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Drivers for Inter-city Innovation Networks Across Chinese Cities: Modelling Physical Versus Intangible Effects

GAO Yujie[1], SCHERNGELL Thomas[2], NEULÄNDTNER Martina[2]

(1. *School of Applied Economics*, *Renmin University of China*, *Beijing* 100872, *China*; 2. *Center for Innovation Systems & Policy*, *Austrian Institute of Technology*, *Vienna* 1210, *Austria*)

Abstract: Cross-region innovation is widely recognized as an important source of the long-term regional innovation capacity. In the recent past, a growing number of studies has investigated the network structure and mechanisms of cross-region innovation collaboration in various contexts. However, existing research mainly focuses on physical effects, such as geographical distance and high-speed railway connections. These studies ignore the intangible drivers in a changing environment, the more digitalized economy and the increasingly solidified innovation network structure. Thus, the focus of this study is on estimating determinants of innovation networks, especially on intangible drivers, which have been largely neglected so far. Using city-level data of Chinese patents (excluding Hong Kong, Macao, and Taiwan Province of China), we trace innovation networks across Chinese cities over a long period of time. By integrating a measure on Information and Communications Technology (ICT) development gap and network structural effects into the general proximity framework, this paper explores the changing mechanisms of Chinese innovation networks from a new perspective. The results show that the structure of cross-region innovation networks has changed in China. As mechanisms behind this development, the results confirm the increasingly important role of intangible drivers in Chinese inter-city innovation collaboration when controlling for effects of physical proximity, such as geographical distance. Since digitalization and coordinated development are the mainstream trends in China and other developing countries, these countries' inter-city innovation collaboration patterns will witness dramatic changes under the influence of intangible drivers.

Keywords: inter-city innovation network; co-patents; information and communications technology development; network structural effect; spatial interaction model; China

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1 Introduction

Cross-region collaboration in innovation activities plays an important role in providing complementary knowledge and promoting knowledge transmission (Morrison et al., 2013; Grillitsch and Nilsson, 2015). It is crucial to avoid regional lock-in and maintain innovation vitality (Boschma, 2005). Previous work has evidenced its positive effect on improving regional innovation ability and innovation efficiency, in particular in times of rising costs for innovation, increasing uncertainty and risks, and rapidly changing global demand patterns (Maggioni et al., 2007; Broekel, 2012; Breschi and Lenzi, 2016; De Noni et al., 2017). Therefore, identifying drivers for cross-region interactions in innovation activities has become one of the main research issues, not only in the scientific context but also in the policy realm (Scherngell, 2021).

For instance, as the innovation policy in the European Union attaches high importance to coordinated know-

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Corresponding author: SCHERNGELL Thomas. E-mail: thomas.scherngell@ait.ac.at

ledge creation (Hoekman et al., 2010), an increasing number of studies have focused on cross-region innovation networks in the EU (Scherngell and Lata, 2013). But, also for other countries, we can observe a growing interest in that direction, for example for China (Jiang et al., 2017) or for the US (Zhao and Isalam, 2017). Typically, empirical studies have utilized concepts and techniques from spatial interaction theory in order to explore drivers of cross-region innovation networks; often in relation to the proximity concept (Boschma, 2005). Here, special emphasis has been put on how different types of proximities, such as geographical proximity, but also technological, cultural, or institutional proximity, affect collaborations in innovation activities between actors located in different regions.

However, previous research only partially accounts for ongoing developments in innovation research, e.g., increasing digitalization. Moreover, some studies suffer from the usage of too rough spatial breakdowns for measuring innovation networks. This study intends to address this research gap by focusing on so far largely neglected drivers of innovation networks by shifting attention to the role of intangible effects, next to traditionally addressed geographical ones. By intangible drivers, we refer to physically ungraspable characteristics, such as network effects put forward by Neuländtner and Scherngell (2020), or effects related to the introduction of new digital technologies. Moreover, we focus on a very interesting geographical environment by directing our lens on China as a specifically attractive case, but as one of the first studies mobilizing spatially very detailed data at the level of Chinese cities, going beyond most previous works at the province level (Scherngell and Hu, 2011).

Accordingly, the objective of this study is to estimate drivers for inter-city innovation networks across Chinese cities, specifically shifting attention to the role of intangible effects related to networks and digitalization. As China aims to be an innovation powerhouse globally and has adopted a series of policies to promote cross-region innovation collaboration, it provides an ideal context for studying regional innovation collaboration in developing countries. In recent years, some researchers have chosen to study the structure and development of Chinese innovation networks at the province or city level, but not at a relational level between these spatial entities (Lu and Huang, 2012; Ma et al., 2015; Sun and Cao, 2015; Sun, 2016; Xie and Su, 2021; Yao and Li, 2022). However, only a few studies explored the determinants of cross-region innovation collaboration, usually just focusing on specific industries and regions (Ma et al., 2014; Li et al., 2015; Dong et al., 2021; Liu et al., 2021), lacking a city-level perspective (Scherngell and Hu, 2011; Pan et al., 2020), or ignoring the long-term evolvement of the mechanism (Jiang et al., 2017).

This study departs from existing literature in the following major aspects. First, we take a dynamic global perspective to reveal the mechanisms of forming a cross-region innovation collaboration network in China. We use the data at the city level and cover all regions and industries. By using cross-sectional network data of four separate periods, we are able to compare the effect change of different determinants over time. Second, this paper provides new insights into the mechanisms of innovation collaboration networks. We integrate two kinds of intangible drivers into the general research framework, which are ICT and a network structural effect. With this, we can make a more profound exploration to identify the mechanisms of Chinese innovation network evolution.

