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Exploring Regional Innovation Growth Through A Network Approach: A Case Study of the Yangtze River Delta Region, China

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Abstract: As the leading urban agglomeration in China, the Yangtze River Delta (YRD) is experiencing a factor-driven to innovation-driven transition. However, the dynamics of regional innovation growth are not yet fully understood. This paper combines the complex network methodology with spatial econometrics to disentangle the contributions of innovation endowments, innovation network flows, and innovation network positions to regional innovation growth, as well as their spatial spillover effects. The primary findings suggest that regional innovation growth results from the networked agglomeration economies, which is shaped by the interactions between agglomeration factors and network factors. Specifically, agglomeration factors play a fundamental role in regional innovation growth. In contrast, network factors, such as the network flows and network positions, may contribute to new path creation by promoting access to external innovation resources. Additionally, the institutional factors show multiplexity in fostering regional innovation patterns. Such findings indicate that the YRD region should shift the innovation growth pattern from competitive involution to mutually beneficial co-operation to reduce regional disparities. In this regard, the institutional capacity of organizing network flows and fostering reciprocal inter-city partnerships has become increasingly critical for promoting sustainable innovation and regional development.

Keywords: network positions; innovation network; regional growth; Yangtze River Delta (YRD); China

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1 Introduction

The regional economic growth of China is highly dependent on labor expansion and capital investment, following a heterogeneous regional model (Wen, 2014; Zhang and Peck, 2016; Lu et al., 2020). Due to the increasing labor costs and intensified competition from other emerging economies, the regional growth of China slows down as marginal benefits disappear eventually. As a result, the development dilemma accelerates the process of transforming from a capital-driven mode to a more high-end and resilient development mode by expanding high-value-added production activities (Zhang and Kloosterman, 2016; Li et al., 2020; Liefner and Losacker, 2020). It has become clear that the traditional development path centered on labor and capital investments is unsustainable, calling for an innovation-oriented regional growth pattern. On this basis, increasing attention has been paid to the concept of network agglomeration economy, which may explain the power of achieving innovation growth through network resources (Ke, 2010; Burger, 2016; Van Meeteren et al., 2016).

Consequently, the network framework and metrics are largely applied to help understand the nature of the

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network agglomeration economy, which inspires related studies including formal partnership relationships (Luo and Shen, 2009), advanced producer services (APS) networks (Derudder et al., 2013; Taylor et al., 2014), and knowledge and technology networks (Li et al., 2015). Furthermore, the concept of computable network capital (Huggins and Johnston, 2010; Huggins and Thompson, 2017) helps to reveal the role of network locations in regional development as a strategic structural resource. The concept of network capital is introduced to emphasize the importance of investments in 'calculative relations' to enhance the organizational knowledge acquisition capabilities and economic returns (Inkpen and Tsang, 2005; Huggins and Johnston, 2010; Van Oort et al., 2010; Huggins and Thompson, 2017; Shi et al., 2021). Unlike traditional network capital based on social capital (Storper and Venables, 2004; Inkpen and Tsang, 2005), the specific manifestation of network capital relies on the structural positions in the network. Huggins emphasized the significance of intercity knowledge flow for regional development and explained the critical contribution of network capital to urban areas caused by network flows (Huggins and Thompson, 2017).

Research on the relationship between network capital (network positions) and regional growth originated from the field of social networks. Some scholars have found that the structural positions of actors are of great significance in accessing the network resources (Burt, 2003). For instance, the gateway positions may help generate network flows. In recent years, it is further proposed that the first-order direct linkage and second-order network positions would collectively affect the urban network (Derudder and Taylor, 2019), which may be positive externalities due to competition for network resources (Tian et al., 2010). However, it should be noted the spatial spillover effects show multiplexity with positive and negative impacts (Wen, 2014; Meijers et al., 2016). As a result, the locational factors are found to be largely unrelated to the network centrality of the universities (Huggins et al., 2020). In regard to the heterogeneous spillovers, scholars further propose two types of innovation strategies underlying indigenous innovation in China, namely closed innovation and open innovation, stressing the innovation modes of 'doing, using and interacting' (DUI) and 'science, technology and innovation' (STI): Closed innovation relies on the DUI-modes of learning, which leads to guanxi-based collaborations in close geographic distance (Burt and Burzynska, 2017); while open innovation is not necessarily guanxi-based, representing the STI-modes of learning (Losacker and Liefner, 2020).

However, few people have performed research into the regional pattern of innovation growth, which forms a gap in the relevant literature on innovation growth. The analysis of the inter-city network focuses on the inter-city connections and hierarchical urban networks while ignoring the role of the spatial effects caused by innovation networks in promoting innovation growth. Most of the Chinese empirical studies focus on traditional factors such as human, capital, and commodity flows, which stresses the role of agglomeration effects in different scales, including provinces (Ying, 2003), municipalities (Tian et al., 2010; Wen, 2014), and specific distance ranges (Ke, 2010). Although considerable studies have emphasized that network flows would help improve urban interconnection and collaboration (Castells, 1996; Coe and Yeung, 2015) and network embeddedness (Capello, 2000; Meijers et al., 2016; Huggins and Thompson, 2017) for regional growth, few studies have focused on the interplay between regional innovation networks and regional innovation growth. In contrast, most empirical studies focus only on the morphology of the network, ignoring the relationship between innovation networks and regional innovation growth. In other words, the interplay between innovation networks and innovation growth has not received much scholarly attention, which may potentially reflect the role of intercity relations under the urban network paradigm (Van Oort et al., 2010).

Therefore, it is necessary to conduct a more in-depth study which stresses the spillover effects of innovation networks on innovation growth. For such a purpose, this study selects the Yangtze River Delta (YRD) region in eastern China as the research area and analyzes the classic urban growth model by examining the dynamics of regional innovation growth through a network lens. By integrating firm data, patent data, and statistical data with spatial metrics, this study aims to investigate the direct and indirect effects on innovation growth and provide responses to the following research questions: 1) How do innovation network flows and positions affect innovation growth? 2) What are the differences between structural positions in promoting the YRD innovation growth? The results could be used to theoretically explain the interactions relations between agglomeration and network economies by examining the determinants and dynamics of regional innovation growth, which may provide insights for regional policies and global comparative research between the YRD region and other urban agglomerations.

2 Materials and Methods

2.1 Study area

As the leading urban agglomeration in China, the Yangtze River Delta (YRD) region is experiencing a transition from factor-driven to innovation-driven, which has been strengthened by regional strategies, such as the plan of the Yangtze River Economic Belt. This study selects the YRD region (Fig. 1) as the research area, including 41 cities in Jiangsu Province, Zhejiang Province, Anhui Province, and Shanghai Municipality, for the following reasons: 1) Beyond the development zone policies, governments in the YRD region have prepared early to cultivate endogenous power for technological innovation. The evolutionary process of the YRD region may shed light upon the catch-up regions and even the worldwide developing economies; 2) The influences of spatial spillovers remain controversy, especially in the heterogeneous Chinese regions, which forms a promising research field. For instance, empirical evidences have been discovered that spatial spillovers produce positive effects in the YRD region and negative effects in the PRD (Pearl River Delta) region (Wen, 2014). Similarly, compared with the PRD and the JJJ (Jing-Jin-Ji, also known as Beijing-Tianjin-Hebei) region, the YRD region is more prominent for including a larger geographical scale and more extensive hinterland. In this regard, the author believes that research projects in the YRD region would be conducive to more comprehensive understandings of the heterogeneous Chinese regional development model.

