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Mapping the structural evolution of intercity patent transfer constrained by space: a case study of China

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ABSTRACT

The patent transfer (PT) has been an essential means of technological catch-up and control for countries and regions. The development and diffusion of PT is influenced by space and network. Analyzing China's patent transfer network (PTN) from 2001 to 2020 through spatial and complex network analysis, we found that the PTN became denser with significant Matthew effect, hierarchical and small-world properties. Beijing, Shanghai, and Shenzhen remained as national hubs, while new hubs like Suzhou, Guangzhou, Foshan, and Hangzhou, acting as intermediates, emerged. Network communities become more homogenised and geographically clustered due to the resonance effect. There was a shift from disperse hubs to spatial agglomerations, with the construction of long-distance shortcuts breaking spatial constraints on intercity patent transfer.

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Patent transfer; spatial diffusion; first-move advantage; resonance effect

Highlights

- Less than 20% of cities account for more than 80% of patent transfers.
- The Gini Index increased dramatically, indicating the Matthew effect.
- The global configuration of urban patent transfer is consistent with Hu's Line, but the emerging bow-and-arrow pattern tends to break Hu's line.
- There is a significant hierarchical and small-world property in the patent transfer network. Beijing, Shanghai, and Shenzhen kept being national hubs. The connections among cities are more frequent and diverse.
- At the early stage, geographic proximity is critical for network evolution. After reaching a certain threshold, its influences on growth become weaker. The cross-hierarchical patent transfer makes the network robust and efficient.
- The number of communities decreases, showing a resonance effect.

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1. Introduction

In the modern knowledge economy, technological innovation drives economic progress, with patent transfer (PT) playing an important role in spreading and commercialising these innovations. Patents are crucial for facilitating the diffusion of technology through licensing agreements (Jin, Mangla, and Song 2022). Patent assignment – the legal transfer process of patenting rights from one entity to another – always involves financial transactions and is a representative type of PT (Maurseth and Svensson 2020). Despite a general increase in patent applications and grants worldwide, the number of patent assignments remains relatively low (Graham, Marco, and Myers 2018). This gap highlights the importance of PT serve as a reliable measurement of innovation power and technology diffusion (Fan, Lian, and Wang 2020).

Studying PT provides critical insights into the mechanisms that propel the flow of knowledge and technology, thereby shaping the innovation landscape across various regions and cities. The research focus on technology transfer, including PT, has evolved to encapsulate the dynamic nature of technological advancements. It includes the exchange of knowledge, information, and innovation across regions, industries, organizations, and the broader domain of science and technology (Bengoa et al. 2021). Extensive research has explored the multifaceted aspects of PT, including absorptive capacity (Chung and Lee 2015), its relationship with scientific advances (Ahmadpoor and Jones 2017; Kwon 2020), influencing factors (Audretsch 2014; Bozeman 2000; G. Weng et al. 2023; Zhang, Duan, and Zhou 2016), policy tools (Grimaldi et al. 2011). Additionally, research has emphasised the core–peripheral structures, spatial auto-correlation, and the influence of PT among different entities such as entrepreneurs, universities, governments, and research institutes (Battistella, De Toni, and Pillon 2016; Donges and Selgert 2019; W. Liu, Tao, and Bi 2022). The effectiveness of technology transfer is influenced by factors related to both the transferor and the transferee (Cho and Shenkoya 2020). Furthermore, with economic geography's focus on technological innovation, research has investigated regional heterogeneity in technological transfer, considering the varying economic, social, and technological endowments across regions (R. A. Boschma and Frenken 2011; Harris 2021). The scale of these studies ranges from global to national and local levels, with a particular emphasis on cities as the primary hubs for the production and transfer of knowledge and technology.

Cities, as hubs of capital, talent, technology, and information (Adler and Florida 2021), are not only important nodes in the economic system but also fundamental units in shaping local technology policies by the government. With the development of transportation and communication infrastructure, modern cities are becoming more interconnected, indicating a change from the 'space of place' to the 'space of flow' (Wu et al. 2022). The combination of econometric models and network analysis methods is particularly significant for understanding the complex interplay of innovation across cities. Within this context, the intercity PT network emerges as a microcosm of the innovation ecosystem, where the exchange of exclusive rights through licensing agreements can significantly influence the technological and economic landscape. The structural properties of intercity PT networks have been a focus of study, revealing the centrality and connectivity of cities within these networks. The existence of core–periphery structures and the role of certain cities as pivotal nodes in facilitating the flow of knowledge and technology are well-documented (Duan, Du, and Grimes 2019). Less developed regions or cities use these networks to access advanced technologies and accelerate their development (Gertler and Levitte 2005). The spatial characteristic of the network also illustrates the potential for knowledge spillover effects and how innovation spreads throughout urban regions (Obschonka et al. 2023).

Current research on urban technological innovation networks has predominantly focused on knowledge collaboration and patent cooperation (Sun 2016; Y. Feng et al. 2022; Li and Phelps 2018; Lim and Han 2023), with limited attention given to intercity PT networks, particularly in China and emphasising less on assessing the evolution of network structures. Meanwhile, the role of geography in PT is still being debated. Therefore, we are curious: How does the PT network evolve to diffuse innovation broadly across space, and in what ways does geography influence these dynamics. Answering these questions will provide empirical results for a better understanding of the interaction between urban innovation networks and the geographical landscape, which in turn can inform policy strategies aimed at enhancing regional innovation capabilities and economic growth.

This article explores the spatial diffusion and structural evolution of intercity PT in China from 2001 to 2020. The subsequent section offers a review of Chinese innovation networks and potential geographic influence. Section 3 outlines the data sources and methodologies employed. The results section, organised into two parts: we examine the uneven development of PTN through statistical and network analysis; then map the spatial diffusion of PT and investigate the resonance effect. Finally, we conclude and list future work.