2 Hypotheses

In the study at hand, we shift attention to two types of intangible determinants for cross-region innovation networks, that is the development stage of a region in information and communication technologies (ICT) and network structural effects. The first intangible driver, ICT, refers to the ability to create technologies facilitating information sharing, information management and communication (Antonelli et al., 2000). The diffusion of ICT promotes the rise of all kinds of online platforms and forums, and increases the frequency of online conferences among geographically distant firms. All of these promote knowledge search and exchange in a new space, namely the virtual space, which facilitates the transmission of both codified and tacit knowledge (Malecki, 2017; Aslesen et al., 2019). Focal agents are able to enlarge the search range in the virtual space from their local region to a greater distance, with relatively low costs (Lyytinen et al., 2016). The reduction of search cost will improve agents' search capacity (Granstrand et al., 1997). Through frequent virtual interactions, agents have increased opportunities to encounter potential partners who possess complementary knowledge, at a lower communication cost and more information (Hancock and Dunham, 2001).

Except for the process of partner seeking, ICT also plays an essential role in facilitating innovation collaboration among remote distant partners. In this process, frequent face-to-face interaction is not needed for daily innovation activities. Constant virtual interaction becomes the main form of collaboration pattern for distant counterparts (Torre, 2011; Hu and Li, 2017). They can communicate via ICT about the regular progress of innovation, problems in technical details, suggestions for improvement and so on. Empirical studies have confirmed that individuals can generate new knowledge through virtual communications even in the absence of physical proximity (Grabher and Ibert, 2014). With the emergence of increasingly sophisticated ICT tools, the innovation process undergoes significant transformation, resulting in a substantial enhancement in the efficiency of distant innovation collaboration (Gassmann, 2006; Marion and Fixson, 2021). Therefore, we propose the following hypothesis:

Hypothesis 1a: *A higher development of ICT in two cities positively affects their collaboration intensity in innovation activities.*

While the recent ICT revolution greatly accelerates ICT development, it is accompanied by a large ICT gap between cities (Song et al., 2020). China has experienced major ICT developments in recent years. At the same time, there exists a large digital divide among cities because of uneven ICT development. The unbalanced development of ICT leads to resource reallocation, enhancing geographical disparities. Recent studies have found that a gap in ICT development enlarges social and economic inequalities (Tewathia et al., 2020; Wang D et al., 2021). Cities with advanced ICT attract more innovation resources inflow, while cities with insufficient ICT development face the dilemma of innovation resources outflow. As ICT-based interaction is the main communication pattern for distant innovation collaboration, agents will take ICT development into consideration when they select partners. If an agent is located in a city with high-level ICT development, it would prefer to choose partners from cities with good ICT conditions. Similar ICT usage habits and levels of ICT dependency level facilitate effective communication patterns among partners. Consequently, cities with comparable levels of ICT development are more likely to establish collaboration relationships. Concerning the gap in ICT development, we propose the following hypothesis:

Hypothesis 1b: *The gap in ICT development between cities will decrease their innovation collaboration possibility.*

As second set of intangible drivers we include is network structural effect. Most existing studies only take exogenous factors into account, ignoring endogenous mechanisms of network evolution (Glückler, 2007). In fact, the present network is also a significant driver of its own evolution (Ter Wal and Boschma, 2009). However, there are limited studies examining the network structural effect empirically. By using European co-publications (Bergé, 2017) and data on European Framework Programmes (Neuländtner and Scherngell, 2020), these studies have confirmed that the similarity of two nodes' network structural characteristics is positively related to their collaboration possibility. Compared with Europe, China is still in the early stages of cross-region innovation collaboration. The large differences in the nodes' structural characteristics in China may result in entirely different network structural effects. This makes it particularly fruitful to consider network structural effects as another intangible driver to analyze the determinants of Chinese innovation networks.

Preferential attachment is another key mechanism of network evolution and development (Barabási and Albert, 1999). It indicates that new actors tend to collaborate with existing well-connected actors; in other words, they tend to collaborate with actors who occupy central network positions. Previous studies have empirically confirmed the existence of preferential attachment in innovation collaboration networks (Newman, 2001; Li et al., 2015; Sun and Liu, 2016; Zhang et al., 2018). In inter-city innovation networks, cities can benefit from connecting with other cities that feature a high number of collaborations in the following aspects. First, such cities are likely to have abundant access to external knowledge components and other resources. By connecting with strongly networked cities, peripheral cities gain opportunities to establish new links with more cities in the future (Bergé, 2017). Second, collaboration inherently involves uncertainty and requires mutual trust (Dodgson, 1993). Active participation in collaboration enhances a city's reputation in this respect (Gu and Lu, 2014). Collaboration with such reputable cities can reduce opportunistic behavior and decrease uncertainty (Fritsch and Kudic, 2016). These considerations lead to the following hypothesis:

Hypothesis 2: *The gap in individual network centralities positively affects innovation collaboration between cities.*

3 Methodology

3.1 Data and construction of the innovation networks

Patent application data are widely used to measure regional innovation (Acs et al., 2002; Dang and Motohashi, 2015) and to reflect cross-region innovation collaboration linkages (Xie and Su, 2021) because of its advantages in publicly accessing detailed and timely innovation information. In this study, we use invention patent application data collected from the Chinese Patent Office (SIPO) to analyze the structure of the innovation collaboration network and the corresponding mechanisms. We exclude utility model patents and design patents, because an invention patent has stricter requirements to be granted and has a higher value; hence, it can act as a better indicator of innovation.

Referring to the general practice of existing research, this paper uses the co-assignee relationship to build the network (Sun and Cao, 2015; Sun, 2016; Pan et al., 2020; Xie and Su, 2021; Hanley et al., 2022; Yao and Li, 2022). The procedure of data screening and processing is as follows. First, we retain jointly applied patents that have two or more assignees. Second, we exclude patents with individual assignees. Third, through the Baidu map application programming interface (API), we obtain the address information of each assignee based on their respective names. Lastly, we allocate patent applications to cities, while excluding patents with assignees from non-mainland China and non-prefecture level cities.

