Credit Risk and financial performance banks: a panel data analysis

Sunil Kumar
Deen Dayal Upadhyaya College, University of Delhi, India
Email: amritsarsk@gmail.com

Vipin Kumar Meena (Corresponding Author)
Deen Dayal Upadhyaya College, University of Delhi, India
Email: vipin@ddu.du.ac.in

Abstract

The NIFTY50 index is the premier benchmark for the Indian stock market, comprising 50 companies from 13 diverse sectors. As five of the country's largest commercial banks are part of this index, their performance indicates the overall market performance. This study aimed to investigate the correlation between credit risk and the financial performance of these NIFTY50-indexed banks. Utilizing secondary data collected from the banks' annual reports over the past decade (2012-2021), the study employed panel data regression analysis to examine the relationship between return on equity and return on asset as measures of financial performance and capital adequacy ratio, net non-performing assets (NNPAs), and cost to income (CI) as measures of credit risk. The results revealed a significant relationship between credit risk and financial performance, with the capital adequacy ratio having no significant impact. The study recommends that NIFTY50-indexed commercial banks implement strategies to lower their CI and NNPAs to improve their financial performance.

Keywords: *Financial Sector; Commercial Banks; Credit Risk; Financial Performance.*

Suggested Citation:
Kumar, S., & Meena, V.K. (2022). Credit Risk and financial performance banks: a panel data analysis. International Journal of Accounting, Business and Finance, 1 (2), 36-47.

1. Introduction

The Indian economy is an emerging economy, and the banking sector significantly contributes to its growth. Any crisis in the banking sector may create a hurdle in India's economic development process (*Das & Ghosh, 2007*). Historically, major economic problems resulted from the banking crisis (*Bsoul et al., 2022*; *Rai et al., 2022*). Hence, banking institutions' financial performance and the banking sector's robustness are the precursors to economic development (*Ahsan, 2016*). The banks' good financial performance leads to the country's financial stability (*Bischof et al., 2021*) and increases the shareholder's value (*Mohiuddin, 2014*). Without banking institutions, a country's business environment will be adversely affected, so the banking sector's smooth functioning is critical to the country's overall growth (*Rai & Pandey, 2022*). The stiff competition among financial institutions, regulatory changes, and uncertain business environment at the national and international levels may threaten the banking sector's financial performance, in other words, risk (*Karmakar & Shukla, 2015*). Risk can be defined as the probability of default, loss, damage, or threat caused by external and internal factors (*Gabriel et al., 2022*; *Inegbedion et al., 2020*). This risk may cause the problem of bank failure (*Ahmed et al., 2022*).

The banks are an essential source of financing for small businesses, households' agriculture, and corporates. Any miscalculation or mispricing of products and services may cause a potential risk for banks (*Das & Ghosh, 2007*). Primarily banks are exposed to credit risk because most are engaged in financing activities (*Ruziqa, 2013*; *Singh & Singh, 2015*). The probability of a loss caused due to the default of loans is known as credit risk in banks (*Hertrich, 2014*). Credit risk is vital for any bank; it arises due to the potential default of any performing loan or the borrower's inability to repay the loan as per the pre-committed loan contracts (*Jayaraman & Srinivasan, 2014*; *Mahmood & Ahmed, 2022*). The default in repayment of loans will adversely affect the banks' profitability because loans are a bank's primary source of income (*Siddique et al., 2020*). The adverse effect of credit risk is not limited to the loan performance but will impact the banks' overall financial performance and stability (*Ameur, 2016*; *Hunjra et al., 2022*).

Credit risk depends upon a bank's asset quality and profitability (*Catherine, 2020*). A bank's size and structural characteristics also trigger credit risk (*Ghosh, 2015*). Further, credit risk can be divided into exposure risk, recovery risk, and default risk (*Singh & Singh, 2015*). Credit risk is a crucial factor for the growth and stability of banking institutions. The bank's financial performance depends upon various internal factors related to credit risk and external factors associated with the macroeconomic environment (*Hossain & Golder, 2022*; *Jreisat, 2020*). Commercial banks should be aware of credit risk identification, measurement, monitoring, and management simultaneously; banks should have adequate capital against the risk incurred (*Siddique et al., 2020, 2022*). Good credit management (*Caruso et al., 2021*; *Hossain & Golder, 2022*; *Sugiharto et al., 2018*) and an increase in the bank's credit portfolio quality catalyze good financial performance (*Singh & Singh, 2015*). The disbursement of loans is the primary source of income generation, which significantly impacts credit risk. Credit risk affects the cost of credit; by reducing it, banks can enhance their profitability (*Ally, 2022*).

Many studies have been conducted on the relationship between credit risk and a bank's financial performance, but very few focus on India (*Hunjra et al., 2022*; *Kumar et al., 2011*; *Prasanth et al., 2020*; *Siddique et al., 2022*). The banking sector's performance in India significantly influences the stock market index. NIFTY50 is the national stock exchange benchmark index out of 5 large commercial banks named AXIS BANK. ICICI BANK, SBI, HDFC BANK, and KOTAK BANK are part of the NIFTY 50 Index (White paper, NSE Indices).

