Bankruptcy Prediction: A Study of Predictive Power of Altman's Model and its Predictors in Indian Corporate Sector

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Abstract

Bankruptcy prediction is the interest area for many academicians and researchers. Many researchers developed the bankruptcy prediction models from time to time. Altman (1968) is a widely used model to predict corporate failure. The present research paper examines the predictive ability of the Altman's model and its variables as predictors of bankruptcy in the Indian corporate sector. By using the sample of 37 defaulted and 37 non-defaulted companies matched by asset size and industry classification, we find that the predictive power of the model is higher in case of defaulted companies than non-defaulted companies. Since almost all the variables used in the model as predictors violates the assumption of normality, thus by applying the Mann-Whitney test and Spearman's Correlation test we observe that all the variables have discriminating power between defaulted and non-defaulted companies and are found to be positively related to Z-score. Predictive power of Altman's model is weaker in the case of non-defaulted companies which leads to decrease in overall accuracy rate of the model.

Keywords: 1.Altman's model, 2.bankruptcy prediction, 3.corporate failure, 4. Z-score.

I. Introduction

Corporate failure can be defined as the firm's inability to meet its financial obligations on time. It implies a situation when the operating cash flows of the firm are insufficient to satisfy its current obligations such as payment to creditors, interest expenses etc. Initial stage of corporate failure can be defined as financial distress which may arise because of temporary cash flow problem. A distressed firm has to face many problems like decrease in market value, suppliers insisting for cash on delivery terms and even cancellation of large orders from the customers. Financial distress is a serious problem for any firm which should be resolved timely otherwise it may lead to the corporate failure. Corporate failures adversely affect every economy and have important consequences for shareholders, creditors, investors, managers, employees and even government. Early prediction of corporate failure is very important to resolve it timely. Corporate failure prediction is the emerging issue of corporate finance and is the interest area of many academicians and researchers. Many bankruptcy models are developed from time to time for predicting the corporate failure. These models can be used to give early warning signals to prevent the situation of bankruptcy to occur. Beaver (1966) is the pioneer study which used the financial ratios to predict the likelihood of corporate failure. To overcome the problem of traditional ratio analysis, Altman (1968) applied Multivariate Discriminant Analysis and developed the model based on five financial ratios to predict the corporate failure. Many researchers developed their own models after the development of Altman's model (Ohlson, 1980; Dambolena and Khoury, 1980; Daily and Dalton, 1994; Liang, 2003; Bandhyopadhyay, 2006; Polisiri, 2009; Xu and Wang, 2009; Campbell et al., 2011 and Tinoco & Wilson, 2013). Altman's model is UK based and hence its applicability for predicting corporate failures in the developing and emerging economies is quiet doubtful. Only a few studies like Bandhyopadhyay (2006) and Desai and Joshi (2015) have tested this model in Indian context. Bandhyopadhyay (2006) re-estimated the Altman's model by employing discriminant analysis and logistic regression and Desai and Joshi (2015) tested the Altman's model and re-estimated the model by applying discriminant analysis. The aim of this paper is to apply the Altman's model in Indian corporate sector and to test the accuracy of the model and the variables used as predictors in the model.

The rest of paper is structured as follows. Next section reviews the literature related to the ability of Altman's model in predicting the likelihood of corporate failure in near future and the effectiveness of financial ratios in predicting such failures. Section III outlines the data and methodology followed in the study. Results and findings are discussed in the section IV. The last section discusses the main conclusions of the study.

