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Moderating Role of Capital Adequacy in the Relationship between Credit Risk and Profitability: An Empirical Study of Public Sector Banks in India

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Abstract: The financial stability and profitability of the Indian banking sector face a major challenge due to the rise in the level of non-performing assets. While previous studies have examined the direct relationship between asset quality and bank performance, limited evidence exists on whether capital adequacy influences this relationship. This study investigates the impact of asset quality on the financial performance of Indian public sector banks and examines the moderating role of the Capital Adequacy Ratio (CAR). The analysis is based on a balanced panel dataset comprising 12 Indian public sector banks over the period 2014-15 to 2025-26, which has 144 bank-year observations. The empirical findings reveal that both GNPAR and NNPAA exert a significant negative effect on ROA and ROE, indicating that deteriorating asset quality adversely affects bank profitability. CAR demonstrates a positive association with profitability in several models. However, the interaction terms between asset quality and CAR are statistically insignificant, suggesting that capital adequacy does not significantly moderate the relationship between non-performing assets and financial performance. Among the control variables, bank size consistently enhances profitability, whereas operating expenses negatively influence performance, while the loan-to-deposit ratio remains statistically insignificant in most models. The study highlights the importance of strengthening asset quality and maintaining adequate capital buffers to improve bank profitability. It contributes to the existing literature by providing robust empirical evidence on the role of asset quality and capital adequacy in shaping the financial performance of Indian public sector banks. It offers useful insights for bank managers, regulators, and policymakers to promote sustainable banking performance and financial stability.

1. Introduction

Public sector banks drive credit distribution and financial inclusion in India, making their financial resilience critical for systemic stability. As financial intermediaries, commercial banks contribute significantly to the efficient allocation of financial resources, thereby fostering economic development and enhancing financial inclusion (Athanasoglou et al., 2008). The profitability and sustainability of banks are therefore very important not only to shareholders but also to regulators, depositors, and the overall economy. However, the ability of banks to generate sustainable profits largely depends on their effectiveness in managing various financial risks, among which credit risk remains one of the most critical. Credit risk is the risk that borrowers may fail to meet their contractual repayment obligations, leading to loan defaults and the accumulation of non-performing assets (NPAs). A sustained increase in NPAs adversely affects banks by reducing interest income, increasing loan-loss provisions, deteriorating asset quality, and restricting future lending activities (Bholat et al., 2016). Consequently, ineffective credit risk management not only diminishes bank profitability but also threatens the stability of the banking system. The global financial crisis of 2008 further underscored the importance of prudent credit risk management and the necessity of maintaining adequate capital buffers to withstand financial shocks (BCBS, 2017). Profitability is widely regarded as one of the most important indicators of a bank's financial health, operational efficiency, and long-term sustainability. Financial performance is commonly measured using accounting-based indicators such as Return on Assets (ROA) and Return on Equity (ROE), which evaluate the efficiency with which banks utilise their assets and shareholders' equity to generate earnings (Koppa et al., 2026). Previous studies have demonstrated that both bank-specific and macroeconomic factors influence profitability; however, credit risk consistently emerges as one of its most significant determinants (Athanasoglou et al., 2008). The Capital Adequacy Ratio (CAR), prescribed under the Basel regulatory framework, serves as a key indicator of a bank's financial strength and resilience (BCBS, 2017). Banks maintaining higher levels of regulatory capital are generally better equipped to withstand credit losses, maintain market confidence, comply with prudential regulations, and sustain lending activities during periods of financial distress, a pattern borne out during the COVID-19 pandemic, when capital adequacy, credit losses, and efficiency ratios all played a measurable role in bank performance (Hawaldar et al., 2022). Existing empirical evidence on the relationship between capital adequacy and profitability remains inconclusive. Several studies report that well-capitalised banks exhibit superior financial performance, as adequate capital enhances solvency, improves public confidence, and reduces the likelihood of financial distress (Mir & Shah, 2022). Conversely, other evidence points to a more complicated picture, as Arun Prakash and Sathya (2020) studied Indian public and private sector banks and found that certain profitability measures actually carry a negative relationship with capital adequacy, suggesting that maintaining higher capital buffers may come with trade-offs rather than a straightforwardly positive payoff. These mixed findings indicate that the influence of capital adequacy on profitability may depend on other bank-specific characteristics and risk conditions. This study investigates the moderating role of capital adequacy in the relationship between credit risk and profitability among 12 Public Sector banks in India by taking 12 years of data from 2014-15 to 2025-26. The findings are expected to provide valuable insights into the existing literature of the banking sector. The banking sector is the cornerstone of the financial system and plays a vital role in promoting economic growth by mobilising savings, facilitating credit creation, supporting investments, and ensuring financial stability. A sound and efficient banking system enhances the allocation of financial resources, strengthens public confidence, and contributes significantly to sustainable economic development. As public sector banks constitute a major share of India's banking industry and are instrumental in implementing government-led financial inclusion and development initiatives, maintaining their financial health is essential for the overall stability and growth of the economy. The financial performance of banks is closely influenced by asset quality and capital strength. Rising levels of non-performing assets (NPAs) adversely affect profitability by reducing interest income, increasing provisioning requirements, and weakening operational efficiency (Pervez et al., 2023), while adequate capital buffers enhance banks' resilience against financial shocks and regulatory risks (Al-Sharkas & Al-Sharkas, 2022). Therefore, examining the relationship between credit risk, capital adequacy, and bank performance is essential for assessing the financial health and stability of public sector banks (Pervez et al., 2023). Furthermore, understanding whether capital adequacy moderates the impact of credit risk on profitability provides valuable insights for policymakers, regulators, and bank management to formulate effective risk management strategies, strengthen capital planning, and ensure the long-term sustainability of the banking sector (Arhinful et al., 2025).

2. Literature Review

A literature review is a critical synthesis and evaluation of existing academic research on a specific topic, undertaken to establish what is already known and to identify gaps for a new study. Research on bank performance has extensively examined the roles of capital adequacy and credit risk as key determinants of profitability and financial stability, with studies spanning different banking systems and drawing attention to the influence of bank-specific characteristics, regulatory requirements, and macroeconomic conditions. To date, the findings remain mixed, particularly on the question of whether capital adequacy softens the adverse effects of credit risk on bank performance. To provide a comprehensive understanding of the existing body of knowledge, the literature is reviewed thematically under the following sub-sections.

