FINANCIAL HEALTH ANALYSIS OF INDIAN BANKING INDUSTRY (Through Discriminant Analysis)

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Abstract

The sound financial health of the banking industry is an essential prerequisite for the economic stability and growth of a country. As a consequence, the assessment of banks' financial conditions is a fundamental goal for regulators. Accurate prediction of the financial performance of banks is of the utmost importance to one and all. The purpose of the present study is to develop a prediction model to predict the financial health of the Indian banking industry with a high degree of accuracy. Public and private sector banks in India are selected as sample units for the study. The present study is based on secondary data gathered from the official site of RBI over a study period of 2013-14 to 2017-18. In the study, the financial health of sample banks is a dependent variable which is a categorical variable in nature, and predictor variables are financial ratios which are metric variables. Discriminant analysis is applied to develop the prediction model. The Discriminant function obtained from the analysis is **D= -2.964 + .180 X1 + .248 X2.** Two ratios, Return on Equity (X_1) and Return on Advances (X_2) identified as significant in Discriminant functions. The model used in this research proved to be highly effective as the model has predicted the status of the financial health of sample banks with high accuracy, i.e., 97.5%. The model's validity test indicates that the Discriminant model is suitable for predicting the financial health of any bank in India.

Key Words: Financial Health, Bankruptcy, Factor Analysis, Discriminant Analysis.
JEL Classification: M40, M41, M49, G21

Introduction

The sound financial health of the banking industry is an essential prerequisite for the economic stability and growth of a country. As a consequence, the assessment of banks' financial conditions is a fundamental goal for regulators. At the International level, banking crises have a long history. In India, also many times, poor performing banks merged with healthy banks. In all cases, banking crises resulted in large losses of wealth & disruptions in the supply of credit for investment and commerce. Fortunately, a banking failure in India has been an uncommon phenomenon because of an effective regulatory mechanism and timely interventions of regulations to save weak banks through necessary mergers and acquisitions. Experience gained from the past banking crises suggests an essential need for identifying banks with potential problems before they face insolvency or financial crises. **(Ecer, 2013)[1]**. Thus the accurate prediction of financial performance is of utmost importance to one and all.

Traditionally to develop the bankruptcy prediction model, researchers have used statistical techniques such as Multiple Discriminant Analysis (MDA) **(Altman, 1968[2], Deakin, 1972[3], Sinkey, 1975[4], Jones, 1987[5])**, Logit **(Ohlson, 1980[6])**, Probit **(Zmijewski, 1984[7]),** and Multiple Linear Regression **(Bakar & Tahir, 2009[8]).** All these techniques identify the relationship between the set of variables. The variables are in the form of dependent variables and independent variables. For the multiple regression and multivariate analysis of variance, dependent and independent variables should be metric variables. There may be situations where independent variables are metric variables in real-life cases, but dependent variables are categorical variables. In this situation where the dependent variable is categorical, Discriminant analysis is the technique for the analysis. (**Hair et al. 2015[9], Bajpai 2011[10]).** In the present study, to check the financial health of the Indian banking industry, a prediction model has been developed. Financial health is the categorical variable (i.e., dependent variable) for the study; hence, the Discriminant analysis technique has been used.

Review of Literature

Accumulating accounting research on predicting business firms' failures has been evolved since **Altman (1968)**[2] used Discriminant Analysis to predict bankruptcy by using financial ratios. Altman developed a z-score model using ratios as its foundation. With the help of the Z- Score model, Altman could predict financial efficiency /bankruptcy up to 2-3 years in advance. Various models have been developed following Altman's z-score model. **Adriatico (2019)**[11] used the Altman Z-Score model and current ratio to predict potential corporate financial distress of Philippine companies. The study's findings revealed that out of selected 45 companies, 35 companies could become financially distressed when subjected to the Altman Z-score model. **Mohammed *et al.* (2017)**[12] compared Discriminant Analysis and the Support Vector Machines method to check the prediction accuracy of both techniques. Discriminant analysis identified 3 ratios with the highest predictive power. **Wijekoon & Azeez (2015)**[13] developed an integrated model using the logistic regression analysis to predict the corporate failure of listed companies in Sri Lanka. The model was able to predict with 88.57% accuracy one year prior to failure. **Jan & Marimuthu (2015)**[14] applied the Altman model to the sample banks in the Islamic banking industry and performed a comparative analysis of their financial characteristics concerning bankruptcy. The study found the Saudi Arabian Islamic banks less bankrupt and Malaysian Islamic banks more bankrupt as they entitled the bottom four positions on the z-score bankruptcy profile list. **Fago (2014)**[15] also developed a statistical model and assessed the significance of variables in predicting financial institution failure in the context of Nepal, using the Discriminant Analysis technique. **Pam (2013)**[16]**, Ante & Ana (2013)**[17]**, Uchenna & Okelue (2012)**[18]**, and Sr. & Ahmad (2011)**[19] investigated the potency of the Multiple Discriminant Analysis model (MDA) in ascertaining the state of health of banks. These studies identified the financial ratios that are most significant in bankruptcy prediction. All reviewed studies concluded that MDA is a potential tool in the prediction of the possible failure

