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Non-performing Loans' Impact on Bank Efficiency: An Empirical Analysis on Chinese State-owned Banks

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MSc in Economics

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Professor Diptes Chandrakante Prabhudas Bhimjee, Assistant Professor (Invited),
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Abstract

This research investigates the impact of non-performing loans on bank efficiency in Chinese state-owned banking sector. The results indicate a negative effect of non-performing loans on bank efficiency in Chinese State-owned banks throughout 2011Q1 - 2021Q3. We take seasonal revenue as the indicator of bank efficiency in our baseline models and seasonal profit denoting bank inefficiency in our robustness test. The findings of our study highlight non-performing loans are an important indicator of bank inefficiency in Chinese SOBs (State-owned banks). We applied Prais-Winsten regression to our panel data, which is a special case of Feasible Generalized Least Squares (FGLS), to correct the serial correlation and cross-sectional correlation of our fixed effect model. The novelty of our paper also lies in the application of FGLS to the study of non-performing loans. Overall, the implication of our research is in line with the extant literature that policy makers should consider reducing non-performing loans in the post-crisis era to improve the efficiency in banks.

Keywords: non-performing loans, bank inefficiency, state-owned banks, China, Prais-Winsten regression

Resumo

Este estudo investiga o impacto dos empréstimos inadimplentes na eficiência dos bancos no setor bancário estatal chinês. Os resultados indicam um efeito negativo dos empréstimos inadimplentes na eficiência bancária em bancos estatais chineses no período de 2011T1 a 2021T3. Consideramos a receita sazonal como o indicador de eficiência do banco nos nossos modelos *baseline* e o lucro sazonal denotando a ineficiência do banco no nosso teste de robustez. Os resultados da nossa investigação colocam em evidência que os empréstimos inadimplentes são um indicador importante de ineficiência bancária em SOBs (bancos estatais) chineses. Aplicamos a regressão de Prais-Winsten - que é um caso especial de Feasible Generalized Least Squares (FGLS) - aos nossos dados em painel, para corrigir a correlação serial e a correlação transversal do nosso modelo *panel data* de efeitos fixos. A inovação da nossa investigação também reside na aplicação de FGLS ao estudo do crédito malparado. Em suma, a implicação da nossa investigação está de acordo com a literatura existente de que os *policymakers* devem considerar a redução de empréstimos inadimplentes na era pós-crise para melhorar a eficiência dos bancos.

Palavras-chave: empréstimos inadimplentes, ineficiência bancária, bancos estatais, China, regressão Prais-Winsten

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Contents

Chapter 1. Introduction

Since the Global Financial Crisis in 2007-2009, Non-Performing Loans (NPLs hereafter) have drawn critical concern from policy makers globally, because massive bank failures were accompanied by a significant and large increase in NPLs, with the corresponding decreased bank efficiency (Phung et al., 2021). In more recent years, when the Covid-19 pandemic brought the world economy into a crisis once again, the significant increase in NPLs as a crisis outcome indicates that it is in policymakers' crucial interest to provide an effective way to resolve and mitigate NPL's (Ari et al., 2020). Moreover, even though Fukuyama & Weber (2008) point out that NPLs are an undesirable byproduct of bank inefficiency, Fiordelisi et al.(2011) further investigate the causal relationship between bank capital, NPLs as risk indicators, and Bank inefficiency (considering revenue and net profit); and these authors find that bank inefficiency Granger causes risks which are measured by statistics relating to NPLs. Our contribution to the extant literature lies in presenting the explanatory power of NPLs in bank inefficiency using Prais-Winsten Regression, which is a special case of Feasible Generalized Least Squares. This technique, which, to the best of our knowledge, has not been applied in the study of NPLs, can be found in any research field when the problem of serial correlation occurs in an AR (1) process in the error term, and this technique strongly increases the efficacy of estimation.

The rest of this paper is structured as follows: chapters 2 and 3 includes an overview of Chinese banking history and a literature review respectively; while the data and methodology, consisting of variables and model specification is explained in chapter 4; chapters 5 and 6 respectively present the empirical results and corresponding robustness checks, followed by chapter 7 which concludes.