2.1. Capital Adequacy and Bank Performance

The link between capital adequacy and bank performance is one of the most widely examined relationships in the banking literature, with most studies treating adequate capital as a core determinant of financial stability and profitability. A foundational contribution came from Athanasoglou et al. (2008), who showed that bank-specific factors, alongside industry-specific and macroeconomic variables, significantly shape bank profitability; their inclusion of control variables such as bank size, loan-to-deposit ratio, and operating efficiency has since become standard practice in empirical work on the subject. Within the Indian context specifically, Mir and Shah (2022) reported that capital adequacy significantly affects profitability, though its influence differs between public and private sector banks. Rahaman and Sur (2025) add further weight to this evidence, identifying capital adequacy as one of the significant factors shaping asset quality and, by extension, performance outcomes among Indian public sector banks. Arun Prakash and Sathya (2020) complicate the picture somewhat, finding a bidirectional relationship in which higher capital levels support performance while, in turn, profitable banks tend to maintain stronger capital buffers. The importance of capital adequacy becomes especially visible during periods of economic distress. Hawaldar et al. (2022) found that capital adequacy, alongside credit losses and operational efficiency, significantly influenced both ROA and ROE during the COVID-19 pandemic. A comparable pattern emerges outside the Indian banking system as well, as Fathihani et al. (2025) found that stronger capital adequacy improved the profitability of Islamic banks in Indonesia, reinforcing the broader view that adequate capital underpins sustainable banking performance across different regulatory and institutional settings.

2.2. Credit Risk and Bank Performance

Credit risk, most proxied by non-performing assets, is consistently identified as one of the strongest determinants of bank profitability, with the bulk of empirical evidence pointing to a negative relationship between deteriorating asset quality and financial performance. In the Indian public sector banking context, Ali and Dhiman (2019) found that capital strength, managerial efficiency, and earnings capacity positively influenced ROA, but that poor asset quality significantly eroded profitability. Rahaman and Sur (2025) similarly point to operating inefficiency and priority sector lending as factors that raise NPA levels among Indian public sector banks, underscoring how internal management practices, not just external shocks, drive asset-quality deterioration. Arun Prakash and Shruthi (2025) extend this line of inquiry by linking rising gross and net non-performing assets to weaknesses in loan appraisal, provisioning, and credit management, suggesting that the roots of the problem often lie in lending discipline itself rather than in macroeconomic conditions alone. This pattern is not unique to India. Madugu et al. (2019) reported comparable, if variable, findings for Ghanaian banks, indicating that the credit risk–profitability relationship holds across different banking systems even as its magnitude shifts. Rakatenda and Sedana (2021) push the analysis further, showing that credit risk affects profitability while simultaneously shaping capital adequacy itself, a finding that hints at a relationship more layered than a simple direct effect.

2.3. Capital Adequacy, Risk Management and Differences across Banking Systems

A separate strand of literature looks at how the relationship between capital adequacy, risk management, and profitability varies across ownership structures. Patel and Kanchan (2024) found that private sector banks in India outperform their public sector counterparts on both profitability and asset quality, a gap they attribute to differences in operational efficiency and risk management practices. Singh (2024) offers a more nuanced picture, observing that while capital adequacy and liquidity affect both ownership groups in broadly similar ways, credit risk and the impact of the COVID-19 pandemic diverge significantly between public and private banks. Jadhav et al. (2021), focusing specifically on risk-taking behaviour, emphasise the role of prudent capital management in sustaining financial stability among private sector banks, while Dadhich et al. (2020) demonstrate using evidence from the global financial crisis that strong capital buffers and effective risk management are essential for banks to weather periods of financial stress. Taking a broader view, Sami et al. (2024) apply the CAMEL framework to assess banking-sector stability and reaffirm the centrality of capital adequacy and asset quality to overall financial soundness.

2.4. Capital Adequacy as a Moderating Mechanism: Emerging Evidence

While the direct effects of capital adequacy and credit risk on bank performance are well established, a smaller and more recent body of work has begun asking whether capital adequacy changes the strength of this relationship, rather than simply adding to it. Linggadjaya et al. (2025) found that capital adequacy significantly moderates the relationship between bank-specific characteristics and profitability among Indonesian banks, while a related Indonesian study reported that stronger capital buffers weaken the adverse effect of liquidity risk on profitability. This provides evidence that capital adequacy can genuinely alter, rather than merely accompany, a bank's exposure to financial risk. This moderating role is also visible outside Southeast Asia; Arhinful et al. (2025), who examined U.S. banks, found that the capital adequacy ratio negatively and significantly moderates the relationship between non-performing loans and bank growth, indicating that well-capitalised banks are better insulated from the growth-eroding effects of asset-quality deterioration (Meliza et al., 2024). This evidence remains thin and is concentrated almost entirely outside the Indian banking system. Rakatenda and Sedana (2021) offer a partial exception, though their focus is on capital adequacy as a mediating rather than moderating variable, showing that credit risk affects profitability indirectly through capital adequacy among rural banks in Bali. Taken together, these studies suggest that capital adequacy's role may extend well beyond that of a direct performance driver. It may actively shape how financial risks translate into profitability, but whether this holds for Indian public sector banks specifically remains largely unexplored.

3. Research Gap

Despite extensive research on capital adequacy, credit risk and bank performance, important gaps remain in existing literature. Most studies have examined capital adequacy and credit risk as independent determinants of profitability (Athanasoglou et al., 2008; Ali & Dhiman, 2019; Hawaldar et al., 2022; Fathihani et al., 2025), while relatively few have investigated whether capital adequacy modifies the impact of credit risk on bank performance. Although recent evidence from Indonesia suggests that capital adequacy can function as a moderating variable (Linggadjaya et al., 2025), similar empirical evidence for Indian public sector banks is largely absent. Furthermore, Rakatenda and Sedana (2021) examined capital adequacy as a mediator rather than a moderator, leaving unanswered the question of whether stronger capital buffers can mitigate the adverse effects of rising non-performing assets on profitability. Accordingly, this study addresses this gap by examining the moderating role of capital adequacy in the relationship between credit risk and bank performance among Indian public sector banks. Unlike previous studies, it employs both Gross Non-Performing Asset Ratio (GNPAR) and Net Non-Performing Assets to Net Advances (NNPAA) as alternative measures of credit risk and evaluates their interaction with capital adequacy in influencing both ROA and ROE. This provides fresh evidence on the resilience-enhancing role of capital buffers in the Indian public banking sector.

3.1. Statement of the Problem

The profitability of Public Sector Banks (PSBs) in India has been significantly affected by rising non-performing assets and increasing regulatory capital requirements (Gaur & Mohapatra, 2021). While adequate capital is essential to ensuring financial stability, persistent credit risk continues to challenge banks' financial performance (Bandyopadhyay, 2022). Existing studies have primarily examined the independent effects of capital adequacy and credit risk on profitability (Rahaman & Sur, 2025; Gaur & Mohapatra, 2021), with limited attention to capital adequacy's moderating role. So, it is important to examine whether the Capital Adequacy Ratio (CAR) influences the impact of credit risk on the profitability of Indian Public Sector Banks. This study seeks to address this issue by analysing the relationships among credit risk, capital adequacy, and bank performance using panel data on Public Sector Banks in India.

