Marginal Effects of Intelligent Risk-management Technology on Commercial Bank Credit Risk: A Heterogeneity Analysis on Banks of Different Categories

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Abstract. With the rapid advancements in artificial intelligence and data analysis, Financial Technology (FinTech) has become increasingly utilized in assessing creditworthiness and monitoring loan utilization of borrowers. This study delves into the nuanced effects of intelligent risk management technology on credit risk across different categories of commercial banks. Employing a two-way fixed effects model, we analyzed data encompassing all publicly listed Chinese commercial banks from 2012 to 2022. The results emphasize that the adoption of intelligent risk management technology significantly reduces credit risk, particularly for city-based banks. Furthermore, our findings indicate that joint-stock banks experience a more substantial effect from intelligent risk management technology compared to state-owned banks. Importantly, these results remain consistent even after employing instrumental variables and conducting rigorous robustness tests.

Keywords: Credit risk, Heterogeneity analysis, Intelligent risk-management technology, Two-way fixed effects model

1 Introduction

In an era where the fusion of technology and finance is no longer a vision but a reality, commercial banks are at the forefront of navigating both the opportunities and challenges presented by Financial Technology (FinTech). The burgeoning growth of artificial intelligence, data science, and other digital technologies has opened new avenues for risk management, particularly in credit risk mitigation. Although both academia and the industry have begun to adopt these innovations, a comprehensive grasp of their implications, particularly concerning credit risk across various categories of commercial banks, remains nascent.

This paper categorizes Chinese commercial banks into three distinct groups: state-owned banks, joint-stock banks, and city banks. State-owned banks receive unique funding from the state and operate under the direct control of the Chinese central finance ministry. On the other hand, joint-stock banks are typically owned by corporate entities, functioning with a high degree of autonomy and pursuing profit maximization as their primary business objective. City banks, meanwhile, are local joint-stock commercial banks formed through the consolidation of local

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financial institutions and the attraction of equity from local enterprises. To differentiate between city banks and joint-stock banks, this paper specifically defines national joint-stock banks as falling within the joint-stock bank category.

Intelligent risk-management technology is a subset of Fintech. The paper aims to scrutinize the marginal effects of intelligent risk-management technology on credit risk within China's commercial banking sector, taking into consideration the heterogeneous impact across different categories of banks. The authors employ a decade-long balanced panel data of all listed commercial banks in China, covering the period from 2012 to 2022. The study also integrates macroeconomic indicators and leverages an intelligent risk-management index generated based on the frequency of intelligent risk-management-related keywords associated with commercial banks in the authoritative news search engine, Baidu. To tackle the intricacies of our research inquiry and account for potential endogeneity, we employ a two-way fixed effects model, instrumental variables, and a battery of robustness tests.

2 Literature Review

Financial Technology, commonly referred to as FinTech, has become a transformative force in the banking sector, affecting various aspects including credit risk management. FinTech encapsulates a plethora of emerging financial products, services, and models facilitated by technological innovations.[1] Within this expansive domain, intelligent risk-management technologies stand out as an important frontier. These technologies comprise a set of data-driven, analytical tools designed to measure, assess, and mitigate credit risk in banking operations. The application of Fintech has been noted to have a dual impact on credit risk. On one side, Cheng and Qu contend that FinTech, especially intelligent risk-management technologies, can aid banks in reducing credit risk.[2] Du, Liu and Lu argued that advances in cloud computing, big data analytics, artificial intelligence, and blockchain provide banks with sophisticated means to improve credit assessments, thereby reducing Non-Performing Loan (NPL) ratios.[3] Nonetheless, Okoli, a prominent scholar, has highlighted the potential risk of heightened credit risk resulting from the excessive use of Fintech. This risk is attributed to the ease in lending rates and an increase in banks' risk appetite [4]. Additionally, Vucinic has issued a cautionary note, emphasizing that an enthusiastic integration of Fintech may lower lending standards, consequently amplifying the likelihood of asset deterioration and financial risks [5]. Consequently, the author advocates for international collaboration among regulators to effectively address the potential risks associated with Fintech.

