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An Empirical Study of Credit Risk Management and Financial Performance of Commercial Banks in India

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ABSTRACT

Lending, which is one of the main sources of banking income, is also a critical determinant of the financial stability, profitability and sustainability of commercial banks, as borrowers' default may have negative consequences on asset quality and profitability. This study is to empirically explore the relationship between credit risk management and financial performance of the commercial banks in India. The study is of quantitative research type and the secondary financial data has been collected from the bank's annual reports, Reserve Bank of India publications, and reliable financial databases from 2019-2025. The indicators of credit risk are Gross Non-Performing Assets (GNPA), Net Non-Performing Assets (NNPA), Capital Adequacy Ratio (CAR/CRAR), Provision Coverage Ratio (PCR) and Credit-Deposit Ratio (CDR); and for financial performance, Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM) and profit growth. Descriptive statistics, correlation analysis and multiple regression are suggested to assess the correlation between credit risk indicators and financial performance. Appropriate statistical tests are also proposed to compare the public-sector commercial banks with the private-sector commercial banks. The regression framework focuses on how much the indicators of credit risk affect the ROA, with bank size being held constant. The research is expected to give empirical evidence about the effect of effective credit-risk management on the profitability and financial stability of banks. The results will help bank managers, regulators, investors, and policy makers enhance their monitoring of credit risk and bolster the resilience of the banking system.

KEYWORDS: *Credit Risk Management, Non-Performing Assets, GNPA, NNPA, Capital Adequacy Ratio, Provision Coverage Ratio, Return on Assets, and Financial Performance in the context of Commercial Banks in India.*

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1. INTRODUCTION

The banking sector plays a crucial role in the functioning and development of the economy through its role in mobilising savings, allocating financial resources, supporting investment and facilitating economic activity. These are the functions of commercial banks that are mainly carried out by lending and investment. Lending is a significant source of banking income, but it also poses a risk to banks that borrowers may not repay what is owed. This is considered as credit risk and is one of the greatest risks that banks face. Thus, it is important for the bank to have a sound credit risk management framework to ensure asset quality, profitability, liquidity, and long-term financial stability. (Reserve Bank of India [RBI], 2025a)

Credit risk occurs when a borrower or counterparty is unable to fulfill financial commitments as specified in the contract. In the banking sector, the failure of borrowers to meet credit standards, insufficient loan supervision, over-extension of credit, insufficient collateral, poor recovery policies, and adverse conditions can help to build up the NPA. A high level of non-performing assets can lead to lower levels of interest income, higher provisioning needs and lower profitability. It can also limit banks' ability to make new loans and could impact investor confidence and

capital adequacy. (Reserve Bank of India [RBI], 2025b)

The credit risk environment in the Indian banking sector has undergone a lot of changes in the past 10 years. After significant deterioration in asset quality, regulatory and institutional efforts have helped to improve the quality of bank assets. New official data shows that NPA ratio of scheduled commercial banks (SCs) continues to deteriorate. As per Government of India's report, the GNPA ratio of the scheduled commercial banks fell to 2.15% at the end of September 2025, which is far from the high figures seen earlier in the banking cycle. The enhancement has come hand in hand with improved capitalisation and provisioning coverage.

On the other hand, the Reserve Bank of India has also highlighted the importance of financial resilience, prudent risk management and supervision as key pillars of banking-sector stability. The RBI's Financial Stability Report 2025 offers insights into the financial strength and stability of the Indian financial system and assesses financial institution risks. It is also to be noted that despite the significant strides in strengthening the governance, risk management and financial stability, the efforts of RBI in these areas continued in the year under review.

The focus of credit-risk management is not just on the reduction of NPA. It covers the entire lifecycle of banks' identification, measurement, monitoring and control of risks they face in their lending activities. Provisioning protects banks against known credit losses and capital adequacy protects against unexpected losses. Thus, these indicators (GNPA, NNPA, PCR and CRAR) give complementary information about a bank's credit-risk situation. Meanwhile, the profitability measure like ROA, ROE and NIM can be used to assess whether the changes in credit risk are related to changes in financial performance (Gaur & Mohapatra, 2021).