3.2. Research Question

- Does credit risk affect the profitability of Indian public sector banks?
- Does the Capital Adequacy Ratio significantly influence the profitability of Indian public sector banks?
- Does the Capital Adequacy Ratio moderate the relationship between credit risk and profitability of Indian public sector banks?

3.3. Objectives of the study are

- To examine the impact of credit risk on the profitability of Indian public sector banks.
- To assess the effect of capital adequacy on the profitability of Indian public sector banks.
- To determine whether capital adequacy moderates the relationship between credit risk and profitability of Indian public sector banks.

3.4. Hypothesis

H_{01}: Gross Non-Performing Asset Ratio (GNPAR) and Capital Adequacy Ratio (CAR) have no significant effect on Return on Assets (ROA).

H_{02}: Gross Non-Performing Asset Ratio (GNPAR) and Capital Adequacy Ratio (CAR) have no significant effect on Return on Equity (ROE).

H_{03}: Net Non-Performing Assets to Net Advances (NNPAA) and Capital Adequacy Ratio (CAR) have no significant effect on Return on Assets (ROA).

H_{04}: Net Non-Performing Assets to Net Advances (NNPAA) and Capital Adequacy Ratio (CAR) have no significant effect on Return on Equity (ROE).

H_{05}: Capital Adequacy Ratio does not moderate the relationship between Gross Non-Performing Asset Ratio and Return on Assets.

H_{06}: Capital Adequacy Ratio does not moderate the relationship between Gross Non-Performing Asset Ratio and Return on Equity.

H_{07}: Capital Adequacy Ratio does not moderate the relationship between Net Non-Performing Assets to Net Advances and Return on Assets.

H_{08}: Capital Adequacy Ratio does not moderate the relationship between Net Non-Performing Assets to Net Advances and Return on Equity.

4. Research Methodology

4.1. Scope

The study focuses on 12 Public Sector banks in India over the period of 12 years from 2014-2015 to 2025-2026.

4.2. Population and Sampling

The population of the study comprises 12 Public Sector Banks operating in India during the study period. The study covers all 12 Public Sector Banks over a period of 12 financial years (FY 2014–15 to FY 2025–

26). Accordingly, the panel dataset consists of 144 bank-year observations (12 banks × 12 years = 144 observations), providing a balanced panel for empirical analysis.

4.3. Sampling Technique

Purposive Sampling Technique is used for selecting all 12 Public Sector Banks in India.

4.4. Research Design

Quantitative and explanatory research design is adopted in this study to examine the impact of non-performing assets on the profitability of Indian public sector banks. The study further investigates the moderating role of Capital Adequacy Ratio (CAR) in the relationship between non-performing assets and bank performance (Khalil, 2026). Panel data analysis using the Pooled Ordinary Least Squares (OLS) regression technique has been employed to estimate the proposed models (Baltagi, 2021). To ensure stable statistical inference when analysing the moderation effects, this study follows the standard methodological guidance for moderated regression established by Aiken and West (1991) and further clarified by Hayes and Preacher (2013). Interaction terms were constructed using mean-centered variables, with each predictor's sample mean subtracted before computing the product term, a procedure that removes the non-essential multicollinearity that arises mechanically between an interaction term and its constituent variables, without altering the interaction coefficient, its significance, or the model's overall fit (Aiken & West, 1991; Shieh, 2010). This study applies the same mean-centering protocol to evaluate the moderating role of Capital Adequacy Ratio in the relationship between credit risk and the profitability of Indian public sector banks.

4.5. Data Source

The study is entirely based on secondary data, which is collected from published annual reports of Indian public sector banks and www.moneycontrol.com website.

4.6. Statistical Tools and Techniques

The study is based on both descriptive and inferential statistical techniques to analyse the relationship between non-performing assets, capital adequacy, and the financial performance of public sector banks. (Koppa et al., 2026)

4.6.1. Descriptive Statistics

Descriptive Statistics is used to summarise and describe the characteristics of the study variables, including measures such as mean, standard deviation, minimum, and maximum values. This helps in understanding the distribution and variability of the data before conducting regression analysis.

4.6.2. Inferential Statistics

Inferential Statistics is used to examine the relationships between the variables and to test the proposed hypotheses. Pooled Ordinary Least Squares (OLS) regression is employed to estimate the impact of Gross Non-Performing Assets (GNPAR), Net Non-Performing Assets (NNPAA), Capital Adequacy Ratio (CAR), and their interaction terms on financial performance indicators (ROA and ROE).

4.6.3. Diagnostic Tests

Diagnostic Tests were conducted to ensure the reliability and validity of the estimated regression models before interpreting the results (Gujarati & Porter, 2009).

Table 1: Diagnostic Tests for Assumptions of Regression Models

Assumption	Test	Purpose
Absence of Multicollinearity	Variance Inflation Factor (VIF)	Examines whether explanatory variables are highly correlated with one another, ensuring stable and reliable coefficient estimates.
Homoskedasticity	White's Test	Examines whether the variance of error terms remains constant across observations, which is essential for efficient and unbiased standard errors.
Absence of autocorrelation	Wooldridge Test (panel data)	Identifies first-order serial correlation among residuals, ensuring residuals are independent over time.
Normality of residuals	Jarque–Bera Test	Assesses whether residuals follow a normal distribution, supporting the reliability of hypothesis testing in finite samples
Linearity/model specification	Ramsey RESET Test	To check whether the functional form is correctly specified, identify omitted variables or incorrect functional relationships.

Source: Self-Compiled

4.7. Variables and Measurement

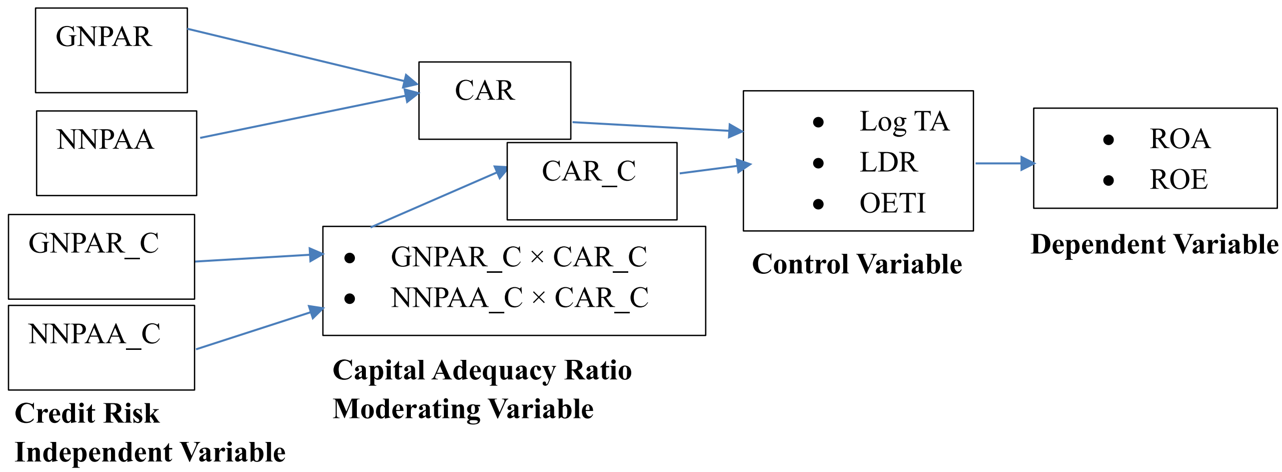
The variable measurements are provided in Table 2.