Moreover, the effects of intelligent risk-management technologies seem to differ across bank categories. Large banks, which mainly serve large enterprises, already have well-established credit systems, and the room for improvement through FinTech may be limited. On the other hand, smaller and medium-sized banks, which serve financially constrained small and micro enterprises, may benefit more from FinTech innovations.[6] These banks have greater risks due to information asymmetry and thus have more to gain from the data-rich solutions offered by intelligent risk-management technologies.

The commonly employed metric to gauge the credit risk in banking institutions is the Non-performing Loan ratio (NPL). Numerous factors can influence the NPL ratio, ranging from macroeconomic indicators to the quality of a bank’s credit portfolio.[7] The study integrates these diverse perspectives by utilizing a balanced panel data set from 42 listed commercial banks in China spanning 2012-2022. This data allows us to examine how the degree of intelligent risk-management technology application, impacts NPL ratios across different categories of banks. In doing so, our study seeks to contribute a nuanced understanding of the role of intelligent risk-management technology in shaping credit risk landscapes, leveraging advanced econometric models to validate our findings.

Here are the contributions of our study. Firstly, it extends beyond the conventional observation of the relationship between FinTech and credit risk. It delves deeper to analyze the underlying mechanisms through which intelligent risk-management technologies influence credit risk. This nuanced understanding holds significant importance for shaping policy decisions. Secondly, our research advances the current methodologies used to quantify banks' integration of intelligent risk-management technologies. Our custom index, developed after a thorough analysis of news articles on the Baidu platform, offers a more comprehensive and logical measure. It effectively captures the annual engagement of individual commercial banks with intelligent risk-management technologies. Lastly, by investigating the distinct impacts of adopting intelligent risk-management technology on credit risk across diverse bank categories, our study provides valuable insights with substantial practical implications. We propose that various categories of commercial banks may benefit from tailoring their strategies for developing intelligent risk-management technology to aptly address credit risk management.

3 Data and Method

This paper adopts the balanced panel data of 42 listed commercial banks in A share Chinese stock market from 2012 to 2022. China's listed commercial banks have a full range of business units, sufficient capital and investment in fintech, with different banking categories covered. Therefore, the study takes the data of all listed commercial banks in China in the past 10 years as the sample.

The quantitative indicators related to credit risk of 42 listed commercial banks in China are obtained from Wind and CSMAR for the period of 2012-2022. Wind is a software developed by Shanghai Wind Information Technology Company Limited, which provides financial data and analytical tools, and is widely recognized by financial academic research institutes in China. CSMAR (China Stock & Accounting Research Database) is a research database serving academic universities and financial institutions. And the research acquires China's macroeconomic indicators for 2012-2022 from the public database of the National Bureau of Statistics of China.

Constructing the Intelligent Risk-management Index: Building on the Basel Committee on Banking Supervision's 2018 framework for fintech business models and insights from Zhang et al. about the various fintech dimensions, we crafted the thesaurus of commercial bank intelligent risk-management application (see Table 1).[6] Harnessing these identified keywords, we utilized web scraping techniques on Baidu to gather a decade's worth of news linked to intelligent risk-management technologies for 42 commercial banks. When creating our intelligent risk-management index, the KMO test scored a promising 0.93, suggesting a strong correlation among the keywords. Additionally, Bartlett's test revealed a significant link between the indicators, showing a χ^2 value of 16135.92 with 1176 degrees of freedom. Using principal component analysis, we identified key factors with eigenvalues greater than 1 and determined their respective scores. We then rotated the loadings matrix for clarity using the maximum variance principle. With regression analysis, we pinned down the factor's scoring coefficients. The culmination of this process resulted in the creation of an index, scaled from 0 to 1. To make it more intuitive, we represent this as scores between 1 and 10, where higher scores indicate a greater embrace of smart risk-management tools.

