the manufacturing industry is the backbone of its cities' economies. Unsurprisingly, the recent increase in granted invention patents is closely related to the manufacturing industry. We thus include the share of manufacturing industry output in regional gross economic output as a proxy for demand for innovation.

In addition to the above control variables, we also include time fixed effects and city fixed effects. From the raw descriptive statistics, we have seen that the core explanatory variables (centrality measures) demonstrate a clear time trend, as cities have become better connected with each other over the years. By controlling for time fixed effects, we can rule out time-related factors that might confound our key explanatory variables. Controlling for city fixed effects teases out time-invariant geographical and socioeconomic factors. For example, cities located in the geographical center of China tend to be more connected to other cities. Hence, by using city fixed effects, we can exclude time-invariant factors that might influence urban innovation performance.

4.4 Statistical Approach

We estimate multiple negative binomial panel regression models to obtain our main result and linear regressions as robustness checks. The dependent variable is the total number of invention patents granted during a four-year window for each city. Negative binomial regressions are designed to deal with count-dependent variables affected by the overdispersion problem. The majority of studies dealing with patents as the outcome variable have used negative binomial regressions (e.g., Guan et al., 2016). To ensure the robustness of our result, we also run a linear regression with different panel specifications. For the linear model, the dependent variable is log-transformed to approximate a normal distribution and to allow interpretation of the results in percentage terms. All of our dependent variables are nonzero positive counts, which allows us to avoid the logarithmic zero problem.

We specify the following basic regression model:

$$y_{it} = \beta X + \alpha_i + \tau_t + \epsilon_{it} \quad (1)$$

The basic form of the model specifies that city-level innovation is a function of independent variables X, including network position measurements and other city-level time-varying control variables. τ_t stands for the time period-specific effect in period t. The term α_i stands for unobserved city-level heterogeneity that directly correlates with city innovation. The random-effects model assumes that α_i is random and is typically subject to a normal distribution with a mean of zero and constant variance and that α_i is uncorrelated with the independent variables X (Wooldridge, 2010). In contrast, the fixed-effects model drops the assumption of no correlation and uses within-transformation to remove the city-specific constant α_i (Wooldridge, 2010). Most network analysis studies using panel data often assume α_i is a random variable of each node i (Ferriani et al., 2009; Guan et al., 2015, 2016; Guan and Liu, 2016). We argue that random effects might be suitable in some cases because the random-effects model assumes α_i to be independent of all the network position measurements. This is often not the case for network centralities and structural holes, because those network position measurements are likely to be correlated with unobserved city heterogeneity. For instance, Beijing hosts many world-renowned universities, which is why it enjoys the central position in the URI network. Those universities are obviously not random factors that arbitrarily appear in any city during different time periods following a stochastic process—on the contrary, such specific factors persist through time. Our reasoning is also confirmed by the Hausman test (Hausman, 1978), which rejects the use of random effects with high confidence and a very low p-value. To better illustrate the result, we use both city random and fixed effects since they both have their own pros and cons. Both results together help us better understand the robustness of the results. The following equation describes the whole model.

$$Pt_{it} = \beta_0 + \beta_1 x_{it} + \gamma Z + Time_t + \epsilon_{it} \quad (2)$$

$$x_{it} \in \{URI.DC_{it}, URI.SH_{it}, URI.CNC_{it}, URI.CC_{it}, \\ II.DC_{it}, II.SH_{it}, II.CNC_{it}, II.CC_{it}\}$$

The dependent variable Pt_{it} stands for total invention patents in city i during period t. The explanatory variable x_{it} is the network position in either the URI or the II network. DC_{it}, SH_{it}, CNC_{it} and CC_{it} stand for, respectively, degree centrality, structural holes, closeness centrality and the ego-network clustering coefficient for node i during period t. We control for the quadratic terms for degree centrality and the clustering coefficient because degree centrality is often shown to have diminishing returns (Ferriani et al., 2009; Guan and Liu, 2016) and the clustering coefficient is documented to have conflicting effects, with a tendency both to increase and to decrease innovation (Uzzi and Spiro, 2005; Fleming et al., 2007a; He and Fallah, 2009). Z represents the city-level time-variant control variables, including city-level GDP, science and technology public expenditure, industrial output share, and total mobile phone users.

