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CORPORATE BANKRUPTCY PREDICTION USING ALTMAN'S Z-SCORE MODEL: THE EFFECT OF TIME AND METHODOLOGY ON ACCURACY OF THE MODEL

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Abstract

The stability of the bankruptcy prediction models and their predictive power is an empirical question in the area of bankruptcy prediction. Altman's Z-score model is pioneer study and widely used to predict the bankruptcy. The aim of the paper is to examine sensitivity of the Altman's model to variations in time and methodology. For this purpose a sample of 74 Indian manufacturing companies equally divided into defaulted companies and non-defaulted companies from 2011-2015 is used. The study investigates the time varying effect on the accuracy of the model by re-estimating the model coefficients using the recent data. In place of Multiple Discriminant Analysis (MDA) logistic regression is employed to examine the effect of change in methodology on the accuracy of the model. The findings of the study reveal that the overall correct classification rate for Altman's model in 2015 found to be only 66.21% which even decreases further in the years prior to 2015. This overall correct classification rate increases to 81.10% when the model is re-estimated by using the recent data and further to 87.83% when logistic regression is applied to re-estimate the model. The research findings strongly confirm that the Altman's model is sensitive to time period variation and change of methodology. The findings of the study suggest that the model coefficients should be re-estimated based on recent data using logistic regression to have better accuracy in bankruptcy prediction.

Keywords: Corporate failure prediction, bankruptcy prediction, Altman's model, correct prediction rate, MDA, Logistic regression.

JEL Classification: G01, G17, G32, G33

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1. INTRODUCTION

Financial ratios have always played an important role in determining the performance and financial state of the companies. The use of financial ratios in forecasting the corporate failures started in U.S.A. during 1930's. Corporate failure can be defined as the situation when a firm seems to be unable to meet its financial obligations on time.

Beaver (1966) compared the financial ratios of bankrupt companies with non-bankrupt companies and revealed that the financial ratios of bankrupt companies found to be greatly different from non-bankrupt companies. Beaver's study concluded that financial ratios can be used to forecast the future financial status of the company. However due to the univariate approach of the study it was found difficult to predict accurately the probability of corporate failure. In 1968, Edward Altman applied the multivariate discriminant analysis and wiped off the limitations of traditional ratio analysis and univariate approach. Altman developed the well known Z-score model based on five financial ratios to predict the likelihood of the corporate failure. Ohlson (1980) applied logistic regression and developed the bankruptcy prediction model based on nine variables. Liang (2003) compared the two widely used techniques, namely multiple discriminant analysis and logistic regression and concluded that the logistic regression has better predictive ability than multiple discriminant analysis. Many other researchers developed their own model by using different variables and methodologies. Once a bankruptcy model is developed it should be consistent in terms of prediction accuracy. Hence, it is necessary to test the predictive accuracy of the bankruptcy prediction models and if needed, to re-estimate the model. Altman's model is well known and widely used model across the world hence it is necessary to test the sensitivity of the Altman's model with change in time period and methodology. Even though Altman's model is commonly used model but there is a limited evidence on the sensitivity of the Altman's model to change in time period and methodology. The research question of the current study is to examine the predictive accuracy of the Altman's model and the effect of change in time period and change in methodology on its predictive accuracy. To study the effect of change in time period on the predictive accuracy of the model, from the model coefficients are re-estimated over using different time period. As the literature supports that the logistic regression is superior to the multiple discriminant analysis, we also examined the effect of change in methodology on the predictive accuracy of the model by using logistic regression.

The paper is structured as follows. Next section describes the literature survey related to predictive accuracy of original and re-estimated Altman's model by using the recent data. Section 3 outlines the data and methodology applied in the study. Results and findings are discussed in the section 4. The last section discusses the main conclusions of the study.