II. Literature Survey

Corporate failure is the situation which arises because of shortage of cash or because of fall in assets' value of the firm. Thus financial ratios like cash flow ratios or solvency ratios can be used to predict the corporate failure in advance. Several studies have been conducted to examine the usefulness of financial ratios for predicting corporate failure. Beaver (1966) reported that cash flow to total debt ratio has higher predictive power and advocates that the selection of financial ratios in predicting corporate failure should be made cautiously because all the ratios are not capable of predicting the corporate failure. Initial studies were uni-variate in nature and used many ratios related to measuring profitability, liquidity and solvency position to access the probability of failure. However the use of financial ratios only for prediction of corporate failure was found to be suffering from limitations of traditional ratio analysis and hence the need to blend the financial ratios with some statistical techniques was recognized. Altman (1968) bridged the gap between the traditional financial ratios and statistical techniques and developed the multivariate model based on Multiple Discriminant Analysis (MDA) and combined the five financial ratios to predict the likelihood of corporate failure in near future. Altman's model gives single score which can be put to use to discriminate between failed and non-failed firms. Altman used the five variables namely, X1 (working capital to total assets), X2 (retained earnings to total assets), X3 (earnings before interest and taxes to total assets), X4 (market value of equity to total liabilities) and X5 (sales to total assets) measuring liquidity, profitability, productivity and sales generating capacity of the firm. MDA is used to classify the number of observations into several groups based on observation's individual characteristics. Another advantage of MDA is that it requires fewer assumptions regarding data and combines the different financial ratios into one common score which remove the limitations of earlier traditional ratio analysis. Ganesalingam and Kumar (2001) observed that the mean of financial ratios for failed companies was lower than the non-failed companies. Agarwal and Taffler (2005) and Bandyopadhyay (2006) indicated that financial ratios were negatively related to probability of failure. It was also reported that the financial ratios of safe companies were much better than failed companies and standard deviations of the financial ratios were also found to be lower in case of safe companies. Some of the studies indicated the significant financial ratios that can be used to discriminate between failed and non-failed firms. Andreica et al. (2010) and Thai, Goh and Teh (2014) tested the reliability of financial ratios for predicting corporate failure and the financial ratios like profit margin, return on assets, return on equity, profit per employee, current ratio, debt equity ratio, total assets growth rate, turnover growth, working capital to total assets, retained earnings to total assets and earnings before interest and taxes to total assets were found to be significant which can be used to discriminate between failed and non-failed firms. Gombola et al. (1987) and Aziz and Lawson (1989) accessed the effectiveness of cash flow ratios in predicting corporate failure and revealed that cash flow ratios like cash flow from operations to assets ratio can be used to predict the likelihood of corporate failure. Several studies like Moyer (1977), Grice and Ingram (2001), Micvdova (2013), Alareeni and Branson (2013), Thai, Goh and Teh (2014), Celli (2015) Desai and Joshi (2015) and Almamy et al. (2016) tested the classification accuracy of Altman's model. It was demonstrated that

Altman's model can be used to better discriminate between failed and non-failed firms and it can be used as early warning signal before going to be bankrupt. It was found that non-failed companies have strong working capital, adequate retained earnings, higher liquidity and profitability. Rim and Roy (2014) revealed that Altman's model has higher classification accuracy and it can be used to replace the complex credit rating models while granting loans by the bank to the customers. Sinkey et al. (1987) examined the cross industry validity of Altman's model by employing it on failed and non-failed commercial banks and reported that this model can be applied to predict the bank failures. Anjum S. (2012) and Rayalaseema and Muhammad P. (2012) applied the Altman's model and reported that it can be used as powerful tool to predict the bankruptcy. As is revealed by the literature that very few studies exist that have explored the predictive power of the Altman's model in Indian context. Moreover the Altman's model was developed nearly five decades ago in a developed country hence, it is necessary to examine whether Altman's model is still a powerful model for predicting corporate failures in a developing country like India.

