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PREDICTING THE CORPORATE DEFAULT: A STUDY OF COMPANIES LISTED BY RBI FOR DEFAULT

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Abstract:

With RBI referring around 40 firms to NCLT for bankruptcy hearing, one important question can be raised is "were there any signals that could have predicted this situation before hand?" This paper tries to answer the above question. Using the same set of companies that were referred by RBI, using their financial data in two different time frames the study tries to analyze five important financial ratios and their role in prediction of corporate failure. The paper also comes up with a model for the same.

Key Words: Bankruptcy, Financial Ratios, Multiple Discrimination Analysis

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Introduction:

In June 2017, Reserve Bank of India announced a list of 12 firms to be dragged to National Company Law Tribunal (NCLT) for prompt insolvency procedures as they assessed to represent 25% of the gross NPAs. In August, 2017 RBI declared another list comprising of 28 more distressedfirms.

Against this backdrop one important question that can be raised is whether or not the distress signals could have been detected in advance. Beaver (1966, 1968) and Altman (1968) did the spearheading works in the territory of prediction of failure. Forecasting a corporate failure is an important issue in any country.Sun et al. (2014) studied various mathematical or statistical models predicting whether a firm will submit to theinsolvency based on the current financial data. In India, such analysis is still evolving (Bandopadhyay 2006 and Gupta 2014) and is largely based on market variables.

This paper focuses on the role of select financial ratios, drawn from the balance sheets and income statements of these 40 companies, could have predicted the probability of default.Section II of this study presents a brief literature review of select studies done in the same field. Section III highlights the Research Methodology and the last section discusses the data analysis and conclusions.

Literature Review:

Beaver (1966) contemplated the corporate distress forecastingmodel in view of budgetary proportions utilizing profile investigation and univariate discriminant analysis. He utilized five proportions viz. cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets and current ratio.

Altaman (1968) also used financial ratios related to profitability, solvency and liquidity with Multiple Discriminant Analysis to calculate Altaman Z score for forecasting the possibility of insolvency.

Sharma and Mahajan (1980), Altaman and Lavallee (1981), Ko (1982) and Izan (1984) were among the few researchers who used Multivariate Discriminant Analysis to predict the corporate failure. On the other hand, Eisenbeis (1977), Karels and Prakash (1987), Nam and Jinn (2000), Fathi and Jean (2001), Ugurlu and Aksoy (2006) and Wang and Deng (2006) pointed out that Multivariate Discriminant Analysis hasconfines as it adopts that independent variables should follow multivariate normal distribution and equal covariance matrix.

After that, emphasis shifted towardsprobit or logit analysis. Martin (1977) and Ohlson (1980)were among the first to apply these techniques, followed by others like Wiginton (1980), Zmijewski (1984),Zavgren (1985), Aziz and Lawson (1989), Platt and Platt (1990), Laviola and Trapanese (1997), Mossman et al (1998), Lennox (1999),Westgaard& Van der Wijst (2001), Bacchetti and Sierra (2003), Altaman and Sobato (2007), Pierri et al (2011) and Dainelli et al (2013).

Other statistical practices have also been introduced, such as Recursive Partitioning (Frydman et al.(1985)), Multidimensional Scaling (Mar Molinero andEzzamel (1991)), etc.Gregory et al. (1991) came up with Catastrophe Theory, Tam and Kiang (1992) founded Neural Networks, Johnsen andMelicher (1994) used Multinominal Logit Models, Zopounidis and Doumpos, 1999 used Multicriteria Decision Aid Methodology and Dimitras et al., 1999 came up with RoughSets. Reviews studies can be found in Jones (1987), Karels and Prakash (1987)and Dimitras et al. (1996).

The broaddeductions from this extensive research effort appear to be that each study gives a sensible separation between failed and non-failed firms, but also, and maybe more fundamentally, that the differentresearches scarcely demonstrate any agreement on what factors are imperativefor failure forecast. Surely, one might say that over 30 years of empirical research oninsolvency expectation neglected to create concession to which factors are great indicators and why.This discord of conclusions can, of course, partly be attributed to the fact that the studies refer tovarious periods, nations and businesses. Another factor may be that essentially all of these studiesdo not have a theoretical framework to guide the empirical research effort. In the absence of a theory thatprovides testable hypotheses, each empirical result has to be evaluated on its own merits and one canonly hope that patterns emerge from the multitude of results. This is clearly not the situation in thedefault estimate.

