Economics

Credit Risk and Financial Sustainability - The Impact of Spatial Organizational Structure of Chinese Commercial Banks

--Manuscript Draft--

Manuscript Number:	ECONJOURNAL-D-23-00182
Full Title:	Credit Risk and Financial Sustainability - The Impact of Spatial Organizational Structure of Chinese Commercial Banks
Article Type:	Research Article
Keywords:	Operational Distance; Functional Distance; Soft Information; Credit Risk; Mediating Effect
Manuscript Region of Origin:	CHINA
Abstract:	Controlling bank credit risk is a key issue for maintaining financial stability, and what role geographic factors play in it is an important issue for scholars and policy makers. Based on the perspective of information asymmetry, we constructed a theoretical model, analyzes the mechanism of geographic factors affecting credit risk, and puts forward a theoretical proposition that the spatial organizations of bank affects the efficiency of soft information collection and processing, which will ultimately affect credit risk. Then, this study collected micro data of Chinese commercial banks from 2011 to 2022. This study used the mediating effect model to empirically analyze the theoretical proposition. This study has found that the distance between bank operations and functional distance hinders the collection and processing of soft information, exacerbating credit risk in banks. Further sample analysis reveals that the mediating role of soft information in spatial organization and credit risk differs between state-owned banks and joint-stock banks. The reason is that the types of customers faced by these two banks are different. Based on this, policy recommendations are put forward such as emphasizing the collection and processing of soft information, encouraging the development of local-based small and medium banks, and reducing information friction.
Manuscript Classifications:	7.1: General; 7.3: Behavioral Finance: Underlying Principles; 7.5: Financial Institutions and Services

Powered by Editorial Manager® and ProduXion Manager® from Aries Systems Corporation

Click here to access/download;Manuscript;Ju2.docx

Credit Risk and Financial Sustainability - The Impact of Spatial Organizational Structure of Chinese Commercial Banks

Chenchen Ma[1,#], Dongshu Cheng[2,#], Mei Ge[3,*], Junrui Cao[4], Jiayang Kou[5], Ziyang Chen[6]

[1] School of Economics and Finance, Xi'an Jiaotong University, Xian, 710061, China.

[2] Guangzhou Institute of International Finance, Guangzhou University, Guangzhou, China. Zhuhai DeltaFit Fin Tech Inc, Hengqin, 519000, China.

[3]Faculty of Business, City University of Macau, Macau 999078, China.

[4] Dongguan Securities Co., Ltd，Dongguan 523000, China

[5] School of Economics, Sichuan Agricultural University, Sichuan, 610000, China.

[6] Guangdong Maoming Health Vocational College, Maoming 525000, China.

*Corresponding Author: Mei Ge (E-mail: m14092100124@cityu.mo)

# Chenchen Ma and Dongshu Cheng made equal contributions to the manuscript， They are co first authors

Abstract: Controlling bank credit risk is a key issue for maintaining financial stability, and what role geographic factors play in it is an important issue for scholars and policy makers. Based on the perspective of information asymmetry, we constructed a theoretical model, analyzes the mechanism of geographic factors affecting credit risk, and puts forward a theoretical proposition that the spatial organizations of bank affects the efficiency of soft information collection and processing, which will ultimately affect credit risk. Then, this study collected micro data of Chinese commercial banks from 2011 to 2022. This study used the mediating effect model to empirically analyze the theoretical proposition. This study has found that the distance between bank operations and functional distance hinders the collection and processing of soft information, exacerbating credit risk in banks. Further sample analysis reveals that the mediating role of soft information in spatial organization and credit risk differs between state-owned banks and joint-stock banks. The reason is that the types of customers faced by these two banks are different. Based on this, policy recommendations are put forward such as emphasizing the collection and processing of soft information, encouraging the development of local-based small and medium banks, and reducing information friction between bank hierarchy.

Keywords： Operational Distance; Functional Distance; Soft Information; Credit Risk; Mediating Effect

1. Introduction

1.1 Background

How to maintain financial stability and prevent financial risks in the face of the comprehensive impact of domestic and foreign uncertain factors is of great significance for the long-term and healthy development of China's economy and the achievement of transformation and upgrading goals. Since China's reform and opening up, the banking industry has been in a dominant position in the Chinese financial system. It played an important role in China's resource allocation and macroeconomic regulation. Controlling credit risks in commercial banks is an important aspect of maintaining financial security. It is also an important issue of concern for economists and policy makers.

Against the backdrop of gradual reform, Chinese commercial banks have undergone a long-term and profound transformation process in both industry structure and technological level. In terms of industry structure, Chinese commercial banks have established strategic goals of building a multi-level financial system and accelerating market-oriented reform of the banking system. The regulatory authorities are gradually relaxing their control over non-state-owned banks and new financial institutions. The number of branches established by non-state-owned commercial banks in different locations is gradually increasing. The distance between banks and enterprises in terms of operations continues to shrink, but the functional distance between the grassroots organization of banks and their headquarters is increasing. In terms of technological level, the application of information technology in banks is increasing, and its use promotes the collection and processing of hard information such as assets, income, and market share. It seems to weaken the importance of the distance between banks and enterprise operations and the functional distance at the bank level. However, information technology does not have an advantage in collecting and processing soft information such as reputation and credit, and geographical factors remain important.

Some scholars believed that information asymmetry is an important reason for the occurrence of bank credit risk (Papi and Sarno, 2017) [1]. Because the market is not completeness, banks have an endogenous motivation to develop and maintain close cooperation with enterprises, so that banks can more easily obtain and screen information and overcome the problem of information asymmetry between banks and enterprises (Bhattacharya and Chiesa, 1995) [2]. Undoubtedly, the rapid development of information technology has reduced the restrictions of geographical factors on

financial activities. However, the development of information technology only widens the scope of the use of hard information by considering the geographical specificity of information dissemination. Therefore, the dissemination of soft information is still subject to the influence of geographical factors. (Petersen and Rajan, 2002) [3].

For businesses such as bank withdrawals and financial transfers, banks can process them based on the customer's hard information. But for controlling credit risk, banks cannot simply be satisfied with collecting hard information about credit targets. More importantly, it is important to collect and process soft information such as reputation, credit, and corporate culture. Commercial banks need to sign different credit contracts according to the soft information conditions of different enterprises. Due to the geographical rootedness of soft information, information technology cannot fully leverage its standardization advantages when financial institutions collect and process soft information. Therefore, information technology cannot necessarily reduce the credit risk generated by information asymmetry (Wan Hongbo and Jia Yunqi, 2018) [4]. China's P2P lending platforms have fully utilized information technology, but financial risk events still occur frequently. Rajan and Seru (2015) [5] pointed out that in the process of credit securitization, American banks excessively relied on hard information collected by modern communication technology. They ignore the collection of soft information. It has led to the inability to confirm the validity of borrower hard information, which has become an important cause of the US subprime crisis. These facts indicated that whether banks can effectively collected and process soft information largely depends on geographical factors. In October 2020, the People's Bank of China publicly solicited opinions on the "Commercial Bank Law of the People's Republic of China (Revised Draft)", which stipulated that local banks are not allowed to conduct business across regions without approval. In February 2021, the China Banking and Insurance Regulatory Commission issued a notice on further regulating the internet loan business of commercial banks, which clearly stipulates that local banks are not allowed to conduct internet loan business across regions. In the current process of deepening reform and constantly changing organizational structure layout in China's banking industry, it is urgent to conduct in-depth research on the impact of geographical factors on bank credit risk. Previous studies have mainly studied bank credit risk issues from aspects such as information asymmetry, relational credit, banking market competition, and debt maturity structure (Behr and Guettler, 2007; Jim é nez and Lopez, 2013; Liang Qi and Hao Yi, 2019) [6-8]. This study found that scholars have paid less attention to the impact of geographical factors.

