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The influence of fintech on the non-performing loan rate of commercial banks Evidence from China

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Master in Economics

Supervisor:
PhD Diptes Chandrakante Prabhudas Bhimjee, Invited Assistant Professor, Iscte-Iul

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BUSINESS SCHOOL

CIÊNCIAS SOCIAIS E HUMANAS

Department of Economics

Department of Political Economy

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Postgraduate life passed quickly, but looking back through the years, my heart is enriched. When I finished this graduation thesis, I felt a sense of relief and a lot of emotion.

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Resumo

Esta Dissertação investiga o impacto do desenvolvimento das fintechs na taxa de maus empréstimos non-performing através de uma análise estatística de dados de vários bancos comerciais chineses durante o período de 2011 a 2019. A abordagem empírica de regressão multinível foi utilizada e os dados extraídos são de bancos comerciais de capital publicamente disperso, estatais, e não-estatais. Ao mesmo tempo, as variáveis macroeconómicas foram adicionadas como variáveis de controle. Os resultados do modelo de efeitos aleatórios indicam que o desenvolvimento das fintechs aumentou ligeiramente a taxa de empréstimos non-performing dos bancos comerciais de capital publicamente disperso, enquanto o impacto do índice fintechs sobre os bancos comerciais não listados não foi estatisticamente significativo. Os resultados também foram sujeitos a testes de robustez.

Palavras-chave: setor bancário chinês, taxa de crédito, fintech, bancos públicos, bancos comerciais

Abstract

This dissertation explore the impact of the development of fintech technology on the non-performing loan rate through statistical analysis of the data of several Chinese commercial banks during the period of 2011-2019. This document employs the multilevel regression analysis, and the data collected include listed commercial banks, state-owned banks, and unlisted commercial banks. At the same time, macroeconomic variables are also added as control variables. The results of the random effects model show that the development of fintech technology has slightly increased the non-performing loan rate of listed commercial banks, while the Fintech index has no statistically significant impact on unlisted commercial banks. The results are also subject to robustness checks.

Key words: Chinese banking industry, non-performing loan rate, fintech, listed banks, commercial banks.

Contents

CHAPTER 1

Introduction

Since the financial reforms that took place in the 1990s, China has made various efforts to deal with the non-performing loans of its commercial banks and has effectively achieved good results, successfully reducing these banks' non-performing loan rate to a more acceptable lower level. At the end of 2015, the balance of non-performing loans exceeded RMB 1.2 trillion, and the non-performing loan ratio also jumped to over 1.5% (Cheng and Qu, 2020).

The non-performing loan ratio has always been an important monitoring target related to commercial banks and their regulatory agencies. It reflects the banks' asset quality and the ability to withstand risks in sustainable and stable operations in the future. A lower level of non-performing loans is also closely related to the healthy performance of the entire macro economy. Therefore, it is of great significance to pay attention to banks' non-performing loans and to critically study its influencing determinants, whether from a micro or macro perspective.

On the other hand, since the 2008 Global Financial Crisis, financial intermediaries have introduced Fintech technology in a constant wave of financial innovation. It is also of practical significance to study the possible impact of this Fintech technology advancement on the rate of non-performing loans (Acar and Tak, 2019).

The present Dissertation is structured as follows: Chapter 2 describes the state-of- the-art literature on this fundamental research topic; Chapter 3 fully describes the main variables and the methodology herein used; Chapter 4 discusses the empirical results and the corresponding implications, including the implementation of robustness checking; lastly Chapter 5 concludes.

CHAPTER 2

Literature review

Non-performing loans constitute an important research topic which typically has significant economic implications from an operational standpoint, and scholars from various countries have carried out a lot of research on it. In terms of the most important influencing factors of the non-performing loan ratio, scholars have mainly focused on the role of macroeconomic environment. For example, Ranciere, Tornell and Westrmann (2006) find that the degree of financial liberalization is negatively correlated with the non-performing loan ratio of banks, through empirical analysis. Berge and Boye (2007) critically analyse the data related to Nordic banks from 1993 to 2005, concluding that the non-performing loan ratio is significantly related to macro factors such as loan interest rate and the unemployment rate. According to Nkusu (2011), the slowdown of economic growth, exchange rate depreciation, and trade contraction will lead to the increase of the non-performing loan ratio of banks. Bock and Demyanets (2012) also draw the conclusion that economic growth is negatively correlated with non-performing loans, using a sample of 25 emerging market countries.

Chinese scholars' research mainly adopts empirical methods and combines macro and micro factors. For example, Cheng (2007) finds that (i) the supervision and management mechanism of commercial banks and (ii) the motivation of borrowers to evade debts are the main reasons for the deterioration of bank credit asset quality. Liang (2012) employs a multiple linear regression model and concludes that GDP growth rate, M2 growth rate, banks' asset-liability ratio, the ratio of loans to total liabilities, and the scale of banks' non-performing loan ratio had some influence.

To sum up, for the factors affecting the non-performing loan ratio, non-Chinese researches mainly use transnational data for macro level analysis, while domestic (ie, Chinese) researches combine both macro and micro factors. However, there are differences in the influence degree and direction of each factor, which may be related, to some extent, to the selection of data (Li et al., 2020). As for the Fintech index variable this dissertation would like to employ, its possible impact on the non-performing loan rationeeds to be transmitted through both of the above-mentioned macroeconomicand and microeconomic factors (Drasch et al., 2018; Yao, 2020; Yang et al., 2021).

The listed banks, especially China's five major banks, are usually the first to benefit from the technical reform of the banks, as the Chinese government tends to give them more favorable policies. On the other hand, these major banks become the first point for the adoption of Fintech technology, which means that they will withstand the impact of the first wave of unknown policies. There is no doubt that the introduction and development of Fintech technology will bring a greater lending platform for the bank, while greater capital means that the bank will have a greater credit risk profile, which is generally not necessarily able to bring future-oriented benefits for banks and other financial intermediaries. The government is usually not able to carry out effective policies at the time of heightened risk, and the new set of policies is available for a new loan platform (Sheng, 2018).