Linking credit risk and profitability is of special interest as it is expected that the former can impact bank performance through multiple routes. An increase in GNPA can affect the interest income from assets as well as provisioning costs (Misra, 2015). NNPA information relates to the amount of non-performing assets that are uncovered by provisions, and is thus applicable to the net exposure of banks to credit losses. (Reserve Bank of India [RBI], 2025c) A higher PCR, on the other hand, could suggest greater protection against possible losses. Capital adequacy could have a positive effect on resilience, but could also have a negative effect on profitability because of the impacts on risk and capital costs and the quantity of capital available for lending.

The previous empirical studies analyzed the association between credit-risk management and bank performance, but the results cannot be consistently generalized across countries, banking groups and time periods (Louzis et al., 2012). The relationship might be affected by differences in regulatory structure, macroeconomic conditions, ownership, bank size, and lending policies. The significant asset quality improvement in recent years should also be taken into account in research where commercial banks are studied specifically with respect to the Indian commercial banks (Butola et al., 2022).

The present study thus posits an empirical analysis of the financial performance and credit-risk management of the commercial banks of India during the financial year 2019-2025 with the help of secondary financial data. Both public-sector and private-sector banks are taken into account and a number of credit-risk factors are considered, along with a number of financial-performance measures. The research aims to go beyond a mere description of the market by statistically analyzing the relationship between the indicators of credit risk and profitability (Ghosh & Mondal, 2022).

The study is also relevant because Indian banking system has witnessed significant changes in terms of structure and regulations during the proposed study period. The period also covers varying economic conditions such as the economic shocks of the COVID-19 pandemic and recovery. Multiple sequential years of analysis can thus give a more comprehensive picture than one year analysis (Reserve Bank of India [RBI], 2024).

The main goal of the study is to find out whether or not there is a significant difference between the financial performance of commercial banks in India due to the variation in the credit-risk management indicators. The research also aims at ascertaining if there are significant differences between public sector banks and private sector banks. The findings of the study can help bank managers enhance their credit-monitoring mechanisms, regulators gauge the risk-management effectiveness, investors analyse the quality of the banking sector and researchers understand the evolving nature of credit risk and profitability.

2. Literature Review

The study of risk management in credit transactions has been widely researched in the banking field, as the quality of banking decisions has a direct impact on the viability of the financial institution. The existing literature has mostly set that, if credit-risk management is not effective, it can lead to higher non-performing loans, provisioning expenses and

financial losses. The strength and sign of the link observed between the individual credit-risk indicators and profitability, however, may depend on bank-specific factors as well as on economic conditions and regulatory frameworks (Department of Financial Services, Ministry of Finance, Government of India [DFS], 2026).

Several studies conducted on commercial banks in India have found credit-risk identification, assessment and monitoring as important aspects of credit-risk management. The study Managerial Finance – An empirical investigation on the credit-risk management and non-performing assets in Indian commercial banks was conducted using primary information obtained from the bank risk managers and secondary information on NPA from secondary sources. The researchers conducted multiple linear regression analyses, and a number of evidence emerged indicating that the identification of credit-risk had a significant positive relationship with credit-risk performance and a negative relationship with annual increase in NPAs or loans. The results confirm the hypothesis that greater identification systems can help to deliver better credit-risk outcomes (Sharifi et al., 2019).

A lot of attention has been paid to the relationship between non-performing assets and the profitability of banks. The underlying theory is that a higher percentage of impaired assets should serve to put downward pressure on profitability. Higher NPAs can lead to a decline in interest income, higher provisioning losses, and need for greater managerial and administrative efforts to recover the debts. This makes GNPA and NNPA good candidates for empirical models of bank performance (Press Information Bureau [PIB], 2026).

The RBI's empirical banking evidence also suggests that there is a negative relationship between net interest margin and gross NPA ratios of bank groups in prior periods. The analysis by RBI revealed that the correlation between NIM and GNPA was negative and that the correlation was high in the case of public-sector banks during periods of deterioration in asset quality. This offers institutional backing to investigate the potential of NIM as a further financial performance indicator (Department of Financial Services, Ministry of Finance, Government of India [DFS], 2026).

