

Examining the Characteristics and Determinants of Technology Transaction Networks in the Chengdu-Chongqing Economic Circle: An Analysis of Patent Trading Data

Xiaohong Li¹, Weijun Zhai², and Ruifeng Hu^{1,2*}

¹ School of Economics, Xihua University, Chengdu, China

² Research Institute of International Economics and Management, Xihua University, Chengdu, China
Email: lixiaohong.xhu@gmail.com (X.L.) weijunzhai.xhu@gmail.com (W.Z.); huruifeng.scu@gmail.com (R.H.)

*Corresponding author

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Abstract—Innovation drives economic development, and the Chengdu-Chongqing Economic Circle prioritizes technological innovation. Patent transfer data reliably reflects technological progress and innovation indices, accurately characterizing urban innovation links. This paper studies the Chengdu-Chongqing Economic Circle using patent transfer data from 2001 to 2020. Employing Social Network Analysis (SNA) and Quadratic Assignment Procedure (QAP) analysis, it explores the spatio-temporal evolution of patent transactions and the factors influencing technology spillover. Results indicate an upward trend in patent transactions, increasing network density, and strengthening clustering coefficients. Node centrality is rising, shifting from a “single-core” to a “multi-level and multi-node” model. Proximity in geography, technology, and institutions significantly promotes patent technology transfer, while economic level, city size, and investment incentives are found not to be primary influencing factors.

Keywords—Chengdu-Chongqing economic circle, patent transactions, evolution, social network analysis

I. INTRODUCTION

Innovation stands as the primary driving force for economic development. China has vigorously pursued an innovation-driven strategy, promoting comprehensive innovation centered on technology (Hu, Xu, Yang, & Ni, 2024). City clusters, as crucial growth pillars (Bu *et al.*, 2024), are pivotal for regional development and constructing innovative nations (Chen, Gao, & Sheng, 2025). The Chengdu-Chongqing city cluster, a vital national hub in western China, receives significant state attention. Patent transaction data is a reliable source for reflecting technological progress (Gong *et al.*, 2025), measuring innovation indices, and identifying key technologies. Moreover, patent transfer effectively characterizes urban innovation linkages (Cui, Ning, Song, & Yang, 2024), improving technology utilization by reducing infringement costs and enhancing innovation efficiency through labor division and technology diffusion (Kwon, 2020). Analyzing patented technology transfer in the Chengdu-Chongqing region offers crucial insights into its technology spillover network characteristics and influencing factors, vital for boosting regional innovation capacity and cooperation. Patent data is frequently used in technology spillover studies; Griliches (Griliches, 1991) pioneered the distinction between “rent spillovers” and “pure knowledge spillovers” using such data. Research indicates that spillover effects are often geographically constrained and influenced by

technological similarity between regions (Debarsy & Le Gallo, 2025), with geographically close firms experiencing positive inter-industry and intra-industry spillovers.

Despite extensive literature, limitations exist. First, most studies focus on developed city clusters like the Yangtze River Delta, Beijing-Tianjin-Hebei, and Guangdong-Hong Kong-Macao, with less attention on the Chengdu-Chongqing Economic Circle. Second, existing literature primarily relies on patent licensing data (Wang, Wang, Lou, & Jin, 2020) with fewer academic results using patent transfer data. Third, while spatial evolution is often examined, temporal dynamics are less thoroughly analyzed, often lacking scientific and detailed time phase divisions.

This paper addresses these gaps by using patent transfer data from 2001 to 2020 to analyze the spatio-temporal evolution and influencing factors of patent transactions in the Chengdu-Chongqing Economic Circle. It employs spatial autocorrelation and social network analysis for a comprehensive spatio-temporal examination. This study aims to provide theoretical references and empirical evidence for future research and the development of the Chengdu-Chongqing Economic Circle.

The contributions of this paper are threefold: 1. It analyzes the network characteristics of technology spillover in the Chengdu-Chongqing Economic Circle from a spatio-temporal perspective and identifies influencing factors, offering insights for regional industrial layout and service planning. 2. It examines factors affecting technology spillover and proposes strategies for promoting patented technology diffusion. 3. It provides theoretical references for subsequent related research, filling a research gap in this specific region.