2. Literature review

2.1. Chinese urban innovation networks

The examination of knowledge and technology flows between cities is rising as a significant trend in the study of intercity networks. Economic, industrial, and infrastructural ties are increasingly interlinking cities, forming complex flow networks (Akhavan et al. 2020; Cheung, Wong, and Zhang 2020; Yeh, Yang, and Wang 2015; T. Li et al. 2020). Aligned with national innovation strategies, scholars have developed diverse innovation networks, including those for knowledge collaboration (Gui, Liu, and Du 2019), technology cooperation (Sternitzke, Bartkowski, and Schramm 2008; Yao, Li, and Li 2020), patent citation (Érdi et al. 2013; Yoon and Park 2004), talent mobility (Zhang et al. 2020), R&D institutions (Hanaki, Nakajima, and Ogura 2010), and venture capital (Wu et al. 2022), to explore urban innovation systems. Social network analysis reveals nuanced patterns of exchange among cities, highlighting the importance of intercity connectivity for innovation (Cao, Derudder, and Peng 2018; Dai et al. 2023; Duan et al. 2019). While coastal megacities like Beijing, Shanghai, and Shenzhen have emerged as innovation hubs, inland cities face challenges in resource allocation and accessing these networks (Dai et al. 2023; Duan, Du, and Grimes 2019).

The evolution of innovation networks is also a vital research area, employing various methodologies and data sources, such as patent citation, cooperation and transactions, to analyze technology dissemination (Caviggioli and Ughetto 2013; Lanjouw and Schankerman 2004; Seo and Sonn 2019; Sun and Liu 2016). These studies have uncovered distinctive patterns in Chinese innovation networks, including the formation of rhombus-like structures and transitions from single-core to multi-center network structures. Some use gravity models to construct innovative network dynamics (Y. Cao et al. 2022; Liu et al. 2021). However, when talking about PT network, most of the researches are conducted based on USPTO and EPO patent data (Ciaramella, Martínez, and Ménière 2017; Serrano 2010; W. Liu, Tao, and Bi 2022) or on a region scale (Ma et al. 2022), which pay little attention on Chinese technology transfer.

2.2. Geographic influence on technology transfer dynamics

In fact, the evolution of China's PTN may be influenced by geographic constraints. Scholars have studied spatial dependence in the process of PT at the provincial level or cities in urban agglomerations, and underscored the importance of regional polycentric spatial organizations and agglomeration effects in knowledge and innovation spillovers, with a focus on the hierarchy and topological characteristics of these networks (G. Zhang, Duan, and Zhou 2016; C. Liu, Niu, and Han 2019; Fan et al. 2023). Meanwhile, Chinese cities exhibit distinct hierarchical and heterogeneous characteristics in terms of their endowments, innovation resources, and development standards, which can potentially lead to variations in the mechanisms of PT across different regions (Gertler and Levitte 2005). Less developed regions or cities use these networks to access advanced technologies and accelerate their development. For instance, Weng et al. (2023) found that dominant factors influencing PT between cities also show spatial heterogeneity, while Jin et al.(2022) discovered that patent inward transfer in developed cities promotes patent inventions, whereas outward PT has a crowding-out effect on the sustainable innovation of underdeveloped cities.

The impact of geographical proximity on network structure is a subject of debate. Empirical studies provide evidence on the substantial role of geographical, cognitive, institutional, social and economic proximity positively affect knowledge and technology spillovers, with geographical proximity indirectly influencing spillovers through its impact on other dimensions of proximity (R. Boschma 2005; G. Gui, Liu, and Du 2018; Zhang, Duan, and Zhou 2016; Y. Li, Xiong, and Hu 2023; Ma et al. 2022). However, while geographical proximity is traditionally seen as beneficial for fostering direct interactions and knowledge spillovers, it can also constrain innovation by reinforcing local norms. From the perspective of The 'Open Windows of Locational Opportunity' concept (R. A. Boschma and Van der knaap 1999), geographical distance can both hinder and promote the creativity of innovation industries, suggesting that while proximity facilitates knowledge sharing, distance can encourage the development of unique innovations. Complex relationship between geographic constraints and the potential for a dispersed innovation landscape, where chance events and the ability to leverage generic resources can lead to the rise of new high-tech industries, even in areas distant from current tech hubs.

Based on the understanding that geographical constraints and proximity factors play a complex role in shaping PT networks and innovation activities, it is clear that the field of economic geography still needs to deepen its research into the impact of geography on technology transfer.

3. Data and methodology

3.1. Data source and processing

We obtained the PT data from the China Intellectual Property Right database (CNIPR) covering the years 2001–2020. Utilised Python crawler programming, we extracted text-format patent assignment records from the database, capturing details like patent ID, address of the assignors (i.e. those transferring patent rights) and the assignee (i.e. those receiving the rights), transfer time, and more. The data is processed follow three steps:

(1) Geocoding. We geocoded the data at the city level by associating address with prefecture cities, allowing us to calculate the number of PT between cities.
(2) Data cleaning. We excluded international PT and those involving Hong Kong, Macao, and Taiwan due to incomplete records. Finally, we got an origination-destination matrix composed of 347 prefecture-level cities in mainland China and 555,557 intercity transferred patents.
(3) Network construction. We then constructed a weighted and directed PT network with cities as nodes, where links denoted PT (either transfer-in or transfer-to) among cities, with link strength reflecting transfer quantities. To address network sparseness, we aggregated the data every five years, creating PT network for 2001-2005, 2006-2010, 2011-2015, and 2016-2020.

3.2. Methodology

3.2.1. Research framework

The structural evolution of intercity PT network and the spatial dynamics that influence the network in different time periods are detected by the combination of complex network and spatial analysis. These approach allows us to identify the dominant cities in the network and trace the pathways through which PT occur (see Figure 1).

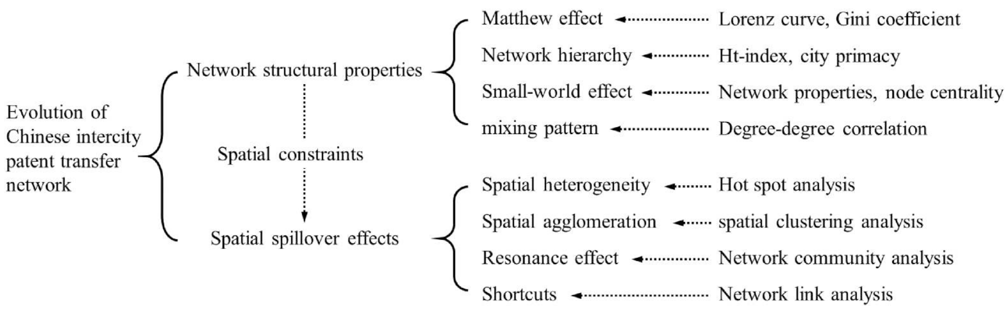

Figure 1. Research framework.

