Impact Of Digital Inclusive Finance Development on The Resistance to Credit Risk in The Financial Industry

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Abstract. The rise of digital inclusive finance has thrown a real curveball at the traditional, bank-dominated financial system. The proliferation of digital inclusive finance has precipitated a paradigm shift within the conventional banking sector. This study investigates the influence of digital inclusive finance expansion on the mitigation of credit risk within the financial industry. The research employs panel data from 29 Chinese provinces spanning 2011 to 2022 and identifies the critical threshold. The findings indicate that the advancement of digital inclusive finance curtails credit risk, a conclusion substantiated by robustness tests. Furthermore, the efficacy of digital inclusive finance in mitigating credit risk is contingent upon regional financial development levels. The impact of digital inclusive finance on credit risk demonstrates heterogeneity across regions. Consequently, the study advocates for the strategic promotion of digital inclusive finance, the customization of financial strategies to regional contexts, and the optimization of resource allocation.

Keywords: Digital inclusive finance, Credit risk, non-performing loan ratio.

1. Introduction

Digital inclusive finance has significantly enhanced financial service accessibility for small and micro-enterprises and rural populations. By Q2 2024, outstanding loans to small and micro-enterprises from banking institutions surged to 78 trillion yuan, a 233% increase from the end of 2018. Concurrently, China's mobile payment penetration reached 86%, reflecting the expansion of digital inclusive finance. This evolution presents both opportunities and challenges. Digital inclusive finance restructures traditional banking operations, fostering innovative financing methods and reducing industry entry barriers. Leveraging internet and high technologies, online financial platforms have expanded service boundaries and user coverage. Financial institutions are actively exploring inclusive finance, collaborating with third-party platforms to broaden service scope to include underserved segments, thereby mitigating overall risk through diversification[1].

The proliferation of digital inclusive finance, while promising, introduces potential risks to the financial market. Specifically, digital inclusive finance can erode bank franchise value by compressing net interest margins via credit rationing and financial disintermediation[2]. Furthermore, digital technology accelerates the transmission of financial risk. Although extant literature offers theoretical support for the relationship between digital finance and regional financial stability, several gaps remain: (1) Direct research on how digital inclusive finance affects commercial bank credit risk is relatively limited, with most studies focus on the broader impact of fintech on commercial bank systemic risk[3-5]. (2) Existing literature often examines this relationship from the perspectives of banking systems and enterprises, while research from a regional perspective is notably lacking. Maintaining regional financial stability is paramount from a regulatory perspective. To assist regulatory bodies in comprehensively understanding the relationship between the development of digital inclusive finance and the credit stability of the financial industry within a region, this research is both urgent and necessary.

The marginal contribution of this paper is reflected in: (1) In terms of research perspective, innovatively adding the regional financial development level as a threshold variable, providing a new research perspective for studying the relationship between the development of digital inclusive finance and the credit stability of the regional financial industry. (2) In terms of research content, providing empirical evidence of the regional differences in how digital inclusive finance affects credit risk, enriching the discussion on digital inclusive finance and regional financial credit risk.

2. Theoretical Mechanisms and Research Hypotheses

2.1. Impact of Localized Digital Inclusive Finance on Financial Sector Credit Risk Mitigation

Based on the financial deepening theory of McKinnon & Shaw, advancements in the financial system — including the enhancement of financial markets and the expansion of digital inclusive finance — can enhance the efficiency of transforming savings into investment. By mitigating information asymmetry, these developments contribute to lowering corporate financing costs and minimizing the risk of debt defaults. The multi-layered nature of regional financial markets can diversify risks through diversified tools. For example, a developed bond market can mitigate the credit risk of excessive concentration in the banking system. Ouma SO and Ndede F [6] believe that digital inclusive finance maintains a stable correlation with banks' non-performing loan ratios. They suggest that the advancement of digital inclusive finance encourages commercial banks to undergo internal business transformations and strengthens their ability to withstand risks, ultimately leading to a reduction in credit risk. Jia Ruan and Ruishi Jiang [7] used commercial bank data from 2011 to 2021 and found that digital inclusive finance significantly lowers the credit risk faced by commercial banks. Futhermore, the risk-mitigating effect is more pronounced for national banks compared to regional ones and banks with higher profitability benefit more from the credit risk reduction brought about by digital inclusive finance. Tan Kaji et al. [8] found that digital inclusive finance helps commercial banks reduce risks by increasing credit supply through technology spillover effects and economic spillover effects, and reducing credit supply through crowding-out effects, thereby improving return on assets, reducing book leverage, and enhancing capital liquidity.

