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Exploring the Spatial Spillovers of Digital Finance on Urban Innovation and Its Synergy with Traditional Finance

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Abstract

Research on the driving role of digital finance in urban innovation is scarce. Most existing literature focuses on whether digital or traditional finance contributes more to innovation, ignoring the spatial spillover effect of digital finance and failing to explore whether digital finance complements traditional finance in promoting innovation. Moreover, current studies focus on the provincial dimension but elaborate very little on the implications of BRI node cities. This study fills in the gaps by focusing on the spatial spillover effects of digital finance on urban innovation and complementary functions of traditional finance. It applies the spatial Durbin model to 26 China BRI node cities from 2013 to 2020. The results indicated that digital finance has a significant positive effect on the innovation level of these cities, suggesting that digital and traditional finance systems are complementary in promoting innovation. Moreover, the evidence of spatial spillover proves that innovations in node cities influence neighboring regions. This paper contributes to the interaction between digital finance and urban innovation with new insights. It also fills the literature gap by underlining the spatial dynamics rather than traditional panel approaches. The results are useful for policymakers in harnessing financial mechanisms for innovation and economic growth.

Keywords:

Digital Finance;

Financial Inclusion;

Innovation Level;

Spatial Spillover;

Belt and Road Initiative; FinTech.

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1- Introduction

Innovation drives countries' sustainability and high-quality economic development and plays an important role in regional competitiveness. Amid the global economic downturn since 2019, the Belt and Road Initiative (BRI) has gained importance in China and in the global economic recovery. In March 2015, China issued the Vision and Actions for Developing the Silk Road Economic Belt and the 21st Century Maritime Silk Road to promote the BRI. This initiative includes 26 node cities in China to support Belt and Road construction. The coastal areas include 16 eastern port cities (Dalian, Fuzhou, Guangzhou, Haikou, Ningbo, Quanzhou, Qingdao, Sanya, Shanghai, Shantou, Shenzhen, Tianjin, Xiamen, Yantai, Zhanjiang, and Zhoushan) [1], five central inland port cities (Changsha, Hefei, Nanchang, Wuhan, and Zhengzhou), and five western port cities (Chengdu, Chongqing, Lanzhou, Xi'an, and Xining). These node cities have become essential strategic fulcrums for promoting technological innovation and economic transformation in China [2].

While innovation cannot be achieved without financial support, China's formal financial system, dominated by bank credit, has developed slowly. China presents the paradox of financial development: research and development and innovation lag rapid economic growth [3-6]. One may argue that there is no academic consensus on whether traditional banking finance can promote innovation. On the one hand, bank development and credit support technological progress

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[7-9]. On the other hand, bank-dominated credit financing has a stronger preference for preserving value and hedging investments. China's formal financial system prefers state ownership, so many bank credit funds are directed to state-owned enterprises. A lot of innovative private enterprises struggle to obtain bank credit support. Severe financing constraints [10, 11] make it difficult to promote innovation.

The recent success of digital finance in China has decreased financial transaction expenses, broadened the reach and eased financial services' access. As financial support is important to international trade development, it is essential to examine whether digital finance complements traditional finance under the current bank-dominated financial system, and how modern digital and conventional finance systems promote research, development, and innovation. The study results provide clues to understanding China's innovative growth miracle [12].

Additionally, international trade promotes technological innovation and economic growth [13]. Subsequently, BRI node cities embrace a more open trading environment and provide ample opportunities for technological innovation driven by digital finance. These cities form a spatial network of digital finance development, trade openness, and technological innovation. However, the spatial correlation of the technological innovation levels between node cities and the spatial effect of digital finance in node cities on technological innovation in neighboring cities remains unknown. Digital finance research can be divided into three categories: academic discussion on existing digital finance [14], the integrated development of digital technology and inclusive finance [15], and the influence of digital finance on capital mismatch [16], carbon emissions [17], and economic growth based on index measurement [14]. Furthermore, digital finance research also encompasses the development of individual digital finance platforms, such as peer-to-peer and crowdfunding platforms, and their effects on innovation and entrepreneurship [18-22].

Although many studies have examined the relationships among traditional finance, innovation, and entrepreneurship, systematic studies on the impact of digital finance on regional innovation are relatively scarce [22]. Currently, most digital finance surveys highlight the digital finance services of traditional finance institutions dominated by banks (e.g., mobile banking) or peer-to-peer online lending and crowdfunding platforms. Against this backdrop, the Digital Finance Research Center of Peking University has compiled the Digital Inclusive Finance Index (PUDIFI) [14], a quantitative study on digital finance. Research on the impact of digital finance on urban innovation is scarce. The existing literature mainly uses a general panel model for empirical analyses. However, it does not cover the spatial spillover effect of digital finance, which fails to capture the spatial effect and limits the reliability and accuracy. Second, existing studies focus more on whether digital or traditional finance promotes innovation; however, whether digital finance complements traditional finance in fostering innovation is often ignored. Third, current research is mainly at the provincial level, and more research is needed on innovation in BRI node cities.

To fill this research gap, this research studies the digital and traditional finance mechanisms and spatial effects on 26 node cities' urban innovation in China using the spatial Durbin model (SDM). It examines whether digital finance complements traditional finance systems to promote research and development as well as innovation, which explains China's innovative growth puzzle. The findings have several practical implications. First, despite ongoing development, China's research and development has room for improvement, and its innovation level needs to meet the national high-quality development requirements. Understanding the relationship between financial development and innovation enables us to understand China's financial mechanisms that drive high-quality economic growth. Second, as technological innovation and sustainable development are vital to China's economic plans, examining node cities' financial supply breakthroughs offers insights into the reasons that power technological innovation, BRI cities and countries' development.

Third, digital finance has gained importance in the financial reform process. Under the financial support policy, it is meaningful to investigate how digital finance influences urban innovation in driving economic development. The findings shall serve as a basis for government departments to evaluate the growth of each region more comprehensively, improve the technological innovation mechanism and efficiency of financial service entities, and formulate better financial regulations. Additionally, as an initiator of the BRI and a country blended with the developed and developing nations' characteristics, the results shall offer insights for other countries along the BRI when they adopt digital finance to drive urban innovation.

2- Theory and Hypothesis

As a new financial mode, digital finance may complement traditional finance systems and support technological innovation in countries, regions, cities, and enterprises through multiple approaches [15-17]. Node cities will be directly affected by digital finance, which will have a spatial spillover effect on neighboring cities.