1.2 Research Objective

Based on the theoretical perspective of adverse selection, this paper studies the relationship between the spatial layout of banking organizations, soft information and credit risk. This study used the mediating effect model to conduct empirical research on this. This article revealed the impact and mechanism of geographical factors on credit risk of commercial banks. The innovation of this article is mainly reflected in the following two aspects. The first is the research perspective of this article. This study investigates the impact of geographic factors on bank credit risk from the perspective of soft information. It supplements and develops research on economic geography and commercial bank credit risk. The existing economic geography literature mainly examines the impact of geographical factors on the availability of corporate credit or local economic development. Their research content rarely involves bank credit risk. These literature on commercial bank credit risk mainly examine the impact of factors such as relationship lending, bank market competition, and debt maturity structure on credit risk. Previous studies rarely involved studying the geographical factors of banks as variables. The second is the research method of this study. This study constructed a mediating effect model to delve into the channels through which geographical factors affect bank credit risk. At present, scholars' research has mainly focused on qualitative analysis and theoretical deduction, although it involves the relationship between geographical factors and bank credit risk. They rarely explore the causal relationship and its channels of action between the two through rigorous quantitative methods.

2. Literature Review

The information asymmetry between banks and borrowers, as well as within commercial banks, hinders the effective allocation of credit resources. Asymmetric information who is an important cause of bank credit risk (Papi and Sarno, 2017) [1]. Because of the market is not completeness, commercial banks have an endogenous motivation to develop and maintain close cooperation with enterprises, so as to facilitate the acquisition and screening of information and overcome the problem of information asymmetry between banks and enterprises (Bhattacharya and Chiesa, 1995) [2]. In recent years, the relaxation of government regulations and the rapid development of information and communication technology have expanded the geographical scope of business operations in China's commercial banking industry. The geographical layout of the banking industry in various countries has undergone varying degrees of changes, and the relationship between banks and enterprises, as well as the relationships between

different levels within banks, have also undergone changes. The role of geographical factors in credit activities has received attention from the theoretical community. The process of collecting and processing information from borrowers by banks includes both information exchange between the bank's operating departments and borrowers, as well as information exchange between different levels within the bank (operating departments and decision-making departments). The relevant literature mainly studies the relationship between geographical factors, bank and enterprise relationships, and bank credit business from these two aspects.

Since the 1990s, with the relaxation of bank regulation by European and American regulatory agencies, the level of cross-regional operations of banks has continued to deepen, leading to a continuous increase in the number of branch offices and business outlets of commercial banks. The geographical distance between banks and enterprises has also increased. Therefore, the impact of the geospatial relationship between banks and enterprises on credit activities has gradually gained attention from the academic community. Financial activities are embedded in a certain natural and cultural geographical environment. Therefore, geographical factors can affect the collection, dissemination, and translation of information, especially soft information, by banks towards enterprises, thereby affecting credit activities (Alessandrini and Fratianni, 2009; Papi and Sarno, 2017) [1] [9]. The rapid progress of communication technology has reduced the geographical constraints on credit activities of banks and enterprises. Petersen (2002) [3] and Liberti (2017) [10] point out that modern communication technology has only expanded the scope of use of hard information. Information technology has no advantage in collecting and processing soft information that is difficult to standardize. The collection of corporate soft information by banks still requires frequent and reliable face-to-face contacts between trading parties. Moreover, the scope of information covered by hard information is limited, and hard information such as credit ratings relies on the information collection process. Its objectivity is inherently influenced by geographical distance.

Some studies have empirically analyzed the relationship between geographic distance and soft information. Agarwal and Hauswald (2010) [11] found through empirical research that the shorter the geographical distance between borrowers and lenders, the more conducive it is for banks to collect customer soft information, and the more fair the bank's credit rating for the customer. Bartoli (2013) [12] found that information technology and geographical factors are complementary rather than substitutive relationships. The impact of this complementary relationship on the spatial

layout of commercial banks and enterprises has received attention from the academic community. He (2013) [13] and Bogdan (2016) [14] analyzed the spatial distribution of business outlets of state-owned and joint-stock banks in China. Their research found that bank branches are often located in economically developed and politically advanced regions. Commercial banks can obtain richer financial information to seize better customer resources. What impact will the advantage of soft information acquisition brought about by the proximity of banks and enterprises have on banks and enterprises? Petersen and Rajan (2002) [3], Agarwal and Hauswald (2010) [11] found empirically based on US data that the closer the geographical distance between banks and enterprises, the higher the credit availability of enterprises and the lower the credit interest rate. Alessandrini and Presbitero (2009) [15] found that the higher the density of bank branches, the lower the sensitivity of a enterprises' cash flow. Bellucci (2015) [16] found that the higher the geographic intimacy between banks and enterprises, the lower the bank's requirements for corporate loan collateral. Bai, Yang and Elyasiani (2022) [17] found that local financial development can shorten the geographical distance between banks and enterprises, promote productivity growth of local enterprises, and the construction of regional financial centers has a positive impact on the productivity growth of enterprises in the city and its surrounding cities, based on micro data of China's manufacturing industry. The greater geographical distance between commercial banks and enterprises may reduce the collection of soft information, thus worsening credit risk.

With the continuous expansion of the business scope of commercial banks, there are more and more bank branchesoperating in different places. Therefore, the impact of the spatial distribution structure of bank hierarchical organizations on credit activities has gradually attracted academic attention. Due to the obvious regional nature of soft information, it is difficult for the decision-making departments of banks to directly contact borrowers in remote areas. Therefore, the grassroots operational departments of banks can better grasp the content of soft information. The collection and processing of soft information by banks can lead to information asymmetry between grassroots operational departments and high-level decision-making departments (Papi and Sarno, 2017) [1]. This information asymmetry can cause many problems. Alessandrini and Presbitero (2009) [18] argued that the farther the physical and cultural distance between the bank headquarters and its branches, the higher the cost of soft information transmission within the bank. It leads to a more severe degree of information asymmetry between the headquarters and its branches. It not only leads to conflicts of

interest between the headquarters and remote branches, but also leads to branch offices abusing their power for their own interests. Stein (2002) [19] analyzed from the perspective of incentive mechanisms that due to the non-standard nature of soft information, the farther the geographical distance between bank hierarchy, the higher the degree of loss of soft information and the lower its utilization rate. It will reduce the incentive for operating departments to collect soft information, thereby having a negative impact on the efficiency of bank operations. Presbitero and Udell (2014) [20] confirmed the above viewpoint through a survey of the Italian banking industry. The study found that bank headquarters tend to restrict the business activities of branch departments in remote areas. Under the premise of the same level of financial health, the farther the geographical distance between the bank operating department and the bank headquarters in a certain region, the more restrictive clauses in the loan contracts signed between the bank and enterprises in that region. Xu and Zou (2010) [21] found through their research on the issue of China's large and medium-sized commercial banks serving small and medium-sized enterprise financing that due to the fact that branch offices have more soft information about enterprises compared to headquarters, excessive use of credit approval authority is not only detrimental to small and medium-sized enterprise financing, but also to bank profitability and local economic development. Agarwal and Hauswald (2010) [11] suggested that in order to solve the problem of soft information transmission between bank hierarchies, commercial bank headquarters should delegate more independent decision-making power to bank branches that are farther away from them.

Through a review of existing literature, it has been found that geographical factors are important factors affecting the efficiency of bank information collection and processing, whether between banks and enterprises or within banks. However, existing literature mainly examines the impact of geographical factors on the availability of corporate credit or local economic development, and rarely studies the impact of bank organizational structure spatial layout on bank credit risk from the perspective of banks themselves. It constitutes the theoretical starting point of this article. This research will establish a theoretical model of Adverse selection of banks and enterprises based on the perspective of information asymmetry to analyze the relationship between the spatial layout of banking organizations and credit risk.

3. Theoretical Analysis

In modern financial intermediary theory, information production is an important function of banks. Existing theoretical and empirical literature indicate that obtaining accurate information about borrowers and their financing projects is an important factor affecting bank loan decisions (Bhattacharya & Chiesa, 1995) [2]. The process of bank credit granting is accompanied by the transmission of both hard and soft information between potential borrowers and banking business departments, as well as the transmission of business departments and decision-making departments within the bank. The decision-making department of the bank makes the final decision on the loan project based on the available information. These decisions are executed by the banking department. They also supervise the borrower's performance of the contract. Geographic factors can affect information exchange between banks and enterprises. It in turn affects the transaction costs of credit activities. The transaction costs generated by information exchange between banks and enterprises reflect the difficulty of bank information production. Therefore, it will affect the way banks generate information and credit behavior. At the same time, transaction costs have an impact on credit risk. Therefore, information production is an important function of banks in modern financial intermediary theory.

