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Fintech and the NPL Provisioning Coverage Ratio:Facilitating or Inhibiting

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Abstract: Fintech has become a crucial driver of technological and business model innovation in modern commercial banking. With its widespread adoption, the impact of fintech on banks' risk management, particularly on the non-performing loan (NPL) provision coverage ratio, has garnered significant attention in both academic and industry circles. Using microdata from 42 listed commercial banks in China's A-share market between 2007 and 2022, this study constructs a theoretical and econometric model to examine this relationship. The findings reveal three key insights: first, fintech significantly suppresses the NPL provision coverage ratio. Second, fintech indirectly promotes risk-taking in China's banking sector by affecting leverage. Third, weighted net risky assets have a negative moderating effect on the relationship between fintech and the NPL provision coverage ratio. These findings offer valuable implications for commercial banks in strategically deploying fintech to prevent and mitigate NPL risks, improve operational performance, and achieve sustainable high-quality growth.

Keywords: Fintech; Non-performing Loan Provision Coverage Ratio; Leverage Ratio; Weighted Net Risk Assets

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1.Introduction

There is growing recognition that the volume or percentage of non-performing loans (NPLs) is closely linked to bank failures and a country's financial health. Particularly after the financial crisis, the rapid rise in subprime mortgage defaults has drawn increasing attention to the issue of NPLs. NPLs refer to loans where the borrower fails to repay the principal or interest as scheduled. These loans are the source of various risks in the financial system, including market, liquidity, and counterparty risks (Benoit et al., 2017), and serve as key indicators of systemic risk accumulation (Ozili, 2020). To address this challenge, banks typically set aside provisions for NPLs, and the higher the NPL coverage ratio, the more effectively they can mitigate the negative impact of credit losses on capital (Lucia et al., 2021). The NPL coverage ratio, an essential metric for assessing a bank's risk resilience and asset quality, helps cover expected losses, reducing the need to rely on bank capital as a buffer for unexpected losses (Laeven & Majnoni, 2003).

With the rapid advancement of information technology, fintech has emerged swiftly on a global scale, ushering China's financial market into a new era driven by digital technologies. Traditional financial institutions are enhancing profitability through digital transformation and fintech in the face of intense competition (Ozili, 2018). Fintech leverages advanced technologies such as big data, artificial intelligence, and blockchain to improve the efficiency and quality of financial

services (Li, 2020; Wu et al., 2023), risk management (Wu et al., 2023; Cheng & Qu, 2020; Colombage, 2023), customer service (Bhasin & Rajesh, 2021), operational efficiency (Bhasin & Rajesh, 2021), and the handling of non-performing loans (Yang et al., 2023). Lucia et al. (2021) studied the determinants of NPL provision coverage ratios in Europe, but research linking fintech and NPL coverage ratios remains limited. The lack of comprehensive studies on the impact of fintech on NPL provision coverage constrains our understanding of fintech's role in managing NPLs and hampers decision-making by policymakers and financial institutions.

Leverage, a key indicator of a bank's capital structure (DeAngelo & Stulz, 2015), measures the ratio of debt to capital. Higher leverage often indicates greater risk-taking, increasing the demands on NPL management and provisioning. Lagged leverage is a significant determinant of NPLs (Ghosh, 2005). Fintech, by enhancing risk management capabilities, may help optimize leverage levels, thereby indirectly affecting the NPL provision coverage ratio. Additionally, weighted net risky assets, which assess the scale and quality of a bank's risk-weighted assets, reflect the overall risk level. Fintech applications, particularly in risk assessment and management, can improve asset quality and accuracy, influencing the calculation of risk-weighted assets—a key factor impacting NPLs (Kartal et al., 2020). However, the mechanisms through which leverage and weighted net risky assets mediate the relationship between fintech and the NPL provision coverage ratio remain underexplored. Thus, further investigation is needed to understand how fintech affects NPL provisioning through leverage and weighted net risky assets.

In summary, stabilizing non-performing loan (NPL) risks is crucial for ensuring national financial security and stability, which in turn supports the high-quality development of China's economy. Based on this, the study constructs an analytical model to examine the relationships between fintech, the NPL provision coverage ratio, leverage, and weighted net risky assets. The aim is to explore how fintech suppresses the NPL provision coverage ratio to improve commercial bank performance.

