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Prediction of Corporate Bankruptcy Based on Financial Ratios using Binary Logistic Regression

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Abstract
The aim of this study is to develop a corporate financial distress prediction model based on financial ratios for listed companies across various sectors in India using binary logistic regression technique. For this, 51 companies listed on Bombay Stock Exchange (BSE) and/or National Stock Exchange (NSE) has been chosen as a sample study. The selected companies were bifurcated in two groups based on financial ratios. The explanatory variables were divided into four categories such as liquidity, solvency, efficiency and profitability ratios based on standard practices followed by financial analysts to draw reliable insights. The t-test was used to check the statistical significance of each independent variable for two groups that is insolvent and solvent. The results of t-test were found statistically non-significant ($p>0.05$) at 5% level of significance in case of fixed assets turnover ratio, interest coverage ratio, number of days in working capital ratio, quick ratio and return on net worth ratio where as others independent variables were found statistically significant ($p<0.05$).The variance inflation factor (VIF) was used for measuring multicollinearity. The independent variables having VIF value less than 5 were used for fitting binary logistic regression model to predict the corporate financial distress. The forecast strength of the logistic regression model was found 96.80% and the goodness of fit of the model was checked by using the Hosmer and Lemeshow test. It is found that the interest coverage ratio, net profit margin and number of days in working capital ratio are significant predictors of corporate insolvency. The findings of the present study can be used to assist in financial decision-making for various stakeholders.
Keywords: Bankruptcy, Logistic Regression, Financial Ratios, PredictionandFinancialDistress

1. Introduction

Financial statements analysis assists in assessing corporate excellence, short-term liquidity and long-term solvency, judging creditworthiness, predicting bankruptcy and assessing market risk. Business uncertainties expose companies to high probabilities of default. A company is insolvent in two cases: first, when the company's external liabilities exceed the assets, and second, when it is unable to settle financial obligations.The ratio analysis isa widely-used tool for financial analysis and its rationale exists in making financial information comparable among intra-firm as well as inter-firmwhich enables equity investors, management &lenders to make better investment and credit decisions.

In late 1960s', various researchers like Beaver 1966; Altman 1968; Ohlson 1980 and Altman *et al.* 1994 had developed bankruptcy prediction models for analysing financial distress of companies. In general, two stage approaches are used for financial distress or bankruptcy prediction. In the first stage, identification of the best financial ratio predictor(s) is carried out. And, in the second stage, we develop suitable statistical techniques to improve the estimators for better prediction accuracy.Various statistical models have been used for bankruptcy predictionincludingunivariate analysis, multivariateanalysis, discriminant function analysis, decision tree analysis, logistic regression and artificial neural networks.

Keeping above facts in mind, the present study has been designed to predict corporate bankruptcy based on financial ratios using binary logistic regression. The study has been divided into five sections. Section 2 provides a review of related literature. The sample data and methodology used in the present study has been given in the section three. The statistical analysis of data and discussions of results is presented in section four. Analysis of data is presented in section four. The last section covers; conclusion, limitations and future aspects of the study.

2. Review of Literature

In this section,we have reviewedseveral empirical studies which have been drawn considerable attention on the use of financial ratios and their usefulness in analysis of corporate failure or success.

Since the 1960's, researchers have employed financial ratios as predictor variables in various statistical models like multivariate analysis,discriminant function analysis and logistic regression analysis to predict corporate bankruptcy. Beaver (1966) found that the financial ratios can predict the likelihood of corporate failure.Altman (1968)developed a model to combine the set of accrual-based financial ratios using multivariate discriminant analysis into a risk measurement score i.e. Z-score used to discriminate between distressed and non-distressed companies.Ohlson (1980)made one of the first attempts to use conditional logit analysis for bankruptcy prediction and found that the best discriminate ratios were total debts to total assets ratio and net profit to total assets ratio as predictor variables for division between insolvent and solvent companies.

Several empirical studies were reported based on the comparison between Altman’s Z-score model&univariate Beaver’s model and their respective predictive powers in corporate financial distress. While analysing the comparison between Beaver’s univariatemodel and Altman’s Z-score model,Holmen (1988) found that the Beaver’s univariate model, especially cash flow to total debt ratio had predicted bankruptcy with fewer errors than the Altman’s Z-score model.Begley*et al.* (1996) in their study found that, in general, Ohlson’s logistic regression model outperformed Altman’s Z-score model.