Table 2: Measurement of variables

Variable Type	Variable	Symbol	Measurement
Dependent Variable	Return on Assets	ROA	Net Profit after Tax ÷ Total Assets
	Return on Equity	ROE	Net Profit after Tax ÷ Shareholders' Equity
Independent Variable	Gross Non-Performing Asset Ratio	GNPAR	Gross NPAs ÷ Gross Advances × 100
	Net Non-Performing Assets to Net Advances	NNPAA	Net NPAs ÷ Net Advances × 100
Moderating Variable	Capital Adequacy Ratio	CAR	Total Capital ÷ Risk-Weighted Assets × 100
	Interaction terms:		GNPAR_C = GNPAR – Mean
	• GNPAR_C × CAR_C		NNPAA_C = NNPAA – Mean
	• NNPAA_C × CAR_C		CAR_C = CAR - Mean
Control Variable	Bank Size	LogTA	Natural Logarithm of Total Assets
	Loan-to-Deposit Ratio	LDR	Total Loans ÷ Total Deposits × 100
	Operating Expense to Total Income	OETI	Operating Expenses ÷ Total Income

Source: Self-Compiled

4.8. Conceptual Framework



4.9. Econometric Models

Two sets of models are estimated to address the study's objectives. Objectives 1 & 2 (Equations 1–4) test the direct effects of credit risk and capital adequacy on profitability. Objective 3 (Equations 5–8) tests whether CAR moderates the relationship between credit risk and profitability. All eight models were estimated using Pooled Ordinary Least Squares (OLS) with cluster-robust standard errors, clustered at the bank level (Arellano, 1987; Petersen, 2009). This approach was adopted in anticipation of within-bank correlation and heteroskedasticity across bank-year observations and does not require the assumption of normally distributed residuals for valid inference at this sample size (N = 144).

Direct Effect Models:

Model 1: $ROA_{it} = \beta_0 + \beta_1 GNPAR_{it} + \beta_2 CAR_{it} + \beta_3 LogTA_{it} + \beta_4 LDR_{it} + \beta_5 OETI_{it} + \varepsilon_{it}$

Model 2: $ROE_{it} = \beta_0 + \beta_1 GNPAR_{it} + \beta_2 CAR_{it} + \beta_3 LogTA_{it} + \beta_4 LDR_{it} + \beta_5 OETI_{it} + \varepsilon_{it}$

Model 3: $ROA_{it} = \beta_0 + \beta_1 NNPAA_{it} + \beta_2 CAR_{it} + \beta_3 LogTA_{it} + \beta_4 LDR_{it} + \beta_5 OETI_{it} + \varepsilon_{it}$

Model 4: $ROE_{it} = \beta_0 + \beta_1 NNPAA_{it} + \beta_2 CAR_{it} + \beta_3 LogTA_{it} + \beta_4 LDR_{it} + \beta_5 OETI_{it} + \varepsilon_{it}$

Moderation Models:

Model 5: $ROA_{it} = \beta_0 + \beta_1 GNPAR\_C_{it} + \beta_2 CAR\_C_{it} + \beta_3 (GNPAR\_C \times CAR\_C)it + \beta_4 LogTA_{it} + \beta_5 LDR_{it} + \beta_6 OETI_{it} + \varepsilon_{it}$

Model 6: $ROE_{it} = \beta_0 + \beta_1 GNPAR\_C_{it} + \beta_2 CAR\_C_{it} + \beta_3 (GNPAR\_C \times CAR\_C)it + \beta_4 LogTA_{it} + \beta_5 LDR_{it} + \beta_6 OETI_{it} + \varepsilon_{it}$

Model 7: $ROAit = \beta_0 + \beta_1 NNPAA\_C_{it} + \beta_2 CAR\_C_{it} + \beta_3 (NNPAA\_C \times CAR\_C)it + \beta_4 LogTA_{it} + \beta_5 LDR_{it} + \beta_6 OETI_{it} + \varepsilon_{it}$

Model 8: $ROE_{it} = \beta_0 + \beta_1 NNPAA\_C_{it} + \beta_2 CAR\_C_{it} + \beta_3 (NNPAA\_C \times CAR\_C)it + \beta_4 LogTA_{it} + \beta_5 LDR_{it} + \beta_6 OETI_{it} + \varepsilon_{it}$

where the subscript *C* denotes mean-centered variables (explained in 4.10), and *i* and *t* index bank and year, respectively.

4.10. Mean-Centering Procedure for Interaction Terms

Moderation terms in Equations 5-8 were constructed by first mean-centering each constituent variable (subtracting its sample mean) before computing the product term. For example, GNPAR_C = GNPAR − $\bar{GNPAR}$, CAR_C = CAR − $\bar{CAR}$, and the interaction term is then computed as GNPAR_C × CAR_C. This procedure follows the standard recommendation for moderated regression analysis (Aiken & West, 1991; Hayes & Preacher, 2013). Interaction terms constructed from raw (uncentered) variables are mechanically correlated with their constituent variables, which can produce very high variance inflation factors purely as an artifact of scale rather than genuine collinearity among substantive constructs (Shieh, 2010). Mean-centering removes this non-essential collinearity, reducing VIFs to below 6 across all four moderation models. It is important to note that mean-centering does not alter the interaction term's coefficient, standard error, t-statistic, p-value, or the model's overall R^2 and F-statistic, only the main-effect coefficients and their interpretation change (Aiken & West, 1991).

4.11. Cluster-Robust Standard Errors

The pooled Ordinary Least Squares (OLS) regression models were estimated using **cluster-robust standard errors** to obtain reliable statistical inference. In panel data, observations within the same bank may exhibit correlated error terms and unequal error variances (heteroskedasticity), which can lead to biased standard errors under conventional OLS estimation. Cluster-robust standard errors adjust for both heteroskedasticity and within-bank correlation of residuals without altering the estimated regression coefficients. This approach provides more reliable hypothesis testing and significance estimates and is widely recommended for panel data analysis (Petersen, 2009; Hoechle, 2007; Stock & Watson, 2008).

4.12. Central Limit Theorem

According to the Central Limit Theorem (CLT), the sampling distribution of the estimated coefficients approaches a normal distribution as the sample size increases, allowing valid statistical inference even when the residuals are not perfectly normal. As the present study is based on 144 bank-year observations, the sample size is considered adequate for applying the Central Limit Theorem. Consequently, the estimated coefficients, standard errors, and hypothesis tests remain reliable despite deviations from normality (Gujarati & Porter, 2009; Wooldridge, 2019).