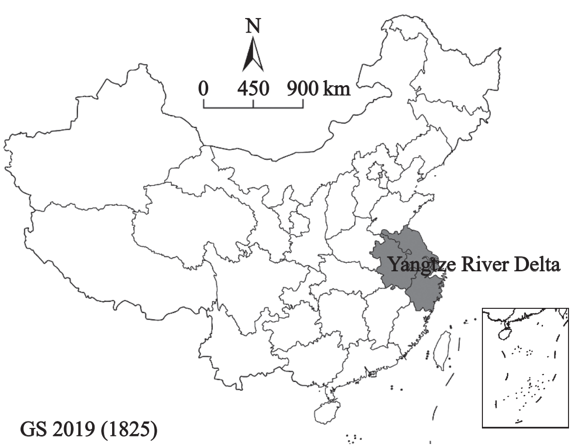

Fig. 1 Location of the Yangtze River Delta region in China

2.2 Model specification

This study follows a two-stage approach to discover the dynamics of regional innovation growth by revealing the network structure and the spatial spillover effects of the YRD innovation network: 1) First, inspired by Shi's methodology on measuring network variables (Shi et al., 2019; Shi and Pain, 2020), the author utilizes the network indicators as proxies of network capital, namely Betweenness, Closeness, Authority and Hub to illustrate network structural positions in revealing the structure of innovation network. 2) After that, based on network capital and other spatial panel data from 2008 to 2018 in the YRD region, the author integrates a framework that combines complex networks with spatial econometrics to detect the determinants and reveal the dynamics of innovation growth.

2.2.1 Measurement of network estimators

For examing the structural features of the innovation network, a group of network estimators from complex network methodology is calculated to illustrate the innovation network structure. The measurements of the network estimators are explained as follows.

Degree centrality is an unweighted measure estimating the number of investments a city receives or directs to other cities. In contrast, weighted degree centrality concerns the number of investments that hi-tech firms receive. In addition to degree centrality, scholars have developed other measurement methods upon degree centralities (Friedkin, 1991), such as betweenness centrality, closeness centrality, hub, and authority. These algorithms are created to overcome the defects that degree centrality exaggerates the differences in the ability of nodes to control the allocation of resources in the network, which can only reflect centrality but not the structural positions of the network nodes.

Betweenness centrality serves as an indicator to measure the number of times a node acts as a bridge in the network. It is measured by the frequency with which the node acts as an hub between the other two nodes, reflecting its ability to influence the network flow.

Betweenness (C_B) centrality can be calculated using the following formula (Brandes, 2001):

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{1}$$

where σ_{st} refers to the shortest path from node s to node t, and $\sigma_{st}(v)$ measures all paths through node v.

Closeness centrality reflects the degree to which a node is located in the center of the network. It measures the proximate functional characteristics of a node in the network. A city with high closeness centrality means a functional central city in the network, and the average path from it to other network nodes is the shortest. Closeness centrality is the reciprocal of the sum of the functional distances between the node and other nodes (Bavelas, 1950; Sabidussi, 1966).

$$C_x = \frac{1}{\sum_y d(y, x)} \tag{2}$$

where, $d(y, x)$ is the shortest functional distance between city x and city y.

Authority and Hub refer to measures of Kleinberg centrality. According to the Hyperlink Guided Topic Search (HITS) algorithm (Kleinberg, 1999), the network comprises hub nodes and authoritative nodes, which serve as links and targets, respectively. Hubs are similar to directories in the search process in the network, reflecting the gateway nodes that direct to many other nodes. Likewise, authoritative nodes are the terminals pointed to by many different nodes. Compared with traditional algorithms, such as Betweenness and Closeness, HITS gives additional weight to the linkages connected to the authority and hub cities. In this sense, a city node with few connections could be authoritative once linked to important hubs and vice versa.

2.2.2 The regional innovation growth model

After calculating the network estimators, the author proposes an improved spatial model upon Huggins' regional growth model (Huggins and Thompson, 2014), which integrates the concept of innovation network capital with network metrics. Specifically, the non-spatial and spatial models, namely the Fixed Effects Model (FE), Spatial Auto-Regressive Model (SAR, also known as Spatial Lag Model, SLM), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM), are introduced to disassemble the direct and indirect effects (spatial spillover effects), by examining the spatial regression results to determine whether non-spatial or spatial factors will give rise to innovation growth.

Inspired by the 'Ha-Howitt' model and the subsequent networked framework (Ha and Howitt, 2007), the regional innovation growth model is constructed based on the Cobb-Douglas production function:

$$Y_{it} = X_i\beta + \mu + \alpha_t \iota_N + \varepsilon_{it} \tag{3}$$

where Y_{it} is the innovation output or innovation agglomeration of city i at time t; X_i is the original input factors of city i; μ represents the location effect term, α_t is a temporary effect term; ι_N is an $N \times 1$ vector related to a constant term parameter; ε_{it} refers to the unobservable random term.

The indirect effects refer to the spatial spillovers in the spatial analysis. In the spatial models, the direct and indirect effects can be explained by the coefficients of the independent variables and spatial lag variables, respectively. However, the basic version of the Cobb-Douglas production function can not recognize the indirect effects caused by spatial factors. Thus the author applies spatial metrics in the model to conduct a more detailed study concerning both direct and indirect effects.

According to Lesage, the SDM model may be more suitable for improving model flexibility and ensuring unbiased estimates (Lesage, 2014), which helps capture the unobservable spatial effects missed by non-spatial models. Innovation activities depend more on innovation flows than commodity flows regarding the influencing factors. Meanwhile, the network positions shaped by capital flow could be strategic resources that directly affect innovation growth. Therefore the model recruits innovation endowment variables X_i, innovation flows variables F_i, innovation network positions variables N_i, and institutional environment variables P_i as independent variables to reveal their direct and indirect effects. To sum up, the spatial model under the SDM model for investigating the dynamics of innovation growth is constructed as follows:

$$\begin{aligned} Y_i = {} & \rho \sum_{j=1}^{n} W_{ij} Y_i + \beta (X_i + F_i + N_i + P_i) + \theta (W_{ij} X_i + W_{ij} F_i + \\ & W_{ij} N_i + W_{ij} P_i) + \mu + \alpha_t \iota_N + \mu_{it} \end{aligned} \tag{4}$$

$$u_{it} = \lambda \mathrm{W} u_{it} + \varepsilon_{it} \tag{5}$$

where Y_i represents the innovation output; X_i measures the variables of innovation endowment; F_i represents the vector of the network flow variables of city i; N_i is the vector of network position variables; P_{ij} is the institutional environment variable; W_{ij} is the spatial weights matrix, representing the neighboring relations between city i and city j. Also, u_{it} is a spatial error term, λ is the coefficient of the spatial error term; ρ is the coefficient of the dependent variable, which reflects the spatial dependence of the model; β is the coefficient of the explanatory variables concerning cities itself, which reflects the direct effects of the explanatory variables; θ is the coefficient of explanatory variables concerning the neighboring cities, which reflects the indirect effects of the explanatory variables.

