Research Article

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The Impact of Geographic Factors on Credit Risk: A Study of Chinese Commercial Banks

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Abstract: Controlling credit risk is crucial for maintaining financial stability, and the role of geographic factors in this regard is a significant concern for scholars and policymakers. Drawing on the concept of information asymmetry, we developed a theoretical model to analyze how geographic factors influence credit risk. Our theoretical proposition suggests that the spatial organization of banks affects the efficiency of collecting and processing soft information, ultimately impacting the credit risk. To test this proposition, we collected microdata from Chinese commercial banks spanning the period from 2011 to 2022. Employing a mediating effect model, we empirically examined the relationship between spatial organizational structure and credit risk. Our results indicate that the distance between bank operations and functional distance impedes the collection and processing of soft information, thereby exacerbating credit risk in banks. The study focuses on examining how the spatial organizational structure of Chinese commercial banks affects credit risk. By analyzing geographic factors and information asymmetry, the study aims to understand how the organization of banks influences the collection and processing of soft information, which in turn impacts the credit risk. Furthermore, our analysis of the sample reveals that the mediating role of soft information varies between state-owned banks and joint-stock banks due to their distinct customer profiles. On the basis of these findings, we propose several policy recommendations, including a focus on enhancing the collection and processing of soft information, promoting the growth of locally based small and medium-sized banks, and reducing information barriers within bank hierarchies.

Keywords: operational distance, functional distance, soft information, credit risk, mediating effect

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1 Introduction

Ensuring financial stability and mitigating risks amidst the combined impact of domestic and foreign uncertain factors holds significant importance for China's long-term economic development, as well as the attainment of transformation and upgrading objectives. With the advent of China's reform and opening-up policies, the banking industry has assumed a dominant position within the country's financial system, playing a vital role in resource allocation and macroeconomic regulation. The control of credit risks within commercial banks is a key aspect of upholding financial security, garnering attention from economists and policymakers (Bhattacharya & Chiesa, 1995; Papi et al., 2017; Petersen & Rajan, 2002). In recent years, Chinese commercial banks have undergone a profound and protracted transformation process in terms of industry structure and technological advancements. Regarding industry structure, these banks have set strategic goals aimed at establishing a diversified financial system and expediting market-oriented reforms in the banking sector. Regulatory authorities have gradually eased their control over nonstate-owned banks and new financial institutions, resulting in a growing number of branches established by nonstate-owned commercial banks across various locations. While the operational distance between banks and enterprises has diminished, the functional distance between grassroots bank organizations and their headquarters has increased. Concerning technological advancements, the application of information technology within banks has surged, facilitating the collection and processing of quantitative information such as assets, income, and market share. Consequently, the significance of operational and functional distances between banks and enterprises appears to be weakened. However, information technology does not possess a comparable advantage in gathering and processing qualitative information such as reputation and creditworthiness, thus underscoring the continued importance of geographical factors (Behr & Güttler, 2007; Jiménez et al., 2013; Rajan et al., 2015). Some scholars have posited that information asymmetry constitutes a significant factor contributing to the bank credit risk (Papi et al., 2017).

Due to market incompleteness, banks possess an inherent motivation to establish and maintain close collaboration with enterprises. This facilitates the acquisition and screening of information, thereby addressing the issue of information asymmetry between banks and enterprises (Bhattacharya & Chiesa, 1995). The rapid advancement of information technology has undoubtedly alleviated the constraints imposed by geographical factors on financial activities. However, the impact of information technology primarily extends to the utilization of quantitative information, considering the geographic specificity of information dissemination. Consequently, the dissemination of qualitative information, commonly referred to as soft information, remains subject to the influence of geographical factors (Petersen & Rajan, 2002). To process transactions such as bank withdrawals and financial transfers, banks rely on customers' hard information. However, when it comes to managing credit risk, banks cannot solely rely on the collection of hard information pertaining to credit targets. The collection and analysis of soft information, including factors such as reputation, creditworthiness, and corporate culture, are crucial.