2-1- Direct Effect of Digital Finance on Hub City Innovation

The inclusive concept of digital finance aligns with the financial needs of enterprises that use innovative technology. Relying on the two pillars of organic fintech integration and the effective empowerment of digital technology, the node cities' innovation is promoted in three main ways [15-17]. First, despite the innovation activities being more likely to fail and the innovation process taking a long time and being unpredictable, it alleviates financial constraints on innovative activities [23]. One example is crowdfunding, which offers a chance for innovation to receive financial support worldwide before the product is ready for sale. Nevertheless, high-quality innovation activities are necessary for industrial development and usually involve external risks such as financing constraints, information asymmetry, and market uncertainty [24]. With new digital technologies, digital finance is more efficient in information collection and processing, risk identification, and management and effectively alleviates the problems of information asymmetry frequently faced by enterprises in the financing process [25, 26]. It also reduces transaction costs, simplifies the capital approval process, improves the credit review system, and meets the demand for capital in technological R&D and innovation activities [27, 28].

Second, business opportunities should be unlocked. Traditional finance restricts the industrial structure upgrade, business model opportunities, and urban agglomerations [25]. Digital technology is an essential driving force in business reform [29]. It positively affects consumer identification, participation, enterprise value delivery, and realization [30]. This encourages continuous technological innovation. Third, it promotes industrial restructuring. The wide application of digital finance enables industrial structure upgrades, maximizes the effect of technological innovation, and improves enterprises' innovation levels. Digital finance helps investors select valuable long-term investments more comprehensively [31], allocate idle social funds effectively, and ensure project sustainability. Digital finance also promotes upgrading industrial structures [16], transforming labor-intensive enterprises to capital- and technology-intensive enterprises. From a regional perspective, upgrading the industrial structure contributes to technology transfer and optimizing factor allocation [25, 32]. Thus, this study proposes the following hypothesis:

H1: Digital finance promotes innovation directly in node cities.

The rationale and process of digital finance's impact on node cities' innovation are illustrated in Figure 1.

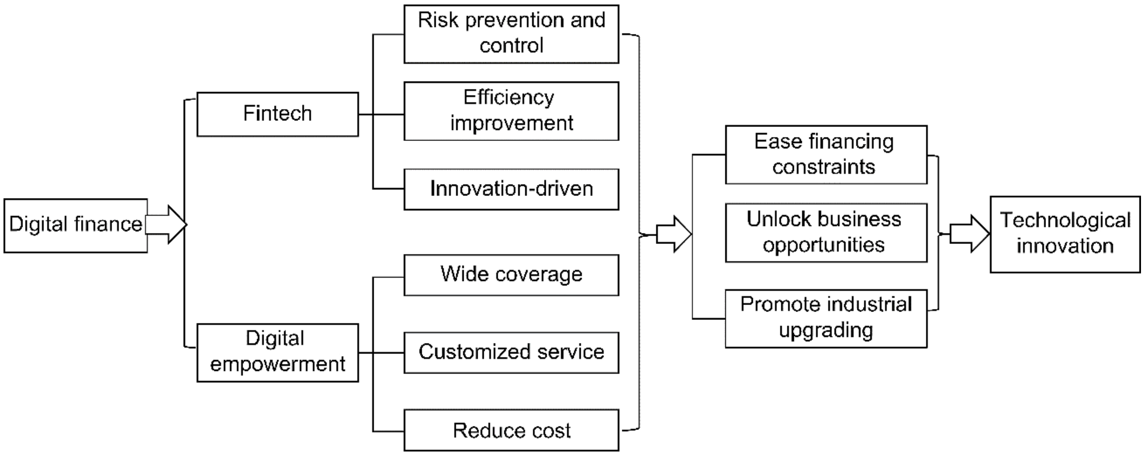

Figure 1. "Innovation-driven" and "Fintech"

The influence of banking and credit market development on innovation is unclear and may depend on the state-owned banks [33]. Bank-dominated credit markets and financial systems appear to stifle innovation. For example, Hsu et al. [34] reported that the development of a bank-dominated credit market hinders the quantity and quality of innovation in high-tech-intensive industries with high reliance on external financing. However, with the gradual diversification of financial suppliers and the upgrading of the financial model, the diversification and marketization of financial supply not only ease the external financial constraints of innovation but also reduce transaction costs and moral hazard due to adverse selection [35].

Although fintech development does not impact the financial system in some countries [36], previous studies show that digital finance channels are more diversified, independent, and market-oriented than traditional finance models. Digital financial services boast advantages such as broad coverage, high efficiency, and low costs [15]. They power the marketization of equity financing and private funding flexibility. This provides opportunities to improve urban technological innovation. Digital finance significantly impacts traditional financial institutions through competition, accelerates the process of digitalization, and markedly improves the service efficiency and quality of conventional financial institutions such as banks. A modern digital and traditional financial system is expected to improve urban innovation. Digital finance injects new energy into financial systems, complements traditional finance, effectively alleviates information asymmetry between tech innovators and capital providers, reduces capital transaction costs through pre-project screening and post-tracking supervision, and significantly improves capital use efficiency.

In addition, while continuous R&D spending is more likely to impact technological innovation positively [37], digital finance provides monetary support for technological innovation projects. This helps avoid project discontinuation owing to a shortage of capital sources and guarantees regular progress in technical research and development. Thus, we posit the subsequent conjecture:

H2: Digital and traditional finance are complementary, helpful in promoting innovation in node cities, and explain the puzzle of China's innovative growth.

2-2- Spatial Diffusion Impact of Digital Finance on Node City Innovation

Technological spillover types have different effects in various fields [38, 39]. Digital finance has built a new, sustainable, comprehensive financial system using information technology tools like the Internet, big data, and cloud computing. Owing to the high correlations between economic relevance, information spillover, and spatial distance, digital finance may have the transmission characteristics of regional diffusion at the technological innovation level [40-42]. Therefore, considering the spatial characteristics, we analyzed the spatial spillover effect of digital finance on technological innovation [43].

The competitive effect is digital finance's first spatial diffusion impact on the node city innovation effect. GDP has long been the primary factor measuring the performance of local governments at all levels in China, which has gradually led to unbalanced and distorted economic development. Since 2013, structural adjustments have been made to the performance evaluation systems of local government officials. Accordingly, GDP growth is no longer the only indicator of officials' performance. Instead, it is evaluated based on economic and social indicators, including economic development, political culture, social progress, improving people's livelihoods, ecological benefits, and environmental preservation. As local officials' promotion assessment includes the environment of regions with similar economic levels, officials in similar stages of economic development have a stronger motivation to learn from each other and increase the policy support of digital finance [44, 45].

