

The Nonlinear Impact of Fintech on Credit Risk in Chinese Commercial Banks

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ABSTRACT

Manuscript type: Research paper

Research aims: This study investigates how Fintech development affects the credit risk of Chinese commercial banks and whether this effect follows a stage-dependent nonlinear pattern.

Design/Methodology/Approach: Using panel data for 94 Chinese commercial banks from 2011 to 2021, this study applies fixed-effects models, alternative Fintech-related indicators, heterogeneity tests, and system GMM estimation.

Research findings: This study finds a significant inverted U-shaped relationship between Fintech and banks' non-performing loan ratios. The estimated turning point of 88.21 lies within the observed sample range, indicating a meaningful stage transition in bank digital transformation. The nonlinear effect is more evident among non-eastern and non-state-owned banks.

Theoretical contribution/Originality: These findings contribute to the literature by linking Fintech, credit risk, turning-point interpretation, and institutional heterogeneity.

Practitioner/Policy implication: The findings offer practical implications for bank managers, investors, and regulators.

Research limitation: The sample period is limited to 2011–2021.

Keywords: Bank Digital Transformation, Commercial Banks, Credit Risk, Fintech, Nonlinear Effects

JEL Classification: G21, G28, O33, C23

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1. Introduction

The rapid expansion of Fintech has reshaped commercial banks' borrower screening, financial service delivery, and credit risk management practices (Zhao et al., 2023). These changes are especially important in China, where commercial banks occupy a central position in the financial system and their risk conditions are closely related to overall financial stability (Ma & Yao, 2021). Technologies including artificial intelligence, big data analytics, blockchain, and mobile platforms may help banks obtain information more efficiently, lower operating frictions, and improve risk monitoring (He et al., 2023; Xie & Wang, 2022). However, Fintech may also create additional pressure by increasing competition, encouraging rapid expansion, and introducing new operational and governance challenges. Therefore, the effect of Fintech on bank risk is unlikely to follow a single direction under all conditions (Fang et al., 2023).

This ambiguity suggests that the relationship between Fintech and bank credit risk is likely to be nonlinear rather than purely linear (Chen et al., 2022; Hu et al., 2024). In the early stages, banks often face high technology investment costs, organisational adjustment pressures, and incentives to expand into unfamiliar digital business areas, all of which may increase risk exposure (Fang et al., 2023; He et al., 2023; Wu et al., 2023). As digital capability improves, banks may gradually develop stronger data governance, more precise credit assessment, better internal monitoring, and more effective risk-control mechanisms (He et al., 2023). This implies a possible inverted U-shaped relationship, in which Fintech initially increases the credit risk of commercial banks but begins to reduce it after a certain threshold is reached (Chen et al., 2022; Wu et al., 2023). Identifying this turning point is important not only for empirical interpretation, but also for understanding when digital investment begins to generate risk-management benefits rather than additional risk pressure.

Existing studies have confirmed that Fintech affects bank credit risk and risk-taking through changes in information processing, credit allocation, competition, and risk management capacity (Cheng & Qu, 2020; Wang et al., 2021; Zhang et al., 2023; Wu et al., 2023). Recent evidence has also shown that this relationship may be nonlinear, suggesting that Fintech may increase bank risk at an early stage but reduce risk after digital capability becomes more mature (Ni et al., 2023). Therefore, the research gap is no longer whether a nonlinear relationship exists, but how this nonlinear effect

should be interpreted and under what conditions it becomes more evident. First, existing nonlinear studies have paid relatively limited attention to whether the estimated turning point falls within the observed sample range, although this is important for distinguishing an economically meaningful stage transition from a boundary-driven statistical result (Lind & Mehlum, 2010; Haans et al., 2016). Second, prior studies usually examine either bank-level Fintech development or the broader digital financial environment, while less attention has been given to whether the nonlinear risk effect remains consistent across these two dimensions (Cheng & Qu, 2020; Zhang et al., 2023; Ni et al., 2023). Third, although ownership structure and regional conditions may influence banks' digital transformation capacity and risk-control effectiveness, the heterogeneity of the nonlinear Fintech-risk relationship across regions and ownership types remains insufficiently examined in the Chinese banking context (Wang et al., 2021; Wu et al., 2023). Accordingly, this study focuses on the nonlinear effect of Fintech on bank risk, proxied by the non-performing loan ratio, and further examines the turning point interpretation, alternative Fintech measures, and regional and ownership heterogeneity.