II. METHODS AND DATA

A. Data Source and Processing

This paper utilizes patent rights transfer data from the “Intellectual Property Public Service Platform” of the China National Intellectual Property Administration (CNIPA) to measure patent transactions. Data mining using Python involved retrieving records with the keyword “transfer” in legal status information, yielding 2,971,236 entries. Stata software was used to extract addresses before and after transfer, filtering out records outside the Chengdu-Chongqing Economic Circle and those with missing addresses. As patent activity in most urban areas of

the Chengdu-Chongqing Economic Circle was negligible before 2001, the study focuses on data from 2001 to 2020, resulting in 10,385 valid patent transaction records. In the temporal analysis, the data is categorized into four phases based on China's Five-Year Plan periods.

B. Methods

1) Social network analysis

Social network analysis of spatio-temporal evolution, network indicators, and centrality(Hu & Xu, 2022).

a) Network Density (D)

Reflects the closeness of network connections. Higher density indicates stronger trading connections.

$$D = \frac{2m}{N(N-1)} \quad (1)$$

Where m is the number of relationships and N is the number of network members.

b) Average Shortest Path (L)

Represents the average shortest distance between node cities. Smaller values indicate better network accessibility.

$$L = \frac{2}{N(N-1)} \sum_{i \neq j} d_{ij} \quad (2)$$

where d_{ij} is the shortest path length between node i and node j .

c) Average Clustering Coefficient (C)

Indicates the overall network clustering, used with average shortest path to assess the small-world property.

$$C = \frac{1}{N} \sum_{i=1}^n \frac{2E_i}{n_i(n_i-1)} \quad (3)$$

where n_i is the number of nodes connected to node i , and E_i is the number of edges between the n_i nodes connected to node i .

d) Degree Centrality $C'_D(N_i)$

Represents the breadth of a city's transactions.

$$C'_D(N_i) = \frac{\sum_{j=1}^g x_{ij}}{g-1}, (i \neq j) \quad (4)$$

where $\sum_{j=1}^g x_{ij}, (i \neq j)$ calculates the number of direct links between city i and the other $g-1$ cities. Diagonal elements in the data matrix are 0.

2) Variables

This paper employs QAP multiple regression analysis.

a) Dependent variable

This paper uses patent transfer data between different cities in Chengdu-Chongqing as the dependent variable. Patent transfer (PT) is a complex process involving negotiations and contract signing, forming inter-city transactional links embedded in social relationships. Considering the 44 cities as nodes, a 44×44 matrix is constructed:

$$P = \begin{pmatrix} P_{1,1} & \cdots & P_{1,44} \\ \vdots & \ddots & \vdots \\ P_{44,1} & \cdots & P_{44,44} \end{pmatrix} \quad (5)$$

Here, P_{ij} denotes the number of patent transfers from city i to city j . The matrix data is normalized using deviation standardization:

$$P = \frac{P_{ij} - \text{Min}(P_{ij})}{\text{Max}(P_{ij}) - \text{Min}(P_{ij})} \quad (6)$$

b) 2. Independent variable:

(1) Geographic Proximity (GP): Measures geographical closeness between two trading entities. Proximity facilitates exchanges and lowers transaction costs, increasing knowledge and technology transfer. Measured by the inverse of geographical distance between representative cities.

$$\begin{aligned} \text{dist}_{ij} = & 6371 \times \{ \arccos[\sin(\text{lat}_i) \sin(\text{lat}_j) \\ & + \cos(\text{lat}_i) \cos(\text{lat}_j) \cos(|\text{long}_i - \text{long}_j|)] \} \end{aligned} \quad (7)$$

where lat and long are latitude and longitude, and 6371 km is Earth's mean radius. Distance is then normalized:

$$\text{Geo}_{ij} = \frac{\text{Max}(\text{dist}_{ij}) - \text{dist}_{ij}}{\text{Max}(\text{dist}_{ij}) - \text{Min}(\text{dist}_{ij})} \quad (8)$$

A value closer to 1 indicates higher geographic proximity.

