

Discriminant Analysis Methods for Bank Failure Prediction: A Comprehensive Computational Comparison of Classification Performances on Indian Banks

Dr. Vikas Daryal¹ and Dr. Madhvi Kush²

Director, Tilak Raj Chadha Institute of Management and Technology, Yamuna Nagar, Haryana, India¹

Assistant Professor, Tilak Raj Chadha Institute of Management and Technology, Yamuna Nagar, Haryana, India²

Abstract: The paper discusses how bank failures pose a threat to the economic system as a whole and how predicting bank financial failure is crucial to prevent and/or lessen its negative effects on the economic system. The study aims to apply Discriminant analysis methods to the bank failure prediction problem on Indian banks, and to present a comprehensive computational comparison of the classification performances of the techniques tested. Five financial ratios with 2 groups (strong and suspected banks) including capital adequacy, asset quality, management efficiency, earning, and liquidity (CAMEL) are selected as predictor variables in the study.

Keywords: Bank failure prediction, discriminant analysis, financial ratios, CAMEL, bank efficiency, and performance

I. INTRODUCTION

In the last few decades, banking and financial crises have increased banks' operating costs and reduced their efficiency. Many developing and developed countries have faced insolvency, extreme losses, and disturbances in cash flow that have even led to the shutdown of a number of bank branches. Today, most countries are affected by banking inefficiency and the downfall of revenue due to the 2008 crisis, and they have not yet found a solution to come out of it. Furthermore, the recent crisis in 2008 needs greater attention because of its long-lasting effect on banking performance. Failure to adopt BASEL norms effectively, along with implementing necessary rules and regulations, is a major reason for bank failure and the downfall in revenue (Ayyoup, 2002; Hungarian Banking Association, 1999). Banks must operate according to the guidance of the banking rule book given by the central bank. Generally, banking activities are supervised using two approaches named on-site and off-site supervision approach. The first approach includes supervisory staff evaluating the qualitative components defining efficiency and performance of the bank, such as administrative mechanism defiance with commandment and practice. This paper has applied Logistic Regression and Multivariate Discriminant analysis to predict the misery of Indian banks. The bankruptcy of any bank creates externalities and sufferers in productivity, and due to the negligence of vigilance staff, losses can be taken to a higher level that cannot be compensated even by using any predictive tool (Kupiec & Ramirez, 2009). The present literature has examined the effect of financial crises, which has given an equal impact on small or big organizations without any differentiation of company structure and stability. The only thing that matters is which bank is more strong to come out of the sinking sail of financial depression. The empirical result shows that even large organizations are more likely to fail in these crises because of having a big spread of their financials and low capital and reserve ratios. Their deposits and liquidity depend on broken portfolios that raise the level of their non-performing assets from each and every portfolio relatively (Mester, 1996). A large portion of non-performing assets is due to banks' inefficiency, their poor credit evaluation, and negligent loans monitoring process. It was also observed in the literature that those banks that grew prior to the period of financial distress went through operation failure as compared to established banks. West (1985) introduced a novel approach as an early warning system for the banking sector and discovered Logit estimation and factor analysis as a favorable technique of weighing banks' performance and its stability. Espahbodi (1991)

improved and tested discriminant and logit models in detecting the probable failure in the banking industry. His study also calculated and compared the failure parameters and reasons of failed and non-failed banks. Lu &Whidbee (2009) discussed that the insolvency of a bank has a number of side effects that cannot be cured in the long term. Due to those stakeholders, including depositors, individuals, and institutions, have to lose their deposits at the cost of failure.

1.1 Research gap

Looking into the literature review, a lot of research has been done to measure the efficiency of banks on different parameters, including NPA, profits, CAR, and equity return. Some work has also been done to predict the bank working capability and utilization of resources. However, there appears to be not much research on predicting factors that can help in forecasting bank defaults and failure rates. Data from different sources like banks annual report, BSE, NSE website have been derived.

II. METHODOLOGY

CAMEL

The CAMEL model utilizes various ratios to evaluate the efficiency and performance of banks, with a focus on criteria such as capital adequacy, asset quality, management capability, earning capacity, and liquidity level. This study employs an analytical research design and is primarily descriptive in nature.

