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Research article

Network structure of urban digital financial technology and its impact on the risk of commercial banks

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Abstract: In the context of the development of digital finance, the complexity of the network formed by urban digital financial technology has been deepening. Based on Chinese city data from 2010 to 2019, this paper conducts a dynamic evaluation of urban digital financial technology through grey target theory and uses social network analysis methods to study the network structure characteristics of urban digital financial technology and its impact on commercial bank risks. The study found that the spatial network of urban digital financial technology shows a trend of complexity and closeness, developed cities occupy a central position in the network of digital financial technology linkages and are net spillovers of urban digital financial technology. Further research on the impact of urban digital financial network structure on commercial bank risk found that both the overall network structure of urban digital financial technology and individual network structure have a significant inhibiting effect on commercial bank risk. Therefore, this paper focuses on the balanced development of digital financial technology in cities, while seeking to further exert the demonstration role of developed cities and achieve the reduction of risk level of commercial banks through the increase of overall network density and the decrease of network efficiency and network hierarchy.

Keywords: digital financial technology, network structure, social network analysis, commercial bank risk

1. Introduction

With the continuous development of science and technology, the financial sector is gradually moving towards digital, and the development of financial technology also shows the characteristics of network and complexity. In recent years, with the support of digital technologies such as big data, artificial intelligence and blockchain, digital financial technology has achieved rapid development and promoted financial development. Mobile payment relying on digital technology shows a rising trend year by year. In 2020, the mobile payment business volume reached 123.22 billion transactions, with the amount reaching 432.16 trillion yuan. In addition, due to the natural agglomeration characteristics of technology development, digital financial technology has significant spatial imbalance characteristics, just like traditional finance [1,2]. At the same time, the digital financial technology between cities does not develop independently but presents a certain spatial correlation [3,4]. Therefore, on the premise of the actual spatial connection between cities, cities need to fully consider their own digital financial technology status and the digital financial technology of related cities, so as to promote financial development through digital financial technology. Digital finance promoted by digital financial technology makes the spatial connection of finance more common and extensive. The spatial connection of urban digital financial technology is not limited to the border on the physical space but gradually presents a multi-threaded complex network structure form [5–7]. Therefore, accurately grasping the development trend of urban digital financial technology related networks, understanding theirs internal correlation structure, identifying the value of each city in the digital financial technology connectivity network, in-depth studying of the digital financial technology related network structure on commercial bank risk, promoting the development of digital finance and implementation, and establishing regional cooperation mechanisms in the field of digital financial technology have important theoretical significance and application value.

Urban digital financial technology is a highly integrated product of finance and technology from the perspective of the city, which refers to the financial technology that can drive financial innovation. In essence, digital finance is a new form of financial service. Its emergence is closely related to its continuous development and financial innovation, which is supported and promoted by digital technology [8,9]. It is this innovation supported by digital technology that makes digital finance, compared with traditional financial services, have lower cost, wider coverage and more efficient risk control methods and can provide more convenient and efficient and affordable services, so as to gain advantages in financial services. First, the traditional financial industry is costly and inefficient and cannot meet personalized needs, which provides opportunities for the development of digital financial technology [10–12]. Under the influence of the excessive expansion of the financial industry, the efficiency of financial operation has been greatly reduced, and the high cost and low efficiency have always been the pain points of the financial industry. In addition, traditional financial institutions mostly take themselves as the center and adopt universal financial products to serve a wide range of greatly differentiated customer groups, which is difficult to use to fully meet the personalized needs of customers. With the support of big data, artificial intelligence, blockchain and other technologies, digital financial technology can greatly reduce transaction costs and improve service efficiency. Intelligent products or services can meet the differentiated financial needs and fully make up for the deficiencies of the traditional financial industry [13,14]. Second, digital financial technology is essentially universal. Its intelligent products can serve the long-tail users, opening a large blue ocean market for the financial industry [3,15]. Due to the high transaction cost, insufficient risk control ability and the existence of information asymmetry, traditional finance excludes small and medium-sized enterprises and low-income people. Digital financial technology, with the advantage of low cost and high efficiency, extends the financial market service boundary. Through intelligent service focus on the long tail segment and meeting 80% of small and medium-sized enterprises and low-income people financial demand, market concentration is higher [16,17].

In the process of giving full play to the incentive effect of technological innovation, digital financial technology has the spatial correlation of regional characteristics. One is the radiation effect. The development of digital financial technology has broken the limitation of geographical space. The financial services enabled by digital financial technology have advantages such as low cost, high efficiency and wide scope, which reduces the marginal influence of geographical restrictions on the financial radiation effect, increases the possibility of digital financial technology radiating outward, and drives the innovation of digital financial technology in the surrounding region [17,18]. The second is the siphon effect. The development of digital financial technology may lead to the digital divide, which will lead to the widening gap between digital finance and cities [19,20]. If a city digital financial technology level is higher, then the city will further improve its demand for key elements such as manpower, financial resources and the human factors and financial elements of cross-regional flow, The human factors and financial factors of the surrounding cities will converge to the cities with high digital financial technology level, while the digital financial technology level of the cities with outflow of factors will fall further behind. [21]. Third, there is the trickle-down effect. Due to the difference of factor endowment among different cities, in the early stage of the development of digital financial technology, cities with factor advantages will promote their development of digital financial technology under the siphon effect. When digital financial technology breaks through a certain critical value, positive spatial spillover will be generated to other cities. Therefore, the spatial flow of digital financial technology makes the technology network and financial network between cities produce linkage effect [22,23].

While promoting social and economic development, digital finance will also have an impact on the risks of commercial banks. At present, there have been relevant studies on the impact of Internet finance, digital finance and fintech on the risks of commercial banks. There are also inconsistent properties in the conclusions of the related studies. First, digital finance may squeeze the business of commercial banks, thus leading to the increase of the risk of commercial banks [24,25]. Then, digital finance can significantly improve the operation efficiency of commercial banks through technology spillover effect, thus reducing the risk of commercial banks [26,27]. Second, the service object of digital finance is the groups not covered by traditional commercial banks. Therefore, digital finance and commercial banks have a complementary relationship, and digital finance does not affect the risks of commercial banks [28]. Finally, the influence of digital finance on the risk of commercial banks has non-linear characteristics. In the different stages of digital finance, the influence of digital finance on the risk of commercial banks is heterogeneous [29–31].

