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Non-performing loans and bank value: The role of loan loss provisioning in US banks

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Abstract

High non-performing loans consistently pose significant risks to bank value. By using a panel data regression model with data on publicly listed US banks, this study reveals that non-performing loans significantly reduce bank value. We found that the negative impact of non-performing loans can be cushioned by increasing loan loss provisions. The findings remain robust with endogeneity tests and fixed effects models. However, its cushioning impact begins to dissipate when loan loss provisions exceed the estimated 7.55% threshold. The cushioning effect is larger for the low prudence banks, and they can also sustain a higher optimal level of provisioning than high prudence banks. Further analysis shows under-provisioning in low prudence banks. These findings highlight the importance of provisioning to mitigate damages of non-performing loans on bank value, and even more so for the low prudence banks.

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1. Introduction

Non-performing loans are widely known to be a risk indicator for banks. A loan that is not repaid by the borrower for more than 90 days is classified as a non-performing loan (Basel Committee on Banking Supervision, 2017a). Non-performing loans hurt bank profits and assets, and thereby bank value. In the event of considerable loan loss, the bank suffers a double adverse impact on its value, as investors will also lose confidence in the bank. The European Central Bank is vigilantly addressing the serious threat of non-performing loans to bank stability. To manage this issue, it has implemented stringent guidelines aimed at curbing non-performing loans (European Central Bank 2017). Despite the detrimental effects of non-performing loans on the financial health of a bank and the stability of the financial market, there are limited empirical studies to investigate the relationship between non-performing loans and bank value. Limitations of past studies are elaborated in the next section.

Banks typically increase their loan loss provisions to manage default risks in periods of elevated non-performing loans. According to Morris et al. (2016) and Leventis et al. (2012), increasing non-performing loans often lead to a corresponding rise in loan loss provisions, which serve as a measure to cover potential default risks. If non-performing loans turn into actual loan losses, loan loss provisions are used to cover the losses to reduce high fluctuations in earnings and to protect bank value. However, there is a limit to which loan loss provisioning can be used for the mitigation of loan default risks. High loan loss provisions will reduce the amount of earnings in the balance sheet, resulting in lower reported profits of banks. This may trigger a negative market reaction and negatively affect the stock price (Elnahass et al., 2014; Balla et al., 2012; Docking et al., 1997) and possibly bank value. Laeven and Majnoni (2003) highlighted that the incurred loss model causes banks to set inadequate provisions during economic booms and excessive loan loss provisions during economic downturns, thereby affecting their capital and damaging financial stability. This suggests the existence of a threshold where provisioning becomes excessive and begins to hurt bank value. Therefore, our paper investigates whether loan loss provisioning mitigates the negative impact of non-performing loans on bank value and what is the optimal extent for such a mitigation measure to remain effective. What is the impact of non-performing loans on bank value when banks have more loan loss provisions? Answering this unexplored question could significantly improve our understanding of the complex dynamics between credit risk, risk management practices, and bank valuation. The investigation of an optimal loan loss provision level sheds light on how banks' strategies to mitigate the credit risk of non-performing loans through loan loss provisions can have unintended consequences on their value. Laeven and Majnoni (2003) also pointed out that banks often delay loan loss provisioning until economic downturns, resulting in substantial adjustments later. Riskier banks with high loan default risks are typically badly affected when such delays cause them to set large provisions. Their findings not only imply that banks face the challenge of setting optimal provisions to safeguard their financial stability, but also that this optimality varies with their risk-taking profiles. In defining the optimal loan loss provision levels for banks, this study takes their risk-taking profiles into consideration. This study contributes to the literature by empirically examining the optimal loan loss provision threshold and its variation across different bank risk profiles to enhance our understanding of how provisioning strategies can balance risk management and bank valuation, and ultimately contribute to more informed decisions on loan loss provisioning in the banking sector.

The scope of this paper is confined to publicly listed US banks for reasons described below. The focus is on perceived bank value, given that the impact of non-performing loans extends beyond direct financial consequences and operates significantly through the lens of bank risk management as perceived by the market. Perceived bank value reflects how stakeholders interpret a bank's risk management practices to deal with its non-performing loan levels. Stakeholders' views of the bank's ability to mitigate the risk of non-performing loans through effective loan loss provisioning shape investor confidence and subsequently play a critical role in determining its value.

The subsequent section explores the literature to highlight the gaps in past studies. Section 3 elaborates on how the variables are measured and the empirical model is specified. The findings and discussion are presented in Section 4, which also includes endogeneity checks and further analyses. The final section concludes the study.

