Study on the Influence of Digital Inclusive Finance on the Credit Risk of Commercial Banks in China

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Abstract. Digital Inclusive Finance (DIF) has improved the convenience and efficiency of financial services, reduced banks' operating costs, and promoted the stability of commercial banks. This study aims to explore the impact of DIF on credit risk in Chinese commercial banks. An empirical analysis is conducted using a fixed effects model. The relationship between the development of DIF and commercial bank credit risk presents an inverted U shape. Initially, the expansion of Internet finance and financial technology companies led to customer loss for commercial banks, reducing traditional business profits and prompting banks to lower loan approval standards to expand their business scale, thereby increasing credit risk. As digital inclusive finance matures and regulatory mechanisms improve, commercial banks collaborate with financial technology companies to form cooperative models that jointly reduce credit risk. Furthermore, the impact of DIF is not significant for nationwide banks and rural commercial banks but has a significant influence on state-owned large banks and urban commercial banks. This study provides valuable references for Chinese commercial banks in promoting DIF, emphasizing the importance of maintaining robust risk management while innovating, and offering theoretical support for financial policymakers.

Keywords: Digital Inclusive Finance, Commercial Banks, Credit Risk.

1 Introduction

In the current financial environment, the rise of Digital Inclusive Finance (DIF) has significantly impacted the business models and risk management strategies of commercial banks [1,2]. The rapid development of financial technology has reshaped traditional financial services, especially in providing financial products to low-income groups and small to medium-sized enterprises (SMEs). This transformation presents both challenges and opportunities for commercial banks. On one hand, financial technology companies have aggressively impacted traditional banking operations by offering low-cost and efficient services. DIF has expanded the reach and depth of services, creating new business opportunities for the banking industry. The Chinese government has emphasized cross-sector collaboration and coordinated innovation be

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tween technology and finance in its 14th Five-Year Plan, guiding commercial banks to optimize services and reduce risks through technological integration [3,4].

DIF plays a vital role for commercial banks, which are also updating their risk management approaches due to its development. At this stage, commercial banks can more easily access customers' credit information and conduct real-time monitoring through digital platforms, thereby reducing credit risk [5,6]. Additionally, DIF enhances the convenience and efficiency of financial services, reduces banks' operating costs, and further promotes the stability of commercial banks.

Based on this context, this study investigates the impact of DIF on credit risk in commercial banks, analyzing its effects from the perspectives of breadth of coverage and depth of usage. The paper collects and analyzes relevant data from major commercial banks in China and constructs a mathematical model to detail the relationship between DIF and credit risk.

2 Research Hypotheses

2.1 Relationship Hypothesis between DIF and Credit Risk of Commercial Banks

The extensive use of digital technologies in inclusive finance has profoundly transformed the competitive dynamics within the financial sector. Traditionally, banks dominated the market, particularly in credit operations. However, with the rise of non-bank financial institutions such as Alibaba and JD.com, which utilize digital technology, these institutions have started to dominate the market in areas such as payments, wealth management, and insurance. This has led to a disruption in traditional banking operations, a reduction in credit scales, and compressed revenues, prompting banks to lower credit approval standards, resulting in a surge of high-risk investments and increased credit risk [7].

From a micro perspective, DIF helps alleviate financing constraints for enterprises by reducing costs and increasing access, thereby promoting financial stability. Nevertheless, as industry regulations improve, the government encourages banks to collaborate with non-bank institutions to share credit information and adopt new technologies to enhance service levels and optimize risk control processes [8]. This not only helps banks identify high-quality customers and reduce non-performing loan ratios but also aids banks in maintaining profitability amidst competition, thus reducing overall credit risk.

Based on the research information, this research suggests that the connection between DIF and the credit risk faced by banks is not simply linear. In the early stages when DIF was less mature, banks experienced increased credit risk as they competed with non-bank financial institutions. However, in the mature phase of DIF, industry regulations have improved, leading to a cooperative competitive relationship between banks and non-bank financial institutions, along with shared credit information, which reduces banks' credit risk.

Hypothesis 1: The relationship between DIF and credit risk in commercial banks exhibits an inverted U shape.

2.2 Heterogeneity Hypothesis of Commercial Bank Size

Commercial banks are primarily categorized into three kinds of banks. The significant differences in scale, target clientele, and development direction mean that the impact of DIF on them will vary. This applies to both the banks' management capabilities and their use of financial technology, resulting in different changes in credit risk.