Based on a 2011-2021 panel of 94 Chinese commercial banks, this study uses the Peking University Digital Transformation Index for Chinese Banks to assess whether Fintech affects bank risk in a nonlinear manner. The fixed-effects estimates reveal an inverted U-shaped pattern. The estimated threshold is 88.21, which falls within the actual range of the digital transformation index observed in the sample. The nonlinear pattern remains robust in a dynamic specification, where the turning point is 94.87, and is further supported by alternative indicators and a system GMM estimation. The heterogeneity analysis shows that this inverted U-shaped relationship is mainly concentrated in non-eastern regions and non-state-owned banks, whereas the evidence is weak or insignificant for eastern-region banks and state-owned banks. By explicitly identifying the turning point, testing its sample relevance, and examining regional and ownership heterogeneity, this study offers a clearer explanation of the conditions under which Fintech affects bank credit risk.

2. Literature Review and Research Hypotheses

Existing studies suggest that Fintech can reshape bank risk through two competing channels. On the one hand, digital technologies improve information processing, customer screening, and internal

control, which may reduce credit risk and enhance bank stability. From this perspective, Fintech can strengthen monitoring capacity, improve loan allocation efficiency, and lower default risk (Yan & Zhu, 2024; Chen & Gao, 2022; Hu et al., 2024). On the other hand, Fintech may intensify market competition, increase technology investment pressure, and encourage banks to expand more aggressively into new business areas, thereby raising risk exposure (Gong & Li, 2020; Wang, 2018). These two channels imply that the effect of Fintech on bank risk is theoretically ambiguous and may not be adequately captured by a simple linear framework.

This ambiguity has led some recent studies to move beyond linear specifications and examine possible nonlinear effects (Ni et al., 2023). A growing strand of literature argues that Fintech may initially increase bank risk because banks face adjustment costs, organisational restructuring, and competitive pressure during the early stage of adoption (Guo et al., 2021; Fang et al., 2023). However, once digital capabilities become more mature, banks may begin to benefit from stronger data governance, more accurate credit assessment, and more effective risk monitoring. In this case, the effect of Fintech on bank risk may follow an inverted U-shaped pattern (Wu et al., 2023). Such a framework is especially useful because it not only reconciles the mixed findings in the literature, but also highlights the importance of identifying the turning point at which Fintech begins to generate net risk-reducing effects.

In China, where banks differ substantially in governance capacity, resource endowment, and technological conditions, these heterogeneities are likely to matter (He et al., 2023). Taken together, these competing mechanisms suggest that the effect of Fintech on bank credit risk may follow an inverted U-shaped pattern rather than a purely linear relationship (Chen et al., 2022). Based on this reasoning, this study proposes the following hypothesis.

H_1 : Fintech has an inverted U-shaped effect on the credit risk of commercial banks.

Regional environment is another important source of heterogeneity. Banks operating in eastern and non-eastern regions face different levels of economic development, digital infrastructure, financial market depth, and competitive intensity. In more developed eastern regions, Fintech may be supported by better technology ecosystems, more mature digital finance usage, and stronger institutional conditions, which could weaken transitional risk pressure (Deng et al., 2021). In non-eastern regions, however, banks

may experience a more uneven Fintech process, in which early-stage expansion and adjustment costs are more salient before the benefits of digital governance fully emerge (Zhao & Tong, 2023). As a result, the nonlinear effect of Fintech on bank risk may vary across regional settings.