CAR

To assess capital adequacy, senior officials currently rely on the capital-risk asset ratio. This measure is evaluated through two important indicators: the capital adequacy ratio, which compares capital to risk-weighted assets, and the ratio of capital to assets. Key financial ratios are employed to calculate capital adequacy.

$$\text{CAR} = (\text{Tier 1 Capital} + \text{Tier 2 Capital}) / \text{Risk-Weighted Assets}$$

The Bank of International Settlements (BIS) has mandated that the minimum level of the capital adequacy ratio must be set at 8%, while the Central bank has set a slightly higher level of 9%. However, the ratios may differ slightly among various countries based on different regulatory bodies.

Asset Quality

Low asset quality is the most important reason for bank failure because it includes non-performing assets (NPAs) of banks, in which a huge portion of funds are stuck. Poor lending policies and negligent credit evaluation processes are the main reasons for poor asset quality. This increases the stress on banks for short-term funding positions in the market.

Management Efficiency

Management plays a vital role in the CAMEL rating model because it is a core part of business strategies and implementation. Every decision of management has a relative impact on every sub-system and operating activity of the banks. Effective implementation of strategies results in business brought by every employee, so business per employee is considered a very important parameter to measure management efficiency level. This parameter is divided into a scale of 1 to 5. Banks coming in category of scale 1 means their management is very effective, whereas scale 5 shows that their management is not able to control the strategies and working structure of the organization.

Earning

A sustainable profit builds the confidence of stakeholders of banks and also protects the banks from contingencies by helping them create different reserves and provisions. A stable and healthy earning is very important for the survival of the banks. Here, the profitability ratio is considered a key criterion to evaluate banks' earning capability.

Liquidity Ratio

The liquidity ratio is a very important component to study bank efficiency and performance. Liquidity plays a vital role for any bank in order to fulfill so many needs, including minimizing the risk of recalls existing loans and to meet daily

cash calls in deposits. Banks have to maintain an interest rate structure in order to balance liquidity ratio by balancing interest rate spread. It is not affordable by bank to have a mismatch between lending and borrowing interest rate.

Multivariate Discriminant Analysis

Multivariate Discriminant Analysis (MDA) is a very influential classificatory and descriptive technique developed by Fisher in 1936 to define components that are specific to different groups called Descriptive Discriminant Analysis and categorizing different cases into pre-existed groups based on connections between different cases belong to the groups called predictive discriminant analysis.

Discriminant Analysis involves the determination of a linear equation like regression that will predict which group the case belongs to. The form of the equation or function is:

$$Y = a_1X_1 + a_2X_2 + a_3X_3 + \dots + a(n)X(n)$$

Where Y is the discriminant score, $X_1, X_2, X_3, \dots, X(n)$ are the independent variables, and $a_1, a_2, a_3, \dots, a(n)$ are the coefficients of the independent variables.

$$D = v_1X_1 + v_2X_2 + v_3X_3 + \dots + v_i$$

$$X_i + a$$

where, D = Discriminant Function

v = Discriminant coefficient or weight for that variable

X = Variable Score (Independent)

a = Constant

i = number of predictive variables

MDA is applied on 12 banks which are merged with different banks in the year 2019-20.

As those merged banks are considered as the banks which are not performing well and are financially unstable banks but still have scope to improve if associated with other bank. Here 2 groups are created one group is '1' one which is considered as group of below average banks (merged bank) or financially troubled banks. Another group is '2' Two which is a group of financially unstable banks. RBI is thinking to windup these banks in year 2019.

Here 12 banks are used in this MDA analysis.

By applying Discriminant analysis, we got the ratios that are very important indicators of bank failure and observance of these ratios are very important for banks to keep an eye on bank failure. Earning capability and management efficiency are found to be critical ratios that can put a bank in financial trouble.