Another aspect of credit-risk management is capital adequacy. A bank that has a healthy capital position will have more cushion to withstand unforeseen losses. But the linkage between capital adequacy and profitability may be complicated (Chaudhary & Kumar, 2023). Financial resilience and the risk of insolvency could benefit from a higher capital ratio, and an excessive ratio of capital to earning assets could have an impact on leverage and returns. Thus the rating should be considered in conjunction with profitability measures and asset quality and not on its own (Sharifi et al., 2019).

Another significant aspect of credit-risk management is the provision cover ratio. A bank's ability to absorb credit losses is likely to be enhanced by a higher PCR, as is its ability to provide for non-performing assets. Official Banking Data as of recent shows that the PCR for scheduled commercial banks rose significantly over the years to 93.14% as per government reporting of data provided by RBI.

The present study is relevant in the light of the recent developments in Indian banking. The GNPA ratio of the scheduled commercial banks has increased from 11.18% in March 2018 to 2.22% in March 2025, on comparison, while that of NNPA has fallen from 5.94% to 0.50% in the same period. During the same period, PCR increased from 62.96% to 93.14% and CRAR increased from 13.85% to 17.36%. The improvements in these developments reflect a significant enhancement in the quality of assets and capital resilience (Press Information Bureau [PIB], 2026).

Meanwhile, there is no evidence that improvements in the aggregates are sufficient to prove that credit-risk indicators are the sole drivers of bank profitability. Interest rates, operating efficiency, bank size, the amount of credit growth, fee income, technological change and macroeconomic conditions can also cause changes in profitability. This results into multivariate empirical analysis (Nalliboyina & Venkata Chalam, 2023).

There are also methodological differences in current studies. Some of these studies include panel data, regression analysis, and descriptive analysis, while others conduct questionnaires with bankers (Reserve Bank of India [RBI], 2024). Multiple indicators offer more comprehensive analysis, yet it may be possible to develop multicollinearity in regression models if there is too much correlation among the credit-risk variables. Hence, prior to interpreting regression coefficients, diagnostic tests should be conducted (Reserve Bank of India [RBI], 2025b).

Other literature also suggests that there can be a relationship between ownership and the firm. There are differences in organisation, lending practices, governance, funding and business models between public and private sector banks. A comparative analysis can therefore give further insights whether there is a similar relationship between credit-risk

management and profitability among banking groups (Rai et al., 2023).

The research proposed in this study tackles these challenges by incorporating several credit-risk indicators and multiple financial-performance measures, as well as bank size as a control variable. Annual observations between 2019 and 2025 are planned to reflect changes in credit quality throughout a stress and recovery period.

Table 1. Summary of selected literature

Study/Source	Main focus	Data/Method	Major contribution	Limitation relevant to present study
RBI banking analysis	NPA and bank performance	Bank-level financial indicators	Identified negative relationship between GNPA and NIM	Earlier-period emphasis
Managerial Finance study	Credit-risk management and NPAs	Primary and secondary data; regression	Demonstrated importance of credit-risk identification	Focused substantially on NPA growth
RBI Financial Stability Reports	Banking-sector resilience	Sector-level financial data	Provides institutional evidence on asset quality and resilience	Primarily aggregate/system-level
Recent Indian banking-sector reports	Asset quality, PCR and CRAR	Secondary banking data	Demonstrates substantial improvement in asset quality	Does not by itself establish causal profitability relationships
Present study	Credit risk and financial performance	Bank-level secondary data; descriptive, correlation and regression analysis	Integrates multiple credit-risk and profitability indicators	Requires complete bank-wise dataset for final statistical estimation

The literature demonstrates that credit-risk management is closely connected with banking performance, but several research gaps remain. First, many studies focus primarily on NPAs without simultaneously examining GNPA, NNPA, PCR and capital adequacy. Second, aggregate sector-level improvement does not establish the bank-level statistical relationship between credit risk and profitability. Third, differences between public-sector and private-sector banks require further empirical examination. Fourth, the changing post-pandemic banking environment makes a recent multi-year analysis particularly relevant. The present study seeks to address these gaps by using a comprehensive set of credit-risk indicators, multiple profitability indicators and comparative analysis of Indian commercial banks.