State-owned large commercial banks primarily serve state-owned enterprises and large private companies that typically have government backing or market influence, thus enjoying policy support and strong resilience to risks. Their cooperation with these businesses is stable, resulting in lower credit risk. In contrast, other commercial banks mainly cater to SMEs and individuals [9]. These customer groups tend to have higher default risks and are sensitive to market interest rates, making them vulnerable to competition from non-bank financial institutions. Under the context of DIF, state-owned large commercial banks, with their substantial capital and early digital transformation, can effectively seize developmental opportunities [10]. Meanwhile, smaller commercial banks face greater development barriers and credit risks. Therefore, this study proposes the following hypothesis.

Hypothesis 2:The effect of DIF on credit risk differs among commercial banks of various sizes.

3 Analysis of the Impact of DIF on Credit Risk in China's Commercial Banks Based on Multiple Regression Models

3.1 Model Construction and Data Sources

During the data selection process, an analysis of different sizes of commercial banks was necessary. Due to the incomplete financial information available for certain commercial banks, data gaps were addressed using Stata to complete some sample data, forming a panel dataset. Forty-one commercial banks were selected for analysis, which includes 6 state-owned large banks, 9 nationwide joint-stock banks, 21 urban commercial banks, and 6 rural commercial banks. The sample data period spans from 2011 to 2020. Data for internal sample variables were sourced from iFinD, while macroeconomic variable data were obtained from the Wind Database. Data regarding the level of DIF development in the regions where the banks operate were obtained from the DIF Index Report released by Peking University.

3.2 Model Construction

According to the research hypotheses articulated above, this paper uses the DIF index as the independent variable to test its effect on commercial bank credit risk, with the model constructed as shown in Formula 1.

$$\mathrm{Z_{it}} = \mathrm{C} + \alpha_1 \mathrm{Z_{i(t-1)}} + \alpha_2 \mathrm{DIFI_{it}} + \alpha_3 \mathrm{DIFIN2_{it}} + \alpha_4 \mathrm{GDP_{it}} + \alpha_5 \mathrm{CPI_{it}} + \alpha_6 \mathrm{M2_t} + \alpha_7 \mathrm{ROA_{it}} + \alpha_8 \mathrm{CTI_{it}} + \alpha_9 \mathrm{LDR_{it}} + \delta_\mathrm{i} + \varepsilon_\mathrm{it} \tag{1}$$

In this formula, Z represents the lagged Z-value of commercial banks because credit risk may have legacy issues. Like loan-related behaviors, past actions can impact future outcomes, so the previous term has been included in the model to avoid endogeneity issues. The square of the DIF index is included to observe non-linear relationships. The constants and error terms are represented by α and ε, respectively. The fixed effect for individual commercial banks is represented by μ, and other variables are included as control variables, see Table 1. For explanatory variables across other dimensions, COV, USE, and DIG represent models derived from substituting DIFI with their respective alternatives.

Table 1. Variable declaration

variable's attribute	Variable name	variable symbol	measuring index
explained variable; variable being explained	Credit risk of commercial banks	Z	The Z value is the standard deviation of (return on assets + capital adequacy ratio) / rate of return on assets, and then the Z value is logarithmic and take the opposite number to adjust the Z value
explanatory variable; explaining variable	The Digital Financial Inclusion Index	DIFI	Digital FPI log
	Coverage breadth index	COV	The coverage breadth index is log 30
	The depth index was used	USE	The depth-exponential log number was used
	Digital degree index	DIG	Digital degree index is log log
Control variable (external macro)	macro-economy	GDP	The growth rate of the GDP
	level of consumption	CPI	consumer price index
	economic policy	M2	Growth in the broad sense of money supply
Control variable (within the bank)	profitability	ROA	Return on equity
	business efficiency	CTI	Cost-income ratio
	Liquidity level	LDR	Deposit and loan ratio