5 Results

Table 1 presents the summary statistics and correlation analysis. The average city-level patent count in the sample is 2,767, while the standard deviation is 9,713. The difference between the mean and standard deviation suggests an overdispersion problem in the count data, ruling out a Poisson regression and justifying the use of a negative binomial model to test our hypotheses. The average city-level GDP is 192 billion yuan from 2001 to 2016, and the standard deviation is 279 billion, suggesting considerable intercity income inequality. Science and technology public expenditure is 85.8 million on average with a high standard deviation of 163.1 million. The average number of mobile phone users in each city is 3.6 million. All the aforementioned economic variables are positively correlated with each other, with correlation coefficients ranging from 0.76 to 0.89. The industrial output share is negatively correlated with the economic indicators, suggesting that a higher development level is associated with a lower industrial output share and thus a higher tertiary output share.

Table 1: Statistical Summary and Correlation Analysis

	SD	Mean	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Patents	9,713.549	2,767.837	1												
2. GDP(million)	279,579.000	192,039.100	0.765	1											
3. ST.Fund(million)	2,230.447	613.972	0.896	0.786	1										
4. Mobile.Users(million)	4.285	3.627	0.803	0.845	0.761	1									
5. IndustryShare	0.097	0.499	-0.199	-0.108	-0.169	-0.150	1								
6. URI.Degree	0.031	0.016	0.696	0.642	0.609	0.701	-0.151	1							
7. URI.StructHoles	0.338	1.226	0.462	0.563	0.405	0.641	-0.039	0.686	1						
8. URI.Closeness	2.407	2.046	0.618	0.688	0.584	0.743	-0.067	0.656	0.817	1					
9. URI.ClustCoefficient	0.139	0.037	0.020	0.062	0.017	0.119	-0.023	0.055	0.197	0.174	1				
10. II.Degree	0.037	0.014	0.778	0.614	0.679	0.679	-0.172	0.773	0.435	0.489	0.031	1			
11. II.StructHoles	0.326	1.208	0.483	0.588	0.442	0.668	-0.076	0.507	0.696	0.722	0.199	0.506	1		
12. II.Closeness	2.962	2.250	0.622	0.625	0.592	0.683	-0.104	0.453	0.572	0.755	0.193	0.542	0.782	1	
13. II.ClustCoefficient	0.152	0.045	0.070	0.129	0.055	0.146	0.023	0.091	0.221	0.255	0.044	0.056	0.215	0.202	1

The next eight variables summarize cities' network positions in both the URI and II networks. The two types of centrality measures are at comparable scales due to the similar density of the two networks. The average degree centrality for the URI network is 0.016, slightly higher than that of the II network, which suggests that there are more total ties in the URI network than in the II network. The nodes are on average closer to each other in the URI than in the II network, as suggested by the closeness centrality, implying a more centralized pattern in the URI network. In terms of the ego networks, the URI network, on average, exhibits large structural holes and a lower clustering coefficient. The structural holes range from 1 to 2 by the constraint formula, with means of 1.226 and 1.208, respectively, for the URI and II networks.

All the variables are positively correlated with the dependent variable. There are high correlation coefficients among the degree centrality, closeness centrality and structural holes variables, ranging from 0.656 to 0.817 for the URI network and 0.506 to 0.782 for the II network. The high correlations suggest a potential multicollinearity problem. To address this concern, we use only one network position measurement for each regression. The following two tables report the regression results.