According to de Roure et al. (2018), firstly, if only some banks are subject to an exogenous increase in regulatory costs, and the unaffected banks are not financially strong enough to replace the reduction in credit supply from the affected banks, then banks in the aggregate will lose market share to P2P lenders. Secondly, P2P platforms make riskier loans than banks make. Thirdly, the risk-adjusted interest rates on bank loans are lower than on P2P loans (Thakor, 2020).

On the basis of existing studies, this dissertation takes commercial banks of China as research objects (included in our adopted sample), including large state-owned commercial banks, listed commercial banks, city commercial banks, to ensure the comprehensiveness and representativeness of the sampled data.

CHAPTER 3

Model

3.1. Data

The data contained in the sample is related to 23 commercial banks from 2011 to 2019, taking into consideration that bank FinTech applications entered the marketplace after 2008. The sampled banks include 11 city commercial banks and 12 listed banks, which include all top 5 of China's state-owned commercial banks. Up to now, there are a total of 16 listed banks in China. Data has been collected on 12 of them, accounting for 75% of the data, in order to proceed with the econometric analysis of this paper.

The fintech index data came from the Baidu Index, a data platform owned by Baidu, China's largest search engine. Most of the financial data comes from the Qian Zhan database and Federal Reserve Economic data, and a small amount of missing data is collected through the CSMAR database.

3.2. Fintech Specific Variables

We employ the Fintech Index ($fintech_{it}$) as the Fintech specific variable, as one of the main explanatory variables. The Fintech Index reflects the country's investment and attention to Fintech technology, which in turn reflects the application scope of Fintech technology in financial institutions. Therefore, we use the Fintech Index as a quantitative indicator to measure the overall development of Fintech technology.

3.3. Financial Industry Specific Variables

The financial industry-specific variables employed in the estimations are: deposits ($deposit_{it}$), loans ($loans_{it}$), the capital adequacy ratio (car_{it}), the core capital adequacy ratio ($ccar_{it}$), the cost-to-income ratio (cir_{it}), the provision coverage ratio (pc_{it}), interest expense (ie_{it}), interest revenue (ir_{it}), and the net interest margin (nim_{it}). (Buchak et al., 2018)

3.4. Macroeconomic Variables

The following macroeconomic variables have been included as control variables for the estimation: broad money ($m2_t$), the inflation ratio ($inflation_t$), gross domestic product (gdp_t).

Table 1 provides the definitions of the variables included in the empirical study.

Table. 1

Variable definition

Variable	Definition
$fintech_t$	The development index of bank FinTech in year t
npl_{it}	The ratio of non-performing loans to total loans for bank i in year t
$deposit_{it}$	The total deposits for bank i in year t
$loans_{it}$	The total loans for bank i in year t
car_{it}	The capital adequacy ratio for bank i in year t
$ccar_{it}$	The core capital adequacy ratio for bank i in year t
cir_{it}	The ratio of total bank cost to total income for bank i in year t
pc_{it}	The ratio of provision coverage to total loans for bank i in year t
ie_{it}	The interest expense for bank i in year t
ir_{it}	The interest revenue for bank i in year t
nim_{it}	The ratio of net interest income to the average size of interest-earning assets for bank i in year t
$m2_t$	The broad money (M2) of China in year t
$inflation_t$	The inflation rate of China in year t
gdp_t	The gross domestic product of China in year t

3.5. Empirical Methodology

To analyze the impacts of banks' FinTech on the ratio of non-performing loans, the following econometric specification (ie regression model) is estimated:

$$npl_{it} = \beta_0 + \beta_1 fintech_{it} + \beta_2 deposit_{it} + \beta_3 loans_{it} + \beta_4 car_{it} + \beta_5 ccar_{it} + \beta_6 cir_{it} + \beta_7 pc_{it} + \beta_8 ie_{it} + \beta_9 ir_{it} + \beta_{10} nim_{it} + \beta_{11} m2_t + \beta_{12} inflation_t + \beta_{13} gdp_t + dummy\ variable + \varepsilon_{it} \quad (1)$$

where i indicates banks and t indicates time. npl_{it} indicates the ratio of non-performing loans for bank i in year t. $fintech_{it}$ reflects the development of Fintech for bank i in year t. Control variables include deposits ($deposit_{it}$), loans ($loans_{it}$), the capital adequacy ratio (car_{it}), the core capital adequacy ratio ($ccar_{it}$), the cost-to-income ratio (cir_{it}), the provision coverage ratio (pc_{it}), interest expense (ie_{it}), interest revenue (ir_{it}), the net interest margin (nim_{it}), broad money ($m2_t$), the inflation ratio ($inflation_t$), and gross domestic product (gdp_t). The dummy variable is equal to 1 if a bank is a publicly listed banks and 0 unlisted banks. ε refers to the error term.

CHAPTER 4

Empirical results

4.1. Descriptive Statistics

Figure 1 shows the development of FinTech during the 2011–2019 period.

Figure. 1 The development of FinTech

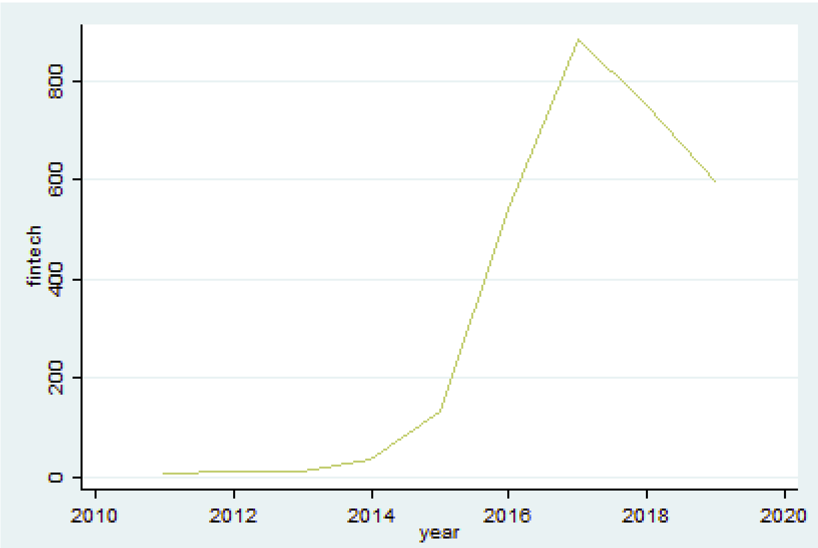

Table 2 shows the descriptive statistics of the variables in the regression analyses. The average of npl_{it} is 1.38874%, the standard deviation is 0.684579, the minimum value is 0.425, the maximum value is 5.59. The average of $fintech_t$ is 330.3789, the standard deviation is 338.9791, the minimum value is 8.35, the maximum value is 885.01