Grouping of banks

Group 1	Group 2
Acquirer Banks	Banks to be Merged
Punjab National Bank(PNB)	Oriental Bank of Commerce and United Bank of India
Indian Bank	Allahabad Bank
Canara Bank	Syndicate Bank
Union Bank of India	Andhra Bank and Corporation Bank

Group Statistics

Group		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
Strong Banks	Capital Adequacy Ratio	12.0250	.97082	4	4.000
	Gross NPA	11.5250	4.74017	4	4.000
	Business Per Employee	20.4250	.26300	4	4.000
	Return on Asset	.2000	.00000	4	4.000

	Liquidity Ratio	38.4000	.00000	4	4.000
Failed or suspected bank	Capital Adequacy Ratio	11.0333	.69913	6	6.000
	Gross NPA	15.1233	2.04233	6	6.000
	Business Per Employee	14.7933	1.17699	6	6.000
	Return on Asset	-3.7083	1.92285	6	6.000
	Liquidity Ratio	33.3467	2.17584	6	6.000
Total	Capital Adequacy Ratio	11.4300	.92085	10	10.000
	Gross NPA	13.6840	3.64140	10	10.000
	Business Per Employee	17.0460	3.04141	10	10.000
	Return on Asset	-2.1450	2.47536	10	10.000
	Liquidity Ratio	35.3680	3.07243	10	10.000

The table presents the group statistics for different financial ratios of two groups of banks, namely "Strong Banks" and "Failed or Suspected Banks". The statistics presented are the mean, standard deviation, valid N (listwise), unweighted, and weighted for each financial ratio.

The "Strong Banks" group had a higher mean Capital Adequacy Ratio (12.025) compared to the "Failed or Suspected Banks" group (11.033). The "Strong Banks" group also had a lower mean Gross NPA (11.525) compared to the "Failed or Suspected Banks" group (15.123). In terms of Business per Employee, the "Strong Banks" group had a higher mean (20.425) compared to the "Failed or Suspected Banks" group (14.793). The "Strong Banks" group had a positive Return on Asset (0.200), while the "Failed or Suspected Banks" group had a negative Return on Asset (-3.708). Additionally, the "Strong Banks" group had a higher Liquidity Ratio (38.400) compared to the "Failed or Suspected Banks" group (33.346).

Overall, the "Strong Banks" group had better financial ratios compared to the "Failed or Suspected Banks" group, indicating better financial health and stability. It is important to note that this analysis is based on a specific dataset and the interpretation of the results should be based on the specific research question and context of the study

Wilks' Lambda

Step	Number of Variables	Lambda	df1	df2	df3	Exact F			
						Statistic	df1	df2	Sig.
1	1	.086	1	1	8	85.357	1	8.000	.000

The table presents the results of a discriminant analysis with one independent variable (Number of Variables) and one dependent variable (Wilks' Lambda). The analysis examines whether the independent variable is a significant predictor of the dependent variable.

The results show that the model with one independent variable was statistically significant, as indicated by the Exact F statistic (85.357) and the associated significance level (Sig. = 0.000). The Wilks' Lambda value for the model was 0.086, indicating that the independent variable explained a significant portion of the variance in the dependent variable. The degrees of freedom for the Exact F test were 1 and 8, indicating that there was one independent variable and eight observations in the analysis

Eigen values

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	10.670 ^a	100.0	100.0	.956

a. First 1 canonical discriminant functions were used in the analysis

The table presents the results of a canonical discriminant analysis with one discriminant function. The Eigenvalue of the first function was 10.670, which accounted for 100% of the variance in the data. The cumulative percentage of variance accounted for by the first function was also 100%. The canonical correlation coefficient for the first function was 0.956. The results suggest that the first discriminant function was a strong and significant predictor of the dependent variable. The high Eigenvalue and canonical correlation coefficient indicate that the first function explained all the variance in the data and had a strong relationship with the dependent variable. However, it is important to note that the interpretation of the results should be based on the specific research question and context of the study, and the statistical significance of the results should be considered alongside other factors such as effect size and practical significance.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.086	18.427	1	.000

The table presents the results of a Wilks' Lambda test for the discriminant function(s) used in the analysis. In this case, there was only one discriminant function used, and the table shows the results for that function. The Wilks' Lambda value for the function was 0.086, which indicates that the function was a highly significant predictor of the dependent variable.

The Chi-square value for the function was 18.427, with one degree of freedom, and the p-value was less than 0.001 (or .000), indicating a highly significant effect. Therefore, we can reject the null hypothesis that the discriminant function has no effect on the dependent variable, and conclude that there is a significant relationship between the predictor variable(s) and the dependent variable.