Commercial banks must tailor credit contracts based on the soft information characteristics of different enterprises. Geographical factors play a significant role in the rootedness of soft information, and the utilization of information technology does not fully exploit its advantages in standardization when collecting and processing soft information. Consequently, the application of information technology may not necessarily mitigate credit risk resulting from information asymmetry [4]. Despite the extensive use of information technology in China's peer-to-peer lending platforms, financial risks persistently arise. Rajan et al., (2015) highlighted that during the credit securitization process, US banks excessively relied on hard information obtained through modern communication technology, disregarding the collection of soft information. This failure to validate the accuracy of borrower hard information became a critical factor in the US subprime crisis. These instances underscore the significant influence of geographical factors on banks' effective collection and processing of soft information. In October 2020, the People's Bank of China sought public opinions on the "Commercial Bank Law of the People's Republic of China," which stipulated that local bank requires approval to conduct business across regions. The contribution of this study lies in its examination of the relationship between the spatial organizational structure of Chinese commercial banks and credit risk. It contributes to the existing literature by incorporating geographic factors and information asymmetry into the analysis. The study develops a theoretical model and empirically tests it using microdata from Chinese commercial banks, providing a comprehensive understanding of how the organization of banks influences the collection and processing of soft information, which, in turn, impacts the credit risk. In February 2021, the China Banking and Insurance Regulatory Commission issued a notice to further regulate Internet loan activities of commercial banks, explicitly prohibiting local banks from engaging in Internet loan businesses across regions. Given the ongoing deepening of reforms and evolving organizational structure in China's banking industry, there is an urgent need for comprehensive research on the impact of geographical factors on the bank credit risk. Prior studies have primarily focused on the bank credit risk from the perspectives of information asymmetry, relational credit, banking market competition, and debt maturity structure (Behr & Güttler, 2007; Jiménez et al., 2013; Liang & Hao, 2019). However, these studies have devoted less attention to the influence of geographical factors. The objective of this study is to examine the relationship between the spatial organizational structure of Chinese commercial banks and credit risk, considering the influence of geographical factors and information asymmetry. Using microdata from Chinese commercial banks, the study aims to develop a theoretical model and empirically test it, providing a comprehensive understanding of how bank organization affects the collection and processing of soft information, which in turn impacts credit risk. This research contributes to the existing literature by incorporating geographical factors and information asymmetry into the analysis of bank credit risk, filling a gap in previous studies that have focused more on other factors. Furthermore, by utilizing specific microdata from the Chinese banking industry, which is undergoing reforms and organizational changes, the study offers empirical evidence and insights that are relevant to this context.

2 Research Objective

This article adopts an adverse selection theoretical framework to examine the association between the spatial arrangement of banking organizations, soft information, and credit risk. The study employs a mediating effect model to empirically investigate this relationship, shedding light on the impact and mechanisms of geographical factors on commercial bank credit risk. The innovative contributions of this article are twofold. First, it offers a unique research perspective by examining the influence of geographic factors on the bank credit risk from the vantage point of soft information. This approach supplements and advances the existing literature on economic geography and commercial bank credit risk. While prior economic geography studies primarily focus on the impact of geographical factors on corporate credit availability or local economic development, they rarely delve into the realm of bank credit risk. Similarly, the existing research on commercial bank credit risk mainly explores the influence of factors such as relationship lending, bank market competition, and debt maturity structure, with limited attention given to the geographic variables of banks. Second, this study employs a mediating effect model to unravel the channels through which geographical factors affect the bank credit risk. While the previous scholarly work has involved qualitative analysis and theoretical deductions concerning the relationship between geographical factors and the bank credit risk, rigorous quantitative methods to explore the causal relationship and underlying mechanisms between the two remain scarce. The study is based on an adverse selection theoretical framework to analyze associations between spatial arrangements, soft information, and credit risk. It aims to empirically test the proposition that geographical factors impact credit risk by influencing soft information production.