3.2.2. Statistical heterogeneity

The statistical heterogeneity of PT across cities is examined through Lorenz curve, Gini coefficient, and the ht-index The Lorenz curve plots ranked cities by PT quantities on the x-axis and cumulative percentage on the y-axis. The Gini coefficient provides a numerical measure of inequality by comparing the areas under the Lorenz curve and the line of absolute equality, ranging from 0 (perfect equality) to 1 (maximum inequality). The ht-index assess the fractal or scaling structure of geographic features (Jiang and Yin 2014). It's calculated using a head/tail split of 40% vs. 60%, to identify hierarchies in a long-tailed distribution dataset (Jiang 2013).

In urban geography, the law of the primate city suggests that massive cities dominate a country's population and economic activity (Jefferson 1989). A primate city stands out for its high socio-economic indicators. The formula for the city primacy of two cities (S_2), four cities (S_4) and eleven cities (S_{11}) are $S_2 = P_1/P_2$, $S_4 = P_1/(P_2 + P_3 + P_4)$ and $S_{11} = P_1/(P_2 + \ldots + P_{11})$. Here P_i represents the PT volume of the i-th city. Ideally, the optimal values of S_2 S_4 and S_{11} are 2, 1, and 1, respectively, with the second city's value being half that of the primate city, the third city being a third of its size, and so on.

3.2.3. Spatial auto-correlation

Innovation activities always exhibit significant spatial dependence, leading to regional spatial agglomeration (Feldman and Kogler 2010). To assess this, we employ Local Moran's I statistic to measure autocorrelation among neighboring spatial units (Anselin 1995). Spatial weight matrices are computed using road distances from the map service API of Amap. Utilising GeoDa software, we generate the Local Indicators of Spatial Association (LISA) cluster maps. These maps reveal positive spatial autocorrelation where nearby observations share similar data values or negative spatial autocorrelation, where adjacent observations exhibit contrasting values.

3.2.4. Complex network analysis

- Properties of network

A network is a simplified depiction of a system that captures only the fundamentals of connection patterns and a little more (Newman 2010). The total number of nodes and edges shows the scale of a network. Network density and the average clustering coefficient are calculated to determine how tightly-knit the network is and the extent of local interconnectivity (Lee, Kogler, and Lee 2019; Watts and Strogatz 1998). A small-world network is characterised by a high clustering coefficient and a low characteristic path length (Watts and Strogatz 1998). A scale-free network usually has a power-law distribution of nodal degrees (Barabási 2009). Community detection using the Louvain algorithm (2008) in software Gephi v9.2.0, segments the network into cohesive subgroups, reflecting the network clustering (Clauset, Newman, and Moore 2004; Girvan and Newman 2002).

- Properties of nodes

Node centrality analysis, including degree, closeness, and betweenness, reveals key nodes in a network (Newman 2010). Degree centrality is the count of edges connected to a node. Closeness centrality is the inverse of the average shortest path length to all other nodes, with higher closeness centrality for nodes closer to others. Betweenness centrality measures the centrality to which a node lies on paths between other nodes, with the count of shortest paths between node pairs passing through it reflecting its betweenness centrality.

The degree correlation describes the mixing pattern of nodal degrees. The degree correlation function k_{nn} defined by Barabási (2015) calculates the average degree of the neighbors of all nodes with degree k. The dependence of k_{nn} on k. For assortative networks, high-degree nodes are more likely to connect to other high-degree nodes.

4. The evolutionary properties of the intercity PT network

4.1. Network growth and densification

Table 1 shows the growth in the number of cities involved in PT, rising from 227 to 346 (out of China's total 347 cities). The densification of network connection is indicated by a network density increase from 0.013–0.245, with the network diameter nearly halved and average link strength increasing sevenfold. Cities collaborate more closer, making PT frequent and convenient. Meanwhile, the average clustering coefficient has grown over threefold, from 0.208 (2001-2015) to 0.698 (2016-2020), indicating a shift from hub-dominated transfers to more diverse 'shortcuts' between cities of varying hierarchies. Figure 2 illustrates PT flows among the top 5% of most active cities.

The PT volume keeps increasing, too. In 2001-2005, the Beijing-Shanghai link had a strength of 49 but in 2016-2020, 22 edges had strengths higher than 1217. Notably, the Shenzhen-Dongguan link had a strength of 4894, followed by Beijing-Hangzhou (2420), Shanghai-Suzhou (2137), Beijing-Shanghai (2108), and Tianjin-Beijing (1853).

4.2. The 20/80 principle of PT and matthew effect

A rise in the total number of PT does not necessarily indicate balanced development of innovation capacities across different regions. Over the last two decades, the Lorenz curve and Gini Index based on each city's PT volume have revealed an innovation 'rich-poor gap' (Figure 3). The Lorenz curve highlights that less than 20% of cities transfer are responsible for over 80% of patents, adhering to the 20/80 principle. The Gini Index experienced a substantial rise, from 0.63 in 2001 to 0.81 in 2010, surpassing the 'severely high' warning line of 0.6, signifying a strong Matthew effect. Even with the significant expansion in PT scope and frequency, the

Table 1. The hierarchies and urban primacy of cities in PTN

Indicators		2001–2005	2006–2010	2011–2015	2016–2020
ht-index		4	4	4	4
hierarchies	national hub	3 (1.3%)	3(1%)	4 (1.2%)	7 (2.0%)
	regional hub	7 (3.1%)	10 (3.3%)	12 (3.5%)	15 (4.3%)
	local hub	38 (16.7%)	32 (10.6%)	42 (12.2%)	47 (13.6%)
	peripheral cities	179 (78.9%)	256 (85.0%)	285 (83.1%)	277 (80.1%)
city primacy	S_2	1.514	1.451	1.922	1.098
	S_4	0.716	0.634	0.767	0.448
	S_{11}	0.425	0.335	0.385	0.196