(2) Technological Proximity (TP): Refers to shared technical experience and knowledge between entities. Shared knowledge facilitates communication and assimilation of tacit knowledge. Measured by the technology structure vector angle:

$$P_{ij} = \frac{f_i f_j'}{\sqrt{(f_i f_i')(f_j f_j')}} \quad (9)$$

where $f_i (f_i = [P_1, P_2, \dots, P_n])$ and $f_j (f_j = [P_1, P_2, \dots, P_n])$ represent proportions of patents in different technological fields (based on Derwent classification/IPC subclasses). A value closer to 1 indicates higher technological proximity.

(3) Institutional Proximity (IP): Similar institutional environments foster shared conduct codes, reduce uncertainty and transaction costs, and facilitate patent transactions. Measured using a dummy variable: 1 if two cities belong to the same province, 0 otherwise.

- (4) Economic Level (EL): This measures the inverse of the difference in economic development, implying that smaller differences lead to higher proximity. However, the discussion points out its non-significance, which aligns with the “lack of apparent differences” hypothesis. It’s better to label it as “Economic Level Difference” or just “Economic Level” as its impact is assessed relative to differences. Here, I’ll use “Economic Level” for consistency with the table. Measured by the inverse of the absolute difference in per capita GDP.

$$\text{Proximity_econ}_{ij} = \frac{1}{|\text{GDP}_i - \text{GDP}_j|} (i \neq j) \quad (10)$$

- (5) City Size (CS): Larger cities tend to attract talent and resources, potentially drawing technology flows. Measured by the reciprocal of the absolute difference in population size.

$$\text{Proximity_pop}_{ij} = \frac{1}{|\text{pop}_i - \text{pop}_j|} (i \neq j) \quad (11)$$

pop_i denotes the population size of the city i .

- (6) Investment Incentives (II): Fixed investment promotes technological adoption, new sector establishment, and economic restructuring. Measured by the inverse of the absolute difference in fixed investment.

$$\text{Proximity_invest}_{ij} = \frac{1}{|\text{invest}_i - \text{invest}_j|} (i \neq j) \quad (12)$$

III. RESULTS AND DISCUSSION

A. Spatio-temporal Characteristics and Evolution of Patent Transaction Networks

We first examine the overall development and structural characteristics of the patent transaction network, followed by an analysis of spatial correlations and the evolution of node centrality.

Table 1. Overall indicators of trading network in Chengdu-Chongqing economic circle

Norm	01–05	06–10	11–15	16–20
Number of areas	25	34	44	44
Number of patent transfers	94	443	2574	7274
Networking density	0.0211	0.0439	0.1216	0.2563
Average path	2.480	2.357	2.011	1.571
Average clustering coefficient	0.214	0.610	0.520	0.654

1) Overall network metrics

Table 1 summarizes the overall network indicators across the four “Five-Year Plan” periods. The results show a clear upward trend in the number of patent transfers and network density. The network density indicator grew particularly faster from 2016–2020 compared to 2011–2015, likely due

to national policy support. Concurrently, the average shortest path consistently decreased, while the average clustering coefficient strengthened. These trends indicate that the patent transaction network in the Chengdu-Chongqing Economic Circle is becoming denser, more accessible, and more clustered over time, facilitating technology exchange and diffusion.

2) Spatial correlation analysis

To further understand the spatial correlation of patent transactions, we computed the global Moran Index for each period, as shown in Table 2. All Moran Index values are positive, indicating a significant positive spatial correlation in patent transactions within the Chengdu-Chongqing Economic Circle, signifying technological spillover. The index generally rose in the first three stages before declining in the fourth. This suggests that spatial agglomeration strengthened initially, where high patent transfer cities tended to trade with similar cities, and low transfer cities traded with others of similar levels. The easing trend in the fourth stage implies more balanced patent transactions.

Table 2. Overall moran’s index in Chengdu-Chongqing region (2001–2020)

Time	“Tenth Five-Year Plan”	“Eleventh Five-Year Plan”	“Twelfth Five-Year Plan”	“Thirteenth Five-Year Plan”
i-value	0.103	0.174	0.247	0.159

Fig. 1 illustrates the localized spatial correlation, revealing distinct agglomeration types: high-high, low-low, low-high, and high-low. The Chengdu-Chongqing patent trading exhibits a diffusion effect, with varying capacities across agglomeration types. Low-low areas demonstrate less technology spillover but strong diffusion, while high-high areas show significant spillover and diffusion, though a tightening effect was observed during the “Thirteenth Five-Year Plan” period. For instance, early high-high agglomerations were noted in Chongqing (Yuzhong and Shapingba districts), expanding with Dadukou and Beibei districts in subsequent periods. Low-low clusters expanded to include regions like Dazu, Tongliang, Kaizhou, Liangping, Dianjiang, and Fengdu, reflecting dynamic shifts in regional patent activity.