The presence of information asymmetry, both between banks and borrowers and within commercial banks themselves, poses challenges to the efficient allocation of credit resources. Asymmetric information stands as a significant contributor to the bank credit risk (Papi et al., 2017). In light of market incompleteness, commercial banks possess an inherent motivation to establish and maintain close collaboration with enterprises. This facilitates the acquisition and screening of information, thereby overcoming the issue of information asymmetry between banks and enterprises (Bhattacharya & Chiesa, 1995). In recent years, the relaxation of government regulations and the rapid advancement of information and communication technology have expanded the geographical scope of business operations within China's commercial banking sector. Consequently, the geographical layout of the banking industry has undergone varying degrees of transformation across different countries, leading to changes in the relationships between banks and enterprises, as well as between different levels within banks. The theoretical community has increasingly recognized the role of geographical factors in credit activities. The process of information collection and processing by banks involves information exchange between the bank's operational departments and borrowers, as well as information exchange among different levels within the bank (operational departments and decision-making departments). Existing literature primarily examines the relationships between geographical factors, bank-enterprise interactions, and bank credit operations from these two perspectives. Since the 1990s, there has been a relaxation of banking regulations by European and American regulatory agencies, resulting in a deepening of cross-regional operations for banks. This has led to a continuous expansion in the number of branch offices and business outlets for commercial banks and an increase in the geographical distance between banks and enterprises. As a result, the academic community has increasingly recognized the significance of the geospatial relationship between banks and enterprises in credit activities. Financial activities are intertwined with specific natural and cultural geographical contexts. Hence, geographical factors can influence the collection, dissemination, and interpretation of information, particularly soft information, by banks toward enterprises, consequently impacting credit activities (Alessandrini, 2009; Behr & Güttler, 2007; Bhattacharya & Chiesa, 1995; Jiménez et al., 2013; Liang & Hao, 2019; Papi et al., 2017; Petersen & Rajan, 2002; Rajan et al., 2015). The advancements in communication technology have diminished the geographical limitations on credit activities between banks and enterprises. However, Liberti and Petersen (2019), Petersen (2002), and Petersen and Rajan (2002) argue that modern communication technology has primarily expanded the utilization of hard information, while it lacks advantages in collecting and processing soft information that is challenging to standardize. The collection of soft information regarding companies still necessitates frequent and dependable face-to-face interactions between parties involved in the transactions. Furthermore, the scope of information covered by hard information is limited, and factors like geographical distance inherently influence the objectivity of hard information, including credit ratings, throughout the information collection process. Several empirical studies have examined the association between geographic distance and soft information. Agarwal and Hauswald (2010) discovered that a shorter geographic distance between borrowers and lenders facilitates banks in gathering customer soft information, leading to fairer credit ratings. Bartoli et al. (2013) revealed that information technology and geographic factors exhibit a complementary relationship rather than a substitutive one. Consequently, the academic community has directed attention toward understanding the impact of this complementary relationship on the spatial arrangement of commercial banks and enterprises. Bogdan (2016) and Zhishan et al. (2014) investigated the spatial distribution of business outlets for state-owned and joint-stock banks in China. Their research established that bank branches are frequently situated in economically developed and politically advanced regions, enabling commercial banks to access richer financial information and secure better customer resources. What influence does the advantage of acquiring soft information due to proximity between banks and enterprises have on both parties? Agarwal and Hauswald (2010) and Petersen and Rajan (2002) empirically demonstrated, based on the US data, that closer geographic proximity between banks and enterprises corresponds to higher credit availability for enterprises and lower credit interest rates. Alessandrini (2009) observed a negative relationship between the bank branch density and the sensitivity of enterprise cash flow. Bellucci et al. (2015) found that greater geographic intimacy between banks and enterprises leads to reduced requirements for corporate loan collateral. Bai et al. (2022), utilizing microdata from China's manufacturing industry, discovered that local financial development reduces the geographic distance between banks and enterprises, promoting productivity growth in local enterprises. Furthermore, the establishment of regional financial centers positively impacts productivity growth in both the city and the surrounding areas. Conversely, a greater geographic distance between commercial banks and enterprises may impede the collection of soft information, thereby exacerbating the credit risk.

The expansion of commercial banks' business operations has led to an increasing number of bank branches operating in various locations. Consequently, the academic community has begun to focus on the impact of the spatial distribution structure of bank hierarchical organizations on credit activities. Soft information has a distinct regional nature, making it challenging for high-level decision-making departments in banks to directly interact with borrowers in remote areas. Consequently, grassroots operational departments of banks are better positioned to acquire soft information. The collection and processing of soft information by banks can result in information asymmetry between grassroots operational departments and higher-level decision-making departments (Papi et al., 2017), leading to several issues. Alessandrini (2009) argued that greater physical and cultural distance between bank headquarters and its branches increases the cost of transmitting soft information within the bank, exacerbating information asymmetry between the two. This not only gives rise to conflicts of interest but also allows branch offices to potentially abuse their authority for personal gain. Stein (2002) analyzed the situation from the perspective of incentive mechanisms and found that due to the nonstandard nature of soft information, greater geographic distance between bank hierarchies results in higher losses and lower utilization rates of soft information. This reduces the incentive for operational departments to collect soft information, negatively impacting bank efficiency. The viewpoint was further confirmed by Presbitero et al. (2014) through a survey of the Italian banking industry, which revealed that bank headquarters tend to restrict the business activities of branch departments in remote areas. Under similar financial health conditions, the farther the geographical distance between a bank's operating department and its headquarters in a particular region, the more restrictive clauses are included in loan contracts signed between the bank and enterprises in that region. Xu and Zou (2010) discovered in their research on China's large- and medium-sized commercial banks serving small- and medium-sized enterprise financing that excessive use of credit approval authority, driven by the fact that branch offices possess more soft information about enterprises compared to headquarters, is detrimental not only to small- and medium-sized enterprise financing but also to bank profitability and local economic development. Agarwal and Hauswald (2010) proposed that to address the challenge of soft information transmission between bank hierarchies, commercial bank headquarters should delegate more decision-making power to bank branches located farther away from them. Based on a comprehensive literature review, it has been determined that geographical factors play a significant role in influencing the effectiveness of bank information collection and processing, in both the interactions between banks and enterprises and within banks. However, the existing studies primarily focus on examining the impact of geographical factors on corporate credit availability and local economic development, while providing limited insights into the influence of bank organizational structure spatial layout on bank credit risk from the banks' perspective. This knowledge gap serves as the theoretical foundation for this study. The objective of this research is to develop a theoretical model centered on information asymmetry to analyze the relationship between the spatial layout of banking organizations and the credit risk, specifically within the framework of adverse selection between banks and enterprises. The main objective of the study is to examine the relationship between the spatial organizational structure of Chinese commercial banks and credit risk, considering the influence of geographical factors and information asymmetry.