Chapter 2. An Overview of Chinese Banking Sector

2.1. Components of Chinese Banking System

According to the List of Financial Institutions in the Banking Sector in China, released by China Banking and Insurance Regulatory Commission in 20th of August in 2021, the modern Chinese banking system consists of the following, until 30th of June 2021:

Table 2. Components of Chinese Banking Sector

Central Bank	People's Bank of China
Policy Banks	Export-Import Bank of China and Agricultural Development of China. China Development Bank used to be among them till its shift to a corporation in 2008, and it is now functioning as the only development financing institution in China.
State-owned Commercial Banks	Bank of China, China Construction Bank, Industrial and Commercial Bank of China, Agricultural Bank of China Bank of Communication, and Postal Savings Bank of China
Other Domestic Commercial Banks, Foreign Banks, and Other Non-Bank Financial Institutions	4599 in total

2.2. History of Chinese Banking System

In a broad sense, modern Chinese banking system can date back to the foundation of Ta-Ching Government Bank in 1905 as the Central Bank of Manchu Qing dynasty. It was then renamed as Bank of China, with the birth of the Republic of China in 1912. It, together with Bank of

Communications founded in 1908, has been performing as a note-issuing bank until the year 1942. Before the People's Republic of China was established in 1949, the People's Bank of China was consolidated out of Huabei Bank, Beihai Bank, and Xibei Farmer Bank in December of 1948. The Chinese Renminbi (RMB hereafter) became the official currency in Mainland China, entering circulation thereafter. Since then, the People's Bank of China had been the only bank in mainland China playing the roles of both central bank and commercial bank until the year of 1979, when Agricultural Bank of China, Bank of China, China Construction Bank, and Industrial and Commercial Bank of China were separated from People's Bank of China one after another. Bank of Communications was the last state-owned bank to be re-established in the 20th century, which marked the initial formation of modern Chinese banking system. The notion 'Big-Five' representing these 5 state-owned banks has been widely used in the reports, analyses, and literatures relating to Chinese banking system. Meanwhile, the fact that they are listed earlier compared to the sixth state-owned bank, Postal Savings Bank of China, which was established later in 2007 and listed in 2016, makes it possible for us to collect relatively more sufficient data about NPLs from their annual and seasonal reports.

Chapter 3. Literature Review

NPLs have for decades been regarded as an indicator of the level of asset quality of the banking industry, having been thoroughly addressed as a research topic since the 1980s (e.g., Meeker & Gray, 1987; Betz et al., 2020). In the aftermath of the 1990s, after the Japanese asset price bubble burst in 1992 and in the aftermath of the Asian financial crisis (which occurred in 1997), a growing number of literature (e.g., Lee, 1997; Horiuchi & Shimizu, 1998; Aghion et al., 2001) started to focus on the research of NPLs as a problem in the aforementioned aspect in Japan, whereas others (Buch, 1995; Kim, 1991; Bhatt & Parekh, 1997; Shajahan, 1998; Lu et al., 2001; Ahmad, 2002; Rajan & Dhal, 2003; Petersson & Wadman, 2004) address the specific cases in Eastern Europe, South Korea, India, China, Malaysia, Italy, and Sweden. Later in the 2000s, researchers' main focus switched to sufficiently large developing or transitioning economies like China and India, pointing out, for example, that biased lending in China (Lu et al., 2005) and lagged leverage in India (Ghosh, 2005) are the main causes of NPLs in these two countries. More recent research, especially those research addressing the aftermath of the 2007–2008 Global Financial Crisis, indicates that NPLs are a key factor representing banks' performance and risks (Fiordelisi et al., 2011), drawing attention from researchers in economics and finance globally.

