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# Research on urban economic centrality in the perspectives of knowledge stocks and flows

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ABSTRACT

In light of the profound advancements in information and communication technologies ushering in the knowledge economy, the urban space is undergoing a transformation from the traditional “space of places” to the emerging “space of flows.” This shift poses questions about the influence of knowledge flows on urban economic centrality. This paper seeks to address this knowledge gap by introducing a theoretical framework that elucidates how knowledge contributes to urban economic centrality. Our analysis focuses on both intra-city knowledge stocks and inter-city knowledge flows. Empirical findings in China highlight that knowledge stocks based on R&D and education levels, along with knowledge flows, significantly and positively influence all four dimensions of centrality. In contrast, knowledge spatial agglomeration within the knowledge stocks exhibits a significant positive correlation solely with power centrality. Additionally, although the knowledge stock structures don’t yield significant results in the diffusion centrality model, for agglomeration and power centralities, a combination of specialized knowledge and telecommunications enhances urban economic centrality, while face-to-face communication strengthens the positive impact of diverse knowledge on urban economic centrality. The results suggest implementing knowledge-based policies tailored to different nodes in the city network is expected to promote sustainable competitiveness in the urban system.

## 1. Introduction

As populations age and natural resources deplete, it is becoming increasingly clear that the economic growth of advanced economies will depend more on knowledge-based productivity. Unlike labor, natural resources, and physical capital, knowledge is non-rival, meaning that its use by one organization or individual does not diminish its availability for others [1]. The era of the knowledge-based economy symbolizes the significant role of generating and applying knowledge in creating wealth within a city [2–4]. At the same time, urban system is undergoing a significant shift. High-speed transportation networks such as roads, railways, and aviation, have notably enhanced the transferability of tangible elements and reduced the spatial distances of interaction, while the high-speed information networks in virtual spaces, like the internet and mobile communication networks, enable cost-effective and instantaneous information exchange between different cities. This emerging urban system paradigm, referred to as the “space of flows”, is gradually supplanting the traditional “space of places” [5]. As the world’s second-largest economy, China is currently in a

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critical period of transitioning from resource and labor-intensive industries to knowledge-intensive industries under the new normal [6]. From the perspective of "space of flows", to explore the impact mechanism of knowledge stock and flows on the agglomeration of wealth in urban system, is fundamental for China to achieve sustainable economic growth under knowledge-driven conditions.

By exploring the roles of knowledge intra-city stocks and inter-city flows in forming the economic centrality in urban system, the paper responses to research gaps from three strands of literatures including location theories for urban system, studies for urban economic networks, as well as literatures for knowledge spillovers. Firstly, while "borrowed size" addressing network externalities based on "space of flows" that cannot be adequately captured by traditional central place theory in urban system, literatures discussing "borrowed size" primarily elucidates urban economic development concerning variations in population size, ignoring the significant role of knowledge [7]. For the second strand of literatures, empirical studies focus on descriptive analysis for characteristics of urban economic networks constructed by inter-city capital flows, without exploring the role of knowledge in the forming the centrality within the urban economic network. Literatures on knowledge spillover consider knowledge stocks and knowledge flows separately without unifying the agglomerative and network externalities into a framework. Additionally, the third strand of literatures mainly focus on the impacts of knowledge spillovers on firm or regional performance, whereas the impacts of the knowledge stock and flows on economic centrality in urban system is rarely discussed. To address the research gaps identified above, the paper incorporates "borrowed size" into central place theory specifically focus on explaining how knowledge stock and flows influencing the economic development in urban system from both agglomerative and network externalities.

Compared to previous literature that emphasizes the promotion of a city's economic status and influence by agglomeration effects, our findings from the perspective of knowledge further highlight that "borrowed size", relative to its own agglomeration, plays a greater role in promoting a city's economic centrality within the urban system. We emphasize that regional collaboration enables us to harness overall regional benefits more effectively, aligning with the requirements of national governance and providing new opportunities for sustainable urban development.

In the course of this research, we employ two methodological approaches: Social Network Analysis (SNA) and spatial econometrics. Social Network Analysis is a method that utilizes graph theory and mathematical techniques to analyze social relationships and network structures among individuals. When applied to cities, SNA helps reveal patterns of connectivity and network structures between them, including link strength, key nodes, and subgroups. This aids in understanding how cities interconnect and influence one another. Incorporating spatial econometrics is motivated by the method's ability to account for the impact of geographical location on the subject of study. It allows for the exploration of spatial structures and interactions within urban data, leading to a better comprehension of urban development, resource allocation, policy formulation, and planning. Consequently, it provides valuable tools for sustainable urban development and issue resolution.

The organization of this paper is as follows. Section 2 provides a literature review and further elaborates on our innovations and contributions. Section 3 constructs a conceptual framework and proposes hypotheses. Section 4 explains the empirical methods. Section 5 elucidates the empirical results. Section 6 discusses the results. Section 7 concludes the findings.

## 2. Literature review

### 2.1. Theories for urban system

Centrality is a key measure of a city's influence within urban systems. Traditionally, urban economic centers were viewed as dense clusters of non-agricultural businesses [8]. However, cities are not standalone entities; they are part of wider urban systems [9]. Christaller's groundbreaking 1933 research introduced the concept of economic centrality and the "central place theory," using location entropy as a method. This theory has been expanded upon to rank cities hierarchically based on factors such as population and GDP [10,11]. The growth of information technology has significantly increased the flows of people, information, and capital between cities, reshaping geographical spaces. However, the "central place theory," despite its importance, has faced criticism for its limited focus on horizontal inter-city relationships.

Camagni et al. (1993, 1994) proposed the urban network paradigm, viewing cities as a network characterized by specialized labor divisions through non-hierarchical connections. This network fosters external economies through cooperative city interactions [12,13]. Castells (1996) furthered this idea with the "space of flows" theory, signaling a shift from static "spaces of places" to dynamic "spaces of flows". This theory suggests that geographical proximity isn't the only source of externalities, but city interactions also generate network externalities [14]. Networked cities can thus benefit mutually from internal cooperation and knowledge exchange [15]. Capello's (2000) urban network overview also emphasizes network externalities, relationships, and cooperation [14]. Meijers and Burger (2015) expanded on the concept of "borrowed size" to capture network externalities not covered by traditional agglomeration economics [7]. Originally introduced by Alonso (1971), "borrowed size" examines the pros and cons of population growth, showing how smaller cities can benefit from the agglomeration effects of larger neighboring cities [16]. It suggests that cities can span multiple spatial scales through inter-city flows, achieving functions individually unattainable without bearing the full agglomeration costs. However, "borrowed size" mainly focuses on urban economic development in relation to population size, overlooking the significant role of knowledge.

### 2.2. Empirical studies for urban economic networks

As urban structures shift from central place systems to network systems, traditional metrics like population and GDP cannot fully encapsulate economic centrality within intricate urban networks. Scholars have shifted focus from the quantities of productive factors to their interconnections within the urban spatial structure [17–19]. Research has expanded beyond urban "hard networks" of infrastructure to "soft networks" centered on enterprise organizations. This research is primarily divided into two approaches. Firstly, scholars like Alderson and Beckfield (2004), guided by the world city hypothesis, used data from the world's top 500 multinational companies and their branches to analyze city significance in the network [20]. Measures used included in-degree, out-degree, intimacy, and betweenness centrality, revealing a skewed distribution of power in the global city system. Secondly, the Globalization and World Cities research group (GaWC) analyzed service connectivity strength among global cities [21]. They used a network model based on relational data targeting specific advanced producer services (APS) companies. Taylor (2001) also constructed a world city network considering the service value of global service companies in each city and the multiplied value of these companies" offices in other cities [22]. However, both approaches failed to cover all enterprise types and relied on internal vertical company connections, lacking real element flow data and struggling to accurately represent inter-city connections.

Recently, scholars have begun to explore horizontal connections between cities based on external enterprise relationships. This approach provides a more comprehensive view of the economic network, commonly used to gain insights into city economic networks and centrality. Xiao and Sun (2023) calculated centrality indicators of urban networks and presented the temporal and spatial evolution process of inter-city corporate investment networks in 338 city regions in China from 1980 to 2017 [23]. Similarly, Zhu et al. (2022) developed network models for foreign direct investment (FDI) in 33 countries within the Organization for Economic Co-operation and Development (OECD) [24]. They discovered that capital flows in global cities increase flows to nearby smaller cities within their regions. However, most research primarily focuses on the descriptive analysis of characteristics of urban economic networks constructed by inter-city capital flows, without exploring the role of knowledge in forming the centrality within the urban economic network.

### 2.3. Knowledge stocks and flows

Economic centrality is primarily driven by knowledge of technological progress in long term [25,26]. In studies related to knowledge stocks, Al-Laham et al. (2011) demonstrated that including human capital and social capital in knowledge stocks slows the decay rate of newly acquired knowledge, enhancing its ability to recognize opportunities for integrating existing and new knowledge components [27]. Furthermore, scholars emphasize the significance of spatial agglomeration in knowledge stocks. Both the new growth theory and new economic geography theory argue that industrial agglomeration, the resulting externalities, and knowledge spillovers significantly impact urban and regional growth [28]. In the process of spatial agglomeration and knowledge spillover, the structure of knowledge stocks plays a critical role in influencing regional innovation and economic performance. While specialized knowledge stocks contribute to economic growth, research increasingly suggests that diversified knowledge stocks foster new ideas, provides essential resources for innovation, and is more conducive to regional growth [29,30]. Moreover, evolutionary economic geographers, represented by Frenken et al. (2007), propose that related variety knowledge stocks effectively promote regional innovation efficiency [31].

In the process of knowledge flows, cities must identify, absorb, and utilize knowledge from external sources to enhance their technological competencies and internal resources [32,33]. Knowledge flows can be characterized through cooperation projects, R&D cooperation networks, talent flows, and technology transfers [34,35]. Jaffe et al. (1993) were pioneers in using patent citations to measure knowledge spillovers [36]. Building on patent cooperation data, Ma et al. (2015) investigated the structure of knowledge flows among cities in China [37]. They found that China's inter-city knowledge flows network is transitioning from a vertical hierarchical system to a horizontal network system, with a quadrilateral spatial pattern forming around Beijing, Shanghai, Guangzhou, and Chengdu.

However, current research tends to study knowledge stocks and knowledge flows separately, focusing more on their impact on firm performance or competitive advantage. Substantial and diverse knowledge stocks provide a broader array of knowledge elements for external knowledge combination and integration, thereby amplifying the scope, efficiency, and adaptability of knowledge absorption. This, in turn, accelerates the conversion of external knowledge into knowledge stocks. Therefore, there is a need to explore how knowledge stocks and flows contribute to the overall dynamics and development of urban areas.