The motivation for this study stems from the importance of the banking sector in the growth and stability of an economy, specifically in the case of India, which is an emerging economy. The banking sector plays a crucial role in financing small businesses, households, agriculture, and corporates, and any crisis in the sector can hinder the economic development process. Additionally, historical evidence has shown that major economic problems can result from banking crises. Therefore, it is essential to assess the financial performance of banking institutions and the robustness of the banking sector in order to ensure economic growth. This study aims to examine the relationship between credit risk and the financial performance of NIFTY50-indexed large commercial banks in India, which are considered a precursor to the overall stock market performance. By understanding the impact of credit risk on the financial performance of these banks, this study aims to provide useful insights for regulators, investors, and bank managers to ensure the smooth functioning of the banking sector and overall economic growth. Therefore, the present study is focused on NIFTY50-indexed banks. This study analyses the relationship between credit risk factors and financial performance factors.

The present study examines the effect of credit risk on the financial performance of banks, using the capital adequacy ratio (CAR), cost to income (CI), and net non-performing assets (NNPA) as credit risk factors and return on assets (ROA) and return on equity (ROE) as financial performance factors. The study uses pooled panel data regression, fixed-effect, and random-effect models to estimate the panel data. The results indicate that an increase in CI and NNPA significantly decreases the ROA and ROE of banks. The study also finds that CAR positively correlates with ROA and ROE but does not significantly impact financial performance. The study recommends that NIFTY50-indexed commercial banks focus on managing their CI and NNPA to improve their financial performance and for regulators and investors to pay more attention to these factors when assessing the credit risk profile of banks and making investment decisions.

The rest of the paper is as follows: Section 2 presents a detailed literature review to draw the hypotheses, variables for analysis, and relevant methodology; Section 3 discusses the data and research methodology; Section 4 presents the results and discussion; and Section 5 comprehends the study's conclusion, implications, limitations, and future scope.

2. Literature review

Credit risk indicators can predict the bank's financial performance (*Gabriel et al., 2022*). CAR and non-performing assets (NPA) significantly impact a bank's financial performance, which can be measured by ROE and ROA (*Oludhe, 2011*). In a panel data regression between credit risk and financial performance, the ROA was used as the proxy for the financial performance of the banks (*Hossain & Golder, 2022*). The better ROA and reduced cost to capital make a bank more efficient as compared to its competitor (*Dinu & Bunea, 2022*).

The ROA is determined by asset quality which is impacted by the percentage of (NPA) non-performing assets (*Das & Ghosh, 2007*). The ratio of NPA to total assets, capital requirement as the proxy of credit risk (*Bayyoud & Sayyad, 2015*), and ROE as the measure of a bank's performance (*Ahmed et al., 2022*) was used in a study that concluded that capital requirement has a positive impact on bank's performance.

The term NPA is defined as "NPA is an asset, including a leased asset, becomes non-performing when it ceases to generate income for the bank." In annual reports of the banks, it is reported as gross non-performing assets (GNPA) and net non-performing assets (NNPA) after subtracting the provisioning amount from the GNPA.

A study on the impact of capital requirement on a bank's performance using a generalized method of moment (GMM) used NPA and CAR as independent variables and ROA and ROE as dependent variables. The results concluded that the capital adequacy ratio (CAR) is an essential predictor of a bank's financial performance (*Hossain & Golder, 2022*). A panel data analysis between capital adequacy requirements and the performance of selected commercial banks indicated that capital adequacy increases the profitability of commercial banks (*Catherine, 2020; Mendoza & Rivera, 2017*). Credit risk significantly affects the ROA (*Bayyoud & Sayyad, 2015*). The alternative options may be used to improve the financial performance of the banks by minimizing the level of credit risks (*Simanjuntak & Demi Pangestuti, 2017*). Hence, we hypothesize that:

H_{1a}: CAR has a positive relationship with ROA

H_{1b}: CAR has a positive relationship with ROE

Credit risk factors like NPA and credit cost have a negative relationship with the financial performance of banks (*Ally, 2022; Kwashie et al., 2022*). The bank's financial performance has a significant relationship with credit risk (*Mohiuddin, 2014*). A study on Kenyan banks (*Oludhe, 2011*) concluded that good credit risk management practices positively correlate with banks' financial performance; similar results were found in a study on Nigerian banks. Poor credit risk management leads to poor financial performance in banks (*Ghosh, 2015*); similar results were found using CAR, credit risk, and financial performance (*Bayyoud & Sayyad, 2015*). Hence, we hypothesize that:

H_{2a}: NNPA has a negative association with ROA

H_{2b}: NNPA has a negative association with ROE

H_{3a}: CI has a negative association with ROA

H_{3b}: CI has a negative association with ROE

The study's objective is to investigate the relationship between credit risk and a bank's financial performance. The present study has considered only banks related parameters as the dependent and independent variables. The current research opted for ROA and ROE as the dependent variables. CAR, NNPA, and CI have been selected as the independent variables.