1) Node centrality and network structure evolution

Fig. 2 demonstrates the rising centrality values of cities, indicating increasing involvement in the Chengdu-Chongqing Economic Circle’s patent trading network. This growth in scale and frequency of patent trading is partly driven by technology spillover effects from developed cities, which improve innovation quality and foster development (Jin, Mangla, & Song, 2022). Chengdu consistently leads in patent transactions, followed by Chongqing’s sub-districts (Shapingba, Yubei, Jiulongpo, Nan’an, Jiangbei). While the gap between Chengdu and Chongqing subgroups is narrowing, Chengdu maintains stronger patent absorption capacity due to its higher development level and capital (Martin & Simmie, 2008).

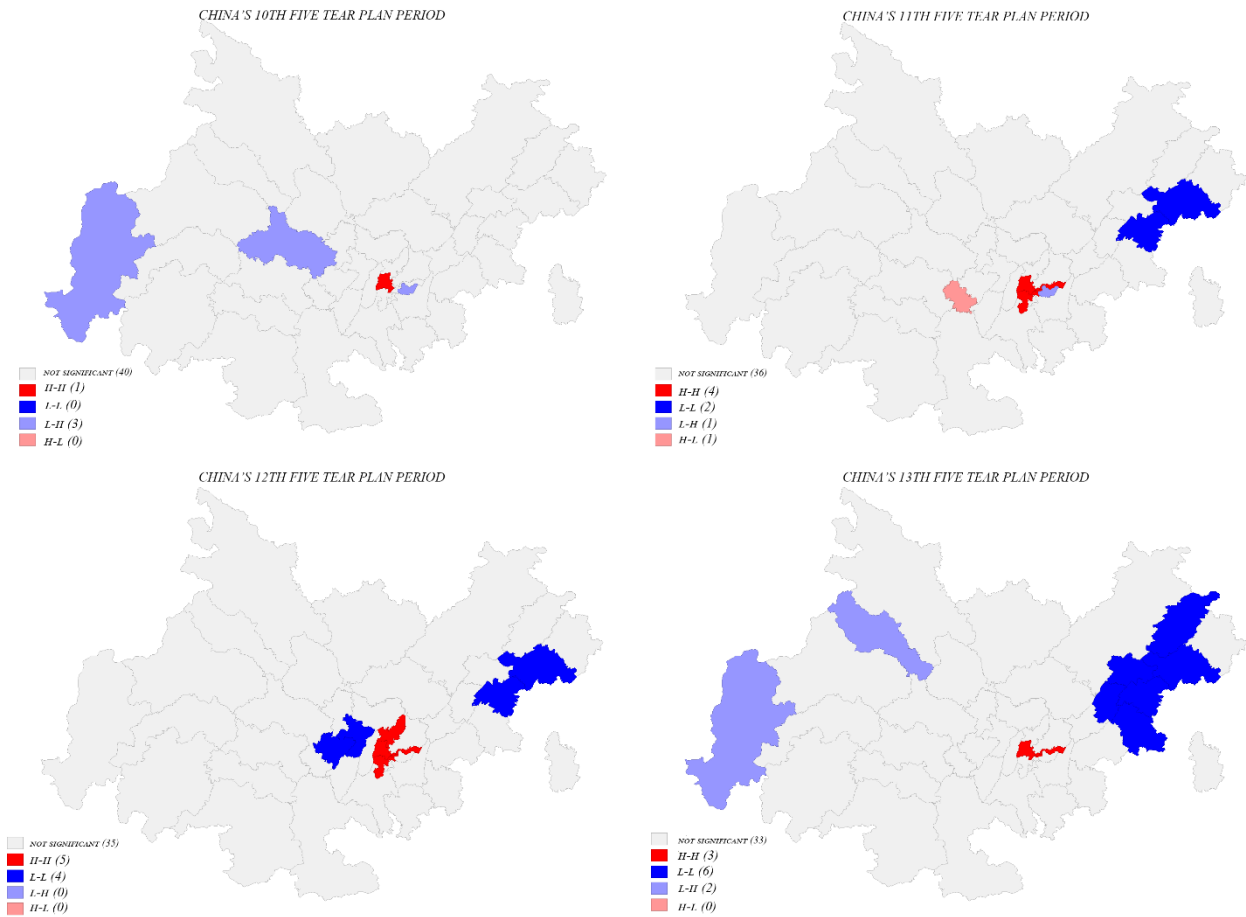


Fig. 1. Spatial correlation analysis of Chengdu-Chongqing region.