With the cleaned Chinese patent database (excluding Hong Kong, Macao, and Taiwan Province of China), we obtain detailed patent application and geographical information from 297 prefecture-level cities and above spanning from 2007 to 2018. So that, we can construct inter-city innovation networks. Specifically, if assignees of a patent are located in different cities, then this patent generates one innovation collaboration linkage between the corresponding city pairs. After repeating this process for all patents, we aggregate all linkages reflected by each patent, and construct city-by-city innovation collaboration intensity matrices every year. Besides, in order to reflect the dynamic mechanism of innovation collaboration and reduce the impact of patent application data fluctuation, we divide the whole period into four subperiods (3-year time window), 2007–2009, 2010–2012, 2013–2015, 2016–2018. Therefore, we have four 297 × 297 matrices for each period, with each element y_{ij} representing the collaboration intensity between city i and city j in the corresponding period.

3.2 The spatial interaction model

A spatial interaction model is generally used to study the determinants of innovation networks (Scherngell and Hu, 2011; Scherngell and Lata, 2013). Based on the typical setting, we introduce two intangible drivers into the model in the following way. First, we introduce an ICT development variable as mass terms into the basic model. Concerning unbalanced ICT development, we further include the ICT gap as a separation variable in the above model. As for the network structural effect, following the estimation strategy in Neuländtner and Scherngell (2020), we include the gap between two nodes' centrality indicators as separation variables. Finally, we adopt the regression model as Eq. (1):

$$Y_{ij} = O_i^{\alpha_1} D_j^{\alpha_2} \exp\left[\sum_{k=1}^{K} \beta_k S_{ij}^{(k)}\right] + \varepsilon_{ij} \quad (1)$$

where Y_{ij} represents the collaboration intensity between city i and city j (i, j = 1, …, 297), which is measured by the number of co-patents between two cities. O_i and D_j are origin and destination variables, being either ICT development or the number of patents; α_1 and α_2 are the estimated coefficients. $S_{ij}^{(k)}$ denotes k separation variables, including the gap of ICT, the gap of nodes' centrality indicators, and other variables measuring different proximity mechanisms. Finally, β_k is the corresponding separation effect parameter, and ε_{ij} is the error term. The detailed definition of the variables can be found in section 3.3.

The model applied in this study takes the specific form of a negative binomial spatial interaction model (Scherngell and Barber, 2009). The main motivation for this is given by the true integer nature and distributional assumptions of the dependent variable, namely cross-city innovation collaborations, i.e., co-patents. Further, the proposed model specification accounts for a high degree of variation (overdispersion) and a large number of zero counts problems. Hence, it is assumed that the dependent variable Y_{ij} follows a negative binomial distribution with expected values as specified in Eq. (2). Compared with the standard Poisson specification that assumes equidispersion (i.e., the conditional mean equals the conditional variance), the negative binomial model explicitly corrects for overdispersion by adding a dispersion parameter. Hence, the negative binomial spatial interaction model takes the following form (Long and Freese, 2006):

$$\Pr\left(Y_{ij} = y_{ij} \middle| \mu_{ij}, \gamma\right) = \frac{\Gamma\left(y_{ij} + \theta\right)}{\Gamma\left(y_{ij} + 1\right)\Gamma(\theta)} \left(\frac{\theta}{\theta + \mu_{ij}}\right)^{\theta} \left(\frac{\mu_{ij}}{\theta + \mu_{ij}}\right)^{y_{ij}} \quad (2)$$

where $\mu_{ij} = E\left[y_{ij} \middle| O_i, D_j, S_{ij}\right] = \exp\left[O_i(\alpha_1) D_j(\alpha_2) S_{ij}(\beta)\right]$. y_{ij} is the observed links between city i and city j. Γ represents the gamma function with a model parameter θ accounting for overdispersion in predictors (Cameron and Trivedi, 1998). Since the dependent variable does not satisfy an independent and normal distribution, we use the Maximum Likelihood (ML) estimation method to estimate the parameters of the model (Cameron and Trivedi, 1998; Neuländtner and Scherngell, 2020).

3.3 Variables

3.3.1 Intangible separation variables

ICT gap $S_{ij}^{(1)}$. Previous studies used various indicators to measure ICT development; for city-level studies, the most often used indicators include internet-broadband, fixed phone, mobile phone, and telecom business revenue. Considering data availability and representativeness at the city level, we select four indicators in this paper: internet-broadband subscriptions (per 100 residents), mobile-cellular telephone subscriptions (per 100 residents), the ratio of telecom business revenue to GDP, and the number of internet access ports (per 100 residents). The first three indicators are primarily associated with communication needs, and the last indicator more accurately reflects the actual supply of internet infrastructure. As internet access port data are only available at the provincial level, we refer to Shen et al. (2023) to disaggregate the data at the city level. Based on the assumption that the distribution of ICT employment in each province is consistent with the distribution of internet access ports, we divide the total number of internet access ports at the city level based on the share of ICT employment in each city in the whole province. Then we employ the principal component analysis method to construct an integrated ICT development index. This method is widely used to construct composite indexes across various research fields (Singh et al., 2009; Démurger and Fournier, 2011; Lu and Huang, 2012). It can overcome the difficulty of reducing data dimensionality by extracting crucial factors from a set of inter-correlated variables (Wold et al., 1987; Abdi and Williams, 2010). For the construction of the gap, we divide the integrated ICT development index into four levels by each period's quantile. If two cities do not belong to the same quantile group, then this variable is equal to 1, and 0 otherwise.

Gap in individual network centralities $S_{ij}^{(2)}$. Following the work of Neuländtner and Scherngell (2020), we use the gap in degree centralities to estimate a network structural effect. The degree centralities are calculated from differences in collaboration links based on accumulated network data. Considering that cross-city innovation collaborations were infrequent in earlier periods, the accumulated network is constructed beginning in 2001. To mitigate concerns regarding endogeneity, the variable is measured with a one-period lag. For example, for the period 2008–2010, the data used to calculate degree centrality is from 2001 to 2007.