2. Non-performing loans, bank value and loan loss provisioning

Non-performing loans are considered the most significant factor in loan losses that affect bank profitability. Some researchers labelled non-performing loans as "financial pollution" for their serious negative impacts on the profitability and liquidity of banks (Barseghyan 2010; Zeng 2012). Past works reported their influence on banks in different aspects such as credit quality, credit risk, profitability, and financial stability (Allayannis, 2009; Messai and Jouini, 2013; Barseghyan, 2010; Ghosh, 2015; González-Hermosillo, 1999; Keeton and Morris, 1987; Nikolaidou and Vogiazas, 2014; Strumickas and Valančienė, 2006; Zeng, 2012; Zhang et al., 2014). Allayannis (2009) and Strumickas and Valančienė (2006) highlighted non-performing loans as the strongest indicator of problematic loans that affect the financial health of a bank unfavourably. Zhang et al. (2014) demonstrated that non-performing loans had been given the highest priority for bank valuation from the experts' perspective compared to capital adequacy, and traditional financial indicators such as ROE and ROA, net profit margin, and loan growth. These studies do not directly quantify the influence of non-performing loans on bank value, a research gap that this study seeks to address.

Sawada (2013) and Niu (2016) are among the very few researchers who investigated the impact of non-performing loans on bank value. Using Tobin's Q ratio valuation regression model, they both came to the same conclusion that non-performing loans hurt bank value. Sawada (2013) studied the impact of revenue diversification on bank value using a sample of 113 Japanese banks, which operate in a different regulatory and financial environment compared to the US banks. Niu (2016) examined the relationship between bank valuation and loan growth using quarterly panel data of 632 US bank holding companies. Bank holding companies have diversified business models (Saunders, Cornett, and Erhemjamts, 2021). Their risk profiles, reporting requirements, and the regulatory frameworks governing them (Board of Governors of the Federal Reserve System, 2023) are different compared to publicly listed US banks. This distinction between them is crucial because non-performing loans have a more significant influence on the financial performance and valuation of banks whose earnings are predominantly derived from lending activities (Ghosh, 2015). Bank holding companies may manage non-performing loans differently due to their ability to offset loan losses with profits from non-banking subsidiaries (Houston, James, and Marcus, 1997).

The bad loan portfolio risks are typically managed through loan loss provisioning. Some researchers affirmed that the level of non-performing loans affects the amount of loan loss provisions of banks (Walter, 1991; Aiyar et al., 2015; Laeven and Majnoni, 2003;

Abdelkader et al., 2009). This was empirically studied by Abdelkader et al. (2009) and Hasan and Wall (2004), who found that non-performing loans had a positive association with loan loss provisions. Higher non-performing loans will result in higher levels of loan loss provisions and reserves to cover potential loan losses to avoid fluctuations in bank earnings (Hasan and Wall, 2004; Laeven and Majnoni, 2003). With this practice, banks may deduct their loan loss reserve from their balance sheet due to the actual loan losses over the reporting cycle to acquire adequate provisions to compensate for potential loan losses (Laeven and Majnoni, 2003). This action would send a negative signal to the market that would result in lower bank stock prices (Docking, Hirschey, and Jones 2000; Balla, Rose, and Romero 2012) and bank value.

On the other hand, setting discretionary loan loss provisioning in response to rising non-performing loans serves as a good discipline for the risk-taking activities of banks (Bushman and Williams, 2012). Managing credit risk from non-performing loans effectively enhances the financial resilience of banks. Bikker and Metzemakers (2005) highlighted that loan loss provisioning is an important tool for earnings management in reducing the volatility in stock price, lowering funding cost and improving external ratings. It signals good risk management and stability of banks, which benefit investors and stakeholders, and reduces the negative impact of increasing non-performing loans on bank value. Therefore, strategic loan loss provisioning may help to protect the financial stability of banks during periods of high non-performing loans, and boost market and investor confidence in banks' risk management. However, excessive provisioning burdens bank profitability. This paper makes a new attempt to assess the optimal level of loan loss provisions that can be employed to address non-performing loan risks.

3. Models and data

We adopt Tobin's Q ratio as the proxy for bank value as the dependent variable. Tobin and Brainard (1976) established Tobin's Q ratio, which compares a company's market value assets to their replacement costs. The formula for Tobin's Q ratio (*tobinq*) is given below:

$$tobinq = \frac{Equity\ Market\ Value + Liabilities\ Market\ Value}{Equity\ Book\ Value + Liabilities\ Book\ Value} \tag{1}$$

Tobin's Q ratio is a popular measure of the value of banks and non-bank firms. A ratio higher than one indicates that the market values a company's assets more highly than its book value. While the ratio could indicate good financial health, it could also mean that the market is optimistic about the company's prospects. In contrast, if the ratio is less than 1, the market may not be very confident in the company. Essentially, the focus of this paper is on the market-to-book value of the banks that takes into account the market valuation of banks, especially when high bad loan portfolios are buffered by high loan loss provisioning. High non-performing loans may lead to loan loss provisioning, which reduces bank profitability and decreases the equity book value in balance sheet. The reduced profitability and lower book values could lead to a lower Tobin's Q ratio if the market perceives the bank as riskier and reduces its market valuation. Therefore, Tobin's Q ratio is selected as it reflects the changes of banks' book value and the market's forward-looking expectations due to the interaction between non-performing loans and loan loss provisions. Tobin's Q ratio is commonly used to value non-bank firms in terms of their company performance (Wernerfelt & Montgomery, 1988), company structure and valuation (Cho, 1998; Demsetz

& Villalonga, 2001), and mergers and acquisitions in the US (Servaes, 1991). Tobin's Q ratio is prevalent and influential in its use as a proxy of bank value to study bank governance (Caprio et al., 2007), board size (Adams & Mehran, 2012; Belkhir, 2009), bank performance during financial crises (Huizinga & Laeven, 2012; Jones et al., 2011; Peni & Vähämaa, 2012), bank risk (González, 2005), stock performance (Sawada, 2013) and bank size and valuation (Minton et al., 2017).