To address the research gaps identified above, this paper integrates the concept of "borrowed size" into central place theory. This approach focuses specifically on explaining the role of knowledge in influencing economic development in urban systems from both agglomerative and network externalities perspectives. By building upon intercity investment relationships grounded in investment and financing among enterprises, this study offers an evaluation of urban network economic centrality from four distinct dimensions. It also illuminates the development of network centrality through a knowledge-oriented perspective. This study considers both intra-city knowledge stocks and inter-city knowledge flows between cities to address their dual effects on urban network economic centrality.

## 3. The analytical framework

Building on previous research, urban centrality is defined in this study as the level of importance a city holds within an urban network, determined by the strength of its intercity relationships. It's crucial to understand that the flow of capital inherently has an expansive nature. Cities with increased capital mobility tend to attract more significant financial investments, leading to the concentration of production resources within their borders [38]. In this study, we represent a city as a "node" within a network. We construct a city economic network based on investment and financing connections between cities. Our analysis specifically focuses on Chinese prefecture-level cities, using the term "nodes" to symbolize the diverse economic functions carried by these municipalities.

We examine the mechanisms by which knowledge influences economic centrality from the standpoint of knowledge activities in different domains, knowledge structure, and knowledge exchange channels. Additionally, it explores the interaction between urban knowledge structure and communication channels (Fig. 1).

### *3.1. The urban economic centrality in "space of flows"*

Castells introduces the concept of the "space of flows," a composition of places and networks. These places dictate the spatial layout based on central nodes within the network, each tied to specific locales with distinct cultural and social conditions. The pivotal role of these central nodes in generating the network's strategic functions forms the crux of global cities' dynamics [5]. Following Castells's (1996) theoretical framework, the urban economic network can be established by connecting cities through investment and financial links [5]. Each city serves as a network "node," representing unique spots characterized by specific cultural and social traits. The interwoven links symbolize investment and financial connections that facilitate economic exchanges and movements among cities. Within this complex network of economic interactions between cities, the concept of "centrality" becomes significant. It signifies the relative importance and prominence of specific cities (nodes) within the network. These pivotal cities assume a critical and irreplaceable role in the network's operation, serving as strategic epicenters for a wide range of economic activities and facilitating the seamless flow of capital, information, and resources.

Previous research has employed various metrics to assess centrality, primarily including agglomeration centrality and diffusion centrality [18,39]. For instance, Liu and Yao (2019) found that the agglomeration characteristics of cities are crucial for identifying and understanding urban spatial structures, and thus, they used agglomeration centrality to examine the centrality of nodes [18]. In the study by Riascos and Mateos (2020), agglomeration (indegree) and diffusion (outdegree) of taxi routes were employed as different dimensions to investigate the centrality of New York City's transportation network [39]. Building upon these studies concerning centrality in urban networks, this research further extends Neal's (2016) power centrality. Complementing this approach with social network analysis methodologies, the assessment of economic centrality expands into four dimensions: agglomeration centrality, diffusion centrality, power centrality, and integrated centrality [40].

Agglomeration centrality refers to the perception of centrality in the city network as a force that concentrates resources. The circulation and reorganization of resources in the network promote the clustering of economic activities. When a city's network links are strategically positioned to facilitate resource agglomeration, its centrality is reflected in new forms, such as becoming a global financial center or a global business service center [41]. Diffusion centrality denotes a central position in the city network that not only promotes resource agglomeration but also facilitates the efficient diffusion of capital, ideas, and people throughout the network if its

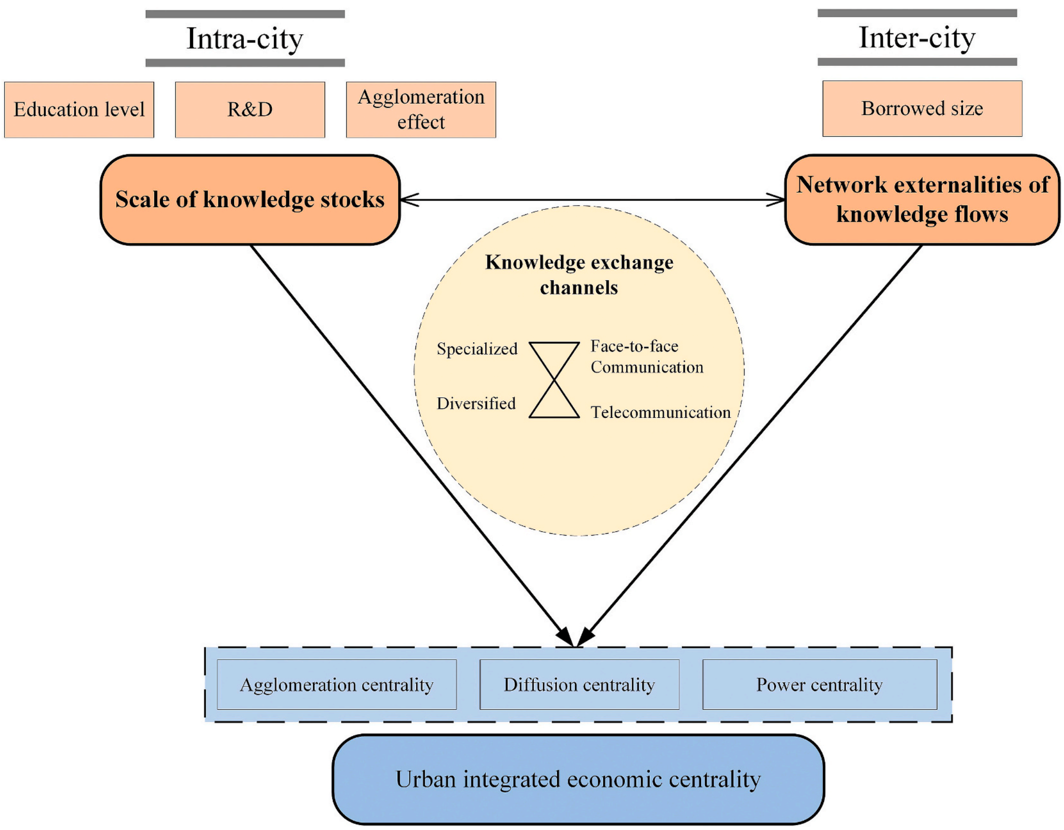


**Fig. 1.** Analytical framework.

link scale is extensive and the hinterland of its links is vast. Power centrality refers to cities with high influence and control over the flow of resources. According to Emerson (1964), power arises not merely from having numerous relationships but specifically from having relationships with dependent actors [42]. In other words, powerful cities may have limited opportunities for direct exchanges, but they exert significant influence over the available opportunities [40]. At last, integrated centrality combines the three functions of centralities (agglomeration centrality, diffusion centrality, and power centrality) to determine a city's comprehensive status within the modern urban network. It considers how well a city concentrates resources, facilitates the spread of economic activities, and controls resource flows. Integrated centrality provides a holistic view of a city's importance and position in the broader economic network.

### *3.2. Intra-city: scale and structure of knowledge stocks*

Knowledge stocks encompass collective knowledge assets available to businesses, organizations, and individuals within the urban setting. The accumulation of knowledge at the city level is a result of learning at the individual, team, and organizational levels, reflecting the city's capacity and potential for knowledge production at a particular moment in time [43]. Cities can deepen their understanding of the functionality of existing knowledge and resources through repeated utilization. They can create novel knowledge or resource combinations by reconstructing existing knowledge and resources and identifying new opportunities across diverse domains. Moreover, knowledge stocks are an essential prerequisite for realizing knowledge flows. Cities with rich knowledge stocks have a greater capacity to generate and disseminate knowledge to other cities. By having a diverse range of knowledge stocks, cities can offer valuable resources that can be shared and exchanged with other cities, fostering the transfer and integration of knowledge.

In conjunction with theories of corporate knowledge management [44,45], some scholars have explored the impact of knowledge stocks on a firm's knowledge innovation performance [46–48]. We extend this theory to urban system, investigating the development of network capital centrality through knowledge stocks. When describing knowledge stocks, we rely on research conducted by Phelps (2007) and Groen (2011), utilizing indicators such as R&D and education levels [49,50]. Besides, scale effects are confined by geographical distance and political barriers, often observed within a city. The accumulation of knowledge stocks in specific areas explains why technologies differ geographically, and technological innovation is currently an essential engine of national economic growth. Therefore, knowledge stock in urban system formed by education level (human), Research and Development (R&D) investment (money), and spatial agglomeration (space), endow cities with enhanced competitiveness in innovation, industrial development, and economic cooperation.

Regions that allocate significant resources to research and development (R&D) are better positioned to absorb, assimilate, and integrate knowledge spillovers from neighboring areas. This strengthens their potential for innovation. Enterprises and research institutions in these cities invest substantially in innovative research, leading to the creation and accumulation of new knowledge. This surge in innovative activities enhances the city's importance within the economic network due to its competitive advantage in generating novel technologies, products, and services. Consequently, this internal technological progress nurtures urban economic centrality, initiating a positive feedback loop.

Moreover, education level reflects the skills and competencies acquired through education, training, and similar processes, which can be translated into tangible goods and services. Knowledge is primarily embedded in the education process. According to comparative advantage theory, countries with a rich human capital base exhibit higher innovation potential and growth rates compared to those with an abundance of unskilled labor [51]. These human resources play a critical role in determining the economic centrality of cities within the economic network. Their continual influx of knowledge and energy into the city's industrial and innovative ecosystem makes them invaluable contributors.

At last, knowledge production exhibits an agglomeration effect, with the strength of its externalities inversely correlated with spatial distance [52,53]. The spatial concentration of human capital and research and development (R&D) investments not only promotes knowledge sharing but also enhances the capacity for "learning by doing." This fosters collaborative innovation among various knowledge-based industries, further amplifying the centrality of cities within the economic network. It positions them as vital hubs for knowledge exchange and economic transactions.

**Hypothesis 1**. Intra-city knowledge stocks including R&D (1.1), educational level (1.2), and agglomeration effects (1.3) are positively related to urban economic centrality.

In addition to scale of intra-city knowledge stocks, structure of knowledge stocks also matters. MAR (Marshall-Arrow-Romer) externalities are rooted in the idea that knowledge spillovers are limited to knowledge within the same category. Thus, they can only be facilitated by the geographical clustering of firms operating within similar industries. In contrast to Marshall, Jacobs underscores that local industrial diversity primarily stimulates knowledge spillovers and, consequently, innovation. The exchange of complementary knowledge drives research and experimentation for innovation, and a more diversified economy enhances these complementary knowledge bases [54]. Nevertheless, there is no consensus in the literature regarding the impact of agglomeration effects. As Frenken et al. (2007) argue, it appears that within a given geographic area, one can observe both the effects associated with specialization and those associated with diversity [31].