The model recruits the spatial distance matrix as the spatial weight parameter to reflect the influence of geographic distance. The measurement of the spatial distance matrix is demonstrated as follows:

$$W_{ij} = \frac{1}{d_{ij}^2}; d_{ij} = \arccos[(\sin\varphi_i \times \sin\varphi_j) + (\cos\varphi_i \times \cos\varphi_j \times \cos(\Delta\tau))] \times R \tag{6}$$

where the spatial matrix W_{ij} is standardized, φ_i and φ_j are the latitude and longitude of the center of the city, $\Delta\tau$ measures the difference of the longitude of the city, and R refers to the radius of the earth.

Multiple tests are performed in the study to determine whether the spatial effects have an influence and what kind of spatial models the paper should apply. Following Anselin and Rey's methods (Anselin and Rey, 1991), multiple tests are applied to compare the models. Precisely, the Robust LM lag and the Robust LM error are calculated to test the robustness of the SAR and SEM models. It is suggested that the SAR model should be recruited once the Robust LM lag indicator shows significant results and vice versa. The comparison between spatial models determines the optimal spatial model. Specifically, the LR test is applied to analyze the SAR, SEM, and SDM models, respectively. The LR test decides whether the SDM model is more reliable than the other models. Similarly, the WALD test is recruited to confirm validity of the SDM model. The simpler model is recommended once the results are significantly positive with pronounced chi-square statistics. Besides comparing models, the Hausman test and the LR test are further applied to determine whether to apply the fixed effects model and what form of the fixed effects should be applied. It is suggested to apply a fixed-effects model when the Hausman test shows significant results and further recommended to recruit a dual fixed effects model once the results of the LR test are both significantly positive.

After that, the spatial regression analysis is performed based on the sample data, including 41 prefecture-level cities in Jiangsu, Zhejiang, Anhui, and Shanghai between 2008 and 2018. In the results, ρ and λ are the coefficients of neighboring cities' dependence and spatial error variables, which can be interpreted to examine the spatial spillover effects in the region. Meanwhile, β and θ are the coefficients of independent explanatory variables and spatial lag variables, which can be further interpreted to identify the direct and indirect effects of the explanatory variable.

2.2.3 Variables and data

Hi-tech firms are the most active entities in cities that directly contribute to innovation. Therefore, the investment data of the hi-tech firms can be excellent data sets for measuring the innovation network estimators, such as innovation network flow and innovation centrality. The geocoded investment data of the firms, including geographic coordinates, may help identify source and destination city nodes to form a network matrix. For instance, the annual patent applications and cumulative patents of the hi-tech firms can be applied as indicators for measuring innovation output and knowledge stock. The investment data of the firms has become widely applied in recent empirical studies to analyze the inter-city network (Shi et al., 2019; Lu, 2020). Regarding the fact that the 'calculative relations' (Huggins and Thompson, 2014) could be clearly illustrated by the frequency rather than the calculative amount of the investments. It is suggested to apply the frequency of investments received by hi-tech firms as the metric of innovation activities to illustrate the inter-city innovation network.

For the above reasons, the study takes the innovation output as the indicator of innovation growth, and further recuits innovation endowment, innovation network flow, innovation network positions, institutional environment as the explanatory variables (Table 1): 1) Innovation output, which serves as the proxy of the dependent variable, is measured by the patent applications of hi-tech firms; 2) Innovation endowment is represented by the innovation stocks, financial and human capital, and the knowledge capital of cities to examine the agglomeration effects; 3) Innovation network flows and innova-

Table 1 Description of explanatory variables related to innovation growth

Subjects	Variables	ID	Description
Innovation endorsement	Innovation capital	lnIC	(Logarithm of) Number of cumulative investments received by the hi-tech firms of the city
	Financial capital	lnFC	(Logarithm of) Year-end financial institution deposit balance of the city
	Human capital	lnHC	(Logarithm of) Number of hi-tech employees of the city
	Knowledge capital	lnKC	(Logarithm of) Cumulative number of patents granted of the city
Innovation network flows	Global innovation flow	lnFIF	(Logarithm of) Frequency of foreign investment received by hi-tech firms in the city
	Inter-region Innovation flow	lnDIF	(Logarithm of) Frequency of investment received by hi-tech firms from outside the YRD
	Regional innovation flow	lnIF	(Logarithm of) Frequency of investment received by hi-tech firms from within the YRD
	Local innovation flow	lnSF	(Logarithm of) Frequency of investment received by hi-tech firms from within the city
Innovation network capital	Authority	INA	Network structural score: capacity of attracting innovation capital from other cities
	Hub	INH	Network structural score: capacity of directing innovation capital to other cities
	Closeness	INC	Network structural score: functional proximity to other cities
	Betweenness	INB	Network structural score: intermediary proximity to other cities
Institutional environment	Openness	OP	The proportion of the total import and export to the GDP
	Market	MKT	The proportion of private enterprises employed in the hi-tech firms
	Government	GOV	The proportion of the fiscal expenditure to the GDP

tion network capital are applied to examine the network effects. Innovation network flows are represented by the region's global, inter-regional, regional, and local innovation investment flows. Meanwhile, Innovation network capital, measured by the network positions, is represented by the variables of Authority, Hub, Closeness, and Betweenness; 4) Innovation environment is represented by Openness, Market, and Government, which illustrate the degree of opening up, marketization, and government intervention, reflecting the institutional 'organizing capacity' (Meijers and Romein, 2003) of the cities; 5) Considering the impact of the city sizes, the Built-up area, and the Population are also included as control variables in the model to avoid the adverse effects caused by potential missing variables.

The data, including the firm data, the patent data, and the statistic data of the YRD region, are mainly derived from the National Bureau of Statistics of China (NBS), the State Intellectual Property Office of China (SIPO, http://pss-system.cnipa.gov.cn/), and the annual reports of hi-tech firms. Specifically, the registration data of the hi-tech firms come from the official website of China that manages the High and New Technology Enterprise (HNTE) program (http://www.innocom.gov.cn/) and the National Enterprise Credit Information Publicity System (http://www.gsxt.gov.cn/). Meanwhile, the patent data of hi-tech firms come from the SIPO. In addition, the statistic data applied in this paper are from different statistical yearbooks (National Bureau of Statistics of China, 2009–2019), including the year-end institutional financial deposit balances, fiscal expenditures, total imports and exports, GDP of the cities, and other information.