Table 2 reports the results of the negative binomial regression with city random and fixed effects. It contains the results of ten regression models, with all the covariates standardized to a mean of zero and a standard deviation of one. We apply city random effects in Models (1) to (5) and city fixed effects in Models (6) to (10). From Models (1) to (4), we test each network position measurement for both the URI and II networks in each regression to avoid potential multicollinearity problems. In Hypothesis 1a, we propose that the degree centrality of a city in a collaboration network positively affects its innovation performance. Model (1) regresses the total patents measure on the degree centralities for both URI and II networks, and the effects are both positive and significant. Thus, Hypothesis 1a is supported. The effect size suggests that a one-standard-deviation increase in URI degree centrality is associated with an increase of approximately 18.3% in total invention patents. The negative coefficient of the squared term suggests a diminishing marginal effect of extralocation interactions: when a city's URI degree centrality is low, an initial positive change in the degree centrality increases the innovation rapidly, but the effect immediately diminishes for relatively high degree centrality (Guan et al., 2016). The effect size for the II networks indicates that a one-standard-deviation increase in the II degree centrality is associated with a 21% increase in total invention patents relative to other cities, and the quadratic term is nonsignificant. In Hypothesis 2, we posit that cities able to fill structural holes in the innovation network tend to have higher innovation performance. Model (2) suggests a significant effect of bridging structural holes in both the URI and II innovation networks; the effect for URI is smaller and less significant than that for the II network. Hence, Hypothesis 2 is confirmed. The positive role of the structural holes measure echoes previous findings (Burt, 2004; Fleming et al., 2007b). In Hypothesis 1b, we postulate that the closeness centrality of a city in a collaboration network positively affects its innovation performance, and in Hypothesis 3, we propose that cities with high clustering coefficients in their ego-network tend to have higher innovation performance. Models (3) and (4) show that the closeness centralities and clustering coefficients of both networks play little role in facilitating city innovation performance. Therefore, both hypotheses are not supported. Model (5) contains all the variables, and the major results continue to hold. The structural hole variable in the URI model ceases to be significant. Ad-

Table 2: Negative Binomial Regression with City Random Effects and Fixed Effects

	Dependent Variables: Total Invention Patents									
	Random-Effect Models					Fixed-Effect Models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
URI.DegreeCentrality	0.183***				0.193**	0.0001				−0.104
	(0.060)				(0.089)	(0.049)				(0.074)
URI.DegreeCentrality2	−0.025*				−0.030*	−0.001				0.007
	(0.014)				(0.016)	(0.012)				(0.014)
URI.StructuralHoles		0.060**			0.059		0.015			0.038
		(0.029)			(0.041)		(0.024)			(0.034)
URI.Closeness			0.058		−0.076			0.041		0.047
			(0.036)		(0.052)			(0.030)		(0.043)
URI.ClusteringCoefficient				−0.021	−0.004				−0.020	−0.014
				(0.050)	(0.050)				(0.041)	(0.041)
URI.ClusteringCoefficient2				0.002	−0.003				0.001	−0.001
				(0.008)	(0.008)				(0.007)	(0.007)
II.DegreeCentrality	0.210***				0.166***	0.146***				0.093*
	(0.055)				(0.062)	(0.045)				(0.050)
II.DegreeCentrality2	0.002				0.015	−0.011				−0.001
	(0.012)				(0.013)	(0.011)				(0.011)
II.StructuralHoles		0.110***			0.133***		0.110***			0.124***
		(0.028)			(0.036)		(0.024)			(0.030)
II.Closeness			0.008		−0.131***			0.006		−0.096***
			(0.034)		(0.041)			(0.029)		(0.034)
II.ClusteringCoefficient				−0.067	−0.072				−0.045	−0.056
				(0.051)	(0.051)				(0.041)	(0.041)
II.ClusteringCoefficient2				0.013	0.013				0.009	0.010
				(0.010)	(0.010)				(0.008)	(0.008)
City.GDP	0.179*	0.080	0.147	0.197**	0.186*	0.036	−0.022	0.037	0.069	−0.009
	(0.103)	(0.097)	(0.099)	(0.099)	(0.105)	(0.083)	(0.080)	(0.081)	(0.081)	(0.086)
City.STExp	−0.151**	−0.073	−0.138***	−0.153***	−0.101*	−0.026	0.009	−0.042	−0.053	0.012
	(0.060)	(0.050)	(0.049)	(0.050)	(0.061)	(0.048)	(0.041)	(0.041)	(0.041)	(0.049)
City.IndustryShare	0.129***	0.140***	0.117***	0.109***	0.140***	0.077**	0.096***	0.078**	0.071**	0.096***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
City.MobileUsers	0.042	0.051	0.069	0.081	0.033	−0.083	−0.092	−0.080	−0.066	−0.093
	(0.086)	(0.083)	(0.085)	(0.085)	(0.085)	(0.071)	(0.069)	(0.071)	(0.071)	(0.070)
Constant	4.798***	4.801***	4.768***	4.717***	4.735***	8.841***	9.178***	9.252***	9.159***	8.984***
	(0.111)	(0.118)	(0.122)	(0.121)	(0.111)	(0.331)	(0.213)	(0.221)	(0.217)	(0.374)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Random Effect	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
City Fixed Effect	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	681	681	681	681	681	681	681	681	681	681
Akaike Inf. Crit.	9,633.187	9,633.963	9,656.549	9,661.104	9,623.113	9,086.070	9,069.156	9,090.965	9,094.914	9,072.984
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 3: Linear Regression with City Random Effects and Fixed Effects