2. REVIEW OF LITERATURE

Earlier literature on corporate failure prediction dates back from 1930's to the mid of 1960's. The prime focus of the studies during this period was on the use of financial ratios to predict the likelihood of corporate failure. These studies were mainly univariate in nature. Beaver (1966) used the financial ratios and developed the univariate model to classify the firm as failed or healthy. Beaver's study was one of the early contributions to predict the corporate failure. Beaver found that only one ratio, namely, the cash flow to debt ratio can be used to predict the likelihood of failure. Because of the use of single variable beaver's model was found to be less effective. Altman (1968) challenged the beaver's univariate approach and introduced the multivariate model, which has proven itself as the most reliable tool of assessing the financial health of the companies. Agarwal and Taffler (2005), tested the predictive power of the Altman's model over the period of twenty five years and revealed that it has true failure forecasting ability. Several studies including 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) analyzed the predictive power of the Altman's model from time to time and found that it has better predictive power and can be used to predict the corporate failure or financial distress. Sinkey et al. (1987) tested the cross industry validity of the Altman's model by using the sample of failed and non-failed commercial banks and reported that Altman's model can be used to predict the bank failures also. Alareeni and Branson (2013) evaluated the Altman's model and concluded that Altman's model can be used to better discriminate between failed and non-failed firms. Non failed firms showed strong working capital, adequate retained earnings, high liquidity and high profitability than failed firms. Working capital to total assets found to be most significant ratio followed by retained earnings to total assets ratio and EBIT to total assets ratio (Thai, Goh and Teh, 2014). Many researchers followed the Altman's model and tested its predictive power in recent times. It is evident in many studies that Altman's model is still effective however its predictive accuracy can be enhanced by re-estimating the coefficients of the model by using recent data or by adding new variables to the model. (Grice and Ingram, 2001; Agarwal and Taffler, 2005; Karas and Rezenakova, 2015; Desai and Joshi, 2015; Almamy et al., 2016 and Singh and Mishra, 2016). After the development of Altman's model many other authors developed their own models by adopting different variables and methodology. Ohlson (1980) developed the logit model for predicting the bankruptcy based on nine variables and reported that logit model overcome the problems of multiple discriminant analysis. Size, financial structure, performance and liquidity found to be most important factors which affect the probability of failure. Karamzadeh (2013) compared the predictive accuracy of Altman's model and Ohlson's model in Iran and reported that Altman's model outperformed the Ohlson's model. Liang (2003) compared two widely used techniques multiple discriminant analysis and logistic regression and concluded that logistic regression

has better predictive power than multiple discriminant analysis. These findings are also in line with Lin (2009) and Polsiri (2009).

Above discussed literature showed that Altman’s model is still effective in predicting the corporate failure as many studies supported the higher accuracy rate of the model. After the development of the Altman’s model many recent trends has been found in the area of bankruptcy prediction model like re-estimation of model by using recent data or by adding new variables to the model. Many studies exhibited that logistic regression based model has better predictive power than the multiple discriminant analysis based model. Most of the studies related to testing and re-estimating the Altman’s model are done in developed economies hence, there is a need to apply the Altman’s model in Indian context and to test whether Altman’s model is sensitive to change in time period and methodology or not.

3. DATA AND METHODOLOGY

For the purpose of the study matched paired sampling technique is used by dividing the companies into two groups, namely, defaulted and non-defaulted companies based on the credit ratings assigned by recognized Indian credit rating agencies. Financial year 2015-16 is selected as base year to decide the sample and company is considered as defaulted if it is rated as defaulted by any of the Indian rating agencies and considered as non-defaulted if rated as highest safety, high safety and adequate safety. Indian listed companies for which data is available for consecutive five years prior to the year in which a company is being considered as default or safe are selected in the sample. For the purpose of matched paired sampling defaulted companies are matched with non-defaulted companies on the basis of year, assets size and industry affiliation. After matching by assets size the average assets size of the defaulted companies (12157.54 cr.) found to be closer to the average assets size of non-defaulted companies (14432.50 cr.) which reduced the probability of bias in sample selection. Following the above mentioned criteria a total sample of 74 manufacturing companies from different seven industries is selected and equally divided into defaulted companies and non-defaulted companies. The current study examines the Altman’s model because of its prominence and effectiveness in the area of bankruptcy prediction. Altman, in 1968 used five financial ratios and developed the bankruptcy prediction model by applying multiple discriminant analysis. MDA is similar to regression analysis which gives the singles score based on the weighted combination of independent variables which can be used to classify the observations into different categories. Discriminant function can be expressed as:

$$Di = \alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \dots + \beta_nX_n \quad (1)$$