The control of risks in the banking sector has been regarded as a vital issue worldwide, which can be empirically verified by the effort made by multiple nations to implement Basel III since 2009. Statistics related to NPLs, e.g., absolute value of NPLs and the ratio of NPLs and total loans of individual banks or specific banking sectors, have been considered as an important indicator of risks for banks or whole banking sectors (Fiordelisi et al., 2011; Haneef et al., 2012; Ari et al., 2021). According to the most recent research, to our best knowledge and until the time of writing of this paper, 'risk factors' are associated with adverse NPL dynamics, which means high NPLs and slow resolution, including high credit growth, high government debt, fixed exchange rates, and high corporate debt with short maturity (Ari et al., 2021).This is in line with the investigation conducted by Fiordelisi et al. (2011), in which the authors use the ratio of NPLs and total loans of each individual bank as an indicator of risks, focusing on European banks, finding that bank inefficiency Granger causes risks but the evidence of the reverse relationship is somewhat limited.

Following the 2020 stock market crash related to the onset of the Covid-19 pandemic, policy makers presently have an urgent and significant interest to implement an effective way to resolve and mitigate NPLs (Ari et al., 2020). For example, a study of Turkish asset management companies' effect on both the NPL market and the bond market observes that increased NPL transactions would be considered a sign of economic recovery because the collectability of bad loans would improve, thus asset management companies can play an important role in the process of NPLs resolution. In other words, their effect of collecting NPLs is indeed worth noting (Pirgaip & Uysal, 2021). Meanwhile, researchers also discover that larger banks' size in post-crisis era helps improve the situation of NPLs issue. The findings of the effects of banks' size are interpreted as bank concentration having a moderating effect of the negative causal effect of policy uncertainty on NPLs (Karadima & Louri, 2021), and as consolidation of banks in the post-crisis era facilitating faster reduction of NPLs in Europe (Karadima & Louri, 2020). All these above-mentioned research denote that increasing individual banks' size through consolidation can be considered by the policy makers as a potential resolution to the NPL problem, together with the effect of asset management companies in the secondary NPL market.

However, whether bank inefficiency causes NPLs or NPLs cause bank inefficiency is still ambiguous and controversial among the extant literature. There are several studies discussing NPLs as an undesirable result of bank inefficiency (Park & Weber, 2006; Fukuyama & Weber, 2008; Hajialiakbari et al. 2013; Fukuyama & Weber, 2015; Kumbhakar et al. 2015; Fukuyama & Matousek, 2017), on which most researchers agree. On the other hand, Zhang, Cai, Dickinson, & Kutan, (2016) points out that an increase in the NPL ratio increases riskier lending, potentially causing further deterioration on loan quality and financial system instability in China. There are several Chinese cases described in Wan (2018), whereby housing prices Grangers causes NPLs but the opposite is rejected. The author also mentions the new "Guidelines of Bank Loan Risk Classification", issued on July 3rd , 2007 by the China Banking Regulatory Commission, making it quite harder to compare NPL data before and after 2007 (Wan, 2018).

In terms of methods applied in the extant literature, pooled OLS (e.g., Phung et al., 2021) has been widely applied. The contribution of our paper lies in this similar exploration in the period of 2007 - 2021 specific to Chinese state-owned banks and the application of Prais-Winsten regression in this format.

Although, as mentioned in our introduction, Prais-Winsten regression has been considered in many fields when the problem of autocorrelation in the error term arises, it is not to be found in the extant literature of NPLs to our best knowledge. Among other studies, this method can be found in Rana et al. (2021), where the authors measure the trend in growth and instability of major spices in Bangladesh. Another one in medical field applying this method is Ferreira et al. (2021), which investigates the impact of 10-valent pneumococcal conjugate vaccine on hospitalization rate of children with pneumonia considering different regions in Brazil. In environmental sciences, Kalbusch et.al (2020) studies the impact of coronavirus (COVID-19) spread-prevention actions on urban water consumption. All the aforementioned literature in different fields encounters the same problem of serial correlation in the error term with the execution of pooled OLS and an alternative solution like Prais-Winsten regression is required to adjust the estimation. Our critical analysis adopts a similar procedure like these, which will be further elaborated in the next section.