This research makes two key contributions: First, it investigates the theoretical mechanisms by which fintech reduces the NPL provision coverage ratio in commercial banks, offering new insights into fintech's impact on bank capital structure and risk asset management. This deepens the understanding of fintech applications in banking. Second, the findings provide a fresh perspective on NPL risk prevention and management in China: they offer theoretical tools for banks to manage NPL risks, provide fintech companies with insights for applying innovative services and products, and offer policy recommendations for regulators to consider fintech's dual impact on bank risk management. This will help promote the healthy development of fintech in banking and ensure financial system stability and security.

2.Theoretical Background and Hypotheses Development

2.1 Literature Review

2.1.1 Information Asymmetry Theory

Information asymmetry arises when parties involved in a transaction possess different levels of information due to varying access and understanding (Marcel et al., 2010). The rise of fintech offers new tools to mitigate information asymmetry by collecting behavioral data and insights from borrowers across multiple dimensions, while AI algorithms can identify hidden risk factors from vast datasets (Chen et al., 2021). In the context of the NPL provision coverage ratio, fintech can effectively reduce NPL rates, thereby lowering the need for high loan loss provisions (Li et al., 2021). However, its impact on the NPL coverage ratio is not solely positive. Over-reliance on technology can introduce new challenges, including information asymmetry and moral hazard (Chen et al., 2022). Borrowers may use technology to falsify information or manipulate data, misleading banks' risk assessment systems (Tatineni & Mustyala, 2024). This could lead banks to relax lending standards and pursue rapid expansion, increasing the proportion of NPLs. In response to the difficulty in accurately assessing borrower credit risk, banks may need to maintain higher loan loss provisions to guard against potential losses (Anastasiou, 2023).

2.1.2 Financial Accelerator Theory

The Financial Accelerator Theory describes the interaction between financial markets and the real economy, highlighting how financial market fluctuations can amplify economic impacts through leverage (Bernanke et al., 2019). In recent years, the rapid development of fintech has enhanced transparency, optimized risk management tools, and expanded financing channels, allowing banks to better identify and manage risks. This enables banks to confidently increase leverage at the same

risk level, pursuing higher returns (Yu, 2024). The application of blockchain technology further ensures data authenticity and immutability, strengthening banks' control over risk (Zhu & Zhou, 2018). However, higher leverage also increases banks' sensitivity to market fluctuations and credit defaults, raising overall risk exposure (Kim et al., 2017; Berg, 2020). This aligns with the core tenet of the Financial Accelerator Theory: changes in financial conditions amplify economic fluctuations through leverage effects (Riccetti et al., 2013). During periods of economic expansion, banks, with improved risk assessment capabilities and higher leverage, can rapidly expand credit, driving economic growth (Chen et al., 2022).

2.2 Hypotheses development

2.2.1 Fintech and the Non-Performing Loan Provision Coverage Ratio

With the rise of fintech, commercial banks, in an effort to remain competitive and gain market share, may intentionally or unintentionally relax credit standards (Li & Zhu, 2021). This relaxation can manifest as reduced stringency in borrower credit qualifications or looser loan conditions. When credit standards are eased, high-risk borrowers who might not have qualified for loans, or would have received smaller amounts, are more likely to obtain financing, significantly increasing the risk of non-performing loans (Vithessonthi, 2016). The rise in NPLs inevitably affects the NPL provision coverage ratio, as banks must allocate more provisions for potential losses, thereby reducing the coverage ratio (Alessi et al., 2021). Additionally, fintech introduces new business models, such as internet lending and digital finance, which come with unique risk transmission channels (Xu et al., 2023). In response to these new dynamics, banks may face delays or inadequacies in risk identification and management, making it difficult to accurately assess and mitigate these risks, further lowering the NPL provision coverage ratio. Based on this analysis, this paper proposes Hypothesis 1:

H1: Fintech has a significant negative impact on NPL provision coverage ratio.