Assuming that the bank's decision-making department is located in location C and the bank's operations department is located in location P. The bank is in a perfect competition environment, and the deposit interest rate is *r*. In an uncertain economic environment, assume that the net return rate of the target enterprise is ω ($\omega \geqslant 0$), the probability distribution function of net return is $F(\omega)$,The probability density function is $f(\omega)$。 Contract theory suggests that due to information asymmetry, verification of any output state requires payment of corresponding fees, and the optimal contract between borrowers and lenders should aim to minimize supervision costs and incentivize borrowers to disclose their true information (Bolton, 2005) [22]. In this environment, Williamson (1986) [23] demonstrated that the optimal form of contract between the borrower and the lender is as follows: When the actual amount that the borrower can repay is equal to or exceeds the agreed repayment target amount, the borrower only needs to repay the agreed amount; When the borrower's actual repayment ability is less than the agreed repayment amount, the borrower needs to repay all of its repayable amounts to the lender. This study suggests that the optimal contract between a company and a bank is when the company's net return rate $\omega \geq R$, the bank charges a loan interest rate of R. When the company's net profit margin$\omega < R$, the loan interest

rate charged by the bank is ω. According to the basic formula of mathematical expectation, the income expectation of a bank is the weighted sum of the bank's income under different repayment capacity states of the enterprise, and the weight is the probability of various states occurring. Therefore, under the above assumptions, the functional expression for the expected income of bank unit loans is:

$$E(\Pi) = E(\Pi_{\omega \geq R}) \cdot P(\omega \geq R) + E(\Pi_{\omega < R}) \cdot P(\omega < R) \tag{1}$$

In the above equation, $E(.)$ is the expected income of the bank under different conditions of corporate returns, and $P(.)$ is the corresponding probability. It can be inferred from the assumption that the probability distribution function of a company's net return rate is $F(\omega)$. The probability density function is $f(\omega)$. When the company's net profit margin $\omega \geq R$, the loan interest rate charged by the bank is R, with a probability of $1 - F(R)$. When $\omega < R$, the interest rate charged by the bank is ω， The supervision cost paid is β_p. The probability density function is $f(\omega)$. Therefore, formula (1) can be rewritten:

$$E(\Pi) = R\big(1 - F(R)\big) + \int_0^R \omega f(\omega) d\omega \tag{2}$$

The expenditure of unit loans includes three parts. Part of it is the interest r paid by absorbing unit deposits. The other two parts are the cost of bank to enterprise information collection caused by information asymmetry between banks and enterprises β_p。 And the operational costs arising from the transmission of information between different levels within the bank β_c。 Due to information asymmetry between banks and enterprises, when the net return rate of enterprises $\omega < R$, if the bank branchesof banks want to observe the true profits of the enterprise, each unit of loan needs to pay the cost of information collection β_p。 After collecting relevant information about loan application enterprises, the bank operations department needs to report the relevant information to the decision-making department. The decision-making department shall decide whether to approve the loan application of the enterprise and supervise the operation department to implement the relevant decisions. The principal-agent problem caused by hierarchical information asymmetry during this process requires banks to pay operating costs per unit of loan β_c。

Therefore, the expected cost function V of unit loans is:

$$E(V) = r + F(R)\beta_p + \beta_c \tag{3}$$

In the above equation, $F(R)$ is the probability of bank supervision costs occurring ($\omega < R$). According to formula (3), The unit loan cost V of a bank is a monotonically increasing function of the information collection cost β_p of the bank towards the enterprise. Therefore, keeping other conditions unchanged, there is a unique value range in this study β_p^*, make the bank's unit loan income equal to the unit loan cost:

$$\Pi(R, F(\omega)) = V(\beta_p^*) \tag{4}$$

Therefore, the balance of payments equation for bank unit loans is：

$$R(1 - F(R)) + \int_0^R \omega f(\omega) d\omega = r + F(R) \times \beta_p^* + \beta_c \tag{5}$$

Through simplification, it can be concluded that:

$$R - \int_0^R F(\omega) d\omega = r + F(R) \times \beta_p^* + \beta_c \tag{6}$$

The information exchange in credit activities exists not only between banks and enterprises, but also between different levels within banks (operating departments and decision-making departments). They are all influenced by geographical factors. Therefore, this article draws on existing literature (Papi and Sarno, 2017; Alessandrini and Fratianni, 2009) [1] [9] and characterizes the geographical factors in credit activities into two parts: "Operational Distance" (i.e. the geographical distance between the bank's operating department and the borrower) and "Functional Distance" (i.e. the geographical distance between the bank's internal operating department and decision-making department). This study discusses their impact on credit risk separately.

The operational distance of a bank measures the geopolitical intimacy between the bank's operating department and the lending enterprise (Papi and Sarno, 2017; Petersen and Rajan, 2002) [1] [3]. Although the advancement of information technology has expanded the scope of hard information usage, in order to prevent credit risks, banks cannot simply be satisfied with collecting hard information such as financial reports from credit recipients. Commercial banks also need to collect and process soft information such as corporate reputation, business leaders' operational capabilities, and risk preferences. Commercial banks use this information to make comprehensive and objective judgments about the financing projects of enterprises (Petersen and Rajan, 2002) [3]. Due to the strong regional nature of soft information, there is no unified quantitative method or evaluation standard. Its collection and translation rely on the local social and cultural environment (Liberti, 2017) [10]. Therefore, the geographical intimacy between the operational departments of commercial banks and local enterprises is particularly important for banks to collect and process soft information.

Banks with geographical proximity advantages can better understand the local social and cultural environment and establish long-term and stable social connections with enterprises. This behavior is beneficial for the bank operation department to collect and interpret information on corporate financing projects, and also for supervising the execution of corporate credit contracts. It reduces the cost of information collection by banks for enterprises. Based on this, this study draws on the setting of bank supervision costs by Jin Hongfei (2020) [24] and Porteos (1995) [25], and sets the expression of the cost β_p of bank information collection for loan enterprises as follows:

$$\beta_p = Ope \times \beta_p^f \tag{7}$$

In the above equation, $\beta_p^f\left(\beta_p^f > 0\right)$ is an indicator of the transparency of the enterprise's own information. Ope represents the operating distance of the bank. The meaning of formula (7) is that the opacity of enterprise information is the basis for the cost of bank information collection in the credit process (Jin Hongfei, 2020; Gou Qin and Huang Yiping, 2014) [24] [26]. The geographical distance between banks and enterprises will exacerbate the difficulty of banks in collecting enterprise information. The larger the operating distance Ope, the lower the degree of geographic intimacy between the bank's operating department and enterprises. Therefore, the higher the cost for banks to collect information from enterprises.

Compared to the measurement of geographic intimacy between banks and enterprises based on operational distance, functional distance reflects the impact of geographic factors on information exchange between internal levels of banks (operational and decision-making departments) (Alessandrini and Fratianni, 2009) [9]. Due to the obvious regional nature of soft information, the greater the spatial distance between bank operational departments and decision-making departments, the lower the degree of geographic intimacy. The difficulty of transmitting and processing soft information within banks also increases. The problem of information asymmetry between bank hierarchy is becoming more severe. Therefore, the geographical distance between bank hierarchy not only incurs information processing costs within the bank, but also leads to conflicts of interest goals between decision-making and operational departments due to information asymmetry between hierarchical department (Agarwal & Hauswald, 2010) [11]. They will undoubtedly reduce the efficiency of bank credit decision-making and increase the operating costs of banks in credit activities. Based on this, referring to the existing literature on the relationship between bank functional

distance and hierarchical information friction [18] [25], this article sets the expression for the internal information processing cost β_c of the bank as:

$$\beta_c = Fun \times \beta_c^f \tag{8}$$

In the above equation, $\beta_c^f \left(\beta_c^f > 0\right)$ represents the reciprocal of the bank's internal control level. Fun represents the bank's distance. The meaning of formula (8) is that the level of internal control in a bank determines the degree of information asymmetry between bank hierarchys (Wang and Zhang, 2019). The functional distance of banks will exacerbate the impact of internal control levels on the degree of information asymmetry between banks. The larger the functional distance Fun, the higher the internal information processing cost of commercial banks.

Combining formula (4), when the bank's credit balance is $\beta_p = \beta_p^*$, there is

$$\beta_p^* = Ope \times \beta_p^{f*} \tag{9}$$

For a specific bank, when the spatial distribution of its operating departments remains unchanged (i.e. Ope is a fixed value), if the enterprise information transparency indicator $\beta_p^f > \beta_p^{f*}$ is used, the bank will be unable to maintain a balance of income and expenditure. Therefore, commercial banks are unable to issue loans to the enterprise. So β_p^{f*} is the minimum requirement for enterprise information transparency in bank credit decisions.