Bhunia and Sarkar (2011)used financial ratios and multiple discriminant analysis for distress prediction of private sector pharmaceutical Indian companies.The study concluded that selected liquidity and profitability ratios weresignificant in predicting company’s distress.Yap*et al.* (2011)studied that the predictive abilities of financial ratios in predicting company failure in Malaysia using a classic univariateapproachfound that the means of the financial ratios showed significant differences between failed&non-failed companies and cash flow to total debt ratio was significant in predicting distress.Maricica and Georgeta (2012)investigated various financial ratios and found significant differences between performing and non-performing companies, especially with regard to profitability, financial position and leverage.Hassani and Parsadmehr (2012)found that independent variables of debt to equity ratio, net profit to net sales ratio & working capital to assets ratio were significant in predicting financial crisis in solvent and insolvent companies.

VenkataRamana*et al.* (2012)predicted the risk of bankruptcyusing financial ratios of selected cement companies in India for the period 2001-2010. The results revealed that the liquidity, working capital turnover, efficiency and solvency position of the selected cement companies were not satisfactory.

Yap*et al.* (2012)found that cash flow to total debts ratio, cash to current liabilities ratio, total debts to total assets ratio, and retained earnings to total assetsratioweresignificant in their predictive power of business failure.Mondal and Roy (2013)concluded that rate of growth of profit after tax and debt to equity ratio were significant predictors of sick companies.Keener (2013) asserted that lower cash to current liability ratio, lower cash flow margins and higher debt to equity ratio were significant in company failure.

Alifiah (2014)carried out financial distress prediction for Malaysian companies and found that debt ratio, total assets turnover ratio, working capital ratio, net income to total assets ratio were significant in predicting financial distress.Al-Kassar and Soileau (2014) employedAltman’s Z-score modelandfound that seven ratios were significant in predicting business failure. Mraihi (2015)developed logistic regression model using twelve ratios and found that the liquidity and solvency ratios have more relevance than profitability ratios in predicting financial distress in companies.Zohra*et al.* (2015) developed logistic regression model using three financial ratios i.e. net working capital to owner`s equity, account receivable turnover ratio, and owner`s equity to fixed assets ratio and were used to discriminate between distressed and non-distressed firms.

Jabeur (2017)confirmed the usefulness of partial least squares logistic regression in predicting financial distress.Agrawal and Maheshwari (2019) used logistic regression and multiple discriminant analysis for listed Indian firms and concluded that industry beta was found statistically significant in predicting defaults and higher industry beta leads to an increased probability of default.Balasubramanian*et al.* (2019)concluded that net asset value, long-term debt-equity ratio, return on investment, retention ratio, age, promoters holdings pledged and institutional holdings are the critical financial and non-financial predictors of financial distress.Ogachi*et al.* (2020) concluded that inventory turnover ratio, asset turnover ratio, debt-equity ratio, debtors’ turnover ratio, current ratio and working capital ratio were most significant for predicting bankruptcy.

In view of the above, the present study is designed to contributein the existing literature by providing empirical evidencesfor prediction of corporate bankruptcy in India based on financial ratios. In this study, various financial ratios i.e. liquidity, profitability, efficiency and solvency have been considered as explanatory variables to measure the probability of bankruptcy by using binary logistic regression technique.

3. Data and Methodology

3.1 Data

The secondary data was extracted for 51 companies (20 insolvent and 31 solvent)from different sectors listed on BSE and/or NSEduring the period 2013 to 2017. The financial ratios have been divided into following categories:

- Liquidity ratios: current ratio, quick ratio and number of days in working capital ratio.
- Profitability ratios: adjusted cash margin,adjusted net profit margin, cash profit margin,gross profit margin, net profit margin, net operating profit per share, operating profit margin, operating profit per share, profit before interest and tax margin,return on assets including revaluations,return on long-term funds and return on net worth.
- Efficiency ratio: asset turnover ratio,fixed assets turnover ratio, return on capital employed and total assets turnover ratio.
- Solvency ratio: Interest coverage ratio.

The t-test was used to examine the discriminating power of financial ratios.The t- test was also used for comparing means of independent variables of solvent and insolvent companies. For this, the following hypotheses were framed:

H_0: There is no significant difference between the mean of independent variables of solvent and insolvent companies.

H_1: There is significant difference between the mean of independent variables of solvent and insolvent companies.

If *p-value* is less than 0.05, we reject the null hypothesis. On the contrary, if *p-value* is greater than 0.05, we do not have enough evidence to reject the null hypothesis.

Since the late 1960s, various statistical models have been used extensively for predicting corporate failure. The binary logistic regression is one of the techniques for analysis of data when the dependent variable is categorical in nature and independent variables are continuous. It permits for prediction of the probability of a discrete outcome from a set of variables that may be continuous, discrete,and dichotomous or a mix of any of these.