To prepare the data for further analysis, the author obtains the list of registered hi-tech firms within the YRD region in 2020 from the official website of China that manages the HNTE program. After that, the data of investments towards the hi-tech firms till 2020, prepared for measuring innovation network flow and innovation network centralities, are derived from the annual reports of hi-tech firms, which are further applied to illustrate the network structure in 2020. Meanwhile, the firm data and patent data of hi-tech firms from 2008 to 2018 are extracted from the National Enterprise Credit Information Publicity System and the SIPO. Due to the lag of patent application, there is a maximum interval of 24 months from patent application to publication. The official website of the patent publicity system has not fully disclosed the patent application data from 2019 to 2020 when the author collects the data (Dec., 2020). Therefore, to accurately describe the dynamics of regional innovation growth through patent application data, the author extracts the sample data including 41 prefecture-level cities in Jiangsu, Zhejiang, Anhui, and Shanghai between 2008 and 2018 to perform the spatial regression analysis.

3 Results

3.1 Structure of the innovation network

3.1.1 Network performance of the cities

This section aims to illustrate the network structure by examining the structural positions of the cities. First, the network estimators of the cities are calculated to reflect the nodal centrality and structural positions. After that, the author illustrates the map that demonstrates the regional innovation pattern based on the representative estimators which are measured by the firm performance within the cities in the YRD region.

Among these estimators, Degree and Weighted Degree measure the degree centralities that reflect the total links connected to a city, while Betweenness, Closeness, Authority, and Hub measure the network positions. Specifically, Betweenness measures the number of paths passing through a node, while Closeness measures the reciprocal of the total path length of a node to other nodes. In parallel to that, a high hub score indicates how attractive the city might be to absorb innovation flows, while a high authority score indicates the extent to which the city serves as a gateway to direct the innovation flows. Compared to Betweenness and Closeness, Authority and Hub are more inter-related concepts that precisely measure the core-periphery structure, reflecting the 'gateway' and 'terminal' positions through a network perspective.

As shown in Table 2, the network estimators of YRD cities are demonstrated given Degree ranking. It can be observed that the ranking measured by Degree is not precisely the same as other rankings, which calls for further comparison. Taking Authority and Hub as criteria of comparison, it can be observed from the rankings that Shanghai and Hangzhou are the core cities of the innovation network that demonstrate high scores in Authority and Hub at the same time. In contrast, Hefei get ranks high in the Hub score but relatively low in the Authority score, while Suzhou, Nanjing, Ningbo, and Wuxi rank high in Authority scores but relatively low in Hub scores.

Table 2 Estimators of the innovation network in the Yangtze River Delta region (2020)

City	Province/Municipal	Degree	Weighted Degree	Authority	Hub	Closeness	Betweenness
Shanghai	Shanghai	79	62982	0.2273	0.2488	1.0000	0.0627
Nanjing	Jiangsu	75	18948	0.2208	0.2366	0.9302	0.0608
Hangzhou	Zhejiang	74	34402	0.2196	0.2387	0.9524	0.0480
Suzhou	Jiangsu	74	22276	0.2221	0.2369	0.9302	0.0460
Hefei	Anhui	73	8926	0.2187	0.2233	0.8889	0.0594
Wuxi	Jiangsu	67	9214	0.2098	0.2214	0.8696	0.0322
Ningbo	Zhejiang	65	13274	0.1908	0.2392	0.9302	0.0220
Jiaxin	Zhejiang	59	6126	0.1696	0.2236	0.8696	0.0179
Changzhou	Jiangsu	59	5512	0.1950	0.1950	0.7692	0.0228
Wuhu	Anhui	59	2392	0.1882	0.1988	0.8000	0.0233
Nantong	Jiangsu	52	3940	0.1743	0.1871	0.7407	0.0127
Shaoxin	Zhejiang	51	4382	0.1280	0.2190	0.8333	0.0136
Huzhou	Zhejiang	51	3448	0.1627	0.1910	0.7692	0.0119
Jinhua	Zhejiang	48	2562	0.1539	0.1805	0.7407	0.0080
Wenzhou	Zhejiang	48	2490	0.1411	0.1977	0.7843	0.0062
Xuzhou	Jiangsu	45	1554	0.1644	0.1434	0.6667	0.0105
Taizhou	Zhejiang	44	2300	0.1143	0.1929	0.7692	0.0062
Zhenjiang	Jiangsu	44	2144	0.1754	0.1514	0.6667	0.0039
Yangzhou	Jiangsu	40	2112	0.1514	0.1472	0.6667	0.0031
Taizhou	Jiangsu	40	1664	0.1579	0.1353	0.6452	0.0043

Notes: only the top 20 cities given the Degree ranking are listed for clarity

3.1.2 Structural positions of the cities

In referring to Liefner's approach on the division of knowledge network (Liefner and Hennemann, 2011), the YRD cities could be further separated into a 2 × 2 matrix by hub and authority scores, consisting of four categories with different structural positions: 1) Gateway and terminal cities. It refers to the cities with high Authority scores and high Hub scores, which serve as gateways and terminals; 2) Terminal cities. These are authoritative cities with low Hub scores, which are not located in the center of the network but serve as the terminals of the innovation flows; 3) Gateway cities. These are hub cities with low Authority scores, which occupy the hub positions of the network, directing the innovation flows into other cities; 4) Peripheral cities. The rest cities located in the periphery of the network are neither hub cities nor authoritative cities.

Fig. 2 demonstrates the core-peripheral structure with cities occupying different structural positions in the YRD innovation network. Following the Jenks optimization method, the network structure can be divided into four regions by dichotomizing the values of Authority and Hub. The cities at the center of the network are the gateway for directing the innovation flows into the YRD region. However, the center area of the network does not entirely overlap with the geographical center area. For instance, Hefei and Wuhu occupied high-level network positions despite their relatively remote locations. In contrast, cities in the geographical periphery may occupy high-level network positions, such as Wenzhou and Taizhou of Zhejiang Province. Compared to the core cities that serve as gateways or terminals, cities in the periphery of the network, such as the cities in the northern Jiangsu region, may show signs of high local innovation agglomeration even though limited by low accessibility to external innovation resources.