Table. 2

The Statistics of Variables

Variable	Observation	Mean	Std. Dev.	Minimum	Maximum
npl_{it}	207	1.38874	0.684579	0.425	5.59
$deposit_{it}$	207	286.637	436.6417	2.174948	1548.197
$loans_{it}$	207	249.2068	380.7446	1.310404	1640.636
car_{it}	207	12.80725	1.8195	6.9	23.07
$ccar_{it}$	207	10.28521	1.949396	6.9	22.03
cir_{it}	207	30.87338	6.443645	16.18	69.61
pc_{it}	207	237.9837	84.38658	93.38	523.1625
ie_{it}	207	9.885189	7.510246	-2.8169	31.04835
ir_{it}	207	46.90838	243.3403	0.859897	2541.974
nim_{it}	207	2.303735	0.594608	1.31	6.99
$fintech_t$	207	330.3789	338.9791	8.35	885.01
$m2_t$	207	133.6889	36.61984	78.04	189.69
$inflation_t$	207	2.524478	1.168389	1.437025	5.553897
gdp_t	207	72.13766	14.07962	49.56273	93.74249

4.2. The impacts of Fintech on the non-performing loan ratio of commercial banks

4.2.1. Random effects model

Before proceeding with the regression analysis, multicollinearity tests of the explanatory variables are performed. The result of Pearson product-moment correlation coefficient catrix (PPMCC) we put them on Appendix. A

Table 3

The impacts of bank FinTech on non-performing loan ratio (Random effects model)

Variables	Model 1	Model 2	Model 3
	npl_{it}	npl_{it}	npl_{it}
$fintech_t$	0.0002199***	-0.0004921	-0. 0001878
	(0.000)	(0.000)	(0.000)
$deposit_{it}$	0.077***	-0.001	0.001**
	(0.014)	(0.016)	(0.000)
$loans_{it}$	-0.090***	-0.001	-0.001***
	(0.015)	(0.020)	(0.000)
car_{it}	-0.013	-0.190***	-0.152***
	(0.024)	(0.059)	(0.039)
$ccar_{it}$	0.028	0.151***	0.123***
	(0.028)	(0.059)	(0.039)
cir_{it}	-0.004	-0.001	0.005
	(0.006)	(0.009)	(0.006)
pc_{it}	-0.003***	-0.006***	-0.004***
	(-0.000)	(0.001)	(0.000)
ie_{it}	-0.003		
	(0.004)		
ir_{it}	0.000		
	(0.000)		
nim_{it}	0.030		
	(0.024)		
gdp_t	-0.019**	0.013	-0.004
	(0.007)	(0.034)	(0.016)
$inflation_t$	0.024*	0.064	0.054**
	(0.014)	(0.059)	(0.028)
$m2_t$	0.014***	0.006	0.012*
	(0.003)	(0.015)	(0.007)
_cons	1.229***	2.180**	1.442***

	(0.003)	(0.956)	(0.475)
N	108	99	207
Within R^2	0.934	0.643	0.658
Adjust R^2	0.9321	0.6933	0.7176
Standard errors in parentheses			
* p<0.10, ** p<0.05, *** p<0.01			

Note: We estimate all regressions using random effects models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Table. 1 for all variable measurements.

Subsequently, in order to proceed with panel data estimation, we usually need to select the most efficient model (from fixed effect model, random effect model and pooled ordinary least squares). The fixed effects model is essentially adding N-1 dummy variables to the traditional linear regression model, so that each section has its own intercept term. The difference in the intercept term reflects certain characteristics of the individuals in the model that will not change over time. The random effects model divides the random interference items in the model into two types. One is the disturbance term that does not change with time, that is, the disturbance term that represents the individual effect. The other is the disturbance term that will change over time, that is, the disturbance term in the usual sense.

Between the fixed effect model and the pooled ordinary least squares, the results of the Wald test and the LR test show that the fixed effect model is the more efficient model. Between the random effect model and the pooled ordinary least squares, the results of the B-P test and the LR test show that the random effect model is the more efficient model. Between the random effect model and the fixed effect model, the results of the Hausman test shows that random effect model is the more efficient model. Therefore, in light of the corresponding test results (Appendix B), the random effect model is used to estimate the panel data (Hausman, 1978).

In Model 1, the sample comprises the dataset of 12 listed commercial banks, including state-owned commercial banks. The statistical results of this model shows that the coefficients of the FinTech special variables ($fintech_t$) is significantly positive at the 1% level. It indicates that the development of fintech technology has increased the non-performing loan ratio of these listed banks. In other words, the development of fintech technology has contributed to the non-performing loan ratio of listed commercial banks between 2011 and 2019, which is not good news for the commercial banks.

In Model 2, the sample comprises 11 unlisted city commercial banks. The statistical results show that the development of fintech technology does not significantly affect non-performing loan ratio of these unlisted city commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_t$) is 0.251.

In Model 3, the sample comprises 23 commercial banks. The statistical results show that the development of fintech technology does not significantly affect the non-performing loan ratio of these commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_t$) is 0.442.

Subsequently, considering the issues of time-series autocorrelation and cross-section heteroskedasticity in the model, we further adopt the GLS estimation method, the estimation method of heteroscedasticity robust and the estimation method considering the high order autocorrelation for Model 2 and Model 3. Although these methods reduce the p- value of the FinTech special variables ($fintech_{it}$) coefficient, they could not obtain a significant coefficient. (Appendix C).