3.3.2 Physical separation variables

Geographical distance $S_{ij}^{(3)}$. We use the Euclidean great circle distance between the geometric centers of two cities to measure geographical distance. Note that, intra-city distances are not set to zero; rather, they are measured as two-thirds of the radius of a presumed circular with the same area as the city (Scherngell, 2021).

Same province dummy $S_{ij}^{(4)}$. Cities in the same province share similar behavior rules and values, resulting in relatively low communication costs between them. More importantly, there exists long-term local protectionism in China, where provincial government implement policies to prevent scarce resource outflows and restrict cross-province trade to protect local industries' development. Thus, firms in different cities are less likely to seek innovation partners in other provinces. We add the same province variable into the basic model, which takes the value of 1 if two cities belong to the same province, and 0 otherwise.

High-speed railway dummy $S_{ij}^{(5)}$. If two cities are connected directly by high-speed railway (HSR) without any transfer, then the variable takes the value of 1, and 0 otherwise. The data of HSR routine and operating information are manually collected from official new sources and the China railway online booking website 12306.cn, which is governed by the National Railway Administration of China.

Technological distance $S_{ij}^{(6)}$. Following the work of Scherngell and Hu (2011) among others, we control for the technological distance between cities to isolate technological effects from geographical effects. It is measured as $1–r^2$, where r equals the Pearson correlation coefficient between two cities' technological space vectors $t(i)$ and $t(j)$. For instance, the technological space vector $t(i)$ is measured by the share of patents in IPC subclass K in city i relative to the total number of patents in city i from 1995 until the end of the studied period t. Technological domains are proxied by two-digit level IPC technological classes.

3.3.3 Mass terms

As mass terms (O_i and D_j), we use the number of patent applications in the respective origin and destination cities (Montobbio and Sterzi, 2013; Marek et al., 2017). This variable represents cities' innovation ability and affects the possibility of participating in innovation collaboration. Besides, according to related literature, we introduce the ICT development variable as mass terms into the basic model (Rodríguez-Crespo and Martínez-Zarzoso, 2019; Wang and Choi, 2019). This variable is measured as previously described and takes the normalized value.

All the variables take log transformation, except for the binary variables. Descriptive statistics and correlation analysis of these variables are reported in Table S3 in Appendix. The correlation coefficients between different independent variables are low in general.

4 Results

4.1 Overall network evolution

The overall network characteristics of the four periods are represented in Table 1. At first glance, the indicators show that the innovation network has changed dramatically during the study period; it has become denser and more integrated. First, an increasing number of cities have begun to construct innovation connections with others. Particularly, in the last period, all cities have integrated into the whole innovation network. It means that peripheral cities have greater innovation demand and more opportunities or channels to connect with other cities. Second, the number of city pairs with positive innovation links has notably increased from 3086 in the first period to 9934 in the last period. As a result, the average distance decreased to below 2, implying that any city needs only one node to connect with any other city. From this trend, we can learn that innovation interaction does not only occur between core cities but also between peripheral cities and other cities.

Despite the increasing density of the innovation network, the trend of an extremely unbalanced distribution of collaboration intensity remains unchanged. As shown in the appendix (Table S1), the Gini index, a measure of inequality in collaboration intensity, is relatively high and has increased during the study period. Considering city pairs that have no collaboration, the inequality of collaboration is even more pronounced, with a Gini index of 0.98 for the whole study period. Table S2 provides a more detailed description of the uneven dis-

Table 1 Overall network characteristics of the inter-city network in China from 2007 to 2018

Period	Number of nodes	Sum of edges	Average distance	Network density	Average degree
2007–2009	256	3086	2.279	0.047	12.008
2010–2012	288	5368	2.069	0.065	18.639
2013–2015	294	7566	1.950	0.088	25.795
2016–2018	297	9934	1.918	0.114	33.541

Notes: The number of total city pairs is 43 956 (297 × 296/2). Number of nodes means numbers of cities that participate in the inter-city innovation networks. Sum of edges means the number of city-pairs that has innovation collaboration. Average distance is defined as the mean value of the distance between all pairs of nodes, the distance is the number of edges along the shortest path connecting any two nodes. Network density is defined as the portion of potential direct links within the innovation network that are actually linked. Average degree simply defined as the mean of all individual degrees. Wasserman and Faust (1994) for details on the formal specification of the measures tribution. It further reveals that most city pairs collaborate less than ten times in each period, whereas the most connected city pair has more than 1000 collaborations.

The inequality of innovation collaboration is also reflected in Fig. 1, which shows the spatial distribution of the degree centrality of China's inter-city innovation network. The degree centrality measures the number of cities that a city has direct links to. As we can see, considerable disparities exist between different cities' degree centralities. In the first period, most cities collaborated only with fewer than ten cities, while Beijing and Shanghai have each established relationships with 177 and 124 cities independently. In particular, Beijing has dominated the innovation network during the whole period; its degree centrality has increased to 279 in the last period. Nevertheless, the figure also reveals that Beijing's dominant position has weakened over time, as all cities were able to collaborate more with other cities. From 2016 to 2018, over 85% of cities had direct links with more than ten cities, with the majority of provin-