	Dependent Variables: Log-tansformed Total Invention Patents									
	Random-Effect Models					Fixed-Effect Models				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
URI.DegreeCentrality	0.198***				0.231**	−0.005				−0.099
	(0.061)				(0.091)	(0.089)				(0.135)
URI.DegreeCentrality2	−0.028*				−0.035**	−0.002				0.004
	(0.015)				(0.017)	(0.016)				(0.020)
URI.StructuralHoles		0.059*			0.056		0.009			0.034
		(0.031)			(0.044)		(0.038)			(0.049)
URI.Closeness			0.052		−0.091*			0.032		0.044
			(0.038)		(0.055)			(0.049)		(0.069)
URI.ClusteringCoefficient				−0.022	−0.006				−0.024	−0.021
				(0.053)	(0.054)				(0.062)	(0.061)
URI.ClusteringCoefficient2				0.002	−0.002				0.002	0.0004
				(0.009)	(0.009)				(0.010)	(0.009)
II.DegreeCentrality	0.240***				0.191***	0.155***				0.093
	(0.058)				(0.066)	(0.056)				(0.069)
II.DegreeCentrality2	0.003				0.016	−0.009				0.002
	(0.013)				(0.013)	(0.013)				(0.014)
II.StructuralHoles		0.120***			0.140***		0.119***			0.134***
		(0.031)			(0.040)		(0.035)			(0.045)
II.Closeness			0.016		−0.133***			0.011		−0.095**
			(0.037)		(0.044)			(0.036)		(0.047)
II.ClusteringCoefficient				−0.080	−0.086				−0.054	−0.066
				(0.053)	(0.055)				(0.071)	(0.071)
II.ClusteringCoefficient2				0.015	0.015				0.011	0.012
				(0.010)	(0.010)				(0.013)	(0.013)
City.GDP	0.216**	0.115	0.191*	0.248**	0.235**	0.073	0.002	0.072	0.106	0.026
	(0.107)	(0.102)	(0.104)	(0.103)	(0.111)	(0.154)	(0.151)	(0.153)	(0.155)	(0.163)
City.STExp	−0.182***	−0.092*	−0.161***	−0.179***	−0.134**	−0.047	0.002	−0.053	−0.065	−0.004
	(0.061)	(0.053)	(0.052)	(0.052)	(0.064)	(0.088)	(0.065)	(0.063)	(0.066)	(0.089)
City.IndustryShare	0.129***	0.140***	0.115***	0.108***	0.141***	0.069	0.089	0.070	0.063	0.088
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.066)	(0.065)	(0.066)	(0.067)	(0.065)
City.MobileUsers	0.052	0.049	0.065	0.077	0.047	−0.105	−0.118	−0.103	−0.092	−0.120
	(0.090)	(0.087)	(0.088)	(0.089)	(0.090)	(0.113)	(0.114)	(0.117)	(0.113)	(0.112)
Constant	4.711***	4.710***	4.676***	4.623***	4.645***	8.823***	9.148***	9.197***	9.092***	8.962***
	(0.108)	(0.117)	(0.121)	(0.120)	(0.109)	(0.425)	(0.244)	(0.247)	(0.241)	(0.543)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Random Effect	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
City Fixed Effect	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	681	681	681	681	681	681	681	681	681	681
R^2						0.967	0.967	0.966	0.966	0.968
Akaike Inf. Crit.	1,464.112	1,456.185	1,477.500	1,498.571	1,500.362					
Note:										*p<0.1; **p<0.05; ***p<0.01

ditionally, closeness centrality for the the II network becomes negative, possibly due to its high correlation with other variables and hence the multicollinearity problem. Thus, it seems that the model with a single network position variable generates more reliable effect estimates.