Research Gap

Various researchers viz. **Altman (1968)**[2], **Adriatico (2019)**[11] **Mohammed *et al.* (2017)**[12] **Wijekoon & Azeez (2015)**[13] have used Discriminant Analysis to predict corporate financial distress. Although, at international level, a lot of work has been done regarding assessment of financial health of banking industry by using multivariate techniques, yet prediction prespective of financial health of banking industry did not analyze. However Multiple Discriminant Analysis **(Pam (2013)**[16]**, Ante & Ana (2013)**[17]**, Uchenna & Okelue (2012)**[18]**, and Sr. & Ahmad (2011)**[19]**), and** Altman model (**Jan & Marimuthu (2015)**[14]), have been used extensively.

After an intense literature review, it concluded that studies related to a prediction model for the banking industry are done using Discriminant Analysis at the international level. But, in the Indian context, no such research has been found. As per best to our knowledge gathered from the literature review, no study has developed a prediction model using India's scheduled commercial banks. The study has not used Altman's model ratios or some other model's ratios. It has find out new ratios that predict status of financial health of sample banks. Thus this study fills a significant gap. Here, an attempt is made to develop a prediction model to predict the Indian banking industry's financial health.

Objectives of the study:

1) To develop a prediction model to predict the financial health of the Indian banking

industry using Discriminant analysis statistical technique.

2) To test the predictive power of the above prediction model.

Hypothesis:

H_{01}: The predictive power of own developed prediction model is satisfactory; it means there is no significant difference between predicted and validity scores of prediction model.

Research Methodology

In the study, the basic secondary data (Financial ratios of sample banks) required for the analysis collected from the Reserve Bank of India **(Database on Indian Economy, RBI).** The present research work used five financial years' data of 2013-14 to 2017-18. A five-year study seems appropriate for establishing a trend in various financial parameters and the country's economic scenario more or less constant for five years.

The scheduled commercial banks in India (Public & Private sectors), chosen as a sample. There are 42 scheduled commercial banks (Public & Private) presently working in India (at the time of writing the paper). Sample banks are selected based on the availability of data for the whole study period. Hence, out of 42 banks, 40 banks have been selected as sample banks from the private and public sectors. Multivariate techniques, i.e., factor analysis and Discriminant analysis used for the study. The 'z' test has been applied to test the hypothesis.

Prior Classification of Sample Units:

Discriminant analysis requires a priori group. The financial health of sample banks is measured based on the average Return on Assets (ROA) of all sample banks as suggested in previous studies. Sample banks have been classified based on their financial health into a priori groups, i.e., weak banks and healthy banks. In the analysis, weak banks denoted '0" and healthy banks '1". The a priori defined group is defined based on the overall average value of return on assets (ROA) of sample banks. The bank, which reported a lower ROA value than the overall average ROA value, referred to a weak bank, and the bank, which said a higher ROA value than the overall average value of ROA of all sample banks,' referred to as a healthy bank **(Kothari & Bhanawat)**[20]. An average of five years of data (2013-14 to 2017-18) has been taken to compute the average ROA of each sample bank. Following the criteria, out of 40 sample banks, 22 banks are recognized as weak banks, and 18 banks are healthy.

Financial Variables

For the present study, 15 financial variables are taken into consideration. The selection criterion for these financial variables is CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earning Capacity, and Liquidity) ratios and financial ratios, as suggested in previous studies. CAMEL ratios are used by the supervisory bank authorities to review the banks' level of risks. The Reserve Bank of India (RBI) use CAMEL rating system to assign a score to each bank on a scale of 1 to 5 **(https://testbook.com/learn/camels-rating-system-in-banking).**

Based on these scores, RBI determines the best and worst bank. Following RBI, the study has also considered CAMEL ratios as financial variables.