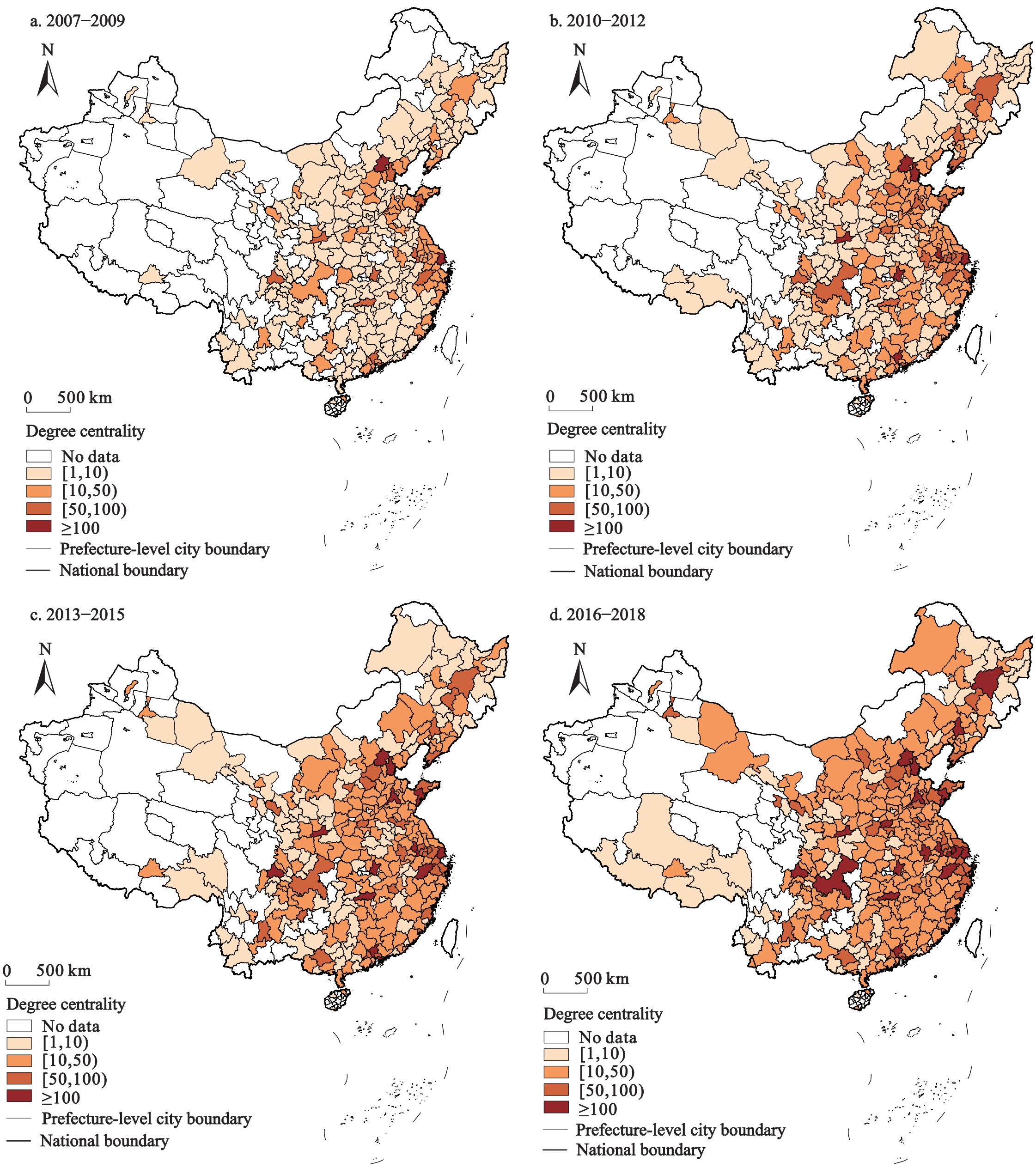

Fig. 1 Spatial distribution of degree centrality of inter-city innovation network in China. Based on the standard map service website of the Ministry of Natural Resources with the approval number GS (2019) 1822, and the boundary of the base map has not been modified

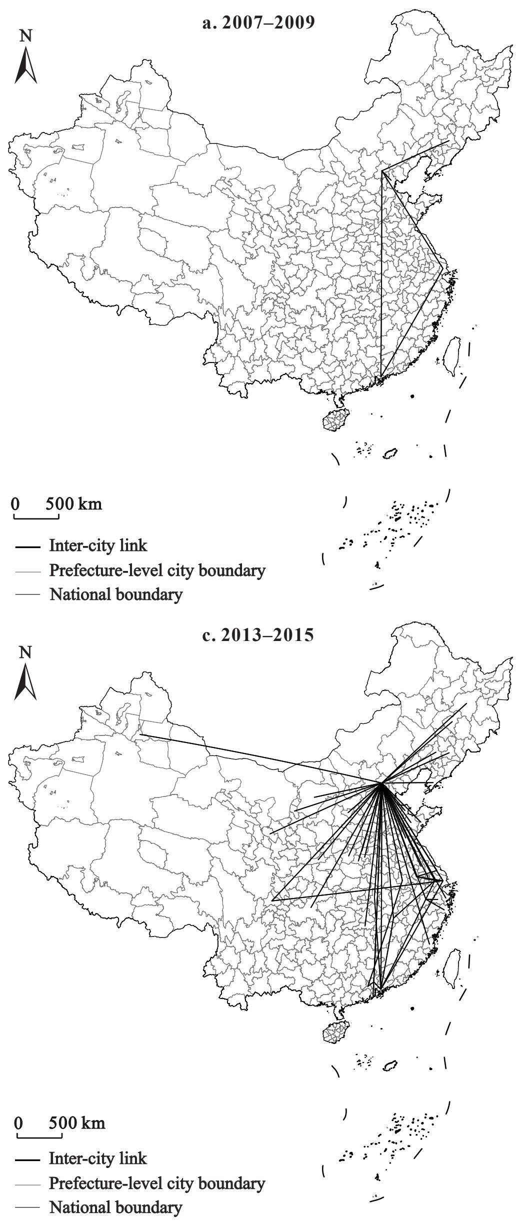

Fig. 2 Spatial structure of inter-city innovation network in China. In order to visualize the network structure more clearly, we only include city pairs with more than 300 collaborations. Based on the standard map service website of the Ministry of Natural Resources with the approval number GS (2019) 1822, and the boundary of the base map has not been modified

cial capital cities and coastal cities (such as Tianjin, Qingdao, Suzhou, and Wuxi) have more than 100 innovation partner cities. Consequently, the Gini index of degree centrality decreased obviously from 0.67 to 0.52, indicating a narrowing gap in degree centrality between cities.