This study substituted formulas (8) and (9) into formula (6) to obtain:：

$$R - \int_0^R F(\omega)d\omega = r + Ope \times \beta_p^{f*} \times F(R) + Fun \times E\left(\beta_c^f\right) \tag{10}$$

$$\beta_p^{f*} = \frac{R - \int_0^R F(\omega)d\omega - \left(r + Fun \times \beta_c^f\right)}{Ope \times F(R)} \tag{11}$$

Because of $E\left(\beta_p^{f*}\right) > 0$, $R - \int_0^R F(\omega)d\omega - \left(r + Fun \times E\left(\beta_c^f\right)\right) > 0$, Therefor：

$$\frac{\partial \beta_p^{f*}}{\partial ope} = -\frac{R - \int_0^R F(\omega)d\omega - \left(r + Fun \times \beta_c^f\right)}{Ope^2 \times F(R)} < 0 \tag{12}$$

$$\frac{\partial \beta_p^{f*}}{\partial Fun} = -\frac{\beta_c^f}{Ope \times F(R)} < 0 \tag{13}$$

According to formulas (12) and (13), it can be seen that the critical value β_p^{f*} of the transparency of enterprise information that can obtain loans is negatively correlated with the operational distance Ope and functional distance Fun of the bank. Due to the

smaller β_p^{f*}, the higher the transparency of enterprise information. The negative correlation between $\beta_p^{f*}$and Ope and Fun indicates that the greater the operational and functional distance of banks, the higher the requirement for information transparency of loan application enterprises. Due to the fact that information transparency is a reflection of the quality of hard information (Xu Zhong and Zou Chuan, 2010; Gou Qin and Huang Yiping, 2014) [21] [26], banks have higher requirements for enterprise information transparency, which means they are increasingly relying on the use of hard information in credit activities. The production of soft information by banks is becoming increasingly scarce. This is because as the operational and functional distance of banks expands, bank branchesmay find it difficult to collect soft information from enterprises or be unable to effectively transmit it to decision-making departments. Therefore, whether from the perspective of soft information collection volume or the efficiency of soft information processing, the expansion of bank operation distance and functional distance will result in a decrease in bank soft information production. Theredore, the process of expanding the operational and functional distance of bank branches is also a continuous suppression of soft information by hard information.

The practical meaning of hard information needs to be interpreted with the help of soft information. As the functional and operational distance of bank branches continues to increase, if banks cannot effectively collect and process soft information, it will be difficult to identify changes in the relationship between enterprise hard information and credit risk. Therefore, the less soft information produced by banks, the greater the difficulty in determining the validity of hard information for loan application enterprises. In this case, banks are unable to differentiate pricing between enterprises with the same hard information characteristics but different levels of risk. Commercial banks can only set loan interest rates based on expected returns.

$$R_b > R > R_g \tag{1.}$$

In the formula, R_b and R_g are the highest interest rates that can be accepted for loans to high-risk and low-risk enterprises, respectively. At this point, only high-risk enterprises will accept loan contracts, while low-risk enterprises will turn to other banks. This leads to a serious problem of adverse selection. It can lead to high risk characteristics in bank loan projects.

Based on the above analysis, this study proposes the following propositions:

Proposition 1: The spatial layout of bank organizations affects credit risk. The greater the operational and functional distance, the higher the credit risk.

Proposition 2: Soft information plays a mediating role in the relationship between bank credit risk and the spatial layout of bank organizations. The larger the operational and functional distance, the less conducive it is to collecting and processing soft information in bank credit activities. It causes an increase in credit risk.

4. Research Design

4.1 Construction of Econometric Models

In order to verify the above proposition, this paper uses the empirical framework of Wen(2004) [27] and Cay & Dursun (2019) [28] to build a mediating effect model to empirically test the proposition proposed in the third part. The explanatory variables are bank geographical factors, including operational distance Ope_{it} and functional distance Fun_{it}. The dependent variable is the bank credit risk Ris_{it}. The intermediary variable is the degree of soft information usage in the bank's credit process Sof_{it}. The mediating effect equations constructed in this study are (15a), (16a), and (17a). On this basis, this study suggests that the differences in Chinese systems may affect the information collection and processing between state-owned and joint-stock banks in China, this article sets the grouping variable *Wdh* for bank property rights attributes, and includes its multiplication term （$Ope_{it} \times Wd\square_i, Fun_{it} \times Wd\square_i, Sof_{it} \times Wd\square_i$） with operational distance, functional distance, and soft information in the independent variables. Extended equations are constructed as shown in (15b), (16b), and (17b). In addition, a set of control variables X_{it} and v_{it} are added to the econometric equation as disturbance terms. The specific settings of the model are as follows.

This study takes the credit risk variable Ris_{it} as the dependent variable, and the operational distance Ope_{it} and functional distance Fun_{it} as the independent variables. This study verifies the overall effect of bank geographical factors on credit risk and constructs econometric models in formulas (15a) and (15b).

$$Ris_{it} = c_{11} + \alpha_{11} Ope_{it} + \alpha_{12} Fun_{it} + \alpha_{13} X_{it} + v_{it} \quad (15a)$$

$$Ris_{it} = c_{12} + \alpha_{21} Ope_{it} + \alpha_{22} Ope_{it} \times Wd\square_i + \alpha_{23} Fun_{it} + \alpha_{24} Fun_{it} \times Wd\square_i + \alpha_{25} X_{it} + v_{it} \quad (15b)$$

Subsequently, this study took the production of soft information as the dependent variable, and the operational distance Ope_{it} and functional distance Fun_{it} as independent variables to verify the impact of local factors on the production of soft information. This study constructed formulas 16 (a) and 16 (b):

$$\mathrm{So}f_{it} = c_{21} + \beta_{11}Ope_{it} + \beta_{12}Fun_{it} + \beta_{13}X_{it} + v_{it} \quad (16a)$$

$$\begin{aligned}\mathrm{So}f_{it} = {} & c_{12} + \alpha_{21}Ope_{it} + \alpha_{22}Ope_{it} \times Wd\square_i + \alpha_{23}Fun_{it} \\ & + \alpha_{24}Fun_{it} \times Wd\square_i + \alpha_{25}X_{it} + v_{it}\end{aligned} \quad (16b)$$

Finally, this study took the credit risk variable Ris_{it} as the dependent variable and the soft information production volume Sof_{it} as the independent variable, while adding operational distance Ope_{it} and functional distance Fun_{it} to verify the impact of soft information on bank credit risk. The models constructed in this study are shown in (17a) and (17b):

$$Ris_{it} = c_{31} + \gamma_{11}Sof_{it} + \gamma_{12}Ope_{it} + \gamma_{13}Fun_{it} + \gamma_{14}X_{it} + v_{it} \quad (17a)$$

$$\begin{aligned}Ris_{it} = {} & c_{32} + \gamma_{21}Ope_{it} + \gamma_{22}Ope_{it} \times Wdh_i + \gamma_{23}Fun_{it} \\ & + \gamma_{24}Fun_{it} \times Wdh_i + \gamma_{25}Sof_{it} + \gamma_{26}Sof_{it} \times Wdh_i + \gamma_{27}X_{it} + v_{it}\end{aligned} \quad (17b)$$

4.2 Variable Design

In order to reduce the impact of data volatility on regression results and to compare the coefficients of variables of different dimensions, this study logarithmized all independent variables during the measurement process (the dependent variable credit default rate itself has low value and volatility, so its initial value is still used). The specific description of variable design is shown in Table 1.

Table 1 Variable Declaration

Category	Symbol	Name	Definition
Dependent Variable	Ris	Credit Risk	Expressed as a percentage of non-performing loans from each bank, the higher the Ris value, the higher the credit risk.
Mediating Variable	$lnSof$	Soft information production volume	Expressed by the natural logarithm of the percentage of non-mortgaged and pledged loans of each bank, the larger the $lnSof$ value, the more soft information production.
Independent Variable	$lnOpe$	Operating Distance	Expressed by the natural logarithm of the operating distance Ope calculated by formula (17).The larger the $lnOpe$ value, the greater the operating distance.
	lnFun	Functional Distance	Expressed by the natural logarithm of the functional distance Fun calculated by formula (18), the larger the value of *lnFun*, the larger the functional distance.