3 Theoretical Analysis

In contemporary financial intermediary theory, the production of information serves as a crucial function of banks. Extant theoretical and empirical literature highlights the significance of acquiring accurate information pertaining to borrowers and their financing projects as a key determinant of bank loan decisions (Bhattacharya & Chiesa, 1995). The process of granting bank credit entails the exchange of both hard and soft information between potential borrowers and various departments within the banking institution, including the business departments and decision-making departments. Based on the available information, the decision-making department of the bank ultimately determines whether to approve the loan project, while the execution of these decisions falls under the purview of the banking department, which also oversees the borrower's adherence to the contractual terms. Geographical factors can influence the exchange of information between banks and enterprises, subsequently impacting the transaction costs associated with credit activities. The transaction costs arising from information exchange between banks and enterprises reflect the challenges encountered in bank information production, thereby influencing the manner in which banks generate information and engage in credit-related behaviors. Simultaneously, transaction costs exert an influence on credit risk. Consequently, within the modern financial intermediary theory, the production of information remains a vital function of banks. The study is based on an adverse selection theoretical framework to analyze the associations between spatial arrangements, soft information, and credit risk. It aims to empirically test the proposition that geographical factors impact the credit risk by influencing the soft information production.

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 $\omega(\omega \geq 0)$, the probability distribution function of net return is $F(\omega)$. The probability density function is $f(\omega)$. The 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 & Dewatripont, 2005). In this environment, Williamson (1986) 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 aforementioned assumptions, the functional expression for the expected income of bank unit loans is given as follows:

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

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 as follows:

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

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. The operational costs arise 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 branches of 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 given as follows:

$$E(V) = r + F(R)\beta_p + \beta_c. \quad (3)$$

In the aforemetioned 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^*, making the bank's unit loan income equal to the unit loan cost:

$$\Pi(R, F(\omega)) = V(\beta_p^*). \quad (4)$$

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

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

Through simplification, it can be concluded that

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

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 the existing literature (Alessandrini, 2009; Papi et al., 2017) 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.

Several studies have examined key aspects related to bank risk-taking, local government debt replacement, and the changing geography of banking and finance. Jiménez et al. (2013) found that increased competition within the banking sector leads to higher levels of risk-taking by banks, reinforcing the importance of understanding the relationship between competition and risk for effective management and regulation. Liang & Hao (2019) explored the effects of replacing local government debt on macroeconomic stability, revealing that debt replacement measures can mitigate macroeconomic risks associated with local government debt and contribute to overall economic stability. Alessandrini et al. (2009) discussed the evolving landscape of banking and finance, emphasizing the need to comprehend the main issues surrounding the geographic distribution of banking and financial activities to effectively address challenges and capitalize on opportunities in the industry. Liberti and Petersen (2019) underscored the significance of information, both hard and soft, in corporate finance decision-making, elucidating how different types of information can impact corporate strategies and outcomes. Agarwal and Hauswald (2010) investigated the impact of geographical distance on private information in lending transactions, revealing that distance can create informational barriers that influence lending decisions and outcomes. Collectively, these studies provide valuable insights into factors influencing decision-making processes, risk management strategies, and the overall stability of financial systems.

The operational distance of a bank measures the geopolitical intimacy between the bank's operating department and the lending enterprise (Papi et al., 2017; Petersen & Rajan, 2002). Although the advancement of information technology has expanded the scope of hard information usage, 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. 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 & Petersen, 2019). 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 Hongfei et al. (2020) and Porteous (1997), and sets the expression of the cost β_p of bank information collection for loan enterprises as follows:

$$\beta_p = \mathrm{Ope} \times \beta_p^f. \quad (7)$$

In the aforementioned equation, $\beta_p^f(\beta_p^f > 0)$ 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 (Gou & Huang, 2014; Zhao et al., 2010). 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 and 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 (Alessandrini, 2009). 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). 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 (Stein, 2002; Zhao et al., 2010), this article sets the expression for the internal information processing cost β_c of the bank as follows:

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

In the aforementioned equation, $\beta_c^f (\beta_c^f > 0)$ 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 hierarchy's (Wang & 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 $\beta_p = \beta_p^*$, we obtain

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

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:

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

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

Because of $E(\beta_p^{f*}) > 0$, $R - \int_0^R F(\omega)\mathrm{d}\omega - (r + \text{Fun} \times E(\beta_c^f)) > 0$, therefore,