Where,

Di = discriminant score

α = intercept

β = beta coefficient (slope)

X = independent variables

Five ratios used in the model relates to liquidity, solvency, profitability and leverage of the firm and produce a single score known as Z-score, which is used to classify the firm as bankrupt or non-bankrupt. Altman's model is as under:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5 \quad (2)$$

Where X_1 , X_2 , X_3 , X_4 and X_5 are accounting ratios used as variables in the model. These variables are explained as under:

- Working capital/total assets (X_1): this ratio measures the liquidity position of the firm in relation to its total capitalisation. Working capital is taken as the difference between the current assets and current liabilities. Decrease in working capital or current assets of the firm increases the chances of financial distress for the firm.
- Retained earnings/ total assets (X_2): it is used as the measure of the cumulative profitability of the firm over the number of years. Generally the old firm has large retained earnings than the new firm which indicates that the chances of default or financial distress are more for the new firms.
- Earnings before interest and taxes/ total assets (X_3): this ratio indicates the earning capacity of the firm after eliminating the effect of interest and taxes. This ratio is very useful because the existence of any firm depends upon the earning capacity of the firm.
- Market value of equity/ total liabilities (X_4): this ratio is also relevant for studying the probability of default or financial distress of the firm. This ratio indicates that as the total liabilities exceed the total assets, the firm becomes insolvent. In other words this ratio capture the market reactions due to decrease in the value of assets of the firm.
- Sales/ total assets (X_5): this ratio relates the firm's sales to the total assets. It measures the sales generating ability of the firm. If firm have higher sales then the probability of default or financial distress decreases.
- Z represents the overall combined score. This score is used to determine the status of any firm. If Z-score is found to be more than 2.99 then the firm is considered as non-bankrupt and firms with Z-score less than 1.81 are classified as bankrupt. Any firm having Z-

score more than 1.81 and less than 2.99 considered in grey zone where bankruptcy cannot be predicted easily. In order to test the sensitivity of the Altman's model to change in time period we re-estimated the model by using recent data from 2011-15 and by applying MDA as originally applied by Altman. Wilks' Lambda is used to analyze the discriminating power of the re-estimated MDA model. Logistic regression is used to re-estimate the model to examine the sensitivity of the Altman's model to change in methodology. Logistic regression is used because it requires less assumptions regarding population and found better than MDA. When the dependent variable under the study is binary or having two possible outcomes 0 and 1 (0 for bankrupt and 1 for non-bankrupt) then logistic regression is applied to establish the relationship. For the purpose of performing logistic regression value 0 is assigned to defaulted companies and 1 to non-defaulted companies. Nagelkerke R square is used as a measure of predictive power of the logit model because it is the adjusted version of Cox and Snell R square. Hosmer and Lemeshow test is also used as test of goodness of fit for logit model. Correct classification rate, overall correct classification rate is used to examine the classification accuracy of the model.

4. RESULTS AND DISCUSSION

When applied the original Altman's model to Indian manufacturing companies it is found that the Altman's model has superior predictive power in case of defaulted companies than non-defaulted companies. Table 1 showed the correct classification rate of the Altman's model which indicated that the classification accuracy of the model is higher in the years near to the year of default. It can also be seen from the table that the correct classification rate of the model in case of non-defaulted companies is very low which reduces the overall correct classification rate of the model.

