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Determinants Of Credit Risk Management In Public Sector Commercial Banks: An Econometric Approach

Dr. Arun Prakash P*, Shruthi P R**

**Assistant Professor, Department of Commerce (Professional Accounting), PSG College of Arts and Science, Coimbatore.*
***Corresponding Author: Shruthi P R, Research Scholar, PSG College of Arts and Science, Coimbatore.*

This paper analyses credit risk management tactics in public sector commercial banks in India from 2009 to 2023, emphasizing econometric models and their effectiveness. This study examines the factors influencing Gross Non-Performing Assets (GNPA) and Net Non-Performing Assets (NNPA) through econometric techniques such as panel data regression, cointegration, and Granger causality tests. Research indicates substantial correlations among credit risk factors, including Loan Loss Provisions, Secured Advances, and the Credit to Deposit Ratio. Prolonged NPAs underscore inadequacies in credit evaluation and recovery processes. The research highlights targeted interventions, technological incorporation, and sophisticated predictive methodologies to improve sustainable banking practices and economic growth.

Key Words: Credit Risk, Non-Performing Assets, Econometric Models, Public Sector Banks, Risk Management.

1. INTRODUCTION

Credit risk management is necessary for the long-term growth and stability of the banking sector. It is critical for public sector commercial banks to have effective strategies in place so that they can assist economic development and serve a varied range of customers, particularly those from economically weaker backgrounds and priority sectors. Robust systems are required to evaluate, track, and reduce credit risk due to the dynamic financial environment and changing legislation.This research delves into the methods used by public sector banks to handle credit risk, with a focus on econometric models that help with decisions. To better understand credit risk characteristics, predict defaults, and improve loan portfolios, these models provide a quantitative framework. Banks can plan for potential hazards and create strategies that take risk-return trade-offs into account by using statisticalmethods and historical data.Examining bank-specific indicators such as non-performing assets (NPAs), credit disbursement patterns, and sectoral performance, this research measures credit risk using GNPA and NNPA as dependent variables, focusing on the period 2009–2023. Management of rising nonperforming assets (NPAs) following the financial crisis of 2008 is discussed in the paper.

1.1 NEED FOR THE STUDY

Financial institutions face an enormous challenge to expansion and profitability in their management of non-performing assets (NPAs). Although nonperforming assets (NPAs) have decreased over time, they continue to have a significant influence on total profitability since they affect ROA and ROE. To maintain financial stability and adhere to regulatory procedures set out by the Reserve Bank of India (RBI) and the Indian government, it is crucial to effectively manage non-performing assets (NPAs).Despite the difficulty of completely getting rid of nonperforming assets, there are steps that may be taken to enhance distressed assets and minimize the impact that they have. The methods used by Indian public sector commercial banks to monitor, control, and lower non-performing assets (NPAs) are the main emphasis of this study. The study intends to solve this important problem by offering insights into enhancing financial performance and sustaining risk-return equilibrium, assuring public sector banks' long-term growth in India's dynamic economic environment.

1.2 STATEMENT OF PROBLEM

In India, public sector commercial banks play a crucial role in driving economic growth and promoting inclusive development. A surge in non-performing assets (NPAs), economic uncertainty, and changing regulatory frameworks were among the major obstacles that these banks encountered from 2009 to 2023. Their ability to achieve socioeconomic goals, as well as their profitability and operational efficiency, were all negatively affected by the credit risk management shortcomings.Reliable data and cutting-edge techniques are essential for effective credit risk management to detect, measure, and mitigate risks. Traditional methods may offer some insights, but they frequently fall short when it comes to addressing the contemporary credit issues that are more complicated. The development of econometric modelling provides a solid foundation for studying risk variables, predicting defaults, and improving loan portfolios.The use of econometric models in public sector banks is still restricted and uneven, despite its potential. This study looks at the tactics these banks used between 2009 and 2023, analysing the obstacles they faced and investigating the data-driven solutions might enhance sustainable banking operations and credit risk management.

1.3 OBJECTIVES OF THE STUDY

1) To analyse the impact of Gross Non-Performing Assets (GNPA) on bank specific credit risk variables of Public Sector Commercial Banks.
2) To evaluate the effect of Net Non-Performing Assets (NNPA) on bank specific credit risk variables of Public Sector Commercial Banks.