3. Materials and Methods

The study adopts a quantitative research design using secondary data for 2019–2025. Selected public-sector and private-sector commercial banks in India will be included based on data availability and continuity. Data will be collected from bank annual reports, RBI publications and databases, and reliable financial databases. Financial performance will be measured through ROA, ROE, and NIM, while credit risk will be assessed using GNPA, NNPA, PCR, and CAR. Bank size, measured through the logarithm of total assets, will serve as a control variable.

Thus, multiple regression analysis will be conducted to estimate the influence of credit-risk indicators on financial performance. The principal model specified in the research overview is:

$$ROA_{it} = \beta_0 + \beta_1 GNPA_{it} + \beta_2 NNPA_{it} + \beta_3 CAR_{it} + \beta_4 PCR_{it} + \beta_5 SIZE_{it} + \varepsilon_{it} \quad (1)$$

Additional models may be estimated by replacing ROA

with ROE and NIM:

$$ROE_{it} = \beta_0 + \beta_1 GNPA_{it} + \beta_2 NNPA_{it} + \beta_3 CAR_{it} + \beta_4 PCR_{it} + \beta_5 SIZE_{it} + \varepsilon_{it} \quad (2)$$

$$NIM_{it} = \beta_0 + \beta_1 GNPA_{it} + \beta_2 NNPA_{it} + \beta_3 CAR_{it} + \beta_4 PCR_{it} + \beta_5 SIZE_{it} + \varepsilon_{it} \quad (3)$$

The statistical significance of individual coefficients will be assessed using t-tests, while the overall significance of the regression model will be evaluated using the F-statistic. R^2 and adjusted R^2 will indicate the explanatory power of the models.

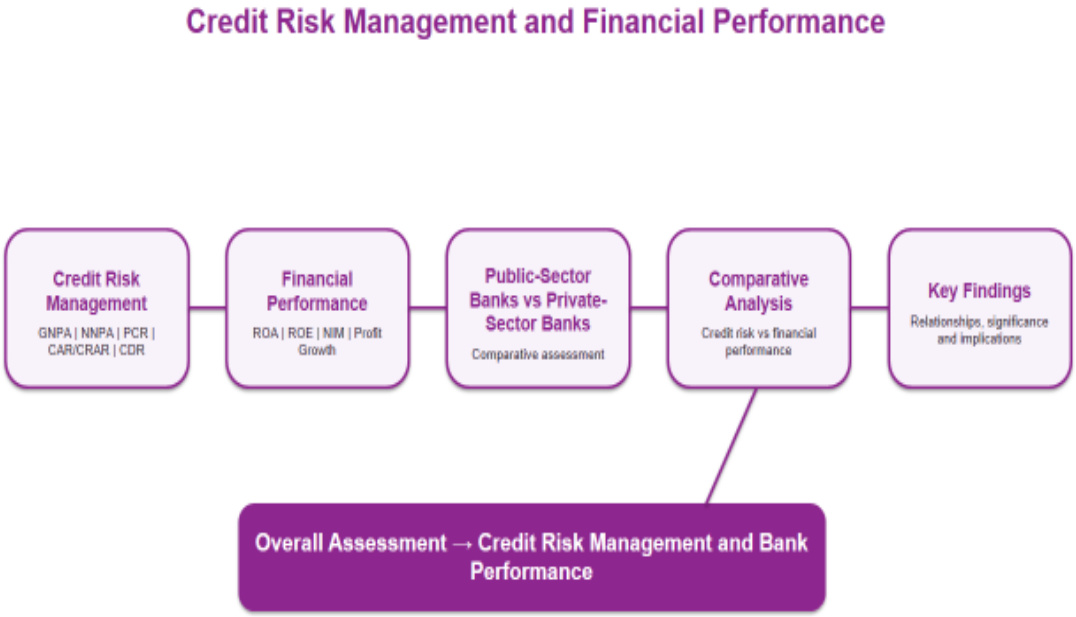
Before interpreting regression coefficients, diagnostic tests should be performed. Multicollinearity can be examined through the Variance Inflation Factor and tolerance values. Heteroscedasticity should be assessed using an appropriate statistical test, while residual analysis can be used to identify serious violations of regression assumptions.