Development of Prediction Model (Analysis and Discussion)

The following procedure is adopted to develop the Discriminant prediction model

Step 1: Selection of Dependent and Independent variables:

The present research study has taken the financial health of 40 scheduled commercial banks (Public & Private sector banks) in India as the dependent variable. CAMEL ratios have been adopted for the selection of independent variables. The study identified 15 independent variables from previous researches. Out of 15 independent variables, those variables are selected that having higher means difference between weak banks and healthy banks. Therefore, Eight variables are chosen to maintain the requirement of factor analysis. Since the sample size of the present research work is 40 and as per the rule of thumb, the ratio between sample units and variables should be 5:1. Hence, out of 15 variables, eight variables are considered for the analysis.

8 independent variables having the highest mean differences are **Capital adequacy ratio, Net NPA to Net Advances, Business per Employee, Profit per Employee, Return on Advances, Return on Assets, Return on Equity, and Credit Deposit Ratio.** The study considered these ratios for further analysis.

Step 2: Factor Analysis:

As per the objective of Discriminant analysis, to find out the variables which discriminate best between weak banks and healthy banks, applied factor analysis on selected eight independent variables mentioned above. The results of factor analysis are as follows:

i) **KMO** measure of sampling adequacy is 0.757 that is more than .50 (Sig. >.50), which indicates the appropriateness of factor analysis for the study. Bartlett's test of sphericity's significant value is .000, which is less than .05 (sig. < .05), indicates that sufficient correlation exists between variables.

ii) **The criterion for Selection of Factors**

The Principal Component Method is applied for the factor analysis. The factor is selected based on eigenvalues. Those factors have more than one eigenvalue chosen for the study. The factor loading is essential in interpreting the factor matrix. Loading ±.50 or greater is considered practically significant in the literature. Thus, variables with ±.70 or greater loadings are selected for factor analysis. Based on these criteria, two factors are chosen, namely **F1, F2**.

Table 1: Factors with their Loading

Factor (F1)	Loading
Return on Assets	0.927
Return on Equity	0.918
Capital adequacy Ratio	0.885

Factor (F2)	Loading
Business per Employee	-0.866
Return on Advances	0.884

Source: SPSS 21 Output

Instead of selecting variables from each factor, the study has formed 6 combinations for further analysis to get more precise results. Discriminant analysis has been applied to these 6 combinations. The following table is showing 6 combinations with their discriminant analysis results.

Table 2 : Discriminant Analysis results on possible Combinations of Factors

Combination No.	Combination	Predicted Score	Wilks' Lamda
1	Return on Assets, Business per Employee	95.0%	0.266
2	Return on Assets, Return on Advances	95.0%	0.263
3	**Return on Equity, Business per Employee**	**97.5%**	**0.247**

4	**Return on Equity, Return on Advances**	**97.5%**	**0.25**
5	Capital Adequacy Ratio, Business per Employee	87.5%	0.308
6	Capital Adequacy Ratio, Return on Advances	90.0%	0.295

Source: SPSS 21 Output

The above table shows combinations formed based on the results of factor analysis and Discriminant Analysis. Out of 6 combinations, those combinations have been taken into consideration that having the highest predicted score. Following this criterion, combinations 3 and 4 have been selected. Both combinations have the same predicted score, i.e., 97.5 %, but their wilks' lambda score is different. The value of Lambda equals one indicates that the group means are equal; however, the small value of Lambda reveals that the group means are different. Here combination 3 (Return on Equity, Business per Employee) reported the lowest Lambda score. Combination 3 was considered first as the final combination for the discriminant analysis. Still, the result of the validity test of the model found only 85%, and the validity test result of combination 4 found 90%, which means this combination of ratios has given a more accurate prediction compared to combination 3. Hence for more precise prediction, combination 4 (Return on Equity and Return on Advances) is considered for further interpretation.

Step 3: Discriminant Analysis

There are two approaches for deriving discriminant function, i.e., (i) enter variables together or simultaneous**,** and (ii) enter variables stepwise. The first method has been adopted in the research. The test of equality of group means shows the variables that should include in the model. As per the discriminant outputs, the p values of both the variables (Return on Equity .000 and Return on Advances .003) are less than the value at a 5% level of significance, i.e., 0.05. The p-value confirms that all the variables differ significantly between the groups. The linear discriminant function derived from the analysis is:

$$D = -2.964 + .180\,X_1 + .248\,X_2$$

Cut off point = -0.59

Where

X_1 = Return on Equity

X_2 = Return on Advances

The classification results table indicates the number and percentage of sample banks classified correctly and incorrectly. The following table reveals the number of sample banks that classified correctly and incorrectly.