1.4 RESEARCH METHODOLOGY

Data Source and Sampling Techniques - Most of the information for the study came from secondary sources, such as financial statements, reports, and analyses of ratios and balance sheets. "Tables based on Accounts" in "Statistical Tables Related to Banks in India," published by the Reserve Bank of India under the Research and Publications tab, is where the crucial financial data and ratios have been gathered from. To make the analysis easier, the data that RBI provides is further compiled. For the 15 years from 2008–09 through 2022–23, this article focuses only on 12 public sector commercial banks.

Tools and Techniques – The study has employed statistical tools to analyse metrics like the mean, standard deviation, minimum, maximum values, Jarque-Bera test and Probability of selected variables through descriptive statistics. Multiple correlation assesses the linear relationship between one dependent variable and two or more independent variables. A multicollinearity test is conducted in cases where certain variables exhibit the same level of implication on the dependent variable, which may result in multicollinearity issues. To evaluate financial models and assist with econometric research, a heteroscedasticity test is performed. Breusch-Godfrey correlation in series The LM test is used to find autocorrelation in the linear regression model's residuals.To use econometric techniques, time series data must be stationary. It describes the range of values that the time series exhibits in relation to its mean. The existence or absence of stationarity in a time series can be determined using the unit root test. The data is considered static if the results of the Augmented Dickey Fuller test show that the mean and variance do not change over time. The long-term correlation between the dependent and independent variables is examined in this study using the Johansen Cointegration test. In addition to evaluating the short-term effects of one variable's change on another, the study employs the Granger causality test to determine if a relationship is unidirectional or bidirectional. To forecast the value of the independent variable, panel data analyses include time-series and cross-sectional data.

Empirical model specification - The predictor variables are fitted into credit risk multivariate regression equations comprising Gross Non-Performing Assets and Net Non-Performing Assets to Total Advances as predicted variables.

$$\mathbf{GNPAit= \alpha it+ \beta 1CRDRit+ \beta 2LLit+ \beta 3PSADTADit+ \beta 4SADTADit+ \beta 5TLTADit+ \xi it.}$$

$$\mathbf{NNPAit= \alpha it+ \beta 1CRDRit+ \beta 2LLit+ \beta 3PSADTADit+ \beta 4SADTADit+ \beta 5TLTADit+ \xi it.}$$

Where α= Constant, $\beta 1 \ldots \beta 5$ = Estimated coefficients, ξ = Error term.

1.5 SUMMARY OF VARIABLES

Table1

Dependent And Independent Variables for Credit Risk analysis

Variable Name and code used	Description of the variables	Rationale of expected relationship	Expected Sign

Gross Non-Performing Asset - GNPA	Gross Non-Performing Asset to Total Advances	Represents the overall health of the banks' loan portfolio	NA
Net Non-Performing Asset	Net Non-Performing Asset to Total Advances	Non-performing assets (NPAs) a lender has after making provisions for potential losses	NA
Independent Variables			
Credit to Deposit Ratio – CRDR	Advances to Deposits	Indicates the use of deposits to generate income and measures the bank's liquidity.	+/-
Loan Loss – LL	Provision for loss loan to Total Advances	Expenses set aside to recover potential losses acting as a financial buffer without impacting stability.	-
Priority Sector Advances to Total Advances - PSATAD	Priority Sector Advances to Total Advances	Funds set off for specific sector in the economy which has the weakness of reducing interest income due to loan waivers.	-
Term loans to Total Advances – TLTAD	Term loans to Total Advances	Improves the financial performance and stability of the commercial banks.	+
Secured Advances to Total Advances - SATAD	Secured Advances to Total Advances	Advances backed by security which are often offered at low interest impacts the business of commercial banks.	-

Table 2 List of Banks Covered Under the Study

S.No	Name of the Bank	Abbreviation	Year of Inception
1	Bank of Baroda	BOB	1908
2	Bank of India	BOI	1906
3	Bank of Maharashtra	BOM	1935
4	Canara Bank	CB	1906
5	Central Bank of India	CBI	1911
6	Indian Bank	IB	1907
7	Indian Overseas Bank	IOB	1937
8	Punjab and Sind Bank	P&SB	1908
9	Punjab National Bank	PNB	1895
10	State Bank of India	SBI	1955
11	UCO Bank	UCO	1942
12	Union Bank of India	UBI	1919