Table 1. Summary of dependent variables and independent variables

Variable type	Factor	Variable name	Symbol	Formula
Dependent Variables	Financial Performance	Return on Asset	ROA	Net Income/Total Assets (*Gardner et al., 2011*)
		Return on Equity	ROE	Net Income /Shareholder's Equity (*Wooldridge et al., 2013*)
Independent Variables	Credit Risk	Capital Adequacy Ratio	CAR	Tier1 Capital + Tier2 Capital / Risk-Weighted Assets (*Simon, 2021*)
		Net Non-Performing Assets	NNPA	Gross NPA – Provisions / Total Advances (RBI)
		Cost to Income	CI	Operating cost / Total Income

Note: This table describes the variables used in the study

Table 1 summarises the dependent variables ROA & ROE and independent variables CAR, NNPA & CI. The ROA & ROE are the proxies for the banks' financial performance. To measure the credit risk of the banks' CAR, NNPA and CI are taken as the independent variables. The study has selected large commercial banks similar in size and age, so the effect of size and age is constant in the research.

3. Data and Methodology

3.1. Data

The study used the model specified in the analyses (*Hossain & Golder, 2022*) and collected the last ten years' data on ROA, ROE, CAR, NNPA, and CI from the annual reports of the five NIFTY50 indexed banks from the financial year 2012 to 2021. The secondary data have been collected from the five NIFTY 50 Indexed banks from 2012 to 2021. The total numbers of observations are 50. The data type is balanced panel data (Gujarati, 2003).

Table 2. Summary statistics

Variable	Mean	Median	Standard Deviation	Min	Max	Observations
ROE	12.1	13.9	5.72	-3.78	20.5	50
ROA	1.24	1.53	0.605	0.0200	2.01	50
CAR	15.7	15.5	1.93	12.1	19.1	50
CI	42.9	44.2	6.94	28.7	55.7	50
NNPA	1.41	0.840	1.38	0.200	5.73	50

Note: This table presents the variables' summary statistics.

The data is analyzed by using Gretl software. *Table 2* presents the descriptive statistics. The summary statistics show that the mean value of ROA, ROE, CAR, CI, and NNPA is 12.1, 1.24, 15.7, 42.9, and 1.41. Similarly, the median value is 13.9, 1.53, 15.5, 44.2, and 0.840. The lowest value of ROE is -3.78, and the maximum value is 20.5. In the case of ROA, the lowest value is 0.020, and the maximum value is 2.01.

The correlation coefficients in *Table 3* indicate the strength of the relationship between the variables. The more than zero value of the coefficient signifies a positive relationship, and the less than zero value denotes a negative relationship between the variables. Capital adequacy positively correlated with ROE and ROE simultaneously; other credit risk-related factors, the CI and NNPA, negatively correlated with ROE and ROA.

Table 3. Correlation Matrix

Variables	ROE	ROA	CAR	CI	NNPA
ROE	1.0000	0.8310	0.0701	-0.4746	-0.6950
ROA		1.0000	0.2335	-0.6669	-0.7375
CAR			1.0000	-0.5252	-0.1811
CI				1.0000	0.4800
NNPA					1.0000

Note: This table presents the variables' correlation matrix.

3.2. Methodology

Recent There are three types of panel data estimation models: (1) Pooled OLS Model, (2) Fixed Effect Model (FEM) (3) Random Effects Model. If the classical linear regression model (CLRM) model does not meet the criteria of BLUE (Best Linear Unbiased Estimation) properties, then pooled OLS model should have been preferred over the CLRM model (*Al-Eitan & Bani-Khalid, 2019*; *Munangi & Sibindi, 2020*). The increased number of observations is the main advantage of the pooled OLS model because the increased number of observations has lowered the standard error compared to the CLRM model (*Baltagi, 2001*). However, a severe issue with pooled OLS model is that the intercept is constant with all cross-sectional units and time-invariant (*Greene, 2003*; *Gujarati, 2003*; *Wooldridge, 2012*). The data can be pooled if all the cross-sectional units have a common intercept and do not have a time series effect.

The regression models are as follows:

$$ROA_{it} = \alpha + \beta_1 CAR_{it} + \beta_2 NNPA_{it} + \beta_3 CI_{it} + \mu_{it} \tag{1}$$

$$ROE_{it} = \alpha + \beta_1 CAR_{it} + \beta_2 NNPA_{it} + \beta_3 CI_{it} + \mu_{it} \tag{2}$$

where α is the intercept, β is the coefficient of independent variables, μ_{it} is the error term.

