Asian Journal of Business Management 3(3): 210-218, 2011
ISSN: 2041-8744

Received: June 09, 2011 Accepted: July 26, 2011 Published: August 20, 2011

Prediction of Financial Distress -A Case Study of Indian Companies

[1]Amalendu Bhunia, [2]Sri Islam Uddin Khan and [3]Somnath Mukhuti
[1]Fakir Chand College, University of Calcutta, Diamond Harbour,
South 24- Parganas, West Bengal, India
[2]Kaliyaganj College, University of Gour Banga, West Bengal, India
[3]IGNOU, India

Abstract: Financial distress is of crucial importance in financial management especially in the case of competitive environment. Failure is not an impulsive outcome and it grows constantly in stages. A spontaneous protective effort could be accommodated if the company is anticipated to be proceeding in the direction of potential bankruptcy and this can help alleviate the financial distress to all investors and decrease the costs of bankruptcy. This study extends a failure prediction model for Indian companies. This study hopes to accommodate some important results relevant to authorities and stakeholders. The capability to detect potential financial problems at a premature stage is absolutely essential because it helps to ensure business, financial, economic and political environment stability. The results show good performance with a highly correct categorization factuality rate of more than 80%. Two ratios were determined significant out of 64 financial ratios utilized in this analysis to discriminate among failed and non-failed companies. The significant variables are cash flow to sales and days Sales in receivable.

Key words: Discriminant analysis, ratios, cash flow, Indian companies, sales

INTRODUCTION

Several recent papers have served to emphasize the need for a timely model of Indian corporate financial failure prediction, the parameters of which are fully in the public domain. First, Campbell *et al*. (2008) show that financially distressed firms have delivered anomalously low returns in the US. There is no UK equivalent to the model they use to estimate distress risk, something we attempt to address in this study. Second, Pope (2010) suggests that factor mimicking portfolios based on financial distress risk may help deliver more powerful factor models of expected returns. In respect of the UK, this suggestion pre-supposes that an appropriate model is available. Of course, with regard to the latter one can make the case for using a model that is well-understood, such as the z-score models of Taffler (1983, 1984) and this is precisely the approach followed in Agarwal and Taffler (2008a), which provides some fascinating evidence that momentum may be a proxy for distress risk. However, in doing so it provides UK evidence that is consistent with the Campbell *et al*. (2008) finding, leaving the conundrum that markets, apparently, do not adequately price distress risk. This alone motivates the search for a "better" distress prediction model that might resolve this anomaly. Third, Agarwal and Taffler (2007) note the dramatic increase in UK firms with "at risk" z-scores from 1997 onwards, which might imply the need for an updated UK prediction model. Fourth, Shumway (2001) shows that a "hazard" or "dynamic logit" model gives better predictive power than a simpler logit model. Chava and Jarrow (2004) develop this further by adding industry controls, and show that such a model can easily be estimated using standard statistical packages. As far as we are aware, these approaches to modelling, combined with the Campbell *et al*. (2008) innovations, have not been attempted in the UK. However, in the current financial climate one scarcely needs to allude to the academic literature to justify an interest in a timely measure of failure prediction - the likely interest from the wider community in such a model is, regrettably, all too obvious.

Financial distress in companies can lead to problems that can reduce the efficiency of management. As maximizing firm value and maximizing shareholder value cease to be equivalent managers who are responsible to shareholders might try to transfer value from creditors to shareholders. The result is a conflict of interest between bondholders (creditors) and shareholders. As a firm's liquidation value slips below its debt, it is the shareholder's interest for the company to invest in risky projects which increase the probability of the firm's value to rise over debt. Risky projects are not in the interest of creditors, since they also increase the probability of the

Corresponding Author: Dr. Amalendu Bhunia, Fakir Chand College, University of Calcutta, Diamond Harbour, South 24-Parganas, West Bengal, India. Tel.: +91-25469048/+91-9432953985

Table 1: Statistics of Indian companies liquidation 9

Year	Petition Filed	Wound up	Wound up (%) over
1995	688	393	57.1
1996	858	485	56.5
1997	637	449	70.5
1998	503	364	72.4
1999	385	229	59.5
2000	273	161	59
2001	279	17	62.4
2002	318	200	62.9
2003	329	204	62
2004	314	314	78
2005	309	188	60.8
2006	305	222	72.8
2007	340	227	66.8
2008	435	295	68
2009	469	368	78.5

Insolvency, Public Trustee's Office, Ministry of Law, India

firm's value to decrease further, leaving them with even less. Since these projects do not necessarily have a positive net present value, costs may arise from lost profits.