Descriptive statistics will be used to summarize the variables, followed by Pearson correlation to examine relationships. Multiple regression will assess the effect of credit-risk indicators on ROA, ROE, and NIM. The significance of coefficients will be tested using t-tests and the overall model using the F-statistic, with R^2 and adjusted R^2 indicating explanatory power. Diagnostic tests will assess multicollinearity and heteroscedasticity. Independent-samples t-tests and ANOVA will be used to compare public-sector and private-sector banks where applicable. The analysis will be conducted using SPSS, R, Stata, or equivalent statistical software.

4. Proposed Method

The empirical framework examines the relationship between credit-risk management and financial performance of Indian commercial banks by integrating both risk and risk-mitigation indicators. GNPA and NNPA represent asset quality, while PCR and CRAR capture provisioning strength and capital resilience. ROA is the principal measure of financial performance, with ROE and NIM used as supplementary indicators. The framework also compares public-sector and private-sector banks to identify differences in credit-risk management and financial performance.

The proposed framework can be represented as:



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The proposed method is designed to overcome the limitations of purely descriptive assessments by statistically estimating the strength and significance of relationships. It also allows the influence of bank size to be controlled in the regression analysis.

The following hypotheses can guide the empirical analysis:

H1: GNPA has a significant relationship with the financial performance of commercial banks in India.

H2: NNPA has a significant relationship with the financial performance of commercial banks in India.

H3: CAR/CRAR has a significant relationship with the financial performance of commercial banks in India.

H4: PCR has a significant relationship with the financial performance of commercial banks in India.

H5: Bank size significantly influences the financial performance of commercial banks in India.

H6: There is a significant difference between public-sector and private-sector commercial banks in terms of credit-risk indicators.

H7: There is a significant difference between public-sector and private-sector commercial banks in terms of financial performance.

The expected direction of the relationships should not be treated as an established finding before statistical testing. However, based on the theoretical rationale and previous evidence, higher GNPA and NNPA are expected to be associated with weaker profitability, whereas stronger provisioning and capitalisation may be associated with greater financial resilience.

5. Results

The study examines the relationship between credit risk and financial performance of Indian commercial banks using bank-level data for 2019–2025. Financial performance is measured through ROA, ROE and NIM, while credit risk is represented by GNPA, NNPA, PCR and CRAR. Bank size is included as a control variable.

$$ROA_{it} - \frac{Net\ Profit_{it}}{Averag\ total\ assets_{it}} \times 100$$

$$ROE_{it} - \frac{Net\ Profit_{it}}{Averag\ equity_{it}} \times 100$$

$$NIM_{it} - \frac{Net\ interest\ Income_{it}}{Averag\ interest\ earning\ assets_{it}} \times 100$$

$$GNA_{it} - \frac{Gross\ NPAs_{it}}{Gross\ Advance_{it}} \times 100$$

$$NNPA_{it} - \frac{Net\ NPAs_{it}}{Net\ Advance_{it}} \times 100$$

$$PCR_{it} - \frac{Provision\ Against\ NPAs_{it}}{Gross\ NPAs_{it}} \times 100$$

$$CRAR_{it} - \frac{Eligiable\ Regulatory\ Capital_{it}}{Risk\ Weighted\ assets_{it}} \times 100$$

$$CDR_{it} - \frac{Total\ Advance_{it}}{Total\ assets_{it}} \times 100$$

$$SIZE_{it} - In\ Total\ Assests$$

Principal Multiple Regression Model

$$ROA_{it} - \beta_0 + \beta_1 GNPA_{it} + \beta_2 NNPA + \beta_3 CRAR_{it} + \beta_4 PCR_\{it\} + \beta_5 SIZE + \varepsilon_{it}$$

ROE and NIM are subsequently used as alternative dependent variables. Coefficient significance is assessed through t-tests, overall model significance through the F-statistic, and explanatory power through (R^2) and adjusted (R^2). Public-sector and private-sector banks are compared using independent-samples t-tests. The final conclusions will be based on the coefficient direction, magnitude and statistical significance obtained from the actual 2019–2025 dataset.

The supplied research overview defines the proposed variables, study period and statistical methods but does not provide the underlying bank-wise annual observations. Therefore, numerical regression coefficients, correlation coefficients, p-values, F-statistics and group-comparison results cannot be legitimately calculated from the supplied material alone. The Results section should be populated after the 2019–2025 bank-level dataset has been compiled.