4 Results Analysis

As shown in Table 2, the regression analyses of the DIF index, coverage breadth index, and usage depth index yield positive coefficients for the explanatory variables across all four dimensions, while the coefficients for the squared variables are negative and significant at the 1% confidence level. The findings reveal an inverted U-shaped relationship between DIF and credit risk in commercial banks. This implies that during the initial phases of DIF's development, non-bank financial entities play a significant role, leveraging their product advantages and digital technologies, reduced the profits of commercial banks, leading them to invest in higher-risk projects to maintain financial balance, which in turn increased credit risk. Additionally, the early-stage shortcomings in credit information also contributed to heightened credit risk. However, as DIF has evolved positively, commercial banks have enhanced their capabilities in financial technology and digital information systems, thereby eliminating previous information gaps and allowing for more effective risk control. Collaboration with non-bank financial institutions also helps stabilize the financial market, gradually reducing credit risk for commercial banks. Hypothesis 1 has been verified through the analyses. This paper has implemented robustness checks by substituting the original Z-value with the ratio of non-performing loans as a representation of credit risk (see Table 3).

Table 2. Interpretation of result

	(1)	(2)	(3)	(4)
DIFI	0.8723			
	(4.0743)			
DIFIN2	-0.0841			
	(-3.9891)			
COV		0.4989		
		(3.0714)		
COVN2		-0.0493		
		(-2.9409)		
USE			0.5874	
			(2.8521)	
USEN2			-0.0539	
			(-2.6975)	
DIG				0.8132
				(4.8471)
DIGN2				-0.0756
				(-4.8340)
L.Z	0.2812	0.2846	0.2838	0.2976
	(8.6040)	(8.6334)	(8.5864)	(9.1881)
GDP	-0.0015	0.0002	0.0008	0.0019
	(-0.5262)	(0.0535)	(0.2788)	(0.9209)
CIP	-0.0009	-0.0031	-0.0050	-0.0032
	(-0.1637)	(-0.5728)	(-0.9470)	(-0.5782)
M2	0.0056	0.0068	0.0082	0.0092
	(2.3533)	(2.7569)	(2.8726)	(5.9259)
ROA	-0.0273	-0.0274	-0.0264	-0.0280

	(-19.4775)	(-19.1608)	(-18.8588)	(-20.2115)
CTI	0.0004	0.0004	0.0008	-0.0004
	(0.4337)	(0.4063)	(0.8326)	(-0.4530)
LDR	-0.0001	-0.0002	-0.0003	-0.0002
	(-0.1467)	(-0.4163)	(-0.6448)	(-0.4811)
_cons	-3.3980	-2.1868	-2.3784	-3.0701
	(-3.8920)	(-2.9670)	(-2.8462)	(-3.9428)
N	369	369	369	369
r2_a	0.8510	0.8481	0.8477	0.8537

From the test results (1), (2), (3), and (4), the relationship between the explanatory and dependent variables remains inverted U-shaped. The regressions for COVN2 about DIG and DIGN2 are not significant, which may be due to the Z-value being a comprehensive credit risk index that is more sensitive to changes in the breadth of coverage in it. In contrast, the ratio of non-performing loans—being a more direct credit quality indicator—may not be as sensitive to the non-linear influences of DIF's breadth. Likewise, the impact of the digitalization level of financial modes on banks' non-performing loan ratios seems limited. This may also stem from insufficient comprehensive data on selected banks and fewer choices for banks with high digitalization. The overall explanatory variable and dependent variable still maintain an inverted U shape, confirming the validity of Hypothesis 1 through the robustness analysis.

Table 3. Robustness test

	(1) NPL	(2) NPL	(3) NPL	(4) NPL
DIFI	2.6552			
	(2.4005)			
DIFIN2	-0.2371			
	(-2.1766)			
COV		1.5511		
		(1.8676)		
COVN2		-0.1324		
		(-1.5446)		
USE			2.9172	
			(2.7646)	
USEN2			-0.2634	
			(-2.5734)	
DIG				0.8339
				(0.9376)
DIGN2				-0.0703
				(-0.8468)
L.NPL	0.1310	0.1313	0.1229	0.1262
	(5.4327)	(5.4505)	(5.1061)	(5.1626)
GDP	0.0585	0.0659	0.0504	0.0615
	(4.0419)	(4.4754)	(3.2073)	(5.4971)