Control Variable	*lnJzd*	Loan Concentration Ratio	Expressed by the natural logarithm of the loan percentage of the top ten customers of each bank, the greater the *lnJzd* value, the higher the loan concentration ratio.
	$lnSize$	Bank Size	Expressed by the natural logarithm of the total assets of each bank (10 billion units), the larger the $lnSize$, the larger the bank size.
	lnCap	Capital Adequacy Ratio	Expressed by the natural logarithm of each bank's total capital to its risk weighted asset percentage, the higher the *lnCap* value, the higher the Capital adequacy ratio level.
	lnMar	Market Environment	Represented by the weighted sum of the marketization indices of the locations of each commercial bank branch. The weight is the proportion of the number of branches of the bank in a certain province to the total number of its branches. The higher the *lnMar* value, the better the market environment faced by bank operations.

4.3 Data Sources

This study selected the panel data of five major commercial banks and twelve joint-stock commercial banks in China from 2011 to 2022 as the research sample. The data for this study comes from the websites of the National Bureau of Statistics, the China Banking Regulatory Commission, various cities' banking regulatory bureaus, financial yearbooks of various provinces and cities, Wind database, China Stock Market & Accounting Research Database, and annual reports of various banks. Among them, the data of the five major state-owned banks and twelve joint-stock banks in China used to calculate the operational distance and functional distance of bank branchesin various provinces and cities from 2011 to 2022 were manually compiled by the author based on the China Banking Regulatory Commission's "Institution Holding Certificate List", "Institution Exit List", the websites of various provincial and municipal banking regulatory bureaus, and financial yearbooks. The financial environment indicators of banks are represented by the "Overall Marketization Index Score" in the "China Provincial Marketization Index Report" by Fan Gang and Wang Xiaolu (2017) [34]. As the latest data in the report is from 2016, this study used the linear difference method to calculate it.

The descriptive statistics of each variable in this study are shown in Tables 2.

Table 2 Descriptive Statistics of Variables

Name	Observations	Mean	Sd.	Min	Median	Max
Ris	204	1.153	0.608	0.100	1.090	4.320
lnSof	204	3.869	0.141	3.467	3.870	4.354
lnOpe	204	3.863	1.461	1.006	4.361	6.667
lnFun	204	1.471	0.429	-0.493	1.666	1.774
lnJzd	204	1.108	0.373	0.482	1.022	2.561
lnSiz	204	3.771	0.235	2.880	3.791	4.669
lnCap	204	2.197	0.172	1.615	2.203	2.586
lnMar	204	5.526	1.318	1.828	5.524	7.789

There are a total of 204 valid observations in the entire sample in Table 2. The standard deviation of each variable is less than the mean. It indicates that the data selected in this article has good quality and there is no extreme value problem. From the minimum and maximum values, there is a significant difference in each indicator within the sample statistical interval. Therefore, the use of panel data in this paper can make a more objective empirical analysis of the issues studied.

5. Empirical Analysis

This study uses the mediating effect model to empirically analyze the theoretical proposition proposed in the third part. The study considering that there may be path dependence in the bank's credit risk indicator *Ris* and soft information indicator *lnSof*. This article places the first-order lag of the dependent variable in the explanatory variable to control the impact of historical factors on the current period's dependent variable. Due to endogeneity issues when placing the lag term of the dependent variable into the independent variable. In this study, the generalized moment estimation (GMM) method is used for regression analysis of the mediating effect econometric equation in order to obtain more accurate and objective results. The GMM estimation method includes two forms: Differential GMM (Diff-GMM) and System GMM (Sys-GMM). Compared to differential GMM, system GMM can solve the problem of weak instrumental variables and improve estimation efficiency. Therefore, this article

chooses the system GMM estimation method. The use of GMM method requires the assumption that the instrumental variables are set reasonably. The model disturbance terms do not have autocorrelation. These two tests can be achieved through Hansen and AR (2) statistics, respectively. The original assumptions are that all instrumental variables are valid and there is no second-order autocorrelation in the model residual term. To control for the impact of heteroscedasticity on regression results, this article used robust standard error in regression.

The use of GMM method for regression requires setting the pre-determined and endogenous variables in the model. In terms of the relationship between the dependent variable bank risk *Ris*, the intermediary variable soft information *lnSof*, and the core explanatory variables bank operational distance *lnOpe* and functional distance *lnFun*, according to the theoretical analysis in this article, operational distance and functional distance can affect credit risk by influencing soft information. However, the spatial layout of banking organizations may also be affected by credit risks and soft information collection. Commercial banks will fully consider their own risk control and information collection capabilities in the region when selecting branch locations. To avoid the impact of endogeneity caused by bidirectional causality on the regression results of this article, the instrumental variable method is adopted in the following regression. Referring to Zhang(2017) [35] approach, this article selects the average values of operating distance *lnOpe* and functional distance *lnFun* of the same type of bank in the same year, *mean_lnOpe* and *mean_lnFun* as instrumental variables for both. For the purpose of robustness test, this paper also gives the regression results of fixed effect instrumental variable regression (FE_IV) and differential GMM (Diff-GMM). If the regression results of the three methods are relatively consistent, it indicates that the regression results in this article are robust.

From the regression results in Table 4 to Table 6, it can be seen that the P-values of Hansen and Ar (2) tests are both greater than 0.1. It indicates that the instrumental variable setting is effective, and there is no sequence autocorrelation in the second-order difference of the perturbation term. Therefore, the regression results of Sys GMM in this article are effective. The regression results of the system GMM (Sys-GMM) are consistent with the coefficient sign and significance of the fixed effects instrumental variable method (FE_IV) and differential GMM (Diff-GMM) regression results. It indicates that the regression results in this article are robust. Therefore, this article will mainly conduct empirical analysis based on the regression results of the system GMM model.

5.1 Analysis of the Overall Effect of the Spatial Layout of Bank Organizations on Credit Risk of Commercial Banks

The regression results of the total effect of the spatial layout of bank organizations on credit risk (formulas 15a and 15b) are shown in Table 3. The dependent variable is the bank's credit risk level Ris. The core explanatory variables are bank operating distance $lnOpe$ and functional distance $lnFun$.

Table 3 Regression Results on the Impact of Spatial Layout of Bank Organizations on Credit Risk

Ris	FE		Diff-GMM		Sys-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
lnOpe	1.425***	1.774***	0.328**	0.758**	0.447***	0.663**
	(4.925)	(2.866)	(2.293)	(2.337)	(2.645)	(2.409)
lnOpe_Wdh		-0.644**		-0.221**		-0.131*
		(-2.302)		(-2.073)		(-1.857)
lnFun	2.355**	0.845**	2.050***	0.796**	2.032**	0.746**
	(2.143)	(2.286)	(2.778)	(2.386)	(2.105)	(2.121)
lnFun_Wdh		2.644***		2.491*		2.385**
		(2.861)		(1.871)		(2.221)
lnJzd	1.137***	1.611***	0.731***	0.743***	0.719***	0.702***
	(4.050)	(3.397)	(3.112)	(2.865)	(3.183)	(2.753)
lnCap	-1.502***	-1.341**	-0.241**	-0.233**	-0.245**	-0.264**
	(-2.999)	(-1.968)	(-2.161)	(-2.279)	(-2.290)	(-2.304)
lnSize	0.320	0.440	0.196	0.302	0.100	-0.005
	(0.916)	(0.903)	(0.904)	(1.329)	(0.789)	(-0.024)
lnMar	-2.434***	-4.646**	-2.098***	-1.624***	-2.238***	-2.194***
	(-3.759)	(-2.462)	(-4.360)	(-3.787)	(-6.040)	(-5.070)
L. Ris			0.593***	0.529***	0.645***	0.620***
			(10.384)	(8.389)	(15.226)	(11.963)
cons	4.965*	-106.326			-3.912***	-2.908***
	(1.831)	(-0.432)			(-5.486)	(-2.845)
N	204	204	187	187	187	187
chi2	67.228	108.156	457.675	471.868	1583.534	815.764
p	0.000	0.000	0.000	0.000	0.000	0.000
Hansen	0.3371	0.4258	0.750	0.955	0.990	0.998
AR(2)			0.106	0.829	0.147	0.575

Note：*** p<0.01, ** p<0.05, * p<0.1.