The existing literature on the characteristics of urban digital financial technology networks and commercial bank risks provides an important reference, but the studies are mainly based on the Digital Finance Index of Peking University [32]. The index takes inclusion as the starting point and takes the degree of digitalization as an important form of financial inclusion. Although it is highly related to digital finance, the research focuses on the reflection of digital finance in the service level, which is still different from the complete concept of digital finance.

Digital finance is a new type of financial service. Its emergence and continuous development are closely related to financial innovation, and financial innovation is supported and promoted by digital technology. It is the innovation supported by digital technology that makes digital finance, compared with traditional finance, have lower costs, wider coverage and more efficient risk control methods, and it can provide more convenient and affordable services, thus gaining advantages in financial services. The development of digital finance is inseparable from the development of digital financial technology. Therefore, this paper takes digital financial technology as the research object, which is more helpful to reflect the impact of digital financial technology on the risk of commercial banks.

Comparing with previous research, this paper has three main contributions. First, we focus on digital financial technology rather than regular digital financial inclusion. Second, we construct spatial correlations determined by the modified gravity model and use social network analysis to explore the spatially relevant network structure of urban digital financial technology. Third, we analyze the centrality of each city in the spatially connected network of digital financial technology, and the position and role of each city in the network are studied, along with their impact on commercial bank risk.

2. Materials and methods

2.1. The measurement of urban digital financial technology

Table 1. The index system of digital finance technology measurement in cities.

First-level indicator	Second-level indicator	Data source
Labor force	Market capitalization of listed financial and technology enterprises	Wind
	Number of information and finance practitioners	EPS
Fund	Fiscal expenditure on science and technology	EPS
Innovation activities	Number of invention patent applications	CSMAR
	Amount of invention patent authorization granted	CSMAR

The measurement of urban digital financial technology is the basis for analyzing the characteristics of its network structure. In order to comprehensively and objectively evaluate urban digital financial technology, this paper uses publicly available data at the city level to form an evaluation indicator system for urban digital financial technology in three areas: labor, finance and innovation activities. The workforce is a key driver in the formation of digital financial technology in cities, and there is a need to engage and collaborate with various actors within cities to strengthen their participation in major digital financial innovation activities. Listed financial and technology companies are important drivers of digital financial technology development, and the larger the market capitalization of a company is, the more it tends to invest in technological innovation. This paper therefore chooses the market capitalization of listed financial and technology enterprises and the number of people working in the information and finance industry to measure the digital financial technology workforce in cities. The development of urban digital finance technology cannot be achieved without financial support, and government financial technology is one of the main sources of urban digital finance technology. Therefore, this paper chooses fiscal technology expenditure to measure the funding of urban digital financial technology. Innovation activities are the main manifestation of the city's digital financial technology. The number of patent applications reflects the city's innovation vitality, and the number of patents granted reflects the city's innovation achievements.

This paper therefore chooses the number of patent applications and patent grants to measure the innovative activities of urban digital financial technology. The indicators for measuring urban digital financial technology are shown in Table 1.

The measurement of urban digital financial technology requires further determination of the weights of each indicator. The grey target theory is an important method for solving dynamic and comprehensive evaluation problems based on grey system theory [33]. This method can not only obtain the evaluation value and ranking results of each evaluation object but also carry out the grading of evaluation objects; at the same time, based on the degree of difference and growth of evaluation indicators, it can determine the evaluation value of each moment of the evaluation object in a certain time period and determine the overall evaluation value. Gray target theory is a kind of gray pattern recognition theory proposed by Professor Deng Julong in 1999. The main idea is to find out the data closest to the target in a set of pattern sequences to build the standard pattern, i.e., the bull's eye; and in the same dimension of Euclidean space, the standard pattern and each pattern constitute the gray target [34]. It consists of two parts: the bull's-eye degree analysis and the contribution analysis [35]. The main purpose of this theory is to set a gray target in the absence of a standard model, find the bull's eye through the gray target theory, then compare the patterns of the indicators with the standard model to find the gray correlation and finally determine the evaluation level by the level classification. This theory is unique in the study of limited data and uncertainty problems, and it has been successful in many areas [36]. For example, aiming at the problem of incomplete information caused by imperfect evaluation indicators and unstable data of port informatization, weighted grey objective theory is introduced to evaluate the status of port informatization [37]. Today, it is widely used in social, economic, management and engineering fields.

The steps to measure urban digital financial technology based on the grey target theory are as follows: First, establish the impact space. In this paper, the evaluation objects are 277 prefecture-level and above cities in China, and the evaluation indicators are all the indicators in Table 1. Second, establish the indicator sequence. That is, the data series of the evaluation objects and evaluation indicators are obtained in chronological order, and the time span studied in this paper is from 2010 to 2019. Third, establish the standard model. That is, determine whether the indicators are positive, negative or moderate indicators. In this paper, the indicators for measuring digital financial technology are all positive indicators, so they have great value polarity, and the maximum value of each indicator series is selected as the standard. Fourth, grey target conversion is carried out. The data of individual indicators are compared with the standard value to obtain the polarity transformed pattern sequence. Fifth, establish the grey correlation difference information space. That is, calculate the information difference between the grey target transformed pattern sequence and the corresponding elements of the standard pattern sequence. Sixth, calculate the bull's-eye coefficient and bull's-eye degree. That is, according to the principle of least information, the bull's-eye coefficient and bull's-eye degree of each index are calculated, and the urban digital financial technology is evaluated according to the value of the bull's-eye degree.