H_2 : The effect of Fintech on the credit risk of commercial banks differs across regions.

Ownership structure may further shape how Fintech affects bank risk. State-owned banks and non-state-owned banks differ in terms of capital strength, governance arrangements, policy burden, technology investment capacity, and organisational flexibility. State-owned banks often possess stronger capital support, broader customer bases, and more abundant resources for large-scale digital investment, which may help them absorb the risks associated with Fintech (Zhao & Tong, 2023). Compared with state-owned banks, non-state-owned banks are more exposed to market competition and may rely more heavily on Fintech to support business expansion and strengthen competitiveness, which could make the risk effect of Fintech more pronounced (He et al., 2023). At the same time, their relatively limited resource buffers may also make the adjustment process more sensitive. Therefore, the impact of Fintech on bank risk may differ across ownership types.

H_3 : The effect of Fintech on the credit risk of commercial banks differs across ownership types.

3. Research Design

3.1 Data Sources

To examine the nonlinear effect of Fintech on bank credit risk, this study constructs a bank-level panel covering 94 Chinese commercial banks during 2011–2021. The Fintech development level (Fin) is measured using the Digital Transformation Index of Chinese Commercial Banks compiled by Peking University (Xie & Wang, 2022). This index reflects the degree of Fintech adoption and digitalisation in each bank's operations and services across different provinces. The sample period covers 2011 to 2021 because bank-level digital transformation indicators, bank financial statements, and regional macroeconomic variables are more consistently available and comparable over this period. Extending the sample beyond 2021 may introduce inconsistencies in data coverage and comparability across

some indicators, so this study retains the 2011–2021 period to ensure a relatively balanced and consistent panel structure. Bank-level financial data is collected from the CSMAR database and the annual reports of individual banks, whereas macroeconomic indicators are taken from the National Bureau of Statistics of China. To reduce the influence of extreme values, all continuous micro-level variables are winsorised at the upper and lower 1% tails. Observations with missing values or abnormal core variables are then removed. The final sample comprises 1,034 bank-year observations.

3.2 *Variable Measurement*

3.2.1 *Dependent Variable*

Bank credit risk is measured by the non-performing loan ratio (NPL), a commonly used indicator of loan quality deterioration (Guo & Zhang, 2024; Yan & Zhu, 2024). A larger NPL ratio suggests that a bank faces heavier credit risk exposure and weaker asset quality.

3.2.2 *Core Independent Variable*

The key independent variable is the level of Fintech development, denoted as *Fin*. We use the Peking University Digital Transformation Index as our measure of Fintech adoption. This index objectively reflects Fintech penetration and digital banking trends in each region, capturing aspects of banks' overall digital strategy, financial service innovation, and IT infrastructure. To test the possible nonlinear relationship, this study further includes Fin^2 , which denotes the squared term of *Fin* (Chen et al., 2022; Ni et al., 2023; Wu et al., 2023). For robustness purposes, this study also employs alternative Fintech-related indicators, including index and its squared term FI^2 , as well as breadth, $breadth^2$, depth, and $depth^2$ (Guo et al., 2020).

3.2.3 *Control Variables*

Following previous studies on bank performance and risk, this study controls for both bank-specific and macroeconomic factors (Qiu et al., 2018; Liu et al., 2019; Zhu et al., 2023; Ying & Zhang, 2020; Yu et al., 2019). The bank-specific variables consist of bank size, capital adequacy ratio, return on assets, and the loan-to-deposit ratio. The macroeconomic variables include regional GDP growth, M2, and inflation. Including these variables helps reduce the influence of bank heterogeneity and external economic conditions on the estimation of credit risk.

Table 1 presents the definitions and descriptive statistics of the variables. It shows that the average NPL ratio in the sample is about 1.431%, with a maximum of 9.56%, indicating considerable variation in credit risk across banks and over time. The Fintech index (Fin) ranges from 0 to 197, reflecting disparities in digitalisation levels. Control variables also show substantial variability.