Table 1. Correct classification rate of original Altman’s model

YEAR	OBSERVED	PREDICTED			Overall accuracy rate (in %age)	Type I Error (in %age)	Type II Error (in %age)
		Defaulted	Non-Defaulted	Correct %age			
2011	Defaulted	29	08	78.38	50	21.62	78.38
	Non-Defaulted	29	08	21.62			
2012	Defaulted	31	06	83.78	54.05	16.22	75.68
	Non-Defaulted	28	09	24.32			
2013	Defaulted	33	04	89.18	56.72	10.82	75.68
	Non-Defaulted	28	09	24.32			
2014	Defaulted	33	04	89.18	60.81	10.82	67.57
	Non-Defaulted	25	12	32.43			
2015	Defaulted	35	02	94.59	66.21	05.41	62.17
	Non-Defaulted	23	14	37.83			

4.1. EFFECT OF CHANGE IN TIME PERIOD ON ALTMAN’S MODEL

To study the time effect on the accuracy of the model the Altman’s model is re-estimated by using recent data from 2011-15 and applying MDA as originally employed by the Altman to develop the model. Table 2 presents the re-estimated MDA model from 2011 to 2015. Wilks’ Lambda is used to examine the discriminating ability of the model which is found to be significant for all the years. Significant p-values of Wilks’ Lambda indicate that the re-estimated MDA model has better discriminating ability. Canonical correlation is equivalent to Karl Pearson correlation which is very useful when there are two categories of dependent variable. Square of canonical correlation is used to find out the percentage of variance explained in dependent variable.

Table 2. Time varying re-estimated Z-score model using MDA

Variables	2011	2012	2013	2014	2015
X1	-2.237	-2.47	2.354	2.505	.746
X2	3.672	15.311	3.343	7.259	4.585
X3	9.521	-1.073	8.593	.558	-2.148
X4	.275	.446	.348	.324	.206
X5	.385	.751	.552	.843	1.265
Intercept	-1.536	-1.179	-1.491	-1.152	-1.196
Canonical correlation	.442	.491	.633	.669	.643
Wilks' lambda	.805	.759	.599	.552	.586
Sig. (P-value)	.010	.002	.000	.000	.000

Table 3 highlights the correct classification rate of re-estimated MDA model. Results showed that correct classification rate of the model has increased in the case of non-defaulted companies. It can also be observed that overall correct prediction rate has significantly increased when we re-estimated the model by using recent data.

Table 3. Correct classification rate of re-estimated Altman’s model using recent data

YEAR	OBSERVED	PREDICTED			Overall accuracy rate (in %age)	Type I Error (in %age)	Type II Error (in %age)
		Defaulted	Non-Defaulted	Correct Percentage			
2011	Defaulted	28	09	75.70	68.90	24.30	37.40
	Non-Defaulted	14	23	62.60			
2012	Defaulted	32	05	86.50	74.30	13.50	37.40
	Non-Defaulted	14	23	62.60			
2013	Defaulted	28	09	75.70	71.60	24.30	32.40
	Non-Defaulted	12	25	67.60			
2014	Defaulted	26	11	70.30	75.70	29.70	18.90
	Non-Defaulted	07	30	81.10			
2015	Defaulted	30	07	81.10	81.10	18.90	18.90
	Non-Defaulted	07	30	81.10			

It can be concluded that the Altman’s model is sensitive to change in time period and should be re-estimated by using recent data to improve the classification accuracy of the model. These findings are similar to the findings of Grice and Ingram (2001), Agarwal and Taffler (2005), Singh and Mishra (2016).

4.2. EFFECT OF CHANGE IN METHODOLOGY ON ALTMAN’S MODEL

To examine the effect of change in methodology applied to develop the model, logistic regression is applied to re-estimate the model instead of MDA. Table 4 presents the results of logit model estimated from 2011-15. Nagelkerke R square is used to measure the percentage of variance explained by the model and Hosmer and Lemeshow (HL) test is also used as test of goodness of fit for logit model. Nagelkerke R square showed that higher percentage of the variance is explained by the model in the years near to year of default. P-value of Hosmer and Lemeshow test is greater than 0.05 which accepts the null hypothesis of the test that model is good fit to data. Omnibus test of model coefficients is also used. This test uses chi square test to examine whether the newly developed model is significantly better than base model or not. Significant value of omnibus test indicates that newly developed model

is significant improvement over previous one. These results are supported by loglikelihood ratio, which decreases from 2011 (82.691) to 2015 (36.882). Decreased value of likelihood ratio indicates that model estimated by using recent data found to be significantly better.