2. REVIEW OF LITERATURE

(Rajalakshmi, 2015) explored the Non-Performing Asset (NPA) recovery patterns of public sector banks in Tamil Nadu. The research was conducted for a period of 13 years from 2001-02 to 2013-14 comprising of nationalized banks, State Bank of India, and its associates. Data on the outstanding credit of the sample banks in Tamil Nadu, categorized by occupation, was collected from the RBI website. The study found that at the beginning of the fiscal year 2001-02, the credit outstanding for nationalized banks stood at 75.04%, decreasing to 64.97% by the end of the financial year 2013-14. Similarly, it was observed that SBI & its associates successfully reduced their NPA from 83.94% in 2001-02 to 75.39% by the end of the financial year 2013-14. So, the study found a decreasing trend on NPA among the sample banks during the study period. The study recommended that preventing loans from becoming non-performing assets would help in achieving long term profits and profitability.

(Sehgal, 2017)conducted an analysis of risk factors and exposure to banks during the periods before and after the financial crises in India. The study aimed to evaluate risk exposure in relation to the capital market and associate with an accounting-based approach. To achieve this objective, the study identified the following variables: Equity risk factor, Interest rate risk, Exchange rate risk, and credit risk based on both market and accounting perspectives. Additionally, bank-specific measures such as Capitalization, Asset quality, Management efficiency, Earnings, Ownership, Size, diversification, and valuation were considered. The data, spanning from 2004 to 2014, underwent panel data multivariate analysis. The findings indicated that during post-crisis period there was an increase in equity and credit risks, and a decrease in interest rate and exchange rate risks. The analysis of the capital market revealed that small-sized, well-capitalized, and diversified private sector banks exhibited lower exposure to risk. Large banks showed higher exposure to equity risk, public sector banks were more prone to credit risk, and private sector banks faced elevated interest rate and exchange rate exposures. The study recommends regular market assessments for timely and efficient information gathering, helping in the development of early warning models for defensive action. Furthermore, it was suggested to implement strategies based on scale efficiency for different banks rather than adopting same strategies for all the banks.

(Rehman, 2019)performed a study to look at the relationship between risk management techniques and the credit risk that Baloch commercial banks faced. With credit risk as the dependent variable, they obtained information by distributing a questionnaire to 250 employees from seven commercial banks in Balochistan. Corporate governance, capital sufficiency, hedging, and diversification were considered as independent variables. Correlation analysis was utilized to examine the information. The results revealed that the bank's capital adequacy ratio has the least impact, with corporate governance having the most impact, diversification performing a major role, and hedging ranking in last.

(PALIT, 2020)carried out a thesis examining the credit risk management in Indian banks, focusing on two public sector banks (State Bank of India and UCO Bank) and two private sector banks (ICICI and HDFC Bank). The research employed a combination of primary and secondary data, employing statistical methods for analysis such as ANOVA, regression, factor analysis, and chi-square. The study considered risk-sharing and outsourcing, exposure and concentration of credit risk, risk identification, forms of credit risk, risk assessment and monitoring, credit risk mitigation, credit risk management process, control mechanisms, and factors posing challenges as independent variables and treated effective risk management in the bank's credit management system as the dependent variable. The results showed that efforts made by banks in the public and private sectors to reduce risk were positively and significantly correlated with the credit risk management procedure. Furthermore, the study recommended that the Reserve Bank of India (RBI) should explore the option of engaging a professional agency for borrower identification and selection to mitigate Non-Performing Assets (NPA). It also recommended that the RBI create an independent rating agency to assess and certify all banks. It was suggested that more Asset Reconstruction Companies be established to provide banks with incentives to sell problematic assets and improve credit risk management. The report also recommended that banks use early signals to enable timely responses to non-performing assets (NPAs). In conclusion, it emphasized the significance of training bank employees and borrowers to help lower the percentage of non-performing assets in India.