The criteria for officials' promotion in China have increased the spatial diffusion impact of digital finance on innovation incentives, and the innovations of node cities influence each other. The second effect is the trickle-down effect. Factor endowment value differences between regions lead to trickle-down results [46]. The trickle-down or leakage effect implies that poor and vulnerable groups and areas are not given preferential treatment in economic development. However, preferential development groups or areas benefit impoverished people and regions through consumption, employment, and other aspects that drive growth and prosperity. Owing to differences in the endowment of resources in different cities, some regions attract more capital and talent under the siphoning effect, thus significantly promoting digital finance development and technological innovation. However, when the first cities develop digital finance and reach a certain level of development, the high population density and excess capital increase the production costs of the first-developed areas. Businesspeople look for new markets to improve their development and expansion and allocate part of their talent, capital, and technology to neighboring regions [47].

Knowledge and technology spillovers promote technological innovation in neighboring cities, and this diffusion effect manifests as a positive spillover [48, 49]. In other words, digital finance exerts a positive spatial diffusion impact on innovation in neighboring node cities [47, 50]. The spatial diffusion impact of digital finance is no [51]. Based on competition and trickle-down effects, digital finance effectively drives node cities to enhance innovation. It forms a healthy competition and spatial spillover in the region, promoting innovation in neighboring node cities. The third is the siphoning effect. The siphoning effect first appeared in fluid physics as a phenomenon caused by the difference in the gravitational force and potential energy between liquid molecules, which caused the liquid to rise and then flow to a lower level [52]. Some scholars have used it to explain capital flows and regional or intercity spatial clustering [53]. As the market supply and demand mechanism influences the price of technological innovation, the heterogeneous pricing of technological innovation factors in different regions promotes the cross-regional flow of factors, causing the spatial spillover of financial factors on technological innovation development. Considering the difficulty and transfer cost of cross-regional factor mobility, this phenomenon will significantly impact neighboring regions.

The fourth factor is the effect of radiation. Digital finance has eliminated the hurdles of traditional finance regarding geographical areas and offers comprehensive coverage, lower costs, and higher efficiency. The negative impact of geographic distance on the financial spillover effect is significantly reduced, and the spatial friction coefficient is lowered. The spillover effects of knowledge, information, and technology are enhanced, thus improving the spatial spillover of digital finance to innovation [40, 41, 54]. Therefore, digital finance complements traditional finance through the radiation effect, and a modern financial system consisting of digital and traditional finance jointly promotes technological innovation in neighboring node cities. Thus, this research advanced the subsequent theoretical proposition:

H3: Digital and traditional finance form a complementary positive spatial diffusion impact and jointly promote technological innovation in neighbouring node cities.

2-3- Other Factors Affecting Innovation of Node Cities

2-3-1- Traditional Financial Development Level

China's direct financing is relatively small, and digital finance as an emerging financing channel requires development time. Hence, loans from traditional finance institutions provide the primary funding source to enterprises during the initial phase of digital transformation. Customers with traditional finance accounts are more willing to increase their digital finance transactions [55]. Thus, digital finance complements traditional financing and promotes innovation. Owing to data deficiency on financial assets and M2 in Chinese provinces and cities, the ratio of financial institutions' loan balances to each region's gross product is usually used in empirical analyses to gauge the maturity of traditional finance in each region [56].

2-3-2- International Trade Environment

International trade and technological progress are interrelated [13, 57]. BRI node cities have a more open trade environment, and technology spillover, learning, market competition, and expansion affect foreign trade. These factors impact developing countries' technological progress [58-60]. Among the primary pathways of international technology spillovers, foreign direct investment (FDI), outward FDI, and external openness, FDI has the most pronounced effect [61]. Advanced external technologies can be introduced through FDI to promote regional technological innovation, which will have international technology spillover effects. These factors positively contribute to research intensity [62].

2-3-3- Industry Structure, Economics Development, Population and Human Capital

An industry-specific environment influences technological innovation, resulting in substantial differences in innovation activities across various sectors [63]. Theoretically, developed regions provide a good R&D environment, fostering more innovation [64]. Additionally, population density has a demand-pull effect on technological innovation. As rural workers migrate to cities, this urbanization facilitates knowledge exchange, innovation, and productivity growth [65]. Innovation is talent-driven, and human capital is crucial for industrial and regional technological innovation [66, 67].

3- Data Acquisition and Methodological Framework

3-1- Data Sources

Data from 2013 to 2020 for 26 Chinese node cities (Figure 2) were selected for the empirical analysis. The digital finance index was obtained from the PUDIFI. The other variables were collected from the China Urban Statistical Yearbook (CUSY).

Figure 2. Distribution of China's 26 node cities

3-2- Variable Description

3-2-1- Dependent Variables

Urban innovation level (Inn): Regarding the quality of innovation, most previous studies have used the number of authorized patent citations as a proxy for innovation quality [32, 60]. However, the Chinese Patent Database does not provide such information. Thus, the natural logarithm of the number of patent authorizations was used to measure the innovation level.

3-2-2- Independent Variables

(1) Digital finance level. This study used the PUDIFI to measure the digital finance level of node cities. The data source of the index was massive internal data from the China Ant Financial Services Group on Inclusive Digital Finance. Based on the principles of balance, comparability, multilevel, digital, and integrity, the PUDIFI was constructed, reflecting the digital finance level in various regions from 2011 to 2020. It covers 31 provinces and cities, 337 prefecture-level cities, and approximately 2800 counties in China (see Appendix I for the details).

This formula is shown in Equation 1*:

$$d = \sum_{i=1}^{n} W_i d_i \tag{1}$$

where d is the comprehensive index, w_i is the normalized weight of each evaluation indicator, d_i is the evaluation score of each indicator, and n is the number of evaluation indicators [14].

(2) Traditional finance level (TF). Direct financing accounts for a relatively small proportion of loans in China, and loans from traditional finance institutions (mainly bank loans) are necessary for enterprises to obtain funds. Therefore, using Feng Lu and Yao's [56] method as a reference, we used the ratio of the financial institutions' loan balance in the node city to the GDP in the node city to reflect the development level of traditional finance.