Fig. 2 illustrates significant inter-city links in the innovation network. It is evident that the structure of the major innovation network is different in the first two periods and the last period. From 2007 to 2012, connections between most cities were very weak. Several cities located in Beijing-Tianjin-Hebei Region, Yangtze River Delta, and Pearl River Delta are main players in inter-city innovation. These cities overcome long-distance barriers and form a triangle structure of innovation connection in eastern China. Since 2012, the major

Table 2 Estimation results of the spatial interaction model

	2007–2009		2010–2012		2013–2015		2016–2018	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Origin and destination variables								
Number of patents	0.986***	0.850***	0.956***	0.700***	1.004***	0.717***	0.691***	0.476***
	(0.0149)	(0.0197)	(0.0125)	(0.0152)	(0.0111)	(0.0129)	(0.00769)	(0.00727)
ICT development stage		0.339***		0.672***		0.988***		2.072***
		(0.0559)		(0.0547)		(0.0533)		(0.0491)
Separation variables								
Geographical distance	−0.482***	−0.492***	−0.500***	−0.548***	−0.583***	−0.689***	−0.523***	−0.700***
	(0.0484)	(0.0488)	(0.0405)	(0.0402)	(0.0373)	(0.0376)	(0.0326)	(0.0335)
Same province	1.616***	1.588***	1.661***	1.627***	1.812***	1.585***	1.721***	1.414***
	(0.116)	(0.117)	(0.101)	(0.101)	(0.101)	(0.0977)	(0.0970)	(0.0875)
High speed railway	0.316	0.300	0.223**	0.272***	0.373***	0.356***	1.074***	0.607***
	(0.230)	(0.223)	(0.106)	(0.0999)	(0.0915)	(0.0843)	(0.0861)	(0.0792)
Gap in ICT development		0.0816		−0.101*		−0.178***		−0.224***
		(0.0769)		(0.0593)		(0.0529)		(0.0469)
Gap in degree centrality		0.230***		0.428***		0.423***		0.429***
		(0.0208)		(0.0218)		(0.0208)		(0.0174)
Technological distance	−0.177***	−0.338***	−0.180***	−0.475***	−0.170***	−0.467***	−0.562***	−0.558***
	(0.0125)	(0.0192)	(0.0118)	(0.0185)	(0.0117)	(0.0184)	(0.0185)	(0.0177)
Constant	−11.94***	−9.557***	−11.80***	−7.298***	−12.60***	−6.574***	−8.723***	−1.394***
	(0.388)	(0.559)	(0.329)	(0.450)	(0.305)	(0.407)	(0.261)	(0.305)
Dispersion (θ)	0.436***	0.333***	1.032***	0.790***	1.373***	1.126***	1.791***	1.351***
	(0.0493)	(0.0506)	(0.0318)	(0.0343)	(0.0242)	(0.0258)	(0.0208)	(0.0215)
Likelihood ratio test	−4711.48	−4588.40	−9450.20	−9044.09	−14665.76	−14025.33	−21515.19	−19318.69
Observations	43956	41905	43956	41905	43956	41905	43956	41905

Notes: several cities in Tibet Autonomous Region and Hainan Province lack ICT infrastructure data (not including Hong Kong, Macao, and Taiwan Province of China). The number of cities included is 289. The sample of every period is (289 × 288)/2 + 289 = 41905. All the variables take log transformation, except binary variables. Standard errors are given in parentheses

network structure has undergone dramatic changes. First, an increasing number of cities participate in collaborations with Beijing, including not only the capital cities of the province but also some peripheral cities (such as Pingdingshan city in Henan Province) and its surrounding cities (such as Langfang City belongs to Beijing-Tianjin-Hebei region). Second, there are strong connections over short distances. Cities within the Yangtze River Delta and Pearl River Delta have begun to establish strong inter-city connections, consistent with the findings of Wang Yue et al. (2021). Third, the main innovation channels exhibit a diamond-shaped structure. Chengdu and Chongqing in the western region become a new vertex in the network, although this vertex's connection to others is still weak.

4.2 Estimation results

Table 2 presents the regression results for the different periods. The first column of each period is the estimation results for the basic model, which includes the number of patent applications, geographical distance, technological distance, the same province dummy, and the HSR dummy. The second column of each period presents the results of the basic model augmented by two intangible drivers. As can be observed, the direction and significance of all variables in the basic model do not change after including new additional variables. The robust regression results indicate that adding two intangible drivers is reasonable and helps explain the formation of the innovation network. We first pay attention to the effects of the intangible drivers, and then compare the changes in the impact of the physical separation variables on the innovation network's evolution.

4.2.1 Effects of intangible drivers

Turning to intangible effects, which is the primary focus of this study, we can indeed identify a statistically significant effect for intangible variables; and this effect tends to increase in magnitude over time. Strikingly, ICT development is highly significant; when two cities exhibit high development in ICT endowment, their collaboration intensity is likely to increase. This effect grows rapidly over the observed period, clearly outpacing the effects of the pure number of patents in a city. During the period from 2007 to 2009, according to column (2), a 1% increase in ICT is associated with a 0.34% increase in innovation collaboration. For the period from 2016 to 2018, the results in column (8) show that a 1% increase in ICT is associated with a 2.07% increase in innovation collaboration. The impact of ICT has grown above five times during the study period. The increasing trend of the ICT effect is consistent with our expectations. On the one hand, ICT development has experienced rapid growth in recent years. Under the implementation of policies such as the national broadband plan, the average value of the integrated ICT index in the last period is nearly three times that of the first period. Thus, the impact of ICT is enhanced with rapid ICT diffusion. On the other hand, agents need time to adapt to virtual interaction facilitated by ICT. As time passes, the penetration of ICT in daily work promotes greater acceptance of collaboration with increasing ICT participation. In addition, our result is in line with Wang and Choi (2019), who found an increasing effect of ICT on BRICS countries' international trade.