Table 1. Thesaurus of Commercial Bank Intelligent Risk-management Application Index

Dimension	Keyword
Online lending	Borrower online scoring, online loan repayment track, customized interest rate, digital loan terms, instant approval, online fundraising, online lending platform, mobile banking, online loan
Basic technology	Fraud Detection, cybersecurity, digital identity verification, privacy computing, machine learnin algorithm, regulatory compliance trackor, artificial intelligence, 5 G infrastructures, network densification, blockchain, clouding computing
Intelligent risk management	Intelligent stress testing, intelligent risk management, digital credit risk control, default prediction model, credit scoring model, customer information trackor, intelligent credit allocation system, behavioral analytic model

The paper focuses on the differences in the impact of intelligent risk-management technology on credit risk of banks with different categories. Therefore, when constructing the regression model, the Non-performing Loan ratio is taken as the dependent variable, the index of the degree of application of banks' intelligent risk-management technology, the index of the state-owned banks, the index of the joint-stock banks, the interaction variable between the index of the state-owned banks and the index of the degree of application of intelligent risk-management technology are taken as the core explanatory variables. And other variables influencing the Non-performing Loan ratio of the banks are also included in the model. And the regression model is set up in the equation (1).

$$NPL_{i,t} = \beta_0 + \beta_1 IRMT_{i,t} + \beta_2 SB_{i,t} + \beta_3 JSB_{i,t} + \beta_4 (IRMT_{i,t} \times SB_{i,t}) + \beta_5 (IRMT_{i,t} \times JSB_{i,t}) + \beta_6 X_{i,t} + \delta_t + \mu_i + \epsilon_{i,t} \quad (1)$$

In equation (1), $X_{i,t}$ denotes control variables, δ_t denotes time fixed effects, μ_i denotes individual fixed effects, $\epsilon_{i,t}$ denotes the random error. Characters of variables are defined in Table 2.

$$When\ SB_{i,t} = 1,\ JSB_{i,t} = 0,\ \frac{\partial NPL_{i,t}}{\partial IRMT_{i,t}} = \beta_1 + \beta_4$$

$$When\ SB_{i,t} = 0,\ JSB_{i,t} = 1,\ \frac{\partial NPL_{i,t}}{\partial IRMT_{i,t}} = \beta_1 + \beta_5$$

$$When\ SB_{i,t} = 0,\ JSB_{i,t} = 0,\ \frac{\partial NPL_{i,t}}{\partial IRMT_{i,t}} = \beta_1 \quad (2)$$

In equation (2), we find that $\beta_1 + \beta_4$ represent the marginal effects of intelligent risk-management technology on credit risk for state-owned banks. $\beta_1 + \beta_5$ represent the marginal effects of intelligent risk-management technology on credit risk for joint-stock banks. β_1 represents the marginal effects of intelligent risk-management technology on credit risk for commercial banks.

After adopting the two-way fixed effects model to regress the panel data, the paper then deals with the endogeneity problem caused by reverse causality by introducing the time lag variable of one core explanatory variable as the instrumental variable and conducting instrumental variable validity tests. Finally, a robustness test of the regression results is conducted by changing the dependent variable and using the R-estimation robust regression method.

Table 2. Definition of Research Variables

Variable Type	Variable Name	Definition	Character
Interpreted variable	Non-performing loan ratio	(Subprime loans + Doubtful loans + Loss-making loans) / Loans * 100%	NPL
	Overdue loan ratio	Overdue loans/Total loans	OL
Core explanatory variables	State bank	Dummy variable, indicate whether the bank is owned by state	SB
	Joint-stock bank	Dummy variable, indicate whether the bank is joint stock	JSB
	Intelligent risk-management technology application index	Generated by NLP, affected by technological investment, number of practitioners and frequency of appearance in relevant news	IRMT
Control variables	Return on asset	Net profit/total assets	ROA
	Asset size	Natural logarithm of total asset size (in million RMB)	AS
	Credit loan ratio	Total credit facilities/total loans	CLR
	Allowance for credit loss	Balance of provision for loan losses/balance of loans	AFCR
	Consumer price index	Cost of market basket in a given year / Cost of market basket in base year) x 100	CPI
	Economic development	GDP growth rate	ED
	Interest rate	RMB lending benchmark rate	IR
	Loan market development	Loan balance of financial institutions/GDP	LMD