The study contends that the economic role of distinct knowledge stock structures is susceptible to the influence of communication modalities. Different knowledge structures interact with communication channels. Telecommunication enhances the positive effect of specialized knowledge structures on economic centrality because it reduces barriers to knowledge exchange. With low barriers, specialized knowledge can be efficiently transmitted through telecommunication methods like document sharing and digital communication platforms. Telecommunication technologies, encompassing digital platforms and virtual networks, expedite the diffusion of specialized knowledge across geographical boundaries. This rapid dissemination makes specialized knowledge more accessible, allowing a broader range of cities to benefit from and contribute to expertise clustering. Efficient exchange of specialized knowledge through telecommunication enhances a city's role as a knowledge and economic hub in the urban network.

However, diversified knowledge requires more face-to-face communication. Firstly, diversified knowledge faces relatively higher barriers to exchange. Face-to-face interactions enable the exchange of "tacit knowledge," which often includes nuanced insights, experiential wisdom, and context-specific understanding. Such knowledge is particularly prevalent within diversified domains and is better communicated through direct, unmediated interactions. Secondly, diversified knowledge often spans multiple disciplines; in-person discussions facilitate the cross-fertilization of ideas, enabling experts to bridge conceptual gaps and foster novelty. In-person exchanges engender serendipitous encounters, chance interactions, and impromptu brainstorming sessions that often lead to breakthrough innovations. Spontaneous interactions are challenging to replicate through telecommunication, making face-to-face communication essential for enhancing economic centrality in diversified knowledge domains. Thirdly, trust and rapport are more effectively established through face-to-face interactions. Given the intricate nature of diverse knowledge collaborations, the establishment of robust relationships among stakeholders enhances the propensity for collaborative endeavors, which, in turn, propels the elevation of urban economic centrality.

**Hypothesis 2.1**. Telecommunication positively moderates the effect of specialized knowledge stock structure on urban economic centrality.

**Hypothesis 2.2**. Face-to-face communication positively moderates the effect of diversified knowledge stocks structure on urban economic centrality.

### *3.3. Inter-city: network externalities of knowledge flows*

Scale effects, as observed by Rosenthal and Strange in 2004, are geographically constrained. However, it's important to note that externalities do not only stem from geographical proximity. The interaction and connection between cities can also give rise to a specific type of externality, variably termed "urban network externalities," "regional externalities," or "externality fields" by scholars such as Phelps (1992), Capello (2000), and Parr (2002) [14,49,55]. The distinction between scale effects and urban network externalities lies in spatial dynamics: scale effects are confined by physical distance and diminish with distance, whereas urban network externalities are not bound by geography and decrease in intensity with the degree of functional interrelations between cities, as noted by Burger and Meijers (2016) [56].

With the progress of globalization and the refinement of industrial chains, the exchange of innovative resources among organizations, regions, and industries has become more frequent. This increased connectivity has led to heightened technical collaboration. Unlike scale effects, the concept of urban knowledge network externalities operates differently. Instead of relying solely on the accumulation of urban knowledge reservoirs, urban knowledge network externalities depend on the intricate web of connections within the network. This complex interconnectivity gives rise to spatial spill-over effects.

This study introduces an innovative expansion of the "borrowed size" concept within the framework of urban knowledge flows. This new idea suggests that cities, regardless of the size of their knowledge reserves, can benefit from borrowing new knowledge and technological advancements from other cities. This is possible due to the advantages of economies of scale, while avoiding the drawbacks of agglomeration [7,57]. A constant flow of knowledge helps firms replenish their knowledge, preventing innovation stagnation caused by entrenched urban knowledge structures. Furthermore, this continuous knowledge exchange provides cities with a steady stream of diverse insights, reducing internal knowledge redundancy and enhancing overall operational efficiency. Consequently, this phenomenon equips cities with the agility required to swiftly adapt to perpetually shifting economic landscapes.

**Hypothesis 3**. Inter-city knowledge flows are positively related to urban economic centrality.

## 4. Methodology

### *4.1. Data sources*

This research is grounded in investment records among Chinese companies. Specific data was retrieved from "Qichacha," a global platform for searching company information, which encompasses information on over 200 million companies in China. This platform maintains synchronized and regularly updated information from the China Administration for Industry and Commerce. The platform offers authentic data that mirrors the direction and flow of funds between companies. The data fields we utilized encompass the addresses of both investing and receiving companies, along with the timestamps of investments. We initially performed data cleaning and processing using Python, which involved the removal of duplicate investments within the same city, non-cash investment activities, and the elimination of outliers. This process yielded 617,152 instances of investment activities between distinct cities in 2017. Following that, we aggregated the flow of funds between companies at the city level, representing it as the "economic intensity" between pairs of cities. We used cities as nodes and depicted the flow of funds as edges, where the direction of funds corresponds to the direction of the edges, and the number of investments determined the edge weight.

Furthermore, this study employed patent transfer data from the incoPat patent database to represent knowledge flows. Because patent information includes author affiliations, address details, and data on organization or individual-level patent transfers, it can be integrated at the city level based on address information. Data cleaning and processing tasks were carried out using Python, which involved the removal of patent transfer activities within the same city and the handling of outliers. This process yielded a total of

104,461 cross-city patent transfer records in 2017, which were then mapped to cities to determine the intensity of knowledge flows between them.

This study gathered Point of Interest (POI) data for scientific research institutions and universities from *AMAP*, a well-known digital map provider, in order to assess the spatial concentration of knowledge entities. In addition, a range of socio-economic indicators, such as "Enrollment in Regular Higher Education Institutions," "Research and Development (R&D) internal expenditure (in 10,000 yuan)," "Road length," "Number of internet service subscribers," "GDP for the year 2007," and "Industrial Employment," were sourced from the *China City Statistical Yearbook (2017)*. Nevertheless, owing to the lack of "R&D internal outlay" and "Road length" data in a few underdeveloped areas like Bazhong, Shannan, Suihua, and others, the final sample for this study comprises 247 Chinese prefecture-level cities. Consequently, there are a total of 247 city nodes and 247 × 247 "city-pair" relationship data, which were utilized to construct the directed weighted network of Chinese cities.

### 4.2. Urban economic recursive centrality

Our analysis is based on records of inter-company investments. Granovetter (2018) defined "regional embeddedness" as the company cluster's dependence on the specific regional environment, including institutional arrangements, social and cultural history, and networks of relationships [58]. Viewed through the lens of "embeddedness," corporate and urban networks are interconnected and mutually embedded. Therefore, inter-company investment connections can be a valuable indicator of the direct interconnectedness of Chinese cities. Based on companies' location and investment relationship data, this paper excludes investment and financing data involving companies located in the same city and utilizes Python to construct a directed weighted urban economic network.

This paper adopts Neal's (2011) concept of recursive centrality and recursive power [40]. Neal's measurement method, known as "recursive," takes into account the influence of indirect connections between cities on urban centrality. It emphasizes that urban centrality depends not only on direct relationships but also on their connected branches. However, "recursive centrality" is traditionally applied to undirected weighted networks, which sum a city's ability to gather and diffuse resources while ignoring flow asymmetry between cities. To address this limitation, we have developed a "recursive" method based on a directed weighted network. We consider urban centrality in terms of recursive agglomeration centrality, recursive diffusion centrality, and recursive power centrality. We argue that the movement of capital is a key indicator of a city's control over resources. Therefore, when calculating recursive power centrality, we focus solely on the intensity of urban financing. Then, the recursive agglomeration centrality ($RAC_i$), the recursive diffusion centrality ($RDC_i$) and recursive power centrality ($RPC_i$) of the city $i$ can be computed as Equation (1) (2) and (3):

$$RAC_i = \sum_j I_{ji} \times IC_j \tag{1}$$

$$RDC_i = \sum_j O_{ij} \times OC_j \tag{2}$$

$$RPC_i = \sum_j \frac{I_{ji}}{IC_j} \tag{3}$$

where $I_{ji}$ contains the strength of connection from city $j$ to city $i$, $IC_j$ is the indegree centrality of city $j$, $O_{ij}$ contains the strength of connection from city $i$ to city $j$, $OC_j$ is the outdegree centrality of city $j$.

Referring to Luo et al.'s (2020) study, which employed the entropy weight TOPSIS method to assess the centrality of cities within the Yangtze River Economic Belt, we adopted the same entropy weight method to combine the centrality indicators into a recursive integrated centrality ($RIC$) [59]. In comparison to subjective weighting methods such as the Delphi method and the analytic hierarchy process, the entropy weight method is regarded as more objective, making it better suited for result interpretation. It leverages the variability between pieces of information for weighting. The model is as Equations (4)–(8):

$$x'_{ij} = \frac{x_{ij} - min_j}{max_j - min_j} \tag{4}$$

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x_{ij}} \tag{5}$$

$$e_j = -k \sum_{i=1}^{n} p_{ij}\, ln\left(p_{ij}\right) \tag{6}$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m} \left(1 - e_j\right)} \tag{7}$$

$$RIC_i = \sum_{j=1}^{m} w_j x'_{ij} \tag{8}$$

where $x_{ij}^{'}$ is the standardized value of each index; $x_{ij}$ is the evaluation index of each city; $min_j$ is the minimum value of the index; and $max_j$ is the maximum value of the index. $e_j$ is the entropy value; $k$ is the constant term, $k = 1/lnm$; $p_{ij}$ is the proportion of the index value of item $j$ of city $i$. $w_j$ is the index weight; $RIC_i$ is the integrated recursive centrality of city $i$..

### 4.3. Measuring knowledge stocks

#### 4.3.1. The scale of knowledge stocks

This paper assesses knowledge stocks by considering the agglomeration of knowledge agents, education levels, and R&D internal expenditure. Local universities and scientific research institutions play a crucial role in nurturing high-level talents for local economic development and supporting industrialized scientific research activities. Therefore, the concentration of scientific research institutions and universities in specific areas is a key consideration. Knowledge clusters are influenced by both spatial distance and scale. In this study, we employ the Density-Based Spatial Clustering of Applications with Noise (DBSACN) algorithm to cluster Points of Interest (POI) data related to scientific research institutions and universities. Unlike traditional clustering methods, the DBSCAN algorithm offers superior performance. It assumes that clusters consist of densely populated regions in the data, while regions with a lower density of points are considered boundaries, potentially containing noise. We configure the DBSCAN algorithm with parameters Eps = 1 km, MinPts = 5, and perform clustering using Manhattan distance. The agglomeration index of knowledge agents is calculated as the number of all points minus the noise points. In our study, we use “Student Enrollment in Regular Higher Education Institutions per 10,000 persons” to measure the education level. Additionally, “R&D internal expenditure” is employed as a representation of R&D.