Chapter 4. Data and Methodology

4.1. The sample

The sample data of this research comes from the annual and seasonal reports of Bank of China, Agricultural Bank of China, Industrial and Commercial Bank of China, China Construction Bank, and Bank of Communication, which consist of five out of six state-owned banks in China. The remaining Postal Savings Bank of China is not included in our critical analysis because its dataset is not complete since it was only listed in 2016, whereas in our analysis we cover the period from 2011Q1 to 2021Q3. Table 4.1 shows the description of variables:

Table 4.1. Variable Description

Variable Type	Symbol	Variable Name	Description
Dependent Variable	Revenue	Quarterly Revenue	Total revenue of each quarter for each bank (in 100 million Chinese yuan)
Explanatory Variable	NPL	Total amount of non-performing loans	Total amount of non-performing-loans at the end of each quarter for each bank (in 100 million Chinese yuan)
	NPL_L_ratio	The ratio between non-performing loans and total loans	Non-performing loans divided by total loans at the end of each quarter for each bank (in 100 million Chinese yuan)
Control Variable	Asset	Total Assets	Total assets at the end of each quarter for each bank (in 100 million Chinese yuan)
	Liability	Total Liability	Total liability at the end of each quarter for each bank (in 100 million Chinese yuan)
	Equity	Total Shareholder’s Equity	Total shareholder’s equity at the end of each quarter for each bank (in 100 million Chinese yuan)
	Total_loans	Total Loans	Total loans at the end of each quarter for each bank (in 100 million Chinese yuan)

Among the above-mentioned variables, NPL and NPL_L_ratio are treated as important explanatory variables in model 1 and model 2, respectively, as the main goal of our analysis is to explore the effect of NPLs on bank (in)efficiency. Revenue is treated as the only indicator of bank (in)efficiency in our baseline models, whereas in our robustness test, Net-profit is also considered as an dependent variable, which will be explained later in chapters 5 and 6. We at the same time select total assets, liability and shareholder's equity as control variables, together with the dependent and explanatory variables to build panel regression models, which will be further elaborated in section 4.2.

4.2. Empirical Model

To study the impact of NPLs on bank efficiency, we select the revenue of banks as an indicator to measure their efficiency, and the amount of NPLs and the ratio between NPLs and total loans as indicators to measure NPLs. We at the same time select total assets, total liability, and total shareholder's equity, which we name as Asset, Liability, and Equity in table 3.1, as control variables, together with the dependent and explanatory variables to build panel regression models as follows:

Model 1:

$$Revenue_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 Asset_{it} + \beta_3 Liability_{it} + \beta_4 Equity_{it} + \beta_5 Total\_loans_{it} + \varepsilon_{it}$$

Model 2:

$$Revenue_{it} = \beta_0 + \beta_1 NPL\_L\_ratio_{it} + \beta_2 Asset_{it} + \beta_3 Liability_{it} + \beta_4 Equity_{it} + \beta_5 Total\_loans_{it} + \varepsilon_{it}$$

where,

i represents bank id,t represents each equi-spaced period (quarters).

$\beta 0$ represents the coefficient of the constant term,

$\beta 1$-$\beta 5$ represents the coefficients of each explanatory and control variable,

ε represents error term.

To avoid or reduce the influence of heteroscedasticity, we apply natural logarithm to all the data except for NPL_L_ratio.

The main difference between Model 1 and Model 2 lies in the different explanatory variables relating to NPL, namely, NPL in model 1 and NPL_L_ratio in model 2. The former captures the change of NPLs in absolute values, whereas the latter considers the change of NPLs relative to total loans. Every 0.01 of change in NPL_L_ratio means the amount of change in NPLs equals 1% of total loans. This is also used as an indicator of risk by Fiordelisi et al. (2011).

Therefore, we explore whether the change of NPLs in absolute value has a similar impact as the ratio between NPLs and total loans, so the two models are estimated separately.