2.2. Construction of urban digital financial technology network

The construction of the spatial correlation network of urban digital financial technology needs to determine the "nodes" in the network and the "lines" that connect nodes. In the network of urban digital financial technology, the "node" in the network means each city, and the "line" in the network means the spatial correlation of digital financial technology in each city. The network was constructed using mainly a gravity model and a VAR model. Considering that the evolution characteristics of the network are difficult to reflect through the network constructed by the VAR model and the sensitivity of the VAR model to the selection of lag order, this paper chooses to use the gravity model to establish the connection between the urban digital financial technologies, make corresponding corrections to the gravity model and construct the following model:

$$r_{ij} = K_{ij}\frac{\sqrt[3]{T_iP_iG_i}\sqrt[3]{T_jP_jG_j}}{D_{ij}^2}, K_{ij} = \frac{T_i}{T_i+T_j} \tag{1}$$

In Eq (1), i and j represent the cities. r_{ij} represents the gravitational force between city i and city j. K_{ij} represents the contribution degree of city i in the digital financial technology association between city i and city j. T_i and T_j represent the digital financial technology of city i and city j. P_i and P_j represent the annual total population of city i and city j. G_i and G_j represent the actual GDP of city i and city j.

D_{ij} represents the comprehensive distance between city i and city j，which means that both geographical distance and economic distance are considered, as shown in Eq (2):

$$D_{ij} = \frac{d_{ij}}{g_i-g_j} \tag{2}$$

In Eq (2), d_{ij} represents the geographical distance between city i and city j. g_i and g_j represent the GDP per capita of city i and city j. According to Eq (1), this paper calculates the gravity matrix between urban digital financial technologies. In order to reduce the interference of weak correlation between urban digital financial technologies, the mean value of each row of the matrix is taken as the critical value. When the element in the matrix is greater than the critical value, it is denoted as 1, which means that city i has an impact on the digital financial technology of city j. When the elements in the matrix are less than the critical value, it is denoted as 0, which means that city i has no impact on the digital financial technology of city j.

2.3. Network feature indicators

2.3.1. Overall network feature index

The overall network characteristics of urban digital financial technology can be reflected through the density, correlation degree, efficiency and hierarchy of the network.

Network density is an indicator reflecting the closeness of urban digital financial technology correlation network. The higher the network density value is, the closer the digital financial technology connection between cities, and the greater the digital financial technology of each city is affected by the spatial correlation network structure of urban digital financial technology. The network density is calculated by the following formula:

$$D = \frac{L}{N\times(N-1)} \tag{3}$$

In Eq (3), D is the network density, L is the sum of the number of 1s in the numbers of the urban digital finance technology correlation network matrix, and N is the number of all cities in the network.

Network correlation degree measures the degree to which the members of the spatial correlation network of urban digital financial technology connect with each other. The greater the network correlation degree is, the fewer isolated cities in the urban digital financial technology correlation network, and the larger the overall network connection range. The network correlation degree is calculated as follows:

$$C = 1 - \frac{V}{N \times (N-1)/2} \tag{4}$$

In Eq (4), C is the network correlation degree, V is the logarithm of inaccessible points in the network, and N is the number of all cities in the network. Network efficiency measures the connection efficiency among cities in the urban digital financial technology association network. The higher the network efficiency is, the less redundant relationship exists in the urban digital finance technology association network, which means that there are fewer paths of association between urban digital finance, and the more fragile the network is. The calculation formula of network efficiency is as follows:

$$E = 1 - \frac{G}{\max(G)} \tag{5}$$

In Eq (5), E is the network efficiency, G is the number of redundancy relations in the network, and theoretically the maximum possible redundancy relation is max (G).

Network hierarchy is an indicator that reflects the hierarchical structure of each city in the network. The lower the network hierarchy is, the looser the hierarchical structure exists in the urban digital financial technology correlation network, and the fewer cities with subordinate and marginal status in the network. The calculation formula of the network hierarchy is as follows:

$$H = 1 - \frac{K}{\max(K)} \tag{6}$$

In Eq (6), H is the network rank degree, K is the logarithm of the symmetric accessible points in the network, and max (K) is the logarithm of the most possible accessible points in the network.

2.3.2. Indicators of individual network characteristics

In this paper, the point centrality, intermediary centrality and proximity centrality of each city are used as the indicators to describe the individual network characteristics of urban digital financial technology. The centrality of point degree measures the centrality of an individual city in the spatial association network of urban digital financial technology. The calculation formula is

$$deg_i = \frac{n}{N-1} \tag{7}$$

In Eq (7), deg is the point centrality, n is the number of cities directly related to the city in the network, and N is the number of all cities in the network. Betweenness Centrality indicates the ability of a city to control the correlation network of digital financial technologies in other cities. The higher the value of mediation center degree means, the more the city can control the mutual actions between digital financial technologies in other cities. The calculation formula is

$$det_i = \frac{\sum_{j<k} g_{ik}(i)/g_{jk}}{[(N-1)(N-1)/2]} \tag{8}$$

In Eq (8), det is the betweenness Centrality, which refers to the total number of shortcuts between cities j and k, and the total number of shortcuts between city j and k passing through city i, and N is the number of all cities in the network.

Proximity centrality measures the degree to which a city in the network is not controlled by other cities in the process of digital financial technology connection; in other words, it refers to the degree to which two cities are directly connected rather than indirectly connected through other cities. The higher the proximity of a city, the closer the average distance to other cities, and the city acts as a "central actor" in the network. The calculation formula is

$$col_i = \frac{N-1}{\sum_j d_{ij}} \tag{9}$$

In Eq (9), col is closeness centrality, which is the shortcut distance between city i and city j. N is the number of all cities in the network.

2.4. Date sources

This paper presents an empirical analysis of the spatial association of urban digital financial technologies using 277 prefecture-level and above cities in China as network nodes from 2010 to 2019. The geographical distance between cities was calculated by the latitude and longitude at which the cities were located using Matlab. All other data were obtained from the China City Statistical Yearbook, EPS database and Wind database.

3. Analysis of the network structure characteristics of digital financial technology

3.1. Analysis of the overall network structure characteristics

In this paper, a modified gravity model is used to construct a network relationship matrix of digital financial technologies in cities and to identify the spatially linked relationships of digital financial technologies. This paper draws the overall network map for 2010 with the help of the Netdraw visualization tool in UCINET, in order to visualize the spatially related network structure pattern of urban digital financial technologies, as shown in Figure 1. The results show that the spatial association of digital financial technology in Chinese cities highlights a more typical network structure pattern, and the larger dots in cities in economically and financially developed regions indicate that these cities are more at the center of the network. The geographical distribution also presents the characteristics of regional agglomeration. The digital financial technology network of southern cities takes Guangzhou and Shenzhen as the core cities, the digital financial technology network of northern cities takes Beijing as the core cities, and the digital financial technology network of eastern cities takes Shanghai, Suzhou and Wuxi as the core cities.