Ferri *et al*. (1998) report that the problems of corporate financial structures have been an important factor in contributing to the Financial Crisis and leading many corporations to bankruptcy. Therefore, there is a need to develop a model to assess the financial health of firms in an Indian context. The research findings from developed economies are not suitable to apply to Indian firms due to the differences in market structures; socio-economic factors, provision and implementation of law, the political environment and accounting standards in these economies, which result in differences in financial reporting (Her and Choe, 1999).

Corporate failures are a common problem of developing and developed economies (Altman *et al*., 1979). It is commonly described as being when an associate of the firm comes up with a resolution that the firm be wound up and assign a liquidator or the associate of the firm can satisfy a meeting of its creditors to deliberate its proposal for a voluntary winding up of the firm. Corporations are not invulnerable to failure, where commonly the firm is not able to meet its liabilities. In the late 1990s, the economic recession invaded all Asian countries including India, which illustrated the need to develop an early alert method to reduce the circumstance of corporate failure among Indian firms.

Table 1 provides the statistics of Indian firm's liquidation. The number of companies winding up escalated since year 1995 to 2009 (for 15 years). Most firms illustrated in Table 1 are small-scale firms that not listed on the Indian Stock Exchange. It is difficult to find the failed firms as described above among Indian listed firms.

Failure is not an impulsive outcome and it grows constantly in stages. There are unique characteristics of failure in firm's financial levels prior achieving total failures. An impulsive protective effort could be accommodated if the company is foreseen to be proceeding in the direction of potential bankruptcy and this can help allay the financial distress to all investors and abate the costs of bankruptcy. It is clear that notwithstanding the tremendous amount of research that has gone into this topic around the world; the predicament of prediction can by no means be absolutely interpreted. This is because prediction is not an actual science and at best, purely a calculated estimate.

Also, the meaningful variable in determining firm's stability and viability varies from territory to territory as sssdocumented in prior researches. In developed economies, most of the users utilized results from the research done in developed economies without making the certain accommodation to regional situations, which will result in misapplication. It is believed that result for India has its particular set of financial ratios in determining company's stability.

In Asian countries, access to literature on this topic is largely unavailable. Business collapses in Asian countries should be deliberately investigated adequate to the increasing expansion of economies that can endanger business performance to meet the treats imposed during economic downturn and this will minimize diminishing credibility of investors and creditors. The objective of this study is to recogniz e the indicative financial ratios which discriminant between failed and non-failed firms. This study hopes to accommodate some important results relevant to authorities and stakeholders. The capability to detect potential financial problems at a premature stage is absolutely essential because it helps to ensure business, financial, economic and political environment stability.

LITERATURE REVIEW

The earliest study using multivariate data analysis on failure prediction was conducted by Altman (1968) by using a set of financial and economic ratios as possible

determinants of corporate failures. The study used sixty-six corporations from manufacturing industries comprising of bankrupt and non-bankrupt firms and 22 ratios from five categories, namely, liquidity, profitability, leverage, solvency and activity. Five ratios were finally selected for their performance in the prediction of corporate bankruptcy and the derived model correctly classified 95% of the total sample (correctly classifying 94% as bankrupt firms and 97% as non-bankrupt firms) one-year prior to bankruptcy. The percentage of the accuracy declined with increasing number of years before bankruptcy.

Altman *et al*. (1977) reported the use of neural network in identification of distressed business by the Italian central bank. Using over 1,000 sampled firms with 10 financial ratios as independent variables, they found that the classification of neural networks was very close to that achieved by discriminant analysis. They concluded that the neural network is not a clearly dominant mathematical technique compared to traditional statistical techniques.

Rushinek and Rushinek (1987) tested data of 30 companies, of which a regional bank believed 13 were bankrupt. The variables utilized were three ratios that the bank believes most essential in making loan decisions, plus four additional ratios preferred by the writer. The variables utilized were net income to sales, EBIT to interest (time interest earned), and Total liabilities/total tangible net worth. They establish that the model precisely categorized 80% of the data. This research suffered from constrained sample size and constrained number of ratios included in the model elaboration. However, the researchers recommended the model as only another device to assist bank loan investigation review the perspective of current or future borrowers.