2.2.2 Fintech, NPL Provision Coverage Ratio, Leverage Ratio

The development of fintech has brought significant transformations to banking. Advanced technologies enable banks to more accurately assess borrower credit risk by analyzing vast amounts of data and employing intelligent models to identify potential risk points (Cheng & Qu, 2020). Fintech also optimizes risk pricing models, ensuring that loan rates appropriately reflect risk levels, which helps banks reduce risk while maintaining profitability (Tan et al., 2024). Additionally, fintech greatly enhances credit approval efficiency, allowing banks to process transactions more effectively and attract high-quality clients (Sun & Zhang, 2023). These improvements collectively reduce the risks and asset quality issues banks face, leading to a decrease in non-performing assets and reducing reliance on external funding (Muganyi et al., 2022). As banks' reliance on external funds decreases, their capital ratios increase, optimizing leverage levels (Barth & Miller, 2018). Higher leverage allows banks to hold more capital to manage various risks, strengthening their ability to withstand risk and reduce non-performing loan rates. Consequently, the need for provisions against non-performing loans decreases, increasing the NPL provision coverage ratio and enhancing the overall systemic risk management in the banking sector (Yin et al., 2022). Based on this analysis, this paper proposes Hypothesis 2:

H2：Leverage serves as a positive mediator between fintech and the non-performing loan provision coverage ratio.

2.2.3 Fintech, Non-Performing Loan Provision Coverage Ratio, and Weighted Net Risky Assets

The application of fintech has significantly improved banks' risk management capabilities. Advanced technologies like big data analytics and artificial intelligence enable banks to identify and address potential risks more efficiently and accurately (Li et al., 2021). This enhancement reduces the likelihood of non-performing loans (NPLs), leading to a decrease in the NPL rate (Wang et al., 2023). The NPL provision coverage ratio is a key indicator of a bank's ability to manage NPL risks; as the NPL rate decreases, the need for provisions also diminishes (Curcio et al., 2023). However, weighted net risky assets (RWA) reflect the risk level associated with a bank's assets. Higher RWA indicates a greater proportion of high-risk assets, necessitating larger capital buffers and provisions to cover potential losses (Baskaya et al., 2023). Despite fintech's ability to enhance risk management and asset quality, high RWA requires banks to maintain higher provision coverage to address potential high risks (Masera, 2019). Thus, high RWA may weaken the positive effect of fintech on reducing the need for NPL provisions. Therefore, RWA acts as a negative moderator between fintech and the NPL provision coverage ratio: the higher the RWA, the weaker the positive impact of fintech on reducing the NPL provision coverage ratio (Zhou & Sun, 2023). Based on this

analysis, this paper proposes Hypothesis 3:

H3：Weighted net risky assets moderate the relationship between fintech and the non-performing loan provision coverage ratio. The higher the weighted net risky assets, the weaker the impact of fintech on the NPL provision coverage ratio.

3.Data and methodology

3.1 Research Sample and Data Sources

Based on the availability of data, 42 commercial banks are selected as the sample for the study. The sample interval of the study is 2007-2022. 473 data were obtained for analysis after removing missing values. Among them, there are 6 state-owned commercial banks, 9 national joint-stock banks and 27 local commercial banks.

3.2 Variable selection

3.2.1 Explained variable: non-performing loan provision coverage ratio (NPL)

This paper uses the NPL provision coverage ratio NPL as an explanatory variable to measure risk taking in the Chinese banking sector. It is calculated using the formula (total provisions/total NPLs) × 100%. Typically, a higher NPL provision coverage ratio implies that a bank has sufficient capital reserves to cover possible NPL losses, thus reducing the risk faced by the bank.

3.2.2 Explanatory variable: financial technology (FI)

Using text mining methods, the process involves the following steps: First, establish an initial vocabulary based on existing literature, categorizing fintech into five key dimensions to determine the vocabulary. Next, use word cloud analysis software to calculate keyword frequencies, quantifying the total occurrences over the annual intervals, which serve as the foundation for constructing the index. Finally, perform principal component analysis and factor analysis, integrating the total occurrences of the keywords to synthesize the Fintech Development Index (FT).