4. Results and discussion

4.1. Pooled OLS model

The pooled OLS model is applied for panel data estimation for ROA and ROE models. The pooled OLS model assumes that µit is not correlated with the independent variables (*Greene, 2003*; *Gujarati, 2003*; *Wooldridge, 2012*), and the intercept does not have cross-sectional and time variations (*Baltagi, 2001*). The results of the pooled OLS regression for both models are presented in *Table 4*. The coefficients, t-statistics, R-squared values, adjusted R-squared values, F-statistic, and D-W test are reported for each model. The coefficients for CAR, CI, and NNPA are negative in both models, indicating that these variables have a negative relationship with ROA and ROE. The R-squared values indicate that both models explain a high percentage of the variation in ROA and ROE. The F-statistic indicates that the model is a good fit for the data. The D-W test indicates that the residuals of both models do not show autocorrelation. The results are statistically significant at the 1% level. The effect of CAR on ROA and ROE is insignificant at all levels. These findings suggest that NIFTY50-indexed banks should focus on managing their CI and NNPA to improve their financial performance.

The test for differing intercepts and the value of the Durbin-Watson test resulted in the Model 1 (ROA Model) having a severe autocorrelation issue (*Gujarati, 2003*). The Woodridge test for autocorrelation also confirms a similar result. The pooled OLS regression models have serious autocorrelation, heteroskedasticity, and multicollinearity problems. The Woodridge test is appropriate to identify the issue of autocorrelation (*Wooldridge, 2012*). White's test is used for heteroskedasticity (*White, 1980*). Various tests to select an appropriate model for the analysis are described in this section.

Table 4. Results of the Pooled OLS model

Variable	Model 1 (ROA)		Model 2 (ROE)	
	Coefficient	t-statistic	Coefficient	t-statistic
β_0	3.86***	5.04	34.65***	3.97
CAR	−0.03	−1.11	−0.56	−1.60
CI	−0.04***	−4.25	−0.24**	−2.19
NNPA	−0.23***	−5.57	−2.45***	−5.12
R^2	0.679673		0.534696	
Adjusted R^2	0.658782		0.504350	
F-Statistic	32.53***		17.62***	
D-W Test	0.63		1.11	

Notes: ** and *** indicate significant values at 5% and 1% levels, respectively. The F-statistic is significant at a 1% level, indicating the goodness of fit for both models.

4.1.1. Woodridge Test for Autocorrelation

For the Woodridge test for autocorrelation, we proceed with the null hypothesis, "H_0: Cov(εit, εi,t−1) = 0 (no autocorrelation)," and the alternate hypothesis, "H_1: Cov(εit, εi,t−1) ≠ 0 (there is autocorrelation). The p-value of Model 1 infers that there is a serious issue of autocorrelation exit, whereas Model 2 is consistent with the null hypothesis and does not show the autocorrelation problem (see *Table 5*).

4.1.2. White's test for heteroskedasticity

For White's test, we hypothesize that "there is no heteroskedasticity in panel data." The pooled OLS regression assumes that homoscedasticity means all the residuals are drawn from the population, which has a constant variance. The problem of heteroskedasticity exists due to significant variation among the variables and their correlation with standard error terms. The increased number of observations may reduce the problem of heteroskedasticity (*Baltagi, 2001*; *White, 1980*)

4.1.3. White's test for heteroskedasticity with robust standard errors

We also apply the White test with robust standard errors. The test results indicate that the problem of heteroskedasticity is still present in Model 1 (ROA model).

The results of the above tests indicate the problem of autocorrelation and endogeneity in the data. This problem exists in the data because the pooled OLS model has cross-sectional and time-invariant intercepts.

4.1.4. Test for differing group intercepts

The test for differing group intercepts was applied to find whether that data was pooled or not pooled. We hypothesize that "the banks have a common intercept." The result indicates that data is pooled in Model 2 and has a common intercept, but model 1 rejects the assumption of a common intercept for all the banks. For the panel data estimation of model-1(ROA model), the fixed-effect or random model can be preferred over the pooled OLS model (*Xu et al., 2007, Ch.32, p.7*).

4.1.5. Breusch-Pagan Test

The Breusch-Pagan test is used to validate the selection between the pooled OLS model and the fixed or random-effect model (*Breusch & Pagan, 1980*). We proceed with the null hypothesis that "the Pooled OLS model is more appropriate than Fixed effect and random-effect models." The test results infer that the pooled OLS model is appropriate for Model 2 (ROE model).

Table 5. Tests to choose the appropriate model

Sr. No.	Test	Estimates	Model-1 (ROA)	Model-2 (ROE)
1.	Woodridge test for autocorrelation	T-Statistics	6.0335	0.003
		P-Value	1.2408	0.282
		Result	H_0- Rejected	H_0- Accepted
2.	White's test for heteroskedasticity	Chi-Square	29.1195	23.5459
		P-Value	0.000	0.005
		Result	H_0- Rejected	H_0- Rejected
3.	White's test for heteroskedasticity with robust standard errors (Arellano)	Chi-Square	13.8896	4.2644
		P-Value	0.030	0.640
		Result	H_0- Rejected	H_0- Accepted
4.	Test for differing group intercepts	F-Statistics	9.4021	1.6719
		P-Value	0.000	0.174
		Result	H_0- Rejected	H_0- Accepted
5.	Breusch-Pagan Test	Chi-Square	15.5658	0.06888
		P-Value	0.000	0.792
		Result	H_0- Rejected	H_0- Accepted