4.2.2. Multilevel Linear Model

In social science research, the problem of group effect or background effect has puzzled researchers for about half a century. Some studies fall into "Ecological Fallacy", where researchers mistakenly apply the results of a group to the situation of individual members of the group. For a long time, social science research has tended to assume this fallacy. In reality, an individual's behavior is influenced by both his own characteristics and his environment. The multilevel linear model bridges this gap by allowing to reconcile the two major dimensions (idiosyncratic characteristics and environment) (Raudenbush and Bryk, 2007; Heil et al., 2009; Albright and Marinova, 2010).

Firstly, look at the problem of data in descriptive statistics.

Table 4 shows that the between and within standard deviations of variables deposits ($deposit_{it}$), loans ($loans_{it}$), the capital adequacy ratio (car_{it}), the core capital adequacy ratio ($ccar_{it}$), the cost-to-income ratio (cir_{it}), the provision coverage ratio (pc_{it}) and the net interest margin (nim_{it}) differ greatly, while the between and within standard deviations of variables of the ratio of non-performing loans (npl_{it}) and the provision coverage ratio (pc_{it}) are almost the sam

Table. 4

The Descriptive Statistics of The Panel Data

Variable		Mean	Std. Dev.	Min	Max	Observations
npl_{it}	overall	1.38874	0.684579	0.425	5.59	N = 207
	between		0.410737	0.839783	1.796087	n = 9
	within		0.56388	0.372653	5.697544	T = 23
$deposit_{it}$	overall	286.637	436.6417	2.174948	1548.197	N = 207
	between		26.94137	228.7153	312.7862	n = 9
	within		435.8987	-22.1841	1522.048	T = 23
$loans_{it}$	overall	249.2068	380.7446	1.310404	1640.636	N = 207
	between		72.33291	151.6532	364.2463	n = 9
	within		374.5573	-109.503	1525.596	T = 23
car_{it}	overall	12.80725	1.8195	6.9	23.07	N = 207
	between		0.577204	11.94576	13.90761	n = 9
	within		1.735799	7.468152	23.12913	T = 23
$ccar_{it}$	overall	10.28521	1.949396	6.9	22.03	N = 207
	between		0.222409	9.842717	10.57217	n = 9
	within		1.93803	6.921981	21.98318	T = 23
cir_{it}	overall	30.87338	6.443645	16.18	69.61	N = 207
	between		1.773812	28.52011	33.46598	n = 9
	within		6.22175	17.54385	67.01795	T = 23
pc_{it}	overall	237.9837	84.38658	93.38	523.1625	N = 207
	between		51.33132	183.3989	313.3214	n = 9
	within		69.04772	88.283	539.3644	T = 23

Note: See Table. 1 for all variable measurements

Table 5

The impacts of bank FinTech on non-performing loan ratio (Multilevel linear model)

Variable	Model. 1	Model. 2	Model. 3
	npl_{it}	npl_{it}	npl_{it}
$deposit_{it}$	0.074***	-0.015	0.001**
	(-0.014)	(0.015)	(0.000)
$loans_{it}$	-0.090***	0.014	-0.001***
	(-0.014)	(0.019)	(0.000)
car_{it}	-0.014	-0.180***	-0.154***
	(-0.022)	(0.060)	(0.038)
$ccar_{it}$	0.033	0.133**	0.125***
	(-0.026)	(0.060)	(0.037)
cir_{it}	-0.006	-0.003	0.006
	(-0.005)	(0.009)	(0.006)
pc_{it}	-0.003***	-0.006***	-0.004***
	(0.000)	(0.001)	(0.000)
ie_{it}	-0.003		
	(-0.004)		
ir_{it}	0.000		
	(0.000)		
nim_{it}	0.027		
	(-0.022)		
$fintech_t$	0.0002247***	-0.0004947	-0.0001538
	(0.000)	(0.000)	(0.000)
gdp_t	-0.019***	0.007	-0.005
	(-0.006)	(0.029)	(0.015)
$inflation_t$	0.023**	0.047	0.055**
	(-0.013)	(0.050)	(0.027)
$m2_t$	0.014***	0.008	0.012*
	(-0.003)	(0.013)	(0.007)
_cons	1.251***	2.380***	1.425***
	(-0.282)	(0.845)	(0.462)
-cons of lnδ_1	-1.892***	-1.443***	-1.459***
	(-0.224)	(0.321)	(0.194)
-cons of lnδ_e	-2.287***	-0.780***	-1.032***
	(-0.073)	(0.076)	(0.052)
N	108	99	207

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Note: We estimate all regressions using random effects models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Table. 1 for all variable measurements.

In Model 1, the sample is comprised of 12 listed commercial banks, including state-owned commercial banks. The statistical results of this model shows that the coefficients of the FinTech special variables ($fintech_{it}$) is significantly positive. It indicates that the development of fintech technology has increased the non-performing loan ratio of these listed banks. In other words, the development of fintech technology has contributed to increasing the non-performing loan ratio of listed commercial banks between 2011 and 2019.

In Model 2, the sample comprised 11 unlisted city commercial banks. The statistical results show that the development of fintech technology does not significantly affect non-performing loan ratio of these unlisted city commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_{it}$) is 0.172.

In Model 3, the sample comprises 23 commercial banks. The statistical results show that the development of fintech technology does not significantly affect non-performing loan ratio of these commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_{it}$) is 0.431.