Research Problem:

Can the probability of a firm being bankrupt be predicted using select financial ratios such as Debt/Equity Ratio, Current Ratio, Interest Coverage Ratio, ROCE, and Operating Cash Flow to Sales?

Hypotheses of the study:

H0: Financial Ratioscannot help in prediction of probability of corporate default

Alternative Hypotheses:

H1: Financial Ratios can help in prediction of probability of corporate default

Methodology and Data Sources:

Methodology

There are numerous options for evaluating likelihood of an organization being bankruptviz., linear regression, logistic regression and 'classification trees'. Nonetheless, the most commonly used method is that ofdiscriminant analysis based on past data of defaults. In the present study, the multiple discriminant analysis (MDA) technique is used for estimation of the distress probabilities of the companies.

Data Sources

The companies selected are the ones mentioned by RBI in two different lists for probe related to corporate default in June and August 2017. Financial data of these companies is sourced from the annual reports and financial databases such as Capitaline and Bloomberg. The companies for which data was not adequately available were dropped from the list.

For the companies so listed, data for two different years was collected, one being 2012 when the companies were in sound health and the other being 2016 when their financial health started slipping down.

In research related to estimating corporate bankruptcy, choosing key financial indicatorsbecomesimperative. There are quite a few ratios that have been recognized by the previous studies as indicators of financial distress. Here, since the companies selected are already distressed, most of the data is not easily available. Hence, using convenient sampling following ratios are taken for the study: Debt Equity Ratio, Current Ratio, Interest Coverage Ratio, Cash Profit Margin and Return on Capital Employed.

Data Analysis and Interpretation

To test the hypothesis of the study the data was analyzed through discriminant analysis. Further, for discriminant analysis, the independent variable is taken as being bankrupt i.e. in this case being listed by RBI a firm which needs to be referred to NCLT.

Table 1 shows the group statistics of the predictor variables in the 2 types of firms that is the firms which aren't listed as bankrupt and those which are listed for bankruptcy.

Table I Group Statistics

Bankrupt (Yes/No)		Mean	Std. Deviation	Valid N (listwise)	
				Unweighted	Weighted
1	Debt/Equity Ratio	5.0641	6.82384	29	29.000
	Current Ratio	.8859	.39387	29	29.000
	Interest Coverage Ratio	-1.0172	4.97989	29	29.000
	ROCE	.2610	3.59315	29	29.000
	Op. Cash Flow to Sales	-.5966	3.72170	29	29.000
2	Debt/Equity Ratio	1.9545	.94642	29	29.000
	Current Ratio	1.2503	1.03305	29	29.000
	Interest Coverage Ratio	2.5152	4.63750	29	29.000
	ROCE	9.3500	5.61910	29	29.000

	Op. Cash Flow to Sales	.2214	.55047	29	29.000
	Debt/Equity Ratio	3.5093	5.07680	58	58.000
Total	Current Ratio	1.0681	.79639	58	58.000
	Interest Coverage Ratio	.7490	5.09126	58	58.000
	ROCE	4.8055	6.54728	58	58.000
	Op. Cash Flow to Sales	-.1876	2.66891	58	58.000

Table 3 shows difference in the means of Debt/Equity Ratio, Current Ratio, Interest Coverage Ratio, ROCE, Operating Cash Flow to Sales amongst the two groups i.e. firms which aren't listed as bankrupt and those which are listed for bankruptcy.

Further, to check the above variables are statistically significant, the table (2) of 'test of equality of group means' is analyzed

Table II Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
Debt/Equity Ratio	.905	5.909	1	56	.018
Current Ratio	.947	3.152	1	56	.081
Interest Coverage Ratio	.878	7.815	1	56	.007
ROCE	.510	53.853	1	56	.000
Op. Cash Flow to Sales	.976	1.371	1	56	.247

Tests of Equality of Group means is used to analyze whether the mean scores of the predictor variables in the 2 groups is statistically significantly different.

From table 2, it is seen that the p-value for the predictor variable Debt/Equity Ratio, Interest Coverage Ratio and ROCEis less than 0.05 thereby proving that the difference in the mean of all these predictor variables in the 2 groups is statistically significant.