Accompanied by the positive effect of ICT, the ICT gap is confirmed to have a negative effect on innovation collaboration. Although this effect was not significant in the first period, it increased moderately in the following period. To analyze the changing impact of the ICT gap on innovation collaboration, we depict the spatial distribution of ICT development for different periods in the appendix (Fig. S1). It is evident that for the first period, most cities' ICT development is at a low level, and the ICT gap is relatively small. More than 80% of the cities have ICT index values below 0.2, and the highest value of the ICT index (Shenzhen) is only 0.41. Hence, the ICT gap is unlikely to exert an impact on innovation collaboration. Later, spatial differences in ICT development began to emerge. From 2010 to 2012, the ICT of coastal cities developed rapidly, with nearly 8% of cities' ICT values exceeding 0.3. In cities like Shenzhen, Hangzhou, Guangzhou, Beijing, and Zhuhai, the ICT index values already exceed 0.4. Significant differences in ICT promote agents to consider ICT similarities when selecting potential partners. As a result, the ICT gap begins to take a negative effect. In the last period, the disparities in ICT development among cities became more evident. The ICT index values of 10 central cities of large metropolitan areas are larger than 0.6, almost twice the national average. At the same time, there are 12 other cities whose ICT index value was less than 0.2. Due to the enormous disparity, the results of the last period indicate that the ICT gap will decrease the possibility of collaboration by 20.07%. By this, hypotheses 1a and 1b are supported, ICT development promotes innovation collaboration with the negative effect of the ICT gap.

With respect to the gap in degree centralities, the results indicate that its effect on innovation collaboration is significantly positive for all periods. The interesting pattern points to a preferential attachment mechanism and a hup-and-spoke network structure, i.e. central hub regions tend to attach emerging peripheral regions trying to enter the network. This result contradicts existing research by Neuländtner and Scherngell (2020), which finds that regions in the European Union are more likely to collaborate with regions with a similar degree centrality. These results are related to the difference in regional innovation capacity disparity. With the implementation of regional integration and smart specialization policy in Europe, most of the regions have the ability to cultivate their specific innovation advantages, and the regional innovation gaps are narrowed according to the European Innovation Scoreboard. Thus, not only core regions, but also other regions that have similar innovation abilities can construct collaboration relationships in Europe. However, the situation in China is different. The distribution of regional innovation resources is seriously uneven, and regional innovation disparity continues to widen. It leads to the outcome that there is a slim possibility for peripheral cities to create useful innovation connections with other peripheral cities. Despite considerable improvement in overall innovation ability in recent years, most cities still prefer to collaborate with cities possessing high degree centrality, as these cities generally have a good reputation, strong innovation ability and wide external knowledge access.

4.2.2 Effects of physical drivers

As for the geographical distance, its effect on innovation collaboration is negative and significant for all periods. It means that distance is still a major barrier to affecting research collaboration. Interestingly, the negative effect is increasing over time. This result seems to contradict our expectations at first glance. However, some researchers have drawn similar conclusions. Ma et al. (2014) confirm that the effect of geographical distance on co-publication has been strengthened in the context of inter-city scientific collaboration in China. Additional research by Liu et al. (2021) has also found that the role of geographical proximity becomes more significant over time in the field of green innovation collaboration. This unusual trend probably can be explained by the following two folds. On the one hand, technology is more complex than before and physical communication for complex knowledge is more effective. More importantly, a large number of cities' innovation ability has been improved significantly since the implementation of the innovative city pilot policy in 2008. Not only big cities like Beijing, Shanghai, and other regional innovation core cities have strong innovation abilities, but less-favored cities also attach great importance to innovation ability cultivation. Thus, it is easier for agents to find partners in surrounding cities than before. After considering transportation and all other costs, agents usually choose partners to have shorter geographical distances. This explanation has also been confirmed in the above analysis of the evolvement of networks.

The estimate for the same province dummy variable indicates that, even when controlling for geographical distance, firms or institutions still have a strong tendency to collaborate with partners in the same province. Keeping all other variables constant, the possibility of collaboration in the same province is 4.11 to 5.09 times compared to cross-province collaboration. For instance, several cities in the Yangtze River Delta for instance, Nanjing (Jiangsu Province) and Hangzhou (Zhejiang Province) exhibit similar technological distance, innovation capacity, and geographical distance to Suzhou (Jiangsu Province); however, Suzhou's innovation collaboration intensity with Nanjing is almost ten times that with Hangzhou during the period from 2016 to 2018. This result has a high correlation with Chinese innovation policy. Although China has long promoted the establishment of industry-university-research institutions innovation system, what can not be neglected is that the local government is the actual executor and promoter (He, 2012). Due to long-standing regional protectionism, local governments encounter difficulties in breaking down administrative boundaries and establishing effective innovation platforms with other provinces (Dong et al., 2021). Most of the innovation collaboration policy aims to provide support for firms or institutions in the same province to maximize local benefit. Since the 18th National Congress of the Communist Party of China, the Chinese government has actively explored and achieved progress in establishing and improving regional cooperation. In 2016, the State Council of China issued the 'National Innovation-Driven Development Strategy Outline', which clearly proposed building a cross-province innovation network for national strategic regions. Subsequently, local authorities began implementing essential policy measures. For example, authorities from Shanghai, Jiangsu, Zhejiang, and Anhui provinces jointly signed a cooperation framework agreement to promote the construction of innovation networks in the Yangtze River Delta. The policy effect is reflected in our estimation, where the coefficient of the same province variable has slightly declined since 2013.