#### 4.3.2. The structure of knowledge stocks

In the study of urban specialization and diversification methods, the approach of calculating specialization and diversification indices based on employment across various industries is widely utilized [17,60]. To measure Marshallian specialization in a city, the urban knowledge structure specialization index ($PS_j$), the most widely used index, is calculated by averaging the specialization of various industries within a city. These calculations are performed using Equations (9) and (10):

$$KS_i = \frac{\sum_j PS_{ij}}{n} \tag{9}$$

$$KS_{ij} = \frac{\frac{E_{ij}}{\sum_j E_{ij}}}{\frac{\sum_i E_{ij}}{\sum_i \sum_j E_{ij}}} \tag{10}$$

where $i$ is a city, $j$ is an industry, $n$ is the number of industries, and $E$ is employment.

For the diversification of the city’s knowledge structure, this paper adopts the Simpson Diversity index, which is calculated using Equation (11):

$$KD_i = 1 - \sum_j \left( \frac{E_{ij}}{\sum_j E_{ij}} \right)^2 \tag{11}$$

where $i$ is a city, $j$ is an industry, $n$ is the number of industries, and $E$ is employment.

This paper assumes that cities with extensive road infrastructure will have a higher frequency of face-to-face communication, while urban telecommunication infrastructure will promote telecommunication. Therefore, we use “Road length” to represent face-to-face communication and “Number of internet service subscribers” to represent telecommunication as channels for knowledge exchange.

### 4.4. Measuring knowledge flows

Patent cooperation and transfer information, as provided by patent databases, are also employed to measure knowledge flows. Patents are known to contain up to 80 % of the technological knowledge currently available [61]. Consequently, patent data is frequently utilized in numerous studies to assess knowledge levels [62–64]. To build a city knowledge network, we used Python and based it on patent transfer data. The degree centrality method of social network analysis (SNA) is then applied to calculate the knowledge flows among cities.

### 4.5. Modeling

Linear regression is a traditional method often used to explore the determinants of a dependent variable. However, it may yield significant deviations when spatial autocorrelation is present between variables. Consequently, scholars frequently turn to spatial econometric models in fields like urban land planning, economic analysis, and environmental studies. These models account for geographic positioning and spatial relationships in urban matters [17,65,66]. In the realm of urban network research, Huang et al. (2020) employed spatial econometric models to develop an urban growth model, investigating the impact of urban network externalities on economic growth [67]. Furthermore, Anselin (2005) has provided reliable guidelines for testing and selecting spatial models [68], as shown in Fig. 2. Initially, a standard centrality model was constructed to estimate urban centrality knowledge values, as shown below in Equation (12):

$$\begin{aligned}\ln(EC_i) = \alpha + \beta \ln\,(stock)_i + \gamma \ln(flow)_i + \delta S_i + \theta \ln \mathrm{C}_i \\ +\rho(S_i - \overline{S})(ln\ C_i - ln\overline{C}) + \sigma X_i + \varepsilon_i\end{aligned} \tag{12}$$

where $EC_i$ is the urban economic centrality (4 types) vector of the city, $\alpha$ is a constant term, $stock_i$ represents knowledge stocks vector, and $flow_i$ represents knowledge flows vector. $S_i$ and $C_i$ represent urban knowledge structure and knowledge exchange channel respectively. $(S_i - \overline{S})(ln\ C_i - ln\overline{C})$ is the centralized interaction term between knowledge structure and knowledge exchange channel and represents the interaction effect of knowledge communication on urban centrality. $X_i$ represents the and control variables vector $\beta$, $\gamma$, $\delta$, $\rho$ and $\theta$ represent the parameters to be estimated, and $\varepsilon_i$ is the error term.

Then, this study uses Moran's I method to evaluate whether there is a spatial correlation between each dependent variable. To address spatial autocorrelation bias and enhance result accuracy, we utilize spatial econometric models. Additionally, we conduct a Lagrange Multiplier (LM) test, building on prior spatial econometric research. Finally, we construct a spatial error model (SEM) as depicted in Equation (13)–(15) to capture the spatial impact of error terms on urban economic centrality:

$$\ln(EC_i) = \beta \ln(stock)_i + \gamma \ln(flow)_i + \delta S_i + \theta\ ln\ C_i +$$

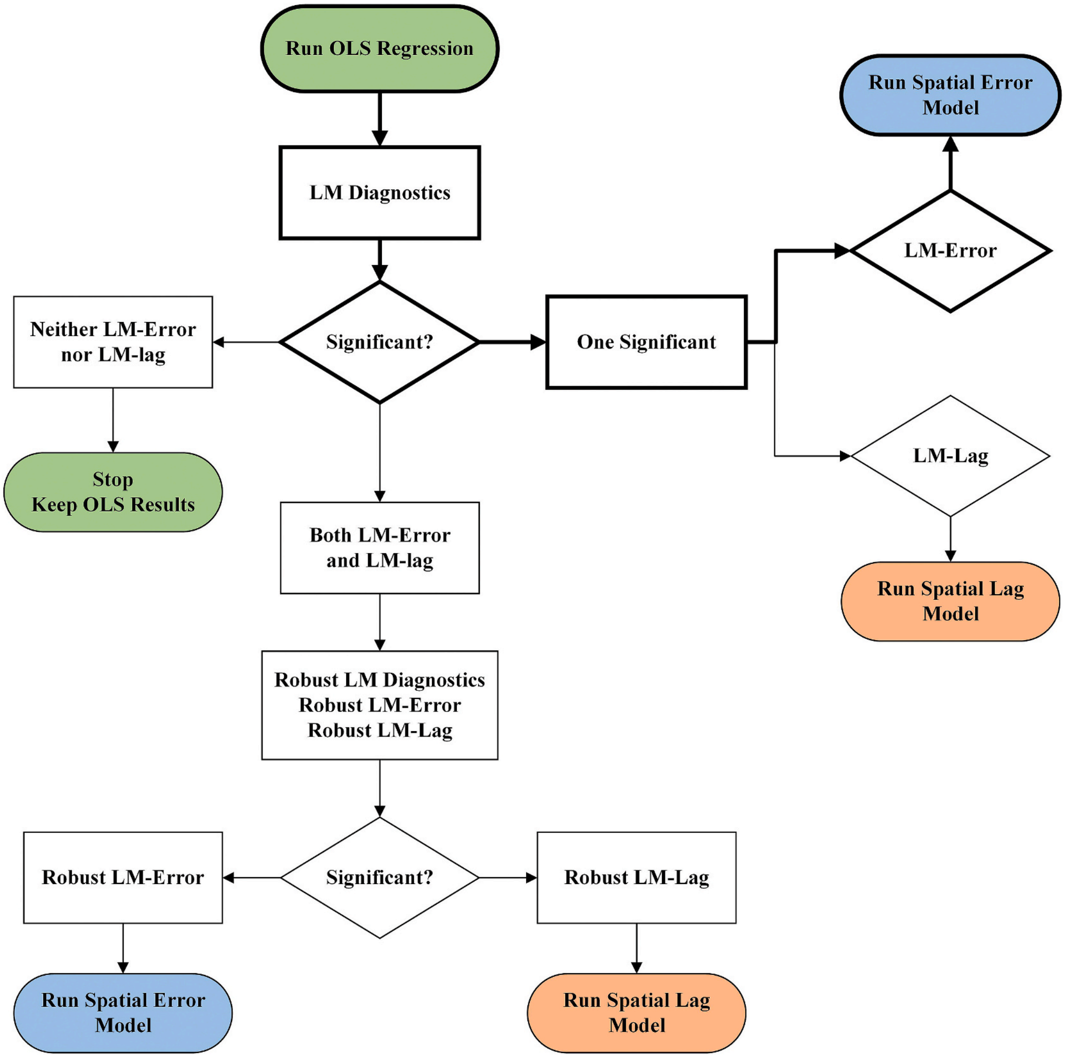


**Fig. 2.** Spatial modeling decision rules.
Source: Anselin (2005)

$$\rho(S_i - \overline{S})(ln\ C_i - ln\overline{C}) + \sigma X_i + \mu \tag{13}$$

$$\mu = \eta Wu + \varepsilon_i \tag{14}$$

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}}, if\ i \neq j \\ 0, if\ i = j \end{cases} \tag{15}$$

where $EC_i$ is the urban economic centrality vector, $W$ is inverse distance weights matrix, indicating the potential interaction strength between cities $i$ and $j$, and $d_{ij}$ is the distance between cities $i$ and $j$; $\eta$ is the spatial autocorrelation parameter, and $\beta$, $\gamma$, $\delta$, $\rho$ and $\theta$ reflect the effects of the characteristic attribute variables on the dependent variable. If coefficient $\eta \neq 0$ and is significant, then there is a spatial correlation error term in the SEM. Additionally, the model includes two robustness tests: 1 % winsorization of continuous variables within the sample and the correction of heteroscedasticity.

## 5. Results

### 5.1. Data descriptions

In this study, we examined a sample of 247 mainland China prefecture-level cities, selecting exploratory variables based on our conceptual framework. Table 1 provides a brief explanation and descriptive statistics for the chosen indicators. In Table 2, we present the rankings of urban economic centrality using various metrics: agglomeration centrality, diffusion centrality, and power centrality. Beijing, Shanghai, and Shenzhen consistently secure the top three positions across all measurement methods, establishing themselves as political, economic, and technological hubs. The recursive integrated centrality (RIC), calculated through the entropy weight method, identifies Beijing, Shanghai, Guangzhou, and Shenzhen as the primary central cities in China's urban network (Fig. 3). Fig. 4 depicts the knowledge flows network, which closely mirrors the economic network.

### 5.2. Baseline results

The results presented in the baseline results (Table 3) demonstrate that knowledge-related variables exhibit distinct effects on urban centrality across the four models. The R-square values range from 0.8200 to 0.8978, affirming the validity of Equation (12). Additionally, the variance inflation factor (VIF) test indicates the absence of a significant multicollinearity issue.