5. Data Analysis and Interpretation

5.1. Descriptive Statistics

Table 3: Descriptive Statistics

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	C.V.
ROA	0.001179	0.00348	-0.032706	0.016425	0.008934	7.5774
ROE	0.010607	0.04702	-0.83351	0.21201	0.15446	14.562
GNPAR	8.2039	7.0000	0.024000	25.000	5.9737	0.72815
NNPAA	3.7072	3.0000	0.0000	15.000	3.3680	0.90851
CAR	12.779	13.205	0.10750	20.530	4.5900	0.35918
NNPAACAR	45.179	41.355	0.0000	147.00	35.675	0.78965
GNPACAR	104.60	96.798	0.0041808	273.50	66.278	0.63361
LogTA	5.7453	5.7404	4.9726	6.8821	0.42468	0.07391
LDR	0.70999	0.72152	0.46988	1.0346	0.098517	0.13876
OETI	0.20969	0.21380	0.078808	0.29997	0.043847	0.20910

Source: Self-Compiled

Table 3 presents the descriptive statistics of the variables used in the study based on 144 bank-year observations. The average Return on Assets (ROA) and Return on Equity (ROE) are 0.12% and 1.06%, respectively, indicating relatively modest profitability among the selected public sector banks during the study period. The mean Gross Non-Performing Assets Ratio (GNPAR) of 8.20% and Net Non-Performing

Assets Ratio (NNPAA) of 3.71% suggest a considerable variation in asset quality across the banks. The average Capital Adequacy Ratio (CAR) is 12.78%, exceeding the regulatory minimum and reflecting an overall sound capital position. The mean values of LogTA (5.75), LDR (0.71), and OETI (0.21) indicate differences in bank size, lending behavior, and operating efficiency among the sampled banks. The coefficients of variation reveal that ROE exhibits the highest relative variability, followed by ROA, indicating greater fluctuations in profitability compared to the other explanatory variables. Overall, the descriptive statistics indicate sufficient variation in the dataset, making it suitable for regression analysis.

5.2. Regression Results

5.2.1. Model 1

$$ROA = -0.0171 - 0.0908(GNPAR) + 0.0919(CAR) + 0.0027(LogTA) + 0.0029(LDR) - 0.0187(OETI) + \varepsilon$$

Table 4: Regression Analysis of Model 1

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.0171	0.0102	−1.681	0.1209	Not significant
GNPAR	−0.0908	0.0156	−5.838	0.0001	Significant (−) ***
CAR	0.0919	0.0230	3.996	0.0021	Significant (+) ***
LogTA	0.0027	0.0007	3.592	0.0042	Significant (+) ***
LDR	0.0029	0.0065	0.451	0.6607	Not significant
OETI	−0.0187	0.0089	−2.096	0.0600	Significant (−) *
$R^2 = 0.7008$					
Adj. R^2 =0.6900					
F (5,11) = 147.58 ($p < .001$)					
DW = 1.873					

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Self-Compiled

Table 4 reports the pooled OLS results for the effect of GNPAR, CAR, LogTA, LDR and OETI on ROA. The model is statistically significant ($F = 147.580$, $p < 0.001$) and explains 70.08% of the variation in ROA ($R^2 = 0.7008$). GNPAR has a significant negative effect on ROA ($\beta = -0.0908$, $p < 0.01$), while CAR ($\beta = 0.0919$, $p < 0.01$) and LogTA ($\beta = 0.0027$, $p < 0.01$) have significant positive effects. LDR is positive but insignificant ($\beta = 0.0029$, $p = 0.6607$). OETI has a negative effect and is marginally significant at the 10% level ($\beta = -0.0187$, $p = 0.0600$). Overall results suggest that asset quality, capital adequacy, and bank size significantly influence ROA, whereas LDR does not.

5.2.2. Model 2

$$ROE = -0.2895 - 1.3584(GNPAR) + 1.2543(CAR) + 0.0710(LogTA) - 0.0473(LDR) - 0.6101(OETI) + \varepsilon$$

Table 5: Regression Analysis of Model 2

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.2895	0.1748	−1.656	0.0999	Significant (−) *
GNPAR	−1.3584	0.2527	−5.375	<.001	Significant (−) ***
CAR	1.2543	0.4884	2.568	0.0113	Significant (+) **
LogTA	0.0710	0.0242	2.936	0.0039	Significant (+) ***
LDR	−0.0473	0.1139	−0.416	0.6783	Not significant
OETI	−0.6101	0.2385	−2.558	0.0116	Significant (−) **
R^2 =0 .5155					
Adj. $R^2 = 0.4979$					
F (5,11) = 29.36 ($p < .001$),					
DW = 1.814					

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Self-Compiled

Table 5 presents the pooled OLS regression results for the impact of GNPAR, CAR, LogTA, LDR, and OETI on ROE. The model explains 51.55% of the variation in ROE ($R^2 = 0.5155$; Adjusted $R^2 = 0.4979$), indicating a moderate model fit. The model indicates that GNPAR has a significant negative effect on ROE ($\beta = -1.3584$, $p < 0.001$), suggesting that higher non-performing assets reduce shareholders' returns. In contrast, CAR ($\beta = 1.2543$, $p = 0.0113$) and LogTA ($\beta = 0.0710$, $p = 0.0039$) exert significant positive effects on ROE, indicating that better-capitalised and larger banks achieve higher profitability. OETI has a significant negative effect ($\beta = -0.6101$, $p = 0.0116$), implying that higher operating expenses reduce financial performance. However, LDR has no significant influence on ROE ($\beta = -0.0473$, $p = 0.6783$

5.2.3. Model 3

$$ROA = -0.0219 - 0.1436(NNPAA) + 0.0702(CAR) + 0.0025(LogTA) + 0.0137(LDR) - 0.0222(OETI) + \varepsilon$$

Table 6: Regression Analysis of Model 3

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.0219	0.0082	−2.670	0.0218	Significant (−) **
NNPAA	−0.1436	0.0248	−5.795	0.0001	Significant (−) ***
CAR	0.0702	0.0379	1.854	0.0907	Significant (+) *
LogTA	0.0025	0.0009	2.884	0.0149	Significant (+) **
LDR	0.0137	0.0047	2.888	0.0148	Significant (+) **
OETI	−0.0222	0.0098	−2.261	0.0450	Significant (−) **
$R^2 = 0.6582$					
Adj. $R^2 = 0.6459$					
$F(5,11) = 236.94$ ($p < .001$)					
DW = 1.846					

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Source: Self-Compiled

Table 6 represents the pooled OLS regression results for the impact of NNPAA, CAR, LogTA, LDR, and OETI on ROA. The model explains 65.82% of the variation in ROA ($R^2 = 0.6582$; Adjusted $R^2 = 0.6459$), indicating a good model fit. The results show that NNPAA has a significant negative effect on ROA ($\beta = -0.1436$, $p < 0.001$), indicating that higher net non-performing assets reduce bank profitability. CAR ($\beta = 0.0702$, $p = 0.0907$), LogTA ($\beta = 0.0025$, $p = 0.0149$), and LDR ($\beta = 0.0137$, $p = 0.0148$) have positive effects on ROA, with CAR being significant at the 10% level and LogTA and LDR at the 5% level. OETI has a significant negative effect on ROA ($\beta = -0.0222$, $p = 0.0450$), suggesting that higher operating expenses adversely affect profitability.

