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Financial Distress: Predictive Power of Multiple Logistic Regressions

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ABSTRACT

Financial distress is a situation where a company is not able to meet or face difficulty to pay off its financial obligations. According to RBI's definition negative working capital, cash loss and negative networth are the factors influencing Distresses. There are lots of causes of corporate failure which includes Profitability, Liquidity and solvency complications. Bankruptcy prediction models are among the techniques and tools for predicting future status of companies which can estimate the bankruptcy probability by compounding a set of financial ratios. This research paper has attempted to device models for predicting probability of financial distresses among the PSUs working under the Engineering sector in Kerala. In order to evaluate the ratios that can influence group status and quantify their connection, Multiple Logistic Regression analysis tool is used. The main uses of logistic regression are that prediction of group membership and provide knowledge of the relationships and strength among the variables.

1. Introduction

Financial statement analysis is described as the process of identifying financial strength and weaknesses of the firm by correctly launching association between the items of the balance sheet and the profit and loss account. It is usually recognized that the objective of financial statement is to offer information about the financial position, performance and changes in financial position of an enterprise that is valuable to a wide range of users in making economic decisions. Financial statement analysis is the method of accepting the risk and profitability of the firm in the course of analysis of reported financial information, by using different accounting tools and techniques for evaluating and pricing credit risk and for fundamental company valuation. The financial strength of the firm is to numerous negotiators in society, including investors, bankers, governmental and regulatory bodies and auditors. It is the duty of the government and the regulatory bodies to observe the general financial status of firm with the aim of make proper economic and industrial policy. Auditors require examining the going concern position of their clients to present a precise report of their financial standing. The failure of firm can have an effect on a number of stakeholders, debtors and employees.

It is apparent that business failure can cause significant trauma to stakeholders. Fitzpatrick (1931) states that seven groups of stakeholders affected by business failure are workers, community, bondholders, merchandise and bank creditors, stockholders, boards of directors, and government. Notwithstanding this, the term 'stakeholder' is defined extensively in subsequent studies but still includes the aforementioned seven groups. Effective business failure prediction can help these stakeholders to avoid and/or at least to reduce the adverse impact of business failure. It is generally accepted that the business failure prediction is widely used for different purposes by stakeholders. Managers/owners, for instance, use business failure prediction as an early warning tool and can take appropriate action to avoid business failure. Investors/shareholders use financial distress prediction to prevent the considerable financial losses they incur when firms become insolvent. Creditors (i.e. bank or financial institutions) use failure prediction techniques to examine the degree of their portfolio risk or to assess the probability of failure for new borrowers. Auditors use failure prediction approaches to evaluate whether or not a firm is on the verge of failure. Finally, regulators use various techniques to monitor the financial position of regulated firms.

Financial Distress is a situation when a company cannot meet or face difficulty to pay off its financial obligations to the creditors. When a company is deemed to be under financial distress and does not take necessary actions in improving its performance or when the situation is not handled well, the company may experience bankruptcy or be forced into liquidating its company in the worst case scenario. In addition to that financial distressed may brings bad reputation for the company because investors would see the company as an incompetent firm. While an extensive literature on financial distress prediction has emerged, many commonly used technique would rate as primitive dated in other fields of social science especially in accounting research. A good number of research studies on company bankruptcy and failure predictions were prepared in developed countries by Beaver (1966) and Altman (1968) in United States,

The objective of this study to identify the determinants of financial distress among PSUs working under the Engineering Sector in Kerala and predicting financial distress with logistic regression

2. Review of Literature

Fitz Patrick analyzed ratios for failed and non-failed firms, at three years period to failure, by selecting 19 companies randomly which had failed during the period of 1920-1929, and choosing a matching sample of 19 successful companies using financial soundness, asset size, sales volume, product line and physical year as matching criteria. Arthur Winker and Raymond