The basic regression model:

$$npl_{it} = \beta_0 + \beta_1 fintech_{it} + \beta_2 deposit_{it} + \beta_3 loans_{it} + \beta_4 car_{it} + \beta_5 ccar_{it} + \beta_6 cir_{it} + \beta_7 pc_{it} + \beta_8 ie_{it} + \beta_9 ir_{it} + \beta_{10} nim_{it} + \beta_{11} m2_t + \beta_{12} inflation_t + \beta_{13} gdp_t + dummy\ variable + \varepsilon_{it} \quad (2)$$

Reassumptions about residuals:

$$\varepsilon_{it} \equiv \delta_t + \gamma_{it} \quad (3)$$

We get a new equation.

$$npl_{it} = \beta_0 + \beta_1 fintech_{it} + \beta_2 deposit_{it} + \beta_3 loans_{it} + \beta_4 car_{it} + \beta_5 ccar_{it} + \beta_6 cir_{it} + \beta_7 pc_{it} + \beta_8 ie_{it} + \beta_9 ir_{it} + \beta_{10} nim_{it} + \beta_{11} m2_t + \beta_{12} inflation_t + \beta_{13} gdp_t + dummy\ variable + (\delta_t + \gamma_{it}) \quad (4)$$

$$\Rightarrow npl_{it} = (\beta_0 + \delta_t) + \beta_1 fintech_{it} + \beta_2 deposit_{it} + \beta_3 loans_{it} + \beta_4 car_{it} + \beta_5 ccar_{it} + \beta_6 cir_{it} + \beta_7 pc_{it} + \beta_8 ie_{it} + \beta_9 ir_{it} + \beta_{10} nim_{it} + \beta_{11} m2_t + \beta_{12} inflation_t + \beta_{13} gdp_t + dummy\ variable + \gamma_{it} \quad (5)$$

where δ_t indicates random intercept, γ_{it} indicates macroeconomic level intercept. The Random intercepts δ_t can be thought of as latent variables, which are not estimated with the fixed parameters β_1 to β_{13}, but the model gives us the technique to estimate the variance φ of δ_t and the variance θ of γ_{it} together (Raudenbush and Bryk, 2007; Wang et al., 2009; Rabe-Hesketh and Skrondal, 2012).

A) Model 1 (Listed banks)

Table 6

The variance components of the null model and random intercept model (Listed banks)

The Null Model		
Fixed-effects Parameters		
_cons	1.25652***	
Random-effects Parameters		
	Estimate	Std. Err.
sd(_cons)	0.1186856	0.055319
sd(Residual)	0.3966257	0.028624

The Random Intercept Model		
Fixed-effects Parameters		
_cons	1.250502***	
Random-effects Parameters		
	Estimate	Std. Err.
sd(_cons)	0.15081	0.033725
sd(Residual)	0.101531	0.007367

Note: We estimate all regressions using maximum likelihood estimation (MLE). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In the null model:

The fixed-effects parameter indicates the average non-performing loan ratio in the sample. The two types of variance component in the random effects section can be used to calculate the ICC (intraclass correlation coefficient) between the levels.

Break down the variation in the dependent variable:

$$ICC_L = \frac{0.1186856}{0.1186856 + 0.3966257} = 0.2303183$$

The results show that about 23.03% of the dependent variables were decomposed to the bank level. Intuitively, the 23.03% difference in the non-performing loan ratio is ‘determined’ by the bank.

In the random intercept model:

The intercept indicates that the expected value of the non-performing loan ratio when all covariates averaged is approximately 1.25%.

Among the random-effect parameters, the variance component of the intercept is larger than the corresponding parameter in the null model, indicating that the inclusion of macroeconomic level covariates does not further explain the partial variation of the dependent variables (0.1186856→0.15081). The value of this parameter is still several times its standard error, indicating that the variable explains only a small part of the variation in the dependent variable.

The proportion of covariates explained at the second level:

$$R_{L2}^2 = \frac{\hat{\varphi}_0 - \hat{\varphi}_1}{\hat{\varphi}_0} = \frac{0.1186856^2 - 0.15081^2}{0.1186856^2} = -0.614597$$

The proportion of covariates explained at the first level:

$$R_{L1}^2 = \frac{\hat{\theta}_0 - \hat{\theta}_1}{\hat{\theta}_0} = \frac{0.3966257^2 - 0.101531^2}{0.3966257^2} = 0.934471$$

The results show that the covariates at the individual level explain more (93.45% > -61.46%), and the individual characteristics at the bank level cause greater differences in the non-performing loan ratio.

The sum of squares of residuals for the null model:

$$\hat{\varphi}_0 + \hat{\theta}_0 = 0.1186856^2 + 0.3966257^2 = 0.171399$$

The sum of squares of residuals for the random intercept model:

$$\hat{\varphi}_1 + \hat{\theta}_1 = 0.15081^2 + 0.101531^2 = 0.033052$$

$$R^2 = \frac{0.171399 - 0.033052}{0.171399} = 0.807163$$

The results show that the included covariates explain 80.72% of the difference in non-performing loan ratio on the whole.

B) Model 2 (City commercial banks)

Table 7

The variance components of the null model and random intercept model (City commercial banks)

The Null Model		
Fixed-effects Parameters		
_cons	1.53298 ***	
Random-effects Parameters		
	Estimate	Std. Err.
sd(_cons)	0.3782498	0.119303
sd(Residual)	0.7779709	0.0586418

The Random Intercept Model		
Fixed-effects Parameters		
_cons	2.379735***	
Random-effects Parameters		
	Estimate	Std. Err.
sd(_cons)	0.2363133	0.0758355
sd(Residual)	0.4585859	0.034798

Note: We estimate all regressions using maximum likelihood estimation (MLE). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In the null model:

The fixed-effects parameter indicates the average non-performing loan ratio in the sample. The two types of variance component in the random effects Chapter can be used to calculate the ICC (intraclass correlation coefficient) between the levels

Break down the variation in the dependent variable:

$$ICC_L = \frac{0.3782498}{0.3782498 + 0.7779709} = 0.327143$$

The results showed that about 32.71% of the dependent variables were decomposed to the bank level. Intuitively, the 32.71% difference in the non-performing loan ratio is determined by the bank.

In the random intercept model:

The intercept indicates that the expected value of the non-performing loan ratio when all covariates averaged is 2.38%.

Among the random-effect parameters, the variance component of the intercept is lower than the corresponding parameter in the null model, indicating that the inclusion of macroeconomic level covariates does further explain the partial variation of the dependent variables (0.3782498→0.2363133). The value of this parameter is still several times its standard error, indicating that the variable explains only a small part of the variation in the dependent variable.