The main aim of the study is to examine the predictive ability of the Altman's model and the variables used in the model as predictors. Altman's model is developed by Edward I. Altman in 1968 which integrated the financial ratios with multiple discriminant analysis (MDA). At that time he was an assistant professor in finance at New York University. Altman's model is based on the sample of 33 failed manufacturing companies and 33 safe manufacturing companies matched by industry and asset size. This model produces the single score known as Z-score based on five financial ratios used as predictors as follows:

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.99X5$$

Where, Z = score

X1 = Working capital / Total assets

X2 = Retained earnings / Total assets

X3 = Earnings before interest and tax (EBIT) / Total assets

X4 = Market value of equity / Total liabilities

X5 = Sales / Total assets

Z-score produced by the model is used to classify the company as failed or safe. The criteria used for this is as under:

If Z-score is 2.99 or more than 2.99 then the company is to be considered *safe* and if Z-score is less than 1.81 then the company is considered to be *failed*. The companies having Z-score between 1.81 to 2.99 are considered to be in *Grey Zone* where probability of failure is not easily predictable.

III. Data and Methodology

The present study is based on a sample of 37 defaulted and 37 non-defaulted companies matched by size and industry. The classification of companies into default and safe category is done using credit ratings given by CRISIL, ICRA or CARE in the year 2015-16. A company is considered as defaulted if it is rated as defaulted by any of these rating agencies. Similarly if a company is rated as highest safety, high safety or adequate safety by any of these rating agencies, then it is considered as non-defaulted company. Further for a company to be included in the sample:

(i) It must be a listed company; and

(ii) Its financial information must be available for consecutive five years prior to the year in which a company is considered as defaulted or safe.

After dividing the companies into defaulted group and non-defaulted group, asset size and industry classification is used to match the companies as earlier used by many researchers. (Altman, 1968; Gombola et al., 1987; Kluger & shields, 1989; Gu and Gao, 2000; Darayseh et al., 2003; Bandyopadhyay, 2006). A minimum and maximum asset size is computed for defaulted companies and then the non-defaulted companies having the asset size within the same range are selected. Matching by assets size has reduced the size disparity between defaulted and non-defaulted companies by selecting the companies having almost similar assets size in both the groups. The assets size of defaulted companies and non-defaulted companies is as under:

Table - 1 Assets size of sample companies

Sample description	Rs. in million		
	Minimum	Maximum	Average
Defaulted companies	244.90	99934.90	12157.54
Non-defaulted companies	1038.30	65125.50	14432.50

Author's computations

The above mentioned selection procedure resulted into a total sample of 74 manufacturing companies comprising 37 defaulted companies and 37 non-defaulted companies having average assets size of Rs. 12157.54 million and Rs. 14432.50 million respectively. The selected companies are from seven different industries. The industry wise classification of the sample companies is given in Annexure-I:

Correct classification rate, overall correct classification rate, type I error and type II error are applied to examine the overall predictive power of the model as earlier used in many research studies. (Altman, 1968; Grice and Ingram, 2001; Liang, 2003; Binti et al., (2010); Alareeni and Branson, 2013; Celli, 2015; Karas and Reznakova, 2015; Almamy et al., 2016; Liang et al., 2016.)

$$\text{Correct classification rate (defaulted companies)} = \frac{\text{number of defaulted companies correctly classfied as failed}}{\text{total number of defaulted companies}} \times 100$$

$$\text{Correct classification rate (non} - \text{defaulted companies)} = \frac{\text{number of non} - \text{defaulted correctly classfied as safe}}{\text{total number of non} - \text{defaulted companies}} \times 100$$

$$\text{Overall correct classification rate} = \frac{\text{total number of companies correctly classfied}}{\text{total number of companies in sample}} \times 100$$

$$\text{Type} - I \text{ error rate} = \frac{\text{number of defaulted companies incorrectly classfied as safe}}{\text{total number of defaulted companies}} \times 100$$

$$\text{Type} - II \text{ error rate} = \frac{\text{number of non} - \text{defaulted companies incorrectly classfied as defaulted}}{\text{total number of non} - \text{defaulted companies}} \times 100$$

$$\text{Overall error rate} = \frac{\text{total number of companies incorrectly classfied}}{\text{total number of companies in sample}} \times 100$$

Shapiro-Wilk test is used to test the normality of variables used as predictors in the model. Since the results of Shapiro-Wilk test shows that most of the variables violate the assumption of normality hence, Mann-Whitney test and Spearman's Correlation test is applied to assess the predictive ability of the variables used in the model.