F. Smith examined 183 firms, which failed between 1923 and 1931 for 10 years prior to the year of failure. The prior 10 years trends of the means of 21 ratios of failed firms were analyzed. M.Tamaris (1956-1960) was the first multivariate study in which weighted composite of several ratios were used to indicate the possibility of failure. W. H. Beaver for the first time in 1966 attempted to demonstrate that the failure of an enterprise could be predicted reliably through the combined utilization of sophisticated quantitative techniques and financial ratio analysis. Altman is known for the development of the Z-Score formula, which he published in 1968. The Z-Score for predicting Bankruptcy is a multivariate formula for a measurement of the financial health of a company and a powerful diagnostic tool that forecasts the probability of a company entering bankruptcy within a 2 year period. David Ewert investigated in 1968 on the basis of information supplied in the Dun and Bradstreet credit reports that ratio can predict non repayment of receivables, keeping 82% accuracy. In 1969 Mare P. Blum constructed a theoretical model based on accounting and financial market data, which was designed to discriminate between failing and non-failing firms. In 1970, Meyer and Pifer attempted to build up a model of prediction of bank failure. Their study indicated the factors affecting bank failure. Such factors were divided into 4 groups, local economic conditions, general economic conditions, quality of management, and integrity of employees. Edminister in 1971 found that using a ratio function could make good predictions. Edward Deakin searched for the linear combination of the 14 ratios used by Beaver which best predicts potential failure in each of five years prior to failure. In 1978 at St. Francisco University by Gordon L.V. Springate, following procedures developed by Altman in the U.S. Springate used step-wise multiple discriminate analysis to select four out of 19 popular financial ratios that best distinguished between sound business and those that actually failed. Fulmer (1984) used step-wise multiple discriminate analysis to evaluate 40 financial ratios applied to a sample of 60 companies - 30 failed and 30 successful. The average asset size of these firms was $455,000.

3. Methodology

Under this study financial distress is defined according to the Reserve Bank of India's definition on sick units. The RBI, defined a sick industrial unit, as the one which has incurred cash losses for one year and in the judgment of the bank, it is likely to continue to incur cash losses for the current year as well as following year and which has an imbalance in the financial structure, such as current ratio of less than 1:1and worsening debt equity ratio. A company is said to be financially distressed when, (a) current ratio is less than one i.e. Company having negative working capital, (b) there were no cash profit and (c) total debt exceeds networth i.e. negative networth. If a company has liquidity, profitability and solvency problem, it is deemed to be in a distressed stage and otherwise presumed as non-distressed state. The analytical tools presented earlier measures the significance of the difference amongst the distressed and non-distressed state. However, it fails to evaluate the relationship of these ratios have with the financial distressed state (group status 0 and 1). In order to evaluate the ratios that can influence group status and quantify their connection, Multiple Logistic Regression analysis tool is used. A logit regression analysis is a form of regression used when the dependent is a dichotomy and therefore can take one of two possible outcomes: distressed or non-distressed. The main uses of logistic regression are that prediction of group membership and provide knowledge of the relationships and strength among the variables.

Unit selected for the study

Out of 9 PSUs working under the Engineering sector, 7 units were selected for this study which is tabulated in Table 1.

Table No.1
List of sample companies and their Distressed state (years)

Company	Distressed State	Frequency (years)	Percent
AUTOKAST LIMITED	0	5	3.3
	1	25	42.4
SAIL-SCL KERALA LIMITED	0	15	9.9
	1	15	25.4
KERALA AUTOMOBILES LIMITEDD	0	23	15.2
	1	7	11.9
THE METAL INDUSTRIES LIIMITED	0	27	17.9
	1	3	5.1
STEEL INDUSTRIALS KERALA LIMITED	0	29	19.2
	1	1	1.7
FOREST INDUSTIRES(TRAVANCORE)LIMITED	0	28	18.5
	1	2	3.4
STEEL AND INDUSTRIAL FORGINGS LIMITED	0	24	15.9
	1	6	10.2
Total	0	151	210
	1	59	

Selection of Variables

Independent variables under this study comprises of 18 ratios from four specific groups representing Liquidity, Cash flow, Profitability and Solvency. The selection of these variables is based on the popularity of the ratios from past research and their past performance in reviewed literature and listed in Table 2.