Table 1: Variable Definitions and Descriptive Statistics

Variable Symbol	Variable Meaning	Sample Size	Mean	Std. Dev	Min	Max
NPL	Non-Performing Loan Ratio	1023	1.431	0.751	0	9.56
Fin	Digital Transformation Index of Chinese Banks	1029	65.61	40.947	0	197
Size	Logarithm of Total Bank Assets	1032	26.602	1.601	23.533	31.191
Ca	Capital Adequacy Ratio	1032	9.688	3.477	0.5	18.02
Roa	Return on Assets	1034	7.53	5.151	0.08	13.84
Ldr	Ratio of Total Loans to Total Deposits	1029	68.911	13.659	24.14	124.01
Gdpr	GDP Growth Rate of Provinces and Municipalities	1031	7.63	2.374	0.5	16.4
M2	Broad Money Supply	1034	11.076	2.241	8.1	13.84
Infla	Consumer Price Index	1033	2.371	1.139	0.98	5.55

3.3 Model Specification

This paper empirically examines the nonlinear impact of Fintech on the credit risk of banks by constructing the following model:

$$Risk_{it} = \beta_0 + \beta_1 Fin_{it} + \beta_2 Fin_{it}^2 + \beta_3 Control_{it} + \alpha_i + \varepsilon_{it}$$

Where $Risk_{it}$ is the dependent variable, representing bank credit risk; Fin_{it} and Fin_{it}^2 are the Fintech index and its square, capturing the linear and quadratic effects of Fintech development; β_1 and β_2 are the

coefficients of the linear and quadratic terms of financial technology, respectively; $Control_{it}$ includes all control variables discussed above; ε_{it} represents the residual term, and a_i represent the individual bank effects.

To test for nonlinearity in the Fintech-risk relationship, this study specifies a fixed-effects panel model with both the digital transformation index and its squared term. A quadratic fixed-effects specification is used to test H_1 by examining whether the linear and squared terms of Fin jointly support an inverted U-shaped relationship.

H_1 is supported if β_1 is significantly positive and β_2 is significantly negative, as this coefficient pattern indicates an inverted U-shaped relationship between Fintech and credit risk. In that scenario, there exists a turning point beyond which Fintech's effect on risk turns from positive to negative. To address H_2 and H_3 , this study further conducts subsample regressions by region and ownership type.

To account for the persistence of bank credit risk, this study further introduces the lagged dependent variable into the specification. This dynamic specification is used to examine whether the main nonlinear relationship remains robust after controlling for the persistence of non-performing loan ratios.

3.4 *Dynamic panel estimation using system GMM*

System GMM estimation is further used to address potential endogeneity concerns. This method is appropriate because bank credit risk may exhibit dynamic persistence, and Fintech development may be jointly determined with banks' risk conditions. Specifically, the model includes the lagged dependent variable to capture the persistence of the non-performing loan ratio, while Fin and Fin^2 are included to test the nonlinear effect of Fintech on bank credit risk. Following the system GMM framework, $L.NPL$, Fin , and Fin^2 are treated as GMM-style instruments, while the remaining control variables are treated as standard instruments. Given the dynamic nature of bank credit risk and the possible endogeneity of Fintech development, the instrument matrix is collapsed and limited to lag 2 to avoid excessive instruments. The specification is validated through the Arellano-Bond AR(1) and AR(2) tests for serial correlation and the Hansen test for instrument validity.