Inlogistic regression model, the assumptions of normality of continuous variables under study andhomoscedastic variance are not required.Despite the fact that logistic regression is not easy to understand and interpret as compared to usual linear regression. Moreover, the focus of logistic regression is to interpret whether the relationship is directly proportional or inversely proportional between each independent and dependent variable.Inthis study, Y is taken as dependent variable which is binary (‘1’ indicates solvent company and ‘0’ indicates insolvent company).

Logistic function for *r* independent variables is:

$$p = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_r x_r}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_r x_r}}$$

Where,

p is the probability that a company will be solvent. The goal is to obtain β_r,r= 1, 2, 3,…..,20. After applying logit transformation, we obtainthe following linear relationship:

$$\text{Logit}\,(Y) = \ln\frac{p}{1-p} = \boldsymbol{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_r x_r}$$

We use the following logistic regression model to predict the company failure:

$$P_i(Y=1) = 1/\,(1+e^{-z})$$
$$= 1/\{1+\exp[-(\beta_0+\beta_1 X_1+\beta_2 X_2+\dots\dots+\beta_{20} X_{20})]\}$$

Where,

$P_i(Y=1)$ = Probability of solvent for i^{th} company;

exp= exponential function;

β_0 = intercept term;

$\beta_1, \beta_{2\dots}, \beta_{20}$ = slope coefficients;

$X_1, X_{2\dots\dots}, X_{20}$= financial ratios

The following table presents 20 financial ratios with their respective notations used in the study:

Table1: Financial ratios (Independent variables)

X_1	Adjusted Cash Margin(%)	X_{11}	No. of days in Working Capital
X_2	Adjusted Net Profit Margin (%)	X_{12}	Operating Profit Margin (%)
X_3	Asset Turnover Ratio	X_{13}	Operating Profit Per Share (₹)
X_4	Cash Profit Margin (%)	X_{14}	Profit before Interest & Tax Margin (%)
X_5	Current Ratio	X_{15}	Quick Ratio
X_6	Fixed Assets Turnover Ratio	X_{16}	Return on Assets including Revaluations
X_7	Gross Profit Margin (%)	X_{17}	Return on Capital Employed (%)
X_8	Interest Coverage Ratio	X_{18}	Return on Long-term Funds (%)
X_9	Net Operating Profit Per Share (₹)	X_{19}	Return on Net Worth (%)
X_{10}	Net Profit Margin (%)	X_{20}	Total Assets Turnover Ratio

The data was analysed using statistical tools like SPSS, R, Microsoft Excel, etc.

4. Results and Discussion

4.1 Student’s t-test

The financial statements of companies were considered to extract various types of ratios namely liquidity ratios, profitability ratios, efficiency ratios and solvency ratios. The Student’st-test was used to examine the significant difference of means of independent variables in solvent and insolvent companies based on these four ratios.

The results of t-test for liquidity ratios, profitability ratios, efficiency ratios and solvency ratios are given in Table 2.

Table 2:Student’s t-test results

Notations used	Independent variables	Sig.
Liquidity Ratios		
X_5	Current Ratio	0.000*
X_{11}	No. of days in Working Capital	0.129
X_{15}	Quick Ratio	0.200
Profitability Ratios		
X_1	Adjusted Cash Margin(%)	0.000*
X_2	Adjusted Net Profit Margin (%)	0.000*
X_4	Cash Profit Margin (%)	0.000*
X_7	Gross Profit Margin (%)	0.000*
X_9	Net Operating Profit Per Share	0.000*

	(₹)	
X_{10}	Net Profit Margin (%)	0.040**
X_{12}	Operating Profit Margin (%)	0.001*
X_{13}	Operating Profit Per Share (₹)	0.000*
X_{14}	Profit before Interest & Tax Margin (%)	0.000*
X_{16}	Return on Assets including Revaluations	0.000*
X_{18}	Return on Long-term Funds (%)	0.000*
X_{19}	Return on Net Worth (%)	0.971
Efficiency Ratios		
X_3	Asset Turnover Ratio	0.000*
X_6	Fixed Assets Turnover Ratio	0.100
X_{17}	Return on Capital Employed (%)	0.000*
X_{20}	Total Assets Turnover Ratio	0.001*
Solvency ratio		
X_8	Interest Coverage Ratio	0.117

*denotes significant at 1% level of significance.
**denotes significant at 5% level of significance.