Table 2
List of Selected Variables

Sr. No.	Selected Ratios	Abbreviations	Symbol
1	Current Assets to Current Liabilities	CACL	X1
2	Cash to Current Liabilities	CASHCL	X2
3	Cash cycle	CASHCY	X3
4	Working Capital to Total Assets	WCTA	X4
5	Sales to Working capital	SWC	X5
6	Cash flow to Interest	CFINT	X6
7	Cash Flow to Total Debt	CFTD	X7
8	Cash Flow to Sales	CFS	X8
9	Cash Flow to Current Liablities	CFCL	X9
10	Fixed asset to Sales	FATO	X10
11	Net profit to Total Asset	NPTA	X11
12	Return on Invested Capital	ROIC	X12
13	Return on capital Employed	ROCE	X13
14	Sales to Total Asset	SALESTA	X14
15	Total Debt to Total Asset	TDTA	X15
16	Total Debt Ratio	TDR	X16
17	Networth to Total Debt	NWTD	X17
18	Networth to Fixed Asset	NWFA	X18

4. Results And Discussions

The descriptive of the variables selected under this study shown in the Table 3.

Table No.3
Descriptive of Variables

Variables	Symbol	Group Status	N	Minimum	Maximum	Mean	Std. Deviation
LIQUIDITY RATIOS							
CACL	X_1	0	149	0.179	10.69	1.80	1.28
		1	59	0.119	0.96	0.55	0.25
CASHCL	X_2	0	149	0.001	4.97	0.21	0.49
		1	59	0.000	0.26	0.04	0.05
CASHCY	X_3	0	151	-1464.000	525.00	31.00	160.00
		1	59	-1808.000	3969.00	-418.00	867.00
WCTA	X_4	0	151	-2.930	0.65	0.24	0.32
		1	59	-4.117	-0.02	-0.85	1.01
SWC	X_5	0	151	-452.255	1396.00	8.66	122.21
		1	59	-29.654	0.00	-3.16	5.26
CASH FLOW RATIOS							
CFINT	X_6	0	151	-66.861	59.15	2.30	10.21
		1	59	-112.072	0.53	-3.55	14.60
CFTD	X_7	0	151	-0.397	1.43	0.07	0.18
		1	59	-0.233	0.05	-0.05	0.06
CFS	X_8	0	151	-0.465	0.45	0.03	0.12
		1	59	-105.142	0.25	-2.00	13.66

CFCL	X_9	0	149	-16.630	5.41	0.30	1.62
		1	59	-10.640	0.10	-0.34	1.43
PROFITABILITY RATIOS							
FATO	X_{10}	0	151	0.069	45.05	10.43	9.43
		1	59	0.016	24.12	4.10	4.86
NPTA	X_{11}	0	151	-1.011	0.35	-0.02	0.14
		1	59	-1.628	0.11	-0.36	0.32
ROIC	X_{12}	0	151	-3.555	1.61	-0.05	0.46
		1	59	-7.130	83.94	1.82	11.20
ROCE	X_{13}	0	151	-0.748	1.07	0.07	0.18
		1	59	-0.472	0.04	-0.09	0.11
SALETA	X_{14}	0	151	0.042	3.37	0.99	0.71
		1	59	0.003	3.50	0.74	0.54
SOLVENCY RATIOS							
TDTA	X_{15}	0	151	0.161	8.60	0.93	0.76
		1	59	0.472	14.32	3.95	3.31
TDR	X_{16}	0	151	0.110	1.13	0.67	0.20
		1	59	0.264	4.87	1.22	1.12
NWTD	X_{17}	0	151	-0.884	5.22	0.43	0.81
		1	59	-1.000	1.12	-0.53	0.45
NWFA	X_{18}	0	151	-22.899	13.27	1.32	4.16
		1	59	-37.940	0.82	-12.28	11.11

0-Non-distressed stage, 1-Distressed stage

Multiple Logistic Regressions

A Multiple Logistic Regression has more than one independent variable (also referred to as predictor variables or covariates). As such, it is analogous to the multiple regression model in the case in which the dependent (response) variable is binary. In Binary coding, a variable can take only one of two values, it is common practice to code that variable using 0 and 1 values. In this study, financially distressed is coded as 1 and financially non-distressed is coded as 0. There are several strategies can be adopted to develop the "best" model for the data.

In the first stage of analysis, put all the variables in the equation. As we can see from the table no.6, the results of the logit analysis on Model 1 takes into account 18 variables initially identified from the popular literature. Looking into the results of the table 4, we can either interpret the logit through co-efficient value or through the Exp(B) or Odd ratio. For the logit model, the co-efficients are calculated through the use of Maximum Likelihood Estimation (MLE) method as opposed the Original Least Squares (OLS) method employed by linear regression. While OLS seeks to minimize the sum of squared distance between the data points and the regression line, MLE seeks to maximize the log likelihood. This reflects how likely the observed values of the dependent variable can be predicted from the observable values of the independent variables. Furthermore, the OLS, the value of the co-efficient refers to the change in the dependent variable as the independent variable changes. In MLE, the slope of the co-efficient is the change in "log odds" of the dependent as the independent change.