5.2.4. Model 4

$$ROE = -0.3516 - 2.1867(NNPAA) + 0.8938(CAR) + 0.0670(LogTA) + 0.1126(LDR) - 0.6602(OETI) + \varepsilon$$

Table 7: Regression Analysis of Model 4

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.3516	0.1541	−2.281	0.0435	Significant (−) **
NNPAA	−2.1867	0.5130	−4.262	0.0013	Significant (−) ***
CAR	0.8938	0.7236	1.235	0.2425	Not significant
LogTA	0.0670	0.0185	3.631	0.0039	Significant (+) ***
LDR	0.1126	0.1034	1.089	0.2994	Not significant
OETI	−0.6602	0.3056	−2.160	0.0537	Significant (−) *
$R^2 = .4862$					
Adj. $R^2 = .4675$					
$F(5,11) = 35.29$ ($p < .001$)					
DW = 1.839					

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Source: Self-Compiled

Ttable 7 presents the pooled OLS regression results for the impact of NNPAA, CAR, LogTA, LDR, and OETI on ROE. The model explains 48.62% of the variation in ROE ($R^2 = 0.4862$; Adjusted $R^2 = 0.4675$), indicating a moderate model fit. The findings reveal that NNPAA has a significant negative effect on ROE ($\beta = -2.1867$, $p = 0.0013$), indicating that higher net non-performing assets reduce shareholders' returns. LogTA has a significant positive effect on ROE ($\beta = 0.0670$, $p = 0.0039$), suggesting that larger banks achieve better financial performance. OETI has a negative effect and is marginally significant at the 10% level ($\beta = -0.6602$, $p = 0.0537$), implying that higher operating expenses may reduce profitability. However, CAR ($\beta = 0.8938$, $p = 0.2425$) and LDR ($\beta = 0.1126$, $p = 0.2994$) do not have a statistically significant influence on ROE.

5.2.5. Model 5

$$ROA = -0.0120 - 0.0851(GNPAR\_C) + 0.1005(CAR\_C) + 0.3621(GNPAR\_C \times CAR\_C) + 0.0026(LogTA) + 0.0035(LDR) - 0.0178(OETI) + \varepsilon$$

Table 8: Regression Analysis of Model 5

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.0120	0.0073	−1.657	0.1258	Not significant
GNPAR_C	−0.0851	0.0170	−5.011	0.0004	Significant (−) ***
CAR_C	0.1005	0.0304	3.306	0.0070	Significant (+) ***
GNPAR_C × CAR_C	0.3621	0.3843	0.942	0.3664	Not significant
LogTA	0.0026	0.0008	3.182	0.0087	Significant (+) ***
LDR	0.0035	0.0061	0.570	0.5804	Not significant
OETI	−0.0178	0.0089	−2.006	0.0701	Significant (−) *
$R^2 = 0.7042$ Adj. $R^2 = 0.6913$ $F(6,11) = 179.88$ ($p < .001$), DW = 1.893					

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Self-Compiled

Table 8 presents the pooled OLS regression results examining the moderating effect of CAR on the relationship between GNPAR and ROA. The model explains 70.42% of the variation in ROA ($R^2 = 0.7042$; Adjusted $R^2 = 0.6913$), indicating a strong model fit. The results show that GNPAR has a significant negative effect on ROA ($\beta = -0.0851$, $p < 0.001$), while CAR ($\beta = 0.1005$, $p = 0.007$) and LogTA ($\beta = 0.0026$, $p = 0.0087$) have significant positive effects. The interaction term (GNPAR × CAR) is positive but statistically insignificant ($\beta = 0.3621$, $p = 0.3664$), indicating that CAR does not significantly moderate the relationship between GNPAR and ROA. LDR has no significant effect ($p = 0.5804$), whereas OETI has a negative effect and is marginally significant at the 10% level ($\beta = -0.0178$, $p = 0.0701$).

5.2.6. Model 6

$$ROE = -0.2319 - 1.2956(GNPAR\_C) + 1.3479(CAR\_C) + 3.9509(GNPAR\_C \times CAR\_C) + 0.0699(LogTA) - 0.0411(LDR) - 0.6006(OETI) + \varepsilon$$

Table 9: Regression Analysis of Model 6

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.2319	0.1570	−1.478	0.1676	Not significant
GNPAR_C	−1.2956	0.4297	−3.015	0.0118	Significant (−) **
CAR_C	1.3479	0.6451	2.090	0.0607	Significant (+) *
GNPAR_C × CAR_C	3.9509	8.7426	0.452	0.6601	Not significant
LogTA	0.0699	0.0174	4.009	0.0021	Significant (+) ***
LDR	−0.0411	0.1505	−0.273	0.7899	Not significant
OETI	−0.6006	0.2739	−2.193	0.0507	Significant (−) *

$R^2 = 0.5168$
Adj. $R^2 = 0.4957$
$F(6,11) = 19.87$ ($p < .001$)
DW = 1.819

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Self-Compiled

Table 9 presents the pooled OLS regression results examining the moderating effect of CAR on the relationship between GNPAR and ROE. The model explains **51.68%** of the variation in ROE ($R^2 = 0.5168$; Adjusted $R^2 = 0.4957$), indicating a moderate model fit. The results indicate that GNPAR has a significant negative effect on ROE (β = −1.2956, p = 0.0118), while CAR (β = 1.3479, p = 0.0607) and LogTA (β = 0.0699, p = 0.0021) have positive effects on ROE, with CAR being significant at the 10% level. The interaction term (GNPAR × CAR) is positive but statistically insignificant (β = 3.9509, p = 0.6601), suggesting that CAR does not significantly moderate the relationship between GNPAR and ROE. LDR has no significant effect (p = 0.7899), whereas OETI has a negative effect and is marginally significant at the 10% level (β = −0.6006, p = 0.0507).