The Fintech Development Index (FT) is synthesized using text mining methods. First, an initial vocabulary is established by categorizing fintech into five dimensions based on existing literature. Next, word cloud analysis software is used to compute keyword frequencies and quantify their total occurrences over annual intervals, which serves as the basis for constructing the index. Finally, principal component analysis and factor analysis are conducted, integrating the total occurrences of the keywords to compile the Fintech Development Index (FT). The keywords are as follows:

Table 1: Keywords

Dimension	Settle a Payment	Risk Management	Information Transmission	Resource Allocation	Technological Base
keywords	Mobile Payment	Cryptography	Electronic Banking	P2P	Big data
	Network Payment	Risk Identification	Information System	Online Lending	Cloud
	Third Party Payments	Risk Assessment	Online Banking	Credit Business	AI

3.2.3. Mediator Variable: Leverage (LEV)

Leverage refers to the ratio of total assets to equity capital on a balance sheet. It is primarily used to measure the level of debt and financial risk of an entity. A higher leverage ratio indicates that the entity is using less of its own capital to control a larger volume of assets, which can potentially lead to higher returns but also involves greater risks. For instance, during adverse economic conditions or asset price fluctuations, the entity may face significant repayment pressure and default risk. In the financial sector, leverage is a critical regulatory metric. For banks and other financial institutions, maintaining an appropriate level of leverage is crucial for ensuring financial stability and safety. Excessive leverage can lead to systemic financial risks.

3.2.4. Mediator Variable: Risk-Weighted Assets (RWA)

Weighted net risky assets represent the net amount of risk-weighted assets after deducting impairment provisions. This measure calculates the total risk-weighted assets of a bank or financial institution based on assigned risk weights for various asset types. It is a key indicator of a bank's risk-bearing capacity and capital adequacy, reflecting the level of risk the bank faces in its operations and the amount of capital required to manage these risks. Regulators typically monitor the weighted

net risky assets of banks, requiring them to maintain adequate capital ratios to ensure sound operations and financial system stability.

3.2.5. Control Variables

The control variables include GDP growth rate (GDPR), equity-to-debt ratio (INV), proportion of shares held by the largest shareholder (TOP1), percentage of independent directors (INDEP), and management expenses (MAS). The mediator variable is leverage (LEV), and the moderator variable is weighted net risky assets (FXZC). The specific settings are as follows:

Table 2: Variable Attributes

Attributes	Variable		prediction method
Explained Variable	NPL	Non-performing loan provision coverage ratio	(Total provisions/total non-performing loans) x 100%
Explanatory Variable	FI	FinTech Index	Text Mining Synthesis
Control Variable	GDPR	GDP current period growth rate	GDP current period growth rate
	INV	Equity to debt ratio	Ratio of total owners' equity to total liabilities
	TOP1	Shareholding ratio of the largest shareholder	Number of shares held by the largest shareholder/total number of shares
	INDEP	Proportion of independent directors	Independent directors divided by number of directors
	MAS	overhead	Banks' total administrative expenses for the year (in billions of dollars)
Mediator Variable	LEV	leverage	Underlying share price / (warrant price ÷ subscription ratio)
Moderator Variable	FXZC	Weighted net risk assets	On-balance-sheet and off-balance-sheet assets are discounted according to different risk factors and then added together to give a total

3.3 Variable selection

Based on the above theory, the models (1), (2), and (3) are constructed as follows:

$$NPL_{it} = \alpha_0 + \alpha_1 FI_{it} + \delta_i \sum Control_{it} + \varepsilon_{it} \quad (Model\ 1)$$

$$NPL_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 RWA_{it} + \beta_3 (FI_{it} + RWA_{it}) + \beta_i \sum Control_{it} + \varepsilon_{it} \quad (Model\ 2)$$

$$RWA_{it} = \gamma_0 + \gamma_1 FI_{it} + \gamma_i \sum Control_{it} + \varepsilon_{it} \quad (Model\ 3-1)$$

$$NPL_{it} = \theta_0 + \theta_1 FI_{it} + \theta_2 L_{it} + \theta_i \sum Control_{it} + \varepsilon_{it} \quad (Model\ 3-2)$$

In the models, the dependent variable NPL_{it} represents the risk-bearing of the Chinese banking industry, and the core explanatory variable FI_{it} is the fintech index. The moderator variable RWA_{it} is the weighted net risky assets, and the mediator variable L_{it} is leverage $\sum Control_{it}$. represents the control variables. The constants are denoted as α_0, β_0, $\gamma_0$and θ_0, with α_1 being the regression coefficient for the core explanatory variable, β_3 the regression coefficient for the moderator variable, δ_i the regression coefficients for the control variables, and ε the error term.