In our critical analysis, for both model 1 and model 2, we firstly consider fixed effect pooled OLS regression as we reject the null hypothesis of Hausman and F-test, which rule out random effects and ordinary least squares as possible alternative methods. However, even in this more suitable fixed effects pooled OLS model the efficacy of estimation is not satisfactory as it exhibits serial correlation in its error term. We arrive at this conclusion by performing the stserial command in Stata. Therefore, we select OLS with panel-corrected standard errors (PCSE) (xtpcse in Stata), which allows for panel heteroskedasticity, panel autocorrelation, and contemporaneous correlation (HPAC hereafter), to correct the fixed effect model, according to Blackwell III (2005). In this format, the parameters are estimated by a Prais-Winsten regression, which is a special case of Feasible Generalized Least Squares.

To the best of our knowledge, feasible generalized least squares is largely efficient in panel regression considering autocorrelation. Inspired by Beguería & Pueyo (2009) and Hansen (2007), we consider Prias-Winsten regression in our analysis, enabling us to correct the fixed effects regression with serial correlation in the error term.

Chapter 5. Empirical Results

5.1. Descriptive statistics

We collected five Chinese state-owned banks' data covering the period 2011Q1 to 2021Q3 from their annual and seasonal reports. The total observation counts to 215. The descriptive statistics are listed in Table 5.1.

Table 5.1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Revenue	215	7.034438	0.49574	5.715019	7.801391
NPL	215	7.056735	0.6268653	5.393218	8.043715
NPL_L_ratio	215	0.013744 2	0.0030985	0.0081	0.024
Asset	215	11.98809	0.483558	10.62832	12.777
Liability	215	11.91175	0.478305	10.56917	12.68339
Equity	215	9.3689	0.5621833	7.771725	10.36198
Total_loans	215	11.36789	0.5052015	10.06231	12.22713

Table 5.1 show that after applying natural logarithm, the average value of revenue, NPSs and NPL/L are 7.032238, 7.056735 and 0.0137442, respectively.

5.2. The regression analysis of NPLs' impact on Bank Inefficiency

5.2.1. Hausman test

Before we estimate the model's regressions, we need to compute the F test, the LM test, and the Hausman test to decide whether we select fixed effects, random effects, or Ordinary Least Squares (OLS hereafter) to do the regression. According to Shin-Ping & Tsung-Hsien (2009), the F test is adopted to determine the selection of fixed effect model and OLS, the LM test is employed to determine the selection of random effect model and OLS, and the Hausman test is conducted to select between random effect and fixed effect model.

Note that in our model, after the application of the F test and the Hausman test, the LM test in no longer needed because the former two is sufficient to rule out OLS and random effect model. Nonetheless, the LM test results can still be found in Appendix A for additional check. The fixed effect and random effect regression can be found in Appendix B and C, respectively.

We hereby explain below the results of the F test and the Hausman test.
First, we execute the F test to model 1, and the results are listed as follows:

Table.5.2.1.1. Results of the F test in Model 1

	F-Statistic	P-value	Rejection of Ho
F test that all u_i=0	65.37	0.0000	yes

We can observe from the result of the F test that significant difference can be seen between individuals under 1% confidence level, thus we reject the null (reject OLS).
After ruling out OLS from model 1, we need to compute the Hausman test to decide whether we use fixed effects or random effects. The results of the Hausman test are as follows:

Table 5.2.1.2. Results of Hausman test in Model 1

	Chi2	P-value	Rejection of Ho
Ho: difference in coefficients not systematic	117.15	0.0000	yes

It can be observed that the P value of Hausman test is 0.0000 which is smaller than the confidence level 0.01. Therefore, we reject the null, and select fixed effects panel regression.
Then we apply the same approach to Model 2:

Table 5.2.1.3. Results of F test in Model 2

	F-Statistic	P-value	Whether Ho is rejected
F test that all u_i=0	65.45	0.0000	yes

We can see from the result of the F test that significant difference can be seen between individuals under 1% confidence level, thus we reject the null for model 2 (reject OLS).
After ruling out OLS from model 2, we need to perform the Hausman test to decide whether we use fixed effects or random effects. The results of Hausman test are as follows:

Table 5.2.1.4. Results of Hausman test in Model 2

	Chi2	P-value	Whether Ho is rejected
Ho: difference in coefficients not systematic	117.22	0.0000	yes

It can be concluded that the P value of the Hausman test is 0.0000 which is smaller than the confidence level 0.01. Therefore, we reject the null, and select fixed effects panel regression for model 2 as well.