5.2.7. Model 7

$$ROA = -0.0186 - 0.1640(NNPAA\_C) + 0.0511(CAR\_C) - 0.6730(NNPAA\_C \times CAR\_C) + 0.0026(LogTA) + 0.0130(LDR) - 0.0226(OETI) + \varepsilon$$

Table 10: Regression Analysis of Model 7

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.0186	0.0051	−3.660	0.0038	Significant (−) ***
NNPAA_C	−0.1640	0.0400	−4.102	0.0018	Significant (−) ***
CAR_C	0.0511	0.0535	0.956	0.3595	Not significant
NNPAA_C × CAR_C	−0.6730	0.9511	−0.708	0.4939	Not significant
LogTA	0.0026	0.0009	2.919	0.0140	Significant (+) **
LDR	0.0130	0.0045	2.890	0.0147	Significant (+) **
OETI	−0.0226	0.0096	−2.349	0.0386	Significant (−) **

$R^2 = 0.6608$
Adj. $R^2 = 0.6459$
$F(6,11) = 268.76$ ($p < .001$)
DW = 1.867

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Self-Compiled

Table 10 shows the pooled OLS regression results examining the moderating effect of CAR on the relationship between NNPAA and ROA. The model explains **66.08%** of the variation in ROA ($R^2 = 0.6608$; Adjusted $R^2 = 0.6459$), indicating a good model fit. The findings state that NNPAA has a significant negative effect on ROA (β = −0.1640, p = 0.0018), while LogTA (β = 0.0026, p = 0.0140) and LDR (β = 0.0130, p = 0.0147) have significant positive effects. OETI has a significant negative effect on ROA (β = −0.0226, p = 0.0386). However, CAR (β = 0.0511, p = 0.3595) and the interaction term (NNPAA × CAR) (β = −0.6730, p = 0.4939) are statistically insignificant, indicating that CAR does not significantly moderate the relationship between NNPAA and ROA.

5.2.8. Model 8

ROE = -0.3280 - 2.6206(NNPAA_C) + 0.4885(CAR_C) - 14.2672(NNPAA_C × CAR_C) + 0.0697(LogTA) + 0.0969(LDR) - 0.6692(OETI) + ε

Table 11: Regression Analysis of Model 8

Variable	Coefficient	Std. Error	t-value	p-value	Result
Constant	−0.3280	0.1062	−3.088	0.0103	Significant (−) **
NNPAA_C	−2.6206	0.8798	−2.979	0.0126	Significant (−) **
CAR_C	0.4885	1.1013	0.444	0.6660	Not significant
NNPAA_C × CAR_C	−14.2672	21.3350	−0.669	0.5175	Not significant
LogTA	0.0697	0.0194	3.587	0.0043	Significant (+) ***
LDR	0.0969	0.1031	0.940	0.3676	Not significant
OETI	−0.6692	0.3022	−2.214	0.0488	Significant (−) **
$R^2 = 0.4900$					
Adj. $R^2 = .4677$					
$F(6,11) = 28.17$ ($p < .001$)					
DW = 1.855					

*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Self-Compiled

Table 11 states the pooled OLS regression results examining the moderating effect of CAR on the relationship between NNPAA and ROE. The model explains 49.00% of the variation in ROE ($R^2 = 0.4900$; Adjusted $R^2 = 0.4677$), indicating a moderate model fit. The results indicate that NNPAA has a significant negative effect on ROE ($\beta = -2.6206$, $p = 0.0126$), while LogTA has a significant positive effect ($\beta = 0.0697$, $p = 0.0043$). OETI has a significant negative effect on ROE ($\beta = -0.6692$, $p = 0.0488$). However, CAR ($\beta = 0.4885$, $p = 0.6660$), LDR ($\beta = 0.0969$, $p = 0.3676$), and the interaction term (NNPAA × CAR) ($\beta = -14.2672$, $p = 0.5175$) are statistically insignificant, indicating that CAR does not significantly moderate the relationship between NNPAA and ROE.

5.3. Diagnostic Tests of the Regression Models

Table 12: Multicollinearity: Variance Inflation Factor (VIF) Results

Variable	Models 1 & 2 (GNPAR)	Models 3 & 4 (NNPAA)	Models 5 & 6 (GNPAR_C × CAR_C)	Models 7 & 8 (NNPAA_C × CAR_C)	Conclusion
GNPAR / GNPAR_C	2.395	–	2.778	–	No multicollinearity
NNPAA / NNPAA_C	–	3.065	–	5.329	No multicollinearity
CAR / CAR_C	2.075	2.981	2.272	4.286	No multicollinearity
Interaction Term	–	–	GNPAR_C × CAR_C = **1.220**	NNPAA_C × CAR_C = **1.876**	No multicollinearity
LogTA	1.261	1.304	1.268	1.318	No multicollinearity
LDR	1.504	1.321	1.515	1.347	No multicollinearity
OETI	1.305	1.299	1.311	1.300	No multicollinearity

Source: Self-Compiled

Table 13: Heteroskedasticity: White's Test

Models	Dependent Variable	TR^2 Statistic	p-value	Conclusion
Model 1	ROA (GNPAR)	23.767	0.0082	Heteroskedasticity Present
Model 2	ROE (GNPAR)	19.266	0.0370	Heteroskedasticity Present
Model 3	ROA (NNPAA)	19.483	0.0345	Heteroskedasticity Present
Model 4	ROE (NNPAA)	16.847	0.0778	No Heteroskedasticity
Model 5	ROA (GNPAR × CAR)	24.736	0.016	Heteroskedasticity Present
Model 6	ROE (GNPAR × CAR)	21.594	0.042	Heteroskedasticity Present
Model 7	ROA (NNPAA × CAR)	22.811	0.029	Heteroskedasticity Present
Model 8	ROE (NNPAA × CAR)	18.138	0.112	No Heteroskedasticity

Source: Self-Compiled

Note: Heteroskedasticity was detected in six of the eight regression models. To account for this issue, all models were estimated using cluster-robust standard errors. This approach provides reliable standard errors and statistical inference even when heteroskedasticity is present [Stock, J. H., & Watson, M. W. (2008); Petersen (2009); Hoechle, D. (2007)]

Table 14: Autocorrelation: Wooldridge Test

Eq	Test Statistic	p-value	Conclusion
1	t = 0.462	0.6529	No autocorrelation
2	t = 0.587	0.5688	No autocorrelation
3	t = 0.932	0.3714	No autocorrelation
4	t = 0.690	0.5046	No autocorrelation
5	t = 0.391	0.703	No autocorrelation
6	t = 0.574	0.577	No autocorrelation
7	t = 0.697	0.500	No autocorrelation
8	t = 0.570	0.580	No autocorrelation

Source: Self-Compiled

Table 15: Normality of Residuals: Jarque–Bera Test

Eq	Test Statistic	p-value	Conclusion
1	χ^2=45.016	<.001	Not normal
2	χ^2=101.870	<.001	Not normal
3	χ^2=90.090	<.001	Not normal
4	χ^2=207.557	<.001	Not normal
5	χ^2=52.999	<.001	Not normal
6	χ^2=111.216	<.001	Not normal
7	χ^2= 81.735	<.001	Not normal
8	χ^2=186.080	<.001	Not normal

Source: Self-Compiled

Note: The Jarque–Bera test evaluated via Gretl's Doornik–Hansen adaptation for finite samples indicated that the residuals were not normally distributed. However, this does not affect the validity of the regression results. Since the study is based on 144 observations, the Central Limit Theorem ensures that the estimated coefficients remain reliable for statistical inference. In financial data, departures from normality are often caused by a few extreme observations rather than problems with the regression model (Önder & Zaman, 2003). This interpretation is further supported by the satisfactory Ramsey RESET test results (Table 10.3.5), indicating that the model is correctly specified.