Table 2 revealed that the independent variables (financial ratios) X_5 from liquidity ratios; except X_{19} from profitability ratios; X_3, X_{17}, and X_{20} from efficiency ratios are found statistically significant. However, X_{11} and X_{15} from liquidity ratios, X_6 from efficiency ratios and X_8 from solvency ratio are observed not significant at 5% level of significance.

4.2 Collinearity Statistics

The Variance Inflation Factor (VIF) was used for measuring the multicollinearity.The value of tolerance less than 0.20 or 0.10 and/or VIF value of 5 and above indicates the presence of multicollinearity.

Tolerance = $1 - R_j^2$

VIF = 1/Tolerance

Where,

R_j^2 = The coefficient of determination of a regression of explanatory j on all the other explanatory variables.

VIF test was performed for multicollinearity analysis and eliminate the variables having VIF value 5 or greater. Based on multicollinearity analysis, the independent variablesX_1, X_2, X_3, X_4, X_7, X_{12} and X_{17} were excluded from the subsequent investigation.The remaining 13 ratios having VIF less than 5 are given in the Table 3 and considered in fitting binary logistic regression model for predicting corporate financial distress.

Table 3:Collinearity Statistics of Ratios

Independent variables	Multicollinearity Statistics	
	Tolerance	VIF
Constant	-	-
X_5	0.536	1.865
X_6	0.861	1.162
X_8	0.967	1.034
X_9	0.329	3.043
X_{10}	0.627	1.594
X_{11}	0.740	1.351
X_{13}	0.203	4.927
X_{14}	0.698	1.433
X_{15}	0.455	2.196
X_{16}	0.248	4.038
X_{18}	0.388	2.577
X_{19}	0.951	1.052
X_{20}	0.397	2.521

4.3 Logit Analysis for Model Fitting

The main objective of the study is to develop a model for predicting the insolvency of the companies based on financial ratios. For this, we need to identify the ratios that are statistically significant for predicting the insolvency of the companies.

The binary logistic regression model was fitted using 13 financial ratios which were found statistically significant after removing multicollinearity. The findings are as follows:

Table 4: Logistic Regression Analysis

Independent variables	B	Wald	Sig-Value
Constant	-0.055	0.001	0.978
X_5	-2.754	1.850	0.174
X_6	-0.052	0.631	0.427
X_8	2.106	6.469	0.011**
X_9	0.003	1.405	0.236
X_{10}	0.243	6.237	0.013**
X_{11}	0.006	3.898	0.048**
X_{13}	-0.022	0.878	0.349
X_{14}	-0.075	0.932	0.334
X_{15}	-3.022	3.502	0.061
X_{16}	0.006	0.498	0.480
X_{18}	-0.026	0.128	0.721
X_{19}	-0.023	2.050	0.152
X_{20}	-0.593	0.322	0.570

**denotes significant at 5% level of significance.

In Table 4, Wald statistic values wereusedto check the contribution of each independent variable.The contribution of explanatory variables X_8, X_{10}, and X_{11} is found statistically significant (p <0.005) in predicting corporate insolvency.The independent variables X_8, X_9, X_{10}, X_{11} and X_{16} have positive coefficients that resulted in increase the chances of bankruptcy. They have more significant contribution for predicting bankruptcy. On the other hand, X_5, X_6, X_{13}, X_{14}, X_{15}, X_{18}, X_{19}, and X_{20} have negative coefficients which reduce the risk of financial distress in listed companies.

The logit function for predicting the corporate insolvency is as follows:

$$Y = \text{In}\left(\frac{p}{1-p}\right) = -0.055 + 2.106X_8 + 0.243X_{10} + 0.006X_{11}$$

The estimated coefficients of the above logistic regression model can be interpreted as follows:

Interest coverage ratio (X_8): This coefficient indicates that if interest coverage ratio increases one unit, the logarithm of chance ratio increases 2.106 units in favour of solvency keeping other conditions constant.

Net profit margin (X_{10}): If other conditions are fixed, the coefficient of X_{10}indicates that if net profit margin increases one unit, the logarithm of chance ratio increases 0.243 units in favour of solvency.

No. of days in working capital (X_{11}): The coefficient of X_{11}indicates that if we increase one unit in no. of days in working capital increases, the logarithm of chance ratio increases 0.006 units in favour of solvency keeping other conditions constant.