4. Empirical Analysis

4.1 Baseline Regression Results

Table 2 presents the baseline regression results on the nonlinear impact of Fintech on the non-performing loan ratio. In Column (1), without controls, the coefficient on the Fintech linear term (Fin) is 0.01682, positive and statistically significant at the 1% level. The coefficient on the quadratic term is -0.00006, negative and significant at 1%. This suggests an inverted U-shaped relationship. Column (2) shows that after adding bank-level and macroeconomic control variables, the relationship remains robust. The linear Fintech coefficient is 0.00608, and the quadratic coefficient is -0.00003, which are both significant at 5% level. The persistence of a positive linear and negative quadratic term confirms the inverted U pattern, thus H_1 is supported. The estimated turning point in the baseline specification with controls is 88.21. Since the observed range of Fin in the sample is from 0 to 197, this turning point lies well within the actual sample range, indicating that the identified nonlinear relationship is economically meaningful rather than a purely mechanical extrapolation.

Among the control variables, profitability is negatively associated with the NPL ratio, while the loan-to-deposit ratio is positively associated with the NPL ratio. GDP growth is also negative and significant, suggesting that both bank-level fundamentals and macroeconomic conditions are related to bank credit risk.

Table 2: Baseline Regression Results and Robustness Tests

Variables	(1) NPL ratio	(2) NPL ratio	(3) NPL ratio	(4) NPL ratio	(5) NPL ratio	(6) NPL ratio
Fin	0.01682*** (5.935)	0.00608** (2.255)				0.00689*** (2.857)
Fin ²	-0.00006*** (-4.235)	-0.00003** (-2.605)				-0.00004*** (-3.218)
FI			0.00876*** (4.905)			
FI ²			-0.00002*** (-5.714)			
Breadth				0.01044*** (5.468)		
Breadth ²				-0.00002*** (-6.701)		

Variables	(1) NPL ratio	(2) NPL ratio	(3) NPL ratio	(4) NPL ratio	(5) NPL ratio	(6) NPL ratio
Depth					0.00235 (1.500)	
Depth ²					-0.00001*** (-3.501)	
L.NPL						0.35102*** (3.952)
Size		-0.12872 (-0.790)	0.01856 (0.081)	-0.09570 (-0.384)	0.22905 (1.255)	-0.18649 (-1.289)
Ca		-0.02274** (-2.002)	-0.00568 (-0.391)	-0.00456 (-0.322)	-0.00317 (-0.230)	-0.00273 (-0.246)
Roa		-0.07455** (-2.599)	-0.06272** (-2.548)	-0.05646** (-2.355)	-0.05771** (-2.276)	-0.06812*** (-2.938)
Ldr		0.01569*** (3.112)	0.01916*** (3.538)	0.01848*** (3.322)	0.02039*** (3.894)	0.00658* (1.669)
Gdpr		-0.02346** (-2.011)	0.00038 (0.033)	0.00890 (0.727)	-0.02669** (-2.436)	-0.03042** (-2.166)
M2		-0.00727 (-0.318)	-0.00364 (-0.195)	0.00872 (0.474)	-0.04411** (-2.064)	0.00746 (0.425)
Infla		-0.05006 (-1.575)	0.07533** (2.595)	0.07386** (2.630)	-0.02627 (-0.920)	-0.08325* (-1.932)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.69823*** (6.641)	4.74182 (1.023)	-0.97377 (-0.156)	1.63341 (0.243)	-4.79385 (-0.941)	6.09404 (1.471)
Sample	1017	1013	1018	1018	1018	916
R ²	0.195	0.278	0.315	0.321	0.314	0.402
Turning point	137.03	88.21	266.18	276.30	137.99	94.87
Observed range	0–197	0–197	18.33–458.97	1.96–433.42	6.76–510.69	0–197
Within observed range	Yes	Yes	Yes	Yes	Yes	Yes

Note: Columns (1), (2), and (6) use Fin and Fin^2 , where Fin^2 denotes the squared term of Fin . Column (3) uses the alternative Fintech indicator FI and its squared term FI^2 ; Columns (4) and (5) use $Breadth/Breadth^2$ and $Depth/Depth^2$, respectively. Turning point is calculated as $-\beta_1/(2\beta_2)$. “Within observed range” indicates whether the estimated turning point lies within the actual sample range of the corresponding explanatory variable. All models are estimated with bank fixed effects, and robust standard errors are clustered at the bank level. t -statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Robustness Checks