Mossman *et al*. (1998) conducted to compare four types of bankruptcy prediction models that are based on financial statement ratios, cash flows, stock returns', and returns standard deviations. They tested four bankruptcy models: Altman's (1968) Z-score model based on financial ratios; Aziz and Lawson (1989) model comprised of cash flows. They found that in the year prior to bankruptcy, the ratio model is the most effective in explaining the likelihood of bankruptcy. In the three years preceding bankruptcy, the cash flow model most consistently discriminates between bankrupt and on-bankrupt firms. The findings suggest different uses for the models, as stakeholders might be particularly interested in cash flow variables as an "early warning" indicators of failure. Alternatively, a large negative shift in accounting ratio variables could be a useful indicator of imminent financial collapse.

Begley *et al*. (1980) incorporated the time "bias" factor into the classic business failure prediction model. Using Altman, (1968) and Ohlson's, (1980) models to a matched sample of failed and non-failed firms from 1980's, they found that the predictive accuracy of Altman's model declined when applied against the 1980's data. The findings explained the importance of incorporating the time factor in the traditional failure prediction models.

Campbell *et al*. (2008) constructed a multivariate prediction model that estimates the probability of bankruptcy reorganisation for closely held firms. Six variables were used in developing the hypotheses and five were significant in distinguishing closely held firms that reorganise from those that liquidate. The five factors were firm size, asset profitability, the number of secured creditors, the presence of free assets, and the number of under-secured secured creditors. The prediction model correctly classified 78.5% of the sampled firms. This model is used as a decision aid when forming an expert opinion regarding a debtor's likelihood of rehabilitation.

METHODOLOGY

The data utilized in this analysis is extracted from the income statements, balance sheets, and cash flow statements of sampled firms attained from the Companies Annual Report accessible from the Indian Stock Exchange. The matched sample design method was applied in this analysis. Each failed company has a non-failed "partner" in the sample. Paired samples of failed and non-failed companies from year of 2001 to 2010 were utilized in this analysis. The definitions of "failure" are: (i) The firms that approved to undertake a restructuring scheme to revive their financial conditions by the Singaporean authorities, (ii) The firms that were put under receivership, (iii) The companies had been incurring losses for three years continuously or more and (iv) The companies had illustrated negative position in cash flow for three years continuously or more.

However, it is difficult to find firms that fall under the first two conditions above. Therefore, our approach is to identify the firms that have the last two definitions above in the period observed.

The used of a matched sample of failed and non-failed firms (one-to-one match) might introduce a potential firm failure bias (Platt and Platt, 1990). It is claimed that the potential for failure is overstated using this technique. However, it is stressed that the bias may or may not be important depending on the usage of the model. If the model is used to rank the firms for the , potential failure in order to perform a more detailed analysis, then the bias is not important. However, if the model is used to identify investment portfolio selection then the bias is significant. Furthermore, Zmijewski (1984) reviewed 17 financial distressed studies that used

Table 2: Name of failed firms

No.	Name of the companies
1	SWS India Holdings Limited
2	Stock Holding Corporation of India Limited
3	Silicon Valley of India
4	Patni Computer Systems
5	Indian Electric Co.
6	Abbott India Limited
7	Bajaj Electricals Limited
8	Chambal Fertilizers and Chemicals Limited
9	Elecon Engineering Company Limited
10	Prem Industries
11	Cameo Healthcare India Pvt. Ltd.
12	Ace Cans Mfg. Ltd.
13	Vijay International
14	DLF Building
15	Hindustan Construction Company
16	Bharat Wagon & Engineering Company Ltd
17	Pantaloon Retail (India) Ltd.

this controversial method found that although a choice based sample bias was present, the results do not indicate significant changes in overall classification and classification rates. Finally, Platt and Platt (1990) urged that one-to-one sampling technique is still an acceptable method in failure prediction studies.

A total of 17 failed companies were identified during the year of determination. Table 2, disclosed the name of failed firms. The failed companies were paired to the non-failed companies using the following criteria:

The sample firms used in this study came from 8 different industries: 2 firms from the investment holding sector, 3 firms from the electronics and information technology, 4 firms from the manufacturing sector, 4 firms from the food and beverages sector and 1 each firm from the properties, construction, engineering and retailing sectors. Due to the restrained sample volume for each industry, the research focuses on the blended industry sector.