3.2 Spatial regression results of the innovation growth

3.2.1 Tests for comparing models

This section compares non-spatial and spatial models, such as FE, SDM, SAR, and SEM, by examining the results of multiple tests. Among these models, the SDM,

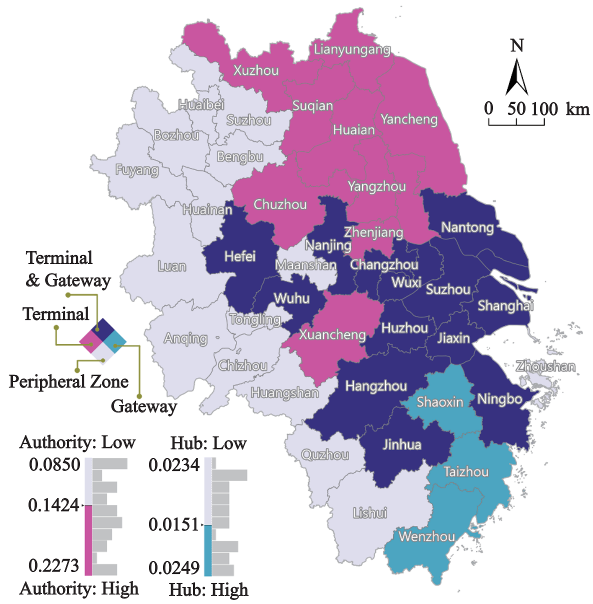

Fig. 2 Structural positions of the Yangtze River Delta cities in the innovation network (2020). In the histograms, the gray rectangles reflecting the distributions of Authority and Hub are dichotomized by the Jenks optimization method

Table 3 Comparison between non-spatial (FE) and spatial (SDM, SAR, SEM) models

Test Stastics	FE	SDM	SAR	SEM
Robust LM lag	5.046^{**}			
Robust LM error	135.498^{***}			
Hausman test	222.566^{***}	−54.65	35.34^{***}	22.61
LR test (individual fixed effects)	42.71^{***}	42.71^{***}	42.71^{***}	42.71^{***}
LR test (time fixed effects)	242.28^{***}	242.28^{***}	242.28^{***}	242.28^{***}
LR test to SDM			79.95^{***}	287.73^{***}
WALD test	87.70^{***}	88.11^{***}	88.11^{***}	88.11^{***}
AIC	215.9931	45.09812	90.76111	302.5379
BIC	289.9995	201.3339	168.879	388.8787

Notes: Robust Standard Error in brackets; $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$; FE, Fixed Effects Model; SDM, Spatial Durbin Model; SAR, Spatial Auto-Regressive Model; SEM, Spatial Error Model; AIC, Akaike Information Index; BIC, Bayesian Information Index

SAR, and SEM refer to spatial models, while the FE refers to the non-spatial model which applies a fix effect approach. Concerning validity and reliability, the spatial models are compared based on the results of multiple tests.

The LM test is primarily used in spatial metrics to comfirm the spatial effcts and compare the robustness of the SAR and the SEM models. According to Table 3, the positive results of Robust LM lag and Robust LM error prove that the model exhibits significant spatial effects that both the spatial error term and the spatial lag term are positively significant, which confirms the influence of spatial effects. Based on the results of LM test, innovation growth proves to be influenced by spatial effects, and the SAR model should be applied when compared with the SEM model.

Furthermore, the results of LR test, WALD test and AIC/BIC test are applied to compare the different spatial models. The LR test reports a significat result that the chi-square statistics of the SAR model and the SEM model to the SDM model are 79.95 and 287.73, respectively, implying the robustness of the SDM model over the others. The results of the WALD test in Table 3 convey that the model's chi-square statistics are 87.70 and 88.11 for non-spatial and spatial models, respectively, both significant at the 1% confidence level, reflecting the excellent adaptability of the SDM model. In addition, the AIC (Akaike Information Index) and BIC (Bayesian Information Index) indicators are used to compare among the spatial models. Regarding the fact that a model with better fit has smaller AIC/BIC, the results indicate that the SAR and the SDM demonstrate minor differences in terms of validity.

Regarding the tests for fixed effects, according to the results of the Hausman test, it is suggested that the non-spatial model, the SDM model, and SAR model apply a fixed-effect approach. Moreover, the non-significant effects of the SEM model indicate that the random-effects model should be applied. In addition, the LR test is applied to compare individual fixed effects, time fixed effects, and double fixed effects. Concerning the results of the LR test, the chi-square statistics of individual fixed effects and time fixed effects are 42.71 and 242.28, respectively, significant at the 1% confidence level, suggesting that the dual fixed effects model should be applied.

In summary, the results of multiple tests demonstrate support for the effectiveness of the SDM model. It is believed that the SDM model is superior to the SAR model and the SEM model. In that regard, the interpretation of the results in this study should prioritize the analysis results of the SDM model.

3.2.2 Direct effects on regional innovation growth

This section discusses the influencing factors of regional innovation growth by interpreting the results of the spatial regression model. According to Table 4, ρ is the coefficient of the spatial interaction term, which characterizes the influence of the dependent variable of neighboring cities on the city itself, reflecting the inter-city spatial spillover effect caused by the dependent variable. λ is the coefficient within the spatial error term, reflecting the interaction effects caused by the city. β and θ are the coefficients of the explanatory variables of the city and its neighboring cities, which represent the direct and indirect effects of the explanatory variables respectively.

In refer to the direct effects demonstrated by the results of the SDM model, innovation growth tends to be significantly shaped by agglomeration and network factors. Specifically, innovation endowment plays a fundamental role in innovation activities, following a path-dependent and self-reinforcing development model. Besides that, considering the endogenous interaction effects of the explained variables, the innovation output of cities has a spatially negative spillover effect on the innovation output of neighboring cities. Specifically, ρ is significantly negative at the 1% confidence level in the SDM model, indicating that the intensity of innovation output of a city is negatively correlated with the power of innovation output of neighboring cities.

However, innovation network flow shows multiplexity when considering its impacts on innovation growth. On the inter-regional, regional, and intra-city level, there is not much evidence that innovation flows would support innovation growth; On the global level, the innovation flow would even harm the innovation output of the YRD cities. Similar results occur when discussing the functions of network structure. According to Table 4, in the SDM and SAR models, Hub is positively associated with innovation output, while Closeness is negatively associated, which suggests that compare to the functionally centered positions measured by Closeness, the gateway positions measured by Hub are more likely to benefit regional innovation growth. Moreover, regarding the direct effects of institutional