(Jamshed, 2023) analyzed the risk factors affecting the asset quality of commercial banks in Pakistan. The research focused on 8 Pakistani commercial banks spanning from 2015 to 2020. Non-Performing Loans (NPL) served as the dependent variable, while explanatory variables included Capital Adequacy Ratio (CAR), Return on Asset (ROA), Return on Equity (ROE), Ratio of Non-Interest Income (NIIT), Ratio of Operating Cost (OCI), Ratio of Liquid Asset (LAT), Log of Asset (LOGA), Ratio of Credit to Asset (RCA), Ratio of Credit to Deposit (RCD), Ratio of Price Earning (RPE), and Earnings per Share (EPS). The investigation was driven by the difficulties Pakistan's banks were facing, which included declining capital levels, diminishing earnings, and deteriorating asset quality. The study determined that the main causes of the reduction in asset quality were low capitalization, low profitability, weak managerial and operational techniques, and a narrow portfolio. Furthermore, a liquidity gap was identified for the Price Earning Ratio, Earnings per Share, Credit to Deposit Ratio, and Liquid Asset to Total Asset Ratio. The findings of the study revealed that several variables had a statistically significant effect on non-performing assets, including price earnings ratio, return on equity, credit to deposit ratio, and bank credit to deposit. The study suggested the banks to improve operating and management efficiency, asset and risk management and liquidity to mitigate non-performing assets, which will eventually improve asset quality and profitability.

3. ANALYSIS AND INTERPRETATION

Table 3 Descriptive Statistics of Bank Specific Credit Risk Variables of Public Sector Commercial Banks

	GNPA	NNPA	CRDR	LL	PSADTAD	SADTAD	TLTAD
Mean	1.79	0.96	4.23	0.40	3.52	4.22	3.99
Median	1.87	1.02	4.26	0.33	3.51	4.44	3.99
Maximum	3.40	2.73	4.45	2.22	4.17	4.60	4.27

Minimum	-0.46	-1.37	3.85	-2.02	3.04	4.24	3.65
Std.Dev.	0.87	0.90	0.11	0.86	0.21	0.07	0.16
Skewness	-0.22	-0.33	-1.27	-0.02	0.18	-0.26	-0.16
Kurtosis	2.10	2.46	4.84	2.43	2.91	2.59	2.34
Jarque-Bera	7.54	5.34	73.73	2.41	1.03	3.31	4.00
Probability	0.02	0.07	0.00	0.30	0.60	0.19	0.14
Sum	322.39	172.87	761.80	72.78	633.32	798.48	718.49
Sum Sq.Dev.	135.60	146.12	2.29	133.61	8.19	0.99	4.31
Observations	180	180	180	180	180	180	180

Table 3 presents the descriptive statistics for bank-specific credit-risk variables of Public Sector Commercial Banks (PSBs) from 2008-09 to 2022-23. This table summarizes data from 12 public sector banks, amounting to 180 observations over the study period. The Gross Non-Performing Assets (GNPA) shows variability, ranging from a minimum of -0.46 to a maximum of 3.40. The mean GNPA is 1.79, with data deviating by 0.87 standard deviation. Net Non-Performing Assets (NNPA) spans from -1.37% to 2.73%, with a mean of 0.96% and a deviation of 0.92 times. The skewness of the dependent variables ranges from -0.33 to -0.22, and kurtosis values range from 2.10 to 2.46. GNPA and NNPA show significant relationships, with p-values less than 0.05. The Jarque-Bera test indicates that the dependent variables are normally distributed, as their values exceed the 0.05 threshold.

Among the independent variables, the Credit to Deposit Ratio (CRDR) ranges from 3.85% to 4.45%, with a mean of 4.23% and a standard deviation of 0.11. Loan Losses (LL) varies between -2.02% and 2.22%, with a mean of 0.40% and a deviation of 0.86. Priority Sector Advances to Total Advances (PSADTAD) has a minimum of 3.04% and a maximum of 4.17%, averaging 3.52% with a deviation of 0.21. Secured Advances to Total Advances (SADTAD) ranges from 4.24% to 4.60%, with an average of 4.22% and a deviation of 0.07. Term Loans to Total Advances (TLTAD) spans from 3.65% to 4.27%, with a median of 3.99% and an average of 3.99%, deviating by 0.16. The skewness of independent variables ranges from -1.27 to 0.18, with kurtosis values between 2.91 and 4.84. CRDR show significant relationships, with p-values less than 0.05. The Jarque-Bera test also confirms that the independent variables are normally distributed, with values exceeding the 0.05 benchmark.These data can therefore be utilized for additional inferential research.

