Asset and Debt Management Ratios in Bankruptcy Prediction - Evidence from India

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Abstract

The purpose of this paper was to attempt an evaluation of effectiveness of asset and debt management ratios as an analytical tool to predict corporate bankruptcy. Earlier, Altman (1968), Ohlson (1980), and Zmijewski (1984) analyzed the power of financial ratios in predicting bankruptcy. This study is an extension of the literature. A set of variables that acted as the best measure of asset and debt management of a corporate were investigated and multiple discriminant analysis was applied. It was found that the new model proved to be significant in predicting bankruptcy.

Key words : **asset and debt management, bankruptcy, long term debt management, market capitalization, cash from operations**

JEL Classification : G21, G17, G33, G32, M4

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Using financial ratios for bankruptcy prediction has been a practice since the mid-1960s. The relevance of traditional ratio analysis has been questioned by the academicians and researchers (Altman, 1968). Traditional ratio analysis depicts regular business performance but does not show the long-term sustainability of an entity. Several models that were developed in the early 1970s and 1980s (Altman, 1968 ; Altman, Haldeman, & Narayanan, 1977 ; Beaver, 1966 ; Deakin, 1972) focused on the ability of financial and economic ratios in predicting bankruptcy. Several researchers identified unique characteristics of business from different angles. Ahuja and Singhal (2014), Sailaja and Hariharan (2017), and Reddy (2012) conducted some of the bankruptcy studies for Indian companies. Yarifard and Ahmadpour (2008) predicted bankruptcy in the Tehran Stock Exchange. All these studies proved that the viewpoint on bankruptcy and business performance keeps changing, and the analysts and standard setters expect new methodologies as well as models with different combinations of variables to predict corporate failure. Our research shows the effectiveness of asset and debt management ratios in identifying corporate distress and failure.

Asset and Debt Management

The prediction of bankruptcy using financial ratios was narrowed down by several researchers from the mid-80s. Ohlson (1980) combined total asset with GNP price level index ; Zmijewski (1984) included net income/total assets ; Zavgren (1985) had various combinations of inventory and capital management ratios ; Casey and

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Bartczak (1985) combined cash flows with liabilities ; Jantadej (2006) used different combinations of cash flows in predicting corporate distress [1].

The combination of asset and debt management plays a crucial role in risk management. Any business entity starts with an asset and ends itself by selling off the assets and transferring the liabilities. Asset - debt management often combines risk management with strategic planning. It is not only about providing solutions to alleviate risks arising from association of asset and liabilities, but also to ensure long - term sustainability by increasing asset value to handle the complications in paying off the debts.

Rating agencies across the world use different combinations of balance sheet variables to check liquidity, solvency, and profitability of corporates. For example, Fitch's financial analysis insists on cash flow measures than equity based ratios such as debt to equity and debt to capital. These ratios largely rely on book valuations and do not give a clear picture on market values or the ability of assets to generate cash to pay off the debts. Fitch also feels book values are not a strong measure to analyze loss given defaults. Standard & Poor's (S&P), on the other hand, focuses more on debt service coverage ratios, that is, ability of a firm to service debt through regular operating earnings. Moody's try to relate capital expenses with debt. The Table 1 shows a clear picture of the financial ratios used by the big three global credit - rating agencies. Going by the ratios given in the Table 1, it is quite clear the rating agencies consider profitability ratios and debt service coverage ratios as the best accounting metrics to measure a firm's performance. Not much weightage is given to market value and asset management as a measure of sustainability.

We have developed a model of asset - debt management (ADM) which includes asset management, debt management, cash flow, equity and sales management, thus depicting a clear picture of current and long-term success and sustainability of corporates and failure of this would end up in bankruptcy.

Sample Set, Data Sources, and Methodology

The population consisted of 81 firms, which included bankrupt and non-bankrupt firms that are listed on the National Stock Exchange (NSE) India. All banking, finance, and insurance firms were excluded from the list. The bankrupt firms were selected from the list released by Board of Industrial and Financial Reconstruction (BIFR) as well as defaulter list released by the Reserve Bank of India (RBI) in the year 2017. The mean value of net worth of these firms is INR 314.09 crores and the non-bankrupt firms were selected randomly from the database. The year of bankruptcy was 2017. Data for all the firms were collected from the CMIE Prowess and Capitaline databases. The firms were selected based on stratified random basis stratified by net worth.