The empirical model consists of Tobin's Q ratio (*tobinq*) as the dependent variable, non-performing loan ratio (*nplratio*) as the key independent variable, and important control variables. The control variables are other bank-related variables that are highly relevant to bank earnings and value. Following past studies, they are return of assets (Caprio et al., 2007), total assets (Dang et al., 2018; Himmelberg and Hubbard, 2000; Linck et al., 2008), loan-to-deposit ratio (Sloman, Garratt, and Guest, 2018), net interest income to earning assets ratio (Fang et al., 2014), deposit growth (Damodaran, 2008), loan growth (Bernanke, Gertler, and Gilchrist, 1996; Niu, 2016), and capital adequacy ratio (Basel Committee on Banking Supervision, 2017b). Model (2) below is employed:

$$\begin{aligned} tobinq_{it} = {} & \beta_0 + \beta_1 nplratio_{it} + \beta_2 nplratio_{it} \text{ x } llpratio_{it} + \beta_3 llpratio_{it} + \\ & \beta_4 lntassets_{it} + \beta_5 loandeposit_{it} + \beta_6 depositgrowth_{it} + \\ & \beta_7 loangrowth_{it} + \beta_8 interestincome_{it} + \beta_9 roa_{it} + + \beta_{10} car_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where β_0 is intercept and ε_{it} is the error term. The loan loss provision ratio (*llpratio*) represents the proportion of provisions for loan losses relative to the total amount of loans. The multiplication of $nplratio_{it} \text{ x } llpratio_{it}$ measures the interaction between non-performing loans and loan loss provisions. *lntassets* is the natural logarithm of total assets. The loan-to-deposit ratio (*loandeposit*) in percentage measures the bank's liquidity. Deposit growth (*depositgrowth*) and loan growth (*loangrowth*) are two common bank-related variables used to assess a bank's business growth. Net interest income to earning assets (*interestincome*) is a ratio that measures bank profitability in percentage terms. *roa* is the return on assets, which is a financial ratio in percentage that measures a bank's profitability in proportion to its total assets. *car* is the capital adequacy ratio in percentage, computed as the total capital divided by total risk-weighted assets. The details on the variables are given in the Appendix.

We apply panel data regression to the time series data of 608 publicly listed US banks sourced from the Thomson Reuters database. The loan loss provisions were calculated using the Incurred Loss Model until it was replaced by the Expected Loss Model beginning January 1, 2018 (IASB 2014; BIS 2017). The data period 2000-2017 is chosen to isolate the effect of the new model, which may lead to a volatile adjustment of loan loss provisions. STATA 16.1 SE software is used to process all the data and estimate the regression. The upper and lower 1% of data points for all the variables were subjected to winsorization to mitigate the effects of outliers (Ghosh and Vogt, 2012; Kwak and Kim, 2017). Additionally, observations outside the range of three standard deviations and of rare occurrence were checked. Nine observations on the loan loss provision ratio unlikely to reflect actual provisioning practices were excluded. These are extreme values that could be due to data entry errors or misreporting.

4. Results and discussions

The estimated models are presented in this section and the results are discussed. Further analyses are conducted to examine loan loss provisioning for banks with different risk-taking profiles.

4.1 Estimation results

The pooled panel regression to analyse the between-bank effects is estimated. The baseline model without considering the impact of non-performing loans is presented in Table 1 (Model (1)). The adjusted R squared increased when non-performing loans and the interaction term between non-performing loans and loan loss provisions are added in Model (2). Non-performing loans have a significant negative relationship with bank value. The results are consistent with Sawada (2013) and Niu (2016). Referring to Model (2), a 1% increase in the non-performing loan ratio reduces Tobin's Q ratio by 0.01, which is approximately 0.98% of the mean Tobin's Q ratio for the sample (1.03, descriptive statistics are presented later in Table 3).

The interaction term is statistically significant. From Model (2), the marginal effect of non-performing loans on bank value is given by $\delta(\textit{tobinq})/\delta(\textit{nplratio}) = -0.0101+0.00217\textit{llpratio}$. This shows that the negative impact of non-performing loans can be cushioned by increasing loan loss provisions. At the mean level of loan loss provisions, this reduction is 0.009, suggesting that loan provisioning offsets about 90% of the drop in the bank value from a 1% increase in the non-performing loan ratio. Investors could view the banks as being more careful in their credit risk management practices when banks increase loan loss provisions. Banks are perceived to demonstrate careful risk governance when they face high non-performing loan risks. It could raise market confidence in the bank's commitment to manage credit risk when loan loss provisions are adjusted periodically to cover the high potential risk of loan losses due to the threat of high non-performing loans. There is a limit, however, to the effectiveness of such a measure and this is investigated further below.