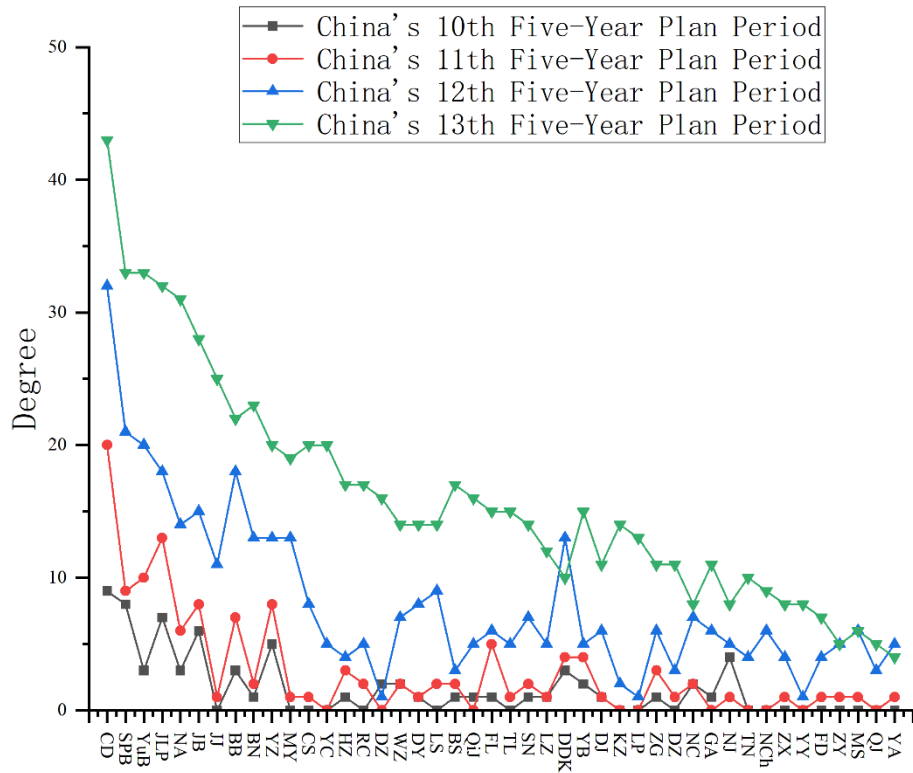


Fig. 2. Spatio-temporal evolution of city centrality in Chengdu-Chongqing.

Fig. 3 visualizes the spatio-temporal evolution of the technology flow network. Node size indicates degree centrality, and connection thickness reflects transaction frequency. The network from 2001 to 2020 shows

diversifying paths and intensifying activity. The network relies on transactions between Chengdu and Chongqing, forming a dual-core leadership that drives neighboring towns (Ali, Cantner, & Roy, 2016). However, transaction

activities in the northeastern and southern city subgroups develop at a slower pace. This is partly because downstream industries may benefit less from technology spillovers than upstream industries, leading to weaker patent exchange (Orlic, Hashi, & Hisarcikilar, 2018). Nevertheless, with ongoing policy promotion and economic growth, regions initially less active are strengthening their absorptive capacity and narrowing the technology gap, leading to more vibrant patent exchanges (Yang, Yu, Wang, Yang, & Zhang,

2021). Early lower technology flows were likely due to institutional quality differences and technological disparities, which improved over time, increasing participation.

For analytical clarity, this paper adopts the spatial city subgroups as defined in the “Master Plan for the Chengdu-Chongqing Economic Circle” (2021), classifying counties (cities and districts) into four subgroups, as detailed in Table 3.