Bankruptcy status of the firm is taken as the dependent variable. Previously, Altman (1968), Altman et al. (1977), Deakin (1972), and Ohlson (1980) also used the same approach. Out of the bankrupt firms, only those that were operating 3 years prior to bankruptcy were considered and this approach ended up in identifying 31 bankrupt firms [2].

Once the bankrupt firms were identified, the non-bankrupt firms were selected and the size of non-bankrupt firms was 50 firms. The advantage of larger non-bankrupt firms is that the sample errors were reduced as the non-bankrupt firms' economic and financial characteristics improved the accuracy in measurements (Lev, 1974). For example, Ohlson (1980) used 2058 non-bankrupt firms and 105 bankrupt firms.

The sample of non-bankrupt firms was stratified by net worth. The mean net worth of these firms is INR 4587 crores. The financials of non - bankrupt firms were matched with the bankrupt firms of the same financial period. Bankrupt firms were asymmetrically smaller in size. Previous studies conducted in this area matched samples to detect the variation based on common characteristics such as asset size, market capitalization, enterprise value, and revenue (Zhang, Hu, Patuwo, & Indro, 1999) ; economic sector (Raghupathi, Schkade, & Raju, 1991) ; and location or geography (Salchengerger, Cinar, & Lash, 1992). Most of the research done previously employed size

Table 1. Financial Ratios Used by the Big Three Rating Agencies to Measure Business Performance of Non-Financial Corporates

RATING AGENCY	FINANCIAL RATIOS
Fitch	**Profitability Ratios:** • EBIT margin • FFO margin • FCF margin • CFO margin • Capex/CFO **Leverage Ratios :** • Total adjusted debt / op EBITDAR • FCF/ Total adjusted debt • Total debt/ capitalization % • Total equity / capitalization % **Coverage Ratios :** • FFO interest coverage • EBITDA/ interest paid • CFO/ capital expenditure
S&P Ratings	**Profitability Ratios:** • EBIT margin • EBIT/ Average of capital at the beginning of the year and capital at the end of the year **Debt Payback Ratios:** • FFO/ debt • Debt/ EBITDA • CFO/ debt • FCF/debt • EBIT / interest
Moody's Analytics	**Profitability Ratios:** • EBITA/average assets • EBITA margin • EBITA / interest expense • FFO + interest expense / interest expense **Debt Ratios :** • Debt/ EBITDA • Debt/ book capitalization • FFO/ debt • Retained cash flow/ debt • CAPEX/ depreciation

Notes : EBIT - Earnings before interest and Tax ; FFO - Funds from Operations; FCF - Free Cash Flow; CFO- Cash from Operations; CAPEX- Capital Expenditure; EBITDA - Earnings before interest depreciation and amortization; EBITA - Earnings before interest, tax, and amortization and industry characteristics in matching samples (Altman, 1968 ; Beaver, 1966 ; Deakin, 1972 ; Leshno & Spector, 1996 ; Zavgren, 1983). The main aim of matching is to reduce random sampling errors and sensitive statistical results. However, Lincoln (1984) argued that the matching impedes the discriminatory power of the matching characteristics. It was to minimize the sampling error as unequal samples were used for analysis.

Development of the Model

After grouping the samples, the financial statement variables were analyzed. Since there were a larger number of variables that looked as strong indicators of asset and debt management that can predict bankruptcy, a set of 15 variables that were found to be significant were combined and a set of six standard ratios were developed that measure debt management, asset management, interest rate, equity and sales management, and cash flows. The following procedures were applied in selecting the six variables :

(i) Evaluation of correlations between the variables.

(ii) Statistical significance of each variable.

(iii) Judgment of analysis.

Multiple discriminant analysis (MDA) was used to develop the model. Multivariate methods gained popularity in the late 1960s. Apart from discriminant analysis, researchers started using rigorous statistical methods, particularly in the area of financial distress. For example, Zmijewski (1984) applied probit regression in predicting bankruptcy applied logit models. Ohlson (1980) developed *O* - score using logit regression. Multiple discriminant analysis proves to be more significant while handling different combinations of ratios.
The discriminant function is as follows:

$$Z = B_0 + B_1X_1 + B_2X_2 \text{ ....} B_nX_n \text{ ....} \qquad (1)$$

where,

Z = Discriminant score,
B_0 = Estimated constant,
B_n = Estimated coefficients,
B_n = Estimated variables.

The objective of the discriminant analysis is to test classification of groups, that is, bankruptcy status of the firm depends on at least one of the estimated variables.