4 Empirical Result

4.1 Descriptive Statistics

According to Vatansever and Hepsen, the Non-performing Loan ratio reflects the proportion of non-performing loans to total loans of the bank.[8] The increase in the Non-performing Loan ratio indicates the increase in credit risk of the bank. Therefore, the paper takes the Non-performing Loan ratio as a quantitative indicator of credit risk of sample commercial banks, and the Non-performing Loan ratio is the main dependent variable of the regression model. In addition, Tsintsadze et al. argue that the overdue loan rate is also an important indicator reflecting the credit quality of banks, which can also be used as a variable to measure credit risk.[9] The paper categorizes Chinese commercial banks as state-owned banks, joint-stock banks, and city commercial banks according to the nature of different banks. Two indicator variables are generated to reflect the category of each bank. The interaction variable of the dummy variable for bank type and the index of the degree of application of intelligent risk-management technology will be the core explanatory variables of the paper.

Moreover, according to Nikolopoulos and Tsalas, the Non-performing Loan ratio of a bank is affected by the macroeconomic environment and bank-specific factors such as the bank's asset size and risk preferences.[10] Therefore, the paper introduces control variables including return on asset, credit loan ratio, natural logarithm of total assets, allowance for credit loss, consumer price index, GDP growth rate, interest rate, and the degree of development of the loan market. Table 2 shows all the variables involved in the study, as well as the meaning and calculation of each variable.

Table 3 shows the descriptive statistics of the variables covered in the paper. Among the dependent variables, the mean of overdue loan ratio is lower than the mean of Non-performing Loan ratio, indicating that on average the overdue loan ratio of commercial banks is smaller than the Non-performing Loan ratio. The standard deviation of Non-performing Loan ratio is 0.682, and the standard deviation of overdue loan ratio is 0.518, which indicates that the dispersion of Non-performing Loan ratio is larger than that of the overdue loan ratio of commercial banks. The state-owned bank and joint-stock bank variables are both dummy variables, and in the sample, there are a total of 6 state-owned banks, 10 joint-stock banks, and 26 city commercial banks. The mean value of the core explanatory variable intelligent risk-management technology application index is 5.016, implying that the on average sample banks are at a medium level of application of intelligent risk-management technology in the past 10 years. The intelligent risk-management technology application index has a large range, which suggests that the application of intelligent risk-management technology from 2012 to 2022 evolves drastically. In addition, the standard deviation of the index is 1.824, which implies that the level of application of intelligent risk-management technology has a certain degree of dispersion, which is favorable for the estimation of regression coefficients. Financial indicators and risk preference indicators that affect banks' credit risk, such as asset size, credit loan ratio, and allowance for credit loss are also shown in Table 3. These indicators have a large degree of dispersion, while the data of macroeconomic variables have a small degree of dispersion. Macroeconomic variables generally do not change much from year to year unless there are severe economic shocks.

Table 3. Descriptive Statistics of Research Variables

	N	Mean	Median	Std. Dev.	Min.	Max.
NPL	420	1.572	1.416	0.682	0.336	11.921
OL	420	1.286	1.249	0.518	0.115	7.652
SB	420	0.123	0.000	0.329	0.000	1.000
JSB	420	0.292	0.000	0.455	0.000	1.000
IRMT	420	3.054	2.280	1.824	0.007	9.176
ROA	420	1.064	0.973	0.732	0.428	3.781
AS	420	23.801	23.528	1.754	10.841	37.490
CLR	420	17.61	16.21	4.109	0.024	48.238
AFCR	420	4.872	4.357	1.496	1.745	16.952
CPI	420	3.055	3.176	0.072	0.614	6.159
ED	420	6.851	6.952	0.018	2.247	9.562
IR	420	4.339	4.357	0.002	3.258	6.831
LMD	420	1.526	1.433	0.745	0.157	7.078

4.2 Hypothesis Development

Venkateswara et al. have concluded the main influence path of intelligent risk-management technology on credit risk.[11] They proposed that intelligent risk-management technology mainly plays a role in the evaluation of borrowers and post-loan management. At the pre-approval stage, intelligent risk-management technology can utilize artificial intelligence technology to capture information about individual borrowers as well as borrowing enterprises from multiple channels, and evaluate the credit limits and credit levels of different borrowers through intelligent scoring systems to assist in loan decision-making. After the loans are granted, the intelligent risk-management technology can set digital risk thresholds and provide early warning of default risk by tracking the negative information of borrowers and the use of loans. Therefore, the paper proposes that the degree of use of intelligent risk-management technology has positive marginal impacts on banks' non-performing loan ratios and can enhance commercial banks' capacity to manage credit risk.