Therefore, Hypothesis 1 is proposed: The growth of regional digital inclusive finance will significantly lower credit risk across the financial sector.

2.2. The Threshold Effect of Financial Development on Digital Inclusive Finance and Regional Financial Risk

Building upon the research of Rioja, F. [9], Law, S. H. [10], it is posited that the risk-mitigating effects of financial development on financial risk are contingent upon a certain threshold. Specifically, in regions characterized by advanced financial development, the extensive coverage of credit data and the maturity of regulatory frameworks mitigate the risks associated with disorderly competition, thereby fostering a positive synergy with digital inclusive finance. Conversely, in financially underdeveloped regions, digital inclusive finance and conventional banking may find themselves locked in a competitive struggle, pushing banks toward riskier borrowers and potentially amplifying credit vulnerabilities. This implies that regional financial maturity can alter digital inclusive finance's effect on credit risk in a non-linear fashion—its influence may change dramatically once local financial systems cross a pivotal development threshold.

Therefore, Hypothesis 2 is proposed: The relationship between digital inclusive finance and regional financial risk hinges on a threshold tied to the region's financial development level.

3. Research Design

3.1. Data Sources

This research leverages a balanced panel dataset covering 29 Chinese provinces between 2011 and 2022, with remote regions excluded owing to substantial data limitations. The primary data source is the CSMAR database. Specifically, digital financial development data is sourced from the provincial-level Digital Inclusive Finance Index provided by the Peking University Digital Finance Research

Center. Missing values in certain data points were addressed using interpolation methods. The data processing software utilized in this study is Stata 18.0.

3.2. Variable Definitions

3.2.1 Explained Variable: Non-Performing Loan Ratio (NPL Ratio)

The NPL ratio—a figure derived from the proportion of subprime, questionably paid, and defaulted loans relative to the total loan portfolio—acts as a vital gauge for the credit risk that financial institutions face.. These loan categories are characterized by borrowers' inability to meet repayment terms, potentially resulting in bank losses. Consequently, the NPL ratio directly quantifies credit risk and reflects the risk profile of commercial bank credit, functioning as a core metric for asset safety assessment. An elevated NPL ratio signifies increased credit risk within the financial sector. Therefore, the NPL ratio is employed as a proxy variable to measure regional credit risk levels.

3.2.2 Explanatory Variable: Digital Inclusive Finance Index

This research employs the Digital Inclusive Finance Index, developed by Peking University's Digital Finance Research Center, as its primary independent variable. Widely cited in scholarly literature, this benchmark has become the gold standard for measuring regional progress in digital financial inclusion. Given its established credibility within academic circles, the study adopts this index as a reliable proxy for assessing local advancements in digital inclusive finance.

3.2.3 Threshold Variable: Regional Financial Development Level

This research utilizes the proportion of outstanding bank loans relative to GDP as an indicator of a region's financial advancement. By examining this metric, how financial leverage stimulates economic expansion can be effectively gauged, offering insights into how effectively monetary resources translate into productive economic activity.

3.2.4 Control Variables

Beyond the financial development indicators analyzed in this study, several additional factors likely affect regional financial industry risk need to be incorporated into the model as control variables. Drawing on the research of Dabla-Norris E [11], Ruan Liyun [12], Cocco J F [13], Lin H [14], and others, we select financial industry size, per capita GDP, social consumption level, per capita disposable income of rural residents, tax burden level, industrial structure, and urbanization rate as control variables.