The dependent variable is defined as the dichotomous event named as a failing or non -failing event. The independent variable is interpreted as the commonly used financial ratios. The ratios used are chosen from those utilized by Beaver (1966) and Altman, (1968). An itemized listing of the variables is accessible in Table 3.

Normality tests: Before the discriminant analysis, normality test was carried out to all independent variables. Two generally utilized tests are the Shapiro-Wilks' test and Lillifors test. The Lillifors test based on alteration of the Kolgomorov-Smirnov test is utilized when means and variances are not known but must be approximated from the data (Norusis, 1999). The Shapiro-Wilks test shows better tools in many statistical conditions correlated to other tests of normality (Izan, 1984). Anyhow, the Shapiro-Wilks' test is well suited to small-size samples.

Table 3: List of ratios examined

V01	Cash flow to sales	V33	Inventory growth
V02	Cash flow to assets	V34	Sales growth
V03	Cash flow to net worth	V35	Depreciation growth
V04	Cash flow to total debt	V36	Dividend growth
V05	Return on Sales (ROS)	V37	Return on opening equity
V06	% Change in ROS	V38	% Change in return on Op Equity
V07	Return on assets	V39	Equity to debt
V08	Return on equity	V40	% Change in equity to debt
V09	Net income to total debt	V41	Equity to long term debt
V10	Current liabilities to total assets	V42	% Change in equity to L T D
V11	Long-term liab. to total assets	V43	Equity to fixed assets
V12	Total liabilities to total assets	V44	% Change in equity to F A
V13	Cash to total assets	V45	Times interest earned
V14	Quick assets to total assets	V46	% Change in interest earned
V15	Current assets to total assets	V47	Profit before Dep. to sales
V16	Working capital to total assets	V48	% Change in P B D to sales
V17	Cash to current liabilities	V49	Pretax income to sales
V18	Quick ratio	V50	% Change in Pretax Inc. to sales
V19	% Change in quick ratio	V51	Sales to inventory
V20	Current ratio	V52	% Change in sales to inventory
V21	% Change in current ratio	V53	Sales to fixed assets
V22	Cash turnover	V54	% Change in total assets
V23	Receivable turnover	V55	% Change in W C to T A
V24	Quick asset turnover	V56	Operating income to assets
V25	Current asset turnover	V57	% Change in Op. Inc. to asset
V26	Working capital turnover	V58	% Change in long term debt
V27	% Change in sales to W. C.	V59	Dividends to cash flows
V28	Net worth to sales	V60	Net Income to cash flow
V29	Asset turnover	V61	Operating profit to sales
V30	% Change in sales to total assets	V62	Return on owners equity
V31	Days sales in receivable	V63	Total assets to net worth
V32	Inventory to total assets	V64	Earning power