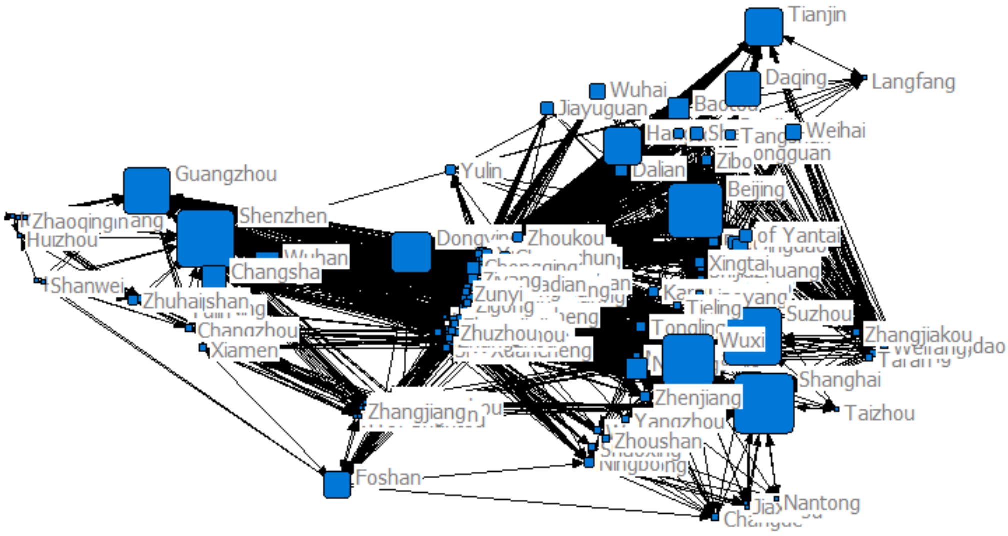

Figure 1. City digital financial technology network linkage map 2010.

3.1.1. Network density

The urban digital fintech spatial network shows a trend of complexity and closeness. Figure 2 depicts the evolutionary trend of the spatial network density of urban digital financial technologies during the sample examination period. From the figure, it can be visually found that, except for 2013, the overall trend of urban digital financial technology spatial association shows a year-on-year increase, with 3754 urban digital financial technology associations in 2010, rising to 13,947 in 2019. Correspondingly, the overall network density of urban digital financial technology associations also shows a year-on-year increase, from 0.0489 in 2010 to 0.1818 in 2019. The year-on-year increase in network density indicates that urban digital fintech is becoming more spatially connected. 2013 saw 11,743 digital fintech connections and a network density of 0.153, the second highest network connectedness after 2018 and 2019, mainly due to the spatial connection of digital fintech facilitated by the opening of Balance of Payments in 2013, and 2013 is also commonly seen as the first year of digital finance development in China.

Although the network density of the sample shows an increasing trend over the observed time horizon, the value of urban digital fintech spatial linkages is not high, with the actual maximum number of relationships existing between urban digital fintech in the sample over the observed time horizon being 13,947 (2019), while the total maximum number of relationships that can be constituted for all cities is as high as 76,452 (277*276), which means that there is still more room for improvement in the connections of digital fintech in cities. Furthermore, although the value of network density is proportional to the spatial association of digital fintech in cities, increasing network density may be accompanied by an increase in the number of redundant connections in the network, which, if it exceeds the carrying capacity of the network, will lead to an increase in the cost of moving technology between cities, thus inhibiting the development of digital finance and socio-economics. It is therefore important to keep the network density within the right range in order to ensure that quantitative optimization is reflected in the digital financial technology network space.

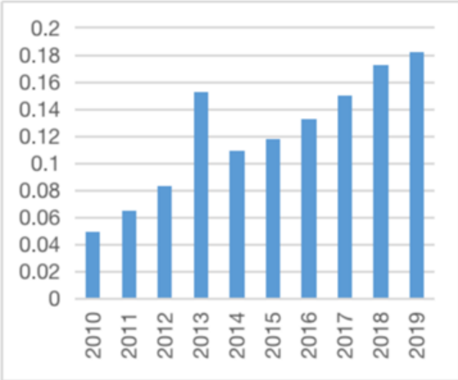

Figure 2. Network density.

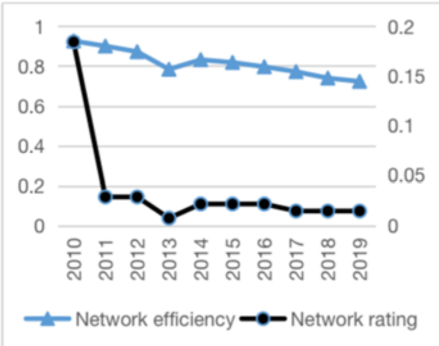

Figure 3. Network efficiency and network hierarchy.

3.1.2. Network relevance

Urban digital finance technology is highly relevant and gradually becoming more stable. This paper assesses the network relatedness of urban digital finance by measuring network relatedness, network rank degree, network efficiency, etc. The measurement results of network relatedness from 2010 to 2019 are all 1, showing that the network structure between urban digital finance technologies has good connectivity. All cities are in the related network of digital finance technologies, and there are no isolated cities. The results of the network ranking are shown in Figure 3, which shows that the network ranking of the spatial association of digital financial technologies in cities during the sample period decreases rapidly from 0.1844 in 2010 to 0.0286 in 2011 and then fluctuates steadily around 0.02, with the lowest network ranking of 0.0072 in 2013. The structure of spatial association of technologies is relatively tight, and since then the interconnection and interaction between urban digital finance technologies have a strong association, mainly because digital finance technologies have broken the limitations of geographical space, and digital finance technologies can communicate regardless of geographical distance. The measurement results show that network efficiency has decreased from 0.9264 in 2010 to 0.7227 in 2019, showing a decreasing trend year by year, indicating an increase in the number of connected relationships between cities in the spatially linked network of digital fintech and a decrease in network vulnerability.