**Table 1**
Description of the variables.

| Category | Indicators | Explanation | Min | Max | Mean |
|---|---|---|---|---|---|
| **Knowledge stocks** | Agglomeration of knowledge agents | The number of POIs of scientific research institutions and universities in the cluster calculated by DBSCAN (point) | 0 | 6826 | 251.4 |
| | Education lever | Students Enrollment of Regular Institutions of Higher Education Per 10,000 persons (person) | 19 | 2767 | 460 |
| | R&D | R&D internal outlay (10000 yuan) | 297 | 15796512 | 596988.0735 |
| | Knowledge structure specialization | $PS_i = \frac{\sum_j PS_{ij}}{n};\ PS_{ij} = \frac{\frac{E_{ij}}{\sum_j E_{ij}}}{\frac{\sum_i E_{ij}}{\sum_i \sum_j E_{ij}}}$ | 0.5191 | 3.2863 | 1.0135 |
| | Knowledge structure diversification | $PD_i = 1 - \sum_j \left(\frac{E_{ij}}{\sum_j E_{ij}}\right)^2$ | 0.5208 | 0.9267 | 0.8361 |
| | Face-to-face communication | Road length (km) | 107.0800 | 10263.16 | 1314.0720 |
| | Telecommunication | The number of subscribers of internet services (10,000 households) | 14 | 681 | 118.4694 |
| **Knowledge flows** | patent transfer | The Node Degree Centrality of Inter-city Patent Transfer Network | 2 | 18785 | 849.5429 |
| **Control variables** | Political factor | Municipality = 2;<br>Provincial capital city and sub-provincial city = 1; others = 0 | 0 | 2 | 0.1296 |
| | Historical factor | GDP 10 years ago (2007) (10000 yuan) | 618352 | 93533200 | 9156472 |

**Table 2**
Centrality of the top 15 cities in China.

| Ranking | City | RIC | City | RAC | City | RDC | City | RPC |
|---|---|---|---|---|---|---|---|---|
| 1 | Beijing | 0.1032 | Shenzhen | 1 | Beijing | 1 | Beijing | 1 |
| 2 | Shanghai | 0.0813 | Shanghai | 0.8409 | Shanghai | 0.9115 | Shanghai | 0.4739 |
| 3 | Shenzhen | 0.0710 | Beijing | 0.8059 | Shenzhen | 0.6550 | Shenzhen | 0.4689 |
| 4 | Guangzhou | 0.0358 | Tianjin | 0.4990 | Guangzhou | 0.3872 | Chengdu | 0.3754 |
| 5 | Hangzhou | 0.0311 | Guangzhou | 0.3809 | Hangzhou | 0.3204 | Kunming | 0.3066 |
| 6 | Tianjin | 0.0306 | Hangzhou | 0.3727 | Tianjin | 0.3158 | Haikou | 0.2968 |
| 7 | Chengdu | 0.0270 | Suzhou | 0.3666 | Suzhou | 0.2051 | Urumqi | 0.2403 |
| 8 | Suzhou | 0.0212 | Ningbo | 0.3161 | Ningbo | 0.1866 | Guangzhou | 0.2240 |
| 9 | Ningbo | 0.0185 | Chengdu | 0.3047 | Nanjing | 0.1526 | Xi"an | 0.2138 |
| 10 | Nanjing | 0.0168 | Nanjing | 0.2311 | Chengdu | 0.1514 | Hangzhou | 0.1944 |
| 11 | Wuhan | 0.0166 | Wuhan | 0.2274 | Zhuhai | 0.1121 | Wuhan | 0.1912 |
| 12 | Haikou | 0.0159 | Chongqing | 0.2122 | Wuhan | 0.1027 | Xining | 0.1818 |
| 13 | Xi"an | 0.0149 | Jiaxing | 0.2050 | Xiamen | 0.0974 | Nanning | 0.1778 |
| 14 | Kunming | 0.0149 | Dongguan | 0.1850 | Dongguan | 0.0966 | Zhengzhou | 0.1698 |
| 15 | Zhengzhou | 0.0134 | Wuxi | 0.1674 | Wuxi | 0.0927 | Lanzhou | 0.1608 |

*Notes:* RIC, RAC, RDC and RPC are normalized.