Table 4: Raw data of normality tests

		Shape		Normality test	
Variables	Details	Skewness	Kurtosis	Stat.	Sig.
V01	Cash flow to sales	- 9.18	109.82	0.24	0
V02	Cash flow to assets	- 2.04	6.612	0.15	0
V03	Cash flow to net worth	2.76	39.53	0.21	0
V04	Cash flow to total debt	- 9.60	105.71	0.11	0
V05	Return on Sales (ROS)	- 9.28	112.19	0.24	0
V06	% Change in ROS	8.03	73.61	0.38	0
V07	Return on assets	- 2.38	7.36	0.20	0
V08	Return on equity	- 0.66	16.96	0.23	0
V09	Net income to total debt	- 9.52	104.45	0.20	0
V10	Current liabilities to total assets	0.74	0.39	0.12	0
V11	Long-term liab. to total assets	0.44	- 0.59	0.08	0.004
V12	Total liabilities to total assets	0.03	- 0.21	0.06	0.10
V13	Cash to total assets	1.26	1.27	0.14	0
V14	Quick assets to total assets	0.36	- 0.17	0.06	0.20
V15	Current assets to total assets	0.17	- 0.16	0.04	0.20
V16	Working capital to total assets	0.68	0.83	0.06	0.20
V17	Cash to current liabilities	11.28	141.97	0.22	0
V18	Quick ratio	11.32	143.07	0.15	0
V19	% Change in quick ratio	9.60	95.35	0.25	0
V20	Current ratio	9.48	92.22	0.16	0
V21	% Change in current ratio	2.93	12.67	0.17	0
V22	Cash turnover	3.39	12.93	0.28	0
V23	Receivable turnover	7.96	67.04	0.53	0
V24	Quick asset turnover	3.42	15.73	0.18	0
V25	Current asset turnover	2.35	11.17	0.15	0
V26	Working capital turnover	8.90	102.00	0.31	0
V27	% Change in sales to W. C.	13.36	185.52	0.39	0
V28	Net worth to sales	5.12	25.82	0.39	0
V29	Asset Turnover	3.06	15.55	0.14	0
V30	% Change in sales to total assets	9.65	113.49	0.17	0
V31	Days sales in receivable	1.44	4.50	0.10	0
V32	Inventory to total assets	2.74	9.51	0.17	0
V33	Inventory growth	4.93	29.56	0.30	0
V34	Sales growth	11.13	140.82	0.38	0
V35	Depreciation growth	4.12	28.25	0.25	0
V36	Dividend growth	- 4.13	32.78	0.23	0
V37	Return on opening equity	6.82	54.12	0.21	0
V38	% Change in return on Op equity	- 4.31	20.37	0.30	0
V39	Equity to debt	- 0.26	25.25	0.47	0
V40	% Change in equity to debt	3.03	10.64	0.47	0
V41	Equity to long term debt	9.74	123.30	0.24	0
V42	% Change in equity to L T D	- 14.01	196.92	0.39	0
V43	Equity to fixed assets	- 13.58	188.46	0.24	0
V44	% Change in equity to F A	- 9.18	109.82	0.42	0
V45	Times interest earned	10.26	114.83	0.35	0
V46	% Change in interest earned	- 9.09	108.57	0.33	0
V47	Profit before Dep. to sales	- 1.52	86.13	0.19	0
V48	% Change in P B D to sales	12.24	161.32	0.12	0
V49	Pretax income to sales	6.00	40.79	0.35	0
V50	% Change in pretax Inc. to Sales	3.37	14.69	0.17	0
V51	Sales to inventory	1.65	6.93	0.43	0
V52	% Change in sales to inventory	- 4.00	72.22	0.36	0
V53	Sales to fixed assets	- 2.17	6.73	0.41	0
V54	% Change in total assets	3.35	59.10	0.26	0
V55	% Change in W C to T A	4.89	58.26	0.39	0
V56	Operating income to assets	7.24	44.74	0.24	0
V57	% Change in Op. Inc. to asset	- 8.14	67.84	0.20	0
V58	% Change in long term debt	- 2.08	49.08	0.24	0
V59	Dividends to cash flows	- 1.62	51.21	0.28	0
V60	Net income to cash flow	- 13.01	179.32	0.27	0
V61	Operating profit to sales	- 9.17	109.92	0.42	0
V62	Return on owners equity	7.10	109.19	0.42	0
V63	Total assets to net worth	1.39	20.19	0.22	0
V64	Earning power	- 2.23	9.19	0.200	0

Table 5: Statistic of normal variable under normality test (untrimmed vs trimmed extreme values)

	Raw data untrimmed		Raw data trimmed	
Variables	Stat.	Sig.	Stat.	Sig.
Panel A: Raw data				
V02	-	-	0.09	0.001
V11	0.12	0.004	0.08	0.005
V12	0.06	0.100	0.07	0.060
V14	0.06	0.200	0.07	0.070
V15	0.04	0.200	0.06	0.200
V16	0.06	0.200	0.05	0.200
V29	-	-	0.08	0.010
V30	-	-	0.09	0.001
V31	--	-	0.09	0.003
Panel B: Square				
V12	-	-	0.09	0.002
V15	0.07	0.020	0.07	0.040
Panel C: Square root				
V10	0.09	0.001	0.10	0.001
V12	0.08	0.002	0.10	0.001
V13	0.07	0.010	0.07	0.040
V14	0.06	0.200	0.07	0.080
V15	0.07	0.020	0.08	0.010
V18	0.09	0.001	0.09	0.001
V20	0.09	0.001	0.09	0.001
V25	0.09	0.002	0.07	0.030
V29	0.09	0.001	0.07	0.040
V31	0.06	0.200	0.06	0.200
V32	0.05	0.200	0.06	0.200
Panel D: Inverse				
V23	0.09	0.001	0.08	0.01
V63	0.06	0.200	0.07	0.07
Panel E: Natural Log				
V10	0.06	0.200	0.05	0.200
V13	0.09	0.002	0.09	0.001
V17	0.05	0.200	0.06	0.200
V18	0.08	0.010	0.05	0.200
V20	0.06	0.200	0.06	0.200
V22	0.06	0.200	0.04	0.200
V24	0.04	0.200	0.05	0.200
V25	0.08	-	0.06	0.200
V29	-	0.005	0.09	0.003
V53	0.05	0.200	0.05	0.200