The regression results in the fifth column of Table 3 show that the regression coefficient of bank operating distance *lnOpe* is 0.447, which is significantly positive at the 1% test level. The coefficient of functional distance *lnFun* is 2.032, which is

significantly positive at the 5% test level. Therefore, Proposition 1 passed empirical testing. It indicates that geographical factors do have an impact on bank credit risk, and the larger the operational and functional distance of a bank, the higher the bank credit risk.The regression coefficient of *lnOpe* is 0.663, and the coefficient of interaction term *lnOpe_Wdh* is -0.131. Both have passed the significance test, indicating that operating distance has a positive impact on bank credit risk for both the five major banks and the twelve joint-stock commercial banks, and has a greater impact on joint-stock banks. The coefficient of *lnFun* is 0.746, and the coefficient of the interaction term is 2.385, both of which are significantly positive at the 5% test level. It indicates that functional distance has a significant positive impact on both the five major banks and joint-stock banks. Unlike the impact of operational distance, functional distance has a more significant impact on the five major banks.

5.2 Analysis of the Impact of Bank Geographic Factors on Soft Information Production

The regression results of the impact of bank geographical factors on soft information production (formulas 16a and 16b) are shown in Table 4. The dependent variable is the soft information production indicator $lnSof$. The core explanatory variables are lnOpe and functional distance $lnFun$.

Table 4 Regression Results on the Impact of Spatial Layout of Bank Organizations on Soft Information

lnSof	FE		Diff-GMM		Sys-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
lnOpe	-0.291**	-0.282*	-0.251*	-0.263**	-0.269**	-0.253**
	(-2.230)	(-1.962)	(-1.866)	(-2.267)	(-2.433)	(-2.206)
lnOpe_Wdh		-0.738		-0.539		0.027
		(-0.624)		(-0.428)		(0.680)
lnFun	-0.378**	-0.448**	-0.719***	-0.804***	-0.503**	-0.325***
	(-2.286)	(-2.216)	(-3.464)	(-2.637)	(-2.090)	(-2.504)
lnFun_Wdh		-0.552**		-0.421**		-0.236***
		(-2.194)		(-2.105)		(-2.580)
lnJzd	0.051	0.076	0.001	0.013	0.004	0.005
	(0.435)	(0.561)	(0.017)	(0.213)	(0.253)	(0.385)
lnCap	-0.181	-0.191*	-0.182**	-0.222***	-0.115***	-0.120**
	(-1.519)	(-1.715)	(-2.039)	(-3.659)	(-2.981)	(-2.145)
lnSize	0.001	0.017	-0.130**	-0.130	-0.016	-0.031
	(0.010)	(0.178)	(-2.417)	(-1.033)	(-0.544)	(-0.713)

lnMar	-0.123	0.024	0.366	0.189	0.233***	0.198**
	(-0.472)	(0.069)	(1.034)	(0.441)	(3.276)	(2.455)
L. Ris			0.764***	0.827***	0.998***	0.868***
			(3.391)	(3.554)	(9.861)	(4.349)
cons	5.359***	7.195			-0.031	0.657
	(11.574)	(0.759)			(-0.057)	(0.559)
N	204	204	187	187	187	187
chi2	971.266	3103.819	68.767	477.854	861.945	236.126
p	0.000	0.000	0.000	0.000	0.000	0.000
Hansen	0.3371	0.3425	0.948	0.986	1.000	1.000
AR(2)			0.392	0.549	0.052	0.087

Note：*** p<0.01, ** p<0.05, * p<0.1.

The regression results in column 5 of Table 4 show that the coefficient of operating distance *lnOpe* for bank branchesin banks is -0.269, and the coefficient of functional distance *lnFun* is -0.503. Both are significantly negative at the 5% test level, indicating that geographical factors will have a negative impact on the production of soft information in banks under certain other conditions. This result is consistent with the theoretical analysis in this article. The larger the operating distance of a bank, the harder it is for the bank to maintain a long-term and reliable business relationship with the enterprise, making it more difficult to collect soft information about the enterprise. The larger the functional distance between banks, the more difficult it is for bank branchesto transmit and translate enterprise soft information within the bank, and the smaller the amount of soft information that is truly used by the bank's decision-making department.

The coefficient of operating distance *lnOpe* is -0.253, which is significantly negative at the 5% test level. The coefficient of the interaction term *lnOpe_Wdh* between the operating distance and the five dummy variables is 0.027, which did not pass the significance test at the 10% test level. It indicates that both the five major banks and joint-stock banks have a negative impact on the production of bank soft information due to operating distance, and the degree of impact is not significantly different among different types of banks. This is because the social embeddedness of soft information determines that the collection of soft information can only rely on frequent physical contact. This is the same for all banks, regardless of their own characteristics. The coefficient of functional distance *lnFun* is -0.325, and the coefficient of cross product term *lnFun_Wdh* is -0.236, both of which are significantly negative at the 1% test level. It indicates that functional distance has a negative impact on the soft information production of both the five major banks and joint-stock banks, and the impact on the five major banks is greater than that of joint-stock banks. Compared to joint-stock commercial banks, the five major banks, as systemically important banks in China, have

a more complex hierarchical structure. Their credit decisions and business strategies are also more cautious. Therefore, there is relatively high-level friction in the transmission of soft information and decision-making transmission process.The functional distance has a more significant impact on the soft information production of the five major elements.

5.3 An Analysis of the Mediating Effect of Soft Information

The mediating effect of soft information on the relationship between the spatial layout of banking organizations and credit risk (Formula 17a, 17b). The regression results are shown in Table 5. The dependent variable is the bank's credit risk level Ris. The core explanatory variable is the soft information production indicator $lnSof$.

Table 5 Regression Results of the Impact of Soft Information on Credit Risk

Ris	FE		Diff-GMM		Sys-GMM	
	(1)	(2)	(3)	(4)	(5)	(6)
lnSof	-1.012***	-1.782**	-0.877**	-1.139***	-0.842***	-1.205**
	(-3.523)	(-2.170)	(-2.559)	(2.637)	(-2.872)	(-2.313)
lnSof_Wdh		0.413***		0.148**		0.206*
		(2.772)		(2.057)		(1.878)
lnOpe	-1.333***	-0.884**	-0.567*	-0.438	-0.154	-0.594*
	(-4.612)	(-1.970)	(-1.958)	(-1.305)	(-1.013)	(-1.781)
lnOpe_Wdh		-1.144**		-3.996		0.780
		(-2.090)		(-0.561)		(1.543)
lnFun	-1.672	-3.016	-1.129	-0.262	0.211	-0.164
	(-1.075)	(-1.061)	(-1.160)	(-0.457)	(0.706)	(-0.564)
lnFun_Wdh		196.100		57.527		0.943
		(0.499)		(0.418)		(0.388)
lnJzd	1.085***	1.618***	1.018**	1.002**	1.004***	1.039***
	(4.305)	(3.278)	(2.098)	(2.008)	(3.024)	(3.336)
lnCap	-1.319***	-1.408*	-0.158***	-1.001***	-1.136**	-2.021***
	(-2.759)	(-1.886)	(-3.048)	(-4.002)	(-2.000)	(-3.097)
lnSize	0.319	0.570	0.249	0.115	-0.035	-0.020
	(0.961)	(1.003)	(1.403)	(0.654)	(-0.248)	(-0.151)
lnMar	-2.559***	-5.204**	-2.014***	-2.326	-2.167***	-2.088***
	(-4.412)	(-2.290)	(-3.820)	(-1.620)	(-5.523)	(-5.281)
L. Ris			0.508***	0.470***	0.640***	0.559***
			(7.776)	(2.633)	(7.851)	(5.720)
cons	-0.456	-104.013			-1.078	-2.045
	(-0.296)	(-0.498)			(-0.434)	(-0.891)
N	204	204	187	187	187	187
chi2	186.220	321.987	14689.358	5005.102	5817.284	3564.547
p	0.000	0.000	0.000	0.000	0.000	0.000

Hansen	0.5141	0.5532	0.9106	0.9585	0.9998	1.0000
AR(2)			0.1998	0.1902	0.1627	0.3706

Note：*** p<0.01, ** p<0.05, * p<0.1.