4.4Goodness of Fit Test

The Cox & Snell and Nagelkerke R^2 tests are used to determine the percentage of the categorical response in binary variable explained by explanatory variables. The Nagelkerke R^2test is an adjusted version of the Cox & Snell R^2 and therefore, it is more reliable. The results are as follows:

Table 5: Cox & Snell &Nagelkerke R^2 test

-2 Log likelihood	35.431[a]
Cox & Snell R^2	0.698
Nagelkerke R^2	0.947

Table 5 indicates that 94.70% of the variation in the dichotomous variable has been explained by the explanatory variables in predicting corporate financial distress of the companies.

The Hosmer and Lemeshow test has been used to test the goodness of fit of the logistic regression model. The result of test is as follows:

Table 6:Hosmer and Lemeshow test results

Chi-square	d.f.	sig.
0.376	6	0.999

Table 6 reveals that the significant value of theHosmer and Lemeshow test is 0.999 which is greater than 0.05, therefore, we do not have enough evidence to reject the null hypothesis. Thus, we conclude that the model is good fit at 5% level of significance.

The prediction power of the model can be found using classification table which is given below:

Table 7: Classification Table

Observed		Predicted		
		Insolvent	Solvent	% correct
Response	Insolvent	96	3	97.0
	Solvent	5	149	96.8
Overall %				96.8

From Table 7, it is observed that the fitted model correctly predicted 97% of all insolvent companies and 96.8% of all solvent companies. It can also be observed that the sensitivity of the model is 96.8% and specificity is 97%. Further, from Table 7, type I error (when an insolvent company is mistakenly put in solvent companies group) is 3% and type II error (when a solvent company is mistakenly put in insolvent companies group) is 3.20% and overall efficiency of the model is 96.8%.

4.5 Receiver Operator Characteristic Curve (ROC)

To obtain ROC curve, True Positive Rate (TPR) or Sensitivity is plotted against False Positive Rate (FPR) or 1–Specificity. ROC depicts the trade-off between sensitivity and specificity. The accuracy of the test is measured by the proximity of the curve to the left-hand side and top border of the ROC curve given in Figure 1.

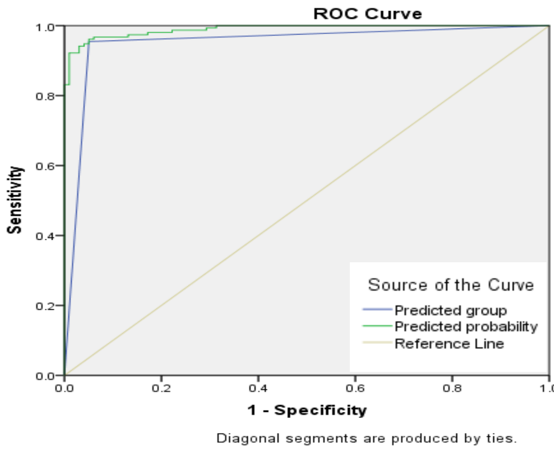

Figure 1: ROC Curve

The Figure 1 depicts that the predicted response and predicted probability lines are closer to the left and top border which indicates that the area under curve is 0.96.

The cut points or cut-values of ROC Curve are given below in Table 8:

Table 8 Coordinates of ROC Curve

Positive if greater than or equal to cut point	Sensitivity (True positive)	1 – Specificity (False Positive)
0.0576967	1.000	0.313
0.2681882	0.974	0.131
0.9590096	0.831	0.000

As per the Table 8, at cut-off score of 0.2681882, we can expect 97.4% of the positive outcomes have correctly classified and 13.1% of the negative outcomes have been incorrectly classified.

5. Conclusion and Suggestions

A good understanding of potential company insolvency is crucial to financial decision making by various stakeholders. In this paper, we propose ratio analysis as an investigative technique for setting insolvency as the financial statements of a company are readily available.The study focuses on predicting corporate insolvency of listed companies in India using logistic regression technique.The study concluded that the interest coverage ratio (X_8) which is solvency indicator, net profit margin (X_{10}) which is profitability indicator and number of days in working capital ratio (X_{11}) which is liquidity indicator are significant predictors of corporate insolvency. The interest coverage ratio shows company's ability to meet its interest obligations and a higher ratio is more desirable for safety and financial health of firm. The profitability ratio is expected to have negative relationship with the probability of financial distress. The liquidity ratio reflects the financial health of a firm. A high level of liquidity is desirable, whereas low liquidity may lead to bankruptcy.

The findings of the study have important implications for lending and investment decisions. Predicting corporate insolvency is highly valuable for credit rating agencies and financial institutions for disbursement loans to companies.

However, all our findings are based on Indian market, so there may be limitations in extending the results of present study to other countries. Further,macroeconomic variables including GNP, inflation rates, interest rates and market structure could be added for prediction of corporate insolvency.

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