➷ **H_0 :** Bankruptcy status does not depend on any of the estimated variables (X_n).

➷ **H_a:** Bankruptcy status depends on at least one of the estimated variables (X_n).

or

H_0: $B_n = 0$, for $n = 1, 2$ .... $p, H_1 : B_n \neq 0$

Researchers have proved that financial ratios have been effective in predicting business failures. Most of the ratios used in the previous studies depicted the financial soundness of the corporates in terms of solvency, profitability, and liquidity cash management. Altman (1968), Deakin (1972), Edmister (1972), Sinkey (1975), Altman et al. (1977), Ohlson (1980), and Altman (1993) used the set of ratios that measure the above factors. A handful of researchers namely, Ohlson (1980), Altman (1993), Deakin (1972), and Altman (1968) focused on the leverage management ratios like total liabilities/total assets, total liabilities + preferred stock / total assets, equity market value/ total capitalization, equity market value / total liabilities, retained earnings/ total assets as part of their research. This research solely focuses on the ratios that depict the effectiveness of asset and debt management and long - term sustainability of business. The combinations of variables show how asset and debt management play a crucial role in delineating the status of bankruptcy of a firm. To put it in a nutshell, it is not only the profitability, liquidity turnover ratios that portray the financial picture, but it is also the debt and the modes of debt repayment followed by the firms, the power of generating income by the firm's assets that give a signal on the financial stability and predict the bankruptcy.

- **(*X*1) Debt/ Net Worth :** This ratio is a stringent measure of financial risk. This is not very popular in literature but it tries to explain the solvency and leverage level of a firm. Furthermore, insolvency occurs when a firm is overburdened by its debt and selling assets will be the only option to pay off the huge quantum of debt.

- **(*X*2) Cash Flow from Operations/ Total Debt :** Cash flow from operations is one of the effective and easiest observations that can depict the liquidity status of a firm. Cash flow from operations is the actual cash that enters the firm through day to day business activity. Managing this component of cash flow gives immense benefit for the firm to pay off the interests regularly.

- **(*X*3) Market Capitalization/ Total Sales :** This is a valuation also termed as price to sales ratio. Since the final ranking of a firm is based on its market price, this ratio appears to be particularly suitable for researchers dealing with corporate distress and failure.

- **(*X*4) Sales/Asset :** This is a standard turnover ratio indicating the ability of a firm's asset in generating sales. This ratio is not statistically significant based on univariate analysis ; however, its relationship with other variables is quite significant.

- **(*X*5) Asset / Equity:** Asset divided by equity is a measure of a firm's leverage level. A high level of this ratio indicates a firm has taken debt merely to stay in its business.

- **(*X*6) Interest Coverage Ratio :** This measure is widely used in bankruptcy prediction. It determines the ability of a firm to pay its interest on debt. The lower the ratio, the greater will be the probability of a firm going bankrupt. This is often calculated by dividing earnings before interest and taxes with interest expense [3].

Analysis and Results

Table 2 shows the mean ratios of bankrupt and non - bankrupt firms. High variations in ratios are observed from year to year. On an average, the debt/net worth (*X*1), asset/equity (*X*5) ratios are lesser for non-bankrupt firms than for bankrupt firms. The interest coverage ratio (*X*6), CFO/debt (*X*2), and MCAP/sales (market capitalization/sales) (*X*4) are higher for non-bankrupt firms compared to the bankrupt ones. The sales/asset ratio does not show much significant variation.

Variable means one year prior to bankruptcy, that is, for the financial year 2017 are displayed in the Table 3.

Table 2. Mean Values of Estimated Ratios

Group	Ratios	2014	2015	2016	2017
Bankrupt	*X*1	4.86	8.91	54.88	9.00
	*X*2	0.11	0.06	0.11	0.12
	*X*3	0.68	2.36	0.29	0.71
	*X*4	1.54	0.12	0.93	0.63
	*X*5	46.46	12.20	39.68	2.89
	*X*6	7.17	-73.57	1.92	-4.47
Non-Bankrupt	*X*1	0.64	0.41	0.39	0.83
	*X*2	44.05	1.84	4.94	3.42
	*X*3	2.97	25.07	4.60	4.05
	*X*4	1.69	1.64	1.43	1.46
	*X*5	1.56	1.38	1.01	1.33
	*X*6	220.56	301.53	277.26	198.86