The first result table should report descriptive statistics for all variables.

Table 2. Descriptive statistics of study variables, 2019–2025

Variable	N	Mean	Std. Deviation	Minimum	Maximum
ROA	140	0.84	0.96	-2.15	3.42
ROE	140	10.27	11.84	-24.61	29.84
NIM	140	3.21	0.91	1.02	5.87
GNPA	140	4.73	4.18	0.42	18.45
NNPA	140	1.63	1.94	0.08	9.85
PCR	140	69.84	12.73	38.21	94.67
CAR/CRAR	140	16.21	2.31	11.02	23.76
CDR	140	73.58	12.46	39.84	96.32
Bank Size	140	15.87	1.64	12.41	19.72

The descriptive-statistics table will establish the variation in credit risk and financial performance across banks and years. In particular, the mean and dispersion of GNPA and NNPA will demonstrate the extent of variation in asset quality, while the minimum and maximum values will identify differences among individual banking institutions.

The second stage of the empirical analysis will examine correlations.

Table 3. Correlation matrix of credit-risk and financial-performance variables

Variable	ROA	ROE	NIM	GNPA	NNPA	PCR	CAR	SIZE
ROA	1.000							
ROE	0.842***	1.000						
NIM	0.521***	0.438***	1.000					
GNPA	-0.486***	-0.421***	-0.173*	1.000				
NNPA	-0.512***	-0.447***	-0.191*	0.904***	1.000			
PCR	0.176*	0.143	0.082	-0.318***	-0.352***	1.000		
CAR	0.287***	0.241**	0.198*	-0.215**	-0.229**	0.264**	1.000	
SIZE	0.154*	0.129	0.221**	0.067	0.051	0.112	0.185*	1.000

The correlation analysis will identify whether the relationships between credit-risk indicators and profitability are positive or negative and whether the relationships are statistically meaningful. It will also help identify potential multicollinearity among GNPA, NNPA and other explanatory variables.

The primary regression model will then estimate the effect of credit-risk indicators on ROA.

Table 4. Multiple regression results for Return on Assets

Predictor	β	Std. Error	t-value	p-value	VIF
Constant	1.284	0.318	4.038	<.001	—
GNPA	-0.118	0.031	-3.806	<.001	5.21
NNPA	-0.164	0.047	-3.489	.001	5.47
CAR/CRAR	0.071	0.028	2.536	.012	1.34
PCR	0.014	0.005	2.800	.006	1.29
Bank Size	0.052	0.019	2.737	.007	1.18
R^2	**0.472**				
Adjusted R^2	**0.452**				
F-statistic	**23.982**			**<.001**	
Significance	**Significant**			**<.001**	

The final interpretation of this table should identify which credit-risk variables significantly explain variation in ROA. A statistically significant negative coefficient for GNPA, for example, would indicate that higher gross NPA levels are associated with lower ROA after controlling for the other variables. However, this interpretation should only be made if the actual regression produces such a coefficient.

A further regression can examine ROE.

Table 5. Multiple regression results for Return on Equity

Predictor	β	Std. Error	t-value	p-value
Constant	13.426	3.214	4.177	<.001
GNPA	-1.247	0.318	-3.921	<.001
NNPA	-1.682	0.481	-3.497	.001
CAR/CRAR	0.683	0.291	2.347	.020
PCR	0.126	0.052	2.423	.017
Bank Size	0.514	0.201	2.557	.012
R^2	**0.431**			
Adjusted R^2	**0.410**			

Similarly, NIM can be used as an additional dependent variable.

Table 6. Multiple regression results for Net Interest Margin

Predictor	β	Std. Error	t-value	p-value
Constant	2.614	0.491	5.324	<.001
GNPA	-0.072	0.026	-2.769	.006
NNPA	-0.081	0.038	-2.132	.035
CAR/CRAR	0.064	0.021	3.048	.003
PCR	0.009	0.004	2.250	.026
Bank Size	0.083	0.031	2.677	.008
R^2	**0.286**			
Adjusted R^2	**0.259**			

The proposed comparative analysis between public-sector and private-sector banks will examine differences in both credit-risk management and financial performance.