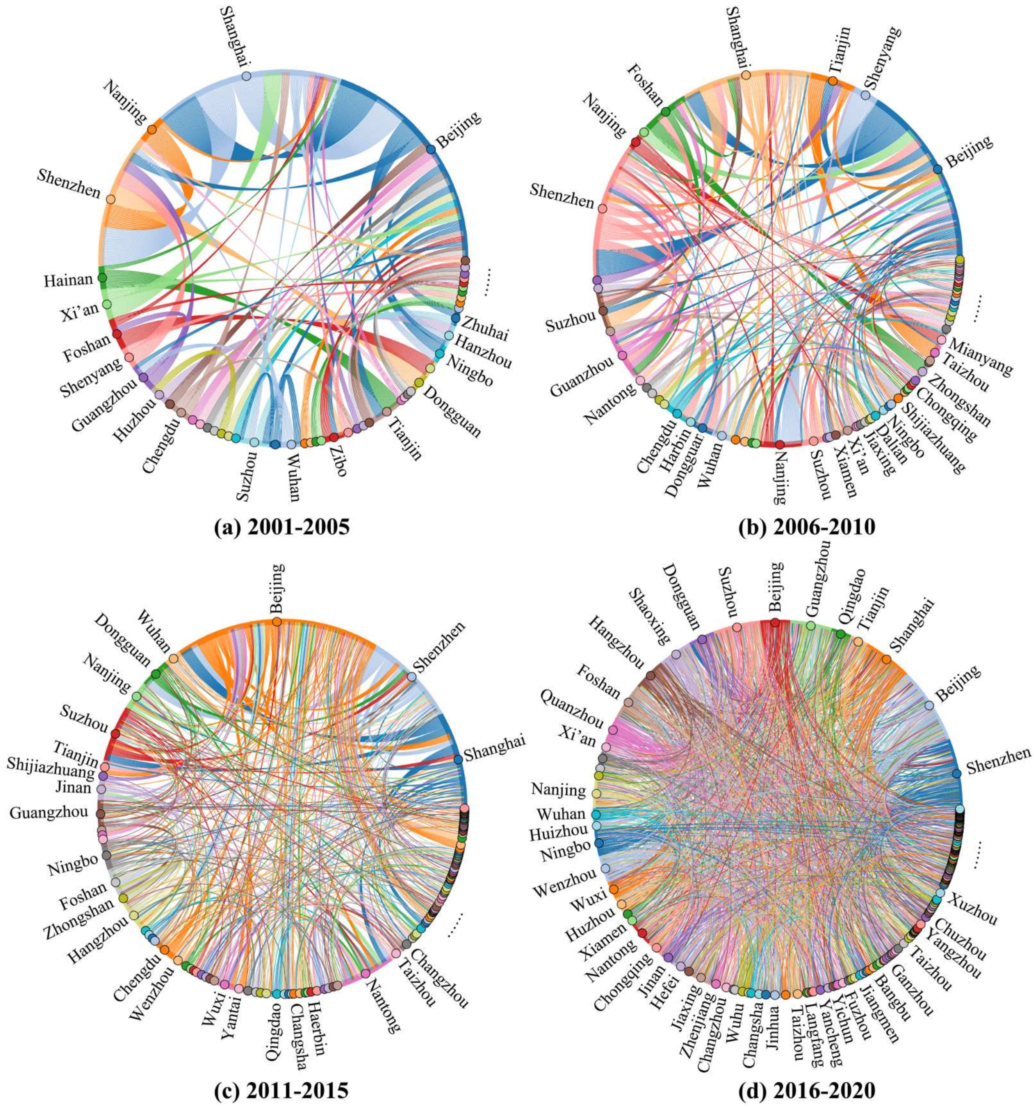

Figure 2. The China's intercity PTN in chord map.

Gini Index remained high after 2015. Although there's a slight decrease, it suggests ongoing urban innovation polarization.

4.3. Relative stability of network hierarchies

The hierarchical structure provides insights into cities' roles in the urban innovation system. Table 1 displays urban hierarchies using the ht-index, which remained stable as at four. This indicates that despite more cities engaging in PT, the hierarchical structure remains fairly constant. Notably, only a few cities serve as national and regional hubs. That is, the entire intercity PT is dominated by a few cities in intercity PT, even as their numbers increase. For instance, Beijing, Shanghai, and Shenzhen were national hubs from 2001 to 2010 with Suzhou joining them from 2011 to 2015. After 2015, Suzhou, Guangzhou, Foshan, and Hangzhou grew into national hubs, mainly in two big urban agglomerations: The Yangtze River Delta and the Pearl River Delta. Opening up policies

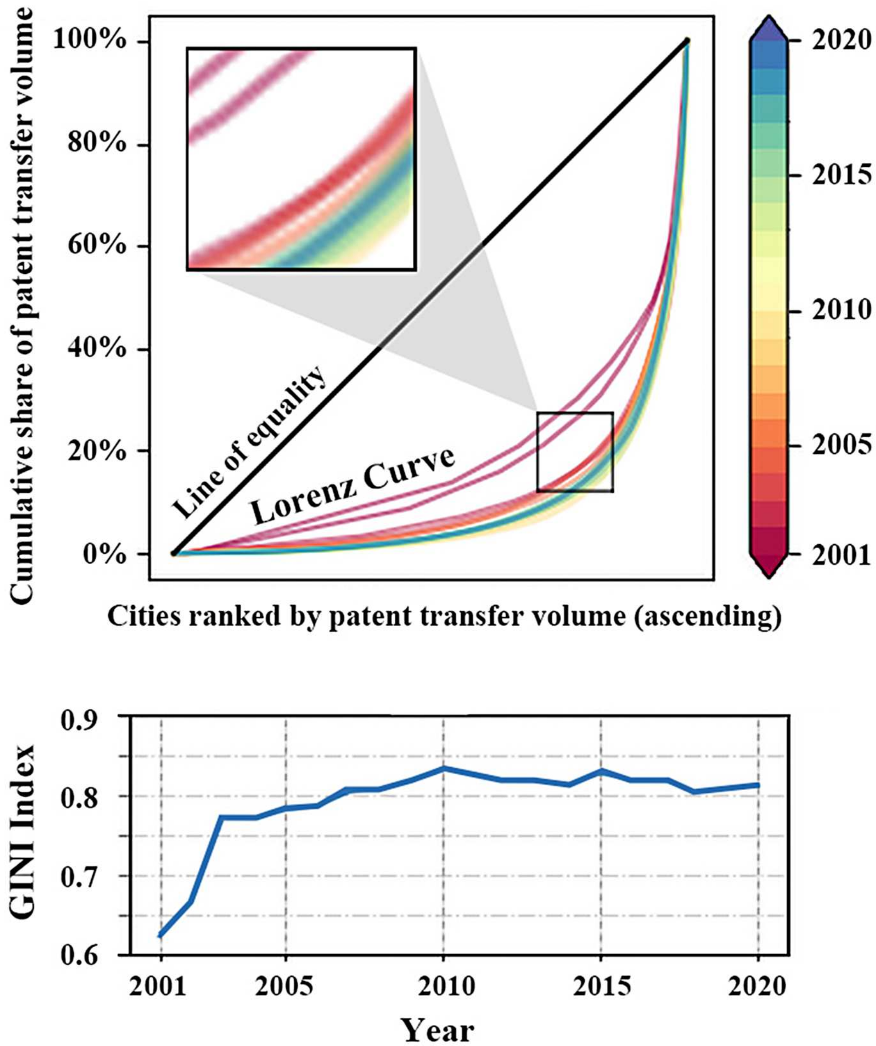

Figure 3. The Lorenz curve and Gini Index of China's intercity PT volume

and industrial upgrading promote regional cooperation, resulting new national and regional hubs with various collaborations.