3-2-2- Control Variables

The control variables selected were as follows: (1) FDI was used to multiply the exchange rate and natural logarithm to measure the international trade environment; (2) industrial structure (Ind) was the proportion of a tertiary industry's output to the region's GDP and measures its industrial structure; (3) economically developed areas provide a good R&D environment for technological innovation, so economic development was measured by the natural logarithm of the regional GDP per capita; (4) densely populated areas have a demand-pull effect on technological innovation, and the ratio of the registered population to the land area by year-end in the region measured population density, while the natural logarithm of this index ensured the scale consistency; and (5) as higher wages attract more talent, and the inflow of talent drives regional technological innovation, urban per-capita wage (Wage) using the natural logarithm of the urban workers' average wage measured human capital. Table 1 lists the definitions of the major variables, which were all obtained from the PUDIFI and CUSY.

Table 1. The main variables

Name	Symbols	Measurement method
Urban innovation level	Inn	Logarithmic Transformation of the patents granted
Digital finance level	IFI	Logarithmic Scaling of Peking University's Index for Digital Financial Inclusion
Traditional finance level	TF	Financial Institutions' Credit Balance /regional GDP
FDI	FDI	Foreign investment used × Exchange rate of the year/gross regional GDP
Industrial structure	Ind	Tertiary industry output value/Gross regional GDP
Economic development	Dev	Logarithmic representation of per capita real GDP
Population density	Den	Year-end household population/land area, the logarithm of population density
Urban per-capita wage	Wage	Logarithmic transformation of the mean urban employee Salary

3-3- Descriptive Statistics

Table 2 shows the descriptive statistics for all of the variables. Digital finance developed substantially from 2013 to 2020. The significant standard deviation of the digital finance level indicates a severe imbalance in node cities. The differences among each variables' values are insignificant, indicating that the dimensions are reasonable. The correlation coefficients between the variables are no greater than 0.7, indicating no serious multicollinearity.

* More detail in the PUDIFI (Guo et al. 2020).

Table 2. Descriptive statistics of the variables

Variable	Mean	Standard deviation	Minimum	Maximum
Inn	10.15	1.373	6.816	12.31
IFI	5.670	0.0655	5.526	5.771
TF	2.099	0.860	0.790	4.487
FDI	0.0232	0.0187	-0.0131	0.0581
Ind	0.594	0.0943	0.406	0.805
Dev	11.75	0.526	10.49	12.97
Den	6.671	0.641	5.540	8.083
Wage	11.57	0.168	11.27	12.09

Correlations

	Inn	IFI	TF	FDI	Ind	Dev	Den	Wage
Inn	1							
IFI	0.359	1						
TF	-0.204	0.160	1					
FDI	0.326	-0.112	-0.087	1				
Ind	0.0270	0.433	0.589	0.0300	1			
Dev	0.571	0.386	0.041	0.248	0.365	1		
Den	0.584	0.214	-0.282	0.173	0.134	0.40	1	
Wage	0.520	0.793	0.219	0.0810	0.537	0.644	0.264	1

Data source: Calculated according to the PUDIFI and CUSY data indicators.

3-4- Research Design

3-4-1- Spatial Autocorrelation Determination

Owing to the difference in the distance between node cities and the solid spatial mobility of the explained variable of technological innovation, the possible spatial correlation of the technological innovation level of node cities should be detected. The leading judgment indicators were Geary's C index and Moran's I. Referring to existing literature practices [68], we calculated Moran's I to measure spatial autocorrelation using the following formula:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{i\neq j}^{n} W_{ij}(Y_i-\bar{Y})(Y_j-\bar{Y})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{2}$$

where *Yi* and *Yj* represent the observed values of the *ith* and *jth* cities, respectively, namely, the level of urban technological innovation; *N* is the number of node cities; and *Wij* is the element in the nested economic geography matrix. The elements on the diagonal of the spatial matrix are zero, and the rows and columns correspond to spatial cells. In general, the global Moran's I ranges between -1 and 1. When the global Moran's I value is 0–1, the sample has a positive correlation in the spatial dimension. Otherwise, the model is negatively correlated with the spatial dimension [69]. The greater the deviation is from 0, the stronger the correlation.

This study computed Moran's I of the innovation level of node cities, and Table 3 shows global Moran's I by year. The global Moran's I of the innovation level of node cities was greater than zero from 2013 to 2020, and the correlation was significant at the 5% level. The clustering of the technological innovation levels of node cities shows a positive spatial autocorrelation. This indicates that, on a global scale, the innovation level of node cities is not entirely randomly distributed but is influenced by the technological innovation activities of other regions with similar spatial characteristics. There may be significant spatial autocorrelation because the spillover effect of innovation has increased over time.

Table 3. Global Moran's I test

Year	2013	2014	2015	2016	2017	2018	2019	2020
Global Moran's I	0.202	0.221	0.191	0.168	0.198	0.194	0.184	0.179
Z	1.997	2.126	1.891	1.707	1.957	1.928	1.873	1.813
P	0.023	0.017	0.029	0.044	0.025	0.027	0.031	0.035

3-4-2- Spatial Heterogeneity Test

Global Moran's I is not an effective measure of the spatial differences in innovation capacity among node cities; therefore, the local Moran's I, which can discern the heterogeneity of the innovation capacity of node cities in the local space [70], should be used. Equation 2 shows the calculation formula:

$$Local\ Moran's\ I_i = \frac{(Y_i-\bar{Y})}{S^2}\sum_{j=1}^{n} W_{ij}(Y_j-\bar{Y}) \tag{2}$$

Based on the local Moran's I, a Moran scatterplot was further drawn and divided into four quadrants (Figure 3). The first quadrant indicates the spatial correlation between its region and the neighboring regions in the form of "high-high" aggregation, the second indicates "low-high" aggregation, the third indicates "low-low" aggregation, and the fourth reflects "high-low aggregation." The Moran scatterplot explores the spatial association pattern of a variable between each city in the sample area and its neighboring urban units. The vertical coordinates represent the statistics of neighboring regions, and the horizontal coordinates represent the region's statistics.

Table 4 and Figure 3 present node cities' spatially related technological innovation characteristics. First, the data were concentrated in the first quadrant of the scatterplot. Including Guangzhou, Shenzhen, and Shanghai, 11 node cities and 10 node cities were far from the origin of the coordinates and in the "HH" area in 2013 and 2020, respectively, showing that high-node cities enclose these node cities with high innovation. This demonstrates that the innovation level of large cities is higher than that of small- and medium-sized cities. These regions lead digital finance and technological innovation.