The proportion of covariates explained at the second level:

$$R_{L2}^2 = \frac{\hat{\varphi}_0 - \hat{\varphi}_1}{\hat{\varphi}_0} = \frac{0.3782498^2 - 0.2363133^2}{0.3782498^2} = 0.609681$$

The proportion of covariates explained at the first level:

$$R_{L1}^2 = \frac{\hat{\theta}_0 - \hat{\theta}_1}{\hat{\theta}_0} = \frac{0.7779709^2 - 0.4585859^2}{0.7779709^2} = 0.657005$$

The results show that the covariates at the individual level explain more (65.70% > 60.97%), and the individual characteristics at the bank level cause greater differences in the non-performing loan ratio.

The sum of squares of residuals for the null model:

$$\hat{\varphi}_0 + \hat{\theta}_0 = 0.3782498^2 + 0.7779709^2 = 0.748312$$

The sum of squares of residuals for the random intercept model:

$$\hat{\varphi}_1 + \hat{\theta}_1 = 0.2363133^2 + 0.4585859^2 = 0.266145$$

$$R^2 = \frac{0.748312 - 0.266145}{0.748312} = 0.644340$$

The results show that the included covariates explain 64.43% of the difference in non-performing loan ratio as a whole.

C) Model 3 (Commercial banks)

Table 8

The variance components of the null model and random intercept model (Commercial banks)

The Null Model		
Fixed-effects Parameters		
_cons	1.38874***	
Random-effects Parameters		
	Estimate	Std. Err.
sd(_cons)	0.3079723	0.0655454
sd(Residual)	0.609539	0.0317744

The Random Intercept Model		
Fixed-effects Parameters		
_cons	1.425488***	
Random-effects Parameters		
	Estimate	Std. Err.
sd(_cons)	0.2323837	0.045169
sd(Residual)	0.3563961	0.0186741

Note: We estimate all regressions using maximum likelihood estimation (MLE). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In the null model:

The fixed-effects parameter indicates the average non-performing loan ratio in the sample. The two types of variance component in the random effects section can be used to calculate the ICC (intraclass correlation coefficient) between the levels.

Break down the variation in the dependent variable:

$$ICC_L = \frac{0.3079723}{0.3079723 + 0.609539} = 0.311315$$

The results show that about 31.13% of the dependent variables were decomposed to the bank level. Intuitively, the 31.13% difference in the non-performing loan ratio is ‘determined’ by the bank.

In the random intercept model:

The intercept indicates that the expected value of the non-performing loan ratio when all covariates averaged is 1.43%.

Among the random-effect parameters, the variance component of the intercept is lower than the corresponding parameter in the null model, indicating that the inclusion of macroeconomic level covariates does further explain the partial variation of the dependent variables (0.3079723→0.2323837). The value of this parameter is still several times its standard error, indicating that the variable explains only a small part of the variation in the dependent variable.

The proportion of covariates explained at the second level:

$$R_{L2}^2 = \frac{\hat{\varphi}_0 - \hat{\varphi}_1}{\hat{\varphi}_0} = \frac{0.3079723^2 - 0.2323837^2}{0.3079723^2} = 0.430639$$

The proportion of covariates explained at the first level:

$$R_{L1}^2 = \frac{\hat{\theta}_0 - \hat{\theta}_1}{\hat{\theta}_0} = \frac{0.609539^2 - 0.3563961^2}{0.609539^2} = 0.658119$$

The results show that the covariates at the individual level explain more (65.81% > 43.06%), and the individual characteristics at the bank level cause greater differences in the non-performing loan ratio.

The sum of squares of residuals for the null model:

$$\hat{\varphi}_0 + \hat{\theta}_0 = 0.3079723^2 + 0.609539^2 = 0.627757$$

The sum of squares of residuals for the random intercept model:

$$\hat{\varphi}_1 + \hat{\theta}_1 = 0.2323837^2 + 0.3563961^2 = 0.181020$$
$$R^2 = \frac{0.627757 - 0.181020}{0.627757} = 0.71164$$

The results show that the included covariates explain 71.16% of the difference in non-performing loan ratio on the whole.

4.3. Robustness Test

In this sub-section, the baseline models' application results are further checked, through the application of robustness tests.

4.3.1. Removing the observations After 2017

We can observe in Figure 1 that since 2011, the Fintech index has been accelerating, but after 2017, the fintech index has suddenly dropped. The development of fintech technology within the Chinese banking industry and other financial industries has largely depended on the Chinese government's policy orientation in the past. For example, the government policy can limit the impact of fintech technology on the financial market for a short period of time, even before the use of fintech technology has been adopted by banks. Therefore, it can effectively limit the non-performing loan rate, and it may also have an unexpected impact on the non-performing loan rate due to policy changes in a given year. One of the possibilities involves trying to exclude data after 2017 and use the random effects model to estimate only the data from 2011 to 2017.

Table 9

The impacts of bank FinTech on non-performing loan ratio (Random effects model)

Variables	Model 1	Model 2	Model 3
	npl_{it}	npl_{it}	npl_{it}
$fintech_t$	0.0000782	-0.0002981	-0.0001694
	(0.000)	(0.001)	(0.000)
$deposit_{it}$	0.069***	-0.009	0.001
	(0.021)	(0.026)	(0.000)
$loans_{it}$	-0.082***	0.009	-0.001
	(0.026)	(0.036)	(0.001)
car_{it}	-0.006	-0.174*	-0.146***
	(0.031)	(0.068)	(0.043)
$ccar_{it}$	0.009	0.144*	0.122***
	(0.031)	(0.070)	(0.042)
cir_{it}	-0.006	0.010	0.014**
	(0.007)	(0.010)	(0.007)
pc_{it}	-0.003***	-0.005***	-0.004***
	(-0.000)	(0.001)	(0.000)
ie_{it}	-0.0001789		
	(0.004)		
ir_{it}	0.0000362		
	(0.000)		
nim_{it}	0.090		
	(0.072)		
gdp_t	-0.036***	-0.003	-0.028
	(0.011)	(0.045)	(0.023)
$inflation_t$	0.017	-0.012	-0.002
	(0.024)	(0.102)	(0.050)
$m2_t$	0.021***	0.009	0.019*
	(0.005)	(0.019)	(0.010)
_cons	1.650***	2.340	2.117**

	(0.622)	(1.802)	(0.948)
N	84	77	161
Within R^2	0.947	0.650	0.684
Adjust R^2	0.9458	0.6748	0.7260
Standard errors in parentheses			
* p<0.10, ** p<0.05, *** p<0.01			

Note: We estimate all regressions using random effects models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Table. 1 for all variable measurements

In Model 1, the sample comprises 12 listed commercial banks. The statistical results show that the development of fintech technology does not significantly affect the non-performing loan ratio of these listed city commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_{it}$) is 0.584.