4.4. Local strengthening of small-world effects

The PT network grew more compact (the characteristic path length and network diameter decreased, while the average clustering coefficient increased) and maintained a small-world property, with a similar characteristic path length to a random network but a significantly larger average clustering coefficient (see Table 2).

The network's small-world property arises from rich hierarchies and diverse shortcuts among various hierarchies (H. Zhang and Li 2012; H. Zhang, Lan, and Li 2022). PT network is the same, where second-tier and third-tier cities increasingly partner with major hubs, and regional hubs acted as intermediates between major hub and lagged cities. Table 3 shows an increase in cities with high betweenness centrality values. During 2001-2015, only Beijing, Shanghai, and Shenzhen had high values, suggesting limited PT among other cities. In contrast, during 2016-2020, a

Table 2. General properties of the PT network

Indicators	2001–2005	2006–2010	2011–2015	2016–2020
Number of nodes	227	318	343	346
Number of edges	652	2719	8442	29186
Network density	0.013	0.027	0.072	0.245
Average link strength	2.371	5.060	10.328	15.523
Diameter	7	6	5	4
Characteristic path length	3.017(3.315)	2.185(2.334)	1.966(1.862)	1.765(1.571)
Average clustering coefficient	0.208 (0.014)	0.381 (0.054)	0.539 (0.139)	0.698 (0.429)

Note: The values in the brace are the indicators of a random network with the same size as the actual PT network, matching the same number of nodes and edges.

Table 3. Distribution of the betweenness centrality of cities.

stage	(0-0.035)	(0.035-0.15)	(0.15-0.3)	(0.3-1)
2001–2005	207 (91.19%)	17 (7.49%)	2 (0.88%)	1 (0.44%)
2006–2010	294 (92.45%)	19 (5.97%)	2 (0.63%)	3 (0.94%)
2011–2015	340 (93.59%)	18 (5.25%)	2 (0.58%)	2 (0.58%)
2016–2020	141 (40.75%)	170 (49.13%)	20 (5.78%)	15 (4.34%)

boarder range of cities not only transferred patents to national hubs but also to regional hubs and weaker cities, enhancing robustness and efficiency of the network.

New connections are mostly shortcuts created by crossing-hierarchical connections, influenced by technology gap. Figure 4 illustrates the relationships between a node's degree k and the average degree of its neighbors with degree k (k_{nn}). A negative relationship exists between k and k_{nn}. It is evident that the connections among vibrant cities became more diverse. Figure 4 also confirms that as peripheral cities enter PT activities, innovation flow between hub cities to other cities becomes more frequent and intense.

5. Spatial constraints on intercity PT

To further explore the possible influences of spatial constraints such as administrative borders, geographical proximity on PT, we analyzed the evolution of spatial heterogeneity and spatial autocorrelation.

5.1. The first mover advantage of political centers and coastal cities

Intercity PT in China shows significant spatial agglomerating and proximity diffusion effects. Using kernel density maps created through Inverse Distance Weighting (IDW), we traced the spatiotemporal PT patterns across four periods in China (Figure 5). Over the past two decades, hotspots have extended from three growth poles (Beijing, Shanghai, and Shenzhen) to regional highlands in the Beijing-Tianjin-Hebei, the Yangtze River Delta and the Pearl River Delta Urban Agglomerations, as well as other new hubs like Chengdu and Chongqing.

The LISA map in Figure 6 illustrates high-high clusters longitudinally spread along the southeast coast, with adjacent cities gaining opportunities to absorb and disseminate patents, becoming crucial hinterlands for regional PT hubs. Coastal cities together form a contiguous bow-shape area, while scattered hubs create an arrow-like axis from Chengdu to Nanjing, Shenyang, and Changchun.

Spatial heterogeneity displays notable differences between coastal-mainland, east–west, and south–north difference. The general pattern aligns with the Hu line (the Heihe – Tengchong line or the Aihui-Tengchong line) (Guo et al. 2014), which signifies the divide in China's population and economic distribution. It indicates that the complex coupling of innovation capabilities and economic disparities further reinforces the spatial heterogeneity of regional development.

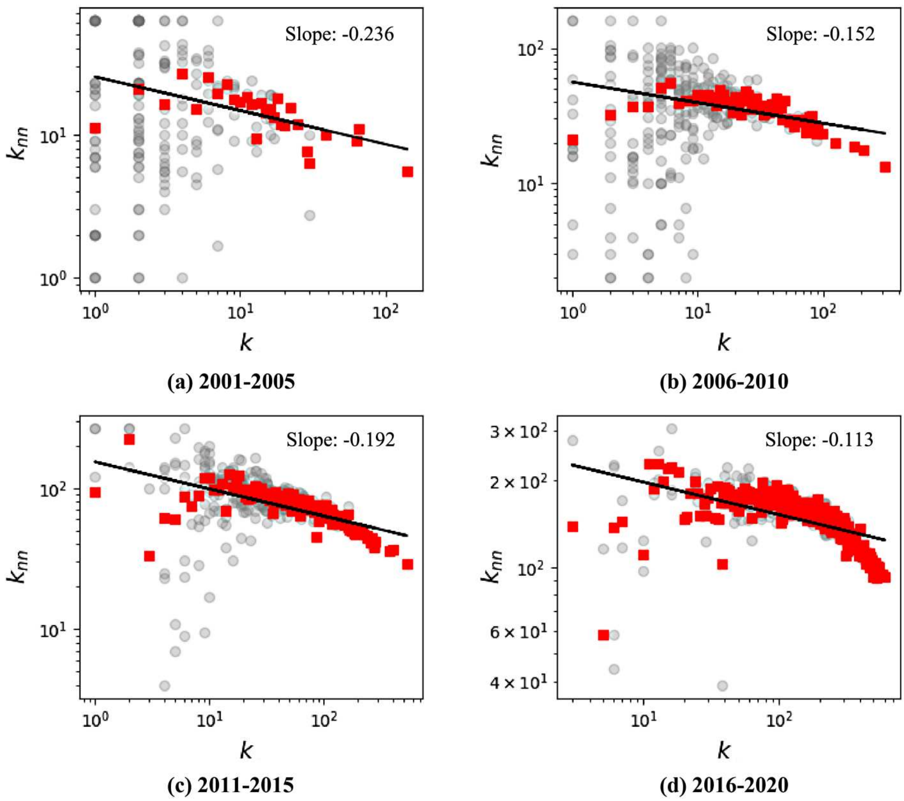

Figure 4. The degree correlation of the China's intercity PTN.