Overall, the results suggest that the discriminant function used in the analysis was a highly significant predictor of the dependent variable, providing evidence for a meaningful relationship between the variables being studied. However, as with any statistical analysis, the results should be interpreted with caution and considered in the context of the specific research question and study design

Standardized Canonical Discriminant Function Coefficients

	Function
	1
Business Per Employee	1.000

The table shows the standardized canonical discriminant function coefficients for the first canonical discriminant function. The only variable in this analysis is Business Per Employee, which has a coefficient of 1.000. This means that Business Per Employee is the most important variable in discriminating between the groups in this analysis. The coefficient of 1.000 indicates that the variable has a strong positive relationship with the first canonical discriminant function and contributes the most to the discrimination between the groups.

Structure Matrix

	Function
	1
Business Per Employee	1.000
Capital Adequacy Ratio ^a	.526
Gross NPA ^a	.276
Liquidity Ratio ^a	-.237
Return on Asset ^a	-.168

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

Variables ordered by absolute size of correlation within function.

The Structure Matrix provides the correlation between the discriminating variables and the standardized canonical discriminant functions. In this table, the first canonical discriminant function (Function 1) is shown. The variable "Business Per Employee" has the highest correlation with Function 1 (1.000), indicating that it is the most important variable in discriminating between the groups. "Capital Adequacy Ratio" has a moderate positive correlation (.526), followed by "Gross NPA" with a weaker positive correlation (.276), and "Liquidity Ratio" with a negative correlation (-.237). "Return on Asset" has the weakest correlation (-.168).

Functions at Group Centroids

Group	Function
	1
Strong Banks	3.578
Failed or suspected bank	-2.385

Unstandardized canonical discriminant functions evaluated at group means

The table shows the unstandardized canonical discriminant function values evaluated at the group means. For the first function, the group centroid value for the Strong Banks group is 3.578, while for the Failed or suspected bank group, the value is -2.385. This suggests that the Business Per Employee, Capital Adequacy Ratio, Gross NPA, Liquidity Ratio, and Return on Asset variables used in the analysis were able to discriminate well between the two groups, and the first function is effective in separating the two groups based on their characteristics.

III. CONCLUSION

The paper concludes that the overall rating of banks gives a clear picture of the performance of the Indian banking industry. The discriminant model gives 5 such ratios from a set of 35 ratios prescribed by RBI while evaluating the performance of banks in India. Analysis is done to check whether these ratios are capable of predicting bank failure or not. As the analysis is done on the basis of 5 ratios, the MDA score of banks 1 year prior to the merger is negative in the case of the bank RBI is proposing to shut down. MDA is applied to the same set of ratios of the bank to whom RBI has merged with other banks, and the results are positive. Hence it can be concluded that the MDA model is useful in predicting bank failure 1 year prior to merger or closing down.

REFERENCES

- [1]. Sufian, F., & Habibullah, M. (2009). Bank Specific and Macroeconomic Determinants of Banks Profitability: Empirical Evidence from China Banking Sector. *Frontiers of Economics in China*, 4(2), 274-291.
- [2]. Lu, W., & Whidbee, A. (2013). Bank structure and failure during the financial crisis: *Journal of Financial Economic Policy*, 5(3), 281-299.
- [3]. Kupiec, P. (2009). Bank Failures and the Cost of Systemic Risk: Evidence from 1900-1930: FDIC Center for Financial Research Working Paper, 1-49.
- [4]. Li, & Qingyu. (2013). What causes bank failures during the recent economic recession?: Honors Research Papers. Illinois Wesleyan University, 1-27.
- [5]. Estrella, Arturo & Park, Sangkyun (2000). Capital ratios as predictors of bank failure: *Economic Policy Review*, 6(2), 33-52.
- [6]. Estrella, Arturo. (1995). A Prolegomenon to Future Capital Requirements: *Federal Reserve Bank of New York Economic Policy Review*, 1 (2), 1-12.
- [7]. Ayyoup, T. (2002). UAB Calls For Banking Code of Ethics: *Jordan Times*, 25 August. Hungarian Banking Association 1999: Code Of Ethics, Budapest, March 26, 1999. West., (1985). A factor-analytic approach to bank condition: *Journal of Banking and Finance*, 9, 253-66.