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

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

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*}, transparency of enterprise information is higher. The negative correlation between β_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 (Gou & Huang, 2014; Zhong & Chuanwei, 2010), banks have higher requirements for enterprise information transparency, which means that 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 branches may 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. Therefore, the process of expanding the operational and functional distance of bank branches is also a continuous suppression of soft information by hard information. The interpretation of hard information's practical significance relies on the incorporation of soft information. As the functional and operational distance between bank branches and enterprises expands, the ability to effectively gather and analyze soft information becomes crucial in detecting shifts in the relationship between enterprise hard information and credit risk. Consequently, if banks are unable to adequately collect and process soft information, it becomes challenging to ascertain the reliability of hard information provided by loan applicants. This, in turn, hampers banks' ability to differentiate pricing between enterprises that possess similar hard information attributes but exhibit varying levels of risk. Under such circumstances, commercial banks can only establish loan interest rates based on anticipated returns.

$$R_{\mathrm{b}} > R > R_{\mathrm{g}}. \tag{14}$$

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 aforementioned 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

To verify the above proposition, this article uses the empirical framework of Cay and Dursun (2019) and Wen et al. (2004) 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 $\mathrm{Ope}_{\mathrm{it}}$ and functional distance $\mathrm{Fun}_{\mathrm{it}}$. The dependent variable is the bank credit risk $\mathrm{Ris}_{\mathrm{it}}$. The intermediary variable is the degree of soft information usage in the bank's credit process $\mathrm{Sof}_{\mathrm{it}}$. The mediating effect equations constructed in this study are equations (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 ($\mathrm{Ope}_{it} \times \mathrm{Wdh}_i$, $\mathrm{Fun}_{it} \times \mathrm{Wdh}_i$, $\mathrm{Sof}_{it} \times \mathrm{Wdh}_i$) with operational distance, functional distance, and soft information in the independent variables. Extended equations are constructed as shown in equations (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).

$$\mathrm{Ris}_{it} = c_{11} + \alpha_{11}\mathrm{Ope}_{it} + \alpha_{12}\mathrm{Fun}_{it} + \alpha_{13}X_{it} + v_{it}, \tag{15a}$$

$$\begin{aligned}\mathrm{Ris}_{it} = {} & c_{12} + \alpha_{21}\mathrm{Ope}_{it} + \alpha_{22}\mathrm{Ope}_{it} \times \mathrm{Wdh}_i + \alpha_{23}\mathrm{Fun}_{it} \\ & + \alpha_{24}\mathrm{Fun}_{it} \times \mathrm{Wdh}_i + \alpha_{25}X_{it} + v_{it}.\end{aligned} \tag{15b}$$

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):

$$\mathrm{Sof}_{it} = c_{21} + \beta_{11}\mathrm{Ope}_{it} + \beta_{12}\mathrm{Fun}_{it} + \beta_{13}X_{it} + v_{it}, \tag{16a}$$

$$\begin{aligned}\mathrm{Sof}_{it} = {} & c_{12} + \alpha_{21}\mathrm{Ope}_{it} + \alpha_{22}\mathrm{Ope}_{it} \times \mathrm{Wdh}_i + \alpha_{23}\mathrm{Fun}_{it} \\ & + \alpha_{24}\mathrm{Fun}_{it} \times \mathrm{Wdh}_i + \alpha_{25}X_{it} + v_{it}.\end{aligned} \tag{16b}$$

Finally, this study examines the relationship between the dependent variable, credit risk (Ris_*it*), and the independent variable, production volume of soft information (Sof_*it*). Furthermore, the impact of soft information on bank credit risk is investigated by incorporating operational distance (Ope_*it*) and functional distance (Fun_*it*). The specific model specifications utilized in this study are presented as equations (17a) and (17b).

$$\begin{aligned}\mathrm{Ris}_{it} = {} & c_{31} + \gamma_{11}\mathrm{Sof}_{it} + \gamma_{12}\mathrm{Ope}_{it} + \gamma_{13}\mathrm{Fun}_{it} + \gamma_{14}X_{it} \\ & + v_{it},\end{aligned} \tag{17a}$$

$$\begin{aligned}\mathrm{Ris}_{it} = c_{32} &+ \gamma_{21}\mathrm{Ope}_{it} + \gamma_{22}\mathrm{Ope}_{it} \times \mathrm{Wdh}_i + \gamma_{23}\mathrm{Fun}_{it} \\ &+ \gamma_{24}\mathrm{Fun}_{it} \times \mathrm{Wdh}_i + \gamma_{25}\mathrm{Sof}_{it} \\ &+ \gamma_{26}\mathrm{Sof}_{it} \times \mathrm{Wdh}_i + \gamma_{27}X_{it} + v_{it}.\end{aligned} \tag{17b}$$

4.2 Variable Design

To minimize the influence of data volatility on regression outcomes and facilitate the comparison of variable coefficients with different scales, this study utilized a logarithmic transformation for all independent variables during the measurement process. However, it is important to note that the dependent variable, credit default rate, exhibits low values and volatility, and therefore, its original values were retained. A detailed description of the variable design can be found in Table 1. The data sources are Chinese commercial bank microdata from 2011 to 2022. The sample consists of five major banks and 12 joint-stock banks' panel data. No information is provided on variable construction.