Table 3: Classification Results Table

Actual	**Predicted**		**Total**
	Weak Banks (0)	**Healthy Banks (1)**	
Weak Banks (0)	21	1	22
Healthy Banks (1)	0	18	18
Total	21	19	40

Source: SPSS 21 Output

In the above table, the diagonal elements of the table represent the correct classification. It is observed from the above table that only 1 item has been wrongly classified out of 40 items. Here, the percentage of cases correctly classified is obtained by summing the diagonal elements and dividing it by the total number of sample banks. The method has given 97.5 % accurate results.

Step 4: Validity Test of Own Developed Model

To test the predicting accuracy of the model, usually, the holdout sample is used in the Discriminant function. But in the absence of a holdout sample, various methods have been proposed in the Discriminant analysis literature **(Altman *et al.*, 1981[21]).** In the present study, also holdout sample has not been used. Therefore the study uses the original sample as a holdout sample **(Al-Osaimy & Bamakhramah, 2004[22])**. The discrimination value (Di) for each bank is computed to classify each item to a priori group. The Di value is computed from the Discriminant function (Di = -2.964 + .180 X1 + .248 X2). The classification has been done by the Critical Value (Dc) Method. As per the classification rule, a sample bank is considered a healthy bank whose Discriminant score is above the cut-off point (-0.59), and a sample bank is regarded as a weak bank whose Discriminant score is below the cut-off point. **The validity test of the Discriminant model has been given in appendix A.**

As per Appendix A, the model has correctly classified 18 weak banks as weak banks out of a total of 22 weak banks. The model has correctly predicted all (18) healthy banks as healthy banks. The relative position of actual and predicted classification is given in the table below. The diagonal elements of the matrix indicate the number of sample banks classified correctly and incorrectly in the table.

Table 4: Confusion Matrix

Actual	**Predicted**		**Total**
	Weak Banks	**Healthy banks**	
Weak Banks (0)	18	4	22
Healthy banks (1)	0	18	18
Total	18	22	40

Source: Own Computation

The above table reveals that only 4 items were classified wrong out of 40. The method has given 90 % accurate results.

Hypothesis Testing

The z test is applied here to check the significant difference between predicted and validity scores at a 5% significance level. The hypothesis that to be tested is as follows:

H_{01}: The predictive power of own developed prediction model is satisfactory; it means there is no significant difference between predicted and validity scores of prediction model.

The result of the **Z test is = 1.386**

Here, the calculated z value is 1.386. The critical value of z for the level of significance .05 is 1.96. Since the computed value of Z = 1.386 is lower than the critical value (1.96), the difference is not significant. Thus H_0 is accepted at a 5% level of significance. The visible difference is occurred just by chance, not due to any significant reason.

Findings

1) The prediction model developed in the study by using Discriminant Analysis is as:
   $D = -2.964 + .180 X_1 + .248 X_2$
2) In the study two important ratios, Return on Equity (X_1) and Return on Advances (X_2) have been identified. Based on these ratios, the financial health of any sample banks can be determined**.**

3) If any bank's Discriminant score is above the cut-off point (-0.59), the bank will be considered as a healthy bank otherwise a weak bank.

Concluding Remark

The model used in this research proved to be highly effective as the model has predicted the status of the financial health of sample banks with high accuracy, i.e., 97.5%. Two financial ratios, Return on Equity and Return on Advances, became significant in Discriminant functions. The result of the validity test of the model also indicates that the developed Discriminant model is suitable for predicting financial health. Here null hypothesis is accepted, which shows no significant difference between predicted and validity scores. The model developed in this study can be used to assess financial health of any banking industry. The model can assist investors, managers, shareholders, financial institutions, auditors to check banks' financial health in India.