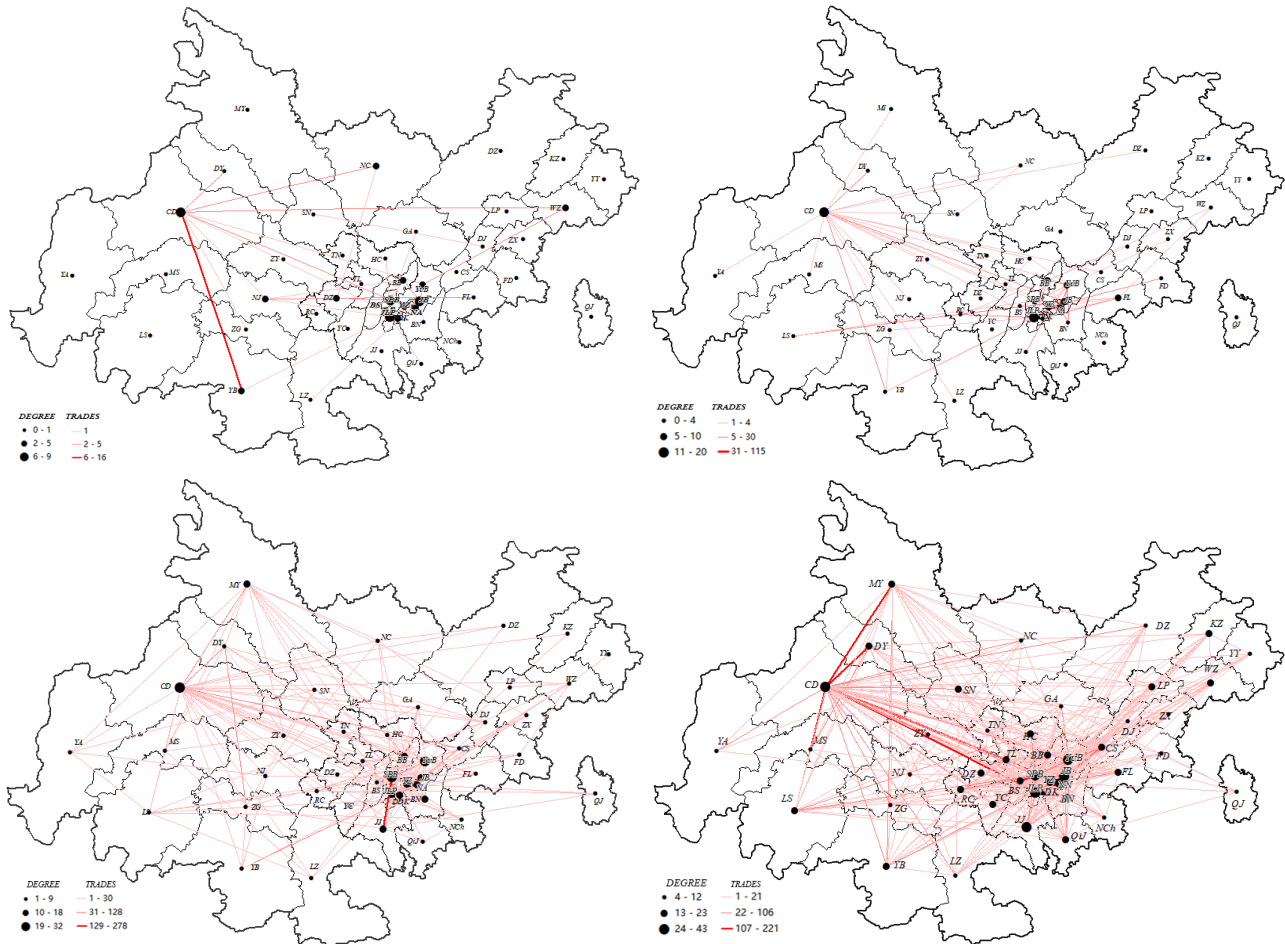


Fig. 3. Spatio-temporal evolution analysis of Chengdu-Chongqing region.

Table 3. Spatial subgroups in Chengdu-Chongqing economic circle.