Table 4. Local Moran's I test results

Variable	Area type	2013	2020
Innovation level	HH	Guangzhou, Shanghai, Shenzhen, Ningbo, Hefei, Changsha, Xiamen, Zhengzhou, Chengdu, Dalian, Qingdao (11)	Guangzhou, Shenzhen, Shanghai, Ningbo, Hefei, Changsha, Xiamen, Chengdu, Zhengzhou, Fuzhou (10)
	LH	Zhoushan, Nanchang, Yantai (3)	Zhoushan, Nanchang, Dalian (3)
	LL	Sanya, Xining, Zhanjiang, Haikou, Lanzhou, Shantou, Fuzhou (7)	Sanya, Xining, Zhanjiang, Haikou, Lanzhou, Shantou, Yantai (7)
	HL	Chongqing, Quanzhou, Wuhan, Xi'an, Tianjin (5)	Chongqing, Quanzhou, Wuhan, Xi'an, Tianjin, Qingdao (6)

Note: The first letter of the "Area type" column refers to the innovation level in node cities, and the second letter refers to the innovation level of neighboring areas.

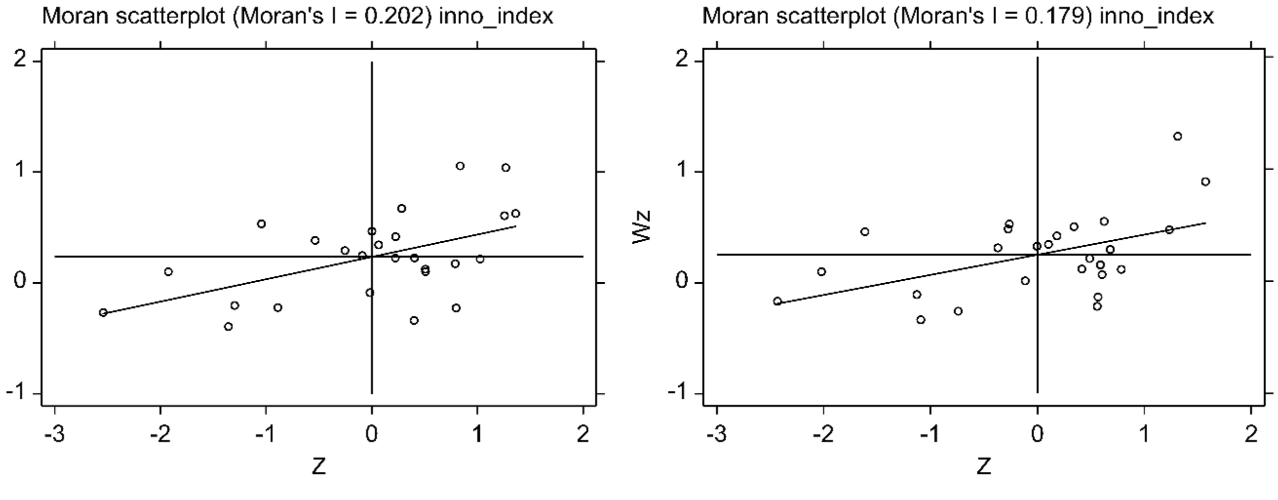

Figure 3. Scatterplot of Moran's I of the innovation capacity of node cities (left: 2013, right: 2020)

Second, the second most clustered data distribution falls on the third quadrant and the LL area. Five-node cities and six-node cities were in the fourth quadrant in 2013 and 2020, respectively, namely the HL area, indicating that low-node cities enclose these node cities with high innovation levels. Three towns were in the fourth quadrant in both 2013 and 2020, namely the LH area, indicating that these node cities with low innovation levels are enclosed by high-node cities, which means that the spatial effect of this small part of cities is not significant enough. Over time, the aggregation type mostly remained the same, and the spatial differentiation of the technological innovation level in node cities was substantial.

In 2013 and 2020, 69.23% and 65.38% of the provinces and cities were in the HH or LL area. Node cities with similar innovation levels tended to cluster in the same quadrant. The distribution of urban technological innovation levels mostly shows that (i) high-node cities enclose cities with high innovation levels and (ii) low-node cities enclose cities with low innovation levels. This further proves the positive spatial autocorrelation of the technological innovation level.

Based on Figure 3 and Table 4, the local Moran's I test results are shown. The distribution of Moran's I shows that spatial correlation is an essential factor in studying the mechanism of innovation; therefore, it is more appropriate to use a spatial econometric model to discuss the innovation level of node cities.

3-4-3- Model Design

Based on the above statistical analysis, we used a spatial econometric regression model rather than a correlation to clarify the impact of each factor and disregard the impact of other factors. The research model developed in this study was as follows:

$$Inn_{it} = \rho \sum_{j=1}^{n} Inn_{jt} + \beta_1 IFI_{it} + \sigma_1 \sum_{j=1}^{n} W_{ij} IFI_{jt} + \beta X_{it} + \xi \sum_{j=1}^{n} W_{ij} X_{it} + \mu_i + \nu_i + \varepsilon_{it} \tag{4}$$

where $\varepsilon_{it} = \lambda \sum_{j=1}^{n} W_{ij} \varepsilon_{it} + \varphi_{it}$; β_1 and β are the coefficients of explanatory variables and control variables, respectively; ξ is the spatial lag of the control variable; μ_i represents the spatial effect of node cities; ν_t is the time effect; ε_{it} and φ_{it} represent the random disturbance term; ρ is the spatial autoregressive coefficient; λ is the spatial error coefficient; and W_{ij} represents the spatial weight matrix that reflects the spatial relationships among node cities. We used an economic geography nested matrix for analysis as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, i \neq j \\ 0, i = i \end{cases} \tag{5}$$

where d_{ij} denotes the distance between node cities, which is calculated using cities' latitude and longitude. The closer the geographical distance between node cities is, the stronger their spatial linkages:

$$W_{ij} = \begin{cases} W_d \times diag(\frac{\overline{GDP_1}}{\overline{GDP}}, \frac{\overline{GDP_2}}{\overline{GDP}}, \ldots, \frac{\overline{GDP_n}}{\overline{GDP}}), i \neq j \\ 0, i = i \end{cases} \tag{6}$$

where W_d is the geographical matrix in (1), $\overline{GDP_n}$ is the mean value of the GDP of the nth node city, and $\overline{GDP}$ represents the average GDP of all node cities. The economic geography nested matrix considers geographical spatial factors and urban economic characteristics, better describing the comprehensive situation of spatial linkages.