Next the Cannoical Correlation coefficient is analyzed. The canonical correlation gives the measure of association between discriminant functions and the 2 groups under study.

Table III Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.186[a]	100.0	100.0	.737

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

As observed from Table 5, the canonical correlation is high at 0.737, which indicates a strong relationship between the predictor variables and the outcome. Squaring the canonical correlation gives us the Effect size. The effect size is the quantitative measure that gives the magnitude of the actual effect of the predictors on the outcome. In this case the effect size is 0.5432 implying that 54.32% of the variation in the outcome i.e.being declared bankrupt are explained by the predictor variables.

Further the study evaluates the statistical significance of the prediction model. Wilk's lambda is used for this purpose.

Table IV Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.457	41.852	5	.000

From table 4 it is seen that the Wilks' lambda is low at 0.457 and the p-value (0.000) is also less than 0.05 hence predictor variables predict the outcome (switching intentions) at a statistically significant level.

Table V Standardized Canonical Discriminant Function Coefficients

	Function
	1
Debt/Equity Ratio	-.287
Current Ratio	.211
Interest Coverage Ratio	.163
ROCE	.867
Op. Cash Flow to Sales	.222

Table 5 indicates that ROCE (0.867) has the highest predicting capability followed by Debt-Equity Ratio (0.287) and Operating Cash flow to Sales (0.222).

Using the Canonical Discriminant Function coefficients as given in table 5, the discriminant model is created

Table VI Canonical Discriminant Function Coefficients

	Function
	1
Debt/Equity Ratio	-.059
Current Ratio	.271
Interest Coverage Ratio	.034
ROCE	.184
Op. Cash Flow to Sales	.083
(Constant)	-.975

Unstandardized coefficients

Hence the discriminant model that predicts the outcome of being declared bankrupt is

Z= - 0.975 -0.059 (Debt Equity Ratio) +0.271 (Current Ratio) + 0.034 (Interest Coverage Ratio) +0.184(ROCE) + 0.083(Operating Cash flow to Sales)

This model tells us that the being declared bankrupt can be predicted using the key ratios listed as the predictor variables. Of the five predictor variables Current Ratio and ROCE have the maximum influence and Interest Coverage Ratio has the least.

The accuracy of the prediction model is analyzed through Table 7 which shows the Classification Results.

Table VII Classification Results[a]

		Bankrupt (Yes/No)	Predicted Group Membership		Total
			1	2	
Original	Count	1	25	4	29
		2	4	25	29
	%	1	86.2	13.8	100.0
		2	13.8	86.2	100.0

a) 86.2% of original grouped cases correctly classified.

From Table 7, it is observed that the hit ratio is very high at 86.2%and thus the model appears to be very good.

Conclusion

The results obtained from this study provide some useful insights into variables in form of key financial ratios that may help in predicting if a particular firm is going towards bankruptcy or not. Debt/Equity Ratio, Current Ratio, Interest Coverage Ratio, ROCE, Operating Cash Flow to Sales are the discriminating factors which divide between the firms which will soon be bankrupt and which will not.

The study proposes a model that can predict the possibility of a firm being bankrupt in a year's span.

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<u>Annexure 1:</u>

Name of the firm	**Year**	**Debt/Equity Ratio**	**Current Ratio**	**Interest Coverage Ratio**	**ROCE**	**Op. Cash Flow to Sales**
Essar Steel Ltd	2012	2.51	0.62	0.36	2.25	0.20
Essar Steel Ltd	2016	6.02	0.6	-0.39	0	0.03
Bhushan Steel Ltd	2012	2.78	0.66	2.3	8.95	0.26
Bhushan Steel Ltd	2016	8.62	0.48	0.09	0	0.07
Bhushan Power & Steel Ltd	2012	3.41	0.8	2.11	7.23	0.26
Bhushan Power & Steel Ltd	2016	6.32	0.61	0.09	0	0.18
Alok Industries Ltd	2012	3.35	1.11	1.65	12.85	-0.01
Alok Industries Ltd	2016	2.99	1.15	-1.35	-13.81	-0.21
Electrosteel Steels Ltd	2012	2.57	0.25	-0.87	0	2.85
Electrosteel Steels Ltd	2016	10.3	0.37	-0.22	0	0.25
Monnet Ispat& Energy Ltd	2012	1.51	1.4	5.25	8.34	0.15
Monnet Ispat& Energy Ltd	2016	5.98	0.62	-0.74	0	0.15