IV. Results and Discussions

Results of Predictive ability of Altman's model

Predictive ability of Altman's model can be judged from the results produced in Table - 2.

Table - 2 Correct classification rate of Altman's model

Years	Predictive accuracy of Altman's Model					
	Defaulted companies		Non-defaulted companies		Overall	
	Number of companies	Percentage	Number of companies	Percentage	Number of companies	Percentage
T-5	29	78.37%	08	21.62%	37	50%
T-4	31	83.78%	09	24.32%	40	54.05%
T-3	33	89.18%	09	24.32%	42	56.72%
T-2	33	89.18%	12	32.43%	45	60.81%
T-1	35	94.59%	14	37.83%	49	66.21%

Author's computations

Table 2 shows that the model has higher predictive power in case of defaulted companies than the non-defaulted companies. The highest correct classification rate of 94.59% is found prior to one year of default in case of defaulted companies and this rate decreases in the periods two, three, four and five years prior to default. Similarly, in case of non- defaulted companies correct classification rate is found to be higher in T-1 period and decreases in T-2, T-3, and T-4 and T-5 periods. Overall correct classification rate also showed the similar trend as found in the case of defaulted companies and non-defaulted companies. It can be seen that the correct classification rate for all the periods is higher in case of defaulted companies than non-defaulted companies. Higher overall correct classification rate of 66.21% is found for T-1 period which decreases in the T-2, T-3, T-4 and T-5 periods. Results also reveal that the model has achieved higher accuracy rate for defaulted companies but found to be weaker in case of non-defaulted companies. Lower accuracy rate of the model in case of non-defaulted companies decreases the overall correct classification rate to 66.21% for one year prior to default which indicates that this model should be used cautiously and there is a further scope for re-estimation of the model to increase the correct classification rate of non-defaulted companies and to increase its overall accuracy rate. Type-I error rate, type-II error rate and overall error rate are also analysed to examine the predictive accuracy of the Altman's model.

Table - 3 Error rate of Altman's model

Years	Error rate of Altman's Model and number of companies incorrectly classified					
	Type - I error rate		Type - II error rate		Overall error rate	
	Number of companies	Percentage	Number of companies	Percentage	Number of companies	Percentage
T-5	08	21.63%	29	78.38%	37	50%
T-4	06	16.22%	28	75.68%	34	45.95%
T-3	04	10.82%	28	75.68%	32	43.25%
T-2	04	10.82%	25	67.57%	29	39.19%

T-1	02	05.41%	23	62.17%	25	33.79%

Author's computations

Table - 3 presents the type-I error rate, type-II error rate and overall error rate of Altman's model when applied to Indian corporate sector. It can be seen that type-I error rate is much lower in the years near to the year of default. Similarly, type-II error rate also found to be lower in T-1 period but its rate is much higher than type-I error rate. Type-I error rate indicates percentage of the defaulted companies wrongly classified as non- defaulted and is considered to be more serious problem than type-II error as it may mislead the investors, creditors or lenders to take their investment decisions. So, type-I error should be lower. This model has lower type-I error rate when applied to Indian corporate sector which indicates that this model has higher default predictive power and can be used to predict the default. On the other hand overall error rate is found to be higher in all the years which mean that this model requires further improvements to reduce the overall error rate and to increase its overall predictive power.

Normality test of the variables

Before analyzing the predictive accuracy of the variables used in the model as predictor, normality of the data is tested using Shapiro-Wilk test. Results of Shapiro-Wilk test are shown in Table - 4.