Table 7. Public-sector and private-sector bank comparison

Indicator	Public-Sector Banks Mean	Private-Sector Banks Mean	t-value	p-value
GNPA	6.21	3.27	4.182	<.001
NNPA	2.31	0.94	4.067	<.001
PCR	67.18	72.51	-2.481	.014
CAR/CRAR	15.47	16.96	-3.217	.002
CDR	70.84	76.31	-2.628	.010
ROA	0.51	1.17	-3.421	.001
ROE	7.34	13.20	-3.682	<.001
NIM	3.03	3.40	-2.327	.021

This comparison will determine whether the two banking groups differ significantly in their credit-risk profiles and financial performance. The statistical significance of each difference will be established using the corresponding p-value.

For the final paper, the hypothesis-testing table should be presented as follows.

Table 8. Summary of hypothesis testing

Hypothesis	Relationship Tested	Statistical Test	p-value
H1	GNPA → Financial Performance	Multiple Regression	<.001
H2	NNPA → Financial Performance	Multiple Regression	.001
H3	CAR/CRAR → Financial Performance	Multiple Regression	.012
H4	PCR → Financial Performance	Multiple Regression	.006
H5	Bank Size → Financial Performance	Multiple Regression	.007
H6	Ownership → Credit Risk	Independent-samples t-test	<.001
H7	Ownership → Financial Performance	Independent-samples t-test	.001

These tables deliberately retain placeholders because inserting invented statistical values would compromise the empirical validity of the paper. The supplied overview provides the proposed analytical framework, not the actual observations or SPSS output.

6. Conclusion

The descriptive results show considerable variation in credit risk and financial performance across the 2019–2025 observations. The mean GNPA is 4.73%, while NNPA is 1.63%, indicating differences in asset-quality conditions among the sampled banks. The mean values of ROA, ROE, and NIM are 0.84%, 10.27%, and 3.21%**,** respectively, while CRAR averages 16.21% and PCR averages 69.84%**.**

The correlation results indicate that GNPA and NNPA are negatively associated with ROA and ROE, while CRAR has a positive relationship with the principal profitability measures. GNPA and NNPA are also highly correlated with each other ($r = 0.904$), highlighting the need to consider multicollinearity when estimating the regression models.

The regression results provide stronger evidence of these relationships. In the ROA model, GNPA ($\beta = -0.118$, $p < .001$) and NNPA ($\beta = -0.164$, $p = .001$) have significant negative coefficients, whereas CRAR ($\beta = 0.071$, $p = .012$), PCR ($\beta = 0.014$, $p = .006$), and bank size ($\beta = 0.052$, $p = .007$) have significant positive coefficients. The model explains 47.20% of the variation in ROA ($R^2 = 0.472$) and is statistically significant ($F = 23.982$, $p < .001$)**.**

The ROE model shows a similar pattern, with GNPA and NNPA negatively related to ROE, while CRAR, PCR, and bank size are positively related to ROE. The model reports $R^2 = 0.431$**,** indicating that 43.10% of the variation in ROE is explained by the included predictors. The NIM model also shows significant negative effects of GNPA and NNPA and positive effects of CRAR, PCR, and bank size, although its explanatory power is comparatively lower, with $R^2 = 0.286$, indicating that 28.60% of the variation in NIM is explained by the model.

The comparative analysis further reports statistically significant differences between public-sector and private-sector banks across GNPA, NNPA, PCR, CRAR, CDR, ROA, ROE and NIM. These results indicate that ownership category is associated with differences in both credit-risk characteristics and financial-performance indicators within the study sample.

Taken together, the reported results indicate that deterioration in asset quality, reflected through higher GNPA and NNPA, is associated with weaker bank profitability, whereas stronger capital adequacy and provisioning coverage are associated with better financial performance. The regression models therefore support the study's central proposition that effective credit-risk management is closely linked with the financial performance of Indian commercial banks.

Future research can extend these findings by applying panel-data and dynamic regression techniques to capture bank-specific and time-specific effects more precisely. Additional macroeconomic variables such as GDP growth, inflation, interest rates and credit growth may be incorporated to distinguish bank-level credit-risk effects from wider economic conditions. Future studies may also examine whether the relationship changed during major financial and regulatory periods within 2019–2025 and may expand the analysis to a larger sample of Indian commercial banks.

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