The reasons for choosing SDM instead of other Spatial Econometric Methods are as follows:

Firstly, comprehensive Spatial Interaction Analysis: The SDM allows for spatial interaction analysis between regions to capture the dependent variable's direct and indirect spatial autocorrelation effects. This is useful for understanding how one region's economic or environmental conditions affect regions nearby.

Secondly, flexibility and Robustness: SDM offers a flexible framework that can be adapted to different specifications, including the spatial lag model (SLM) and the spatial error model (SEM). It provides a more robust analysis that accounts for spatial lags and correlated errors.

Thirdly, weaken the bias of estimates: According to LeSage and Pace [71], the SDM considers the spatial dependence of dependent variables, independent variables, and perturbations, which can more effectively weaken the bias of estimates caused by missing variables than traditional least squares estimates, thus solving the endogeneity problem [72].

However, SDM has limitations that may affect the results. Thus, we reduce their impact by using reasonable model settings, data structure matching, and necessary statistical tests as follows:

1. ***Arbitrary Weight Matrix Selection*****:** One major criticism of spatial econometric models like SDM is that the arbitrary weight matrix (W) choice significantly affects the results. Thus, this study justifies the choice of W based on theoretical and empirical considerations.
2. ***Interpretation Challenges*****:** As incorporating spatial spillovers complicates the parameters' interpretation, this study restricted results interpretation in specific applications to avoid overgeneralization problems.
3. ***Model Specification*****:** Similar to any econometric model, SDM is subject to misspecification risk. Omitting important variables or incorrect spatial structure may cause model estimation bias. Thus, this study specifies the model carefully by considering all relevant variables and structures and performing robustness checks at different levels.
4. ***Data Requirements*****:** SDM requires sufficient observations to estimate the additional parameters associated with spatial interactions. While the data is robust enough to support SDM adoption, the model may not perform well when a smaller data sample is used.

4- Analysis and Outcomes

4-1- Baseline Test and Analysis

Before the model estimation, the type of spatial panel model must be determined. Following Elhorst [73], the model's applicability was tested using the Wald and LR tests to determine whether the SDM could be divided into an SLM or an SEM model. The test results in Table 5 show that the Wald and LR results reject the original hypothesis, which means that the SDM is not divisible into SLM or SEM models.

Table 5. Wald and LR test results

Test	Value	*P*
Wald-spatial lag	28.75	0.0002
LR-spatial lag	20.82	0.0041
Wald-spatial error	30.94	0.0001
LR-spatial error	25.71	0.0006

This study controls the time and personal effects of managing the endogeneity caused by missing essential variables in the econometric model.

As shown in Table 6, Model 1 includes only the explanatory variable of traditional finance, and Model 2 includes only the explanatory variable of digital finance. Model 3 adds the interaction of digital and traditional finance, and Model 4 consists of both digital and traditional finance.

Table 6. SDM estimation results

	Model 1		Model 2		Model 3		Model 4	
Variable	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**	**Coefficient**	***t*-value**
Digital finance level			2.0641***	3.18	1.6810***	2.59	1.6634**	2.56
Traditional finance level	0.1411***	2.76					0.1189**	2.34
Traditional finance level × Digital finance level					0.0211**	2.40		
FDI	0.93597	0.83	0.2950	0.27	0.5560	0.51	0.6092	0.56
Industrial structure	0.3597	0.62	0.2151	0.37	0.0199	0.03	0.0666	0.11
Economic development level	0.2694	1.41	0.1495	0.81	0.2269	1.20	0.2288	1.21
Population density	0.6181**	2.44	0.5971**	2.38	0.6705***	2.70	0.6722***	2.70
Urban per-capita wage	0.4073**	1.99	0.2999	1.47	0.3231	1.59	0.3271*	1.61
W × Digital finance level			2.4739	1.92*	1.5773	1.22	1.5725	1.22
W × Traditional finance level	0.3770***	2.80					0.2731**	1.99
W × Traditional finance level × Digital finance level					0.0428*	1.80		
W × FDI	-2.7053	-0.95	-3.4618	-1.21	-3.3259	-1.19	-3.1124	-1.11
W × Industrial structure	-2.1076*	-1.73	-2.1464*	-1.77	-1.1268	-1.77*	-2.1308*	-1.78
W × Economic development level	0.2141	0.55	-0.2486	-0.69	0.0092	0.02	0.0521	0.13
W × Population density	1.1429***	2.45	1.1448***	2.45	1.1925***	2.60	1.1956***	2.61
W × Urban per-capita wage	-1.0734	-1.47	-1.2481*	-1.69	-1.3563*	-1.86	-1.3045*	-1.79
σ^2	0.0250***	10.18	0.0251***	10.17	0.0241***	10.19	0.0240***	10.19
City, year	Controlled		Controlled		Controlled		Controlled	
R^2	0.1678		0.7495		0.7637		0.7661	
Observations	208		208		208		208	

Note: The asterisks denote statistical significance at the 1%, 5%, and 10% thresholds, correspondingly and the same as in following Table 7 and 8.

Table 7. Effect decomposition of the SDM

Variable	Direct effect		Indirect effect		Total effect	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
Digital finance level	1.7127***	2.60	1.7431	1.35	3.4558**	2.50
Traditional finance level	0.1220**	2.38	0.3024**	2.04	0.4244***	2.70
FDI	0.5086	0.47	-3.0964	-1.05	-2.5879	-0.78
Industrial structure	0.0897	0.16	-2.2405*	-1.72	-2.1508*	-1.65
Economic development level	0.2305	1.26	0.0529	0.13	0.2834	0.74
Population density	0.6988***	2.89	1.3351***	2.68	2.0339***	3.67
Urban per-capita wage	0.3157	1.55	-1.4048*	-1.88	-1.0890	-1.35

Table 8. Results of the robustness test

	(1)	(2)	(3)	(4)	(5)
Variable	Tail reduction treatment	Join the total import and export trade	Replace FDI with total import and export trade	Remove the variable FDI	Remove FDI and industrial structure
Digital finance level	1.2547* (1.76)	1.3265** (2.11)	1.3405** (2.13)	1.6614** (2.56)	1.6808*** (2.63)
Traditional finance level	0.1527 ** (2.53)	0.0901* (1.82)	0.0911* (1.83)	0.1192** (2.33)	0.1257** (2.49)
W × Digital finance level	1.5747 (1.21)	1.5842 (1.27)	1.6435 (1.31)	1.6090 (1.24)	1.3463 (1.04)
W × Traditional finance level	0.2813** (1.82)	0.2835** (2.15)	0.2767** (2.11)	0.2689** (1.97)	0.2453* (1.80)
σ^2	0.0247*** (10.20)	0.0221*** (10.17)	0.0225*** (10.17)	0.0242*** (10.19)	0.0247*** (10.19)
Control variable	Controlled	Controlled	Controlled	Controlled	Controlled
City, year	Controlled	Controlled	Controlled	Controlled	Controlled
R^2	0.7814	0.7783	0.7585	0.7538	0.7706
Observations	208	208	208	208	208

Note: Owing to space limitations, the effect decomposition results for the control variables are not reported.