Note: This table presents the result of various tests to select an appropriate model for the analysis

4.1.6. Test for multicollinearity

The OLS regression model assumes no relationship exists between independent and predictor variables. The correlation coefficient between predictors is the most straightforward measure to identify the problem of multicollinearity in panel data (*Gujarati, 2003*; *Sutikno, 2022*). The correlation coefficient > 0.811 indicates the presence of multicollinearity in the panel data (*Dougherty, 2011*; *Kennedy, 2008*). The variance inflation factor (VIF) value determines the multicollinearity in the data set. VIF > 1 means multicollinearity is not present (see *Table 6*).

Table 6. The value of variance inflation factors (VIF) for the test of multicollinearity

Independent Variables	VIF Value	Result
CAR	1.393	No multicollinearity
CI	1.751	No multicollinearity
NNPA	1.311	No multicollinearity

Note: This table indicates that the no multicollinearity issue is present.

4.2. Fixed effect model and random effect model

The results of the fixed-effect and random-effect models in *Table 7* show that CI and NNPA significantly affect ROA. However, the effect of CAR on ROA is insignificant. In the case of the fixed-effect model, the intercept is constant with time but varies with each cross-sectional unit. It is assumed that µit is not correlated with explanatory variables (*Baltagi, 2001*; *Wooldridge, 2012*).

Table 7. Results of the fixed and random-effects model

Variable	Model 1 (ROA) Fixed effects		Model 1 (ROA) Random effects	
	Coefficient	t-statistic	Coefficient	t-statistic
β_0	4.43***	7.13	4.34***	6.85
CAR	−0.05	−1.53	−0.05	−1.53
CI	−0.05***	−6.03	−0.05***	−5.95
NNPA	−0.09*	−1.97	−0.12***	−2.66
R^2	0.83		0.81	
Adjusted R^2	0.27		0.38	
F-Statistic	29.50		23.51	
D-W Test	0.81		0.81	

Notes: *, **, and *** indicate significant values at 10%, 5%, and 1% levels, respectively. The F-statistic is significant at a 1% level, indicating the goodness of fit for both models.

The estimation results show an error due to the correlation between unobserved and explanatory variables. When unobserved and explanatory variables are independent, it means the intercept of the ROA model is time-varying and cross-sectional varying. Using the random effect model (*Baltagi, 2001*) is appropriate for the panel data estimation of the ROA model.

Further, the Hausman test is used to choose between the fixed and random effect models (*Farrar & Glauber, 1967; Haitovsky, 1969*). With the null hypothesis, "H0: REM is more appropriate than FEM," we proceed with the Hausman test. The Chi-square value is 5.51, and the p-value is 0.014. Hence, we accept the null hypothesis that Random Effect Model is more appropriate than Fixed Effect Model.

Toward home, we find that the pooled OLS regression is the appropriate technique to find the relationship of ROE with CAR, NNPA, and CI. The random effect model is the best fit to analyze the relationship between ROE and banks' credit risk. *Table 8* provides an overview of the test of hypotheses and estimation results.

Table 8. Summary of hypotheses

Hypothesis	Model	Dependent Variable	Independent Variable	p-value	Result
H_{1a}	1	CAR	ROA	0.1269	Reject
H_{2a}	1	NNPA	ROA	0.0079	Accept
H_{3a}	1	CI	ROA	<0.0001	Accept
H_{1b}	2	CAR	ROE	0.1171	Reject
H_{2b}	2	NNPA	ROE	<0.0001	Accept
H_{3b}	2	CI	ROE	0.0338	Accept

Note: This table summarizes the results of the hypothesis testing.

5. Conclusions, limitations, and future scope

The present study has tested the effect of credit risk on the financial performance of banks. Establishing the causal relationship between credit risk factors CAR, CI, and NNPA and financial performance factors ROA and ROE have been considered independent and dependent variables. The pooled panel data regression, fixed-effect model, and random effect model were used for panel data estimation. The results indicate that an increase in the CI and NNPA significantly decrease the ROA of banks; similarly, the ROE also has a significant and negative relationship with CI and NNPA (*Siddique et al., 2022*). The literature suggests that the lack of supervision and monitoring is the primary reason for the increase in cost to income and NNPA of the banks. The increase in NPA causes credit risk for the banks. The capital adequacy ratio positively correlates with ROA and ROE but does not significantly impact financial performance. It is mandatory to maintain a minimum capital requirement by a bank, but the change in CAR does not significantly affect the banks' financial performance. The financial performance of five large NIFTY50-indexed banks is vital for the economy and market, so policymakers can design specific strategies to reduce the cost of income and NPA.