Additionally, the proximity diffusion of PT is more pronounced in southeast China, emphasising the importance of the first move advantage in innovation diffusion. Coastal cities enjoyed the advantage in resource absorbing and technology circulation due to their solid economic foundation, policy support, infrastructure, capital, talent and high-degree openness. They effectively harnessed resources and formed innovative technology circulation channels through collaboration between research institutions, enterprises, and the cooperation of multinational enterprises (Balland, Boschma, and Frenken 2022). According to the National Bureau of Statistics of China, the presence of over 3,000 patent agencies in three main urban agglomerations before 2021, compared to less than 1500 in other provinces. The aid of resources and policy benefits have fostered a synergistic environment conducive to innovation hub upgradation (Ferrary and Granovetter 2009).

5.2. Homogenization of network communities

Our analysis of network community structure where cities of the same community are color-mapped in Figure 7.

Over time, smaller communities consolidated into larger ones, with a notable reduction in their number. Initially, nine communities existed, primarily composed of spatially dispersed cities except for Chengdu-Chongqing and the Shandong Peninsula regions. The period of 2006–2010 saw eight communities, still with a focus on spatial dispersion. By 2011-2015, northern cities grouped into the Beijing community, while several cities in Guangdong province and Sichuan province joined the Shenzhen community. The Yangtze River Delta region also formed a large community. From 2016

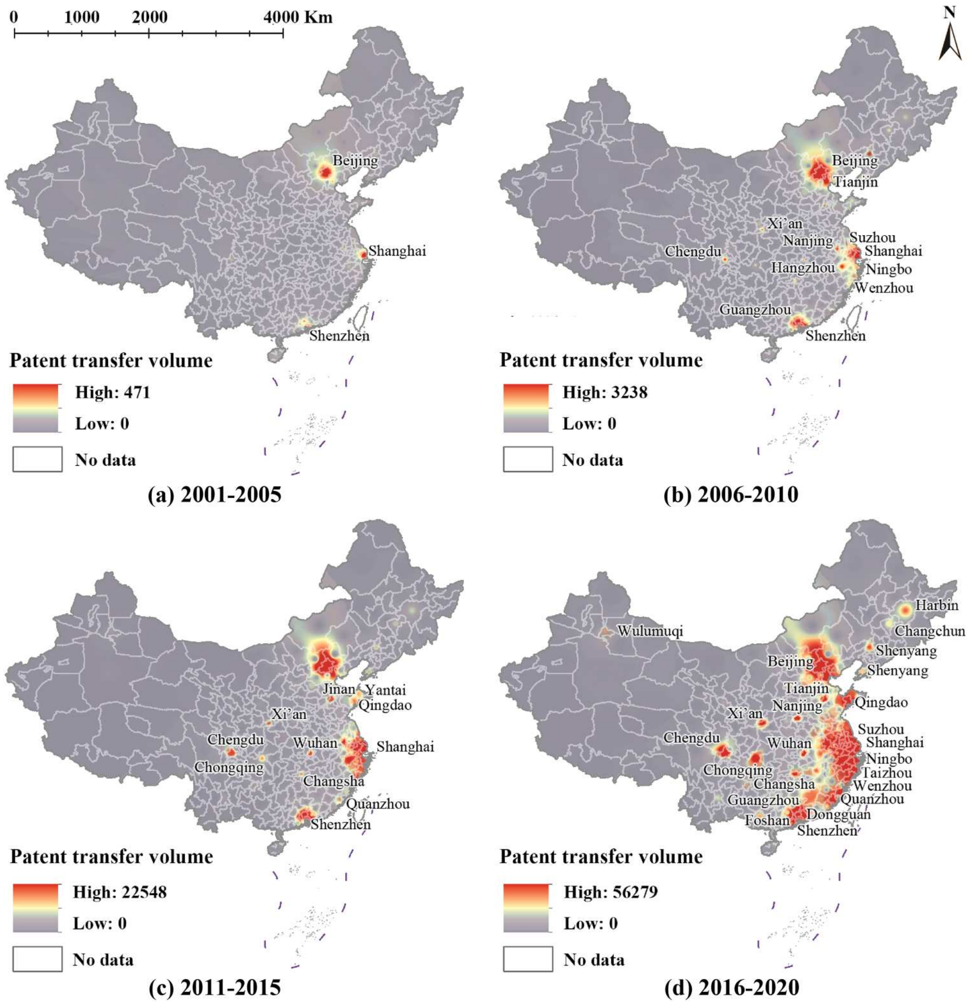

Figure 5. The kernel density maps of China's intercity PT volume.

to 2020, further consolidation occurred, with the Shandong, Yunnan and Wuhan communities merged into the Beijing community, and the Pearl River Delta community and Yangtze River Delta community expanding their reach.

The evolution of community structure is influenced by factors like proximity, the industrial chains, economic cooperation and changing policies (Fan et al. 2021). The decrease in community modularity suggests a shift from intra – to inter-community transfers, reflecting the non-spatial nature of PT network and the diminishing impact of geographic distance.

Additionally, a resonance effect is observed as cities form tighter spatial clusters from scattered colors, suggesting a decrease in spatial constraints. This is evident in the emergence of localised communities like the IT and manufacturing hubs around Shenzhen and the advanced manufacturing cluster in Foshan. Shenzhen has attracted talent in IT, telecommunication, electronic engineering, and internet industries, benefiting from Chinese industrial innovation and industrial upgrading (Fan, Zhang, and Wang 2022). Nearby Dongguan and Foshan is actively building advanced manufacturing clusters with Shenzhen's support (Cai et al. 2023), while Guangzhou and Huizhou work on constructing a comprehensive industrial chain, coordinating and benefiting from the resonance effect.