5.2.2. Test for Heteroscedasticity and Serial Correlation

After confirming the fixed effects regression model, we start the panel regression to our models. Before we give an explanation to our results, we need to conduct tests for heteroscedasticity and autocorrelation on our fixed effect regression model. The results are listed below:

Table 5.2.2.1. Test for Heteroscedasticity in Model 1

	Chi2	P-value	Whether Ho is rejected
Ho: sigma(i)^2 = sigma^2 for all i	6.42	0.2671	no

Table 5.2.2.2. Test for Heteroscedasticity in Model 2

	Chi2	P-value	Whether Ho is rejected
Ho: sigma(i)^2 = sigma^2 for all i	6.34	0.2747	no

For both models 1 and 2, we can see from their corresponding tests of heteroscedasticity that their P values are greater than 10%, thus we do not reject the null and conclude that the results of our fixed effect regression model are homoscedastic.

Table 5.2.2.3. Test for Autocorrelation in Model 1

	Chi2	P-value	Whether Ho is rejected

H0: no first-order autocorrelation	13.590	0.0211	yes

Table 5.2.2.4. Test for Autocorrelation in Model 2

	Chi2	P-value	Whether Ho is rejected
H0: no first-order autocorrelation	13.578	0.0211	yes

It can be seen from the test results of autocorrelation for models 1 and 2 that their P values are both lower than 5%. Therefore, we can reject the null under 95% confidence level, and conclude that adjustments or corrections need to be applied due to the presence of autocorrelation for both models 1 and 2.

5.2.3. Prais-Winsten corrected regression

Since there is autocorrelation in our models, we select Prais-Winsten regression to conduct the correction of our regression. The below are the regression results after correction:

Table 5.2.3. Prais-Winsten Regression Results

	Revenue	
VARIABLES	Model 1	Model 2
NPL	-0.197**	
	(-2.56)	
Asset	5.975	2.821
	(0.34)	(0.16)
Liability	-4.171	-1.242
	(-0.25)	(-0.08)
Equity	-0.638	-0.455
	(-0.51)	(-0.37)
Total_loans	0.105	-0.048
	(0.55)	(-0.24)
NPL_L_ratio		-13.498**
		(-2.51)
Constant	-8.724*	-6.973
	(-1.91)	(-1.57)
Observations	215	215
R-squared	0.990	0.990
Number of Bank_id	5	5

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

We can see from Prias-Winsten regression results that, on model 1, there is a significant negative relationship between NPL and Revenue under the confidence level of 95%, with the coefficient of -0.197, meaning that for every 1% increase in NPLs, there will be 19.7% decrease in revenue. We can see a similar result in model 2 as well. In model 2, we also observe a significant negative relationship between NPL_L_ratio and Revenue, with the coefficient of -13.498, denoting a 0.01 increase in NPL/L corresponding to a 13.498% decrease in revenue.

Chapter 6. Robustness Tests

To conduct our robustness test, we select net profit as our dependent variable to again execute a robustified Prais_Winsten regression. The results are as follows.