The findings of this study are consistent with previous research on the relationship between credit risk and the financial performance of banks. Many studies have found that CI and NNPA are key credit risk indicators that significantly impact the financial performance of banks. When the number of non-performing assets increases, it causes a decrease in the proportion of assets that generate interest income, leading to a decline in interest income. This, in turn, results in a decrease in the ROA. Our findings are in line with *Bawa et al. (2019)*. Similarly, *Dsouza et al. (2022)* found that CI has a negative effect on the ROE of banks in India. However, the findings of this study regarding the insignificance of CAR in affecting ROA and ROE are somewhat different from previous studies, which have found that CAR is a significant indicator of credit risk that affects the financial performance of banks. For example, a study by *Shabani et al. (2019)* found that CAR positively impacts the ROA and ROE of banks in Kosovo.

Based on the findings of this study, it is recommended that NIFTY50-indexed commercial banks focus on managing their CI and NNPA to improve their financial performance. This could be done by implementing cost-saving measures such as streamlining operations, reducing overhead expenses, and taking steps to recover or write off non-performing assets. Additionally, NIFTY50-indexed banks should closely monitor their NNPA levels and take appropriate measures to bring them under control. Furthermore, these findings also have practical implications for bank regulators and investors. Regulators should pay more attention to CI and NNPA when assessing the credit risk profile of banks and make sure that the banks are taking appropriate measures to control these factors. Investors should also be aware of the level of CI and NNPA when evaluating the financial performance of banks and make investment decisions accordingly. Lastly, these findings suggest that NIFTY50-indexed commercial banks should focus on increasing their CAR and reducing their CI and NNPA to improve their financial performance.

The literature suggests that banking structure and demographic factors like gender and education of borrowers impact the financial performance of the banks, so; the study can be applied in various countries and regions. Future research studies can incorporate other bank-specific factors, macroeconomic factors, and behavioral biases to establish a more robust relationship between credit risk and financial performance. The present study was limited to up to five large-size banks in India; future research may incorporate more banks varying in size and age. There are a few potential areas for future research that would build upon the findings of this study. The study can be extended to a larger sample of banks or other countries to determine the generalizability of the findings. The relationship between credit risk and financial performance can be examined in more detail by including other credit risks measures, such as loan-to-value ratio, debt-to-equity ratio, and provision coverage ratio. The study can be extended to examine the effect of other factors, such as macroeconomic variables and bank-specific characteristics, on the relationship between credit risk and financial performance. The study can be extended to examine the effect of different regulatory policies on the relationship between credit risk and financial performance. The study can be extended to examine the impact of the recent COVID-19 pandemic on the relationship between credit risk and the financial performance of banks. It could explore how banks have responded to the crisis, how they have been affected and how they have managed the risk associated with the pandemic. Overall, these potential avenues for future research would further deepen our understanding of the relationship between credit risk and the financial performance of banks and provide useful insights for regulators, investors, and bank managers.

Declaration of Conflicting Interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding information

The author declared no financial support for the research, authorship, and/or publication of this article.

Acknowledgments: None

References

Ahmed, H. M., El-Halaby, S. I., & Soliman, H. A. (2022). The consequence of the credit risk on the financial performance in light of COVID-19: Evidence from Islamic versus conventional banks across MEA region. *Future Business Journal*, *8*(1), 21. https://doi.org/10.1186/s43093-022-00122-y

Ahsan, M. K. (2016). Measuring Financial Performance Based on CAMEL: A Study on Selected Islamic Banks in Bangladesh. *Asian Business Review*, *6*(1), 47–56. https://doi.org/10.18034/abr.v6i1.26

Al-Eitan, G. N., & Bani-Khalid, T. O. (2019). Credit risk and financial performance of the Jordanian commercial banks: A panel data analysis. *Academy of Accounting and Financial Studies Journal*, *23*(5), 1–13.

Ally, Z. (2022). The Impact of Credit Risk and Bank-Specific Drivers on Banks' Performance: Evidence from the UAE Region. *International Journal Of Management & Information Technology*, *17*, 33–47. https://doi.org/10.24297/ijmit.v17i.9264

Ameur, I. G. Ben. (2016). Explanatory Factors of Credit Risk : Empirical Evidence from Tunisian Banks. *International Journal of Economics, Finance and Management*, *5*(1), 21–29.

Baltagi, B. H. (2001). *Econometric Analysis of Panel Data* (2nd ed.). John Wiley.