4.3 Data Sources

This study selected the panel data of 5 major commercial banks and 12 joint-stock commercial banks in China from 2011 to 2022 as the research sample. The data for this study come 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 5 major state-owned banks and 12 joint-stock banks in China used to calculate the operational distance and functional distance of bank branches in 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 Xiaolu and Gang (2017). 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 Table 2.

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

Table 1: Variable declaration

Category	Symbol	Name	Definition
Dependent variable	Ris	Credit risk	Expressed as a percentage of nonperforming 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 nonmortgaged and pledged loans of each bank, the larger the $\ln \mathrm{Sof}$ value, the more soft information production
Independent variable	$\ln \mathrm{Ope}$	Operating distance	Expressed by the natural logarithm of the operating distance Ope calculated by formula (17).The larger the $\ln \mathrm{Ope}$ 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.
	$\ln \mathrm{Size}$	Bank size	Expressed by the natural logarithm of the total assets of each bank (10 billion units), the larger the $\ln \mathrm{Size}$, 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

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

is a significant difference in each indicator within the sample statistical interval. Therefore, the use of panel data in this article can make a more objective empirical analysis of the issues studied.

5 Empirical Analysis

This study applies a mediating effect model to empirically analyze the theoretical proposition proposed in the third section. Recognizing the potential presence of path dependence in the bank's credit risk indicator (Ris) and soft information indicator (lnSof), the study incorporates the lagged value of the dependent variable in the explanatory variable to control for the influence of historical factors on the current period's dependent variable. However, to address endogeneity issues associated with including the lagged term of the dependent variable in the independent variable, the study employs the generalized method of moments (GMM) estimation for regression analysis of the mediating effect econometric equation, aiming to obtain more accurate and unbiased results. The GMM estimation method includes two forms: differential generalized method of moments (Diff-GMMs) and system generalized method of moments (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 the 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 study employs GMM to address endogeneity. System GMM is chosen over differential GMM to effectively handle weak instruments and improve efficiency, ensuring appropriate technique selection. In our study, we employ the GMM to mitigate endogeneity concerns arising from the inclusion of lagged dependent variables as explanatory variables. By utilizing instrumental variables, the GMM method facilitates consistent and efficient estimation, thereby enhancing the validity of our findings. We specifically choose the system GMM approach over differential GMM due to its capacity to effectively handle weak instrumental variables and improve estimation efficiency. This deliberate selection ensures that the adoption of the GMM method is grounded in methodological considerations rather than arbitrary choice. Regarding the selection between fixed effects (FE) and random effects (RE), we justify our preference for FE estimation. We underscore that FE estimation allows us to account for unobservable time-invariant heterogeneity across banks, a crucial aspect in our study. By incorporating FE, we effectively address potential omitted variable bias originating from unobserved factors that may impact both the explanatory variables and the dependent variables.

The use of the GMM method for regression requires setting the predetermined 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 the approach in the literature, 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 the robustness test, this article also gives the regression results of fixed effect instrumental variable regression (FE_IV) and Diff-GMM. If the regression results of the three methods are relatively consistent, it indicates that the regression results in this article are robust.

The existing literature in the field of banking and finance has explored several important aspects related to bank stability, risk governance, and the impact of financial technology (FinTech) on financial stability. This literature review will discuss three relevant studies that contribute to our understanding of these topics. Nguyen (2022a) investigates the relationship between audit committee structure, institutional quality, and bank stability in ASEAN countries. The study finds that a strong audit committee and higher institutional quality are associated with enhanced bank stability. The findings highlight the importance of effective governance mechanisms in mitigating risks and promoting financial stability in the banking sector. In another study by Nguyen (2022b), the determinants of bank risk governance structure are examined through a cross-country analysis. The research identifies various factors that influence the choice of risk governance structures in different countries. The study emphasizes the significance of regulatory frameworks, legal systems, and market characteristics in shaping risk governance practices in banks.

The impact of FinTech development on financial stability in emerging markets is explored by Nguyen (2022c). The study investigates the role of market discipline in moderating the relationship between FinTech development and financial stability. The findings suggest that a well-functioning market discipline mechanism can mitigate the potential risks associated with the rapid growth of FinTech and contribute to overall financial stability in emerging markets.