Table - 4 Results of Shapiro-Wilk test

Years	Sample description	Variables used in Altman's Model				
		X1	X2	X3	X4	X5
T-5	Statistic (defaulted)	.975	.926	.985	.633	.758
	P-value	.545*	.016	.898*	.000	.000
	Statistic (non-defaulted)	.951	.863	.981	.601	.962
	P-value	.103*	.000	.775*	.000	.223*
	Statistic (defaulted)	.947	.979	.945	.676	.893
T-4	P-value	.076*	.705*	.068*	.000	.002
	Statistic (non-defaulted)	.962	.954	.988	.654	.959
	P-value	.235*	.133*	.947*	.000	.187*
T-3	Statistic (defaulted)	.932	.891	.911	.543	.872
	P-value	.026	.002	.006	.000	.001
	Statistic (non-defaulted)	.966	.972	.982	.664	.966
	P-value	.316*	.453*	.798*	.000	.311*
T-2	Statistic (defaulted)	.935	.841	.831	.774	.915
	P-value	.032	.000	.000	.000	.008
	Statistic (non-defaulted)	.925	.935	.987	.701	.916

	P-value	.016	.033	.931*	.000	.009
T-1	Statistic (defaulted)	.864	.631	.554	.773	.924
	P-value	.000	.000	.000	.000	.015
	Statistic (non-defaulted)	.952	.974	.947	.712	.933
	P-value	.111*	.536*	.077*	.000	.028

* p > .05 which indicates that data is normally distributed.

Table - 4 shows that majority of the variables are not normally distributed. If the variable is found to be normally distributed for both groups that is defaulted companies and non-defaulted companies only then it is considered as normally distributed because variables for both groups should be normally distributed to compare their means. It can be seen from the table that out of twenty five paired observations only five paired observations (X1 & X3 for T-5 period and X1, X2 & X3 for T-4 period) are found to be normally distributed. As the results of Shapiro-Wilk test indicated that the most of the paired observations violates the assumption of normality, hence non parametric test are applied to compare the means of the defaulted companies and non-defaulted companies.

Predictive power of the variables used in the model as predictors

As it is revealed by Shapiro-Wilk test that the data is not normally distributed, thus non parametric test are used to compare the predictors of defaulted companies and non-defaulted companies. Reason for applying non parametric test is that these tests do not require the normality assumptions regarding the data. To test the predictive ability of the variables used in the model as predictors Mann-Whitney test which is similar to the independent two sample t test is applied. However, Mann-Whitney test compares the mean ranks of the groups rather than comparing the actual means of the groups. The null hypothesis of the Mann-Whitney test is that the mean ranks of two groups are not statistically different. If the p-value is found be less than the selected level of significance then the null hypothesis is rejected. Rejection of null hypothesis of Mann-Whitney test shows that the mean ranks of two groups are significantly different. Similarly, if the p-value is found to be greater than the selected significance level then it indicates that the means ranks of two groups are equal or do not differ significantly.

Table - 5 Results of Mann-Whitney test

Years	Sample description	Variables used in Altman's Model				
		X1	X2	X3	X4	X5
T-5	Mean rank (defaulted)	36.78	28.43	29.03	26.19	32.03
	Mean rank (non-defaulted)	38.22	46.57	45.97	48.81	42.97
	P-value	.775	.000**	.001**	.000**	.029*
	Mean rank (defaulted)	34.49	28.59	29.70	25.78	32.78
T-4	Mean rank (non-defaulted)	40.51	46.41	45.30	46.22	42.22
	P-value	.228	.000**	.002**	.000**	.059
T-3	Mean rank (defaulted)	33.05	24.76	25.35	23.35	30.14

	Mean rank (non-defaulted)	41.95	50.24	51.65	51.65	44.86
	P-value	.075	.000**	.000**	.000**	.003**
T-2	Mean rank (defaulted)	28.59	23.09	24.00	21.76	29.51
	Mean rank (non-defaulted)	46.41	51.11	51.00	53.24	45.49
	P-value	.000**	.000**	.000**	.000**	.001**
T-1	Mean rank (defaulted)	27.38	19.65	22.11	21.35	29.35
	Mean rank (non-defaulted)	47.62	55.35	52.89	53.65	45.65
	P-value	.000**	.000**	.000**	.000**	.001**

** significant at 1% level

* significant at 5% level

As it can be seen from table – 5 that all the variables used in model as predictor are significantly different for one and two years prior to year of default. Mean ranks of all the variables are found to be significantly different for defaulted companies and non-defaulted companies, which indicates that all the variables have ability to discriminate between defaulted companies and non-defaulted companies. One variable X1 for T-3 period, two variables X1 & X5 for T-4 period and one variable X1 for T-5 period are found to be insignificant, which indicates that the discriminating power of the variables is more in the years near to default. To examine the predictive power of the variables we can also compare the mean values of defaulted companies with the mean values of non-defaulted companies.