Bayyoud, M., & Sayyad, N. (2015). The Relationship between Credit Risk Management and Profitability between Investment and Commercial Banks in Palestine. *International Journal of Economics and Finance*, *7*(11), 163. https://doi.org/10.5539/ijef.v7n11p163

Bawa, J. K., Goyal, V., Mitra, S. K., & Basu, S. (2019). An analysis of NPAs of Indian banks: Using a comprehensive framework of 31 financial ratios. *IIMB Management Review*, 31(1), 51–62. https://doi.org/10.1016/j.iimb.2018.08.004

Bischof, J., Laux, C., & Leuz, C. (2021). Accounting for financial stability: Bank disclosure and loss recognition in the financial crisis. *Journal of Financial Economics*, *141*(3), 1188–1217. https://doi.org/10.1016/j.jfineco.2021.05.016

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, 47(1), 239–253. https://doi.org/10.2307/2297111

Bsoul, R., Milhem, M., & Odat, M. (2022). Determinants of Banks' Credit Risk: Evidence from Jordanian Banks Listed on Amman Stock Exchange. *Academic Journal of Interdisciplinary Studies*, *11*(5), 197–209. https://doi.org/10.36941/ajis-2022-0135

Caruso, G., Gattone, S. A., Fortuna, F., & di Battista, T. (2021). Cluster Analysis for mixed data: An application to credit risk evaluation. *Socio-Economic Planning Sciences*, *73*. https://doi.org/10.1016/j.seps.2020.100850

Catherine, N. (2020). Credit Risk Management and Financial Performance: A Case of Bank of Africa (U) Limited. *Open Journal of Business and Management*, *08*(01), 30–38. https://doi.org/10.4236/ojbm.2020.81002

Das, A., & Ghosh, S. (2007). Determinants of Credit Risk in Indian State-owned Banks: An Empirical Investigation. *Economic Issues Journal Articles*, *12*(2), 27–46. https://EconPapers.repec.org/RePEc:eis:articl:207das

Dinu, V., & Bunea, M. (2022). The Impact of Competition and Risk Exposure on Profitability of the Romanian Banking System during the COVID-19 Pandemic. *Journal of Competitiveness*, *14*(2), 5–22. https://doi.org/10.7441/joc.2022.02.01

Dsouza, S., Rabbani, M. R., Hawaldar, I. T., & Jain, A. K. (2022). Impact of Bank Efficiency on the Profitability of the Banks in India: An Empirical Analysis Using Panel Data Approach. *International Journal of Financial Studies*, 10(4), 93. https://doi.org/10.3390/ijfs10040093

Dougherty, C. (2011). *Introduction to econometrics*. Oxford university press.

Farrar, D. E., & Glauber, R. R. (1967). Multicollinearity in Regression Analysis: The Problem Revisited. *The Review of Economics and Statistics*, *49*(1), 92. https://doi.org/10.2307/1937887

Gabriel, D., Riak, A., Candidate, P., Bol, D., & Bill, A. (2022). The role of credit management on financial performance. In *IJRDO-Journal of Social Science and Humanities Research*.

Gardner, J. C., McGowan Jr, C. B., & Moeller, S. E. (2011). Using Accounting Information For Financial Planning And Forecasting: An Application of the Sustainable Growth Model Using Coca-Cola. *Journal of Business Case Studies*, 7(5), 9. https://doi.org/10.19030/jbcs.v7i5.5599

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, *20*, 93–104. https://doi.org/10.1016/J.JFS.2015.08.004

Greene, W. H. (2003). *Econometric analysis*. Prentice Hall.

Gujarati, D. N. (2003). *Basic econometrics*. McGraw Hill.

Haitovsky, Y. (1969). Multicollinearity in Regression Analysis: Comment. *The Review of Economics and Statistics*, *51*(4), 486. https://doi.org/10.2307/1926450

Hertrich, M. (2014). Does Credit Risk Impact Liquidity Risk? Evidence from Credit Default Swap Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2426979

Hossain, M. K., & Golder, U. (2022). The Impact of Credit Risk Management on the Financial Performance of the Banks Listed on the Dhaka Stock Exchange: A Two-Step System Generalized Method of Moments Panel Data Analysis. *The Economics and Finance Letters*, 9(2), 273–290. https://doi.org/10.18488/29.v9i2.3195

Hunjra, A. I., Mehmood, A., Nguyen, H. P., & Tayachi, T. (2022). Do firm-specific risks affect bank performance? *International Journal of Emerging Markets*, *17*(3), 664–682. https://doi.org/10.1108/IJOEM-04-2020-0329

Inegbedion, H., Vincent, B. D., & Obadiaru, E. (2020). Risk management and the financial performance of banks in Nigeria. *International Journal of Financial Research*, *11*(5), 115–128. https://doi.org/10.5430/IJFR.V11N5P115

Jayaraman, A. R., & Srinivasan, M. R. (2014). Analyzing profit efficiency of banks in India with undesirable output – Nerlovian profit indicator approach. *IIMB Management Review*, *26*(4), 222–233. https://doi.org/10.1016/J.IIMB.2014.09.003

Jreisat, A. (2020). Credit risk, economic growth and profitability of banks. *International Journal of Economics and Business Research*, *20*(2), 152–167. https://doi.org/10.1504/IJEBR.2020.109150

Karmakar, M., & Shukla, G. K. (2015). Managing extreme risk in some major stock markets: An extreme value approach. *International Review of Economics & Finance*, *35*, 1–25. https://doi.org/10.1016/J.IREF.2014.09.001

Kennedy, P. (2008). *A guide to econometrics*. John Wiley & Sons.