Moreover, Zhang et al. Point out that commercial banks of different categories differ in terms of Non-performing Loan ratio.[12] State-owned banks are subject to stricter policy controls and have a complicated approval process for loans with high amounts, and thus the Non-performing Loan ratio can generally be maintained at a low level. Joint-stock banks, on the other hand, have a higher risk appetite than state-owned banks due to their demand for high asset returns. City banks often face higher Non-performing Loan ratio than state-owned banks because they need to obey the commands of local governments to finance local small and medium-sized enterprises. Therefore, the paper hypothesizes that there is a significant difference in the marginal effect of intelligent risk-management technology on credit risk for banks with different categories. In addition, considering that the state-owned banks are strictly regulated by the Chinese central government in terms of lending and have less risky behavior, the hypothesis is that the marginal effect of intelligent risk-management technology on credit risk of state-owned banks is smaller than the marginal effect of intelligent risk-management technology on credit risk of city banks and joint-stock banks. Compared with city banks, joint-stock banks may have more mature credit risk management systems due to their larger business scale. And city banks mainly serve local small and medium-sized enterprises that are less risk-resistant and originally have low abilities of risk management. Therefore, the paper hypothesizes that the marginal effect of the intelligent risk-management technology on credit risk of joint-stock banks is smaller than the marginal effect of the intelligent risk-management technology on credit risk of city banks.

4.3 Regression Analysis

The paper adopts a two-way fixed effects model, which is conducted by using the decentralized approach. The first columns of the fixed effects model in Table 4 show the regression results of the model. It is found that the effects of the core explanatory variables on the Non-performing Loan ratio are all significant at the 1% level of significance level. The results show that the degree of application of intelligent risk-management technology is negatively correlated with the Non-performing Loan ratio of commercial banks, and the results are significant at the 1% significance level. Chinese commercial banks can effectively reduce credit risk by increasing the application of intelligent risk-management technology. The regression coefficients of intelligent risk-management technology application index*state bank and intelligent risk-management technology application index*joint-stock bank variables are both negative at the 1% significance level, implying that the marginal effect of the intelligent risk-management technology on Non-performing Loan ratio of city banks is the highest. Moreover, the regression coefficients of intelligent risk-management technology*state bank variables are smaller than those of intelligent risk-management technology*joint-stock bank variables, which implies that the marginal effect of intelligent risk-management technology on Non-performing Loan ratios of joint-stock banks is larger than that of state-owned banks.

The effect of macroeconomic variables on Non-performing Loan ratios has also been analyzed. The model results show that GDP growth rate, consumer price index and the degree of development of the loan market all have a negative correlation with the Non-performing Loan ratio of Chinese commercial banks, but the significance level differs. The effect of GDP growth rate on the Non-performing Loan ratio is significant at the 1% significance level, and the effect of the degree of loan market development on the Non-performing Loan ratio is significant at 5% significance level. And the effect of the consumer price index on Non-performing Loan ratio is not significant. Moreover, the regression results show that credit loan ratio, return on asset and allowance for credit loss all have significant effects on Non-performing Loan ratio. The increase in credit loan ratio leads to an increase in Non-performing Loan ratio. However, return on asset and allowance for credit loss have a negative correlation with Non-performing Loan ratio. The R^2 of the fixed effects model is 0.424, which means that 42.4% variation of Non-performing Loan ratio can be explained by the independent variables in the model.