Models (6) to (10) lay out the same model configurations as in the previous models and include city fixed effects. The fixed effects dramatically change the results for the URI network in that the previous significant coefficients of the degree centrality and structural holes variables become nonsignificant. In contrast, for the II network, degree centrality and structural holes continue to be significant, albeit with a slightly lower effect size, and hence offer evidence in support of Hypothesis 1a and Hypothesis 2. The effect size suggests that a one-standard-deviation increase in degree centrality and structural holes in the II network increases total invention patents by 14.6% and 11%, respectively. Compared with the random-effects regressions, the inconsistency of the results for degree centrality and structural holes in the URI model with city fixed effects is evidence of a strong correlation between unobserved city-level heterogeneity and the URI network position measurements. This is actually not very surprising, since universities and research institutes—key contributors to URI network positions—are heavily concentrated in major cities, such as Beijing and Shanghai. Universities and research institutes are mostly publicly funded, established institutions that are not subject to temporary changes in economic conditions. In contrast, firms, as the main actors in the II networks, form intercity research collaboration networks through searching and matching processes, and their activities are less correlated with city-specific effects. On balance, the results from the random- and fixed-effects models suggest strong evidence in support of Hypothesis 1a and Hypothesis 2 for the II network, inconclusive evidence on both hypotheses for the URI network, and no evidence in support of either Hypothesis 1b or Hypothesis 3 for the URI and II networks.

Robustness Check

Table 3 reports the results of linear regressions of the same regression models with log-transformed dependent variables; the effect estimates are very similar to those in Table 2, suggesting that the results are robust. Next, to better illustrate the change in results from different model specifications, we additionally estimate pooled and between estimators of the linear panel models. Table 4 summarizes the coefficients resulting from all six types of panel regressions. Models (iv) to (vii) are extracted from Tables 2 and 3.

The pooled model ignores the unobserved heterogeneity and runs a simple OLS regression using the panel data. Compared to the random- and fixed-effects models, the pooled model generates highly significant coefficients with large effect sizes. In addition to degree centrality and structural holes, the closeness centralities of both networks are positive and significant. The

Table 4: Summary and Comparison of Panel Regression Results of Different Models

Models	Coefficients							
	$URI.DC$	$URI.SH$	$URI.CNC$	$URI.CC$	$II.DC$	$II.SH$	$II.CNC$	$II.CC$
(i). Linear Pooled:	0.831***	0.533***	0.605***	0.283**	0.342***	0.418***	0.283***	0.137
(ii). Linear Between:	1.528***	0.819***	1.387***	0.396	0.348	0.746***	0.554***	0.322
(iii). Linear Prov-FE:	0.943***	0.484***	0.509***	0.045	0.456***	0.255***	0.152**	-0.056
(iv). Linear RE:	0.198***	0.059*	0.052	-0.022	0.240***	0.120***	0.016	-0.080
(v). NegBinomial RE:	0.183***	0.060***	0.058	-0.021	0.210***	0.110***	0.008	-0.067
(vi). Linear FE:	-0.005	0.009	0.032	-0.024	0.155***	0.119***	0.011	-0.054
(vii). NegBinomial FE:	0.0001	0.015	0.041	-0.020	0.146***	0.110***	0.006	-0.045
Note:	*p<0.1; **p<0.05; ***p<0.01. Linear Prov-FE is a pooled linear regression with province dummies as controls. NegBinomial means negative binomial regressions. We include time fixed effects for all regressions except for the between estimator.							

effect sizes of degree centrality and structural holes in the URI network are notably greater than those in the II network, suggesting that innovative cities are more highly associated with central positions in the URI network than with similar positions in the II network. The between estimator runs an OLS regression using the average of the independent variables for each city, thus totally ignoring within-city variation and only focusing on cross-sectional variation. The coefficients are even more inflated than those in the pooled model, especially for the URI networks. II network degree centrality ceases to be significant, likely due to the decreased number of observations after averaging the variables. Figure 7 graphically illustrates the change in the effect estimates over different model specifications. The lines, shaped by the estimated coefficients, describe the effect of degree centrality and structure on city innovation. The effect size noticeably declines as we use more robust estimation models and focus on the within variation. Despite these changes, the degree centrality and structural holes variables for the II network maintain their positive coefficients.