Kumar, M., Arora, A., & Lahille, J.-P. (2011). Construct of credit risk management index for commercial banks. *Banks and Bank Systems*, *6*(1), 16–17.

Kwashie, A. A., Baidoo, S. T., & Ayesu, E. K. (2022). Investigating the impact of credit risk on financial performance of commercial banks in Ghana. *Cogent Economics and Finance*, *10*(1). https://doi.org/10.1080/23322039.2022.2109281

Mahmood, N. S., & Ahmed, E. M. (2022). Mediating effect of risk management practices in Iraqi private banks financial performance. *Journal of Financial Services Marketing*. https://doi.org/10.1057/s41264-022-00155-y

Mendoza, R., & Rivera, J. P. R. (2017). The effect of credit risk and capital adequacy on the profitability of rural banks in the Philippines. *Scientific Annals of Economics and Business*, *64*(1), 83–96. https://doi.org/10.1515/saeb-2017-0006

Mohiuddin, G. (2014). Use of CAMEL Model: A Study on Financial Performance of Selected Commercial Banks in Bangladesh. *Universal Journal of Accounting and Finance*, *2*(5), 151–160. https://doi.org/10.13189/ujaf.2014.020504

Munangi, E., & Sibindi, A. B. (2020). An empirical analysis of the impact of credit risk on the financial performance of South African banks. *Academy of Accounting and Financial Studies Journal*, *24*(3).

Oludhe, J. (2011). The Impact of Credit Risk Management on Financial Performance of Commercial Banks in Kenya. *Masters Thesis of Business Administration*, *1*(5), 22–37.

Prasanth, S., Nivetha, P., Ramapriya, M., & Sudhamathi, S. (2020). Factors affecting non performing loan in India. *International Journal of Scientific and Technology Research*, *9*(1), 1654–1657.

Rai, A. K., Yadav, K. P., Mallik, A., & Gupta, P. (2022). Impacts of bank mergers on shareholder's wealth. *International Journal of Accounting, Business and Finance*, *1*(1), 8–14. https://doi.org/10.55429/ijabf.v1i1.16

Rai, V. K., & Pandey, D. K. (2022). Does privatization of public sector banks affect stock prices? An event study approach on the Indian banking sector stocks. *Asian Journal of Accounting Research*, *7*(1), 71–83. https://doi.org/10.1108/AJAR-06-2021-0078

Ruziqa, A. (2013). The impact of credit and liquidity risk on bank financial performance: The case of Indonesian conventional bank with total asset above 10 trillion rupiah. *International Journal of Economic Policy in Emerging Economies*, *6*(2), 93–106. https://doi.org/10.1504/IJEPEE.2013.055791

Shabani, H., Morina, F., & Misiri, V. (2019). The Effect of Capital Adequacy on Returns of Assets of Commercial Banks in Kosovo. *European Journal of Sustainable Development*, 8(2), 201. https://doi.org/10.14207/ejsd.2019.v8n2p201

Siddique, A., Khan, M. A., & Khan, Z. (2022). The effect of credit risk management and bank-specific factors on the financial performance of the South Asian commercial banks. *Asian Journal of Accounting Research*, *7*(2), 182–194. https://doi.org/10.1108/AJAR-08-2020-0071

Siddique, A., Masood, O., Javaria, K., & Huy, D. T. N. (2020). A comparative study of performance of commercial banks in ASIAN developing and developed countries. *Insights into Regional Development*, *2*(2), 580–591. https://doi.org/10.9770/ird.2020.2.2(6)

Simanjuntak, R. H., & Demi Pangestuti, I. R. (2017). Enhancing banking performance by reducing risk: A preliminary study on the productive credit-Based loan portfolio. *International Journal of Applied Business and Economic Research*, *15*(15), 157–167.

Simon, L. (2021). Capital requirements in a model of bank runs: The 2008 run on repo. *Latin American Journal of Central Banking*, 2(3), 100038. https://doi.org/10.1016/j.latcb.2021.100038

Singh, P., & Singh, K. (2015). Efficiency Assessment Parameters of Public Sector Banks in India. *Global Business Review*, *16*(6), 1112–1126. https://doi.org/10.1177/0972150915597616

Sugiharto, T., Sulistiowati, N., & Nofiyanti, R. (2018). Factors affecting the financial performance of rural banks in Indonesia. *International Journal of Business and Management Science*, *8*(1), 109–129.

Sutikno, H. T. (2022). Financial Performance and Financial Sustainability: The Role of Institutional Ownership as Moderating Variable. *Journal of Economics, Finance and Management Studies*, *05*(04). https://doi.org/10.47191/jefms/v5-i4-25

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, *48*(4), 817. https://doi.org/10.2307/1912934

Wooldridge, J. M. (2012). *Introductory Econometrics* (5th ed.). South-Western Cengage Learning.

Xu, H., Lee, S. H., & Eom, T. H. (2007). *Introduction to Panel Data Analysis* (Ch.32. p. 7). https://doi.org/10.1201/9781420013276.ch32