Table 4. Regression Results of the Fixed Effects Model With Instrumental Variables

	Fixed Effects Model				Fixed Effects Model			
	(1).NPL		(2).NPL(IV)		(1).OL		(2).OL(IV)	
	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats	Coeff.	t-stats
IRMT	-0.362***	-3.021	-0.485***	-3.827	-0.037**	-1.963	-0.032**	-1.862
SB	0.872***	4.662	0.869***	4.524	0.598***	4.242	0.537***	4.018
JEB	0.613***	3.290	0.725***	3.819	0.462***	3.189	0.479***	3.223
IRMT*SB	-1.928***	-8.871	-2.014***	-9.432	-1.316***	-7.923	-1.267***	-7.368
IRMT*JEB	-1.623***	-6.982	-1.824***	-8.216	-1.188***	-6.318	-1.033***	-6.001
ROA	-1.639***	-7.213	-1.434***	-6.168	-0.068**	-2.269	-0.074**	-2.346
AS	-0.017*	-1.623	-0.028*	-1.723	-0.002	-0.230	-0.002	-0.183
CLR	0.656***	3.341	0.430***	3.298	0.715***	5.152	0.728***	5.637
AFCR	-0.093**	-2.191	-0.121**	-2.246	-0.117**	-2.438	-0.135**	-2.773
CPI	-0.002	-0.124	-0.001	-0.102	-0.003	-0.318	-0.005	-0.386
ED	-0.677***	-3.456	-0.846***	-4.903	-0.056**	-2.015	-0.078**	-2.458
IR	0.004	0.421	0.004	0.397	0.038**	1.968	0.046**	2.006
LMD	-0.034**	-1.863	-0.048**	-1.922	-0.084**	-2.914	-0.070**	-2.672
F-Stat	78.421		93.582		62.431		71.048	
R^2	0.424		0.481		0.214		0.326	
N	420		420		420		420	

The first two columns take NPL as the dependent variable. And the last two columns take OL as the dependent variable. IV denotes instrumental variables. *** represents 1% level of significance, ** represents 5% level of significance, and * represents 10% level of significance.

4.4 Endogeneity

Katsiampa et al. argue that there exists reverse causality between fintech investment of commercial banks and non-performing loan rates. Commercial banks may increase their investment in fintech due to the increase in Non-performing Loan ratio and thus hope to curb the increase in Non-performing Loan ratio through the adoption of fintech. Therefore, to deal with the endogeneity problem caused by reverse causality, the paper introduces the time lag variable of the intelligent risk-management technology application index as an instrumental variable, which is denoted as $IRMT_{i,t+1}$. The index of the degree of application of intelligent risk-management technology in year t+1 is correlated with the index of the degree of application of intelligent risk-management technology in year t. Moreover, the index of the degree of application of intelligent risk-management technology in year t+1 does not have a direct impact on the Non-performing Loan ratio in year t. Therefore, $IRMT_{i,t+1}$ is a reasonable instrumental variable.

The second column of the fixed effects model indicates the regression results after the introduction of instrumental variables. The significance and signs of the regression coefficients of the explanatory variables do not change significantly after the introduction of instrumental variables. The absolute value of the regression coefficients of the core variables increases, implying that the marginal effect of the core variables on the Non-performing Loan ratio of commercial banks increases. In addition, the difference between the marginal effects of intelligent risk-management technology on Non-performing Loan ratio of banks with different categories increases. In the two-stage regression in which the instrumental variable is introduced, the F-value of the first-stage regression is 21.456, which is greater than 10, implying that the correlation between the instrumental variable and the core explanatory variable is verified.

4.5 Robustness Analysis

The overdue loan ratio shows the share of overdue loan balances in the total loan balances, implying the bank credit quality. To test the robustness of the model, the paper replaces the Non-performing Loan ratio with the overdue loan ratio as the dependent variable. The regression model is set as the equation (3).

$$OL_{i,t} = \alpha_0 + \alpha_1 IRMT_{i,t} + \alpha_2 SB_{i,t} + \alpha_3 JSB_{i,t} + \alpha_4\left(IRMT_{i,t} \times SB_{i,t}\right) + \alpha_5\left(IRMT_{i,t} \times JSB_{i,t}\right) + \alpha_6 X_{i,t} + \delta_t + \mu_i + \epsilon_{i,t} \quad (3)$$