Table 4 Multiple Correlation of Bank Specific Credit Risk Variables of Public Sector Commercial Banks

VARIABLES	CRDR	LL	PSADTAD	SADTAD	TLTAD
CRDR	1.00				
LL	-0.29	1.00			
PSADTAD	-0.46	0.39	1.00		

SADTAD	-0.20	0.26	0.27	1.00	
TLTAD	0.01	-0.13	-0.02	0.02	1.00

Table 4 describes the correlation matrix of 5 Bank specific credit risk variables of Public Sector Commercial Banks. An analysis of the correlation matrix reveals the strength and direction of the relationships between the variables. Additionally, the correlation matrix shows the data's multicollinearity components. The CRDR demonstrates a weak and negative correlation between all of the variables, with the exception of TLTAD. The association between CRDR and TLTAD is marginal (0.01) but positive. The LL shows a positive association with PSADTAD of 0.39% and with SADTAD of 0.26%, suggesting that there is a minor rise in provisions for advances in relation to increased loan losses. There is a slight positive connection between PSADTAD and SADTAD of 0.27 %. TLTAD is clearly independent of all the other variables since it shows very little correlation with others. This low correlation among variables implies that these bank-specific credit risk variables are not highly collinear and can be combined in regression models without a substantial risk of multicollinearity issues. Consequently, they exhibit consistent performance as predictors in models that assess the credit risk of public sector banks.

Table 5 Heteroskedasticity test of Bank Specific Credit Risk Variables of Public Sector Commercial Banks

F-Statistics	1.47752	Prob.F (5,173)	0.1995
Obs*R-squared	7.33076	Prob. Chi-Square (10)	0.1972

Table 5 presents the Heteroskedasticity test results for Bank-Specific Credit Risk factors of Public Sector Commercial Banks. The F statistic and observed R-squared values are 1.477 and 7.331, respectively. The chi-square p-value above the significance level of 0.05, indicating that the data do not reject the null hypothesis, hence suggesting the lack of significant heteroskedasticity. Consequently, this model can be employed in regression analysis to yield efficient estimates, accompanied by reliable standard errors, resulting in accurate results for public sector bank credit risk assessment.

Table 6 Breusch – Godfrey Serial Correlation LM Testof Bank Specific Credit Risk Variables of Public Sector Commercial Banks

F-Statistics	1.79793	Prob.F (2,170)	0.1688
Obs*R-squared	3.70781	Prob. Chi- Square (2)	0.1566

Table 6 illustrates the Breusch – Godfrey Serial Correlation LM Testof Bank Specific Credit Risk Variables of Public Sector Commercial Banks. The observed R-Squared value of 3.708 is utilized to identify serial correlation; the p-value of 0.1566, exceeding the significance threshold of 0.05, suggests that we do not reject the null hypothesis. This indicates the absence of serial autocorrelation, allowing these credit risk indicators to be utilized for model estimation, hence providing an efficient and trustworthy hypothesis testing.

Table 7 Augmented Dickey Fuller Unit Root Test of Bank Specific Credit Risk Variables of Public Sector Commercial Banks

VARIABLES	**LEVEL**	**FIRST DIFFERENCE**	**ORDER OF INTEGRATION**
GNPA	-10.05432	-9.879309	I(I)
NNPA	-9.529464	-9.407303	I(I)
CRDR	-6.722400	-12.17467	I(I)
LL	-9.248289	-10.34924	I(I)
PSADTAD	-3.339657	-12.16791	I(I)
SADTAD	-4.262725	-12.83950	I(I)
TLTAD	-4.149120	-15.98698	I(I)

The Augmented Dickey Fuller Unit Root test of bank specific credit risk variables of Public Sector Commercial Banks is presented in Table 7. For a regression model to be constructed, the variables must be stationarity. Level testing revealed that few variables were non-stationarity. Initial differencing is carried out to construct a robust regression model. As a result, the ADF test values significantly decline, often dropping below critical cutoffs. The data appears to be stationary based on this. With this, we can rule out the idea that the differenced data does not have a unit root.