In the fifth column of Table 5, the regression coefficient of the intermediate variable soft information production index $lnSof$ is -0.842, which is significantly negative at the 1% significance level. It indicates that the production of soft information has a significant negative impact on bank credit risk. The lower the production of soft information, the higher the level of bank credit risk. Based on the fact that the soft information indicator $lnSof$ in Table 4 has significantly negative coefficients for operating distance *lnOpe* and functional distance *lnFun,* it can determine that soft information has a significant mediating effect on the relationship between the spatial layout of banking organizations and credit risk. Proposition 2 has passed empirical testing, stating that the spatial layout of bank organizational structures will have an impact on credit risk by influencing the production of bank soft information. The larger the operational and functional distance of a bank, the lower its soft information production capacity, which in turn leads to an increase in bank credit risk. It indicates that the rapid development of modern communication technology helps to reduce geographical restrictions on financial activities. It largely expands the scope of hard information usage. The geographical environment can still exert influence on financial activities through the collection, dissemination, and translation of soft information.

In column 6, the coefficient of $lnSof$ is -1.205, which is significantly negative at the 5% test level. The coefficient of the cross-product term *lnSof_Wdh* between $lnSof$ and the five major banks dummy variable *Wdh* is 0.206, which is significantly positive at a 10% confidence level. It indicates that the impact of soft information on credit risk varies among different types of banks, and the impact on joint-stock banks is more pronounced. Therefore, based on the regression results in Table 4, the mediating effect of soft information on the spatial layout of bank organizations and credit risk varies between the five major banks and joint-stock banks.

5.4 A Comparative Analysis of the Difference of Mediating Effect

From Table 6, it can be seen that the mediating effect of soft information on functional distance and credit risk is greater than that on operational distance and credit risk, whether in the entire sample or in the five major banks and joint-stock banks. In this study, we found that the mediating effect of *lnSof* on *lnOpe* and *Ris* is 0.253, and the mediating effect between *lnFun* and *Ris* is 0.560. The former is about 45% of the latter. In the sample data, the size of the mediating effect of *lnSof* on lnOpe and *Ris* is

0.305, and the size of the mediating effect on *lnFun* and *Ris* is 0.391. The former is about 78% of the latter.

This empirical study found that for the **five major banks,** soft information has a more significant mediating effect on the relationship between functional distance and credit risk compared to operational distance. For joint-stock banks, the mediating effect of the size of soft information on operational distance and functional distance, as well as the difference between them and credit risk, is not significant. This study suggests that the reason for this is that as large state-owned commercial banks, the five major banks mainly face large enterprises as their clients. Compared to small and medium-sized enterprises, the financial information of large enterprises is more transparent and their reputation is more guaranteed. In addition, the five major banks also have implicit government guarantees for state-owned enterprise loans, so the information collected and used by the five major banks in credit transactions with large enterprises is mainly "hard information". The impact of geographical factors on soft information and thus credit risk is mainly reflected in the hierarchical communication within banks. Small and medium-sized banks, such as joint-stock banks, mainly face credit targets for small and medium-sized enterprises. These enterprises face issues such as opaque financial information and insufficient collateral. When joint-stock banks provide loans to these small and medium-sized enterprises, the collection and use of soft information is even more important for controlling credit risks. Therefore, for joint-stock banks, the impact of geographical factors on soft information and credit risk is reflected not only in the information exchange between bank hierarchy, but also in the information exchange between banks and customers. In addition, the intermediary role of operating distance, functional distance, and credit risk in joint-stock banks is greater than that of soft information in the five major banks. Compared with the five major banks, geographical factors have a more significant impact on the credit risk of joint-stock banks through soft information due to different customer groups.

Table 6 Comparative Analysis of Soft Information mediating effect

Group	Independent Variable	Mediating Variable	Dependent Variable	a	b	Mediating Effect (a×b)
Full Sample	*lnOpe*	*lnSof*	*Ris*	-0.269	-0.842	0.226
	lnFun			-0.503		0.422
Joint-stock Bank	*lnOpe*	*lnSof*	*Ris*	-0.253	-1.205	0.305
	lnFun			-0.325		0.391
	lnOpe	*lnSof*	*Ris*	-0.253	-0.999	0.253

Five Major Banks	*lnFun*			-0.561		0.560

6. Conclusion and Suggestion

6.1 Conclusion

With the development of information and communication technology, the limitations of geographical factors on financial activities are constantly decreasing. The spatial layout of hierarchical institutions in China's banking industry is also undergoing profound changes. However, scientific and technological progress and financial innovation cannot necessarily reduce the degree of information asymmetry between the trading parties in financial activities. The exchange of soft information between banks and enterprises is still influenced by geographical factors. Based on the research findings of Shelomentsev et al. (2021)[35], this study fully considers the close relationship between information exchange between banks and enterprises and credit risk control. Therefore, exploring the impact and path of the spatial layout of banking institutions on credit risk is of great significance for the current transformation of China's commercial banking industry.

In view of this, this study theoretically analyzes the relationship between the spatial layout of banking organizations, soft information production and credit risk from the perspective of information asymmetry, and empirically analyzes it with the help of the mediating effect model. This study found that:

(1) The spatial layout of bank organizational structures will have an impact on credit risk. The greater the operational and functional distance, the higher the level of credit risk.

(2) Soft information has a mediating effect on the relationship between geographic factors and credit risk. The larger the operational and functional distance of a bank, the more unfavorable it is for the bank to collect and process soft information of the enterprise. This has led to an increase in credit risk for commercial banks.

(3) The negative effect of functional distance on the soft information production of Chinese commercial banks is particularly evident. The impact of operational distance on soft information collection did not show significant heterogeneity among different types of commercial banks.

6.2 Suggestion

Based on the research conclusions of this article, the following suggestions are proposed.

Firstly, the management of commercial banks should pay attention to the role of bank branchesin soft information collection during the transformation and upgrading process. In the process of transformation and upgrading, China's banking industry should have a correct understanding of the complementary rather than substitutive relationship between communication technology and geographic factors. Commercial banks can move to digitalization for relatively standardized and low-risk business operations such as deposit and withdrawal, financial management and settlement. Commercial banks should fully consider the role of bank branchesin collecting and processing soft information for credit and other businesses involving more information exchange and higher income risk. On the one hand, the spatial layout of bank branches should start from the needs of bank customer service and bank development. They conduct personalized design for the location, quantity, products, and service methods of bank branchesthrough scientific research, analysis, and quantitative evaluation. Such behavior can reduce geographical restrictions on the collection and transmission of soft information. On the other hand, while commercial banks actively adopt modern technologies such as credit scoring systems, bank decision-making departments should also strengthen positive incentives for bank branchesto collect soft information. They should attach importance to and encourage bank branchesto establish stable and reliable communication mechanisms with local enterprises. Managers of commercial banks should actively collect enterprise soft information, and use hard information and soft information together, so as to reduce the degree of information asymmetry between banks and enterprises as much as possible, and thus reduce credit risk.

Secondly, China's commercial bank managers should promote the reform of the bank's internal organizational management structure, and reduce the information friction between bank branches and decision-making departments. They need to ensure that the internal management level of the bank matches the expanding size and geographical scope of the bank, and improve the efficiency of information transmission between decision-making departments and bank branches, especially those operating in different locations. On the one hand, it is necessary to break organizational rigidity, improve organizational flexibility, promote flat management reform of banks, optimize organizational systems, and reduce information friction and communication costs

among internal levels of banks. Banks need to ensure that decision-making departments can fully utilize the information collected by bank branches to make correct and efficient decisions and reduce credit risks. On the other hand, commercial banks need to reasonably set up the credit approval authority of grass-roots branches. Especially, branches located in more remote areas should be given higher autonomy in decision-making to avoid the adverse impact of excessive credit approval power on information risk control caused by inter level information friction and conflicting interests and objectives.