Table 5.3.5 Linearity/ Model Specification: Ramsey RESET Test

Eq	Test Statistic	p-value	Conclusion
1	F = 1.541	0.218	Linear function & correctly specified
2	F = 1.229	0.2960	Linear function & correctly specified
3	F = 0.003	0.9970	Linear function & correctly specified
4	F = 0.109	0.8970	Linear function & correctly specified
5	F = 0.361	0.697	Linear function & correctly specified
6	F = 0.587	0.557	Linear function & correctly specified
7	F = 0.951	0.389	Linear function & correctly specified
8	F = 0.954	0.387	Linear function & correctly specified

Source: Self-Compiled

6. Findings

Credit risk significantly reduces bank profitability, regardless of measure or profitability indicator used. Both Gross NPA Ratio (GNPAR) and Net NPA Ratio (NNPAA) exert a negative and statistically significant effect on both ROA and ROE across all direct-effect models and retain their significance in the moderation models. Capital adequacy improves profitability, though less consistently for ROE. CAR shows a positive and significant effect on ROA in Models 1, 3 (10% level), and 5, but not Model 7. Its effect on ROE is significant when paired with GNPAR but not when paired with NNPAA. This indicates capital adequacy's protective effect on shareholder returns is somewhat sensitive to how credit risk is measured, and less robust than its effect on asset returns. Bank size consistently improves profitability**.** LogTA is positive and statistically significant in all eight models, indicating that larger banks in the sample achieve superior profitability, plausibly through economies of scale, greater diversification, or stronger market positioning. Operating efficiency and lending intensity play a secondary, more selective role. OETI is negative across all eight models, reaching conventional significance in most but only marginal (10%) significance in a few ROE specifications. LDR is significant only in the NNPAA-ROA specifications, suggesting lending intensity's effect on profitability is not uniform across model specifications. Capital adequacy does not significantly moderate the credit risk–profitability relationship. Across all four moderation models, the interaction term between CAR and the credit-risk measure (GNPAR or NNPAA) is statistically insignificant regardless of whether profitability is measured by ROA or ROE. Capital adequacy improves profitability directly, and credit risk reduces it directly, but the strength of the credit-risk–profitability relationship does not itself depend on the level of capital adequacy in this study. Model diagnostics support the reliability of these findings**.** All eight models are free of problematic multicollinearity (following mean-centering), free of first-order autocorrelation, and correctly specified (Ramsey RESET). Heteroskedasticity, present in six of eight models, and non-normality of residuals, present in all eight, were addressed through cluster-robust standard errors and the Central Limit Theorem. These are not treated as threats to inference given the sample size (N = 144), consistent with Petersen (2009) and Önder & Zaman (2003).

7. Conclusion

This study examined the effect of credit risk and capital adequacy on the profitability of Indian public sector banks, and tested whether capital adequacy moderates the relationship between credit risk and profitability, using panel data from 12 banks over 12 years (N = 144) and eight pooled OLS model specifications estimated with cluster-robust standard errors. (Sharma et. al., 2021) The results consistently show that higher non-performing assets, whether measured gross or net, significantly reduce both return on assets and return on equity, while stronger capital adequacy and larger bank size are associated with higher profitability. These direct effects are robust across all model specifications and diagnostic checks. In contrast, the moderation analysis finds no statistically significant evidence that capital adequacy alters the strength of the credit risk -profitability relationship, a result that holds consistently across both non-performing asset measures and both profitability indicators. Collectively, these findings suggest that capital adequacy and asset quality operate as independent, rather than interacting, drivers of profitability. Being well-capitalised doesn't protect a bank from the profitability hit of rising non-performing assets as the two effects work side by side, not against each other. Effective asset-quality management, therefore, remains essential for Indian public sector banks irrespective of their capital position, and should not be treated as a substitute for maintaining strong capital buffers, or vice versa.

Banks should strengthen credit risk management as the primary strategy for improving profitability: Since both Gross NPA Ratio (GNPAR) and Net NPA Ratio (NNPAA) have a consistently negative and statistically significant impact on both ROA and ROE, banks should prioritise measures that reduce non-performing assets. This can be achieved through rigorous credit appraisal, continuous monitoring of loan accounts, early warning systems, timely recovery mechanisms, and prudent loan restructuring. Banks should maintain adequate capital buffers to enhance financial performance: The positive relationship between Capital Adequacy Ratio (CAR) and profitability, particularly ROA, suggests that maintaining strong capital adequacy contributes directly to better financial performance. Therefore, banks should maintain capital levels above the regulatory minimum prescribed under the Basel III framework. Banks should pursue sustainable growth and operational efficiency to improve profitability: The consistent positive effect of bank size indicates that larger banks benefit from economies of scale, wider diversification, and stronger market presence. Accordingly, banks should focus on sustainable expansion through business diversification, technological innovation, digital banking initiatives, and strategic branch optimisation. Simultaneously, the negative coefficient of operating expenses to total income (OETI) suggests that improving operational efficiency through cost control, process automation, and productivity enhancement can further strengthen profitability. Regulatory and managerial efforts should focus on direct improvements in capital and asset quality rather than expecting capital adequacy to offset credit risk: The insignificant interaction between CAR and credit risk measures indicates that higher capital adequacy does not weaken the adverse effect of credit risk on profitability. Therefore, policymakers and bank management should treat capital adequacy and credit risk management as complementary but independent policy objectives. Regulatory authorities should continue emphasising stringent NPA monitoring and risk-based supervision.

The study contributes to the banking and finance literature by testing the moderating role of capital adequacy in the credit risk–profitability relationship using two alternative and commonly used measures of non-performing assets (gross and net). For bank management and regulators, the findings reinforce that credit risk management and capital adequacy maintenance are both independently important levers for profitability, and should be pursued as complementary rather than substitutable strategies. Since capital adequacy does not appear to buffer the profitability impact of rising non-performing assets in this sample, the results suggest that banks cannot rely on strong capital buffers alone to offset the profitability consequences of deteriorating asset quality, active NPA management remains necessary regardless of a bank's capital position.

The study is limited to public sector banks and a 12-year panel data. Extending the analysis to a longer time horizon spanning multiple credit cycles, or including private sector banks, may reveal whether the moderating role of capital adequacy differs across ownership structures or economic conditions. Future research could also explore alternative moderators (such as bank-level governance quality or loan concentration) or nonlinear specifications of the credit risk–profitability relationship.

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