Table 1 provides detailed definitions of the variables employed in this study.

Table.1. Variable Definition Table

Type	Variable	Symbol	Description
Explained Variable	Non-Performing Loan Ratio	npl	Non-Performing Loan Balance / Total Loan Balance
Explanatory Variable	Digital Inclusive Finance Index	dig	Peking University Digital Inclusive Finance Index
Threshold Variable	Regional Financial Development Level	dev	Loan Balance of Financial Institutions / GDP
Control Variables	Financial Industry Scale	finsize	Value Added of Financial Industry / GDP
	Per Capita GDP	rjgdp	GDP / Population
	Social Consumption Level	consumption	Total Retail Sales of Consumer Goods / GDP
	Per Capita Disposable Income of Rural Residents	rural_income	Yuan
	Tax Burden Level	tax	Tax Revenue / GDP
	Industrial Structure	structural	Tertiary Industry Output /Secondary Industry Output
	Urbanization Rate	urbanrate	Urban Population/Total Population

The descriptive statistics of the relevant variables are shown in Table 2.

Table.2. Descriptive Statistical Table

Variable	Symbol	Sample Size	Mean	Standard Deviation	Minimum Value	Maximum Value
Non-Performing Loan Ratio	npl	348	0.0018	0.0014	0.000350	0.0119
Digital Inclusive Finance Index	dig	348	312.4	118.7	7.580	467.2
Financial Industry Scale	finsize	348	0.0730	0.0324	0.0265	0.196
Per Capita GDP	rjgdp	348	5.910	3.099	1.602	19.00
Social Consumption Level	consumption	348	0.396	0.0613	0.213	0.610
Per Capita Disposable Income of Rural Residents	rural_income	348	1.406	0.638	0.428	3.973
Tax Burden Level	tax	348	0.0836	0.0290	0.0355	0.188
Industrial Structure	structural	348	1.363	0.755	0.527	5.244
Urbanization Rate	urbanrate	348	0.605	0.121	0.350	0.896
Regional Financial Development Level	dev	348	1.514	0.449	0.671	2.774

3.3. Model Construction

3.3.1 Baseline Regression Model

To delve into the tangible effects of regional digital inclusive finance growth on the resilience of provincial financial sectors against credit risk, this study utilizes a comprehensive panel dataset encompassing 29 Chinese provinces over the period of 2011 to 2022. A two-way fixed-effects model is constructed as the baseline regression model, which is specified as follows:

$$npl_{it} = \alpha_0 + \alpha_1 dig_{it} + \varphi_j controls_{jit} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

In this context, the subscripts i and t denote province and year, respectively. The dependent variable, denoted as npl_{it}, represents the non-performing loan ratio for province i in year t. The primary explanatory variable, dig_{it}, quantifies the digital inclusive finance development level for province i in year t. Control variables, collectively termed $controls$, encompass financial industry size $finsize$, per capita real GDP $rjgdp$, social consumption levels $consumption$, per capita disposable income of rural residents $rural\_income$, tax burden levels tax, industrial structure $structural$, and urbanization rate $urbanrate$. Furthermore, μ_i, θ_t, and ε_{it} represent province-fixed effects, time-fixed effects, and the random error term, respectively.

3.3.2 Threshold Effect Model

A panel threshold model is developed to explore the non-linear relationship between digital inclusive finance and credit risk in regional financial sectors. If only one threshold exists, a single threshold model is employed, as formulated below:

$$npl_{it} = \alpha_0 + \alpha_1 dig_{it} I(dev_{it} \le q) + \alpha_2 dig_{it} I(dev_{it} > q) + \varphi_j controls_{jit} + \mu_i + \theta_t + \varepsilon_{it} \tag{2}$$

Where $I(\cdot)$ denotes the indicator function; *dev* represents the threshold variable, with one threshold variable in this study, namely, the level of regional financial development; α_1 captures the influence of digital inclusive finance on regional financial sector credit risk when $Q \le q$, and α_2 reflects its impact when $Q > q$. A threshold effect exists when $\alpha_1 \neq \alpha_2$; otherwise, it does not.