Consistent with previous studies, the construction of HSR has an obvious impact on innovation collaboration (Dong et al., 2020; Hanley et al., 2022; Yao and Li, 2022). Although this effect is not significant in the first period, it turns out to be positive and has an increasing trend in the subsequent period. The results confirm that the opening of HSR effectively reduces transportation costs and facilitates the flow of R&D personnel between cities. By this, the barrier caused by geographical distance can be relieved to a certain extent. In the period from 2016 to 2018, the estimates of the full model indicate that the possibility for cities connected by HSR to build innovation collaboration is approximately two times that of the other cities. Regarding the insignificant effect in the first period, it may be caused by the lag-behind effect. Moreover, the increasing trend of HSR is also confirmed in the work of Yao and Li (2022).

Technological distance is a control variable. The estimated coefficient of technological distance is negative and significant for all periods and reaches the largest value in the last period. This finding is in line with the work of Liu et al. (2021) which mainly focuses on green technology, and the study by Balland et al. (2013) which examines firms as the unit of analysis. The reason for the result may have been that increasing technological complexity makes it a better choice for a city to narrow its technology domain and cultivate innovation advantage in some specific fields. Thus, the importance of technological distance in inter-city collaboration has been enhanced over time.

5 Conclusions and Implications

Drivers for cross-regional innovation networks have gained increased interest in the recent past, not only from a scientific perspective, but also in the policy realm. This is, on the one hand, related to theoretical considerations and empirical insights describing collaboration as an essential impetus for successful innovation, and, on the other hand, to the increased availability of systematic data on such network arrangements in the innovation process. From a geographical perspective, specifically the collection of information on innovation networks at more detailed geographical breakdowns by massive geocoding of addresses of innovating actors has been of most crucial importance in this context.

This study aims to explore the role of intangible drivers, specifically focusing on ICT and network structural effects, in the formation of an inter-city innovation network. We shift our attention to China, one of the most interesting areas of study in this respect, not only because few works exist in general, but also because of increasing policy efforts to support cross-region networks in order to promote more cohesive development across China in the future. While many previous works just go down to the province level, we have mobilized original data on inter-city innovation networks reflected in co-patents collected for the time period 2007–2018 between 297 prefecture-level cities. A network analytical approach has been put forward to characterize and explore the evolution of the innovation networks from a descriptive perspective, while we specify negative binomial spatial interaction models to estimate the relationship between the observed collaboration intensity and intangible characteristics of the cities, most importantly the differing and dynamic ICT development stages of the cities, but also their positioning in the network as a whole refers to network structural effects.

The results are promising, both in enriching the existing literature investigating drivers of innovation networks, but also in a Chinese innovation policy context. First, we can indeed identify a statistically significant effect of intangible separation variables, and this effect tends to increase over time in magnitude. Second, results show that a higher ICT development gap among cities has a significant negative effect on their collaboration probability, while the ICT development stage itself plays a very crucial role in promoting cross-region innovation collaboration. Third, the effect of the ICT development stage strongly grows over time, clearly outpacing the effects of the pure number of patents in a city. Fourth, the study points to some mechanisms of preferential attachment in terms of network structural effects; the gap in degree centrality positively influences the networking probability between two cities. This is a fascinating observation, showing that large Chinese cities tend to integrate peripheral cities into the network, rather than putting an emphasis on collaboration with other centers, at least in relative terms. Fifth, effects related to physical proximity largely stay in line with previous works, underlining the negative effects of geographical distance, despite the increasing relevance of ICT. Notable in the context of physical drivers is also the increasingly significant role of high-speed railway connections between cities as a remarkable accelerator of their collaboration propensity.

The findings have important implications for future policy practice, in particular in a Chinese context, but also in general. First, governments should implement cohesive policies between cities to support cross-city innovation collaboration. As the existing network will influence future network evolvement, it is important to control network structural effects to change the unbalanced collaboration situation in China. Local government should take responsibility for breaking regional protectionism and promoting collaborative regional innovation. Drawing on the experience of the Yangtze River Delta and other leading regions, government can initiate efforts to build cross-region innovation platforms and construct cooperation framework agreements in related urban agglomeration areas. Balancing innovation collaboration in smaller regions with close economic interactions helps gradually form a more integrated network in the whole country. Second, it is necessary to intensively promote ICT development in peripheral regions. The results are evident that ICT development exerts an increasing influence on innovation collaboration. In the digital era, lagging ICT development will put peripheral regions at a disadvantage in accessing external knowledge. Improved ICT conditions may provide peripheral regions with more opportunities to utilize external knowledge and participate in innovation networks. In 2022, the Chinese government started to go in that direction and approved the construction of eight national computing hubs; most of the hubs are located in ICT less-developed regions (e.g. Zhongwei City in Ningxia Hui Autonomous Region, Ulanqab City in Inner Mongolia Autonomous Region). Strengthening ICT infrastructure in these regions will reshape Chinese economic geography in the near future. Policymakers in other developing countries should also invest more in peripheral regions to construct a more integrated innovation network.

In terms of directions for future research, at least three folds come to mind. First, the integrated ICT index can be further improved by incorporating additional data to reflect the quality of ICT development in cities. Second, considering the endogenous evolution of the innovation network, it could be suitable to employ Temporal Exponential Random Graph Model (TERGM), which is able to estimate the network structural effects based on the assumption of node and link dependence. Third, follow-up studies can analyze the effects of intangible drivers in different geographical distances or technology domains and compare these effects with physical drivers in more detail.

Supplementary

Tables S1–S3 and Fig. S1 could be found at http://egeoscien.neigae.ac.cn/indexcn.htm

Conflict of interest

The authors have no competing interests to declare that are relevant to the content of this article.

Author Contributions

All authors contributed to the study conceptualization and design. Gao Yujie: conceptualization, data collection and analysis, methodology, writing-original draft; Thomas Scherngell: conceptualization, writing-review and editing, supervision; Martina Neuländtner: conceptualization, writing-review and editing. All authors have read and agreed to the published version of the manuscript.

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