We have estimated multiple empirical models using panel regressions. Now the question boils down to which model—random- or fixed-effects—we should give credence to. There exists a trade-off between fixed and random effects. On the one hand, fixed-effects models are considered a more robust inference method—unlike the random-effects model, which assumes zero correlation between the city-specific parameter α_i in Equation (1) and the network position. On the other hand, the fixed-effects model fails to account for between-city variation and only explains within-city variation (Schunck and Perales, 2017). The random-effects estimator partially accounts for between-city variation because it uses a matrix-weighted average of the fixed-effects and between estimator (Hausman and Taylor, 1981; Baltagi, 2008). Moreover, the random-effects model appears to be the favored specification among social network studies using panel regression methods (Ferriani et al., 2009; Guan et al., 2015, 2016; Guan and Liu, 2016). However, we conduct a Hausman test on the linear specifications, and it suggests that the assumption underpinning the

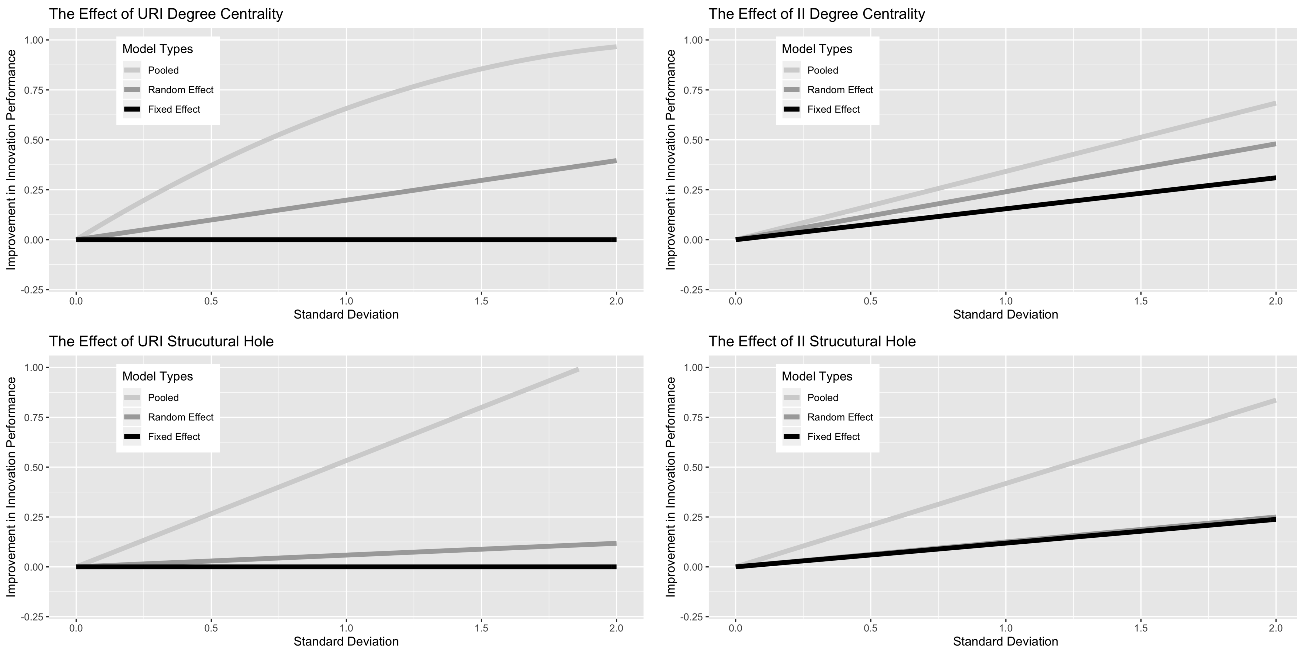

Figure 7: Effect of Changing Network Centrality on Urban Innovation

random-effects model is not satisfied. Despite this difference, both models prove the significant effect of degree centrality and structural holes on city innovation in the II network, thereby confirming Hypotheses 1a and 2. From the fixed-effects model, one-standard-deviation increases in the II degree centrality and structural holes increase city innovation by 14.6% and 11%, respectively. From the random-effects model, a one-standard-deviation increase in degree centrality in both networks increases city innovation by approximately 20%, and a one-standard-deviation improvement in the bridging of structural holes increases innovation by 6% to 11%.

6 Conclusion and Implications

Despite growing research on collaborative innovation networks due to the importance of innovation cooperation and teamwork in national innovation systems, little effort has been made to conduct network studies using cities as nodes, relative to an abundance of literature using individuals, organizations, provinces, and countries as nodes. This study fills this gap and argues that cities thrive in terms of innovation if they can draw resources from extralocal interactions. We investigate the effect of structural embeddedness in extralocal interactions on city innovation using social network theory. In addition, the existing literature largely centers on developed countries using USPTO or EPO patent data, which fail to capture the significance of recent innovation advances in China. In this research, we use a comprehensive data set on SIPO patents granted from 2001 to 2016 to study intercity innovation networks in China. We document the rapid evolution of the intercity R&D collaboration system from an initially sparse network into a full-blown complex network over the last 16 years and describe six major features of the structure and evolution of this network in China during that period. Furthermore, we examine how extralocal interactions affect city innovation by investigating the role of each city's network structure in facilitating its own innovation. Using various panel regression model specifications, we find evidence to support our arguments, with features of network structure such as degree centrality and structural holes positively affecting innovation in cities.