Bold areas are the variable normally distributed

The null hypothesis will be rejected for large values of Kolgomorov Smirnov D-statistics.

According to Norusis (1999) advised that for most statistic tests, it is adequate that the data are approximately normally distributed.

Table 4, disclosed the Kolgomorov Smirnov tests (altered for Lillifors). Only three variables (V14, V15 and V16) are normal and two variables (V11 and V12) are almost normal out of sixty-four variables were tested. The other variables significantly exit from normality assumptions with excessive skewness statistics and peaked distribution. Accordingly, we exclude the hypothesis null that all of the financial ratios examined are normally distributed.

In orderto enhance the normality, data transformation processes were implemented. There are several approaches to data transformation methods supported in the literature, such as natural Log, Square Root, Square and Inverse. Natural logs and square roots suffer in that they cannot be employed if the ratios are negative (Ezzamel *et al*., 1996). Another option that can be utilized to eliminate this complication such as adding or subtracting a constant or engaging squares of ratio or inverse of the ratio. Ezzamel *et al*. (1996) suggested that such techniques tend to emphasize the distortion by extreme values giving correlatively more weight to large observations. In this analysis, four accepted transformation approaches are discussed, natural log, square root, square, and inverse transformation were utilized (Table5).

Before data transformations were implemented, variable number V14, V15, and V16 are normal and, V11 and V 12 are almost normal. The Kolgomorov-Smirnov statistic (KS) and the significance level were enhanced after elimination of extreme values.

Under the square transformation technique, there is no variable that is normally distributed but variable number V15 is near normally distributed before transformation, the number increased to two under nearly normal distribution when the extreme values were eliminated. The new variable is V12. Under square root transformation, Three variables found normal (V14, V31 and V32) and eight variables found almost normal (V10, V12 V13, V15, V18, V20, V25 and V29) before elimination of extreme values. The number decreased to two in normal (V31 and V32), increased to nine in almost normal (V10, V12, V13 V14, V15, V18, V20, V25 and V29) when the extreme values were eliminated.

Under the natural log transformation, it is found that six variables were normal and three were nearly normal before elimination of extreme values and the number increased to eight (variables number V18 and V 25 are the new variables) in normal distribution and the number decreased to two (V18 was deleted) in near normal distribution. Finally, under inverse transformation, It is found that one variable was normal and nearly normal before elimination of extreme values and the number decreased to zero in normal distribution and the number increased to one (V63 was is the new variable) in near normal distribution.

It is proven that elimination of extreme values enhances the normality degree of variables. Natural log transformation more performed compares to other types of transformation; the square transformation are the worst where no variables were determined normal under this alternative. This condition established the reason developed by Ezzamel *et al*. (1996) that the approach would give more weight to large observations.

The natural log transformation is responsive to elimination of extreme values that documented the enhanced number in variables. Also there is an enhancement in KS statistics and significance level.

RESULTS AND DISCUSSION

Utilizing samples of failed and non-failed companies as the categorization variables and the ratios as the independent variables, a forward stepwise multivariate discriminant analysis was used to determine the discriminating power of the variables. In stepwise estimation, independent variables were entered into the discriminant function one at a time on the basis of their discriminating power. This method starts by selecting the single outstanding discriminating variable. The first variables are then matched with each of the other independent variables one at a time, and the variables that are outstandingly able to enhance the discriminating power of the function in coalition with the first variable are selected. The third and any following variables are selected in the same method.

The normal variables were entered into the discriminant analysis. Five groups of potential variables were examined1. The Mahalanobis D^2 method was utilized in this process. Mahalanobis D^2 was used to select the variable that develops the highest separation for the pair of groups, which are precise at a particular step. This process starts with all of the variables excluded from the model and chooses the variable that's topmost in the Mahalanobis distance between the groups. As an additional means of interpreting the relative discriminating power of the independent variables, F test was utilized.