Table – 6 Mean values of variables used as predictors for defaulted and non-defaulted companies

Years	Sample description	Variables used in Altman's Model				
		X1	X2	X3	X4	X5
T-5	Mean values (defaulted)	.0638	.0136	.2287	.2582	.9159
	Mean values (non-defaulted)	.0676	.0604	.3793	1.084	1.0275
	Mean difference	-.0036	-.0468	-.1505	-.8257	-.1088
	Mean values (defaulted)	.0426	.0091	.1985	.1559	.8963
T-4	Mean values (non-defaulted)	.0754	.0441	.3373	.7779	1.0537
	Mean difference	-0.327	-.0532	-.1387	-.6220	-.1574
T-3	Mean values (defaulted)	.0272	-.0536	.0912	.1067	.8238
	Mean values (non-defaulted)	.0902	.0549	.3719	.7012	1.1009
	Mean difference	-.0629	-.1085	-.2807	-.5944	-.2771
T-2	Mean values (defaulted)	.0298	-.0785	.0426	.0786	.8026
	Mean values (non-defaulted)	.1033	.0602	.3957	.9258	1.1097

	Mean difference	-.1331	-.1388	-.3531	-.8471	-.3071
T-1	Mean values (defaulted)	-.1462	-.2263	-.2534	.0847	.7700
	Mean values (non-defaulted)	.1141	.0552	.3577	1.7917	1.1102
	Mean difference	-.2604	-.2815	-.6106	-1.706	-.3402

It can be seen from Table - 6 that the mean difference for all the variables is found to be negative for all the years which indicated that the mean value of the variables for defaulted companies is lower than the non-defaulted companies. The trend graphs of the mean values of variables used as predictors in the model are given in Annexure –II. Mean values for all the variables of defaulted companies becomes much lower in the years near to year of default. All the mean values of the variables of the defaulted companies becomes lowest prior to the one year of default and showed the deteriorating trend from five years prior to the default to one year prior to default. It can be concluded that falling trend in all the variables results into the increase in the likelihood of failure or default in the near future. We also extended our analysis by computing the correlation of all the variables with Z-score. As earlier discussed that data is not normally distributed, hence Spearman's rank correlation is applied instead of Karl Pearson's correlation. Results of the Spearman's correlation are presented in the table - 7. Results showed that only two variables namely X2 and X3 are significantly correlated with Z-score in all the years. Variable X4 found to be significantly correlated with Z-score in all the years except in T-4 period followed by X1 which is found to be significantly correlated with Z-score only in T-5 and T-1 period. Variable X5 found to be insignificant in T-2 and T-1 period for both the groups.

Table - 7 Correlation of predictors of the Altman's model with Z-score (Spearman's correlation)

Years	Sample description	Variables used in Altman's Model				
		X1	X2	X3	X4	X5
T-5	Z-score (defaulted)	.359	.597	.618	.327	.667
	Sig. (2-tailed)	.029*	.001**	.000**	.048*	.000**
	Z-score (non-defaulted)	.485	.777	.808	.830	.336
	Sig. (2-tailed)	.002**	.000**	.000**	.000**	.000**
	Z-score (defaulted)	.307	.452	.539	.260	.692
T-4	Sig. (2-tailed)	.064	.005**	.001**	.120	.000**
	Z-score (non-defaulted)	.467	.743	.749	.797	.417
	Sig. (2-tailed)	.004**	.000**	.000**	.000**	.010**
T-3	Z-score (defaulted)	.075	.688	.797	.416	.674
	Sig. (2-tailed)	.659	.000**	.000**.677	.000**	.000**
	Z-score (non-defaulted)	.424	.705		.792	.380