Time-specific macroeconomic shocks could drive bank value and the level of non-performing loans. Besides that, unobserved and time-invariant attributes of banks may simultaneously impact both these variables. Three additional models are estimated to address these concerns. Model (3) incorporates year-fixed effects to control for time-specific shocks that affect all the banks in a given year, such as interest changes and economic cycles. The bank-fixed effect model advocated by Gormley and Matsa (2014), augmented with year-fixed effects, is estimated in Model (4), aiming to control for time-invariant bank-specific heterogeneity, such as management style, risk appetite or institutional factors. The coefficients of non-performing loans in these two models remain negative and significant, indicating that higher non-performing loans reduce bank value. The interaction terms are also positive and significant, suggesting that loan loss provisions mitigate the negative effect of non-performing loans. These results show that the effects of non-performing loans and loan loss provisions are not driven by common time trends or time-invariant banking factors. While the results reported earlier remain robust, it should be noted that the estimated effects of non-performing loans are 13 to 15% of that of Model (2). The coefficients of the interaction term are also smaller, and they are 18 to 21% of that estimated in Model (2).

Model (5) builds on Model (4) by clustering the standard errors at the bank level to account for within-bank serial correlations. Non-performing loans and the interaction term become insignificant. The loss of significance suggests that the effects, while economically meaningful, are sensitive to intra-bank error correlation, potentially due to persistent non-performing loan profiles and loan provisioning behaviors within banks over time (Berger and DeYoung, 1997; Bikker and Metzemakers, 2005) that reduce the power of the fixed effects models.

Table 1 Estimation results

	Model (1) Baseline	Model (2) Interaction effects	Model (3) Year effect only	Model (4) Bank- and year-fixed effects	Model (5) Bank- and year-fixed effects with bank clustering
nplratio		-.01010***	-.00151***	-.00128***	-.00128
		(.00128)	(.00041)	(.00042)	(.00084)
nplratioxllpratio		.00217***	.00045***	.00038***	.00038
		(.00052)	(.00011)	(.00011)	(.00032)
llpratio	-.00679***	-.01223***	-.00585***	-.00571***	-.00571**
	(.0016)	(.00307)	(.00125)	(.00126)	(.0024)
lntassets	.00287***	.0035***	.00602***	.00212	.00212
	(.0006)	(.0006)	(.00126)	(.00237)	(.00474)
loandeposit	-.00025***	-.00029***	-.00049***	-.00054***	-.00054***
	(.00006)	(.00006)	(.00005)	(.00005)	(.00012)
depositgrowth	-.00047**	-.00047**	-0.0001	-.00001	-.00001
	(.00021)	(.00021)	(.00008)	(.00008)	(.00015)
loangrowth	.00084***	.00062***	-.00002	-.00002	-.00002
	(.00023)	(.00023)	(.0001)	(.0001)	(.00016)
interestincome	.00736***	.00842***	.01365***	.01490***	.0149***
	(.00143)	(.00153)	(.00119)	(.00128)	(.00343)
roa	.02446***	.02135***	.00837***	.00787***	.00787***
	(.0019)	(.00185)	(.00105)	(.00107)	(.0018)
car	-.00088***	-.00076***	-.00098***	-.00135***	-.00135***
	(.00025)	(.00026)	(.00018)	(.00019)	(.00047)
Constant	.97624***	.98592***	.9413***	.99972***	.99972***
	(.01335)	(.01364)	(.02657)	(.03872)	(.0747)
No. of observations	5088	4941	4941	4941	4941
Adjusted R^2	0.20051	0.26250	0.3760	0.3545	0.3545
Bank clustered	Yes	Yes			Yes
Year clustered	Yes	Yes			

Note: Tobin's Q ratio is the dependent variable. See Appendix for the definitions of the other variables. Models (1) and (2) are the OLS estimation results from pooled panel data regression models with double-clustered standard errors reported in parentheses. Models (3) and (4) are year-fixed effect and bank- and year-fixed effects models, respectively. Model (5) includes bank- and year-fixed effects, and the standard errors are clustered at the bank level. The estimated fixed effects are not reported but are available on request. *** and ** refer to statistical significance at the 1% and 5% levels, respectively.