Table 4 Estimated model results of direct and indirect effects

Variables	FE	SDM	SAR	SEM
Coefficients associated with neighbors' dependence (ρ)		−0.801***	−0.240	
		(0.2795)	(0.2102)	
Coefficients associated with the spatial error term (λ)				0.898***
				(0.0234)
Direct effects of explanatory variables (β)				
Innovation capital	0.693**	0.217	0.317	0.168
	(0.315)	(0.280)	(0.270)	(0.146)
Financial capital	−0.00841	0.00533	−0.0190	0.139
	(0.0681)	(0.0868)	(0.0870)	(0.0892)
Human capital	0.774*	0.0869	0.298	0.00135
	(0.399)	(0.359)	(0.325)	(0.0991)
Knowledge Capital	0.581***	0.231***	0.263***	0.313***
	(0.0559)	(0.0624)	(0.0574)	(0.0502)
Global innovation network flow	−0.388***	−0.407***	−0.459***	−0.381***
	(0.115)	(0.0946)	(0.0924)	(0.0694)
Inter-region innovation network flow	0.237	0.0439	0.148	0.227**
	(0.178)	(0.142)	(0.142)	(0.0987)
Regional innovation network flow	−0.00775	0.0626	−0.0525	−0.0652
	(0.269)	(0.229)	(0.225)	(0.132)
Local innovation network flow	0.427**	0.181	0.428**	0.486***
	(0.216)	(0.179)	(0.176)	(0.124)
Innovation network authority	4.468*	2.342	3.772*	4.401***
	(2.596)	(2.069)	(2.087)	(1.671)
Innovation network hub	8.225***	13.70***	11.48***	13.04***
	(2.570)	(2.300)	(2.211)	(1.688)
Innovation network closeness	−4.141***	−9.508***	−8.137***	−7.099***
	(1.447)	(1.431)	(1.309)	(0.997)
Innovation network betweenness	−4.575	4.920	0.367	−4.305
	(5.019)	(4.222)	(4.242)	(2.860)
Openness	0.0358	0.205	0.0557	0.315
	(0.515)	(0.400)	(0.429)	(0.417)
Market	−1.827*	−2.456***	−2.895***	−0.987***
	(0.947)	(0.836)	(0.792)	(0.298)
Goverment	0.125	0.00828	0.0864	0.233
	(0.156)	(0.134)	(0.140)	(0.152)
Indirect effects of explanatory variables (θ)				
Innovation Capital		−1.339	−0.0587	
		(1.903)	(0.0817)	
Financial Capital		−0.592	0.00262	
		(0.376)	(0.0215)	
Human capital		3.119	−0.0532	
		(2.592)	(0.0900)	

Table 4 (Continued)

Variables	FE	SDM	SAR	SEM
Knowledge capital		0.829^{***}	−0.0479	
		(0.314)	(0.0444)	
Global Innovation Network Flow		0.142	0.0821	
		(0.595)	(0.0740)	
Inter-region Innovation Network Flow		−1.114	−0.0262	
		(0.970)	(0.0401)	
Regional Innovation Network Flow		3.526^{**}	0.0115	
		(1.443)	(0.0543)	
Local Innovation Network Flow		-4.124^{***}	−0.0738	
		(1.308)	(0.0781)	
Innovation Network Authority		-37.43^{***}	−0.649	
		(13.48)	(0.739)	
Innovation Network Hub		6.100	−2.050	
		(13.82)	(1.860)	
Innovation Network Closeness		-25.96^{***}	1.465	
		(9.379)	(1.304)	
Innovation Network Betweenness		29.97	−0.0753	
		(28.68)	(0.949)	
Openness		1.267	−0.00798	
		(2.305)	(0.105)	
Market		0.0690	0.513	
		(4.913)	(0.485)	
Goverment		−0.689	−0.0157	
		(0.873)	(0.0382)	
Population	Control	Control	Control	Control
Built-up Area	Control	Control	Control	Control
Time effect	Fixed	Fixed	Fixed	Random
Location effect	Fixed	Fixed	Fixed	Random
Oberservations	451	451	451	451

Notes: Robust Standard Error in brackets; $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$; FE, Fixed Effects Model; SDM, Spatial Durbin Model; SAR, Spatial Auto-Regressive Model; SEM, Spatial Error Model

environment variables, only the degree of marketization are poven to benefit innovation output, other institutional factors, such as openning up and government intervention, have not received enough confirmation according to the model results.

3.2.3 Indirect effects on regional innovation growth

Regarding the indirect effects, the results indicate that the accumulation of knowledge capital would produce positive spillovers on the clustering of innovation factors in neighboring cities. In contrast, continuous local and regional innovation network flow, along with high-level innovation network positions measured by Authority and Closeness, would negatively affect the innovation output in neighboring cities. In the SDM model, knowledge capital and regional innovation flow are the only positive variables for indirect effects on innovation growth. According to Table 4, the coefficients (θ) of local innovation network flow (intra-city innovation self-flowing network) are mostly negatively related, indicating that the intra-city innovation network flow will also not benefit the innovation output of neighboring cities in the YRD region.

Additionally, concerning the endogenous interaction effects, the innovation output is negatively related to the innovation output of neighboring cities. According to Table 4, ρ is significantly negative at the 1% confidence level in the SDM model, indicating that the innovation output of the cities in the YRD region is negatively related to the innovation output of the neighboring areas. Such results implicate that within the YRD, the competitive effect of adjacent cities on innovation factors is stronger than the spillover effect. In addition, the increase in the level of innovation agglomeration of cities is related to a possible decline in the level of innovation agglomeration in neighboring cities.

Different from the simply positive effects (Meijers et al., 2016), the results coincide with previous studies which comfirm that cities can 'borrow' network capital with both positive and negative impacts from the regions around them (Hesse, 2016; Shi and Pain, 2020). Such results are different from general perceptions, which believe that a city will benefit from its neighboring cities' growth (Wen, 2014). In other words, there is a negative spatial spillover effect of innovation output within the YRD region. The competitors from the cities would possibly weaken the innovation output of their cities.

4 Discussion

4.1 Dynamics of regional innovation growth

As the results indicate, the YRD innovation growth are fundamentally determined by agglomeration effects, which is consistent with the findings of a nation-scale analysis covering 617 Chinese cities in 2005 (Ke, 2010). Besides that, the results further confirm the key role of two-way interactions between agglomeration economies and network economies, which can be categorized by the fundamental drivers for regional innovation growth, namely innovation endowment, network flow, innovation network capital, and institutional environment.

Following path-dependent rules, agglomeration factors may promote innovation output and increase regional disparities. For instance, the accumulation of innovation capital, financial capital and knowledge capital would effectively promote the innovation output, which may contributes to the uneven development consequently. Depite the leading role of spatial dependence, innovation network flows are conductive to promote innovation growth, while the structural positions of cities in the innovation network may bring direct and indirect effects. Lastly, the institutional environment indicators are not positively related to innovation growth. As observed in the results, the degree of marketization is even negatively associated with the innovation output.

Despite the local innovation agglomeration of the authoritative cities, the gateway cities occupies more advantageous positions in the regional innovation network. According to the results, in terms of direct effects, the hub positions of the cities will significantly promote their innovation output. However, in regard to the indirect effects, Closeness and Authority are negatively related to spillovers to neighboring cities. Such findings align with Burt's conclusion that the hub positions can help create synergies, improving the local competitiveness (Burt, 2003), which stress the strategic role of the high-level positions in maintaining regional innovation growth.

To sum up, the results indicate that most explanatory variables tend to produce negative spillovers on the neighboring cities in terms of indirect effects. In other words, the competition effects overweight the cooperation effects in the YRD region, which metaphorizes the underlying competition for innovation resources and network positions. Consequently, agglomeration shadow (Tervo, 2010) may occur around cities with high-level innovation network positions, commonly known as the phenomenon of 'dark under the lamp.' Therefore, effective policy tools should be focused on the organizational capabilities of directing network flow to enhance regional collaboration. In that sense, good initiatives might be establishing cross-border cooperation organizations, encouraging cross territorial institutional cooperation, and promoting the inter-regional flow of tangible and intangible factors.