Table 3. Equality of Group Means

	Wilks' Lambda	*F*	*df*1	*df*2	Sig.
*X*1	.888	9.817**	1	78	.002
*X*2	.961	3.196	1	78	.078
*X*3	.752	25.73**	1	78	.000
*X*4	.889	9.743**	1	78	.003
*X*5	.998	.120	1	78	.730
*X*6	.956	3.573	1	78	.062

Notes: ** denotes significance at .01 level

F-test was carried out to assess the individual discriminating ability of the ratios and overall predictive power of the model. Variables are found to be significant at different means, indicating a strong variation between the groups. The *p* - values (shown in Table 2) are less than .01 for *X*1, *X*3, and *X*4, proving the ratios to be significant contributors in determining bankruptcy.

Variables *X*1 and *X*5 are expected to have lower values for non-bankrupt firms as they deal with the debt "component". The coefficient signs of these two variables are found to be negative, which proves that a firm's potential to fail depends on higher *X*1 and *X*5. Based on the results, the null hypothesis (H_0) is rejected and the alternative hypothesis (H_1) is accepted.

The resulting discriminant function is as follows:

$$Z = -.005\,(X_1) + .002\,(X_2) + .005\,(X_3) + .234\,(X_4) - .004\,(X_5) + .001\,(X_6) \quad .... \qquad (2)$$

To begin with, the format of the presentation of the results is explained. In multiple discriminant analysis, the data is classified into two groups, namely bankrupt firms and non - bankrupt firms. The results are shown in the following format.

"*A*, *A*1" indicate number of hits or correct classifications and *"E"* denotes number of misses or misclassifications. *E*1 denotes type I error and *E*2 denotes type II error. The sum of the diagonal divided by the

Table 4. Model Results

Classification Results, Original Sample

	Number Correct	Percent Correct	Percent Error	*n*	Predicted		
					Actual	**Group1**	**Group2**
					Group 1	A	E1
					Group 2	E2	A1
Type I	A	A%	E1%	*n* (Group 1)			
Type II	A1	A1%	E2%	*n* (Group 2)			
Total							

total number of firms considered in the sample give the overall percentage of success of multiple discriminant analysis. The *A*%, *A*1%, and *E*% represent the percentage of success and misses in the respective groups (see Table 4). The percentage (%) mentioned in the tables is more like a coefficient that is measured in regression analysis that explains the percentage of variation in the dependent variable. The model's accuracy in predicting bankruptcy was observed. A series of four tests were performed for 4 consecutive years prior to default and the last one being the overall analysis for all the 4 years put together. The firms filed for bankruptcy and were declared bankrupt in the year 2018. The model was tested for the years 2017, 2016, 2015, and 2014 [4].

(1) Classification Results (a) 2017- One Year Prior to Failure : The firms' data for the year 2017 were collected since it was just one year prior to bankruptcy. There were a lot of other signs of failure like low profits, low revenue, and fall in share prices. The firms were classified into bankrupt and non-bankrupt using discriminant functions. The model was run for 81 firms and is accurate in classifying 84.75% of the original group cases. Type I error is found to be 6.5% and type II error is 24% (Table 5).

(2) Classification Results (a) 2016 - Two Years Prior to Failure : The second test was performed to ascertain the ability of the firms to discriminate firms using data 2 years prior to bankruptcy. The results show the model has classified 84.75% of the original group cases correctly. Type I and type II errors remain the same as seen in the first test (Table 6).

(3) Classification Results (a) 2015 - Three Years Prior to Failure : The third test was done with data three years prior to bankruptcy. The model classifies 80% of the original group cases with increase in type I error to 26 % and

Table 5. Results for 2017

Classification Results, Original Sample

	Number Correct	Percent Correct	Percent Error	*n*	Predicted		
					Actual	**Group 1**	**Group 2**
					Group 1	29	2
					Group 2	12	38
Type I	29	93.5	6.5	31			
Type II	38	76	24	50			
Total	67	84.75	30.5	81			

Note: 84.75% of the original grouped cases are classified correctly.

Table 6. Results for 2016

Classification Results, Original Sample

	Number Correct	Percent Correct	Percent Error	*n*	Predicted		
					Actual	Group1	Group
					Group 1	29	2
					Group 2	12	38
Type I	29	93.5	6.5	31			
Type II	38	76	24	50			
Total	67	84.75	30.5	81			

Note: 84.75% of the original grouped cases are classified correctly.