	Sig. (2-tailed)	.009**	.000**	.000**	.000**	.020*
T-2	Z-score (defaulted)	.234	.589	.522	.452	.595
	Sig. (2-tailed)	.164	.000**	.001**	.005**	.000**
	Z-score (non-defaulted)	.375	.584	.684	.864	.311
	Sig. (2-tailed)	.022*	.000**	.000**	.000**	.061
T-1	Z-score (defaulted)	.593	.788	.826	.443	.317
	Sig. (2-tailed)	.000**	.000**	.000**	.006**	.056
	Z-score (non-defaulted)	.628	.699	.729	.946	.278
	Sig. (2-tailed)	.000**	.000**	.000**	.000**	.096

** significant at 1% level

* significant at 5% level

It can be observed from the Spearman's correlation that all the variables are positively correlated with Z-score for both defaulted companies and non-defaulted companies. It indicates that decrease in any of the variables used as predictors in the model results into the higher chances of failure or default because all the variables are positively correlated to Z-score and decrease in any variable will decrease the Z-score.

V. Conclusions

The aim of the paper is to apply the Altman's model in Indian corporate sector and to test the accuracy of the model and the variables used as predictors in the model. Altman's model is applied on the matched paired sample of 37 defaulted and 37 non-defaulted companies. To examine the predictive ability of the Altman's model correct classification rate, overall correct classification rate, type I error rate and type II error rate are used. It is observed that model has achieved higher predictive power in case of defaulted companies than non-defaulted companies. The highest correct classification rate of 94.59% is found prior to one year of default in case of defaulted companies and 37.83% in case of non-defaulted companies and this rate decreases in T-2, T-3, and T-4 period. Overall correct classification rate also showed the similar trend as found in the case of defaulted companies and non-defaulted companies. Higher overall correct classification rate of 66.21% is found for T-1 period which decreases in the T-2, T-3, T-4 and T-5 period. Altman's model has lower type-I error rate when applied to Indian corporate sector which indicates that this model has higher default predictive power and can be used to further predict the default but it should be used cautiously because overall error rate is much higher which indicates that there is a further scope for improvement in the model to increase the correct classification rate of non-defaulted companies and to increase its overall accuracy rate. Results of Mann-Whitney test showed that the mean ranks of two groups are significantly different. All the variables used in model as predictor are found to be significantly different for one and two year prior to year of default. It indicates that all the variables have ability to discriminate between defaulted companies and non-defaulted companies. A few variables are found to be insignificant for other periods, which indicate that the discriminating power of the variables is more in the years near the year of default. Comparison of mean values of defaulted companies and non-defaulted companies indicates that difference of mean values is negative for all the variables which means the mean values of the variables for defaulted companies is lower than non-defaulted companies. Mean values of all the variables for both defaulted companies and non-defaulted companies showed deteriorating trend which shows that the means values are much lower in the years near to the year of default. All the variables are found to be positively correlated with Z-score for both defaulted companies and non-defaulted companies. It indicates that increase in all the variables used as predictors in the model results into increase in Z-score and increase in Z-score leads to lower probability of failure or default. Thus, it can be concluded that Altman's model achieved higher accuracy rate for predicting the default when applied to Indian corporate sector. It is also observed that all the variables have discriminating power between defaulted and non-defaulted companies and are found to be positively related to Z-score. Predictive power of Altman's model found to be weaker in the case of non-defaulted companies which lead to increase in the overall error rate. Thus, there exists further scope for improvement in the model by re-estimating it or by adding new variables to it so that overall accuracy rate of the model can be increased and overall error rate is decreased.