Composition of urban subgroups	County (city, district)
Chengdu Urban Subgroup	Chengdu, Deyang, Mianyang, Ziyang, Suining, Meishan, Leshan, Ya'an
Southern Cities Subgroup	Yibin, Neijiang, Zigong, Luzhou
Chongqing Urban Subgroup	Qijiang, Nanchuan, Changshou, Jiangjin, Yongchuan, Hechuan, Nan'an, Bishan, Dazhu, Rongchang, Tongliang, Tongnan, Guang'an, Fuling, Beipei, Dadukou, Jiulongpo, Yuzhong, Jiangbei, Yubei, Shapingba
Subgroup of north-eastern cities	Nanchong, Dazhou, Wanzhou, Yunyang, Dianjiang, Fengdu, Zhongxian, Kaizhou, Liangping, Qianjiang

B. Drivers of Technology Spillover in Chengdu-Chongqing Region: A QAP Analysis

1) QAP correlation analysis

Table 4 presents the QAP correlation analysis results. Patent Transfers (PT) are positively correlated with Geographic Proximity (GP), Technological Proximity (TP), and Institutional Proximity (IP), but negatively correlated with Economic Level (EL). Geographic proximity shows positive correlations with technology, institutions, City Size (CS), and Investment Incentives (II). Institutional proximity correlates positively and significantly with city size and investment incentives. However, the correlation between

city size, investment scale, and patent transaction data in the Chengdu-Chongqing region is not significant, suggesting their limited influence on transaction data in this study.

Table 4. Correlation analysis of variables

Variables	PT	GP	TP	IP	EL	CS
PT	-					
GP	0.19***	-				
TP	0.184***	0.161*	-			
IP	0.141***	0.473***	-0.067	-		
EL	-0.016**	-0.01	-0.046	0.008	-	
CS	0.027	0.096**	-0.035	0.152***	0.004	-
II	-0.006	0.087**	-0.021	0.122***	-0.008	0.018

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$

2) Analysis of QAP multiple regression results:

The regression results in Table 5 demonstrate that geographic proximity positively affects technology spillover in Chengdu-Chongqing. Closer cities are more likely to engage in tech transactions due to convenient factor flows. Similarly, technological proximity positively impacts spillovers, as cities prefer patent deals with similar tech structures. These findings align with prior research on tech spillovers between geographically and technologically similar units (Helmets, 2019). Institutional proximity also positively affects technology spillovers, leading to more patent transactions between cities with similar institutional structures, particularly within the same province. This may be because similar institutions create cost-saving spillovers, making inter-regional patent transactions more convenient and economical (Hu, Fisher-Vanden, & Su, 2020). Conversely, the estimated coefficients for Economic Level (EL), City Size (CS), and Investment Incentives (II) are not statistically significant. This indicates that these factors are not critical determinants of technology spillover in the Chengdu-Chongqing region. The non-significance of economic level could be attributed to a lack of significant differences in economic development among cities within the region, making it difficult to establish patent transfer relationships based solely on this disparity.

Table 5. Regression analysis results

Variable	Unstd. Coefft	Std. Coeff	p-value	p-value1	p-value2
Intercept	-0.056	0			
GP	0.041	0.117	0.008	0.008	0.992
TP	0.056	0.170	0	0	1
IP	0.013	0.098	0.008	0.008	0.993
EL	-0.034	-0.008	0.441	0.56	0.441
CS	0.006	0.007	0.267	0.267	0.733
II	-0.087	-0.025	0.083	0.917	0.083

IV. CONCLUSIONS

This paper analyzes the spatio-temporal evolution and drivers of technology spillover networks in the Chengdu-Chongqing Economic Circle (2001–2020) using patent transfer data, social network analysis, and spatial autocorrelation.

The study reveals four key findings: First, patent transaction scale and intensity in the Chengdu-Chongqing Economic Circle are rising, with hotspots centered in Chengdu and Chongqing's core districts (e.g., Yubei, Jiulongpo). Second, patent transactions exhibit spatial agglomeration, dominated by high-high and more pervasive low-low patterns. Third, the network is transitioning from a monocentric to a polycentric structure; while path creation surpasses dependence, Chengdu maintains a noticeable "siphon effect" on neighboring resources. Finally, geographic, technological, and institutional proximity significantly drive transfers, whereas economic scale and investment incentives are not the primary determinants. The paper offers three policy insights: First, leverage core cities' intermediary roles to bridge the "east-west, north-south" patent gap and reduce cross-regional transaction costs. Second, optimize industrial layouts in Sichuan and Chongqing to achieve economies of scale and foster specialized innovation clusters. Third, attract top innovators to less developed subregions by improving patent protection and the overall innovation environment.