Table 6. Results of Robustness Test

	Net_profit	
VARIABLES	Model 3	Model 4
NPL	-0.405***	
	(-3.29)	
Asset	-34.830	-44.415
	(-1.25)	(-1.60)
Liability	33.643	42.565
	(1.30)	(1.64)
Equity	1.457	2.039
	(0.75)	(1.05)
Total_loans	1.290***	0.970***
	(3.98)	(2.79)
NPL_L_ratio		-26.837**
		(-3.11)
Constant	-2.622	1.707
	(-0.36)	(0.24)
Observations	215	215
R-squared	0.968	0.968
Number of Bank_id	5	5

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

It can be inferred from the robustness test results that, explanatory variables such as NPL and NPL_L_ratio still have significant negative effects on Net_profit as a robustness test variable. This is quite consistent with our baseline models, further demonstrating the stability of our model applications. Therefore, we can conclude that the result of the negative effect of NPLs on bank efficiency is indeed robust.

Chapter 7. Conclusion

We explore the explanatory power of NPLs and the ratio between NPLs and Loans on banks' revenue and net profit, taking them into account as indicators for bank (in)efficiency for the case of the China's State-Owned Banks, for the 2011-2021 period. Revenue is the dependent variable, while NPL (in volume and ratio) are the main explanatory variables. For our robustness tests, we include net profit. We address Chinese State-Owned Banks, using Prais-Winsten regression to correct for autocorrelation in the error terms of models 1 and 2 found in Hausman test. We conclude that in Chinese State-Owned Banks, NPLs have a significant negative impact on Bank efficiency.

Fixed effect pooled OLS was initially considered for our models, but the findings were impacted by the existence of autocorrelation in the error term, which lowers the efficacy of estimating the model. Therefore, we switched to Prais-Winsten regression, which is a special case for Feasible Generalized Least Squares, because it allows for panel heteroskedasticity, panel autocorrelation, and contemporaneous correlation (HPAC). Some limitations include dataset issues and the relatively small number of State-Owned Banks (although our research includes the overwhelming majority of Chinese Banks in this banking segment).

The findings are in line with the extant literature sharing a common view on NPLs, which states that NPLs are an important indicator of bank inefficiency. We further emphasize the explanatory power of this variable, pointing to the associative relationship between NPL's and Bank revenue. Our findings might shed light on the future research regarding application of Prais-Winsten regression, or more generally Feasible Generalized Least Squares, for researchers to investigate larger datasets of NPLs in other banking segments in China or in other countries.

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Appendix

Appendix A

Results of LM Test in Model 1

	Chi2	P-value	Rejection of Ho
Ho: no serial correlation in the error term	0.00	1.0000	no

Results of LM Test in Model 2

	Chi2	P-value	Rejection of Ho
Ho: no serial correlation in the error term	0.00	1.0000	no

*Note that the null hypothesis is not rejected for these two LM tests, so we conclude that we accept OLS instead of random effect models. However, since in the analyses we firstly employed the F test and selected fixed effect models instead of OLS, there is no need to conduct LM tests anymore as OLS has already been excluded. Nevertheless, the LM test results are consistent with our analyses.

Appendix B

Fixed Effect Estimation of Model 1 and 2

	Fixed effect	
VARIABLES	Model 1	Model 2
NPL	-0.028	
	(-0.78)	
Asset	0.339	0.015
	(0.05)	(0.00)
Liability	-0.070	0.239
	(-0.01)	(0.04)
Equity	0.114	0.150
	(0.23)	(0.30)
Total_loans	0.263**	0.217
	(1.98)	(1.54)
NPL_L_ratio		-2.984
		(-1.25)
Constant	-0.068	0.177
	(-0.03)	(0.09)
Observations	215	215
R-squared	0.888	0.888
Number of Bank_id	5	5

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

Appendix C

Random Effect Estimation of Model 1 and 2

	Random effect	
VARIABLES	Model 1	Model 2
NPL	-0.147***	
	(-3.77)	
Asset	-10.521	-13.145
	(-0.99)	(-1.24)
Liability	11.110	13.561
	(1.12)	(1.38)
Equity	0.063	0.221
	(0.09)	(0.30)
Total_loans	0.606***	0.477***
	(3.75)	(2.76)
NPL_L_ratio		-10.513***
		(-3.89)
Constant	-5.630**	-4.260
	(-2.10)	(-1.61)
Observations	215	215
Number of Bank_id	5	5

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