3.2. *Analysis of the structural characteristics of individual networks*

This section conducts network centrality analysis by measuring point centrality, Betweenness centrality and proximity centrality to examine and reveal the status and role of cities in the spatially connected network of digital fintech. Due to the large number of cities in the sample, Table 2 only lists the cities ranked in the top 30 in terms of point centrality average from 2010 to 2019.

3.2.1. Point centrality

Urban digital financial technology shows the characteristics of overflow from developed to less developed regions. According to the results of the point centrality measurement, the average value of the point centrality of 277 cities in China is 19.058, and there are 57 cities above this average. The five highest cities are Shenzhen, Suzhou, Beijing, Shanghai and Wuxi, in order, and these cities have more relationships with other cities in the digital financial technology network relationship. Among them, Shenzhen has the highest point centrality, of 98.913, which is due to the spatial association and spatial spillover between Shenzhen's digital financial technology and other cities, indicating that Shenzhen is at the center of the digital financial technology spatial network of Chinese cities. The top cities are basically in the Yangtze River Delta and Pearl River Delta regions, except for the background, indicating that the Yangtze River Delta and Pearl River Delta regions play a strong role in influencing the spatial association and spatial spillover effect of digital financial technology in China. Liuzhou, Jiangmen, Fangchenggang, Yangjiang and Zhaoqing are in the last five in terms of intermediary centrality, indicating that these cities have less digital fintech connections with other cities. Further from the results of the city out-degree and in-degree measurements, the average value of out-degree for 277 cities is 33.16, with 59 cities having an out-degree greater than the average, and the five cities with the highest out-degree are Shenzhen, Suzhou, Shanghai, Beijing and Wuxi, in order, which have strong digital financial technology spillover effects on other cities. 277 cities have an average value of out-degree of 33.16, with 115 cities having an out-degree greater than the average, and the top 5 cities were Karamay, Baotou, Yulin, Weihai and Hohhot.

These cities have a strong reliance on other cities for digital financial technology. It can be seen that all economically developed cities have a significantly greater degree of digital financial technology out than in, indicating that economically developed cities are the main spillover group in the digital financial technology network.

Table 2. Network centrality analysis of digital finance technology in cities.

City	Point center degree			Close to the	Intermediary
	central	out-degree	in-degree	center	center degree
Shenzhen	98.913	273	50	98.925	6.455
Suzhou City	96.739	266	51	96.503	2.416
Beijing Municipality	92.391	255	49	92.929	7.794
Shanghai Municipality	92.391	255	49	92.929	1.963
Wuxi City	91.304	252	52	92	1.933

Continued on next page

City	Point center degree			Close to the center	Intermediary center degree
	central	out-degree	in-degree		
Guangzhou City	90.217	249	41	91.089	8.165
Nanjing City	89.493	246	57	90.196	2.253
Hangzhou City	87.681	240	61	87.342	4.328
Wuhan City	84.058	231	49	85.981	2.693
Changsha City	80.797	222	40	83.636	3.413
Dongying City	80.435	219	46	82.143	2.15
Foshan City	80.072	219	62	81.416	4.21
Ningbo City	77.899	212	57	81.176	1.973
Tianjin Municipality	76.087	208	48	79.769	3.535
Qingdao City	75.000	201	65	78.409	3.465
Zhenjiang City	63.768	169	54	71.875	1.088
Jinan City	57.246	147	55	66.99	0.979
Dongguan city	56.159	150	58	58.475	1.612
Changzhou City	52.536	145	28	67.813	1.056
Hefei City	52.536	141	39	67.153	0.368
Chengdu City	47.464	129	20	64.637	0.53
Daqing city	47.464	115	63	50.457	2.141
Baotou City	46.377	104	83	50.091	6.673
Nantong City	44.565	120	22	63.741	0.141
Yantai City	42.391	89	66	47.504	1.503
Zhuhai city	40.217	110	37	62.443	1.029
Shaoxing city	38.768	98	40	60.659	0.344
Zibo City	36.594	85	52	49.819	0.415
Karamay City	35.145	5	96	20.674	0.5
Weihai City	34.420	52	73	43.26	1.54
……	……	……	……	……	……
mean	19.058	33.16	33.16	47.037	0.466

3.2.2. Proximity centrality

Economically and financially developed cities are more likely to be actors in the digital fintech network. According to the proximity measure, the average proximity of 277 cities in China is 47.037, with 57 cities above this average, and the five highest cities are Shenzhen, Suzhou, Beijing, Shanghai and Wuxi, in that order. The higher the proximity to the center is, the more likely it is to be intrinsically connected to other cities in the urban digital fintech network, and therefore these cities have a dominant position in the urban digital fintech network. This is mainly because these cities are ahead of other cities in terms of economy, finance and technology, and they have a more efficient flow of technological resources between them and other cities, as well as a stronger ability to access technological resources. Shenzhen has the highest proximity to the center, at 98.925, indicating that other cities are closest to Shenzhen in the digital financial technology network, and Shenzhen is at the center of the entire digital financial technology network. As a famous city of innovation in China, Shenzhen is also at the forefront of digital financial technology in the country. Sanya, Zhengzhou, Urumqi, Jiuquan and Karamay are in the bottom five in terms of proximity to the center, indicating that these are marginal actors in the digital fintech network due to their level of financial development and geographical location.

3.2.3. Betweenness centrality

The bridges communicated in the urban digital financial technology linkage network have geographical characteristics. According to the results of the proximity centrality measurement, the average value of intermediary centrality of 277 cities in China is 0.466, and there are 52 cities above this average, with the five highest cities being Guangzhou, Beijing, Baotou, Shenzhen and Chongqing, in that order. The higher the intermediary centrality, the more likely it is to be a bridge in a city's digital fintech network. Cities with a high degree of intermediary centrality have a greater ability to control technology exchanges between other cities in the digital financial technology network, and cities with a high degree of intermediary centrality show geographical characteristics and are distributed in all regions. Among them, Guangzhou has the highest intermediary centrality of 8.165, which indicates that Guangzhou, as the trade capital of China, also carries the central position of digital financial technology exchange. Yingtan, Langfang, Urumqi, Sanya and Zhengzhou are in the bottom five in terms of betweenness centrality, indicating that these cities are at the periphery of the digital fintech network and that digital fintech changes are more influenced by the top-ranked cities.