From the regression results in Tables 4–6, it can be seen that *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 Sys-GMM are consistent with the coefficient sign and significance of the FE_IV method and 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

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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Regression results on the impact of spatial layout of Bank Organizations on soft information

ln Sof	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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

variable is the bank's credit risk level Ris. The core explanatory variables are bank operating distance ln Ope and functional distance ln Fun.

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 5 major banks and the 12 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 pertaining to the impact of geographical factors on the production of soft information in banks (expressed as equations (16a) and (16b)) are provided in Table 4. The dependent variable used in the analysis is the indicator of soft information production, which is represented by its natural logarithm (lnSof). The key explanatory variables of interest include the logarithm of operational distance (lnOpe) and the logarithm of functional distance (lnFun).

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

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: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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 branches to 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

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
Five major banks	lnOpe	lnSof	Ris	−0.253	−0.999	0.253
	lnFun			−0.561		0.560

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 (Formulas 17a and 17b). The regression results are presented in Table 5. The dependent variable is the bank's credit risk level Ris. The core explanatory variable is the soft information production indicator $\ln \mathrm{Sof}$.

Table 5 presents the estimated coefficients and statistical significance for different specifications of the model using FE, difference generalized method of moments (Diff-GMM), and Sys-GMM techniques. The coefficients reveal the relationship between variables and credit risk. Notably, an increase in soft information is associated with a significant decrease in credit risk, as indicated by the coefficient for lnSof. Conversely, an increase in operational distance is linked to a significant increase in credit risk, as shown by the coefficient for lnOpe.

In the fifth column of Table 5, the regression coefficient of the intermediate variable soft information production index $\ln \mathrm{Sof}$ 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 $\ln \mathrm{Sof}$ in Table 4 has significant 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 $\ln \mathrm{Sof}$ is −1.205, which is significantly negative at the 5% test level. The coefficient of the cross-product term lnSof_Wdh between $\ln \mathrm{Sof}$ 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."

A study examined the management of skill certification in online outsourcing platforms, specifically focusing on buyer-determined reverse auctions. The results provided insights into the dynamics of skill certification and its impact on online outsourcing platforms. Another investigation explored the implications of an accelerated green patent examination for innovation benefits, particularly in terms of private economic value and public environmental benefits. This study aimed to enhance understanding of the relationship between green patent examination and innovation outcomes. In addition, research delved into strategies for enhancing technological innovation efficiency in the medical manufacturing sector in China, utilizing a three-stage DEA model and corporate governance configurations. The study offered valuable insights into improving technological innovation Canfei and Hao (2013); Feng et al. (2017); Hongbo and Yunqi (2018); Jie et al., (2017); Zhonglin et al. (2004). Moreover, a study employed a dynamic network approach to analyze systemic risk in commodity futures markets, with a specific focus on the context of commodity futures. This research contributed to the understanding of systemic risk in financial markets. Another research proposed an intelligent investment strategy for stocks based on a support vector machine parameter optimization algorithm (He et al., 2023; Li et al., 2021; Nguyen, 2022a,b,c; Qiu et al., 2023; Xu et al., 2024). The study demonstrated the potential of machine learning techniques in financial analysis and decision-making. Furthermore, an innovative algorithmic approach was introduced for credit rating using an RBF neural network optimal segmentation algorithm. This study made a significant contribution to the field of credit rating. The influence of group identity on bidding behavior in a repeated lottery contest was investigated through the analysis of event-related potentials and electroencephalography oscillations.

This research shed light on the role of social factors in economic decision-making. Factors influencing multiteam digital creativity during the transition phase were explored through cross-validation analysis, providing valuable insights into the dynamics of digital creativity in a multiteam context. The relationship between fintech, financial constraints, and outward foreign direct investment (OFDI) in China was examined, revealing how fintech facilitates OFDI and mitigates financial constraints for Chinese firms. The study highlighted the role of fintech in promoting international investment. In addition, the influence of group membership on the hold-up problem was investigated using event-related potentials and oscillations, uncovering the neural mechanisms underlying the impact of group membership on economic decision-making (Chen et al., 2023; Hao et al., 2023; Li & Sun, 2021; Wang et al., 2023). Another study explored the trading behavior of individual investors and examined gender differences in tolerance of sex crimes, utilizing evidence from a natural experiment. This research deepened our understanding of the relationship between individual investors' trading behavior and social attitudes. The innovation effect of administrative hierarchy on intercity connection was studied, employing machine learning techniques to analyze twin cities. The research illuminated the role of administrative hierarchy in fostering innovation and collaboration between cities. Furthermore, a proposal was made to construct an agricultural information system based on the Internet of things, utilizing a deep belief network. This study showcased the potential of deep learning techniques in developing advanced agricultural information systems. Finally, a deep neural network-based decision method was developed for financial risk prediction in the carbon trading market, offering a novel approach to assessing financial risk in this context (Gao et al., 2023; Hao et al., 2023; Luo et al., 2022, 2023). Recent research in economics has yielded significant findings across various areas. Studies on knowledge spillovers in Chinese mega-economic zones, the relationship between oil prices and exchange rates in South Asia, the impact of financial literacy on economic growth in Eastern Europe, and the effectiveness of different childcare policies have provided valuable insights. These findings contribute to our understanding of knowledge diffusion, the complexities of oil price dynamics, the importance of financial literacy, and the need for diverse policy approaches. Ultimately, they inform decision-making and policy formulation in a wide range of economic contexts (Gao et al., 2022; Huang et al., 2022; Luo et al., 2023; Osuna, 2021; Pașa et al., 2022).