Multiple Logistic Regression Analysis: Model-1

From the co-efficient (B) presented in the Table 4, as per Wald statistics, the significant predictors are CACL and NPTA @ 5% level of significance. Predicted variables are inversely related with financial distress. When other variables are constant, one unit increase in CACL and NPTA, the log odds of the variables being reclassified from distressed to non-distressed decreased by 8.08 and 11.75.

Since the measure and interpretation of co-efficient are sometimes being confusing, a more natural interpretation of the logit results can be achieved through the use of Exp(B) or Odd ratio. Exp(B) is the probability of the event occurring dividing the probability of non-occurring. Exp(B) represents the ratio-change in the odd of the event for a one unit change in the predictor. If its value is 1, the chances of becoming distressed is 0.5, if it is greater than 1, the chance of become distressed will be more than 0.5. The Exp(B) of WCTA, CFTD, CFCL, TDR and NWTD are approximately 8, 23093, 2, 5 and 11 respectively. So, for every unit increase in WCTA,CFTD, CFCL, TDR and NWTD, logit anlaysis argued that the odds of distress occurring 8, 23093, 2, 5 and 11 times more likely to be a member of a distressed group. The dominant variable is CFTD.

Table No. 4
Multiple Logistic Regression Results of Variables influencing Financial Distress

Variables in the Equation							
Variables	**Symbol**	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**

CACL	X_1	-8.082	3.285	6.054	1	0.014*	0
CASHCL	X_2	-7.239	7.489	0.935	1	0.334	0.001
CASHCY	X_3	0.001	0.002	0.36	1	0.549	1.001
WCTA	X_4	2.131	4.43	0.231	1	0.631	8.423
CFINT	X_5	-0.044	0.075	0.336	1	0.562	0.957
CFTD	X_6	21.56	11.9	3.283	1	0.070	23093
CFS	X_7	0.072	0.286	0.063	1	0.802	1.074
CFCL	X_8	0.174	0.348	0.25	1	0.617	1.19
TDTA	X_9	-0.878	1.447	0.368	1	0.544	0.415
FATO	X_{10}	-0.131	0.149	0.764	1	0.382	0.878
SWC	X_{11}	-0.007	0.008	0.737	1	0.391	0.993
NPTA	X_{12}	-11.917	4.963	5.765	1	0.016*	0
ROIC	X_{13}	0.048	0.067	0.512	1	0.474	1.049
ROCE	X_{14}	-11.746	10.841	1.174	1	0.279	0
SALETA	X_{15}	-0.722	1.334	0.292	1	0.589	0.486
TDR	X_{16}	1.592	1.772	0.807	1	0.369	4.913
NWTD	X_{17}	2.44	1.595	2.341	1	0.126	11.474
NWFA	X_{18}	-0.675	0.361	3.484	1	0.062	0.509
Constant	β_0	4.987	2.34	4.543	1	0.033*	146.506

Model Summary

-2 Log likelihood	42.772	Chi-square	205.338
Cox & Snell R Square	0.627	df	18
Nagelkerke R Square	0.901	P-value	0.000*

Classification Table

Observed		Predicted		
		Non-Distressed	Distressed	Percentage Correct
		0	1	
Non-Distressed	0	146	3	98
Distressed	1	6	53	89.8
Overall percentage				95.7

Cut value is 0.50

**@5% level of significance*

Model summary part of the table indicated that the model is statistically significant [-2log likelihood (42.772), Chi-square = 205.338, p<0.001 with df=18]. Nagelkerke's R square (0.901) pointed out that a perfectly strong relationship exists between prediction and grouping. The classification part of the table indicates that the overall prediction success was 95.7% and for non-distressed and distressed groups are 98% and 89.8% respectively. As the theoretical probability for being a distress or a non-distress is greater than or less than 0.50, the cut off value is taken as 0.50.