We contribute to the empirical study of extralocal interactions by conducting empirical analysis and estimating regressions with network positions as the independent variables. The bulk of empirical social network studies implicitly assumed the exogeneity of network positions and thus inferred a causal relationship for such effects (Phelps et al., 2012). However, observational data are often subject to severe barriers to causal inference (Gangl, 2010). One major problem arises from the assumption that unobserved individual-level heterogeneity is not correlated with independent variables (in our case network position), which often does not hold in the real world (Phelps et al., 2012). To tease out the unobserved individual-level heterogeneity, it is necessary to apply panel regression methods and use panel data with observations of the same individual over multiple periods. However, Phelps et al. (2012) pointed out in their survey that only 35% of network studies used panel data, that only half of those utilized panel regression estimations and that almost all interpersonal network research used cross-sectional variation. Such cross-sectional studies also include recent studies, such as those by Guan et al. (2017) and Li et al. (2019). Many studies using longitudinal data applied random effects in panel regression models (Ferriani et al., 2009; Guan et al., 2015, 2016; Guan and Liu, 2016), and a few used fixed-effects models (Yan and Guan, 2018). We have compared the regression results of multiple model specifications. The pooled and between models generate results that differ extensively from the estimates produced by the random- and fixed-effects models, suggesting that the cross-sectional variation is insufficient to allow for rigorous causal inferences. Furthermore, for network studies that address higher-level nodes, such as cities, regions, and countries, a fixed-effects model might be more appropriate to account for unobserved individual heterogeneity because compared to individuals and organizations, geographical areas contain more unobserved characteristics that persist through time. Therefore, we argue that future studies should use panel regressions and especially the fixed-effects model to better identify a causal effect of network structures and positions.

6.1 Theoretical Implications

Our findings have some major theoretical implications. First, our study contributes to the existing cities and innovation literature by identifying the structure and dynamics of China's intercity innovation collaboration network. Our research supports the argument that innovation is not entirely endogenous to cities and that extralocal interactions are just as powerful as local interactions in stimulating innovation in cities that are part of innovation networks. We particularly theorize and confirm that cities are more able to capitalize on the benefits of extralocal interactions when they have higher degree centrality and when they fill larger structural holes. Such cities should thus have higher innovative capacities and perform better in terms of innovation. The evidence clearly lends support to the argument that proximity needs to be understood in a sociological rather than a geographic sense (Granovetter, 1985; Boschma, 2005; Shearmur, 2012). We also predict positive effects on city innovation of closeness centrality and the cluster coefficients of cities in extralocal interactions but find little evidence to support these arguments. Future studies may investigate the effects of these network properties on innovation in cities in other research contexts to generalize the research findings.