For robustness, the bank-level digital transformation index is replaced with the Peking University Digital Financial Inclusion Index. The main *Fin* variable captures the digital transformation of individual commercial banks, whereas the Digital Financial Inclusion Index is a province-level measure that reflects the broader digital financial environment in the province where a bank operates. The overall index, denoted as *FI*, captures the general level of provincial digital financial inclusion. Breadth measures the coverage of digital financial services, while depth reflects the intensity of digital financial service usage. In the matched bank-year sample, the average values of *FI*, breadth, and depth are approximately 251.17, 233.34, and 255.17, respectively.

In Column (3), *FI* enters positively and its squared term enters negatively, both at the 1% significance level, with an estimated turning point of 266.18. This turning point is slightly above the sample mean of *FI* and lies within its observed range of 18.33 to 458.97. From the perspective of Chinese banks, this suggests that the effect of the provincial digital financial environment turns from risk-increasing to risk-reducing after *FI* exceeds about 266.18. In Column (4), breadth and breadth² also support a significant inverted U-shaped relationship, and the corresponding turning point is 276.30. The breadth result similarly indicates that wider coverage of digital financial services is needed before the risk-reducing effect becomes clearer. In Column (5), depth is not statistically significant, although depth² remains significantly negative, so the evidence from usage depth is weaker and should be interpreted more cautiously.

Then, to further examine the robustness of the baseline findings, this study introduces the lagged dependent variable into the regression model to account for the persistence of bank credit risk. As shown in Column (6) of Table 2, the coefficient on *L.NPL* is significantly positive, indicating that the non-performing loan ratio exhibits a clear dynamic persistence effect. More importantly, the coefficient on *Fin* remains significantly positive and the coefficient on *Fin*² remains significantly negative, which suggests that the inverted U-shaped relationship between Fintech and the non-performing loan ratio is preserved after controlling for the dynamic effect. The estimated turning point in this specification is 94.87, which lies within the observed range of *Fin* from 0 to 197. The turning point of 94.87 is close to the baseline turning point of 88.21 and remains within the observed range of *Fin*, suggesting that the dynamic specification does not materially change the main interpretation.

Overall, the results remain consistent when Fintech is measured by banks’ own digital transformation and when it is measured by the broader provincial digital financial environment.

4.3 *Dynamic Panel Estimation Using System GMM*

Table 3 presents the system GMM results for the dynamic specification. The lagged NPL ratio is positive and significant at the 10% level, indicating persistence in banks’ credit risk. The signs of the core Fintech variables remain consistent with the baseline findings: Fin is positive, whereas Fin² is negative and statistically significant. This coefficient pattern provides further support for the inverted U-shaped effect of bank digital transformation on the non-performing loan ratio after considering the dynamic adjustment of credit risk and possible endogeneity. The implied turning point is about 88.46, which falls within the observed range of the bank digital transformation index and is close to the baseline estimate of 88.21. Therefore, the stage transition identified in the fixed-effects model remains stable in the dynamic panel setting.

The post-estimation tests provide additional support for the dynamic panel specification. The AR(1) result is significant, whereas the AR(2) result is insignificant, indicating that the NPL equation does not suffer from second-order serial correlation. The Hansen test also supports the overall validity of the instrument set. In addition, the model uses 14 instruments, which is far fewer than the 94 banks in the sample, reducing concerns about excessive instruments in the system GMM estimation.