4. Empirical Analysis

4.1. Baseline Regression Analysis

As shown in Table 3, after accounting for control variables, the development of digital inclusive finance exhibits a significantly negative effect on the credit risk undertaken by the regional financial sector. This finding suggests that digital inclusive finance plays a substantial role in mitigating local financial industry credit risk, thereby providing support for Research Hypothesis 1.

Table.3. Baseline Regression Results

	(1)	(2)	(3)
VARIABLES	npl	npl	npl
dig	-0.000**	-0.000*	-0.001*
	(-2.65)	(-1.90)	(-1.83)
Controls	NO	YES	YES
Constant	0.002***	0.007	0.065
	(5.97)	(1.59)	(0.12)
Observations	348	348	348
Number of ids	29	29	29
Company FE	YES	YES	YES
Year FE	YES	YES	YES

4.2. Robustness Tests

4.2.1 Lagged Explanatory Variables

To account for the potential lagged effects of digital inclusive finance, the model incorporates the lagged term of digital inclusive finance development. The explanatory variables are lagged by one period, and the model is subsequently re-estimated. As reported in Model (3) of Table 3, the coefficient of digital inclusive finance development on regional financial credit risk remains significantly negative. This result indicates that digital inclusive finance consistently enhances the region's capacity to withstand credit risk, thereby confirming the robustness of the baseline regression findings.

4.2.2 Endogeneity Test

To mitigate estimation errors caused by endogeneity issues, we further employ the two-stage least squares (2SLS) method for endogeneity treatment. We select the one-period lagged digital inclusive finance index as the instrumental variable. The instrumental variable regression results are shown in Table 4. In the first-stage regression results, the instrumental variable is significantly positively correlated with the impact of digital inclusive finance at the 1% level, satisfying the first-stage requirement of the 2SLS method. In the second-stage regression, the correlation coefficient between the instrumental variable and regional financial risk is 0.000, which is significantly positive at the 10% level.

Table.4. Endogeneity Test Results

	(1)	(2)
	First Stage	Second Stage
VARIABLES	dig	npl
L.dig	0.373***	0.000*
	(8.0598)	(1.7028)
Controls	YES	YES
Observations	348	348
Number of ids	29	29
Kleibergen-Paap rk LM statistic	Chi-sq (1) =40.88	P-val=0.0000
Cragg-Donald Wald F statistic	75.68	
Kleibergen-Paap Wald rk F statistic	64.96	

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3. Threshold Effect Test

The threshold effect was initially tested, with the results reported in Table 5. The analysis indicates that the regional financial development level successfully passes the single threshold test, while the double and triple threshold tests are not supported. Accordingly, a single threshold model is adopted for subsequent analysis.

Table.5. Threshold Effect Test Results

Threshold Variable	Model	F-statistic	P-value	Bootstrap Samples	Threshold		
					1%	5%	10%
Regional Financial Development Level	Single Threshold	2.7217**	0.0085	300	20.477	14.710	12.544
	Double Threshold	2.6665	0.0084	300	18.500	14.454	11.199
	Triple Threshold	2.5547	0.0080	300	89.104	56.554	47.048

In addition, the threshold value for the single threshold model is estimated. As shown in the regression results presented in Table 6, the estimated threshold value for the regional financial development level is 1.3517.