3.3. Block model analysis

Table 3. Density matrix and image matrix of the correlation section of urban digital financial technology.

Section	Receive the total relationship		Send out the total relationship		Expected internal relationship scale (%)	Actual internal relationship scale (%)
	Within the section	Outside the section	Within the section	Outside the section		
The first section	840	3952	840	1412	51.45	17.53
The second section	475	1905	475	655	33.70	19.96
The third section	36	818	36	1167	5.07	2.99
The fourth section	158	1001	158	4442	8.7	3.43

Note: proportion of expected internal relationship = (number of cities Within the section -1) / (total number of cities in network-1); proportion of actual internal relationship = (number of relationships within section) / (total number of section overflow relationship).

In order to further reveal the spatial clustering characteristics of the city digital financial technology association network, this paper adopts the CONCOR method, with 2 as the maximum segmentation degree and 0.2 as the concentration criterion, to divide 277 cities into four sections. The results of the section division are shown in Table 3. The first section contains 143 cities, with representative cities such as Lanzhou, Hulunbeier, Jilin, Shenyang, Ulu Wuqi, Yinchuan and other cities with poor geographical location; the second section contains 94 cities, with representative cities such as Guiyang, Kunming, Nanchang, Nanning and other cities with average regional economy; the third section contains 15 cities, with representative cities such as Chengdu, Dalian, Jinan, Xi'an and other regional economic and financial cities; the fourth section contains 25 cities with representative cities such as Beijing, Guangzhou, Hangzhou, Shanghai, Shenzhen and other influential cities in the region.

There are significant spatial linkages and spillover effects of digital fintech between sections. According to the measurement, there are 9185 correlations in the overall city digital financial technology correlation network, while there are 1509 correlations between city digital financial technology sections and 7676 correlations between sections and sections. Among them, a total of 2252 spillover relationships exist in the first section, of which 840 are internal to the section and 3952 relationships are received from other sections' spillover, with an expected internal relationship ratio of 51.45% compared to an actual internal relationship ratio of 17.53%. The section takes on far more digital fintech spillover from other cities than it does to other cities, making the first section a net benefit for digital financial technology. There are a total of 1130 spillover relationships in the second segment, of which 475 are internal to the segment, and 1905 are from the reception of spillover from other segments, with an expected internal relationship ratio of 33.70% and an actual internal relationship ratio of 19.96%. The second segment is also a net beneficiary of digital finance technology. There are a total of 1203 spillover relationships in the third segment, of which 36 are internal relationships and 818 relationships are received from other segments, with an expected internal relationship ratio of 5.07% and an actual internal relationship ratio of 2.99%. The third section is therefore a two-way spillover section of digital financial technology, playing the role of intermediary and bridge in the city's digital financial technology linkage network. There are a total of 4300 spillover relationships in the fourth section, of which 158 are internal to the section and 1001 are received from other sections, with the expected internal relationship ratio being 8.70% and the actual internal relationship ratio being 3.43%. Therefore, the fourth section is the net spillover section of digital finance technology.

Table 4. Density matrix and image matrix of the correlation section of urban digital financial technology.

Section	Density matrix				Like matrix			
	1	2	3	4	1	2	3	4
The first section	0.041	0.017	0.319	0.14	0	0	1	1
The second section	0.011	0.054	0.016	0.204	0	0	0	1
The third section	0.517	0.026	0.171	0.053	1	0	1	0
The fourth section	0.752	0.699	0.293	0.263	1	1	1	1

There is asymmetry in the spillover between the sections. The density matrix of each associated section is calculated based on the distribution of urban digital financial technology association between each section, combined with the overall section's network density of 0.1201, which is taken as 1 if the section's density is higher than 0.1201 and 0 if the section's density is lower than 0.1201, in order to achieve the conversion of the multi-valued density matrix to the like matrix, and the results are shown in Table 4. There is no digital fintech spillover between the first section and the second section, but there is bi-directional spillover with the third and fourth sections. There is a two-way spillover between the second section and the fourth section only. There is a two-way spillover between the third section and the first section, receiving a one-way spillover from the fourth section.

4. Analysis of the impact of digital financial technology networks on commercial bank risk

Commercial bank risk is more frequently evaluated. Based on capital asset pricing theory commercial bank risk can be assessed in terms of volatility of share prices, probability of default [38]. Based on the degree of asset losses that can be sustained, the asset capital ratio can be used to assess commercial bank risk [39]. As the research perspective of this paper is urban, and most urban commercial banks are not listed companies, it is not possible to calculate commercial bank risk in terms of share price volatility and probability of default, and the capital asset ratio does not reflect the amount of risky assets actually held by the commercial. The Z-value is therefore chosen to assess the risk of commercial banks [40]. The Z-value assesses the probability of insolvency of commercial banks from the perspective of internal corporate governance and is calculated as follows: $Z_{it} = |ROA_{it} + CAR_{it}| \div \sigma_{it}(ROA_{it})$, with i and t denoting the commercial bank and the year, respectively. A smaller Z-value indicates a higher risk for the commercial bank.

On the basis of portraying the characteristics of urban digital financial technology network structure, in order to further study the impact of urban digital financial technology network on the risk of commercial banks in terms of both overall network structure and individual network structure, the deposit to loan ratio, the degree of financial development and total assets were also selected as control variables. The deposit-to-loan ratio is the ratio of total loans divided by total deposits; the degree of financial development is the proportion of total loans to GDP; and the size of total assets is the natural logarithm of total assets of commercial banks. This paper constructs the following benchmark model for empirical testing.

$$z_t = \alpha_0 + \alpha_1 Net_t + \sum X + \varepsilon \tag{10}$$

$$z_{it} = \alpha_0 + \alpha_1 Cen_{it} + \sum X + \varepsilon_{it} \tag{11}$$

The explanatory variable Z in Eq (10) is commercial bank risk, the main explanatory variables Net are three indicators of the overall network structure characteristics of network density, network hierarchy and network efficiency, X is the relevant control variable, t is the year and, ε is the residual term.

The explanatory variable Z in Eq (11) is commercial bank risk, the main explanatory variable Cen is the three individual network structure indicators of point centrality, proximity centrality and betweenness centrality, X is the relevant control variable, I is city, t is year, and ε is the residual term.