Table 3: System GMM Estimation Results

Variables	NPL Ratio
L.NPL	0.2741* (0.1591)
Fin	0.0138** (0.0063)
Fin ²	-0.000078*** (0.000028)
Size	-0.1073** (0.0468)
Ca	-0.0178 (0.0144)
Roa	-0.0185** (0.0093)

Variables	NPL Ratio
Ldr	0.0069* (0.0041)
Gdpr	-0.0347** (0.0167)
M2	-0.0089 (0.0202)
Infla	-0.0622 (0.0438)
Observations	916
Number of banks	94
Number of instruments	14
Wald $\chi^2(10)$	3372.75 [p = 0.000]
AR(1) test	z = -2.63 [p = 0.009]
AR(2) test	z = -1.49 [p = 0.137]
Sargan test	$\chi^2(3) = 5.08$ [p = 0.166]
Hansen test	$\chi^2(3) = 4.51$ [p = 0.212]

Notes: The dependent variable is the non-performing loan ratio (NPL). One-step system GMM estimates are reported, with robust standard errors in parentheses. L.NPL, Fin, and Fin² are treated as collapsed GMM-style instruments using lag (2,2), while the remaining regressors are treated as standard instruments in the levels equation. AR(1) and AR(2) denote the Arellano-Bond tests for first- and second-order serial correlation in first-differenced residuals. The Hansen test reports the test of overidentifying restrictions. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The implied turning point is approximately 88.46, which lies within the observed range of the bank digital transformation index.

4.4 Heterogeneity Analysis

There are pronounced differences in economic development and fintech infrastructure between China's eastern coastal provinces and its central and western regions (Li, 2024). Eastern regions such as Beijing, Shanghai, Guangdong have more advanced Fintech ecosystems, higher internet penetration, and more digitally experienced customers, whereas non-eastern regions (central and western provinces) generally have less mature digital financial infrastructure. We split the sample based on each bank's geographical region (eastern vs non-eastern) and present results in Columns (1) and (2) of Table 4. The regional heterogeneity results show that the nonlinear relationship is mainly concentrated in non-eastern regions. Specifically, the coefficients on Fin and Fin² are not statistically significant in the eastern subsample, while Fin is significantly positive and Fin² is significantly negative in the non-eastern subsample. This indicates that H_2 is mainly supported by the non-eastern subsample.

To test H_3 , this study further splits the sample into state-owned banks and non-state-owned banks. Columns (3) and (4) of

Table 4 report the ownership heterogeneity results. In the state-owned bank subsample, the coefficients on *Fin* and *Fin*² remain directionally consistent with an inverted U-shaped relationship, but the statistical support is relatively weak. This result should therefore be interpreted with caution, especially given the much smaller number of observations in this group. In contrast, the non-state-owned bank subsample shows a significantly positive coefficient on *Fin* and a significantly negative coefficient on *Fin*², which supports a robust inverted U-shaped relationship. This finding implies that the nonlinear impact of Fintech on the non-performing loan ratio is more strongly reflected in non-state-owned banks, possibly because these banks face stronger market competition, tighter resource constraints, and a more sensitive balance between digital expansion and risk control.

Overall, the heterogeneity results suggest that the nonlinear risk effect of Fintech is not uniform across banks, but is primarily driven by non-eastern and non-state-owned subsamples.

Table 4: Heterogeneity Regression Results

	(1) Eastern	(2) Non-eastern	(3) State-owned	(4) Non-state-owned
Fin	0.00341 (1.090)	0.01452*** (3.115)	0.01272 (2.059)	0.00654** (2.404)
Fin ²	-0.00002 (-1.116)	-0.00009*** (-3.593)	-0.00005 (-2.031)	-0.00004*** (-2.906)
Size	-0.21207 (-1.143)	0.14511 (0.476)	-0.60339 (-1.205)	-0.11824 (-0.712)
Ca	-0.00726 (-0.460)	-0.02636 (-0.937)	-0.09216 (-1.857)	-0.02542** (-2.152)
Roa	-0.06653** (-2.146)	0.01089 (0.252)	-3.02990** (-4.420)	-0.07761** (-2.497)
Ldr	0.01187** (2.310)	0.01773** (2.347)	-0.00548 (-0.962)	0.01615*** (3.182)
Gdpr	-0.02178* (-1.745)	-0.01038 (-0.419)	-0.00179 (-0.148)	-0.02131* (-1.702)
M2	-0.00757 (-0.399)	-0.09002* (-1.782)	0.05387* (2.161)	-0.00285 (-0.110)
Infla	-0.08161* (-1.938)	0.03417 (0.732)	-0.07918** (-3.710)	-0.04727 (-1.407)
Bank FE	YES	YES	YES	YES
Sample size	689	324	55	958
Within R ²	0.158	0.467	0.669	0.278