Table 7. Results for 2015

Classification Results, Original Sample

	Number Correct	Percent Correct	Percent Error	*n*	Predicted		
					Actual	Group1	Group
					Group 1	23	8
					Group 2	7	43
Type I	23	74	26	31			
Type II	43	86	14	50			
Total	67	80	40	81			

Note: 80% of the original grouped cases are classified correctly.

Table 8. Results for 2014

Classification Results, Original Sample

	Number Correct	Percent Correct	Percent Error	*n*	Predicted		
					Actual	Group1	Group
					Group 1	27	4
					Group 2	16	34
Type I	27	87	12.9	31			
Type II	34	68	32	50			
Total	67	77.5	44.9	81			

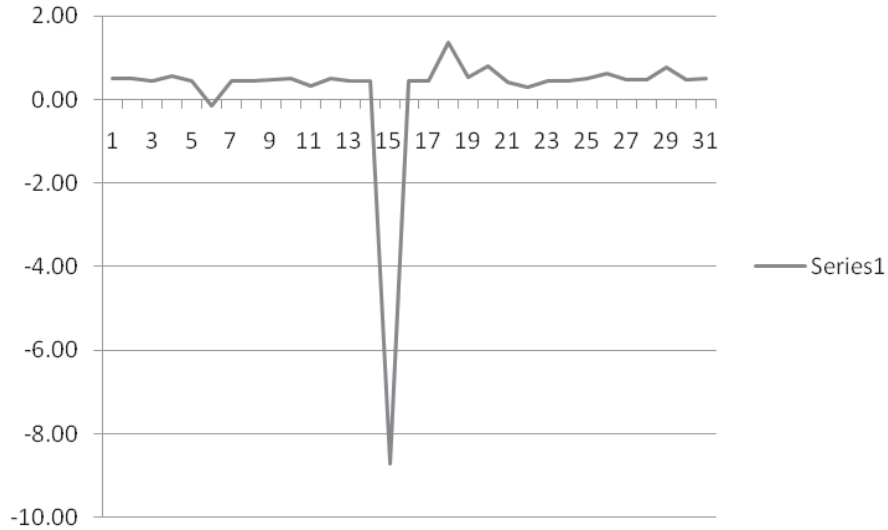
Notes: 77% of the original grouped cases are classified correctly.

type II error decreases to 14%. Still, the model proves to be accurate at 80% (Table 7).

(4) Classification Results (a) 2014 - Four Years Prior to Failure : The model is 77% accurate, with type I error being 12.9% and type II error being 32% . The financials and the share value of the firms gave good indications of bankruptcy this year (Table 8). The percentage of predictive accuracy shows a lower value for the year 2014, which is 4 years prior to failure.

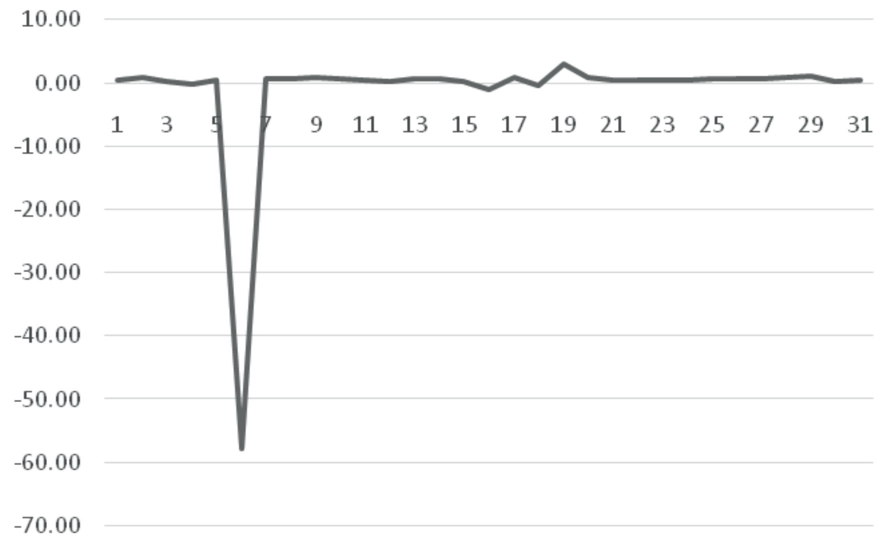
Figure 1, Figure 2, and Figure 3 display the *Z* score value of the 31 bankrupt firms for the years 2017, 2016, and 2015.

Figure 1. Chart Showing *Z* Scores for the Year 2017



Note : Firm numbers are displayed near the *X* axis.