ABG Shipyard	2012	2.2	0.88	1.84	14.28	-0.18
ABG Shipyard	2016	0	1.06	-2.21	0	-19.87
JaypeeInfratech Ltd	2012	1.28	1.7	25.82	13.78	0.29
JaypeeInfratech Ltd	2016	1.45	1.5	0.56	3.8	1.10
LancoInfratech Ltd	2012	1.14	1	1.21	4.63	0.46
LancoInfratech Ltd	2016	3.65	0.76	0.41	0	-0.60
Jyoti Structures Ltd	2012	1	1.52	1.67	23.58	-0.02
Jyoti Structures Ltd	2016	10.01	1.23	0.16	0	-0.64
Amtek Auto Ltd	2012	0.84	1.43	3.12	7.57	0.59
Amtek Auto Ltd	2016	2.1	0.58	0.01	0	0.24
Era Infra Engineering Ltd	2012	1.89	1.38	1.73	15	0.03
Era Infra Engineering Ltd	2016	36.47	1.09	-0.75	0	0.44
Jaiprakash Associates Ltd	2012	2	1.16	1.72	9.41	0.14
Jaiprakash Associates Ltd	2016	1.95	1.37	-0.06	0	0.42
Videocon Industries Ltd	2012	1.57	1.56	1.74	7.28	-0.40
Videocon Industries Ltd	2016	2.32	1.98	0.97	6.72	0.49
JayaswalNeco Industries Ltd	2012	1.47	0.87	1.47	10.34	0.06
JayaswalNeco Industries Ltd	2016	1.92	0.75	0.81	2.86	0.17
Visa Steel Ltd	2012	5.03	0.36	0.82	0	0.64
Visa Steel Ltd	2016	0	0.32	-0.26	0	-0.36
Essar Projects India Ltd	2012	1.92	1.27	2.29	17.74	-0.10
Essar Projects India Ltd	2016	3.04	1.05	0.5	5.25	0.23
SEL Manufacturing Company Ltd	2012	1.98	1.22	1.63	9.01	0.00
SEL Manufacturing Company Ltd	2016	4.37	1.44	0.27	0	0.05
Asian Colour Coated Ispat Ltd	2012	1.76	1.32	4.28	10.5	-0.07
Asian Colour Coated Ispat Ltd	2016	2.7	1.2	-0.03	-0.21	-0.03

Uttam Galva Steels Ltd	2012	2.05	0.96	1.57	12.11	0.12
Uttam Galva Steels Ltd	2016	3.77	0.59	-0.45	-4.84	0.12
Castex Technologies Ltd	2012	1.22	2.73	2.23	9.47	0.13
Castex Technologies Ltd	2016	1.8	0.78	-0.13	0	0.36
Ruchi Soya Industries Ltd	2012	1.92	1.02	1.4	12.57	0.03
Ruchi Soya Industries Ltd	2016	1.9	0.87	0.03	0.47	0.00
Nagarjuna Oil Refinery Ltd	2012	0	6	0	0	0.00
Nagarjuna Oil Refinery Ltd	2016	0.03	0.18	-26.67	0	0.00
Unity Infraprojects Ltd	2012	1.26	1.39	2.24	17.16	0.04
Unity Infraprojects Ltd	2016	8.13	1.07	-0.53	0	-0.15
IVRCL Ltd	2012	1.11	0.88	0.86	7.77	0.07
IVRCL Ltd	2016	6.19	0.74	-0.64	0	-0.06
Orchid Pharma Ltd	2012	1.78	0.79	1.5	8.38	0.44
Orchid Pharma Ltd	2016	10.52	1.02	0.19	0	0.24
BILT Graphic Paper Products Ltd	2012	2.17	0.57	1.55	10.16	0.16
BILT Graphic Paper Products Ltd	2016	3.21	0.74	1.04	7.33	-0.03
Jai Balaji Industries Ltd	2012	2.35	0.65	-0.22	0	0.10
Jai Balaji Industries Ltd	2016	0	0.86	-0.61	0	-0.13
Uttam Galva Metallics Ltd	2012	2.61	0.76	1.67	10.79	0.18
Uttam Galva Metallics Ltd	2016	1.1	0.68	0.41	0	0.24