The last two columns of Table 4 show the regression results after adopting the overdue loan ratio as the dependent variable in Equation (3). The intelligent risk-management technology application index has a negative correlation with overdue loan ratio, and the effect is significant at the 1% level of significance. The paper finds that the marginal effect of intelligent risk-management technology on the overdue loan ratio of state-owned banks is lower than that of joint-stock banks. And the marginal effect of intelligent risk-management technologies on overdue loan ratio in joint-stock banks is lower than that of city banks. Compared with the regression results with Non-performing Loan ratio as the dependent variable, the difference in the marginal effect of intelligent risk-management technology for banks with different categories is reduced in this model, but the results are still significant at the 1% significance level. The decrease in the absolute value of the regression coefficients of the core explanatory variables may be attributed to that the overdue loan ratio is subject to strict national regulation. Therefore, the overdue loan ratio has been kept at a relatively low level, with less room for improvement through intelligent risk-management technologies.

In addition, compared with the previous fixed-effects model with Non-performing Loan ratio as the dependent variable, the absolute values of the regression coefficients of the macroeconomic variables increase and the significance of the interest rate regression coefficients improves. Except consumer price index, the effect of other macroeconomic variables on overdue loan ratio is significant at the 5% level of significance level. The reason may be that deterioration in the economic environment leads to a decrease in the level of the profit of the borrower, which in turn affects the repayment ability of the borrower and increases the overdue loan ratio.

To decrease the effect of outliers on the regression coefficients, the paper uses the R-estimation method, which is a classical robustness regression method. Different from the least squares method of minimizing the sum of squares of the residuals as an estimation method, R-estimation method has an objective function in equation (4).

$$a(i) = \sqrt{12}\left(\frac{i}{n+1} - \frac{1}{2}\right)$$

$$D_R(\hat{\beta}) = \sum a\left(R(r_i)\right)\left(y_i - x_i\hat{\beta}\right) = \frac{\sqrt{12}}{n+1}\sum\left[R(\mathrm{r_i}) - \frac{\mathrm{n+1}}{2}\right]\mathrm{r_i} \quad (4)$$

Equation (4) shows the R estimating model. It incorporates a function of the rank order of the residuals as a down-weighting function of the outliers, which lessens their impact on the estimates and satisfies the robustness criterion.

In equation (4), r_i denotes the residuals, $R(r_i)$ denotes the rank of the residuals, $a(i)$ denotes the scoring function, $D_R(\hat{\beta})$ is the objective function when conducting regression.

The results of the R estimation indicate that the signs and significance level of core explanatory variables remain constant as the results in the fixed-effects model. And the R^2 of the model increases because the R estimation model weakens the effects of bias caused by outliers.

5 Conclusion

The paper empirically investigates the correlation between the implementation of intelligent risk-management technology and credit risk within Chinese commercial banks. Utilizing a balanced panel dataset encompassing all publicly listed Chinese commercial banks over the period of 2012-2022, we also explore the varying marginal effects of intelligent risk-management technology across different bank categories. Employing the two-way fixed effects model, our findings demonstrate a noteworthy reduction in credit risk for commercial banks because of heightened utilization of intelligent risk-management technology. Specifically, city banks exhibit the most substantial reduction in credit risk, showcasing the most significant marginal effect. Conversely, state-owned banks experience a smaller marginal effect compared to joint-stock banks. This heterogeneity in effects across distinct bank categories is statistically significant at the 1% level of significance. Importantly, our empirical findings remain robust and consistent following a battery of robustness tests.

To conclude, our research offers practical policy insights. Notably, intelligent risk-management technology holds untapped potential in alleviating credit risk among state-owned banks. Adjusting regulations, especially regarding medium-risk lending, by the central finance ministry could help these banks leverage this potential. Additionally, focusing on city banks, local governments can play a supportive role by introducing favorable policies like tax incentives to encourage the adoption and development of intelligent risk-management technology. Allocating resources and emphasizing personnel training are also vital strategies for city banks. However, it's important to acknowledge the study's focus on Chinese commercial banks. In the ever-evolving landscape of Fintech, future research could widen its scope to encompass other countries and explore broader risk management aspects like operational and market risks, providing a more holistic view of the global fintech impact on the banking sector.

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