Thirdly, commercial banks, especially small and medium-sized commercial banks, should prudently carry out cross regional operations. In the process of expanding the business scope of commercial banks in China, only the economic development level of the target area is often considered. This business philosophy has led to a high degree of similarity in the cross regional business models of Chinese commercial banks. However, this study indicates that geographical factors remain important for financial activities. The soft information accumulated by commercial banks in local operations is difficult to transfer with the banks' remote operations. This leads to banks' newly established branches in different locations being less well-known and credible than local banks and national commercial banks, resulting in lower bargaining power. It is difficult for relationship based banking services established locally based on soft information to be fully carried out in different locations. Therefore, the simple geographical expansion of China's commercial banks cannot guarantee the improvement of banking business scale and profitability. In addition, banks have limited ability to collect information on remote markets. It is difficult for them to fully understand the operational, financial, and credit information of enterprises applying for loans in remote areas. Therefore, it is easy for commercial banks to have Adverse selection in the process of credit. It has increased the difficulty of risk control for banks. Therefore, whether from the perspective of competitiveness or risk management, commercial banks should prudently conduct cross regional operations, fully consider the financial ecological environment of remote markets and their own adaptability. Bank managers should carefully analyze whether their business methods can interact with the local regional culture, and then root their business goals in the local macroeconomic development plan. Only in this way can commercial banks gradually reduce the geographical disadvantages brought by remote operations, improve the business scale and profitability of remote branches, and reduce credit risks caused by information asymmetry.

History has shown that every important financial innovation comes with unprecedented financial risks. The outbreak of P2P online lending and cross regional credit risks for small and medium-sized banks in China indicates that China's financial institutions are currently unable to fully break free from geographical constraints. The correct understanding of the limitations of financial technology by the government and banking practitioners is conducive to finding a balance between Financial innovation and risk prevention. This study emphasizes the importance of geographical factors in the process of bank credit risk control, not as a negation of fintech, but as an exploration of the limitations of fintech. Bartoli (2013) [12] pointed out that information technology and geographical factors complement each other rather than replace each other. However, due to limitations in length and data availability, this study did not further analyze the interaction between these two parts, which is also one of the directions for further research in the field of financial geography.

Reference

[1] Papi L, Sarno E, Zazzaro A. The geographical network of bank organizations: issues and evidence for Italy[M]//Handbook on the Geographies of Money and Finance.Cheltenham: Edward Elgar Publishing, 2017: 156–197.

[2] Bhattacharya S, Chiesa G. Proprietary information, financial intermediation, and research incentives[J]. Journal of Financial Intermediation, 1995, 4(4): 328-357.

[3] Petersen M, Rajan R. Does distance still matter? The information revolution in small business lending[J]. The journal of Finance, 2002, 57 (6): 2533-2570.

[4] Wan Hongbo, Jia Yunqi. A Study on the Impact of Geographical Distance between Parent and Subsidiary Companies on Audit Quality - Based on the Intermediary Role of Internal Control [J]. Audit and Economic Research, 2018, 33 (2): 50-59.Rajan U, Seru A, Vig V. The failure of models that predict failure: Distance, incentives, and defaults[J]. Journal of Financial Economics, 2015, 115 (2): 237-260.

[5] Behr P, Guettler A. Credit risk assessment and relationship lending: An empirical analysis of German small and medium- sized enterprises[J]. Journal of Small Business Management, 2007, 45(2): 194-213.

[6] Jiménez G, Lopez J A, Saurina J. How does competition affect bank risk-taking?[J]. Journal of Financial stability, 2013, 9(2): 185-195.

[7] Liang Qi, Hao Yi. Research on Local Government Debt Replacement and Macroeconomic Risk Mitigation [J]. Economic Research, 2019 (4): 18-32.

[8] Alessandrini P, Fratianni M, Zazzaro A. The changing geography of banking and finance: The main issues. [M]//The Changing Geography of Banking and Finance.New York:Springer, 2009: 1-11.

[9] Liberti J, Petersen M . Information: Hard and soft[J]. Review of Corporate Finance Studies, 2019, 8(1): 1-41.

[10] Agarwal S, Hauswald R. Distance and private information in lending[J]. The Review of Financial Studies, 2010, 23 (7): 2757-2788.

[11] Bartoli F, Ferri G, Murro P, et al. SME financing and the choice of lending technology in Italy: Complementarity or substitutability?[J]. Journal of Banking & Finance, 2013, 37 (12): 5476-5485.

[12] He Canfei, Liu Hao. Banking Reform and the Spatial Layout of State owned Commercial Bank Network - Taking Industrial and Commercial Bank of China and Bank of China as Examples [J]. Geography Research, 2013,32 (1): 111-122.

[13] Li Zhishan, Huang Guangqing, Chen Fenggui. A Study on the Geographical Distribution Characteristics of China's National Joint Stock Commercial Banks [J]. Economic Geography, 2014, 34 (2): 19-27.

[14] Bogdan, T. . (2016). Determinants of capital flows to emerging market economy: a case of ukraine. transformation in business & economics, 15(1), 127-146.

[15] Bellucci A, Borisov A, Giombini G, et al. Collateral and local lending: Testing the lender-based theory[R]. IAW Diskussionspapiere, 2015.

[16] Tao Feng, Hu Jun, Li Shitian. How does the financial geography structure affect enterprise productivity—— Also on the structural reform of the financial supply side [J]. Economic Research, 2017 (9): 55-71.

[17] Bai, G. , Yang, Q. , & Elyasiani, E. . (2022). Managerial risk-taking incentives and bank earnings management: evidence from fas 123r. Sustainability, 14.

[18] Stein J. Information production and capital allocation: Decentralized versus hierarchical firms[J]. The journal of finance, 2002, 57 (5): 1891-1921.

[19] Presbitero A, Udell G, Zazzaro A. The home bias and the credit crunch: A regional perspective[J]. Journal of Money, Credit and Banking, 2014, 46 (s1): 53-85.

[20] Xu Zhong, Zou Chuanwei. Design of internal loan approval authority allocation and incentive mechanism for banks under the framework of hard and soft information [J]. Financial Research, 2010, 8:1-15.

[21] Bolton P , Dewatripont M . Contract Theory[M]. MIT Press Books, 2005.

[22] Williamson S D . Costly monitoring, financial intermediation, and equilibrium credit rationing[J]. Journal of Monetary Economics, 1986, 18(2):159-179.

[23] Jin Hongfei, Li Hongji, Liu Yinlu. Financial technology, banking risk, and market crowding out effects [J]. Financial Research, 2020, 046 (005): 52-65.

[24] Porteous D J . The geography of finance: Spatial dimensions of intermediary behaviour.[J]. Tijdschrift Voor Economische En Sociale Geografie, 1997, 88(5):501-502.

[25] Gou Qin, Huang Yiping. Analysis of the Determinants of Credit Ration in China - Evidence from the Enterprise Level [J]. Financial Research, 2014, (08): 1-17.

[26] Wen Zhonglin, Zhang Lei, Hou Jietai. Mesomeric effect test procedure and its application [J]. Journal of Psychology, 2004, 36 (05): 614-620.

[27] Zhao X, Lynch G, Chen Q. Reconsidering Baron and Kenny: Myths and truths about mediation analysis[J]. Journal of consumer research, 2010, 37 (2): 197-206.

[28] Cay, D. , Goker, N. , & Dursun, M. . (2019). Modelling r&d strategy to fulfil customer demands through digital transformation. WSEAS Transactions on Business and Economics, 16.

[29] Wu Long. Venture capital, certification effect, and bank loans for small and medium-sized enterprises [J]. Economic Management, 2019, 041 (002): 172-190.

[30] Zhu Jigao, Rao Pingui, Bao Mingming. Equity Structure, Credit Behavior, and Bank Performance: An Empirical Study Based on Data from Urban Commercial Banks in China [J]. Financial Research, 2012 (7): 31-47.

[31] Wang Xiuli, Bao Mingming, Zhang Longtian. Financial Development, Credit Behavior, and Credit Efficiency: An Empirical Study Based on Urban Commercial Banks in China [J]. Financial Research, 2014, (7): 94-108.

[32] Li Shusheng, Guan Yanfeng. Capital constraints, bank heterogeneity, and credit risk sensitivity [J]. Economic and Management Research, 2018 (5): 51-60.

[33] Wang Xiaolu, Fan Gang. Marketization Index Report by Province: 2016 [M]. Beijing: Social Science Literature Publishing House, 2017.

[34] Zhang Jie, Zheng Wenping, Xinfu. China's relaxation of bank regulation, structural competition, and corporate innovation [J]. China's Industrial Economy, 2017 (10): 120-138.

[35] Shelomentsev, A. G. , Goncharova, K. S. , Stepnov, I. M. , Kovalchuk, J. A. , Lan, D. H. , & Golov, R. S. . (2021). Strategic innovation as a factor of adaptation of national economies to the development of global value chains. Sustainability, 13.