4.Results

4.1 Descriptive statistics

Descriptive statistics for the variables are presented in Table 3. The mean of the non-performing loan provision coverage ratio (NPL) is 269.54, with a standard deviation of 102.126, indicating significant variation in the NPL coverage ratio among the sample banks. The fintech index (FI) ranges from a minimum of 6.974 to a maximum of 11.056, suggesting a generally high

level of fintech adoption among the sample banks. The equity-to-debt ratio (INV) has a standard deviation of 0.023, with a minimum value of 0.043 and a maximum of 0.313, reflecting a relatively low level of financial leverage among the sample banks. No anomalies were detected in the statistical values of other variables, suggesting that estimation biases due to outliers can be ruled out.

Table 3: Descriptive Statistics of Variables

Attributes	Variable		N	Mean	S.E.	Min	Max
Explained Variable	NPL	Non-performing loan provision coverage ratio	456	269.542	102.126	55.843	778.120
Explanatory Variable	FI	FinTech Index	305	9.050	0.890	6.974	11.056
Control Variable	GDPR	GDP current period growth rate	462	1.664	0.309	1.200	2.400
	INV	Equity to debt ratio	425	0.078	0.023	0.043	0.313
	TOP1	Shareholding ratio of the largest shareholder	451	21.435	15.489	4.310	67.720
	INDEP	Proportion of independent directors	396	0.323	0.136	0.000	0.571
	MAS	overhead	462	296.218	508.598	4.324	2259.450
Mediator Variable	LEV	leverage	239	6.603	0.949	3.620	9.680
Moderator Variable	FXZC	Weighted net risk assets	435	8.711	1.761	5.416	12.287

4.2. Correlation Analysis

To determine the presence of correlations between variables, a correlation analysis was conducted. The results indicate a significant negative correlation between the core explanatory variable (FI) (fintech index) and the dependent variable (NPL) (non-performing loan provision coverage ratio), suggesting that regression analysis is feasible. Additionally, control variables such as the proportion of shares held by the largest shareholder, the percentage of independent directors, and management expenses also show a significant negative relationship with the NPL coverage ratio. Furthermore, most correlation coefficients between other explanatory variables are less than 0.6, suggesting that severe multicollinearity issues are unlikely.

Table 4: Correlation Analysis

Variable	NPL	FI	GDPR	INV	TOP1	INDEP	MAS
NPL	1.000						
FI	-0.270***	1.000					
GDPR	0.048	0.018	1.000				
INV	-0.062	0.010	-0.029	1.000			
TOP1	-0.221***	0.625***	0.014	-0.090*	1.000		
INDEP	-0.175***	0.100*	-0.031	0.050	0.272***	1.000	
MAS	-0.143***	0.761***	-0.020	0.021	0.682***	0.271***	1.000

Standard errors are in parentheses.

Significance levels: $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

4.3 Multicollinearity Test

Given that some control variables had correlation coefficients greater than 0.6 in the correlation analysis, a variance inflation factor (VIF) test was conducted to further assess multicollinearity, as shown in Table 3. The VIF values for all variables are well below 10, indicating that there are no severe multicollinearity issues and regression analysis can be performed.

Table 5: Multicollinearity Test

Variable	VIF	1/VIF
MAS	2.86	0.3500
FI	2.60	0.3848
TOP1	1.97	0.5086
Indep	1.07	0.9324
INV	1.03	0.9747
GDPR	1.01	0.9941

4.4 Regression Analysis

Based on Model (1), the relationship between the fintech index and the non-performing loan provision coverage ratio (NPL) was analyzed using regression, as shown in Table 6. Column (1) presents the regression results without control variables, while Column (2) includes control variables. In both cases, the core explanatory variable, fintech index (FI), shows a significant negative effect at the 1% level, indicating that fintech has a suppressive effect on the NPL coverage ratio.

Specifically, Column (2) shows that the regression coefficient for the fintech index (FI) is -33.846 at the 1% significance level. This result suggests that an increase in the fintech index significantly reduces the NPL coverage ratio.

In summary, fintech development has a dual impact on the risk exposure of Chinese banks. On one hand, fintech enhances risk management capabilities by leveraging technologies such as big data analysis and artificial intelligence to more accurately assess borrower credit risk. This reduces the non-performing loan rate and, consequently, the need for loan loss provisions, thus improving the provision coverage ratio. On the other hand, emerging fintech business models can introduce new risk challenges. For example, areas such as P2P lending and virtual currencies may have regulatory gaps and legal risks, potentially leading to issues like fund misappropriation and fraud, thereby increasing the risk of non-performing loans. At the current stage, the negative effects of these new risks outweigh the positive impacts of fintech, leading to the regression results showing an adverse effect of fintech on risk exposure in the Chinese banking sector.