Table 8 Johansen's Cointegration between GNPA&Its Bank Specific Variables of Public Sector Commercial Banks

Cointegration	**Eigen Value**	**Trace Statistic**	**Critical Value (5%)**	**Max Eigen Value**	**Critical Value (5%)**
CRDR	0.37	278.26	69.81	81.77	33.88
LL	0.33	196.48	47.86	70.62	27.58
PSADTAD	0.26	125.87	29.80	52.01	21.13
SADTAD	0.21	73.85	15.49	41.27	14.26
TLTAD	0.17	32.59	3.84	32.59	3.84

Table 8 shows the Johansen's cointegration of GNPA and bank specific parameters to public sector commercial banks. If the Max Eigen or Trace statistic is greater than the critical value at the 5% level of significance, then the null hypothesis can be rejected. The trace statistics and Max Eigen values of all the independent variables of the public sector commercial bank are greater than the critical values, indicating a long-term cointegrating relationship with GNPA. This correlation over the long term suggests that these bank-specific measures may serve as predictors or contributors to GNPA in public sector commercial banks, as they are strongly correlated with the level of non-performing assets.

Table 9 Johansen's Cointegration between NNPA&Its Bank Specific Variables of Public Sector Commercial Banks

Cointegration	Eigen Value	Trace Statistic	Critical Value (5%)	Max Eigen Value	Critical Value (5%)
CRDR	0.40	282.31	69.81	89.59	33.88
LL	0.30	192.71	47.86	61.56	27.58
PSADTAD	0.27	131.15	29.80	54.72	21.13
SADTAD	0.21	76.44	15.49	40.56	14.26
TLTAD	0.19	35.88	3.84	35.88	3.84

Table 9 explains the Johansen's Cointegration between NNPA and its Bank specific variables of public sector commercial banks. The significance of the cointegration relationship between the independent and dependent variables is shown by the Eigen value. At a value of 0.40, the CRDR has a strong relationship. It is followed by the Provision for loss loan (LL) at 0.30, the PSADTAD at 0.27, the SADTAD at 0.21, and the TLTAD at 0.19. At the 5% level of significance, all the variables indicate a long-term cointegrating relationship with NNPA, as their Trace statistics and Max Eigen values are greater than the critical value. The results show that these variables have potential for long-term usage in predicting Net non-performing asset model.

Table 10 Granger Causality Test ofGNPA&Its Bank Specific Variables of Public Sector Commercial Banks

Null Hypothesis	F-Statistics	Probability Value	Conclusion
CRDR does not Granger Cause GNPA	6.481	0.002	Rejected H_0
GNPA does not Granger Cause CRDR	6.748	0.002	Rejected H_0
LL does not Granger Cause GNPA	2.673	0.072	Rejected H_0
GNPA does not Granger Cause LL	5.077	0.007	Rejected H_0
PSADTAD does not Granger Cause GNPA	0.249	0.779	Accepted H_0
GNPA does not Granger Cause PSADTAD	4.749	0.009	Rejected H_0

SADTAD does not Granger Cause GNPA	4.063	0.019	Rejected H_0
GNPA does not Granger Cause SADTAD	0.933	0.395	Accepted H_0
TLTAD does not Granger Cause GNPA	0.993	0.372	Accepted H_0
GNPA does not Granger Cause TLTAD	1.445	0.239	Accepted H_0

Table 10 explains the Pairwise Granger Causality of GNPA and its bank specific variables of Public Sector Commercial Banks. The evidence suggests a bidirectional link for CRDR and LL, as the null hypothesis is rejected in both directions (significance value < 0.05). It follows that alterations in CRDR and LL might anticipate alterations in GNPA and inversely. The null hypothesis is rejected in only one direction for PSADTAD and SADTAD, suggesting a unidirectional relationship with GNPA. Since the null hypothesis is not rejected, there is no evidence of a causal link between TLTAD and changes in GNPA.