Models 2–4 in Table 6 demonstrate that the core explanatory variable of digital finance level is positively correlated with the explained variable urban innovation level at the 5% significance level, confirming H1: Digital finance can promote the urban innovation level of China's node cities.

Considering R^2 and the variables' significance, Model 4 (with digital and traditional finance) performs the best, which shows that digital finance can become a powerful complement to the traditional financial system and promote innovation in cities and enterprises [15-17], and Model 1 (with only traditional finance) performs the worst, which proves that the financing constraints faced by enterprises under the conventional financial system are relatively severe [10, 11]; it is difficult to promote innovation effectively. Model 1's performance (R^2) significantly improves after adding digital finance, and the sum of the coefficients of the two core variables (1.6634+0.1189=1.7823) dramatically improves compared with traditional finance (0.1411). The R^2 of Model 2 is slightly lower than those of Models 3 and 4. This proves H2, which states that digital and traditional finance complement each other and jointly promote the innovation level of node cities, thus explaining the "mystery of China's innovative growth." [15].

Table 6 considers the spillover effects of the variables on the urban innovation level in other regions (where W is considered). In Model 2, digital finance is positively correlated with the innovation level in node cities at the 10% significance level. Digital finance improves technological innovation in the node cities in a region. Compared with model 1, which only has traditional finance, and model 4, which added digital, R^2 is significantly higher. The sum of the coefficients of the two weighted core variables (1.5725+0.2731=1.8456) is greatly improved compared with the coefficient of traditional finance alone (0.3770). This verifies H3, which states that digital and traditional finance form a complementary and positive spatial diffusion impact due to competition effect [44, 45], trickle-down effect [48, 49], and siphon effect [53], jointly promoting innovation in neighboring node cities [40-42].

The regression results based only on the above SDM are insufficient to clarify the full impact of digital finance on the innovation of node cities. To further study the spatial effect, based on Model 4 with the best regression effect in Table 6 and following LeSage & Pace [71], we decompose the total effects of digital finance into direct and indirect effects. Among them, the direct effect reflects the influence of the region's digital finance level on its technological innovation. By contrast, the indirect effect indicates the effect of the city's digital finance level on the technological innovation of the neighboring node city, namely the spatial diffusion impact. According to the SDM decomposition results in Table 7, digital finance has a positive spatial diffusion impact. The stronger the digital finance of a city is, the higher the urban innovation level in neighboring node cities, indicating an apparent positive diffusion impact. The direct result is significant and positive, suggesting that a region's digital finance level promotes technological innovation for digital finance's wide coverage, higher efficiency, low cost, and other advantages [15]. After adding the digital finance variables, traditional finance's direct and indirect effects are significantly positive, further supporting H2 and H3.

Among the control variables, per-capita wages and population density significantly promote innovation in node cities. The per-capita wage level exerts a negative spatial diffusion impact on innovation in neighboring cities. Wage levels in neighboring cities are negatively affected because resources and labor may be attracted to cities with higher wages, reducing economic activity and job opportunities in neighboring cities. The higher the per-capita wage level of node cities, the more talent will be attracted from neighboring node cities, weakening the latter's innovation [66, 67]. Population density records a positive spatial diffusion impact on the innovation of neighboring node cities, demonstrating that a higher population density of node cities may benefit knowledge exchange and innovation and promote the innovation of neighboring node cities [65].

5- Robustness Check

To check the model's robustness and prevent the impact of outliers on the results, a tail reduction treatment (deleting the extreme value of 1% of all the variables) [74] was performed; Column (1) of Table 8 shows the estimation results. The results after this treatment indicate that digital finance facilitates innovation in node cities at the significance level of 10%, which is consistent with the results of the SDM without the tail reduction treatment.

Considering the possible impact of imports and exports on urban innovation, this study finds the natural logarithm of total imports and exports as a missing variable [75]. According to the regression results in Column (2) of Table 8, digital finance promotes technological innovation in node cities at the 5% significance level, consistent with the results without missing variables.

Considering that the estimation results of FDI in the SDM mentioned above are not significant enough and considering the possible impact of total import and export trade on urban innovation, this study replaced the original FDI control variable with the natural logarithm of total import and export trade as the control variable. According to the estimation results in Column (3) of Table 8, digital finance promotes urban innovation in node cities at the significance level of 5%, which accords with the results before replacing the control variables [76].

Considering the estimated results of FDI and industrial structure are insignificant in the SDM, this study performed stepwise regression to test the model's robustness. According to the regression results in Columns (4) and (5) of Table 8, digital finance positively influences the technological innovation of node cities at a 5% significance level [15], which is lower and more significant than the results obtained before performing stepwise regression.

All the estimation results in Table 8 further support H1 and confirm the robustness of the model.

6- Discussion

This study examines the impact of fintech on traditional finance, digital finance on innovation, and a city's digital finance on neighboring cities' urban innovation. As the usage of traditional finance and digital finance is a norm in modern financial development, the results can be generalized to other countries. Nevertheless, in some countries, fintech development has not affected financial systems. For example, although fintech is gaining attention in Japan, the overall makeup and operation of the country's financial system have not changed significantly because of increased fintech development and acceptance. Most people resist using smartphones to conduct financial transactions [36]. Unlike Iwashita's [36] findings, Model 1 indicates that the performance of traditional finance has improved significantly after the introduction of digital finance. The sum of the coefficients of the two core variables (digital and traditional finance levels) is higher than that of conventional finance, indicating that the development of digital and traditional finance complements each other and jointly promotes innovation in node cities. The main difference between Japan and China is the government's promotion of digital finance.