Additionally, the analysis of control variables indicates that the equity-to-debt ratio (INV) and the proportion of independent directors (INDEP) have a significant suppressive effect on the non-performing loan provision coverage ratio (NPL). In contrast, the current GDP growth rate (GDPR), the shareholding ratio of the largest shareholder (TOP1), and management expenses (MAS) did not show a significant impact on the NPL coverage ratio in this study.

Table 6: Baseline Regression

Variable	(1)	(2)
	NPL	NPL
FI	-31.754***	-33.846***
	(9.526)	(11.927)
GDPR		9.875
		(12.172)
INV		-444.919**
		(215.186)
TOP1		0.649
		(0.776)
INDEP		-161.337*
		(87.487)
MAS		-0.003
		(0.026)
Cons	549.758***	632.922***
	(85.211)	(111.750)
N	305	294
R-squared	0.073	0.078

Standard errors are in parentheses.

Significance levels: p < 0.1 (*), p < 0.05 (**), p < 0.01 (***).

4.5 Robustness Test

In order to avoid the impact of outliers on the regression results, the data are shrink-tailed at the 1% and 99% quantiles for robustness tests, and the results are shown in column (1) of Table 7. At the same time, considering that the new crown epidemic shock may cause errors on the regression results, the study excludes the data in 2020 using the exclusion of the special period sample size for the robustness test, the results are shown in Table 7 column (2). The robustness test regression results are basically consistent with the benchmark regression in terms of both the direction of impact and significance, indicating that the model is highly robust and the regression results are reliable.

Table 7 Robustness Tests

Variable	(1)	(2)
	NPL	NPL
	Shrinking	Excluding special period sample sizes
FI	-34.185***	-35.260***
	(12.031)	(12.600)
GDPR	9.343	5.847
	(12.158)	(26.441)
INV	-540.448**	-474.381**
	(264.987)	(238.914)
TOP1	0.676	0.518
	(0.784)	(0.802)
INDEP	-158.233*	-178.357*
	(87.471)	(98.063)
MAS	-0.005	-0.000
	(0.027)	(0.027)
Cons	642.961***	661.794***
	(113.783)	(126.449)
N	294	252
R-squared	0.075	0.093

Standard errors are in parentheses.

Significance levels: p < 0.1 (*), p < 0.05 (**), p < 0.01 (***).

Variable	(1)	(2)
	TSLS-Stage1	TSLS-Stage2
		NPL
L.FI	0.702***	
	(0.048)	
		-40.227**
		(15.934)
GDPR	-0.007	11.169
	(0.067)	(15.215)

Variable	(1)	(2)
	TSLS-Stage1	TSLS-Stage2
		NPL
INV	0.260	-114.673
	(0.906)	(207.464)
TOP1	0.004**	-1.197**
	(0.002)	(0.477)
INDEP	-0.634*	-179.884**
	(0.333)	(77.737)
MAS	0.0002***	0.034*
	(0.000)	(0.020)
Cons	2.720***	699.403***
	(0.458)	(145.572)
N	254	254
R-squared		0.172
Anderson canon. corr. LM statistic		115.394***
Cragg-Donald Wald F statistic		205.637
Stock-Yogo 10%		16.38

4.6 Endogeneity test

To address potential endogeneity affecting the regression results, we use the lagged core explanatory variable, L.FI, as an instrument and apply Two-Stage Least Squares (TSLS) to handle endogeneity. In the first stage of TSLS, the instrument generates a predicted value for the fintech index (FI)ˆ. In the second stage, this predicted value is used to regress on the non-performing loan provision coverage ratio (NPL). The LM statistic rejects the null hypothesis of insufficient instrument identification, and the Wald F statistic exceeds the Stock-Yogo critical value at the 10% level, indicating that the instrument is valid. The regression coefficient for (FI)ˆ is -40.227, aligning with the direction of the baseline regression but differing in magnitude and significance. This suggests that endogeneity has not significantly affected the regression results, further confirming the robustness and reliability of the model.