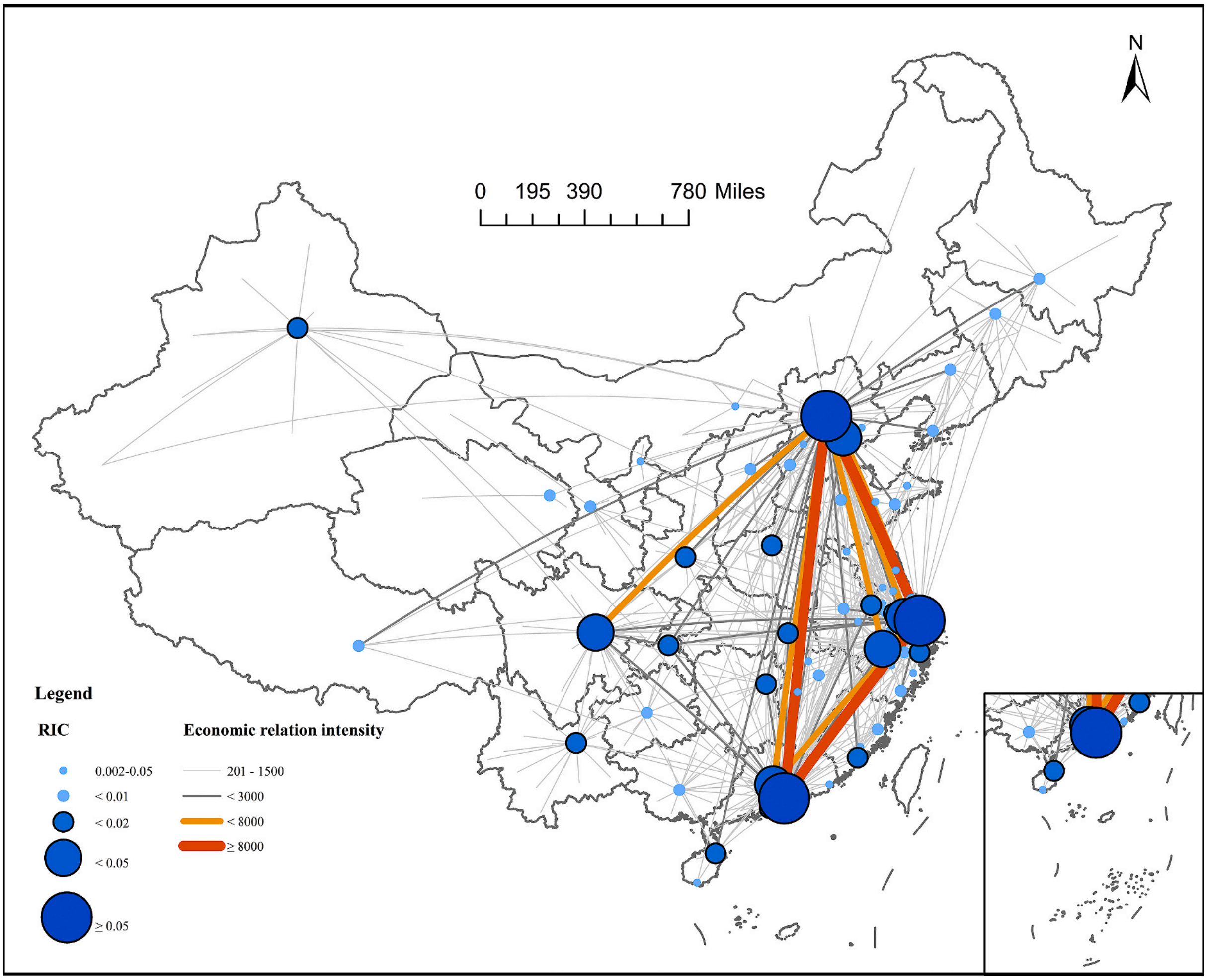


**Fig. 3.** Urban economic network in China, 2017.

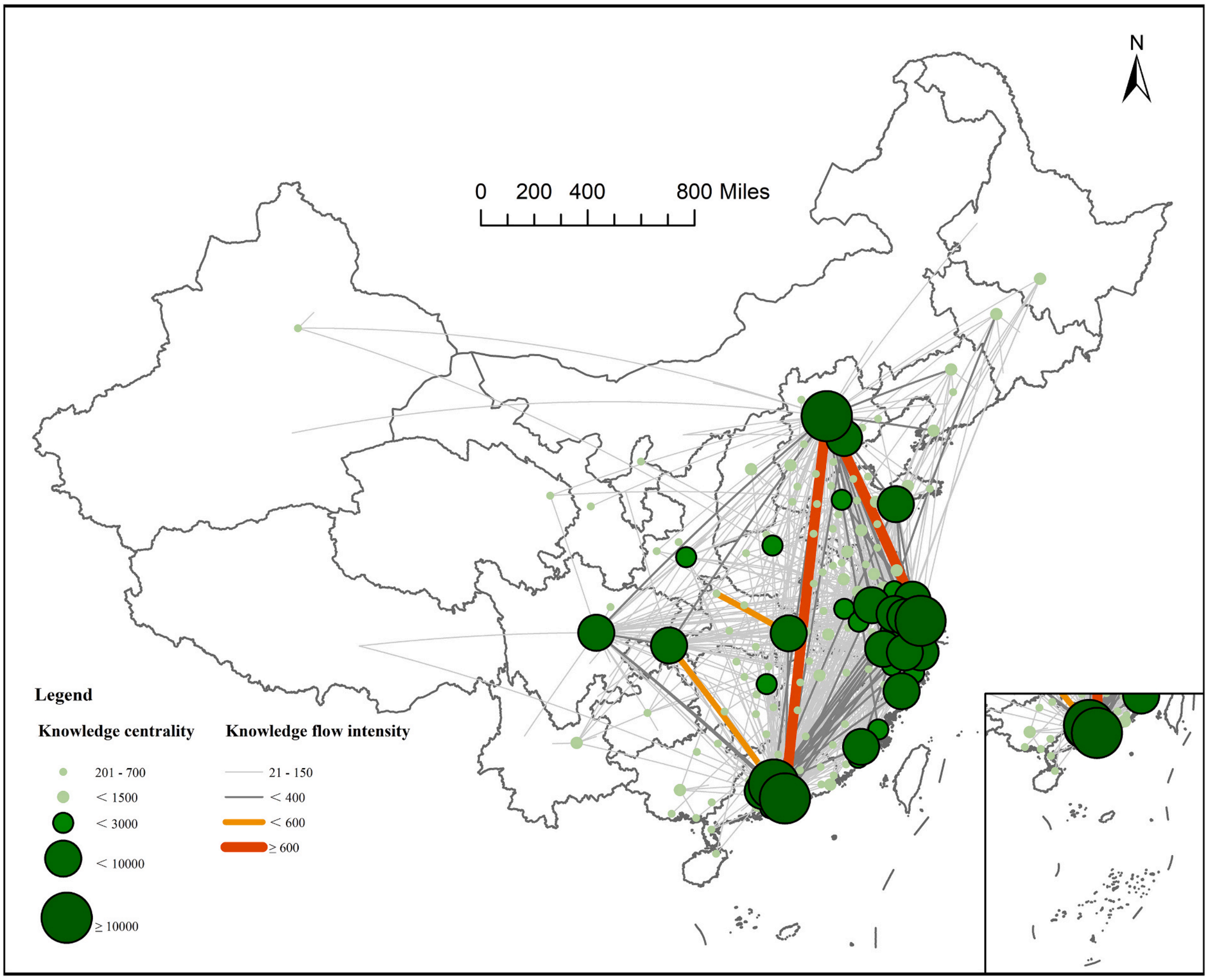


**Fig. 4.** Urban knowledge network in China, 2017.

**Table 3**
Baseline results.

| VAR | RAC model | RDC model | RPC model | RIC model | Vif |
|---|---|---|---|---|---|
| Knowledge stocks | | | | | |
| Agglomeration of knowledge agents | −0.0427 | 0.0160 | 0.1091 ** | 0.0179 | 4.68 |
| Education level | 0.1712 *** | 0.0900 * | 0.1244 ** | 0.1273 *** | 1.64 |
| R&D | 0.1146 *** | 0.1526 *** | 0.0651 | 0.0983 *** | 5.06 |
| Specialized knowledge structure | 0.6806 *** | 0.4500 ** | 0.6491 *** | 0.6405 *** | 4.36 |
| Diversified knowledge structure | −1.7096 ** | −2.1791 ** | −0.6762 | −1.8859 *** | 2.69 |
| Face-to-face communication | 0.2294 *** | 0.3262 *** | 0.2037 ** | 0.2764 *** | 4.80 |
| Telecommunication | 0.1823 ** | 0.1987 * | 0.0756 | 0.1793 ** | 5.94 |
| Specialized knowledge structure * Face-to-face communication | −0.0287 | 0.0115 | −0.2021 | −0.1208 | 2.67 |
| Specialized knowledge structure * Telecommunication | 0.3958 ** | 0.2080 | 0.3440* | 0.3712 ** | 4.61 |
| Diversified knowledge structure * Face-to-face communication | 1.2737 | 1.73677 | 1.3998 | 1.5603 * | 6.19 |
| Diversified knowledge structure * Telecommunication | −3.3953 *** | −2.8979 ** | −3.3400 *** | −3.3604 *** | 5.34 |
| **Knowledge flows** | 0.2828 *** | 0.2809 *** | 0.0817 | 0.2199 *** | 5.19 |
| **Control variables** | | | | | |
| Political factor | 0.7366 *** | 0.8731 *** | 1.3938 *** | 1.1012 *** | 2.37 |
| Historical factor | 0.0371 ** | 0.1389 | 0.0944 ** | 0.0425 | 7.79 |
| Constant | 10.8527 *** | 8.3314 *** | −5.9878 *** | −12.5522 *** | |
| $R^2$ | 0.8774 | 0.8904 | 0.8200 | 0.8978 | |
| Rbar-squared | 0.8700 | 0.8838 | 0.8092 | 0.8917 | |
| Mean VIF | | | | | 4.52 |

*Notes:* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

### 5.3. Spatial econometric models of urban economic centrality

#### 5.3.1. The economic agglomeration centrality model

Significant spatial autocorrelation is observed for RAC; Moran's I is 0.3436 at the 99 % confidence level. Lagrange multiplier tests are employed to discern whether the spatial autocorrelation originates from spatial lag or error, aiding in the determination of whether SEM or SLM constitutes a more robust model for estimation. The findings presented in Table 4 indicate that the coefficients of the LM test for spatial error are statistically significant. As a result, we incorporate spatial autocorrelation into the regression in the form of error. When evaluating the three models, measures of goodness-of-fit suggest that Model (4) yields the best fit, and empirical results align with research hypotheses. Drawing on the results outlined in Table 4, the coefficients of education level and R&D emerge as positive and statistically significant, signifying that education level and R&D contribute to an increase in overall RAC. Moreover, knowledge flows exhibit a positive association with RAC, indicating that a 10 % increase in knowledge links could elevate RAC by 1.952 %, in line with Hypothesis 3. For an interpretation of the impact of interaction effects of knowledge exchange on RAC, Table 4 presents the results of interaction term coefficients. The findings imply that the interaction between them exerts a positive influence on RAC. Specifically, the interaction coefficient between specialized knowledge structure and telecommunication communication stands at 0.2567, and it achieves significance at the 95 % level. This outcome supports Hypothesis 2.1, suggesting that telecommunication communication fosters the positive influence of specialized knowledge structure on urban economic centrality. Additionally, the interaction coefficient between diversified knowledge structure and telecommunication communication also emerges as positively significant, aligning with Hypothesis 2.2. This result signifies that face-to-face communication positively moderates the impact of diversified knowledge structure on urban economic centrality.

#### 5.3.2. The economic diffusion centrality model

The outcomes are displayed in Table 5, revealing that Moran's I is 0.3172, exceeding 0, which signifies a positive correlation in our data regarding RDC. To refine the model selection, we conducted LM-tests, and both the LM-error and Robust LM-error tests showed statistical significance. Consequently, the estimation results of the SEMs are utilized to delve deeper into the effects of knowledge. The $R^2$ values of the SEMs suggest that the final model boasts the best goodness-of-fit. The association between knowledge stocks and economic centrality in the RDC model mirrors that in the RAC model. Specifically, the coefficients for education level and R&D stand at 0.1149 and 0.1603, respectively, implying that RDC could increase by 0.1149 % and 0.1603 %, in accordance with the expectations laid out in Hypothesis 1.2 and Hypothesis 1.3. Moreover, the coefficient for knowledge flows between cities is positively significant, aligning with the anticipated directions set forth in Hypothesis 3. However, in contrast to the RAC model, the interaction effect does not attain statistical significance in the RDC model. This indicates that the impact of knowledge exchange outcomes on RDC is not significantly influenced by communication channels.

**Table 4**
Results of RAC SEMs.

| VAR | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Knowledge stocks** | | | | |
| Agglomeration of knowledge agents | 0.0746 ** | | | −0.0029 |
| Education level | 0.1403 *** | | | 0.1571 *** |
| R&D | 0.1172 *** | | | 0.0931 *** |
| Specialized knowledge structure | | | 0.6090 *** | 0.6134 *** |
| Diversified knowledge structure | | | −2.3314 *** | −1.5666 ** |
| Face-to-face communication | | | 0.3147 *** | 0.1981 *** |
| Telecommunication | | | 0.4056 *** | 0.2264 *** |
| Specialized knowledge structure * Face-to-face communication | | | −0.2007 | −0.0751 |
| Specialized knowledge structure * Telecommunication | | | 0.4185 *** | 0.2567 ** |
| Diversified knowledge structure * Face-to-face communication | | | 1.6637 ** | 1.3189 ** |
| Diversified knowledge structure * Telecommunication | | | −2.5841 *** | −2.6086 *** |
| **Knowledge flows** | | 0.3042 *** | | 0.1952 *** |
| **Control variables** | | | | |
| Political factor | 0.8406 *** | 0.8694 *** | 0.8857 *** | 0.7623 *** |
| Historical factor | 0.4867 *** | 0.4465 *** | 0.2456 *** | 0.0627 |
| constant | 6.7031 *** | 8.1480 *** | 10.3624 *** | 11.0922 *** |
| lambda | 0.8140 *** | 0.6420 *** | 0.7750 *** | 0.7400 *** |
| R-squared | 0.8693 | 0.8606 | 0.8775 | 0.9011 |
| Rbar-squared | 0.8666 | 0.8589 | 0.8723 | 0.8951 |
| log-likelihood | −75.5899 | −78.6456 | −66.3698 | −38.6506 |
| Moran"s I test | 0.3436 *** | 0.3436 *** | 0.3436 *** | 0.3436 *** |
| LM test | | | | |
| LM test-spatial lag | 0.7463 | 0.0449 | 8.3453 *** | 0.2736 |
| Robust LM test-spatial lag | 0.2067 | 0.1321 | 6.7352 *** | 0.1518 |
| LM test-spatial error | 296.2638 *** | 50.6182 *** | 147.2659 *** | 38.9710 *** |
| Robust LM test-spatial error | 295.7243 *** | 50.7055 *** | 145.6558 *** | 38.8491 *** |

*Notes:* ***p < 0.01, **p < 0.05, *p < 0.1.

**Table 5**
Results of RDC SEMs.

| VAR | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Knowledge stocks** | | | | |
| Agglomeration of knowledge agents | 0.1269 *** | | | 0.0578 |
| Education level | 0.0947 ** | | | 0.1149 *** |
| R&D | 0.2124 *** | | | 0.1603 *** |
| Specialized knowledge structure | | | 0.3715 ** | 0.3942 ** |
| Diversified knowledge structure | | | −2.2934 *** | −1.4757 * |
| Face-to-face communication | | | 0.4701 *** | 0.2943 *** |
| Telecommunication | | | 0.3806 *** | 0.1472 |
| Specialized knowledge structure * Face-to-face communication | | | −0.0758 | −0.0373 |
| Specialized knowledge structure * Telecommunication | | | 0.2747 | 0.1337 |
| Diversified knowledge structure * Face-to-face communication | | | 1.0145 | 0.8788 |
| Diversified knowledge structure * Telecommunication | | | −1.3262 | −1.4537 |
| **Knowledge flows** | | 0.3480 *** | | 0.1936 *** |
| **Control variables** | | | | |
| Political factor | 0.9220 *** | 1.0324 *** | 1.0489 *** | 0.8467 *** |
| Historical factor | 0.6026 *** | 0.7066 *** | 0.4471 *** | 0.1881 * |
| constant | 3.1874 *** | 3.2169 *** | 5.8528 *** | 7.5751 *** |
| lambda | 0.8120 *** | 0.6020 *** | 0.7520 | 0.7550 *** |
| R-squared | 0.8948 | 0.8766 | 0.8904 | 0.9130 |
| Rbar-squared | 0.8926 | 0.875 | 0.8858 | 0.9078 |
| log-likelihood | −109.0453 | −122.5559 | −111.0524 | −83.1290 |
| Moran"s I test | 0.3172 *** | 0.3172 *** | 0.3172 *** | 0.3172 *** |
| LM test | | | | |
| LM test-spatial lag | 0.8944 | 0.0160 | 4.6027** | 0.0149 |
| Robust LM test-spatial lag | 0.2404 | 0.0039 | 3.4337 * | 0.1128 |
| LM test-spatial error | 262.6267 *** | 52.9798 | 103.0587 *** | 64.9644 *** |
| Robust LM test-spatial error | 261.9727 *** | 52.9676 | 101.8898 *** | 65.0623 *** |

*Notes:* ***p < 0.01, **p < 0.05, *p < 0.1.