Note: This table reports the heterogeneity regression results by region and ownership structure. Columns (1) and (2) present the results for eastern and non-eastern regions, respectively. Columns (3) and (4) report the results for state-owned and non-state-owned banks, respectively, where state-owned banks refer to the six major state-owned commercial banks. Fin^2 denotes the squared term of Fin . All models include bank fixed effects, and robust standard errors are clustered at the bank level. t-statistics are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Conclusion

Using panel data for 94 Chinese commercial banks during 2011–2021, this study investigates whether Fintech affects bank credit risk in a nonlinear manner. The empirical results show that Fintech has a significant inverted U-shaped effect on the non-performing loan ratio, which is consistent with studies showing that Fintech may have nonlinear effects on bank risk rather than a purely linear impact (Chen et al., 2022; Ni et al., 2023; Wu et al., 2023). In the baseline fixed-effects specification with controls, the estimated turning point is 88.21, while in the dynamic specification it is 94.87, and both turning points lie within the observed range of the digital transformation index. Additional robustness checks based on alternative fintech-related indicators generally support this nonlinear pattern, although the result based on depth is weaker because its linear term is not statistically significant. Furthermore, the system GMM results continue to show a significantly positive coefficient on Fin and a significantly negative coefficient on Fin^2 , with an implied turning point of approximately 88.46. This result indicates that the nonlinear effect of Fintech on the NPL ratio remains stable after the model incorporates credit risk persistence and possible endogeneity.

The heterogeneity analysis further indicates that this nonlinear relationship is not uniform across all banks. Instead, it is mainly concentrated in non-eastern regions and non-state-owned banks. In the eastern subsample, the coefficients on the linear and quadratic terms are not statistically significant, whereas in the non-eastern subsample the inverted U-shaped relationship is clearly supported. Similarly, the nonlinear pattern is strongly reflected in non-state-owned banks, while the results for state-owned banks are directionally consistent with an inverted U-shape but statistically weaker. These findings suggest that the credit risk effect of Fintech depends not only on the stage of digital development, but also on differences in regional environment, governance conditions, and resource endowment, which is consistent with prior evidence that bank characteristics, regional digital infrastructure, and institutional conditions shape the risk consequences of Fintech adoption (Deng et al., 2021; Fang et al., 2023; He et al., 2023; Zhao & Tong, 2023).

The findings also provide practical implications for bank managers, investors, and regulators. For bank managers, digital transformation should not be treated as automatically risk-reducing; instead, digital expansion should be accompanied by stronger data governance, internal control, and credit risk management, especially during the transition stage. For investors, the risk implications of bank digital transformation should be assessed together with banks' digital development stage, ownership structure, and regional environment. For regulators, supervision should focus not only on encouraging digital transformation, but also on whether banks have sufficient risk-management capacity during the transition process, particularly for non-state-owned banks and banks in non-eastern regions.

Nevertheless, this study still has some limitations. First, the sample period is limited to 2011–2021 because bank-level digital transformation indicators, bank financial statements, and regional macroeconomic variables are more consistently available and comparable during this period. Extending the sample beyond 2021 may introduce inconsistencies in data coverage and comparability across some indicators. Second, the risk measure used in this study is based on the non-performing loan ratio, which mainly captures an observable credit risk outcome rather than all dimensions of bank risk. Future research may extend the sample period when more consistent post-2021 data become available and examine whether the nonlinear effect changes under more recent stages of digital transformation.

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