CIP	-0.1693	-0.1720	-0.1957	-0.1854
	(-5.9680)	(-6.1518)	(-7.1462)	(-6.2999)
M2	0.0305	0.0369	0.0248	0.0288
	(2.5182)	(2.9378)	(1.7175)	(3.5782)
ROA	-0.0662	-0.0654	-0.0658	-0.0703
	(-10.1898)	(-9.9294)	(-10.2042)	(-10.7962)
CTI	-0.0097	-0.0089	-0.0103	-0.0116
	(-2.0325)	(-1.8261)	(-2.1975)	(-2.3915)
LDR	0.0071	0.0072	0.0071	0.0058
	(3.4677)	(3.5295)	(3.5116)	(2.8507)
_cons	11.1414	14.1543	13.3344	17.9466
	(2.4665)	(3.7524)	(3.1272)	(4.3238)
N	369	369	369	369
r2_a	0.5921	0.5931	0.5892	0.5798

According to Table 3 formula (1), the banks are grouped according to their size, namely, large state-owned banks, national joint-stock banks, urban commercial banks and rural commercial banks in turn. Regardless of any bank, the explanatory variables are positive, the square of explanatory variables are negative, the results are inverted U trend, and significance can be found that national Banks and rural Banks are not significant, the national Banks should be these Banks usually have strong business competitiveness and extensive business scope, but they are invested in digital transformation and innovation aspect investment may be insufficient, leading to digital pratt & whitney financial direct impact on its credit risk is not obvious. However, rural commercial banks, these banks mainly serve rural areas, may be due to the limitations of infrastructure and technology application, and the penetration and effect of DIF is inferior to that of urban areas, so the impact shown in the data is small. Therefore, the national banks and rural banks are not significant. Large banks and urban commercial banks are more prominent, while large state-owned banks usually have strong financial strength and government background, which allows them to make large investments in technology and infrastructure. This investment can accelerate the digitization and automation of banking services, effectively reduce operational risk, and improve service efficiency. Urban commercial banks, although not as large as big state-owned banks, are usually located in economically developed urban areas where customers are more accustomed to using digital financial services. Therefore, city commercial banks can quickly adapt to the market demand and launch adaptable financial products, so their performance is more significant. Consequently, Hypothesis 2 validates that the influence of DIF on credit risk differs among commercial banks of varying sizes.

Through empirical analysis, this chapter demonstrates that the association between DIF and the credit risk of commercial banks exhibits an inverted U-shaped trend, confirming that the effects of DIF on credit risk vary by bank size. Specifically, DIF does not significantly affect nationwide joint-stock banks and rural commercial banks, while it has a notable impact on large state-owned banks and urban commercial banks. Finally, this conclusion is supported by substituting the non-performing loan ratio as the explanatory variable, as shown in table 4.

Table 4. Scale-wise heterogeneity test

	(1) State-owned large z	(2) nationwide z	(3) City business z	(4) Rural business z
L. Z	0.274	0.317	0.263	0.296
	(0.117)	(-0.074)	(-0.045)	(0.113)
DIFI	1. 594	0. 763	0.748	0.878
	(0. 721)	(-1.063)	-0.335)	(-0.618)
DIFIN2	-0.149	-0.085	-0.073	-0.084
	(-0.069)	(0.101)	(-0.033)	(-0.060)
GDP	-0. 001	-0. 003	-0.002	-0.005
	(-0.004)	(-0.009)	(-0.005)	(-0.008)
CIP	0. 010	-0.011	0.003	-0.008
	(0.010)	(0.017)	(0.009)	(0.016)
M2	0.005	0.006	0.005	0.009
	(0.004)	(0.008)	(0.004)	(0.006)
ROA	-0. 028	-0.031	-0. 028	-0.030
	(0.004)	(0.005)	(0.002)	(0.005)
CTI	0. 005	-0.002	0.001	-0.004
	(0.003)	(0.003)	(0.001)	(0.002)
LDR	-0.000	0.001	0.000	-0.003
	(0.002)	-0.002	-0.001	-0.002
_cons	-6.646	-1.397	-3.506	-2.580
	(2.605)	(3.882)	(1.389)	(2. 596)
N	54.000	81.000	189.000	54.000
r2	0.935	0.837	0.856	0.853

5 Discussion

First, considering the inverted U-shaped relationship between the development of DIF and credit risk for commercial banks, the government should reinforce risk regulation in the early stages of promoting DIF. For internet finance and fintech companies, strict business regulations should be established to prevent chaotic expansion that could adversely affect commercial banks. At the same time, encouraging cooperation between commercial banks and fintech companies in the development of risk prevention technologies can facilitate shared risk management.