4.2 Endogeneity checks

To address endogeneity concerns, the dynamic panel model suggested by Wintoki et al. (2012) is employed. A dynamic model takes into consideration the persistence in bank value over time. The difference generalized method-of-moments (GMM) method is used to correct for potential biases arising from unobserved heterogeneity, fixed effects and endogeneity. The two-step estimators are estimated using instrumental variables that include Tobin's Q ratio, non-performing loan ratio, and loan loss provision ratio of at least two-period lags, and the other explanatory variables are treated as exogenous. The results are in Table 2. Model (1) includes bank-fixed effects to account for time-invariant bank-specific heterogeneity. The coefficients of the non-performing loan ratio and the interaction term are both significant and of the right signs, suggesting that non-performing loans negatively impact bank value while loan loss provisions mitigate this effect. This finding shows that endogeneity does not weaken the findings reported earlier. However, adding year-fixed effects in Model (2) renders both the variables insignificant. The attenuation of their significance may stem from the persistence of non-performing loans and loan loss provisions within banks over time, thus reducing within-year variation and making the effects harder to detect (Berger & DeYoung, 1997; Bikker & Metzemakers, 2005). In both models, the Arellano-Bond first-order AR test is significant and the second-order AR test is not significant, confirming no second-order autocorrelation in the differenced residuals. From these results, there is no evidence that the instrumental variables are invalid. The lagged independent variables models are estimated in (3) and (4) to deal with endogeneity by using one-year lags of the explanatory variables. This offers an appropriate response to mitigate reverse causality concerns as per Bellemare, Masaki, and Pepinsky (2017). The findings show a significant negative effect of non-performing loans and a significant positive lagged interaction term, especially in Model (3). The results confirm that the baseline results hold after lagging one period to address simultaneity, providing evidence that endogeneity does not undermine the earlier conclusions.

4.3 Further analyses on loan loss provisioning

This section conducts further analyses to explore loan loss provisioning for banks with different risk-taking profiles.

4.3.1 Bank prudence

Banks require adequate capital to operate their lending operations, generate profits, and provide a financial cushion in periods of stress. Capital adequacy ratio, the total of Tier-1 and Tier-2 capitals divided by total risk-weighted assets, is commonly used by regulators to determine the capital adequacy of banks. According to the Basel III regulation, banks must maintain a capital adequacy ratio of at least 10.5% (Basel Committee on Banking Supervision, 2011). Estrella et al. (2000) and Jokipii and Milne (2011) used the capital adequacy ratio as a measure of bank prudence. They demonstrated that a higher capital adequacy ratio indicated better prudence in banking practices, where effective risk management led to lower probabilities of bank failure.

This section profiles the characteristics of two groups of banks based on capital adequacy ratio. The mean capital adequacy ratio for each bank over the sample period is computed and the median of their values is obtained. The banks with a mean capital adequacy ratio lower (higher) than the median are referred to as low (high) prudence banks. The descriptive statistics are given in Table 3.

Table 2 Endogeneity checks

Variable	(1) Difference GMM with bank-fixed effect	(2) Difference GMM with bank- and year-fixed effects	(3) Lagged explanatory variables	(4) Lagged explanatory variables with bank- and year-fixed effects
L.tobinq	.58163***	.33818***		
	(.05255)	(.05016)		
nplratio	-.00897***	-.00115	-.00873***	-.00157
	(.00232)	(.00123)	(.00122)	(.001)
llpratio	-.0188***	-.00257	-.00954***	-.00438*
	(.00503)	(.00324)	(.00341)	(.00228)
nplratioxllpratio	.0023***	.00011	.00192***	.00046*
	(.00087)	(.00037)	(.0005)	(.00024)
lntassets	-.01748***	-.00958	.00416***	-.00086
	(.00499)	(.01302)	(.00065)	(.00447)
loandeposit	-.00119***	-.00066***	-.00044***	-.00045***
	(.00033)	(.00019)	(.00005)	(.00009)
depositgrowth	.00077**	.00032	-.0004	-.00003
	(.00031)	(.0002)	(.00028)	(.00012)
loangrowth	-.00088**	-.00031	.00071**	.00005
	(.00043)	(.00027)	(.00031)	(.00013)
interestincome	.00749	.00925**	.00793***	.00925***
	(.00575)	(.00465)	(.00175)	(.00286)
roa	.0082*	.00443	.02162***	.00706***
	(.00443)	(.00305)	(.00235)	(.00163)
car	-.00043	-.00157*	-.0002	-.00045
	(.00106)	(.00088)	(.00024)	(.00036)
Constant			.97377***	1.06126***
			(.01403)	(.0673)
No. of observations	4141	4141	4690	4690
Adjusted R^2			.24323	.5347
AR (1) – p-value	0.000	0.000		
AR (2) – p-value	0.172	0.553		

Note: Tobin's Q ratio is the dependent variable. *L.tobinq* is *tobinq* lagged one year. See Appendix for the definitions of the other variables. Standard errors are reported in parentheses. Models (3) and (4) are estimated with the independent variables lagged one year. ***, ** and * refer to statistical significance at the 1%, 5% and 10% levels, respectively.

The difference in mean capital adequacy ratio between the low and high prudence banks is statistically significant (t-statistic = -38.4137, p-value = 0.0000), showing a strong contrast in the risk-taking profile of both groups of banks. Despite the small difference in the mean of the non-performing loan ratio between the low and high prudence banks, the value is significantly higher for the latter group (t-statistic = -2.0135, p-value = 0.0441). Given their stronger capital position, this may signal risk-taking appetites to lend to riskier borrowers or operate in volatile markets. Low prudence banks, constrained by a weaker capital position, might adopt a conservative lending strategy. The group with a higher capital adequacy ratio could also have raised their capital reserve, either from awareness of higher credit risk or compelled to do so by the regulators due to poorer loan quality. In other words, the boosted capital adequacy ratio does not guarantee loan quality. The loan loss provisioning behaviors and the market perceptions of bank value do not vary significantly between the low and high prudence banks. These findings suggest that differences in further analyses comparing these two groups of banks are mainly attributed to bank prudence as defined by the capital adequacy ratio.