Table 11 Granger Causality Test ofNNPA&Its Bank Specific Variables of Public Sector Commercial Banks

Null Hypothesis	**F-Statistics**	**Probability Value**	**Conclusion**
CRDR does not Granger Cause NNPA	6.517	0.002	Rejected H_0
NNPA does not Granger Cause CRDR	4.567	0.011	Rejected H_0
LL does not Granger Cause NNPA	1.432	0.242	Accepted H_0
NNPA does not Granger Cause LL	22.759	1.701	Accepted H_0
PSADTAD does not Granger Cause NNPA	1.924	0.149	Accepted H_0
NNPA does not Granger Cause PSADTAD	3.036	0.050	Rejected H_0
SADTAD does not Granger Cause NNPA	3.266	0.041	Rejected H_0
NNPA does not Granger Cause SADTAD	3.432	0.034	Rejected H_0
TLTAD does not Granger Cause NNPA	1.361	0.259	Accepted H_0
NNPA does not Granger Cause TLTAD	3.871	0.023	Rejected H_0

The Granger causality link between NNPA and bank-specific factors of public sector commercial banks is discussed in Table 11. According to the findings, NNPA has a reciprocal association with CRDR and SADTAD, implying that both variables are affected by and contribute to NNPA. Additionally, NNPA has a one-way impact on PSADTAD and TLTAD, which suggests that changes in NNPA can predict these factors. Since neither variable predicts the other, LL and NNPA do not significantly correlate. Based on these findings, CRDR, SADTAD, PSADTAD, and TLTAD could be included in public sector bank NNPA prediction models.

Table 12 Hausman Test of Credit Risk and its Bank Specific Variables of Public Sector Banks

Dependent Variable	Test Summary	Chi-Sq. Stat	Chi-Sq.d.f.	Prob.	Effect
GNPA	Cross Section random	16.2149	5	0.0063	Fixed
NNPA	Cross Section random	6.0413	5	0.3022	Random

Table 12 explains the Hausman Test of credit risk and its bank specific variables of public sector commercial banks. The association between GNPA and its independent variables can be better predicted using the Fixed Effect Model, as the p-value is less than 0.05, indicating that the test rejects the null hypothesis. When building a model for NNPA, it is recommended to utilize the Random Effect Model because the p-value is more than 0.05.

Table 13 Panel Data Regression Model of Credit Risk and Its Bank specific Variables of Public Sector Banks

Dependent Variable	Model 1 – GNPA		Model 2 – NNPA	
Independent Variables	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
C	-4.50	0.101	-8.117	0.015
CRDR	-0.752	0.052	0.010	0.982
LL	0.791	0.000	0.862	0.000
PSADTAD	0.466	0.050	-0.539	0.039
SADTAD	1.316	0.007	2.320	0.001
TLTAD	0.483	0.051	0.073	0.786
R-squared	0.865		0.758	
Adjusted R-squared	0.852		0.751	
F-statistic	65.245		109.169	
Prob(F-statistic)	0.000		0.000	
Durbin-Watson stat	1.043		0.980	

Table 13 explains the Panel Data Regression model of credit risk management by Public Sector Commercial Banks. CRDR exhibits a negative coefficient and statistically significant effect on GNPA suggesting that it reduces GNPA, potentially because more efficient credit utilization could lower the likelihood of loans turning non-performing. The provision for Loan

Loss (LL) has a positive coefficient of 0.791 with high significance of 0.000, implying a strong association with GNPA. This reflects that banks with higher GNPA are more likely to have more allocation for NPA provisions. It also implies that the increased provisions have adverse effect on profitability. Priority Sector Advances to Total Advance (PSADTAD) exhibits a positive coefficient (0.466) and a marginally significant relationship (0.050), suggesting an increase in PSADTAD would slightly increase GNPA. These are advances which carry high chances of default risk and subsequently may turn into non-performing assets. Secured Advances to Total Advances (SADTAD) exhibits a strong significance of 0.007 with a positive ecoefficiency of 1.316, indicating high default risk possibly due to collateral foreclosure difficulties or industry-specific issues. It is inferred that though advances are secured through collateral assets banks have an increased NPA. Term Loans to Total Advances (TLTAD) displays a positive (0.483) and a significant relationship (0.051) with GNPA, suggesting that long term risk may be associated with increased risk due to macro-economic instability, inefficiency of management and other unprecedent factors.