Secondly, given the heterogeneous effects on different types of commercial banks, differentiated policies should be implemented. Nationwide joint-stock banks and rural commercial banks should increase their investments in digital transformation and innovation to enhance service capabilities and risk control levels. State-owned large banks should continue leveraging their capital strength and policy advantages to accelerate digital transformation. Urban commercial banks should further expand digital financial services to meet market demands while also strengthening their risk management systems.

Lastly, it is essential to improve the legal and regulatory framework surrounding DIF, clarifying the rights and responsibilities of all parties involved to regulate market practices effectively. Additionally, enhancing consumer rights protection and increasing consumers' awareness and trust in DIF is crucial. Through collaborative efforts among governments, financial institutions, technology companies, and all sectors of society, the sustainable and healthy development of DIF can be promoted, thereby providing strong support for risk management in Chinese commercial banks.

6 Conclusion

First, the impact of DIF on credit risk in commercial banks is shown to be inverted U-shaped. In the initial stages of the expansion of internet finance and fintech companies, commercial banks experienced customer attrition, which decreased traditional business profits and led banks to lower loan approval standards to expand their business, ultimately increasing credit risk. As DIF matures and market regulatory mechanisms improve, banks begin to establish cooperative relationships with fintech companies, forming partnerships to jointly mitigate credit risk.

Secondly, heterogeneity tests indicate that the influence of DIF on credit risk is not significant for nationwide joint-stock banks and rural commercial banks, but it has a significant impact on state-owned large banks and urban commercial banks. Nationwide joint-stock banks may be underinvesting in digital transformation and innovation, while rural commercial banks face infrastructure and technology constraints, leading to minimal effects from DIF. With their ample capital strength and government support, state-owned large banks can accelerate their digital transformations and enhance service efficiency. Urban commercial banks, catering to customers who are more accustomed to digital financial services, can swiftly adapt to market demands, thus experiencing more pronounced effects from DIF.

Although this paper explores the multifaceted impacts of DIF on credit risk, certain limitations remain. First, the study predominantly relies on quantitative data, potentially overlooking qualitative factors such as customer psychology and behavioral changes. Second, the limited time span of the data might fail to comprehensively represent the rapidly evolving financial environment. Additionally, the research primarily focuses on the situation in China, lacking comparative analyses with other countries or regions, which may affect the generalizability and external validity of the results. Lastly, due to time constraints, the influence of some relevant variables could not be incorporated into the analysis.

References

1. He, D.X., Miao, W.L.: Financial exclusion, financial inclusion, and the construction of china's inclusive financial system, Finance and Trade Economy (03), 5-16 (2015).
2. Chen Chen, Wu Di. Innovation in Inclusive Financial Services from the Perspective of Regional Coordination [J]. Contemporary Finance & Economics, 2023 (07): 49 - 60.
3. Guo Feng, Wang Yaopei. Fintech Facilitating the Development of Inclusive Finance: Achievements, Challenges and Prospects [J]. Journal of Financial Research, 2023 (01): 1-17.
4. Xing, Y.: Inclusive finance: a basic theoretical framework. International Financial Research (09), 21-37 (2016)
5. Bei Duoguang, Zhang Rui. The New Logic of the Development of Inclusive Finance in China [J]. Finance & Trade Economics, 2022 (09): 5-19.
6. Zhao, T.: A brief analysis of the basic characteristics and prevention strategies of credit risk in China's SMEs. Times Finance (1), 112-113 (2015).
7. Li Jianwei, Liu Chang. The Path of Reshaping the Inclusive Finance Ecosystem under Digital Transformation [J]. Studies of International Finance, 2024 (03): 34 - 45.
8. Xu, H.F., Liu, X.H., Zheng, X.P.: Research on risk status assessment of small and medium-sized commercial banks in china—a case study of listed urban commercial banks. Financial Theory and Practice (8), 62-70 (2019).
9. Zhang, J.H., Wang, P.: Banking risks, loan scale, and legal protection levels. Economic Research **47**(5), 18-30+70 (2012).
10. Yu, B., Wu, H.H.: Banking competition, rising interbank leverage, and commercial bank credit risk. Economic Research **46**(2), 36-51 (2022).