Table 3 Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
(1) All banks (564 banks)				
Bank value	1.03073	0.07110	0.80184	1.78318
NPL ratio	1.61013	2.31564	0.00000	31.51000
LLP ratio	0.50902	0.89644	-2.26755	12.76762
CAR	15.56207	5.53791	7.98000	47.01000
(2) Low prudence banks (264 banks)				
Bank value	1.03130	0.06419	0.80184	1.78318
NPL ratio	1.55252	2.36771	0.00000	31.51000
LLP ratio	0.51267	0.83858	-1.99007	10.48310
CAR	13.02328	1.89835	7.98000	31.07000
(3) High prudence banks (177 banks)				
Bank value	1.03021	0.07687	0.80184	1.78318
NPL ratio	1.66478	2.26413	0.00000	31.51000
LLP ratio	0.50563	0.94699	-2.26755	12.76762
CAR	17.92424	6.65423	7.98000	47.01000

Note: NPL refers to non-performing loans. LLP refers to loan loss provisions. CAR refers to the capital adequacy ratio. Low prudence banks have mean CAR smaller than the median. High prudence banks have mean CAR larger than the median.

4.3.2 Optimal provisioning

Earlier results show that the impact of non-performing loans on bank value is reduced when loan loss provisioning is adequate. However, excessive provisioning burdens the profitability of banks. This section investigates the optimal level of provisioning that is acceptable before its negative effects on bank value set in. To find this turning point, an additional quadratic interaction term is added into equation (2) as follows:

$$\begin{aligned} tobinq_{it} = \beta_0 + \ & \beta_1 nplratio_{it} + \beta_2 nplratio_{it} \text{ x } llpratio_{it} + \gamma nplratio_{it} \text{ x } llpratio_{it}^2 + \\ & \beta_3 llpratio_{it} + \beta_4 lntassets_{it} + \beta_5 loandeposit_{it} + \beta_6 depositgrowth_{it} + \\ & \beta_7 loangrowth_{it} + \beta_8 interestincome_{it} + \beta_9 roa_{it} + \ + \beta_{10} car_{it} + \varepsilon_{it} \qquad (3) \end{aligned}$$

The results are presented in Table 4. The marginal effect of non-performing loans on bank value at different levels of loan loss provisioning is plotted in Figure 1. The result reveals an inverted U-shaped curve where higher loan loss provisions initially mitigate the negative impact of non-performing loans on bank value up to an inflection point of 7.55% for the sample that includes all the banks (computed from column (1)). Beyond this threshold, the cushioning impact of loan loss provisioning begins to dissipate, as excessive provisioning signals financial distress and reduces profitability.

Table 4 Estimations by different levels of capital adequacy ratios

Variable	(1) All banks	(2) Low Prudence Banks	(3) High Prudence Banks
nplratio	-.00223***	-.00182***	-.00199***
	(.00048)	(.00057)	(.00077)
nplratioxllpratio	.00151***	.00143***	.00105**
	(.00029)	(.00041)	(.00044)
nplratioxllpratio^2	-.0001***	-.00006	-.00007**
	(.00002)	(.00004)	(.00003)
llpratio	-.00795***	-.00821***	-.00682***
	(.00137)	(.00176)	(.00204)
lntassets	.00201	.0008	.00184
	(.00236)	(.00279)	(.00382)
loandeposit	-.00054***	-.0004***	-.0006***
	(.00005)	(.00008)	(.00007)
depositgrowth	0.00001	.00002	.00009
	(.00008)	(.00011)	(.00012)
loangrowth	-.00003	-.00002	-.00017
	(.0001)	(.00012)	(.00015)
interestincome	.01494***	.01871***	.01256***
	(.00128)	(.00166)	(.0019)
roa	.00815***	.00862***	.00907***
	(.00107)	(.00135)	(.00163)
car	-.00131***	-.0037***	-.00102***
	(.00019)	(.00043)	(.00024)
Constant	1.00173***	1.06948***	.99289***
	(.03865)	(.04939)	(.05984)
No. of observations	4941	2425	2516
Adjusted R^2	0.56485	0.68119	0.48622
Inflection point (%)	7.5500	11.9167	7.5000

Note: Tobin's Q ratio is the dependent variable. See the Appendix for the definitions of the other variables. These are the OLS estimation results from pooled panel data regression models with bank- and year-fixed effects. The standard errors are reported in parentheses. CAR refers to the capital adequacy ratio. Low prudence banks have mean CAR smaller than the median. High prudence banks have mean CAR larger than the median. The inflection points mark the maximum loan loss provision ratio that can be held by the banks before the marginal effect of non-performing loans on bank value starts to drop. *** and ** refer to the statistical significance at the 1% and 5% levels, respectively.