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.

6 Conclusion and Suggestion

6.1 Conclusion

The research article acknowledges various limitations of the study. First, the utilization of microdata obtained from Chinese commercial banks raises concerns regarding the availability and quality of the data, as its accuracy and completeness have the potential to influence the study's findings. Second, the study's focus on Chinese commercial banks restricts the generalizability of the findings to other banking systems or countries, as differing regulatory frameworks, market conditions, and cultural factors may impact the relationship between spatial organizational structure and credit risk in alternative contexts. Third, despite the utilization of econometric techniques, the presence of endogeneity issues remains a possibility, which may be attributed to unobserved factors or reverse causality, potentially affecting the estimated coefficients. Finally, the theoretical model and empirical analysis may oversimplify the intricate dynamics involved in credit risk and spatial organizational structure, thereby neglecting other pertinent factors and mechanisms that could influence the investigated relationship. The article recommends several future directions, including conducting cross-country analysis to offer a broader perspective and identify commonalities or distinctions across diverse banking systems. Furthermore, longitudinal analysis is advised to examine the evolving relationship between spatial organizational structure and credit risk over time, while qualitative research methods can provide deeper insights into the underlying mechanisms. In addition, exploring the efficacy of specific policy interventions intended to mitigate credit risk associated with spatial organizational structure could offer valuable guidance for policymakers and industry practitioners.

With the advancements in information and communication technology, geographical constraints on financial activities are diminishing. The spatial arrangement of hierarchical institutions within China's banking industry is also undergoing significant changes. However, despite scientific and technological progress and financial innovation, the reduction of information asymmetry between parties involved in financial transactions is not guaranteed. The exchange of soft information between banks and enterprises continues to be influenced by geographical factors. Drawing on the research findings of Shelomentsev et al. (2021) [35], this study recognizes the close connection between information exchange and credit risk control in the banking sector. Therefore, investigating the impact and pathways of spatial organization in banking institutions on credit risk is of great importance for the ongoing transformation of China's commercial banking industry. In light of this, this study conducts a theoretical analysis of the relationship between the spatial layout of banking organizations, soft information production, and credit risk from the perspective of information asymmetry. Furthermore, an empirical analysis is performed using a mediating effect model. The study's findings are as follows:

(1) The spatial organization of bank structures has an influence on credit risk, with greater operational and functional distances associated with higher levels of credit risk.
(2) Soft information acts as a mediating factor in the relationship between geographic factors and credit risk. Banks with larger operational and functional distances face challenges in collecting and processing soft information from enterprises, resulting in increased credit risk for commercial banks.
(3) The negative impact of functional distance on soft information production is particularly pronounced in Chinese commercial banks. The influence of operational distance on soft information collection does not exhibit significant heterogeneity among different types of commercial banks.

The findings of this study have significant economic and financial implications. First, the study emphasizes the importance of considering the spatial layout of banking institutions when evaluating credit risk. Higher operational and functional distances between banks are associated with increased credit risk, indicating the challenges faced by geographically dispersed banks in effectively managing risk. To address this, banks should focus on improving communication channels, information-sharing systems, and risk management practices to bridge spatial gaps. Second, the study underscores the critical role of soft information as a mediator between spatial factors and credit risk. Banks with larger operational and functional distances struggle to acquire and process soft information, leading to heightened credit risk. Enhancing information exchange mechanisms and utilizing advanced technologies can facilitate the collection, analysis, and utilization of soft information, thereby enhancing credit risk assessment and management. Finally, the study reveals the detrimental impact of functional distance on soft information production in Chinese commercial banks, highlighting the importance of organizational structure and cross-functional coordination in generating and utilizing soft information. Banks should optimize their internal processes and promote collaboration to facilitate soft information production, enabling more accurate credit risk assessment and informed lending decisions. These implications emphasize the significance of spatial organization, soft information exchange, and effective risk management practices for financial institutions.

6.2 Suggestion

Based on the research conclusions of this article, the following suggestions are proposed. First, the management of commercial banks should pay attention to the role of bank branches in 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 branches in 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 branches through 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 branches to collect soft information. They should attach importance to and encourage bank branches to 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.

Second, 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.

Third, 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 and 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 et al. (2013) 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.

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