CRDR does not exhibit statistical significance as the p-value is more than 0.05, indicating no meaningful impact on NNPA. LL is highly significant with a p-value of 0.000 and it has a positive effect on NNPA with a coefficient of 0.862. This indicates a close relationship between loan loss provisions and net non-performing assets. PSADTAD has a negative and a significant relationship, implying that PSADTAD could reduce NNPA. This could reflect regulatory relief or targeted measures that mitigate defaults in priority sectors. SADTAD has a positive and highly significant impact as their p-value and coefficient are 0.001 and 2.320 respectively. This mirrors the trend seen with GNPA, possibly indicating sectoral or collateral challenges that affect secured advances. TLTAD is not significant in this model as the p-value is 0.786 which is less than 0.05, implying no meaningful impact of term loans on NNPA.

The model summary shows that the selected regressors effectively explain GNPA and NNPA to a degree of 86.5 % and 75.8% respectively. It shows the high explanatory power of regressors on GNPA and NNPA. The Adjusted R-Square values of chosen regressors are 0.852 and 0.751 confirming the model fit of GNPA and NNPA. The F-Statistics and p-value of both the models indicate that the model exhibits an overall significance The Durbin-Watson statistic value is less than 2, indicating that there is no autocorrelation among the data observations.

4. FINDINGS AND SUGGESTION

Findings

- CRDR, LL, SADTAD, and TLTAD are important factors in determining GNPA, or gross non-performing assets.
- Provisioning and secured loans are the main causes of net non-performing assets (NNPA), which are significantly impacted by LL and SADTAD.
- As a measure of the risk and regulatory interventions in priority lending, the Priority Sector Advances to Total Advances (PSADTAD) had a mixed effect, affecting GNPA favorably while NNPA was mitigated.

- The results of the regression analysis showed that the variables that were chosen had a strong explanatory power (NNPA: 75.8% and GNPA: 86.5%).
- Inadequate credit monitoring, recovery, and evaluation practices are highlighted by persistently high GNPA and NNPA levels.
- Collateral foreclosure issues or weakness specific to certain industries may have contributed to the very high default risks seen with secured loans.
- The bidirectional causation between CRDR, LL, and GNPA shows how credit growth, loan losses, and asset quality are always interacting with one other.

Suggestions

- Better risk profiling should be a priority in the credit assessment process, especially for secured loans and advances to the priority sector.
- Proactively monitor borrower behaviour and financial health with comprehensive frameworks.
- Improve provisioning strategies to find the best balance between reducing risk and making money, especially since loan losses are increasing
- Reducing delays in identifying distressed assets requires the establishment of early-warning methods.
- Address sectoral vulnerabilities and increase collateral management to tailor strategies for secured advances.
- Reducing defaults requires thorough evaluation of term loans that take operational and macroeconomic risks into account.
- Develop sector-specific risk guidelines and borrower evaluation standards in conjunction with the Reserve Bank of India (RBI).
- Promote the use of cutting-edge credit risk management tools by public sector banks and teach employees the best ways to use them.
- Enhance econometric insights with artificial intelligence and machine learning to monitor credit risk in real-time and conduct predictive modelling.
- Make an investment in digital systems to automate the recovery and disbursement of credit.

5. CONCLUSION

A review of public sector commercial banks' credit risk management practices from 2009 to 2023 shows that data-driven and strategic methods are crucial for reducing risks and making banks more stable. The results highlight the fact that a number of factors affect NPAs, including the Credit to Deposit Ratio (CRDR), Loan Loss Provisions (LL), Secured Advances to Total Advances (SADTAD), and Priority Sector Advances to Total Advances (PSADTAD). Persistently high nonperforming assets (NPAs) show that credit assessment, monitoring, and recovery procedures are inefficient, even though econometric models proved useful for anticipating and managing credit risks.
The study highlights the need of enhancing credit risk strategies with the use of sector-specific interventions, advanced analytical techniques such as econometric modelling and machine learning, and strong borrower profiling. For public sector banks to accomplish their economic

development goals and experience sustainable growth, it is crucial for them to improve operational efficiency, increase regulatory compliance, and promote technological integration. The findings of this study lay the groundwork for future investigations into the changing dynamics of credit risk and the use of cutting-edge quantitative methods to improve risk management strategies.

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