Table.6. Threshold Effect Test Results

Threshold Type	Estimate	95% Confidence Interval
Single Threshold	1.3517	[1.2956,1.3597]

Following the estimation of the single threshold model, the corresponding results are reported in Table 7, which reveals that the regression analysis, utilizing regional financial development as the threshold variable. It demonstrates statistical significance for social consumption levels, tax burden levels, industrial structure, and urbanization rates. Specifically, social consumption levels exhibit a negative impact on credit risk within the regional financial sector, significant at the 5% level. An increase in consumption levels typically reflects augmented disposable income and stable employment, thereby enhancing repayment capacity and reducing the probability of loan defaults. Tax burden levels also negatively influence credit risk, achieving a 1% significance level. Regions with higher tax burdens often enforce stricter tax regulations, promoting financial transparency and reducing tax evasion, thus improving the credibility of credit assessments and mitigating information asymmetry. Furthermore, industrial structure and urbanization rates negatively affect credit risk, with a 10% significance level, while other variables' significance levels and coefficient signs remain consistent.

Based on Tables 6 and 7, the single threshold model, with regional financial development as the threshold variable, categorizes the sample into two distinct regimes. The impact of digital inclusive finance on regional financial industry credit risk exhibits heterogeneity across these regimes. Specifically, when the level of regional financial development is less than or equal to 1.3517, the effect of digital inclusive finance on regional financial credit risk is positive, albeit statistically insignificant. In contrast, when regional financial development surpasses the threshold of 1.3517, the effect turns negative, though it remains statistically insignificant. These findings suggest that the influence of digital inclusive finance on the credit risk of regional financial industries is contingent upon the level of regional financial development.

Table.7. Threshold Effect Test Results

Variable	Standard Error	Standard Error	t-statistic
finsize	1.1248	0.7761	1.45
rjgdp	-0.0259	0.0165	-1.56
consumption	-0.0347**	0.1435	-2.42
rural_income	-0.1725	0.1650	-1.05
tax	-1.9432***	0.5793	-3.36
structural	0.2678*	0.1385	1.93
urbanrate	0.8967*	0.4429	2.02
constant	-0.0750	0.0002	-0.09
Threshold Variable≦1.3517	0.0000	0.0001	0.53
Threshold Variable＞1.3517	-0.0001	0.0002	-0.86

To further validate the authenticity of the threshold value, this paper presents a single-threshold LR test graph. According to the principles of the threshold model, the minimum point in the LR graph, which is 3, is the threshold estimate. When the likelihood ratio (LR) associated with the threshold estimate is below the critical value of 7.3523, the threshold estimate is considered to pass the test. As shown in Figure 1, the minimum point of the threshold value falls below the critical value, indicating that the threshold estimate is statistically significant.