In Model 2, the sample comprises 11 unlisted city commercial banks. The statistical results show that the development of fintech technology does not significantly affect non-performing loan ratio of these unlisted city commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_{it}$) is 0.602.

In Model 3, the sample comprises 23 the commercial banks. The statistical results show that the development of fintech technology does not significantly affect non-performing loan ratio of these unlisted city commercial banks. The p-value of the coefficient of the FinTech special variables ($fintech_{it}$) is 0.557.

4.3.2. Removing several bank special variables

In view of the lack of data related to the balance data of variables interest expense (ie_{it}), interest revenue (ir_{it}) and net interest margin (nim_{it}) of some unlisted city banks, these variables are not included in Model 2 and Model 3. In order to exclude the significant coefficients of the fintech variables in Model 2 and Model 3 due to the lack of these variables, these variables are also removed from Model 1, and the random effects model is re-specified.

Table 10

The impact of bank FinTech on the non-performing loan ratio (Random effects model)

Variables	Model 1
	npl_{it}
$fintech_t$	0.0002303***
	(0.000)
$deposit_{it}$	0.068***
	(0.014)
$loans_{it}$	-0.087***
	(0.014)
car_{it}	-0.008
	(0.023)
$ccar_{it}$	0.031
	(0.027)
cir_{it}	-0.008
	(0.006)
pc_{it}	-0.003***
	(-0.000)
gdp_t	-0.018***
	(0.007)
$inflation_t$	0.021
	(0.013)
$m2_t$	0.013***
	(0.003)
_cons	1.374***
	(0.295)
N	108
Within R^2	0.932
Adjust R^2	0.9324

Note: We estimate all regressions using random effects models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Table. 1 for all variable measurements

In Model 1, the sample comprise 12 listed commercial banks, including state-owned commercial banks. The econometric results of this model show that the coefficients of the FinTech variable ($fintech_{it}$) is significantly positive. It indicates that the development of fintech technology has increased the non-performing loan ratio of these listed banks. In other words, the development of fintech technology has contributed to the increase of the non-performing loan ratio of listed commercial banks between 2011 and 2019.

CHAPTER 5

Conclusion

The present Dissertation addresses the impact of Fintech Index on the non-performing loan ratio of Chinese commercial banks. In the empirical analysis (Chapter 4), the results show that, in addition to the degree of development of fintech technology, at the macro level, the broad money ($m2_t$), the inflation ratio ($inflation_t$), the gross domestic product (gdp_t) also have a statistically significant effects on banks' non-performing loan rates. At the micro level, total deposits ($deposit_{it}$), total loans ($loans_{it}$), and the provision coverage ratio (pc_{it}) have a statistically significant impact on the non-performing loan ratio.

The statistical results of the models shows that the coefficients of the FinTech index ($fintech_{it}$) is significantly positive. The coefficients of the total deposits ($deposit_{it}$), the broad money ($m2_t$) and the inflation ratio ($inflation_t$) are significantly positive. The coefficients of the gross domestic product (gdp_t), the total loans ($loans_{it}$), and provision coverage ratio (pc_{it}) are significantly negative.

A faster growth rate indicates that the country's macroeconomy is in a state of rapid development, bank operating efficiency is rapidly improving, and bank profitability is enhancing, thereby reducing the banks' non-performing loan rates. Conversely, when the macroeconomy tends to be in a downturn, investment shrinks, and business operations are difficult to conduct, as it may not be possible to repay bank loans on time, thus leading to an increase in the non-performing loan rate. Therefore, gross domestic product (gdp_t) is negatively correlated with the non-performing loan ratio of the listed commercial banks.

The money supply ($m2_t$) is affected by monetary policy, and the inflation rate ($inflation_t$) is largely affected by the money supply. The issuance of more money by the Central Bank usually leads to currency depreciation and an increase in inflation. When a given country implements a loose monetary policy to stimulate the economy, banks have ample liquidity and can issue more loans. However while expanding the scale of loans, bank may lower loan standards, resulting in higher risk projects also obtaining financing. The quality of credit assets typically declines and non-performing loans typically increase. Accordingly, the broad money ($m2_t$) and the inflation ratio ($inflation_t$) are negatively correlated with the non-performing loan ratio of the listed commercial banks (Michaël, 2015; Brooke and Ketchley, 2018).

The provision coverage ratio (pc_{it}) can reflect the ability of commercial banks to resist risks and make up for loan losses. A higher provision coverage ratio indicates that banks have a strong sense of risk prevention. Such banks will also be cautious and comply with regulations when conducting business, which keeps the non-performing loan ratio at a relatively low level. If a bank's provision coverage ratio is low, it indicates that the bank is not sufficiently aware of risk management and may have a higher non-performing loan ratio. Therefore, the provision coverage ratio is negatively correlated with the non-performing loan ratio of the listed commercial banks.

A higher deposits-to-loans ratio means that under the same deposit support, the bank has a larger loan scale and faces greater risks. It belongs to the type of risk appetite and has a high non-performing loan ratio. The low deposit-loan ratio indicates that banks are more conservative in their business, take less risk, and have a low rate of non-performing loans. Therefore, the deposits-to-loans ratio ($\frac{deposits_{it}}{loans_{it}}$) is positively correlated with the non-performing loan ratio of the listed commercial banks.