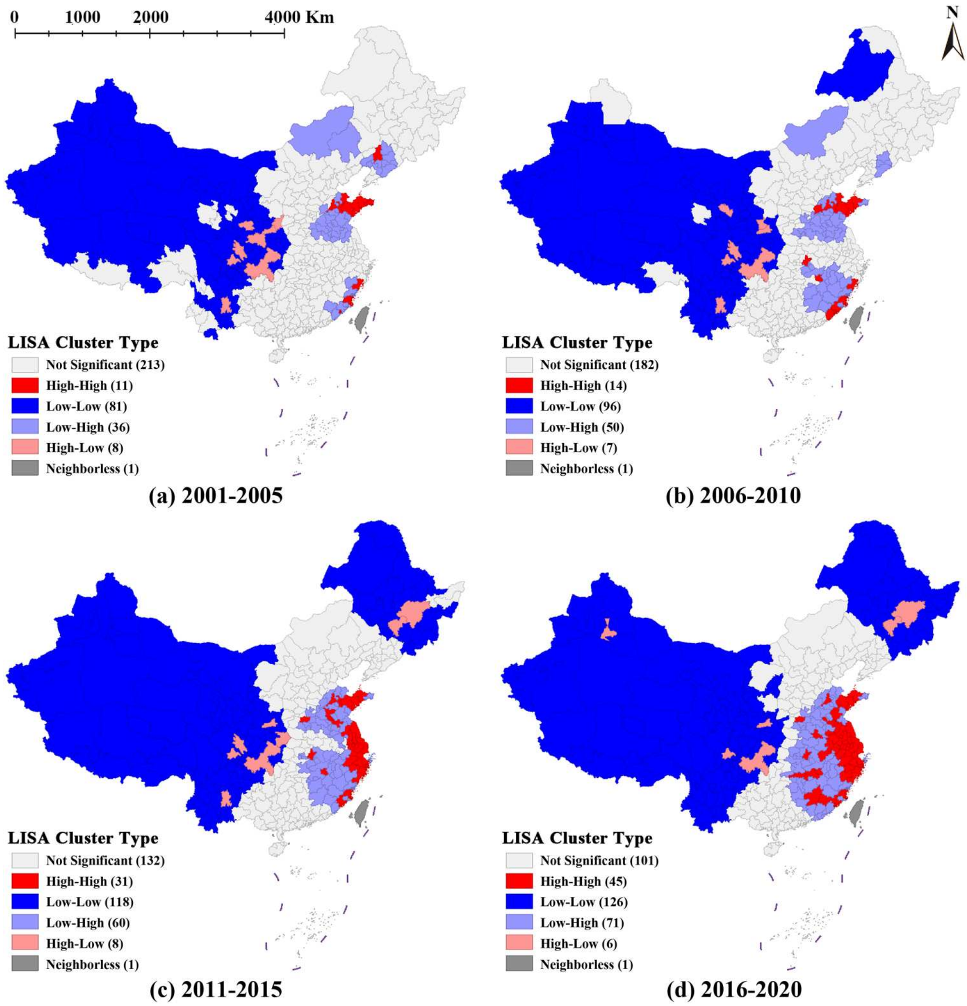

Figure 6. The LISA cluster map of China's intercity PT volume.

5.3. The emergence of long-distance shortcuts

The network density in 2016–2020 is twentyfold that of 2001-2005, with characteristic path length halved (see Table 1), signifying the creation of new intercity shortcuts across various hierarchies. Focusing on the evolution of network links (Figure 8), in the early stage, most links are concentrated among hubs or nearby cities. As noted by previous research (1965), spatial agglomeration can significantly boost efficiency during the early stages of development. However, beyond a certain threshold, its impact on growth weakens and can even hinder innovation expansion. Lagging regions, unable to diversify into highly complex activities, struggled in the peripheral layer. The innovation strategy might disproportionately benefit already developed regions, creating a feedback loop of spatial inequality. Figure 8(c,d) reveal the construction of increasingly more long-distance links from small and mid-sized cities to hubs. This is evident in the active patent exchanges between Northwest China's cities and the hubs of Beijing, Shanghai, and Shenzhen, which are indicative of a strategic shift towards more integrated and equitable regional development.

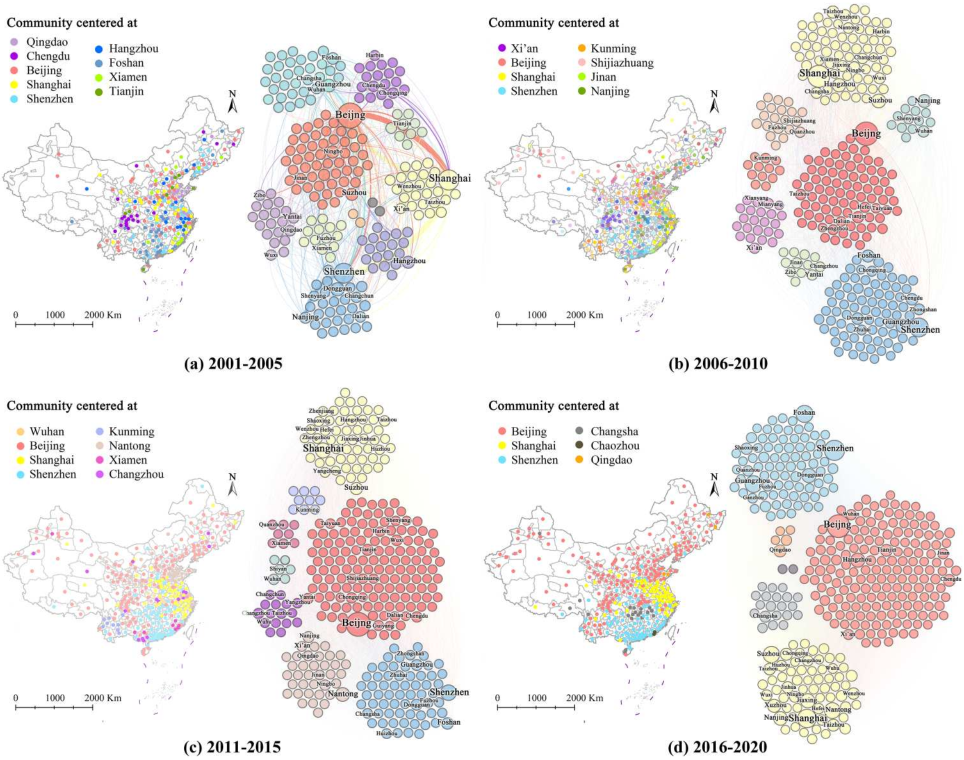

Figure 7. Communities in the China's intercity PTN.