Figure 2. Chart Showing *Z* Scores for the Year 2016



Note: Firm numbers are displayed near the *X* axis.

The *Z* score value for most of the bankrupt firms falls below .8 for the year 2017, that is, one year prior to bankruptcy. For the years 2016 and 2015 (2 and 3 years prior to bankruptcy), the *Z* score value falls between .8 to 1.4. The average *Z* score value for non - bankrupt firms comes to be 1.36. Therefore, we conclude that : Firms with *Z* score above 1.36 are found to be safe and can sustain their position for a longer period. Firms with *Z* score between .8 to 1.36 fall under the grey area and can sustain, subject to improvement of the above ratios. Firms with *Z* score less than .8 are subject to failure and are likely to file for bankruptcy [5].

Figure 3. Chart Showing Z Score for the Year 2015

Note: Firm numbers are displayed near the *X* axis.

Implications and Conclusion

Based on the above results, the bankruptcy prediction model is accurate in predicting failure up to 4 years except for the variable - market capitalization, which is more significant in predicting failure 1 year before bankruptcy compared to 2 or 3 years before bankruptcy as shown in Table 1. This shows that the share value starts declining 3 to 4 years after other signs of business failure like low profits and higher value of debt shows up. The Table 1 shows the average value of the predicted variables each year.

The two most important conclusions are the ratios started showing weaker responses as the bankruptcy approaches, like negative market capitalization and negative asset/equity. The debt ratios : debt/net worth and CFO/debt sources sustain in the same position through the 4 years, which makes them the most accurate variables in evaluating business failure. The degree of seriousness is measured by the yearly changes in the ratios.

The previous studies proved the reliability of the financial variables in predicting bankruptcy. Altman (1968) proved that the multi discriminant model using the financial variables was accurate in predicting bankruptcy for 2 years; Beaver (1966) proved that firms exhibit failure tendencies 5 years prior to failure. Our study shows a similar result, the average value of predictive variables depicted in Table 2 shows that the signs of failure are seen 4 years prior to failure. Long term debt management (LDM), which is a subset of asset and debt management, is an influential predictor of bankruptcy. This means that the debt value and shareholder value maximization cannot be adjusted in a short term. These variables depict that debt management and shareholder value of a firm show signs of failure 4 years prior to bankruptcy.

Limitations of the Study and Scope for Further Research

The sample size of the bankrupt firms was limited to the availability of data in the Capitaline and CMIE prowess databases. Machine learning has become a popular method in bankruptcy prediction these days. The predictive ability of these variables can be tested using machine learning techniques like classification and regression trees (CART) and random forest model.

End Notes

[1] The predictive power of financial ratios has been analyzed by several authors like : Altman (1968), Zmijewski (1984), Ohlson (1980), Beaver (1966), Deakin (1972), Casey and Bartczak (1985), and Jantadej (2006). We have combined few variables that fall under the category of asset liability management. Long-term debt management, which is considered to be a branch of asset liability management, plays a crucial role in our research.

[2] In India, a large number of corporate failures were seen in the years 2013 - 2016. Corporates like Kingfisher and Malvika Steel shut their operations in the year 2013.

[3] Altman et al. (1977) redeveloped the *Z* - score by excluding the sales/asset ratio as it proved to be insignificant during the previous study (Altman, 1968). We have, however, included it in our study for two reasons : (a) considering its relationship with other variables, (b) the ability of a firm's asset to generate sales proves as a classic measure of asset liability management.

[4] The model has not been tested for the year 2013, that is, the 5th year prior to bankruptcy as the predictive power of the model starts declining from the 3rd year onwards.

[5] The *Z* value cut offs are slightly different from Altman (1968) and Altman et al. (1977) as their model did not include the "debt component". Any ratio with the "debt component" is expected to have a negative sign and to increase the probability of non-failure a firm, it is expected to have lower debt.

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Appendix. Abbreviations

ADM	Asset -Debt Management
LDM	Long Term Debt Management
BIFR	Board of Industrial and Financial Reconstruction
RBI	Reserve Bank of India
MCAP	Market Capitalization
CFO	Cash from Operations
EBIT	Earnings before Interest and Tax
FFO	Funds from Operations
FCF	Free Cash Flow
CAPEX	Capital Expenditure
EBITA	Earnings before Interest Tax and Amortization
EBITDA	Earnings before Interest Tax Depreciation and Amortization

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