### 5.3.3. *The economic power centrality model*

Moran's Index was presented in Table 6 to assess the presence of spatial correlation within the dataset. The findings indicated that all Lagrange Multiplier tests for spatial errors (both simple and robust) exhibited significance, indicating the existence of spatial dependence between variables. Consequently, it was recognized that the OLS model might be biased. Furthermore, the results

**Table 6**
Results of RPC SEMs.

| VAR | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Knowledge stocks** | | | | |
| Agglomeration of knowledge agents | 0.1776 *** | | | 0.1165 *** |
| Education level | 0.1000 ** | | | 0.0994 ** |
| R&D | 0.0879 ** | | | 0.0960 ** |
| Specialized knowledge structure | | | 0.5972 *** | 0.5841 *** |
| Diversified knowledge structure | | | −0.9086 | −0.6511 |
| Face-to-face communication | | | 0.3803 *** | 0.2373 *** |
| Telecommunication | | | 0.3639 *** | 0.1234 |
| Specialized knowledge structure * Face-to-face communication | | | −0.3806 ** | −0.3412 ** |
| Specialized knowledge structure * Telecommunication | | | 0.4438 ** | 0.3326 ** |
| Diversified knowledge structure * Face-to-face communication | | | 1.7904 * | 1.7164 * |
| Diversified knowledge structure * Telecommunication | | | −2.6588 ** | −2.6425 ** |
| **Knowledge flows** | | 0.2256 *** | | 0.1175 ** |
| **Control variables** | | | | |
| Political factor | 1.2110 *** | 1.4149 *** | 1.3103 *** | 1.0992 *** |
| Historical factor | 0.4806 *** | 0.5846 *** | 0.3140 *** | 0.1560 |
| constant | −10.1342 *** | −10.6610 *** | −9.2287 *** | −7.7285 *** |
| lambda | 0.6800 *** | 0.6670 *** | 0.6720 *** | 0.7300 *** |
| R-squared | 0.8286 | 0.8011 | 0.8284 | 0.8561 |
| Rbar-squared | 0.8250 | 0.7986 | 0.8211 | 0.8475 |
| log-likelihood | −110.4102 | −128.1665 | −110.1053 | −89.7270 |
| Moran"s I test | 0.0639 *** | 0.0639 *** | 0.0639 *** | 0.0639 *** |
| LM test | | | | |
| LM test-spatial lag | 4.1378 | 0 | 0.9090 | 0.3030 |
| Robust LM test-spatial lag | 1.9956 | 5.0457 ** | 8.3057 *** | 8.6575 *** |
| LM test-spatial error | 34.607 *** | 12.9689 *** | 10.7575 *** | 17.2306 *** |
| Robust LM test-spatial error | 32.4647 *** | 18.0146 *** | 18.1543 *** | 25.5850 *** |

*Notes:* ***p < 0.01, **p < 0.05, *p < 0.1.

underscored that, among the spatial regression models assessed, the Spatial Error Model (SEM) remained the most suitable choice. When comparing the four models, Model (4) emerged as the best fit based on goodness-of-fit measures. The outcomes of the RPC model diverge from those of the RAC and RDC models. In line with Hypothesis 1, the coefficients for the agglomeration of knowledge agents, education level, and R&D variables associated with knowledge stocks—are all positive and statistically significant. The results presented in Table 6 offer substantiating evidence for a positive correlation between knowledge flows and RPC. The findings related to the interaction term align with Hypothesis 2.1 and Hypothesis 2.2. Notably, we observe that the interaction between specialized knowledge structure and telecommunication significantly and positively contributes to enhancing RPC. In contrast, the interaction between diversified knowledge structure and telecommunication fails to exhibit significance.

#### 5.3.4. The economic integrated centrality model

Following the approach used in the preceding models, we initially employed Moran's I statistics to assess the spatial autocorrelations of RIC. The outcomes, as detailed in Table 7, reveal that both Moran's I and Robust LM (error) exhibit significance at the 0.01 level for RPC. Consequently, we opted for the SEM approach and evaluated the goodness-of-fit using $R^2$, finding that Model (4) demonstrated the best fit. Among the three variables linked to knowledge stocks, the coefficients for education level and R&D are positively significant at the 99 % confidence level. This suggests that cities with higher education levels and greater R&D investments are likely to exhibit higher RIC values. The outcomes from various models consistently highlight the positive and significant coefficients associated with knowledge flows variables. This substantiates the notion that knowledge flows contribute to the enhancement of overall urban economic centrality, aligning with Hypothesis 3. Furthermore, when examining the potential interaction effects between the structure of knowledge exchange and the communication channels' influence on urban economic centrality, we identify significant positive interactions. Specifically, the interaction effects between specialized knowledge structure and telecommunication, as well as between diversified knowledge structure and face-to-face communication, exhibit significance in predicting RIC. These findings offer further confirmation of Hypothesis 2.1 and Hypothesis 2.2.

### 5.4. Robustness test results

This paper tested the robustness of the results using two methods: 1 % winsorization of the continuous variables in the sample and the correction of heteroscedasticity. The results demonstrate that both the truncation process and the application of White's heteroscedasticity correction to standard errors in the regression analysis did not significantly alter the direction of the core independent variable coefficients. This further substantiates the robustness of our findings. Detailed results of the robustness tests are presented in Table 8 and Table 9.

**Table 7**
Results of RIC SEMs.

| VAR | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Knowledge stocks** | | | | |
| Agglomeration of knowledge agents | 0.1208 *** | | | 0.0473 |
| Education level | 0.1152 *** | | | 0.1240 *** |
| R&D | 0.1349 *** | | | 0.1078 *** |
| Specialized knowledge structure | | | 0.5690 *** | 0.5916 *** |
| Diversified knowledge structure | | | −2.2187 *** | −1.5752 ** |
| Face-to-face communication | | | 0.4077 *** | 0.2690 *** |
| Telecommunication | | | 0.4031 *** | 0.1975 ** |
| Specialized knowledge structure * Face-to-face communication | | | −0.2786 ** | −0.2023 |
| Specialized knowledge structure * Telecommunication | | | 0.4476 *** | 0.3096 ** |
| Diversified knowledge structure * Face-to-face communication | | | 1.7659 ** | 1.5871 ** |
| Diversified knowledge structure * Telecommunication | | | −2.4754 *** | −2.5325 *** |
| **Knowledge flows** | | 0.2996 *** | | 0.1687 *** |
| **Control variables** | | | | |
| Political factor | 1.0606 *** | 1.1872 *** | 1.1485 *** | 0.9821 *** |
| Historical factor | 0.5253 *** | 0.5359 *** | 0.2856 *** | 0.0924 |
| constant | −17.9076 *** | −16.9798 *** | −14.6838 *** | −13.4717 *** |
| lambda | 0.7450 *** | 0.4920 *** | 0.6530 *** | 0.6760 *** |
| R-squared | 0.8855 | 0.8711 | 0.8915 | 0.9143 |
| Rbar-squared | 0.8832 | 0.8695 | 0.8869 | 0.9091 |
| log-likelihood | −73.6765 | −83.0474 | −64.5807 | −35.6306 |
| Moran"s I test | 0.2465 *** | 0.2465 *** | 0.2465 *** | 0.2465 *** |
| LM test | | | | |
| LM test-spatial lag | 9.7604 *** | 10.5111 *** | 0.7788 | 9.4958 *** |
| Robust LM test-spatial lag | 5.0292 ** | 8.6839 *** | 0.1813 | 7.7712 *** |
| LM test-spatial error | 230.0952 *** | 32.0872 *** | 63.8747 *** | 31.5170 *** |
| Robust LM test-spatial error | 225.3640 *** | 30.2601 *** | 63.2772 *** | 29.7924 *** |

*Notes:* ***p < 0.01, **p < 0.05, *p < 0.1.

## 6. Discussion

Comparing the results of the aforementioned models, we can observe that knowledge stocks, along with research and development (R&D) activities, and educational levels within knowledge stocks, have a notably positive impact on various forms of centrality. In contrast, knowledge spatial agglomeration within the knowledge stocks exhibits a significant positive correlation solely with RPC. This suggests that for cities with higher RPC levels, elements such as schools, research institutions, and libraries have become crucial entities for connecting inner and outer regions. Furthermore, in the case of RDC, the interaction between knowledge structure and communication channels is not statistically significant. However, for RAC and RPC, telecommunications enhance the positive influence of specialization on centrality, while face-to-face communication strengthens the role of diverse knowledge.

Comparing our research findings with prior studies reveals both similarities and distinctions. Concerning the knowledge stocks, it is evident that both education levels and R&D exert significant influences on economic centrality. Research conducted by Suwandaru et al. (2021) and Ershova et al. (2019) also underscores the pivotal role of education and human capital in bolstering competitiveness and fostering sustainable economic growth [69,70]. Furthermore, in addition to education, various theories and empirical models, such as Inekwe (2015), Edquist and Henrekson (2017), and Hong (2017), have increasingly recognized R&D as a fundamental driver of economic growth [71–73]. Regarding the spatial agglomeration of knowledge, discussions in the 1980s suggested that advancements in information and telecommunications technology might reduce the need for physical proximity, potentially diminishing the significance of agglomeration economies, as observed by Glaeser and Kahn (2001) and Audirac (2005) [74,75]. However, our findings are consistent with those of Giuliano et al. (2019), indicating that even in the information age, agglomeration continues to explain centrality, especially in the context of RPC within our study [76].

In terms of knowledge flows, we find a positive correlation with all four dimensions of economic centrality, which aligns with Hypothesis 3. This discovery highlights the significant role that knowledge flows play in boosting economic centrality. While prior research has explored the impact of knowledge flows on innovation performance through the lens of enterprise organization [77,78], and some scholars have examined knowledge flows using patent data, such as Li and Phelps (2019) identifying an increasing role as a knowledge hub in China's Yangtze River Delta [79]. Previous studies haven't explicitly emphasized the influence of knowledge flows on shaping urban capital centrality. However, our research points to the fact that the intensity of inter-city knowledge flows positively impacts network capital centrality. This implies that the concept of "borrowed scale" within urban knowledge flows significantly contributes to enhancing urban network capital centrality.