The inflection points differ significantly between the two groups of banks (see columns (2) and (3)). The inflection point for low prudence banks of 11.92% is substantially higher than the 7.50% for high prudence banks. A check of the sample values shows that 0.16% of all the banks have loan loss provision ratios above the threshold of 7.55%. None of the low prudence banks exceeded the threshold, while 0.24% of the observations among the high prudence banks have provisioned more than the threshold. The provisioning thus far has been largely below the threshold levels to offset the negative impact of non-performing loans on bank value.

The U-shaped curve moves up and to the right for banks with lower mean capital adequacy ratios. This shift indicates that the marginal impact of non-performing loans on bank value is larger for low prudence banks at a same level of provisioning, underscoring the importance of provisioning to low prudence banks for mitigating loan default risks. The higher threshold for banks with lower CAR may reflect an aggressive provisioning strategy needed to offset the negative effects of non-performing loans. In contrast, the lower threshold for high prudence banks reflects a more conservative approach consistent with their stronger capital base. These findings have critical implications for bank management and regulators. For low prudence banks, the higher inflection point indicates greater tolerance for provisioning, but their limited capital necessitates vigilant monitoring to avoid a sharp value drop post-threshold. High prudence banks can leverage their higher CAR to mitigate non-performing loans effects on bank value efficiently, which allows them to avoid excessive provisioning that could erode profitability.

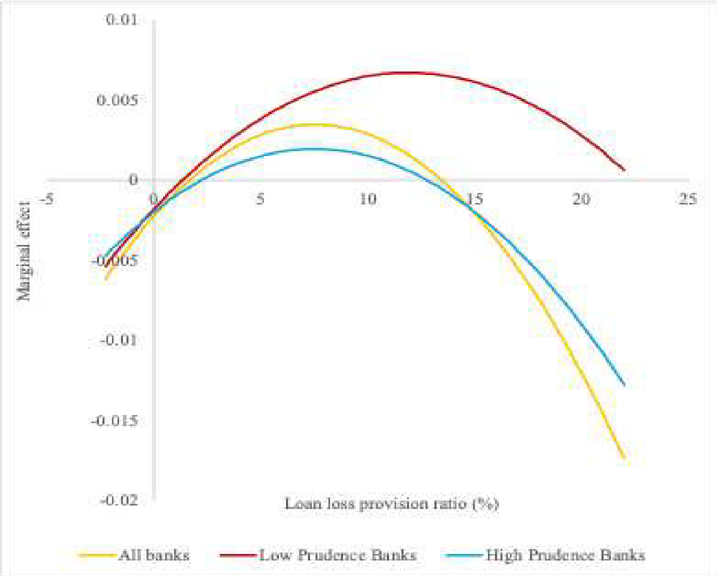

Figure 1 Marginal effect of non-performing loans on bank value at different levels of loan loss provisions

4.3.3 Loan loss provisioning gap

Loan loss provisioning is a key indicator of a bank's management strategy to buffer against loan default risks. An efficient market forms rational expectations about a provision that should be set aside by the bank based on their perceived risks of the bank. In this section, we investigate this perceived risk management based on expectations and compare it against the actual loan loss provisions reported by the banks to identify potential misalignment among banks with differing levels of prudence.

To quantify this discrepancy, the provisioning gap serves as a key indicator. It is defined as the difference between the actual loan loss provisions (Actual LLP) a bank sets aside and the expected loan loss provisions (Expected LLP) based on its risk profile. The formula is:

$$\text{Provisioning Gap} = \text{Actual LLP} - \text{Expected LLP} \tag{4}$$

The provisioning gap quantifies the misalignment between actual risk management embodied in provisioning decisions and perceived risk management as reflected in the Expected LLP formed from perceived risks. A positive provisioning gap suggests over-provisioning, while a negative provisioning gap indicates under-provisioning.

The Expected LLP is estimated using a panel data regression model, where the dependent variable is the loan loss provision ratio (*llpratio*), and the independent variables reflect factors influencing provisioning selected with the support of the literature. The independent variables are non-performing loans (Laeven and Majnoni, 2003), total assets (Bushman and Williams, 2012), return on assets (Bikker and Metzemakers, 2005), capital adequacy ratio (Amemed et al., 1999), loan-to-deposit ratio (Ozili, 2017) and loan growth (Foo et al, 2010). The regression model is:

$$llpratio_{it} = \beta_0 + \beta_1 nplratio_{it} + \beta_2 lntassets_{it} + \beta_3 roa_{it} + \beta_4 car_{it} + \beta_5 loandeposit_{it} + \beta_6 loangrowth_{it} + \varepsilon_{it} \quad (5)$$

The predicted loan loss provision ratios from the regression are the market expected provisions based on their assessment of risks and assets of a bank.

All the independent variables of the estimated model reported in Table 5 are significant. High non-performing loans are a strong driver of loan loss provisioning, consistent with the response of banks to credit risks by setting aside provisions to buffer against potential loan defaults. The provisioning gaps are given in Table 6. Significant under-provisioning is found for the low prudence banks. The actual loan loss provisioning falls short of expectations based on their risk profile. The high prudence banks are significantly over-provisioned. The actual loan loss provisioning exceeds that expected by the market. The t-test provides compelling statistical evidence of a systematic difference in the risk management between low prudence and high prudence banks. These results indicate that low prudence banks appear to lag in aligning provisions with risks, possibly due to capital constraints. High prudence banks might have exercised more caution on the credit risk and provided beyond immediate needs.