Digital finance boosts technological innovation in neighboring cities. At the 10% significance level, digital finance positively correlates with innovation in node cities. These results align with previous research [47, 50]. For example, fintech-based innovation drove the development of Prompt Pay as a customer-to-customer electronic payment transfer, connecting citizens' identities and mobile phone numbers to customers' bank accounts [50]. Previous research suggests that different technological spillover types are impacted differently in various fields. For example, the degree of agricultural economic development, per-capita real GDP, and urbanization have considerably boosted China's agricultural green technological progress in neighboring areas. By contrast, the internal agricultural structure and labor level impede agricultural green technological progress (AGTP) in local and neighboring regions [38]. Tan et al. [39] reported that mergers and acquisitions and FDI lead to more spillovers than greenfield investments under diverse entry modalities. This study revealed a positive geographic spillover effect on digital finance. That is, the higher a city's digital finance level is, the better the level of urban innovation in neighboring node cities.

Similar to most of the research, this research has limitations. Although there are 66 countries in the BRI, owing to data availability, this study included only 26 Chinese node cities to study the influence of digital finance on urban innovation. With the gradual increase in the impact of the BRI, the data availability and transparency of countries along the BRI will continue to increase; therefore, more sample countries and node cities should be included in future research. Moreover, if the scientific and technological infrastructure supporting the development of digital finance in countries along the route is extremely poor or the digital divide is large, the popularity of digital finance applications may be limited, limiting the spillover effect to urban innovation.

7- Conclusions and Recommendations

Developing digital finance and improving urban innovation are necessary to achieve high-quality economic growth across China. With the general principle of "forge ahead, explore, and innovate," China considers that the development of inclusive finance is of practical significance for investigating the mechanism between digital finance development and urban innovation. This study constructed an SDM based on panel data from 26 Chinese node cities in 2013 and 2020. The results show a positive spatial correlation between the urban innovation levels of node cities, with most node cities in the first quadrant. High-level innovation node cities surround other cities with high innovation levels. Indeed, digital finance alleviates financial constraints, and sufficient financial sources improve node cities' technological innovation levels. Second, the SDM results indicate that digital finance stimulates urban innovation in node cities. Third, digital and traditional finance complement each other, jointly boost the improvement of node cities' innovation levels, and form a positive spatial diffusion impact. They jointly promote the progress of the innovation level of neighboring node cities, explaining the mystery of China's innovative growth. Finally, per-capita wages and population density significantly promote innovation in node cities. The per-capita wage level is negative, whereas population density exerts a positive spatial spillover impact on neighboring node cities' innovation.

The interaction mechanism between China's digital finance and urban innovation can be constructed from the three dimensions of coverage, depth, and degree of digitalization of digital finance to realize the development of digital finance and urban innovation. First, considering the incentive of digital finance on urban innovation in node cities, promoting digital finance development fosters urban innovation. Second, digital and traditional finance institutions complement node cities' innovation and neighboring node cities. A modern financial system of digital and traditional finance should be built to form an excellent financial ecology for the synergistic development of the two and create favorable conditions for enhancing the innovation capacity of node cities. Third, high per-capita wage powers the innovation capacity of node cities. Talent schemes and training aid digital finance development and technological innovation. A diversified talent training system that focuses on technology innovation teams' formation, a talent incentive scheme and an R&D environment tailored to local conditions, and making full use of the advantages of digital finance are important for node cities' innovation. Besides, building a human resources and technological innovation alliance between the region and neighboring cities avoids vicious and low-level competition for homogeneous resources between regions, promotes win/win cooperation, develops interregional human resources and technological innovation industrial chains, and jointly improves the technological innovation level. This will provide full play to the positive diffusion effect, alleviate the unbalanced pattern of the technological innovation levels among node cities, and synthetically assist digital finance development and urban innovation.

8- Declarations

8-1- Author Contributions

Conceptualization, X.S.; methodology, X.S.; validation, W.W.; formal analysis, W.W.; data curation, W.W.; writing—original draft preparation, X.S., X.Q., and R.Y.M.L.; writing—review and editing, R.Y.M.L. All authors have read and agreed to the published version of the manuscript.

8-2- Data Availability Statement

The datasets are available from the corresponding author on reasonable request.

8-3- Funding

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8-5- Institutional Review Board Statement

Not applicable.

8-6- Informed Consent Statement

Not applicable.

8-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Appendix I

The PUDIFI includes three first-level dimensions (breadth of coverage, depth of use, degree of digitalisation), 11 second-level dimensions (Alipay account coverage rate, payment service, monetary fund business, credit operations, insurance business, investment business, credit business, mobility, affordability, creolisation, and facilitation), and 33 specific indicators (number of Alipay accounts per 10,000 people, the proportion of Alipay card binding users, average number of bank cards bound to each Alipay account, number of payments per capita through Alipay account, payment amount per capita through Alipay account, number of active users with high frequency as a percentage of those active once a year or more, number of purchases of Yu'e Bao* per capita, purchase amount of Yu'e Bao per capita, number of people who buy Yu'e Bao per 10,000 Alipay users, number of users with Internet consumer loans per 10,000 adult Alipay users, number of loans per capita, loan amount per capita, number of Internet micro and small business loans per 10,000 adult Alipay users, average number of loans per household for micro and small operators, average loan amount for small and micro operators, number of insured users per 10,000 Alipay users, number of insurance policies per capita (Li et al. 2024)†, amount of insurance per capita, number of Alipay users per 10,000 people involved in Internet investment and wealth management, number of investments per capita, investment amount per capita, number of calls per natural person credit, number of users using credit-based services per 10,000 Alipay users, percentage of mobile payment transactions, percentage of mobile payment amount, average loan interest rate for small and micro operators, average personal loan interesft rate, percentage of payment transactions, proportion of payment amount, proportion of sesame credit pledge free transactions, proportion of sesame credit pledge exemption amount, proportion of the number of payments made by the user's QR code, and proportion of amount paid by user QR code)

* Yu'e Bao is a value-added service launched by Alipay. Users can obtain certain returns by transferring their funds into Yu'e Bao. Yu'e Bao connects with several money funds, which invest in money market instruments such as deposits, certificates of deposit, short-term bonds, and central bank bills.

† Li, P., Liu, J., Lu, X., Xie, Y., & Wang, Z. (2024). Digitalization as a Factor of Production in China and the Impact on Total Factor Productivity (TFP). Systems, 12(5), 164. doi:10.3390/systems1205016