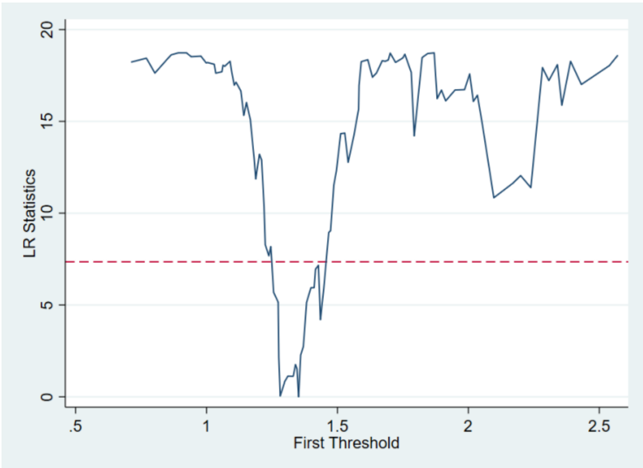

Figure.1. Single Threshold LR Test Diagram

4.4. Regional Heterogeneity Analysis

The analysis partitions the sample into four regional sub-samples: the Eastern, Central, Western, and Northeastern Economic Zones, as detailed in Table 8. Column (1) presents the regression results for the Eastern Economic Zone, column (2) for the Central Economic Zone, column (3) for the Western Economic Zone, and column (4) for the Northeastern Economic Zone. The coefficient of the Digital Inclusive Finance Index is significantly negative in the Eastern Economic Zone, whereas it is significantly positive in the Central Economic Zone. This implies that the Eastern Economic Zone is able to strengthen the resilience of its regional financial industry against credit risk under the influence of digital inclusive finance, whereas the Central Economic Zone exhibits a weakening of its regional financial industry's resilience to credit risk under similar conditions. This disparity arises because the Central Economic Zone exhibits a slower pace of economic development compared to the Eastern Economic Zone, coupled with differences in the financial environment. The Central Economic Zone demonstrates lower levels of financial service intensity, financial service scope, and the size of its high-end financial user base relative to the Eastern Economic Zone. Consequently, provinces within the Central Economic Zone are more adversely affected by the impact, compounded by their smaller scale of development and weaker risk resistance capabilities, leading to a greater propensity for capital shortages, which in turn impacts their credit risk profiles.

Table.8. Heterogeneity Tests Based on Economic Zones

VARIABLES	(1) Eastern	(2) Central	(3) Western	(4) Northeastern
	npl	npl	npl	npl
dig	-0.000**	0.000*	-0.000	-0.000
	(-3.04)	(2.32)	(-1.37)	(-0.29)
Controls	YES	YES	YES	YES
Constant	0.003	-0.016	0.025*	0.009
	(0.46)	(-0.98)	(1.91)	(0.82)
Observations	120	72	120	36
Number of id	10	6	10	3
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

5. Conclusions and Recommendations

The rapid proliferation of digital innovations—including big data analytics, blockchain technology, and cloud computing—has driven the advancement of digital inclusive finance, fundamentally altering credit risk dynamics within regional financial systems. The analysis yields three principal findings:

First, digital inclusive finance significantly mitigates credit risk within regional financial sectors, a result that remains robust across various validation techniques, including lagged variable regressions and instrumental variable analyses to address potential endogeneity issues.

Second, the risk-reducing effect of digital inclusive finance is conditioned by the level of regional financial development. Specifically, credit risk suppression is observed only when the regional financial development index exceeds the identified threshold of 1.3517, emphasizing the critical role of financial maturity.

Third, substantial regional heterogeneity is evident. While digital inclusive finance enhances the resilience of financial systems to credit risk in the more economically developed eastern regions, it appears to weaken such resilience in the central economic zone, highlighting the necessity for region-specific policy interventions.

Based on the above conclusions, this paper puts forward the following recommendations:

Firstly, the advancement of digital inclusive finance is paramount for mitigating financial risk. Digital inclusive finance improves operational efficiency, optimizes financial structure, and strengthens risk resilience, potentially reducing regional credit risk. Policymakers should prioritize digital finance development, capitalizing on its risk prevention capabilities. Policy support should facilitate the digital transformation of traditional financial institutions and stimulate novel digital financial services. Investment in financial infrastructure is essential to accelerate digitalization, enhance regional interconnectedness, and promote comparative advantages, fostering collaborative supply chains and coordinated industrial development. Tax incentives should stimulate high-tech innovation and R&D, thereby elevating technological innovation and driving digital inclusive finance.

Secondly, differentiated financial development strategies tailored to specific regions are crucial. For regions with high financial development, innovation pilot programs should be initiated. For regions with lower financial development, infrastructure development should be prioritized, with central government financial support for credit information data platforms and mandates for commercial banks' digital transformation.

Thirdly, optimizing resource allocation across regions is essential to mitigate regional development disparities. Given heterogeneous economic strengths and varying digital financial development levels, the impact of digital inclusive finance on mitigating credit risk differs. The state should optimize resource allocation, accelerate regional digitalization, and balance technological innovation, facilitating cross-regional capital flows. Eastern regions should maintain their digital financial development advantages. To narrow intra-regional disparities and foster sustained economic growth, the central and western regions are advised to utilize governmental support by strengthening both the penetration and usage intensity of digital inclusive finance.

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