4.1. Analysis of the impact of overall network structure on commercial bank risk

In this paper, the natural logarithm of the Z-value of commercial banks is used as the explanatory variable in the analysis of the overall network structure on commercial bank risk, and three indicators of the overall network structure characteristics, namely, network density, network hierarchy and network efficiency, are used as explanatory variables respectively to construct an econometric model for further analysis. As the overall network structure only covers a period of 10 years, the conventional least squares test was used, and the results are shown in Table 5.

Table 5. The influence of the overall network structure on the risks of commercial banks.

variable	Risk of commercial banks		
model	(1)	(2)	(3)
constant term	12.7037*** (0.1094)	13.5248*** (0.0882)	16.6335*** (0.3762)
network density	5.7504*** (0.8490)		
Network rating		-3.4387** (1.4370)	
Network efficiency			-3.9582*** (0.4594)
Deposit and loan ratio	-0.0157** (00054)	-0.0078 (0.0086)	-0.0157** (0.0054)
Total assets scale	0.4241 (0.2301)	0.1666 (0.2913)	0.4229 (0.2305)
Financial development degree	0.1050** (0.0377)	0.0522 (0.051)	0.1589** (0.3852)
R^2	0.8515	0.4172	0.9207
sample capacity	10	10	10

Note: The standard errors are included in parentheses; *, * *, and * * * represent P < 0.10, P < 0.05, and P < 0.01, respectively.

The increase in network density of urban digital financial technology helps to reduce commercial bank risk. The regression coefficient of network density is 5.7504, indicating that the network density of urban digital financial technology has a significant dampening effect on commercial bank risk. The increase in network density indicates that the overall network is more widely connected and that some cities that were on the periphery of the digital financial technology network can narrow the gap with other cities by connecting to more cities. Therefore, from a network density perspective, the interconnectedness of city digital fintech can better reduce commercial bank risk.

The decrease in network ranking of city digital fintech helps reduce commercial bank risk. The regression coefficient of network grade is -3.4387, indicating that the network grade of urban digital financial technology has a significant negative impact on commercial bank risk. The decrease in network hierarchy indicates that the hierarchical structure of the overall network has become smaller, resulting in a shift from a subordinate relationship with one-way connections to an equal position with two-way connections, thus contributing to the overall improvement of urban digital finance technology. Therefore, from the perspective of network hierarchy, the hierarchical digital fintech network linkage structure should be dismantled to the maximum extent possible, and the voice of marginal cities in the digital fintech linkage network should be increased.

A decrease in the network efficiency of digital fintech in cities helps to reduce commercial bank risk. The regression coefficient of network efficiency is -3.9582 indicating that the network efficiency of urban digital fintech has a significant negative impact on commercial bank risk. The decrease in network efficiency of urban digital financial technology indicates that the increase in connectivity in the network of urban digital financial technology linkages has broken the dominance of individual cities in the network, resulting in a narrowing of the gap in digital financial technology between cities in the network, which in turn improves the overall digital financial technology. Therefore, from the perspective of network efficiency, it is important to enhance the connectivity between cities' digital financial technologies, reduce the cost of digital financial technology exchange, and improve the stability of the network of cities' digital financial technology linkages, thus enabling commercial banks to reduce their risks.

4.2. Analysis of the impact of individual network structure on commercial bank risk

Cities involving city commercial banks were used as the study sample in the analysis of the impact of individual network structure on commercial bank risk. After excluding the sample that did not involve city commercial banks, 61 cities were retained. The natural logarithm of the z-values of city commercial banks was chosen as the explanatory variable, and the three individual network structure indicators of point centrality, proximity centrality and betweenness centrality were regressed on the panel data model for each city. The Hausman test was used to determine the fixed effects and random effects of the panel data model [41,42]. The results of the empirical regression using the fixed effects model through the test are shown in Table 6. The regression coefficients of the core variables all passed the significance test at the 1% level, the fit was good, and the following conclusions can be drawn.

Table 6. The influence of individual network structure on the risks of commercial banks.

variable		City commercial bank risk	
model	(4)	(5)	(6)
constant term	13.7203*** (2.8447)	10.5692*** (2.266)	10.1731*** (0.0544)
Point center degree	0.1510*** (0.0026)		
Close to the center		0.0226*** (0.0034)	
Intermediary center degree			0.1456*** (0.4450)
Deposit and loan ratio	-0.1405 (0.1551)	-0.1814 (0.1428)	-0.2606* (0.1551)
Total assets scale	0.0247*** (0.0068)	0.0175*** (0.0062)	0.0221*** (0.0069)
Financial development degree	0.0072 (0.0084)	0.0071 (0.0079)	0.0078 (0.0086)
R2	0.3343	0.4069	0.3020
Hausman	0.000	0.000	0.000
sample capacity	610	610	610

Note: The standard errors are included in parentheses; *, * *, and * * * represent P < 0.10, P < 0.05, and P < 0.01, respectively.

The increase in the point centricity of the urban digital financial technology network has the effect of reducing the risk of commercial banks. The regression coefficient for point centrality is 0.151, indicating that the point centrality of city digital fintech has a significant positive impact on commercial bank risk. This implies that the more extensively cities are connected to other cities in the digital financial technology linkage network, the higher the degree of network connectedness, enhancing the impact of the overall digital financial technology network structure on the commercial bank risk of individual cities and reducing the commercial bank risk of cities. Therefore, for cities with a small degree of point centrality and a high level of commercial bank risk, the level of commercial bank risk can be effectively reduced by strengthening digital fintech linkages with other cities.

An increase in the proximity centrality of a city's digital financial technology network can help reduce the level of commercial bank risk. The regression coefficient of proximity centrality is 0.0226, indicating that the proximity centrality of city digital financial technology has a significant positive impact on commercial bank risk. The higher the degree of proximity to the center is, the smaller the digital financial technology gap with other cities. The stronger the digital financial technology exchange with related cities is, the easier it is to reduce the risk level of commercial banks through digital financial technology.