4.2 Network effects of structural positions

In terms of direct effects, the hub positions of cities are positively correlated with the innovation output of the cities, while Closeness are negatively related. Such results indicate that the cities will benefit from gateway positions rather than functionally centered positions in regard to promoting innovation output. In terms of indirect effects, it could be observed that the functionally centered positions of the YRD cities would produce negative impacts on the innovation output of neighboring cities, which implies that structural positions, such as authoritative positions and hub positions, would not always promote the innovation output of the neighboring cities. In other words, there is no sufficient evidence that network flows will benefit innovation growth for sure, although it plays a significant role in fostering innovation agglomeration, which helps the local region grow into an innovation cluster, as previous research implies (Shi and Pain, 2020).

Accordingly, it could be identified that innovation network capital, which are measured by network positions, plays a multiplexed role in the evolution of regional innovation process. The structural positions of cities in the innovation network will produce both positive and negative effects, which can be also referred as endogenous interaction effects. For instance, the increasing in knowledge capital stock and external innovation network flows may simultaneously promote the local innovation output and generate negative spillovers on the innovation output of the neighboring cities.

For that reason, it is equally important to consider the direct and indirect effects caused by the network spillovers when discussing the functions of network positions. Regarding the fact that cities would benefit from the hub or gateway positions when accessing external innovation flows, it becomes critical for cities to occupy advantageous positions in maintaining innovation growth. In brief, the regional innovation process serves as a result of local innovation agglomeration and network inflows. Though local innovation agglomeration initiates the regional innovation process, it should be noted that access to external innovation resources guarantees the sustainable growth of local innovation agglomeration, which could be prominently influenced by the structural positions of the cities in the innovation network.

5 Conclusions

The study analyzes the determinants of regional innovation growth, interpreting the dynamics of regional innovation brought by networked agglomeration economies, which responds to the crucial research questions: "How does the innovation network affect the regional innovation growth and what is the role of network positions in promoting innovation growth?" The results suggest that the network effects of the YRD innovation network remain multiplexed. Unlike the simply positive impacts caused by innovation endowments, the innovation network might boost regional innovation growth by simultaneously bringing positive and negative impacts. Consequently, cities occupying dominant network positions may benefit from access to external resources, but negatively affect the neighboring cities nevertheless.

Specifically, the study explains the two-way interactions between agglomeration and network economies under the regional innovation dynamics by examining the direct and indirect effects. Regarding the direct effects, spatial dependence caused by agglomeration factors such as innovation endowments has laid foundation for developing innovation activities. For instance, knowledge capital will significantly promote innovation output of the cities in the YRD region. In addition, network factors such as innovation network flows and positions may also considerably affect innovation growth. In other words, network flows may produce effects directly while network positions may indirectly promote innovations output by creating advantageous positions for accessing external innovation resources. Such findings further reveal the key functions of the bridging and brokering network positions, which help the geographically peripheral cities become gateways of the innovation network and consequently generate possibilities for new path creation.

Regarding the indirect effects, the negatively significant results of local innovation network flows indicate that intra-city innovation network self-flows may not possibly benefit innovation output of neighboring cities. Furthermore, the negative spillovers observed in the results exhibit the fact that the discrete and competitive inter-city relations have made major contributions to shaping the YRD innovation economy. It could be further speculated that the YRD cities tend to demonstrate prominent trade-off relations rather than reciprocal relations in terms of innovation activities. In this regard, subsequent research should be devoted to an in-depth exploration of the negative effects brought by network spillovers on neighboring cities. In sum, such findings stress the differences between knowledge-based innovation activities and capital-based production activities, calling attention to transforming the regional development model from competitive involution to mutually beneficial cooperation to reduce regional disparities.

Therefore, it has become increasingly critical to develop a novel governance framework that monitors the urban agglomerations and their network positions in the region. The policymakers should take good advantage of innovation networks while avoiding the adverse impacts brought by network diseconomies. More attention should be focused on the small cities surrounding the higher-ranking cities in the innovation network to reduce the negative impacts of 'agglomeration shadows'. For the purpose of fostering a regional networked economy, the governments should give support to the local innovators and gradually shift their roles from participators to rulemakers, so as to indirectly rather than directly promote regional innovation growth.

References

Anselin, L, Rey S, 1991. Properties of tests for spatial dependence in linear regression models. *Geographical Analysis*, 23(2): 112–131. doi: 10.1111/j.1538-4632.1991.tb00228.x

Bavelas A, 1950. Communication patterns in task-oriented groups. *The Journal of the Acoustical Society of America*, 22(6): 725–730. doi: 10.1121/1.1906679

Brandes U, 2001. A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*. 25(2): 163 –177. doi:10.1080/0022250x.2001.9990249

Burt R S, 2003. The social structure of competition. In Cross R (eds.). *Networks in the Knowledge Economy*. Oxford: Oxford University Press, 57 –91. doi:10.1093/oso/9780195159509.001.0001

Burt R S, Burzynska K, 2017. Chinese entrepreneurs, social networks, and *guanxi*. *Management and Organization Review*, 13(2): 221–260. doi: 10.1017/mor.2017.6

Coe N M, Yeung H W C, 2015. *Global Production Networks: Theorizing Economic Development in an Interconnected World*. Oxford: Oxford University Press. doi:10.1093/acprof:oso/9780198703907.001.0001

Capello R, 2000. The city network paradigm: measuring urban network externalities. *Urban Studies*, 37(11): 1925–1945. doi: 10.1080/713707232

Castells M, 1996. The space of flows. In Castells M. *The Rise of the Network Society*, Hoboken, NJ: Wiley-Blackwell, 1: 376–482. doi: 10.1002/9781444319514.ch6

Derudder Ben, Taylor Peter James, Hoyler Michael et al., 2013. Measurement and interpretation of connectivity of Chinese cities in world city network, 2010. *Chinese Geographical Science*, 23(3): 261–273. doi: 10.1007/s11769-013-0604-y

Derudder B, Taylor P J, 2019. Multiple geographies of global urban connectivity as measured in the interlocking network model. In Schwanen T and Van Kempen R. (eds.). *Handbook of Urban Geography.* Cheltenham: Edward Elgar Publishing. 77–102. doi: 10.4337/9781785364600

Friedkin N E, 1991. Theoretical foundations for centrality measures. .*American Journal of Sociology*, 96(6): 1478–1504. doi: 10.1086/229694

Ha J, Howitt P, 2007. Accounting for trends in productivity and R&D: a Schumpeterian critique of semi-endogenous growth theory. *Journal of Money, Credit and Banking*, 39(4): 733–774. doi: 10.1111/j.1538-4616.2007.00045.x