Despite these research results, limitations exist. This paper focuses solely on patent transactions within the Chengdu-Chongqing Economic Circle, omitting transactions with external regions. Future research will expand data scope to include external influences, as they also impact internal dynamics.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Xiaohong Li: Conceptualization, Methodology, Formal analysis, Data curation, Writing-original draft. Ruifeng Hu: Conceptualization, Resources, Writing-review & editing, Supervision, Funding acquisition. Weijun Zhai: Conceptualization, Resources, Writing-review & editing, Supervision; all authors had approved the final version.

REFERENCES

- Ali, M., Cantner, U., & Roy, I. 2016. Knowledge spillovers through FDI and trade: The moderating role of quality-adjusted human capital. *Journal of Evolutionary Economics*, 26(4): 837–868.
- Bu, X., Li, Y., Lai, W., Yao, C., Liu, Y., et al. 2024. Innovation and development of the aquaculture nutrition research and feed industry in China. *Reviews in Aquaculture*, 16(2): 759–774.
- Chen, L., Gao, L., & Sheng, S. 2025. Dynamics of regional intellectual property systems in China: A spatiotemporal synergy analysis. *World Patent Information*, 81: 102359.
- Cui, Z., Ning, Y., Song, J., & Yang, J. 2024. Impact of National Innovative City Policy on Enterprise Green Technology Innovation—Mediation Role of Innovation Environment and R&D Investment. *Sustainability*, 16(4): 1437.
- Debarys, N., & Le Gallo, J. 2025. Identification of Spatial Spillovers: Do's and Don'ts. *Journal of Economic Surveys*, 39(5): 2152–2173.
- Gong, H., Zou, H., Liang, X., Meng, S., Cai, P., et al. 2025, March 1. *A Global Dataset Mapping the AI Innovation from Academic Research to Industrial Patents*. arXiv. <https://doi.org/10.48550/arXiv.2503.09257>.
- Griliches, Z. 1991, July. *The Search for R&D Spillovers*. National Bureau of Economic Research. <https://doi.org/10.3386/w3768>.
- Helmets, C. 2019. Choose the Neighbor before the House: Agglomeration Externalities in a UK Science Park. *Journal of Economic Geography*, 19(1): 31–55.
- Hu, R., & Xu, W. 2022. Exploring the Technological Changes of Green Agriculture in China: Evidence from Patent Data (1998–2021). *Sustainability*, 14(17): 10899.
- Hu, R., Xu, W., Yang, Y., & Ni, G. 2024. A Combined Scientometric and Meta-analysis Exploration of Eco-innovation: Evolution and Determinants. *Journal of the Knowledge Economy*, 15(1): 3174–3201.
- Hu, Y., Fisher-Vanden, K., & Su, B. 2020. Technological spillover through industrial and regional linkages: Firm-level evidence from China. *Economic Modelling*, 89: 523–545.
- Jin, P., Mangla, S. K., & Song, M. 2022. The power of innovation diffusion: How patent transfer affects urban innovation quality. *Journal of Business Research*, 145: 414–425.
- Kwon, S. 2020. How does patent transfer affect innovation of firms? *Technological Forecasting and Social Change*, 154: 119959.
- Martin, R., & Simmie, J. 2008. Path dependence and local innovation systems in city-regions. *Innovation*, 10(2–3): 183–196.
- Orlic, E., Hashi, I., & Hisarcikilar, M. 2018. Cross sectoral FDI spillovers and their impact on manufacturing productivity. *International Business Review*, 27(4): 777–796.

Wang, L., Wang, Y., Lou, Y., & Jin, J. 2020. Impact of different patent cooperation network models on innovation performance of technology-based SMEs. *Technology Analysis & Strategic Management*, 32(6): 724–738.

Yang, W., Yu, X., Wang, D., Yang, J., & Zhang, B. 2021. Spatio-temporal evolution of technology flows in China: Patent licensing networks 2000–2017. *The Journal of Technology Transfer*, 46(5): 1674–1703.

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