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Annex

Annex A Pearson Product-Moment Correlation Coefficient Matrix (PPMCC)

	npl_{it}	$deposit_{it}$	$loans_{it}$	car_{it}	$ccar_{it}$	cir_{it}	pc_{it}
npl_{it}	1						
$deposit_{it}$	-0.067	1					
$loans_{it}$	-0.049	0.991*	1				
car_{it}	-0.268*	-0.116	-0.106	1			
$ccar_{it}$	-0.132	-0.369*	-0.348*	0.858*	1		
cir_{it}	0.100	-0.324*	-0.322*	-0.324*	-0.234*	1	
pc_{it}	-0.739*	-0.060	-0.065	0.269*	0.233*	-0.129	1
$fintech_t$	0.413*	0.226*	0.243*	-0.057	-0.162	-0.161	-0.492*
$m2_t$	0.512*	0.264*	0.289*	-0.054	-0.156	-0.181	-0.529*
$inflation_t$	-0.298*	-0.127	-0.114	0.135	0.127	0.070	0.350*
gdp_t	0.510*	0.262*	0.290*	-0.051	-0.145	-0.179	-0.506*

* p<0.05

	$fintech_t$	$m2_t$	$inflation_t$	gdp_t
$fintech_t$	1			
$m2_t$	0.876*	1		
$inflation_t$	-0.383*	-0.517	1	
gdp_t	0.821*	0.989*	0.534*	1

* p<0.05

Annex B. Hausman Test

	Coefficients			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed effect	Random effect	Difference	S.E.
$deposit_{it}$	-0.00049	0.000591	-0.00108	0.000752
$loans_{it}$	-0.00065	-0.00083	0.00018	9.63E-05
car_{it}	-0.13049	-0.15237	0.02188	0.018256
$ccar_{it}$	0.094664	0.123363	-0.0287	0.025378
cir_{it}	0.001312	0.005329	-0.00402	0.004054
pc_{it}	-0.00392	-0.00386	-6.1E-05	0.000121
$fintech_t$	-0.00019	-0.00015	-3.4E-05	2.63E-05
gdp_t	-0.00455	-0.00449	-5.4E-05	0.000804
$inflation_t$	0.033412	0.054216	-0.0208	0.013192
$m2_t$	0.012108	0.012418	-0.00031	0.000906

b = consistent under $H_O$and H_a; obtained from xtreg

B = inconsistent under H_a, efficient under H_O; obtained from xtreg

Test: H_O: difference in coefficients not systematic

chi2(10) = (b-B)'([$(V_b - V_B)^{-1}$](b-B) = 7.90

Prob>chi2 = 0.6385

($V_b - V_B$ is not positive definite

Annex C.

C1. Listed Commercial Banks (GLS & PCSE)

Variables	GLS	PCSE
	npl_{it}	npl_{it}
$fintech_t$	0.0001686***	0.0001792
	(0.002)	(0.181)
$deposit_{it}$	0.0747939***	0.0796616***
	(0.000)	(0.000)
$loans_{it}$	-0.0778114***	-0.082522***
	(0.000)	(0.000)
car_{it}	0.0132813	0.0113644
	(0.180)	(0.609)
$ccar_{it}$	-0.0319395**	-0.0263664
	(0.020)	(0.325)
cir_{it}	0.0033698	0.0032682
	(0.215)	(0.414)
pc_{it}	-0.0028021***	-0.0027765***
	(0.000)	(0.000)
ir_{it}	0.0000102	0.0000266
	(0.548)	(0.420)
nim_{it}	0.0106104*	0.0247081**
	(0.064)	(0.050)
gdp_t	-0.0107494***	-0.0175805*
	(0.005)	(0.075)
$inflation_t$	0.0237823***	0.0161002
	(0.002)	(0.391)
$m2_t$	0.0110059***	0.0135266***
	(0.000)	(0.003)
_cons	1.113826***	1.195724***
	(0.000)	(0.000)
N	108	108

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

C2. Unlisted City Commercial Banks (GLS & PCSE)

Variables	GLS	PCSE
	npl_{it}	npl_{it}
$fintech_t$	-0.0004441***	-0.000529***
	(0.000)	(0.000)
$deposit_{it}$	-0.017622***	-0.0129409
	(0.002)	(0.250)
$loans_{it}$	0.0178301	0.0113529
	(0.015)	(0.402)
car_{it}	-0.0633289***	-0.1285901**
	(0.007)	(0.044)
$ccar_{it}$	0.0489511*	0.0808092
	(0.104)	(0.276)
cir_{it}	-0.0005988	-0.0030162
	(0.875)	(0.785)
pc_{it}	-0.0056035***	-0.0058399***
	(0.000)	(0.000)
gdp_t	0.0109833*	0.0076663
	(0.096)	(0.526)
$inflation_t$	0.0048578	0.027626
	(0.691)	(0.191)
$m2_t$	0.0055239*	0.0078727
	(0.065)	(0.161)
_cons	1.920846***	2.455416***
	(0.000)	(0.006)
N	99	99

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

C3. Commercial Banks (GLS & PCSE)

Variables	GLS	PCSE
	npl_{it}	npl_{it}
$fintech_t$	-0.0000548	-0.0001797
	(0.693)	(0.180)
$deposit_{it}$	0.0010106***	0.0007159***
	(0.000)	(0.002)
$loans_{it}$	-0.0012295***	-0.0009956***
	(0.000)	(0.000)
car_{it}	-0.0535724**	-0.0976024**
	(0.064)	(0.051)
$ccar_{it}$	0.0769842**	0.0833806
	(0.054)	(0.125)
cir_{it}	-0.0029226	0.0067333
	(0.730)	(0.474)
pc_{it}	-0.0039506***	-0.0041867***
	(0.000)	(0.000)
gdp_t	-0.0081101	-0.0016107
	(0.408)	(0.871)
$inflation_t$	0.0105648	0.031925*
	(0.600)	(0.093)
$m2_t$	0.0120093***	0.0106341**
	(0.007)	(0.023)
_cons	1.365096***	1.29209**
	(0.002)	(0.044)
N	207	207

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01