Within the knowledge structure framework, scholars advocating for knowledge diversity argue that excessively high specialization levels can lead to "congestion effects" that outweigh agglomeration spillovers [28,54,80]. In contrast, some researchers contend that specialized production is more efficient, emphasizing that exchanging similar knowledge is more effective for enhancing urban economic centrality than exchanging different types of knowledge [81,82]. Regarding knowledge communication channels, certain scholars emphasize the concept of tacit knowledge to underscore the importance of face-to-face contact for effective knowledge dissemination [83,84]. Our research results demonstrate that both diversified and specialized knowledge structures contribute to the enhancement of RAC and RPC. However, our study distinguishes itself from previous literature by explicitly examining the interaction between knowledge structure and communication channels. In the RAC and RPC models, telecommunications enhance the efficiency of exchanging specialized knowledge, while face-to-face communication promotes diversified knowledge exchange. These findings validate our theoretical assumptions. Face-to-face contact can mitigate the negative impact of diversified knowledge structure on urban economic centrality, while telecommunications can strengthen the positive impact of a specialized knowledge structure. This outcome may be attributed to distinct knowledge barriers in specialized and diversified knowledge structures. In the exchange of knowledge of the same type, telecommunications can enhance the efficiency of transmitting specialized communicative knowledge through methods such as phone calls, networks, and faxes. However, for different types of knowledge exchanges, face-to-face knowledge exchange is crucial for transmitting tacit knowledge.

## 7. Conclusions and future prospects

### 7.1. Conclusions

This paper provides a theoretical exploration of the influence mechanism of knowledge on urban economic centrality through intra-city knowledge stocks, inter-city knowledge flows, and knowledge exchange channels. In our empirical study, we use data on inter-firm investment relationships and patent transfers, constructing urban network models and assessing centrality using SNA methods. To investigate how knowledge affects urban capital centrality, we apply spatial econometrics, specifically the SEM.

The findings of this study suggest that knowledge has varied effects on different centralities. Our results indicate that knowledge stocks based on R&D and education levels, along with knowledge flows, significantly and positively influence all four dimensions of centrality. In contrast, knowledge spatial agglomeration within the knowledge stocks exhibits a significant positive correlation solely with RPC. Additionally, although the knowledge structure doesn't yield significant results in the RDC model, for RAC and RPC, a combination of specialized knowledge and telecommunications enhances urban economic centrality, while FTF communication strengthens the positive impact of diverse knowledge on urban economic centrality. In summary, tailoring knowledge-based policies to different nodes within the city network can enhance sustainable competitiveness in the urban system.

**Table 8**
Winsorized spatial error model results.

| VAR | RAC | RDC | RPC | RIC |
|---|---|---|---|---|
| **Knowledge stocks** | | | | |
| Agglomeration of knowledge agents | −0.0004 | 0.0558 | 0.1149 *** | 0.0460 |
| Education level | 0.1555 *** | 0.1124 ** | 0.0962 ** | 0.1222 *** |
| R&D | 0.1034 *** | 0.1664 *** | 0.1065 *** | 0.1180 *** |
| Specialized knowledge structure | 0.6972 *** | 0.5249 ** | 0.7062 *** | 0.7107 *** |
| Diversified knowledge structure | −1.6802 *** | −1.6935 ** | −0.8412 | −1.7478 *** |
| Face-to-face communication | 0.1849 *** | 0.2933 *** | 0.2243 *** | 0.2556 *** |
| Telecommunication | 0.2147 *** | 0.1444 | 0.1275 | 0.1949 ** |
| Specialized knowledge structure * Face-to-face communication | −0.0071 | 0.0142 | −0.3715 ** | −0.1873 |
| Specialized knowledge structure * Telecommunication | 0.2748 | 0.2260 | 0.4540 ** | 0.3958 ** |
| Diversified knowledge structure * Face-to-face communication | 1.4053 | 0.7629 | 1.9573 * | 1.7076 * |
| Diversified knowledge structure * Telecommunication | −2.9112*** | −1.7261 | −3.0649 *** | −2.8655 *** |
| **Knowledge flows** | 0.2092 *** | 0.2145 *** | 0.1233 ** | 0.1856 *** |
| **Control variables** | | | | |
| Political factor | 0.7407 *** | 0.7946 *** | 1.0533 *** | 0.9368 *** |
| Historical factor | 0.0611 | 0.1775 * | 0.1604 | 0.0913 |
| constant | 11.0727 *** | 7.6556 *** | −7.8119 *** | −13.5140 *** |
| lambda | 0.7430 *** | 0.7500 *** | 0.7400 *** | 0.6770 *** |
| R-squared | 0.9034 | 0.9130 | 0.8576 | 0.9153 |
| Rbar-squared | 0.8976 | 0.9078 | 0.8490 | 0.9102 |
| log-likelihood | −34.4658 | −81.1089 | −86.2817 | −32.7212 |

*Notes:* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

**Table 9**
Linear regression results with heteroscedasticity correction.

| VAR | RAC | RDC | RPC | RIC |
|---|---|---|---|---|
| **Knowledge stocks** | | | | |
| Agglomeration of knowledge agents | −0.0427 | 0.0160 | 0.1091 | 0.0179 |
| Education level | 0.1712*** | 0.0900 | 0.1244* | 0.1273** |
| R&D | 0.1146** | 0.1526** | 0.0651 | 0.0983* |
| Specialized knowledge structure | 0.6806*** | 0.4500 | 0.6491** | 0.6405** |
| Diversified knowledge structure | −1.7096 | −2.1791* | −0.6762 | −1.8859* |
| Face-to-face communication | 0.2294*** | 0.3262*** | 0.2037* | 0.2764*** |
| Telecommunication | 0.1823 | 0.1987 | 0.0756 | 0.1793 |
| Specialized knowledge structure * Face-to-face communication | −0.0287 | 0.0115 | −0.2021 | −0.1208 |
| Specialized knowledge structure * Telecommunication | 0.3958** | 0.2080 | 0.3440 | 0.3712* |
| Diversified knowledge structure * Face-to-face communication | 1.2737 | 1.7367 | 1.3998 | 1.5603 |
| Diversified knowledge structure * Telecommunication | −3.3953** | −2.8979* | −3.3400* | −3.3604** |
| **Knowledge flows** | 0.2828*** | 0.2809*** | 0.0817 | 0.2199*** |
| **Control variables** | | | | |
| Political factor | 0.7366*** | 0.8731*** | 1.3938*** | 1.1012*** |
| Historical factor | 0.0371 | 0.1389 | 0.0944 | 0.0425 |
| constant | 10.8527*** | 8.3314*** | −5.9878*** | −12.5522*** |
| lambda | 0.7430 *** | 0.7500 *** | 0.7400 *** | 0.6770 *** |
| R-squared | 0.8700 | 0.8838 | 0.8092 | 0.8917 |

*Notes:* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

### *7.2. Implications on theory and practice*

The findings of this research hold significant implications for existing theories in the field. First, it differs from prior urban network studies by focusing on intercity investment relationships and evaluating urban network economic centrality from a knowledge-oriented perspective. Second, it uniquely considers both knowledge stocks within cities and knowledge flows between cities, providing a more comprehensive understanding of the knowledge economy's impact on urban networks. Lastly, it explores the interactive effects between face-to-face and non-face-to-face communication and specialized and non-specialized knowledge, enhancing our theoretical understanding of factors influencing urban network centralities. These contributions enrich the theoretical framework for analyzing urban economic networks.

This research also has important managerial implications and practical recommendation. This study attempts to enhance our understanding of how urban knowledge influences capital networks in the context of "space of flows". Additionally, it endeavors to offer city sustainable growth strategies from the standpoint of knowledge innovation. For policymakers and city planners, recognizing the distinct functions of urban systems, such as agglomeration, diffusion, power, and integration, is essential. By doing so, they can tailor their strategies to the unique needs and strengths of their cities. This targeted approach can lead to more effective and efficient allocation of resources, ultimately fostering economic growth and innovation. There are some general recommendations that can be applied to enhance the economic centrality of all types of cities. Firstly, there is a need to improve educational support, especially for the children of migrant workers. This may involve increasing the number of schools and educational resources in these cities while implementing policies to ensure equal access to education for all children. Besides education, it is essential to promote R&D expenditures and regional innovation through the agglomeration and diffusion capacity of central cities. This can be achieved by providing incentives for business investment in R&D activities, fostering collaboration between universities, research institutions, and industries, and establishing innovation centers or technology parks to facilitate knowledge sharing and cooperation. Secondly, research emphasizes the importance of promoting knowledge flows between cities. To break down knowledge barriers, policies related to regional innovation integration should be implemented. This may involve facilitating collaborative research efforts between cities, promoting talent mobility across different regions, and encouraging the sharing of patents and intellectual property rights. Thirdly, research results indicate the need to establish a city-industry innovation system with specialized division of labor, and the government should pay more attention to industrial upgrading. In particular, efforts should be made to promote the development of the manufacturing industry, shifting its focus from basic processing and manufacturing to high-end activities such as research and design. This can be achieved by providing incentives for businesses to invest in advanced manufacturing technology, fostering collaboration between manufacturers and research institutions, and supporting initiatives that promote innovation and sustainable manufacturing practices. Additionally, upgrading transportation infrastructure can enhance the intensity of face-to-face interactions between knowledge entities.

To promote the development of different types of economic centrality cities, various measures should be taken. For power-centric cities, it is essential to focus on the development of backbone road networks and consider the growth of cities with high population density in underdeveloped regions. Providing infrastructure support and offering preferential policies can attract businesses and industries to these areas, thus promoting economic growth and development in previously lagging regions. It can help revitalize underdeveloped regions and enhance their connectivity to more developed areas. This can spur economic growth and create a more balanced economic landscape. For agglomeration, power, and integrated-centric cities, specialized knowledge exchange can be achieved through non-face-to-face communication. Encouraging and supporting remote work, virtual meetings, and online training enables professionals to collaborate and share knowledge without being limited by geography. This helps break down geographical barriers, promote resource and knowledge sharing, and enhance cities" innovation capabilities and competitiveness. On the other hand, diverse knowledge requires face-to-face communication, and one way to foster this is by establishing industrial clusters with diverse communication opportunities. The government can actively support the construction of such industrial clusters. These clusters can attract businesses, research institutions, and specialized talents from different fields, forming ecosystems for knowledge cross-fertilization and innovation collaboration. The government can provide tax incentives, land subsidies, and other encouraging measures to attract more businesses and innovators to join these clusters, promoting industrial upgrading and development in cities.

### *7.3. Limitations and future prospects*

Given the cross-sectional nature of the data used, it's important to acknowledge that potential endogeneity effects cannot be entirely eliminated. In future research, it is advisable to explore dynamic models that can address the complexities of knowledge and leverage advancements in data collection technology. Moreover, in the context of knowledge innovation-driven industrial transformation, digital technology plays a pivotal role in shaping the future industrial landscape. Therefore, the future research agenda should prioritize the role of digital technology in driving upgrades to industrial structure [85,86].

## Data availability statement

The data presented in this study are available on request from the corresponding author.

## Ethics declarations

Informed consent was not required for this study because this study did not involve experiments on participants and patients.

## CRediT authorship contribution statement

**Yang Zhang:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Naling Lin:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Jianping Gu:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Deheng Zeng:** Writing – original draft, Formal analysis, Data curation.

## Declaration of competing interest

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

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