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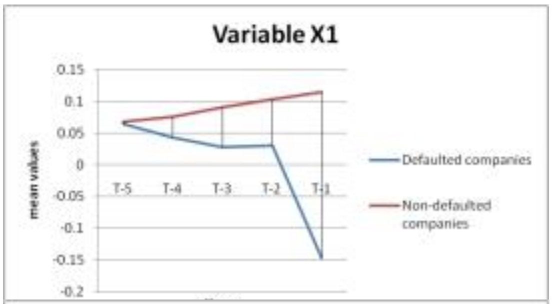
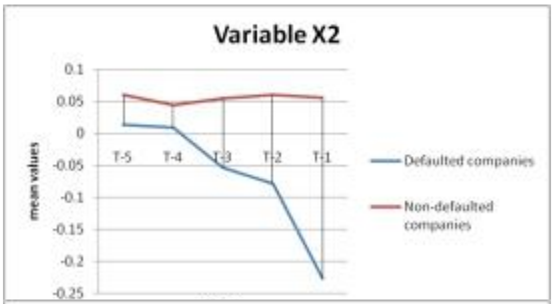
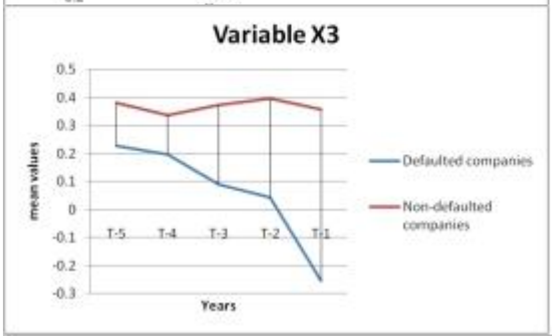
Annexure-I
Industry wise classification of sample companies

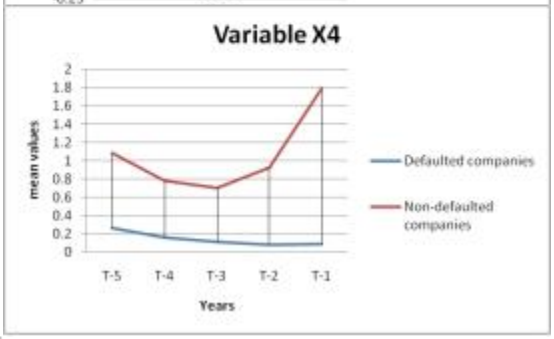
Industry	Defaulted companies	Non-defaulted companies
Chemicals and chemical products	07	07
Construction materials	01	01
Foods and agro based products	06	06
Metals and metal products	10	10
Misc. Manufacturing	03	03
Textiles	08	08
Transport equipment	02	02
Total	37	37

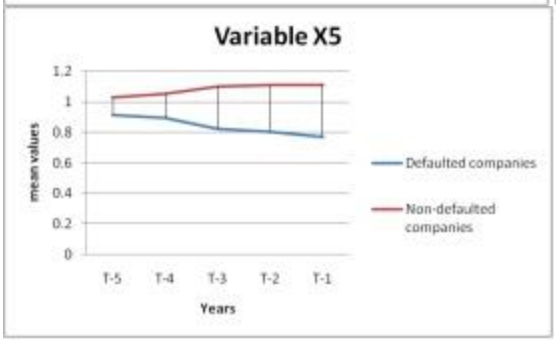
Annexure-II
Mean values of variables used as predictors in Altman's model


Variable X1
mean values
T-5 T-4 T-3 T-2 T-1
Defaulted companies
Non-defaulted companies


Variable X2
mean values
T-5 T-4 T-3 T-2 T-1
Defaulted companies
Non-defaulted companies


Variable X3
mean values
T-5 T-4 T-3 T-2 T-1
Years
Defaulted companies
Non-defaulted companies


Variable X4
mean values
T-5 T-4 T-3 T-2 T-1
Years
Defaulted companies
Non-defaulted companies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mean values
T-5 T-4 T-3 T-2 T-1
Years
Defaulted companies
Non-defaulted companies