Table 5 The estimated model for loan loss provisions

Variable	Coefficient
nplratio	.10061***
	(.00518)
lntassets	.31091***
	(.03365)
roa	-.58245***
	(.01229)
car	-.00596**
	(.0027)
loandeposit	.00305***
	(.00066)
loangrowth	-.00432***
	(.00061)
Constant	-3.00868***
	(.71781)
No. of observations	5188
Adjusted R^2	.62695

Note: Loan loss provision ratio is the dependent variable. See Appendix 1 for the definitions of the other variables. The model is the OLS estimation results from pooled panel data regression models with bank and fixed effects. The standard errors are reported in parentheses. *** and ** refer to statistical significance at the 1% and 5% levels, respectively.

Table 6 Loan loss provisioning gaps

Banks	No. of observations	Mean of the gap	Standard error	95% Confidence interval
Low Prudence	2548	-0.07239	0.01251	[-0.09693, -0.04786]
High Prudence	2640	0.06987	0.01459	[0.04127, 0.09848]

Note: Low prudence banks have mean CAR smaller than the median. High prudence banks have mean CAR larger than the median. The gap is calculated as the actual minus the expected loan loss provision ratio. The t-statistic for testing the difference between the two means is -7.3801 (p-value = 0.0000).

This finding extends the works of Bushman and Williams (2012) on discretionary provisioning and provides some insight into the gap between the perceived and actual risk management of low and high prudence banks. The provisions of low prudence banks may be lower than necessary to inflate short-term earnings but risking future stability. The over-provisions of high prudence banks may be used to signal soundness but at the expense of profitability. While the mitigating effects of loan loss provisioning are larger for the low prudence banks, the results imply that provisioning has not been sufficiently leveraged by these banks.

5. Conclusion

This study provides empirical evidence from panel data regression analyses on publicly listed banks in the US that non-performing loans significantly lower bank value. The negative impact due to the risks of non-performing loans could be mitigated by higher loan loss provisioning, that could be perceived by the market as better risk governance. However, there is a threshold in provisioning to this mitigating effect. Categorising the banks according to their prudence defined by capital adequacy ratio, low prudence banks can sustain a higher optimal level of provisioning than high prudence banks. The mitigating effects of provisioning are also larger for the low prudence banks. Despite this, further findings showing under-provisioning in low prudence banks suggest that provisioning has not been sufficiently leveraged.

We identify some key implications. This study underscores the interaction between loan loss provisioning with non-performing loans in managing credit risks, providing a guide to bank managers and investors to quantify and estimate the impact of this interaction on their bank value when non-performing loan risks are high. The results indicate that increasing loan loss provisions when banks are faced with rising risk of non-performing loans could signal to the market their effective management of credit risk to enhance financial stability. The effectiveness of this measure has a limit, and this limit is higher for banks with lower capital buffers. While banks could improve their non-performing loan risk management through loan loss provisions, they must be monitored to avoid over-provisioning that affects bank value. As a practical implication, banks should prioritize strengthening their risk governance frameworks and keep sufficient reserves to cushion potential financial distress. They must maintain adequate provisions to buffer against potential losses while managing the impact on their bank value when non-performing loans are high. As an accountable governance practice, default risk management should align with loan quality and operate below the optimal levels of loan loss provisioning to protect the interest of stakeholders.

Appendix

Variable	Measurement
Non-performing loan ratio	A ratio in percentage measures the loan payment that is due over 90 days compared to total loans. (Non-Performing Loans / Total Loans) x 100. It is the proxy to measure non-performing loans.
Loan loss provision ratio (*llpratio*)	[Loan Loss Provisions / Total Loans] x100
Natural logarithm of total assets (*lntassets*)	The total assets of a bank transformed into natural logarithm.
Loan to deposit ratio (*loandeposit*)	[Total Loan / Total Deposits] x100
Deposit Growth (*depositgrowth*)	[(Total $Deposit_t$ - Total $Deposit_{t-1}$) / Total $Deposit_{t-1}$] x100.
Loan Growth (*loangrowth*)	[(Total $Loan_t$ - Total $Loan_{t-1}$)/ Total $Loan_{t-1}$] x100
Net interest income to earning assets ratio (*interestincome*)	Net Interest Income / Average of Last Year's and Current Year's (Total Investment + Net Loans) x100. This formula is from the Thomson Reuters database.
Return on Assets (*roa*)	Net Income - Bottom Line + ((Interest Expense on Debt-Interest Capitalized) x (1-Tax Rate)) / Average of Last Year's (Total Assets - Customer Liabilities on Acceptances) and Current Year's (Total Assets - Customer Liabilities on Acceptances) x100. This formula is from the Thomson Reuters database.
Capital Adequacy Ratio (*car*)	[Total Capital/Total Risk-weighted Assets] x100

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