Table 8 Endogeneity test (IV-TSLS)

Variable	(1)	(2)
	TSLS-Stage1	TSLS-Stage2
	(FI)ˆ	NPL
L.FI	0.702***	
	(0.048)	
(FI)ˆ		-40.227**
		(15.934)
GDPR	-0.007	11.169
	(0.067)	(15.215)
INV	0.260	-114.673
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	TSLS-Stage1	TSLS-Stage2
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R-squared		0.172
Anderson canon. corr. LM statistic		115.394***
Cragg-Donald Wald F statistic		205.637

Standard errors are in parentheses.

Significance levels: $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

4.7 Mediating Effect

This study investigates the impact mechanism of financial technology on risk-taking in Chinese banks using leverage ratio (LEV) as a mediating variable. Table 9 employs a three-step method to explore the potential mediating effect. However, Column (2) shows no significant impact of financial technology (FI) on leverage ratio (LEV), and Column (3) shows no significant impact of leverage ratio (LEV) on non-performing loan provision coverage ratio (NPL). These non-significant results may be due to insufficient sample size. To address this, we further employ the bootstrap sampling method, conducting 300 iterations. Results are presented in Table 10. Table 10 reveals that while financial technology (FI) has a total suppressive effect on NPL, it exerts an indirect positive effect on NPL through leverage ratio (LEV). This suggests that financial technology has an indirect facilitating effect on risk-taking in Chinese banks by influencing leverage ratio.

Specifically, financial technology enables banks to more accurately assess borrower credit risk, optimize risk pricing models, and improve credit approval efficiency. These improvements reduce the risks and asset quality issues faced by banks, thereby decreasing their reliance on external funding and affecting their leverage ratios. An increased leverage ratio enhances the banking sector's ability to withstand various risks, lowers non-performing loan rates, reduces the need for provisions for bad loans, and increases the non-performing loan provision coverage ratio. Ultimately, this contributes to the enhancement of systemic risk management within the banking industry.

Table 9: Mediating Effect Analysis

Variable	(1)	(2)	(3)
	NPL	Lev	NPL
FI	-33.846***	-0.123	-34.117***
	(11.927)	(0.116)	(11.699)
GDPR	9.875	-0.141	3.309

Variable	(1)	(2)	(3)
	NPL	Lev	NPL
	(12.172)	(0.103)	(10.883)
INV	-444.919**	2.538	-37.050
	(215.186)	(2.223)	(226.422)
TOP1	0.649	-0.039***	-1.443
	(0.776)	(0.010)	(0.886)
INDEP	-161.337*	2.076**	63.012
	(87.487)	(0.881)	(89.463)
MAS	-0.003	0.002***	0.061**
	(0.026)	(0.000)	(0.029)
LEV			0.823
			(6.895)
Cons	632.922***	7.221***	543.833***
	(111.750)	(1.100)	(122.180)
N	294	217	217
R-squared	0.078	0.105	0.113

Standard errors are in parentheses.

Significance levels: p < 0.1 (*), p < 0.05 (**), p < 0.01 (***).

Table 10 Mediated effects: bootstrap (300) sampling method

	Coefficient	standard error	Z-value	95% confidence interval	
				Low	High
Indirect Effect	9.242**	4.485	2.06	0.452	18.033
Direct Effect	-55.946***	12.385	-4.52	-80.220	-31.672

Standard errors are in parentheses.

Significance levels: p < 0.1 (*), p < 0.05 (**), p < 0.01 (***).

4.8 Moderating Effect

This study uses the weighted risk assets (RWA) as a moderating variable. After centering the independent and moderating variables, an interaction term (X) is created. The regression results are presented in Table 11. Column (2) shows that the interaction term X is significant at the 1% level, indicating that RWA moderates the relationship between fintech and the non-performing loan (NPL) coverage ratio. The negative coefficient for the interaction term X suggests a negative moderating effect.

RWA is an important indicator for assessing a bank's capital adequacy and risk exposure, while the NPL coverage ratio reflects the bank's provisions for potential losses from bad loans. The negative moderating effect of RWA indicates that fintech development influences the relationship between RWA and the NPL coverage ratio. Specifically, fintech advancements improve banks' risk management efficiency and precision. Through technologies such as big data analysis and artificial intelligence, fintech enables more effective identification and management of potential risks, thereby reducing NPL rates and the need for provisions. Consequently, as fintech levels rise, RWA decreases, and the NPL coverage ratio is likely to improve.