6. Conclusion and future work

Patent transfer (PT) is essential for cities and nations to access external technologies. It is also an essential indicator for capturing the complexity of technology flow. By applying statistical, spatial and network analysis on China's PTN in 2001-2020, we find that: The PTN became denser with significant Matthew effect, hierarchical and small-world structure. Beijing, Shanghai, and Shenzhen remained as national hubs, while new hubs like Suzhou, Guangzhou, Foshan, and Hangzhou emerged, benefiting from the first-mover advantage. The Matthew effect is evident, with less than 20% of cities dominating up to 80% of PT. Despite new national and regional hubs growth, top cities kept their dominance by cooperating with cities of different hierarchies, acting as intermediates, and strengthening their cooperation with hub cities. These findings are consistent with the unbalanced innovation pattern of China observed in earlier studies (Seo and Sonn 2019; Yao, Li, and Li 2020; Zhang et al. 2020). Furthermore, network communities become more homogenised and geographically clustered due to the resonance effect. There was a shift from disperse hubs to spatial agglomerations, with the construction of long-distance shortcuts breaking spatial constraints on intercity PT.

Compared to existing literature, this paper may contribute in several ways: (1) Unique intercity perspective on technology transfer. In contrast to the fields of management, economics, or science and technology policy, where enterprises, industries, and nations are frequently the focus of research, our research studies technology transfer from a unique perspective which is the intercity scale, enabling efficient identification of geographic patterns and technological flow evolutions. (2) In-depth analysis of China's PT network. Focusing on PT in China, it offers insights into market-driven innovation knowledge collaboration, joint patent applications, and other forms of innovation networks. (3) Integration of geographical and network theories. Departing from traditional technology transfer theories, this study employ geographical analysis and complex network theories to

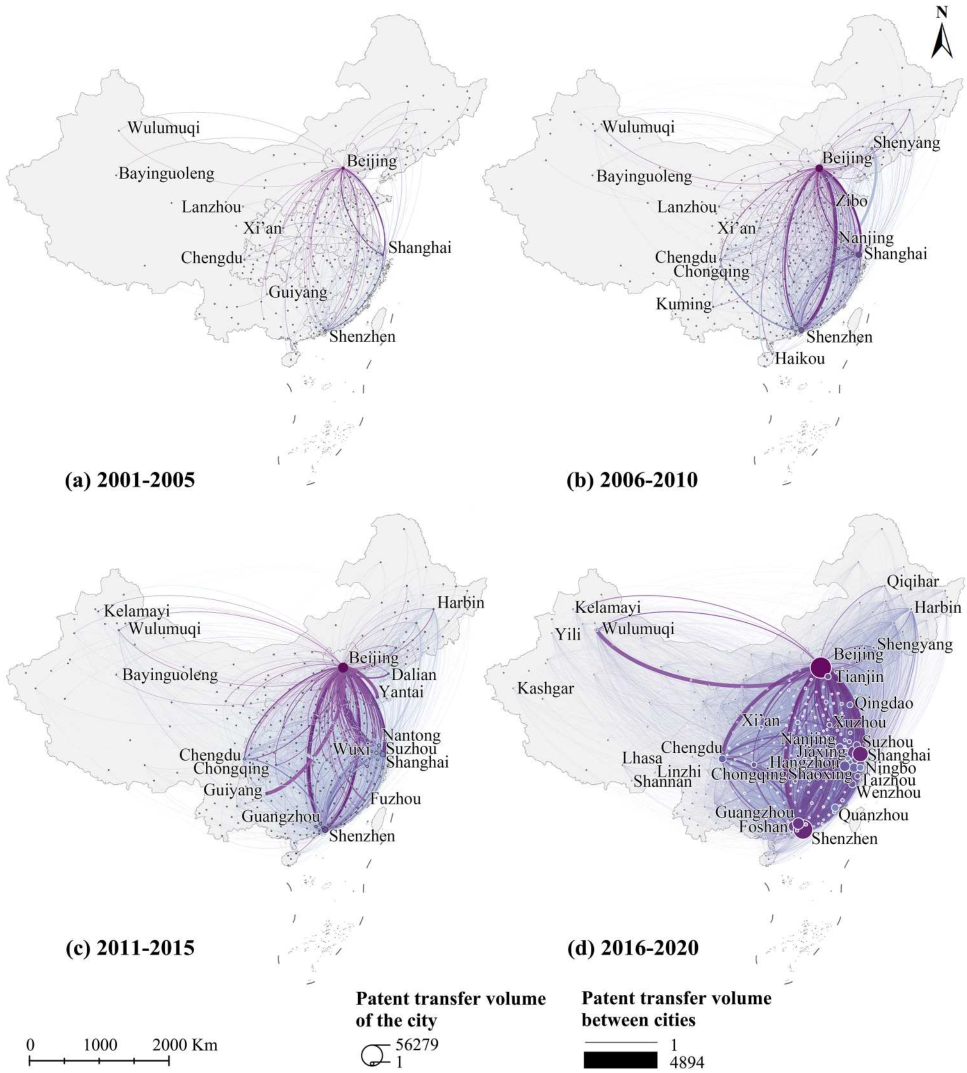

Figure 8. Spatial Evolution of China's intercity PTN.

investigate the complex geographical processes of PT. To the best of our knowledge, we may have been among the first to use degree correlation analysis, community analysis and spatial diffusion theories to explain the evolution of technological innovation networks. Future research on innovation activities should pay more attention to spatial effects.

Finally, some policy implications can be drawn from the research results. Firstly, the government can enhance innovation absorption capacity of backward cities in central and western China through policy and investment, reducing the negative impact of polarised development. Second, the government can also fostering intra-regional or cross-regional PT channels to promote the exchange of innovation resources.

Future works will delve into the factors influencing PT and examine the roles of cities in national and international PT. Besides, collecting more detailed information on PT, including patent type, themes and inventor backgrounds will allow for a comprehensive study of PT's spatiotemporal evolution across various disciplines. Additionally, the interplay between PT and urban development is also a subject worthy of further investigation.

Authors contribution

Bihong YANG: methodology, data curation, formal analysis, writing. Hong ZHANG: conceptualization, methodology, writing, supervision, funding acquisition. Fei FAN: resources, formal analysis, writing – review & editing, funding acquisition. Ruijie HUANG: data curation, formal analysis.

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Data availability statement

The data is available on request as there is another ongoing research.

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