The prediction model was generated, as illustrated below:

$$Z = 0.873 + 8.951X1 - 0.138X2$$

where;
Z = Overall Index
X1 = Cash flow to Assets (V02)
X2 = Square root Days Sales in Receivable (V31)

The outcomes show that the failed group centroid (Dependent variable (DV) = 0) is –0.792 and the non-failed group (DV = 1) centroid is 0.775. Z-scores measure these centroids. The overall mean or called cutting score is equally to zero2.

Table 6 lists down the statistics indicated, captioned together with the significant variables, which were examined by the stepwise process, and two variables were determined to be significant.

Utilizing the stepwise process, the significant variable has been recognized and this process eliminates the non-significant variables from entering the function. According the analysis carried out, variables V02, V12, V14, V16, V18, V31 and V33, the discriminant loadings and univariate F values, the ranking of discriminating power of variables are recognized. In two variables function, V02 discriminates the most with the topmost discriminant loading and F-statistics, and V18 discriminates the least.

Table 6: Summary of interpretative measures

		Discriminant loading		Univariate F-ratio	
Variables	Standard weight value	Value	Rank	Value	Rank
V02	0.95	0.93	1	101.91	1
V12	NI	- 0.06	5	NI	NI
V14	NI	0.12	3	NI	NI
V16	NI	0.04	6	NI	NI
V18	NI	- 0.02	7	NI	NI
V31	- 0.36	- 0.31	2	57.97	2
V33	NI	0.07	4	NI	NI

NI: not included

Table 7: Validation outcomes

		Predicted group membership		Total	
Original	Count	DV	0	1	
		0	72.0	22.0	94
	%	1	12.0	84.0	96
		0	76.6	23.4	100
		1	12.5	87.5	100
Cross-validated		0	71.0	23.0	94
		1	12.0	84.0	96
	%	0	75.5	24.5	100
		1	12.5	87.5	100

Justification of the discriminant outcomes: This section elaborates on the validity of the discriminant function. For that reason, we are required to elaborate validation matrices for both the analysis sample and the cross-validated validation. In the earlier section, we have determined the cutting score, which is equal to zero. The process is as follows:

- Categorize a company as failed companies if its discriminant score is positive value
- Categorize a company as non-failed company if its discriminant score is negative value

Utilizing this precedent, the SPSS generated justification matrices for the observations in the examine sample. The validation outcome of the analysis sample is illustrated in Table 7.

It is determined that the model factuality is up to 82.1 percent (average of correct categorization of DV = 0 at 76.6% and DV = 1 at 87.5%). In the cross-validated approach, the categorization factuality was determined at 81.6% (average of correct categorization of DV = 0 at 75.5% and DV = 1 at 87.5%). This outcome indicates that the model is valid for application.

CONCLUSION

The outcome shows good performance with a highly correct categorization factuality rate of more than 80%.

The outcomes (V02 and V31) are very significant variables to identifying distress of the Indian firms.

Two ratios were determined significant out of 64 financial ratios utilized in this analysis to discriminate among failed and non-failed companies. The significant variables stated below are in accord with their discriminating power or position in condescending series:

- Cash flow to Sales (V02)
- Days Sales in Receivable (V31)

The significant variables captioned could assist the users of the results to generate a similar framework of advanced indicator mode to either avoid or mitigate impending difficulty.

The following are the possible entities to utilize the characteristic failure and non- failure result:

- The result can determine the risk postulate to that future customer. Additionally, this result can be utilized as a yearly appraisal of customer's financial situation in making decisions to renew or continue the loan provided
- Investor can utilize the results to reach a certain conclusion. The result can contribute in advance an indication of the financial situation to aid the investor's selection of companies

ACKNOWLEDGMENT

This is my proud privilege of expressing my deepest sense of gratitude and indebtedness to the Chief Librarian of the Indian Institute of Management (IIM), Kolkata; Commercial Library, Kolkata, Indian Statistical Institute, Kolkata and General Managers of selected companies under the study for having given me the required information that has formed the basis of this study.

REFERENCES

Agarwal, V. and R.J. Taffler, 2007. Twenty-five years of the Taffler z-score model: Does it really have predictive ability? Account. Busin. Res., 37(4): 285-300.