An increase in the betweenness centrality of a city's digital financial technology network helps to reduce the level of risk of commercial banks. The regression coefficient of betweenness centrality is 0.1456, indicating that the betweenness centrality of digital financial technology in cities has a significant positive impact on commercial bank risk. Cities at the center of the network will play an intermediary role in the digital financial technology linkage network, spilling digital financial technology from other cities to other cities through the intermediary effect, strengthening the spatial spillover effect to other cities and thus reducing the level of commercial bank risk.

4.3. Robustness analysis

The stability of the empirical results is tested in the following two aspects: oO the one hand, the sample is sub-sampled by geographical area based on the characteristics of the sample data, and the test results are roughly the same as the results of this paper. On the other hand, the Z-value of urban commercial banks was replaced by the non-performing loan rate, and the significance level was approximately the same as the results of this paper, which proved the stability and reliability of the empirical results of this paper.

5. Conclusions

Based on data from 277 cities above prefecture level in China from 2010 to 2019, this paper examines the spatial network structure of digital financial technology from a network structure perspective, constructs a modified gravity model to determine the spatial association relationships between cities and establishes networks and further uses social network analysis methods to empirically analyze the structure of digital financial technology association networks in Chinese cities and their impact on commercial bank risk. The following key conclusions were drawn.

First, in terms of the overall network structure characteristics, the urban digital financial technology spatial network shows a trend of complexity and closeness. The network density of digital financial technology linkages in cities has been increasing year by year, and the linkages between digital financial technologies in cities are getting closer and closer. The network of urban digital financial technologies is strongly connected, with universal spatial connection and spatial spillover characteristics. Network efficiency and network hierarchy show a decreasing trend, and the network stability of urban digital financial technology is becoming stronger. The barriers in the network space of digital financial technology are reduced, and the network association is more complex.

Second, from the perspective of individual network structure characteristics, urban digital financial technology shows the characteristics of overflow from developed regions to less developed regions, and developed cities dominate in the network. Beijing, Shanghai, Guangzhou, Shenzhen and other developed cities occupy a central position in the digital financial technology linkage network and at the same time act as intermediaries and bridges in the network, playing an important role in the transfer and communication of factors between cities. These developed cities spill over to other cities in the network through their own advantages in digital financial technology, while other cities can rarely spill over to these developed cities, and there is a significant asymmetry in the spatial spillover effect of digital financial technology.

Third, from the results of the block model analysis, there is asymmetry in the spillover between the four blocks of urban digital financial technology. The first and second blocks are the net beneficiaries of digital financial technology in cities, with representative cities such as Lanzhou, Hulunbeier, Jilin, Shenyang, Ulu Wuqi and Yinchuan, which are poorly located, and cities with average regional economies such as Guiyang, Kunming, Nanchang and Nanning; the third block is the two-way spillover block of digital financial technology, which plays the role of intermediary and bridge in the network of urban digital financial technology linkages. The third section is the two-way spillover section of digital financial technology, which plays the role of intermediary and bridge in the digital financial technology linkage network of cities. The fourth area is the net spillover area of digital financial technology, with representative cities such as Beijing, Guangzhou, Hangzhou, Shanghai and Shenzhen being influential cities in the region.

Fourth, from the results of the digital financial technology network structure on commercial bank risk, both the overall network structure of digital financial technology in cities and the individual network structure have a significant impact on commercial bank risk. A significant reduction in the level of commercial bank risk can be achieved through an increase in overall network density and a decrease in network efficiency and network hierarchy. Increases in point centrality, proximity centrality and intermediation centrality of individual networks also have a significant dampening effect on the level of commercial bank risk in their respective cities.

This paper tries to propose that we should focus on the balanced development of digital financial technology in cities, further exert the demonstration role of developed cities, and achieve the reduction of risk level of commercial banks through the improvement of overall network density and the decrease of network efficiency and network hierarchy.

First, commercial banks should actively explore the reasonable use of financial technology tools and instruments to effectively improve the utilization rate and effectiveness of financial technology. By establishing a multi-channel cooperation mechanism between commercial banks and fintech companies, they can achieve effective “integration” with fintech companies with their professional and capital advantages, including entering the fintech ecosystem by investing in fintech companies to form alliances, integrating online and offline channels and interactive platform innovation, and innovating loan-based management and process systems. A series of measures, including the integration of online and offline channels and interactive platform innovation, lending-based management and process systems, effectively stimulate the “catfish effect” of fintech and promote the development of commercial banks. On the other hand, commercial banks that are qualified to do so will set up bank-based fintech companies that focus on technology and system provision or financial product (service) provision. The bank-based fintech companies can contribute to the high-quality development and digital transformation of the bank group, while exporting technology and platform systems and financial products (services) to the industry, enhancing the brand influence of the bank group in the banking industry value chain system. In addition, strengthening inter-network cooperation in financial technology among small and medium-sized commercial banks, through alliance cooperation, can to a certain extent avoid the disadvantages of small and medium-sized banks in terms of capital, talent and geography, thus enabling small and medium-sized commercial banks to "group together," improve their financial technology layout and application, and combine the advantages of small and medium-sized banks in terms of brand and offline channels to continuously improve their financial technology application. The second is to develop a reasonable digital financial strategy and a reasonable digital financial strategy.

Second, we should formulate a reasonable digital financial technology network layout strategy and promote the balanced development of digital financial technology network in cities with the demonstration role of developed cities. On the one hand, commercial banks choose a closed-loop ecological or open ecological strategy to build platform finance, continuously integrate products, channels and back office and other related resources, connect bank customers with various participants in the ecosystem and realize an integrated ecosystem that integrates finance and non-finance, finance and scenarios. On the other hand, it is recommended that commercial banks use financial technology and localization to simplify business processes and service delivery methods, continue to enhance "differentiated" competitive advantages, focus on market segments, provide specialized and refined inclusive financial services for communities and small and micro enterprises, and meet the diversified financial service needs of "long-tail" groups. The company will continue to improve the "differentiated" competitive advantage, focus on market segments, provide professional and refined inclusive financial services for communities, small and micro enterprises, meet the diversified financial service needs of the "long tail" group, and promote the overall network density and network efficiency through policy guidance, as well as the decline of network level to achieve the risk control of commercial banks.

Conflict of interest

The authors declare there is no conflict of interest.

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