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Appendix:

"Appendix A"

Validity Test of Weak Banks

S. No.	Name of the Bank	Status	X_1= Return on Equity	X_2 = Return on Advances	D_i	D_c - 0.59	
1	ALLAHABAD BANK	weak	-6.13	9.20	-1.79	$D_i < D_c$	Weak
2	ANDHRA BANK	weak	-2.44	10.30	-0.85	$D_i < D_c$	Weak
3	BANK OF BARODA	weak	1.29	7.37	-0.90	$D_i < D_c$	Weak
4	BANK OF INDIA	weak	-5.41	7.81	-2.00	$D_i < D_c$	Weak
5	BANK OF MAHARASHTRA	weak	-3.51	9.49	-1.24	$D_i < D_c$	Weak
6	CANARA BANK	weak	0.03	9.43	-0.62	$D_i < D_c$	Weak
7	CENTRAL BANK OF INDIA	weak	-11.09	10.32	-2.40	$D_i < D_c$	Weak
8	CORPORATION BANK	weak	-4.60	9.85	-1.35	$D_i < D_c$	Weak
9	DENA BANK	weak	-7.01	9.50	-1.87	$D_i < D_c$	Weak
10	IDBI BANK LIMITED	weak	-12.72	9.69	-2.85	$D_i < D_c$	Weak
11	INDIAN OVERSEAS BANK	weak	-17.43	9.74	-3.69	$D_i < D_c$	Weak
12	ORIENTAL BANK OF COMMERCE	weak	-7.88	9.64	-1.99	$D_i < D_c$	Weak
13	PUNJAB AND SIND BANK	weak	1.12	9.92	-0.30	$D_i >$ Dc	Healthy
14	PUNJAB NATIONAL BANK	weak	-3.72	8.69	-1.48	$D_i < D_c$	Weak
15	SYNDICATE BANK	weak	-0.97	8.43	-1.04	$D_i < D_c$	Weak
16	UCO BANK	weak	-8.99	8.65	-2.44	$D_i < D_c$	Weak
17	UNION BANK OF INDIA	weak	1.22	9.02	-0.50	$D_i >$ Dc	Healthy
18	UNITED BANK OF INDIA	weak	-7.36	9.79	-1.86	$D_i < D_c$	Weak
19	CATHOLIC SYRIAN BANK LTD	weak	-5.97	11.89	-1.09	$D_i < D_c$	Weak
20	JAMMU & KASHMIR BANK LTD	weak	2.80	10.52	0.15	$D_i >$ Dc	Healthy
21	LAKSHMI VILAS BANK LTD	weak	2.74	11.14	0.30	$D_i >$ Dc	Healthy
22	THE DHANALAKSHMI BANK LTD	weak	-20.41	11.46	-3.80	$D_i < D_c$	Weak

Validity Test of Healthy Banks

S. No.	Name of the Bank	Status	X1= Return on Equity	X2= Return on Advances	D_i	D_c -0.59	
1	STATE BANK OF INDIA	Healthy	6.21	8.47	0.26	D_i> Dc	Healthy
2	INDIAN BANK	Healthy	7.19	9.28	0.64	D_i> Dc	Healthy
3	VIJAYA BANK	Healthy	7.47	9.72	0.80	D_i> Dc	Healthy
4	AXIS BANK LIMITED	Healthy	11.84	9.56	1.55	D_i> Dc	Healthy
5	CITY UNION BANK LIMITED	Healthy	16.33	12.15	3.00	D_i> Dc	Healthy
6	DCB BANK LIMITED	Healthy	11.85	11.47	2.02	D_i> Dc	Healthy
7	FEDERAL BANK LTD	Healthy	10.07	10.48	1.45	D_i> Dc	Healthy
8	HDFC BANK LTD.	Healthy	18.94	10.83	3.14	D_i> Dc	Healthy
9	ICICI BANK LIMITED	Healthy	11.39	9.29	1.40	D_i> Dc	Healthy
10	INDUSIND BANK LTD	Healthy	16.48	11.91	2.97	D_i> Dc	Healthy
11	KARNATAKA BANK LTD	Healthy	10.54	11.04	1.68	D_i> Dc	Healthy
13	KOTAK MAHINDRA BANK LTD.	Healthy	12.94	11.87	2.32	D_i> Dc	Healthy
14	NAINITAL BANK LTD	Healthy	11.15	11.08	1.80	D_i> Dc	Healthy
15	RBL BANK LIMITED	Healthy	10.06	10.86	1.54	D_i> Dc	Healthy
16	SOUTH INDIAN BANK LTD	Healthy	9.87	10.73	1.48	D_i> Dc	Healthy
17	TAMILNAD MERCANTILE BANK LTD	Healthy	12.22	11.64	2.13	D_i> Dc	Healthy
18	YES BANK LTD.	Healthy	20.51	11.19	3.51	D_i> Dc	Healthy

Source: Own Computation