Hesse M, 2016. On borrowed size, flawed urbanisation and emerging enclave spaces: the exceptional urbanism of Luxembourg, Luxembourg. *European Urban and Regional Studies*, 23(4): 612–627. doi: 10.1177/0969776414528723

Huggins R, Johnston A, 2010. Knowledge flow and inter-firm networks: the influence of network resources, spatial proximity and firm size. *Entrepreneurship & Regional Development*, 22(5): 457–484. doi: 10.1080/08985620903171350

Huggins R, Thompson P, 2014. A network-based view of regional growth. *Journal of Economic Geography*, 14(3): 511–545. doi: 10.1093/jeg/lbt012

Huggins R, Thompson P, 2017. Networks and regional economic growth: a spatial analysis of knowledge ties. *Environment and Planning A:Economy and Space*, 49(6): 1247–1265. doi: 10.1177/0308518X17692327

Huggins R, Prokop D, Thompson P, 2020. Universities and open innovation: the determinants of network centrality. *The Journal of Technology Transfer*, 45(3): 718–757. doi: 10.1007/s10961-019-09720-5

Ke S, 2010. Agglomeration, productivity, and spatial spillovers across Chinese cities. *The Annals of Regional Science*, 45(1): 157–179. doi: 10.1007/s00168-008-0285-0

Kleinberg J M, 1999. Authoritative sources in a hyperlinked environment. *Journal of the ACM (JACM)*, 46(5): 604–632. doi: 10.1145/324133.324140

LeSage J P, 2014. Spatial econometric panel data model specification: a Bayesian approach. *Spatial Statistics*, 9(9): 122–145. doi: 10.1016/j.spasta.2014.02.002

Li D, Wei Y D, Wang T, 2015. Spatial and temporal evolution of urban innovation network in China. *Habitat International*, 49(49): 484–496. doi: 10.1016/j.habitatint.2015.05.031

Li X, Hui E C, Lang W et al., 2020. Transition from factor-driven to innovation-driven urbanization in China: a study of manufacturing industry automation in Dongguan City. *China Economic Review*, 59: 101382. doi: 10.1016/j.chieco.2019.101382

Liefner I, Hennemann S, 2011. Structural holes and new dimensions of distance: the spatial configuration of the scientific knowledge network of China's optical technology sector. *Environment and Planning A, 2011*, 43(4): 810–829. doi: 10.1068/a43100

Liefner I, Losacker S, 2020. Low-cost innovation and technology-driven innovation in China's machinery industry. *Technology Analysis & Strategic Management*, 32(3): 319–331. doi: 10.1080/09537325.2019.1656333

Losacker S, Liefner I, 2020. Implications of China's innovation policy shift: 'Does indigenous' mean closed? *Growth and Change*, 51(3): 1124–1141. doi: 10.1111/grow.12400

Lu J, Sun D, Yu J et al., 2020. 'Local versus nonlocal' enterprise linkages of global cities: a comparison between Beijing and Shanghai, China. *Complexity*, 1–13. doi: 10.1155/2020/8918534

Luo X, Shen J, 2009. A study on inter-city cooperation in the Yangtze River Delta region, China. *Habitat International*, 33(1): 52–62. doi: 10.1016/j.habitatint.2008.04.002

Meijers E J, Romein A, 2003. Realizing potential: building regional organizing capacity in polycentric urban regions. *European Urban and Regional Studies*, 10(2): 173–186. doi: 10.1177/0969776403010002005

Meijers E J, Burger M J, Hoogerbrugge M M, 2016. Borrowing size in networks of cities: city size, network connectivity and metropolitan functions in Europe. *Papers in Regional Science*, 95(1): 181–198. doi: 10.1111/pirs.12181

National Bureau of Statistics of China. *China City Statistical Yearbooks*. Beijing: China Statistics Press, 2009−2019. (in Chinese)

Inkpen A C, Tsang E W, 2005. Social capital, networks, and knowledge transfer. *Academy of Management Review*, 30(1): 146–165. doi: 10.5465/amr.2005.15281445

Sabidussi G, 1966. The centrality index of a graph. *Psychometrika*, 31(4): 581–603. doi: 10.1007/BF02289527

Shi S, Wall R, Pain K, 2019. Exploring the significance of domestic investment for foreign direct investment in China: a city-network approach. *Urban Studies*, 56(12): 2447–2464. doi: 10.1177/0042098018795977

Shi S, Pain K, 2020. Investigating China's mid-yangtze river economic growth region using a spatial network growth model. *Urban Studies*, 57(14): 2973–2993. doi: 10.1177/0042098019894232

Shi S, Wong S K, Zheng C, 2021. Network capital and urban development: an inter-urban capital flow network analysis. *Regional Studies*, 1–14. doi: 10.1080/00343404.2021.1955098

Storper M, Venables A J, 2004. Buzz: face-to-face contact and the urban economy. *Journal of Economic Geography*, 4(4): 351–370. doi: 10.1093/jnlecg/lbh027

Taylor P, Derudder B, Hoyler M et al., 2014. City-dyad analyses of China's integration into the world city network. *Urban Studies*, 51(5): 868–882. doi: 10.1177/0042098013494419

Tervo H, 2010. Cities, hinterlands and agglomeration shadows: spatial developments in Finland during 1880–2004. *Explorations in Economic History*, 47(4): 476–486. doi: 10.1016/j.eeh.2010.05.002

Tian L, Wang H H, Chen Y, 2010. Spatial externalities in China regional economic growth. *China Economic Review*, 21: S20–S31. doi: 10.1016/j.chieco.2010.05.006

Van Oort F, Burger M, Raspe O, 2010. On the economic foundation of the urban network paradigm: spatial integration, functional integration and urban complementarities within the Dutch Randstad. *Urban Studies*, 47(4): 725–748. doi: 10.1177/0042098009352362

Van Meeteren M, Neal Z, Derudder B, 2016. Disentangling agglomeration and network externalities: a conceptual typology. *Papers in Regional Science*, 95(1): 61–80. doi: 10.1111/pirs.12214

Wen Y, 2014. The spillover effect of FDI and its impact on productivity in high economic output regions: a comparative analysis of the Yangtze River Delta and the Pearl River Delta, China. *Papers in Regional Science*, 93(2): 341–365. doi: 10.1111/pirs.12086

Ying L G, 2003. Understanding China's recent growth experience: a spatial econometric perspective. *The Annals of Regional Science*, 37(4): 613–628. doi: 10.1007/s00168-003-0129-x

Zhang J, Peck J, 2016. Variegated capitalism, Chinese style: regional models, multi-scalar constructions. *Regional Studies*, 50(1): 52–78. doi: 10.1080/00343404.2013.856514

Zhang X, Kloosterman R C, 2016. Connecting the 'workshop of the world': intra- and extraservice networks of the Pearl River Delta cityregion. *Regional Studies*, 50(6): 1069–1081. doi: 10.1080/00343404.2014.962492