Table 11 Moderating Effects

Variable	(1)	(2)
	NPL	NPL
FI	-28.810**	-13.688
	(13.388)	(13.986)
lnFXZC	-9.086	-26.522**
	(10.969)	(11.699)
GDPR	9.375	10.840
	(12.175)	(12.177)
INV	-435.712**	-327.206
	(215.665)	(214.038)
TOP1	0.799	0.168
	(0.796)	(0.738)
INDEP	-144.530	-103.259
	(89.843)	(88.251)
MAS	0.009	0.087**
	(0.030)	(0.035)
X		-24.113***
		(7.137)
Cons	656.552***	668.524***
	(115.698)	(110.366)
N	294	294
R-squared	0.078	0.179

Standard errors are in parentheses.

Significance levels: $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

5. Conclusions and Discussion

This study examines the impact of financial technology (FinTech) on the non-performing loan (NPL) coverage ratio of Chinese commercial banks from 2007 to 2022. It contributes to the theoretical understanding of factors affecting NPL coverage ratios by exploring both the mediating role of leverage ratio and the moderating role of risk-weighted assets. The findings provide clear guidance for the future development of FinTech in banking and financial risk management. The key conclusions are: Fintech has a significant negative impact on the non-performing loan (NPL) provision coverage ratio, indicating that currently, fintech adversely affects risk management in China's banking sector. Fintech indirectly enhances risk management in China's banking sector by influencing leverage ratios. The weighted net risk assets have a negative moderating effect on the relationship between fintech and the NPL provision coverage ratio. These findings are crucial for regulators. Chinese commercial banks should also adopt more targeted policies. Based on these conclusions, the following policy recommendations are proposed:

First, enhance the supervision of fintech. Establish a comprehensive regulatory framework and implement specific policies targeting fintech to ensure transparency, security, and compliance in fintech operations. Additionally, employ real-time monitoring and risk assessment technologies such as big data and artificial intelligence to continuously track fintech's impact on banking operations and promptly identify and address potential risks.

Second, optimize bank leverage management. Set reasonable leverage ratio limits for banks to prevent systemic risks associated with excessive leverage. Furthermore, strengthen internal management and control of leverage ratios to ensure they remain within safe limits.

Third, increase the non-performing loan (NPL) provision coverage ratio. Require banks to increase NPL provisions in line with rising risk assets to enhance their risk resilience. Additionally, adjust NPL provisioning strategies dynamically based on market conditions and risk profiles to ensure the coverage ratio adapts to changes brought about by fintech advancements.

Fourth, promote the coordinated development of fintech and traditional banking. Encourage collaboration between fintech companies and traditional banks to jointly develop new financial products and services, thereby mitigating risks associated with competition. Additionally, support the integration of fintech within the banking sector, ensuring that it enhances operational efficiency and service quality while maintaining safety and compliance.

Bankers should place significant emphasis on the application of fintech and its impact on overall risk management when enhancing the NPL provision coverage ratio. In this context, leverage (LEV) serves as a crucial mediating variable that effectively influences the NPL coverage ratio, while the weighted net risk assets (RWA) play an important moderating role. Banks should tailor and optimize the use of fintech based on their specific business characteristics and operational models to better manage NPL risks. Additionally, banks must remain vigilant about the potential risks introduced by fintech, particularly concerning credit and liquidity risks. Joint-stock commercial banks should leverage their fintech strengths to innovate and refine their NPL provision management mechanisms. Regional banks should align their unique market positioning with fintech advancements, continuously enhancing their innovation capabilities to achieve more robust risk management and business growth.

From a Theoretical Perspective. Firstly, this study enriches the literature on fintech and the non-performing loan (NPL) provision coverage ratio by providing both theoretical and empirical evidence on how fintech impacts micro-level risks differently across banks. Secondly, the findings offer a deeper understanding of the various channels through which fintech influences the NPL provision coverage ratio, and underscore the significance of leverage and weighted risk assets.

This study is limited by its focus on commercial banks, and future research could expand the sample to include a broader range of financial institutions as regulatory and disclosure standards in China improve. Additionally, while this study provides a theoretical analysis of fintech's impact mechanisms, further empirical validation of these mechanisms is needed in future research.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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