Second, we contribute to the theoretical discourse by introducing the division between URI and II collaboration types. The literature has used patent collaborations to represent connections in a network without considering the type of interorganizational collaborators. Research and development collaboration involved with universities and research institutes differs from that between firms in various ways, including the knowledge base, conduciveness for knowledge transfer, and other aspects that impact information flows between cities. Our descriptive statistics document the rapid growth of collaboration for copatenting; in addition, the relative share of URI collaboration compared to II collaboration declines over the whole period. We carry out empirical network analysis on the intercity system considering both URI and II networks and compare how network positions in the two types of networks affect city innovation. Our comparison yields mixed interpretations. The pooled and between estimators suggest that the URI network effects are greater than the II network effects. The random-effects model reports a modest difference between the two. The fixed-effects model shows that only in II networks do the degree centrality and structural holes variables improve city innovation. We conclude that at least for the within variation, the effect size is greater in the II network than in the URI network. In other words, for a city, being able to increase its central position in the II network makes it more innovative, but this is not the case for the URI network. Using rigorous and robust methods, we establish the causal linkage for the II network.

Third, our results suggest that indirect ties, namely, closeness centrality and the clustering coefficient within the city network, are not as important as direct ties, such as degree centrality. Indirect ties might play an important role in interpersonal networks in that one can easily approach a friend's friends (Zuo et al., 2014; Marineau et al., 2016) or in that the cohesiveness of a team can impact everyone (Uzzi and Spiro, 2005). However, intercity linkages do not work like personal social ties. It is difficult for a city to access knowledge and innovation resources through an indirect tie the way an individual might ask for a favor from a friend's friend. A city is a large, internally complex, and spatially distributed collective rather than a simple and unitary actor (Phelps et al., 2012). Thus, networks of different levels are unlikely to be isomorphic to each other, especially when high-level nodes such as cities and countries are considered. Due to this limited isomorphism and the lack of studies on intercity innovation networks, we propose that more innovation studies should be conducted at the city level to examine the network structure properties of innovation networks.

6.2 Practical Implications

We find that a high degree of extralocation interaction, manifested by a central position in collaboration networks, facilitates the knowledge and information flows that are crucial for urban innovation. The implication for policymakers is to lower the costs and remove the barriers to intercity research collaborations and any other form of extralocal interaction. In particular, policymakers should encourage local firms in their cities to increase their ability to absorb and transfer technology inflows as well as develop an effective collaborative strategy to occupy central places and span structural holes within the intercity network. Additionally, effective endeavors include building telecommunication and transportation infrastructures to better connect cities, providing financial subsidies for intercity R&D collaboration, especially for smaller cities that lack internal resources, and attracting subsidiary companies owned by major innovative corporations, because organizational proximity is conducive to collaboration and knowledge transfer.

6.3 Limitations

This study has several limitations. First, patent data may not necessarily be a perfect indicator of innovation in cities. For example, Acs et al.'s (2002) research finds that patents offer a relatively accurate assessment of the geography of product innovation across US metropolitan areas (MSAs) but are less valid for smaller cities or nonurban areas and for other types of economic innovation. Furthermore, invention patents only record major product innovations and do not document incremental innovations (Acs et al., 2002); patents may record new ideas that some large firms have no intention of bringing to market (Heller, 2008); and some smaller firms may choose to rely on secrecy rather than publicize their inventions (Griliches, 1998). Second, the study does not consider innovation variables that are particular to the Chinese context. For instance, state-owned enterprises (SOEs), informal guanxi networks, and province-specific innovation policies all play an important role in the Chinese economy and innovation. Third, a multilevel network analysis at the organization, city, and province levels might reveal deeper insights into the effects of innovation networks on innovation in cities.

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