Agarwal, V. and R.J. Taffler, 2008a. Comparing the performance of market-based and accounting-based bankruptcy prediction models. J. Banking Finance, 32(8): 1541-1551.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Finance, 23: 589-609.

Altman, E.I., T.K.N. Baidya and L.M.R. Dias, 1979. Assessing potential financial problems for firms in Brazil. J. Banking Finance, 12(2): 9-24.

Altman, H.N., 1977. Zeta Analysis: A new model to identify bankruptcy risk of corporation. J. Bank. Finance, pp: 29-54.

Aziz, A. and G.H. Lawson, 1989. Cash flow reporting and financial distress models: Testing of Hypotheses. Financial Manage., 18: 55-63.

Beaver, W.H., 1966. Alternative financial ratios aspredictors of failure. J. Account. Revi., 43: 71-11

Begley, J., J. Ming and S. Watts, 1995. Bankruptcy Classification Errors in the 1980's: An Empirical Analysis of Altman and Ohlson's Models. Unpublished Manuscript. University of British Columbia.

Campbell, J.Y., J. Hilscher and J. Szilagyi, 2008 In search of distress risk. J. Finance, 63(6): 2899-2939.

Chava, S. and R. Jarrow, 2004. Bankruptcy prediction with industry effects. Revi. Finance, 8(4): 537-569

Ezzamel, M., D.R. Gwilliam and K.M. Holland, 1996. Some pirical vidence rom publicly quoted UK companiesn he relationship between the pricing of audit and non-audit services. Account. Bus. Res., 27(1): 3-16.

Ferri, G., H. Hahm and P. Bongini, 1998. Corporate Bankruptcy in Korea: Only the Strong Survive, World Bank Report.

Her, Y.W. and C. Choe, 1999. A Comparative Study of Australian and Korean Accounting Data in Business Failure Prediction Models. La Trobe University Working Paper 99.07.

Izan, H.Y., 1984. Corporate distress in Australia. J. Bank. Finance, 8(2): 303-320.

Mossman, C.E., G.G. Bell, M. Swartz and H. Turtle, 1998. An empirical comparison of bankruptcy models. Financial Rev., 33: 35-54.

Norusis, M.J., 1999. SPSS for Windows: Base System User's Guide release 6.0., SPSS Inc.: Chicago

Ohlson, James A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. J. Accounting Res., 18(1): 109-131.

Pope, P.F., 2010. Bridging the gap between accounting and finance. Br. Count. Rev., 42(1): 88-102.

Platt, H.D. and M.B. Platt, 1990. Development of class of stable predictive variables: The case of bankruptcy prediction. J. Bus. Finance Account., 17(1): 31-51.

Rushinek, A. and S.F. Rushinek, 1987. Using financial ratios to predict insolvency. J. Busin. Res., 15: 93-100.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. J. Bus., 74(1): 101-124.

Taffler, R.J., 1983. The assessment of company solvency and performance using a statistical model: A comparative UK-based study. Account. Bus. Res., 15(52): 295-307.

Taffler, R.J., 1984. Empirical models for the monitoring of UK corporations. J. Bank. Finance, 8(2): 199-227.

Zmijewski, M.E., 1984. Methodological issues related to the imation financial istress rediction models. J. Account. Res., 22: 59-82.

End notes:

1 The correlation analysis was implemented on variables that were normal under the normality tests (constraint to variables that do not have feasibility to be a negative value). Variables probably have negative value, for example, profit and cash flow ratio were eliminated from this analysis due to complication in transforming them utilizing natural log and square root. Also, a number of variables that are statistically normal but with low significance level were incorporated. Our method is to elaborate a number of independent variable groups, which absolutely incorporate the highly correlated variables and analyze them to obtain the power of discrimination among, failed and non-failed groups instead of deleting it. Therefore, a variable selected and associated variable that are highly correlated with it will not incorporate in a similar group and will create other groups for following analysis. The optimum group with elevated achieves ratio will be selected as the final independent variables.

2 The overall mean was calculated as follow; $Z = (N_0Z_0+N_1Z_1)/(N_0+N_1)$; where Z is a critical cutting score, N_0 are the number of observations in non-failed group, Z_0 is the centroid for non-failed group, N_1 are the number of observations in failed group and Z_1 is centroid for failed group.