Multiple Logistic Regression Analysis: Model-2

Beginning with the 18 variables, Model 2 uses Stepwise regression with a p-value equal to 0.50 to automatically determine which variables should be added or dropped from the model. Although the procedure run the risk of modeling the noise in the data, it is useful particularly for exploratory purpose. As our study into the factors influencing financial distress lack a theoretical underpinning to guide research, stepwise regression allows us to explore possible relationships. The results depicted in the Table 5, based on the stepwise procedure, factors deemed significant predictors of financial distress are CACL, TDTA, NPTA and NWFA. Looking into the Table 5, all variables have negative co-efficient values and indicated that an inverse relationship with the dependent variable. Negative relationship is to be expected that the greater likelihood of these distress as the value of these ratios deteriorates. One unit decrease in CACL, TDTA, NPTA and NWFA , the log odds of the company being reclassified from Non-Distressed to Distressed increased by 7.2, .93,6.00 and .29 respectively.

For this the prediction would be as follows:

$$P = \left[\frac{e^{-56.351+(56.312X_1)+(-3634.7X_5)}}{1+e^{-56.351+(56.312X_1)+(-3634.7X_5)}} \right]$$

Where P is the probability and if the value of P is greater than 0.5, then the company belongs to a financially distressed one.

Model summary part of the table indicated that the model is statistically significant [-2log likelihood (56.363), Chi-square = 191.728, p<0.001 with df=4]. Nagelkerke's R square (0.864) pointed out that a perfectly strong relationship exists between prediction and grouping. The classification part of the table indicates that the overall prediction success was 93.8% and for non-distressed and distressed groups are 96% and 88.1% respectively. As the theoretical probability for being a distress or a non-distress is greater than or less than 0.50, the cut off value is taken as 0.50.

Table No.5
Multiple Logistic Regression Results of Modified Variables influencing Financial Distress

Variables in the Equation							
Variables	Symbol	B	S.E.	Wald	df	Sig.	Exp(B)
CACL	X_1	-7.293	1.604	20.68	1	0.000*	0.001
TDTA	X_9	-0.937	0.376	6.225	1	0.013*	0.392
NPTA	X_{12}	-6.008	1.82	10.902	1	0.001*	0.002
NWFA	X_{18}	-0.289	0.124	5.469	1	0.019*	0.749
Constant	β_0	5.347	1.478	13.094	1	0.000*	210.029
Model Summary							
-2 Log likelihood			56.363		Chi-square		191.728
Cox & Snell R Square			0.602		df		4
Nagelkerke R Square			0.864		P-value		0.000*
Classification Table							
Observed			Predicted				
			Non-Distressed		Distressed	Percentage Correct	
			0		1		
Non-Distressed		0	143		6	96	
Distressed		1	7		52	88.1	
Overall percentage						93.8	
Cut value is 0.50							

**@5% level of significance*

In analyzing the comparison between the variables, this study would to be significant with those previously conducted; the predictive abilities of liquidity, profitability and solvency ratios are in line with our expectations. Deakin (1972) found that liquidity as represented by WCTA was the best predictor of potential distress reclassification both in the near term (1 year prior to the event) and in the long-term (5 year prior to the event. Altman (1968) found WCTA to be the least predictive variable under his study. For profitability ratios, NPTA was deemed to be the second predictor by Beaver (1966). Able to accurately predict potential distress 87% of the life time 1 year prior to the event and 72% of the time 5 year before, the ability to generate profits appears to be significant in ensuring a firm's continued survival. Deakin (1972) found that long-term solvency ratios as represented by TDTA could significantly predict the potential distress up to five years prior to financial distress. For cash flow ratios Altman (1968), argued for the inclusion of cash flow ratios for predicting financial distress. He pin down that CFTD would accurately predict financial distress reclassification with 87% one year before the event with 78% accuracy up to 5 years before the event.

5. Conclusion

As we review back the results of the logistic regression analysis, the variables are discriminate distressed and non-Distressed company are based on their profitability, liquidity and solvency positions. The study found CACL is the proxy from liquidity, NPTA is the proxy from profitability and two discriminate factor from solvency category such as TDTA and NWFA. These variables discriminate the financially distressed and non-distressed company with predictive accuracy of 93.8%. These proxy variables are having inverse relationships with financial distress. Explanatory variables with a positive coefficient increase the probability of financial distress because they reduce ey towards one, with the results that the financial distress probability function approaches 1/1 or 100%. One unit decrease of predictive variables leads to the likelihood of distress and findings of this study adhere to the literature relating to the financial distress definition given by RBI.

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