Table 4. Logistic regression based Z-score model

Variables	2011	2012	2013	2014	2015
X1	-1.627	-.462	3.847	4.969	2.249
X2	-4.504	14.813	4.720	7.364	35.238
X3	13.845	-3.104	14.439	-2.75	-15.109
X4	.947	1.553	2.041	7.168	2.983
X5	.253	.799	.685	1.125	1.400
Intercept	-1.983	-1.461	-2.701	-3.400	-1.577
Omnibus test of model coefficients (chi-square statistics)	19.895	23.787	41.193	55.461	65.764
P-value	.001	.000	.000	.000	.000
-2loglikelihood	82.691	78.799	61.393	47.124	36.882
HL test (P-value)	.617	.351	.982	.996	.952
Nagelkerke R²	.314	.367	.569	.703	.785

Results of correct classification rate of the re-estimated Altman’s model by using logistic regression are presented in the table 5. It shows that change in methodology from MDA to logistic regression significantly improves the correct prediction rate. As shown in the table 5 that the overall correct prediction rate has increased from 81.10% to 87.83% in 2015 and also increased in the years prior to 2015.

Table 5. Correct classification rate of logistic regression based Altman’s Z-score model

YEAR	OBSERVED	PREDICTED			Overall accuracy rate (in %age)	Type I Error (in %age)	Type II Error (in %age)
		Defaulted	Non-Defaulted	Correct Percentage			
2011	Defaulted	29	08	78.38	66.67	21.62	43.25
	Non-Defaulted	16	21	56.75			
2012	Defaulted	30	07	81.08	74.32	18.92	32.44
	Non-Defaulted	12	25	67.56			
2013	Defaulted	30	07	81.08	77.02	18.92	27.03
	Non-Defaulted	10	27	72.97			
2014	Defaulted	32	05	86.48	85.13	13.52	16.22
	Non-Defaulted	06	31	83.78			
2015	Defaulted	34	03	91.89	87.83	08.11	16.22
	Non-Defaulted	06	31	83.78			

This significant increase in the overall correct prediction rate supported that Altman’s model is sensitive to change in the methodology adopted to estimate the model. It can also be concluded that the logistic regression is superior to MDA because it has higher predictive power than MDA. These findings are similar to the findings of Liang (2003), Lin (2009) and Polsiri (2009).

5. CONCLUSION

The present study examined the sensitivity of Altman’s model to change in time period and methodology in Indian context. Results showed that the correct prediction rate of Altman’s model for non-defaulted companies is very low when applied in Indian context. As the original Altman’s model is developed by using the data from US companies thus this may be the reason of the low predictive power of the model when applied to developing countries like India. Another reason for the low predictive power of the model in Indian context may be that the coefficients of the variables used in model were estimated in 1968 and this relationship of the variables used in the model might have changed over the time. Thus it is necessary to examine the sensitivity of the Altman’s model to change in time period. To study the time effect on the accuracy of the model we re-estimated the Altman’s model by using recent data and logistic regression is used to study the effect of change in methodology. Results showed that overall correct classification rate of the model increased to 81.10% in 2015 when applied the re-estimated model based on recent data. Logistic regression is used to examine the sensitivity of the Altman’s model to

change in the methodology and it is observed that change in methodology from MDA to logistic regression significantly improves the overall correct prediction rate, which has further increased to 87.83% for 2015. It can be concluded that the Altman's model is sensitive to change in time period and methodology. Hence, Altman's model should be re-estimated by using the recent data before applying it to predict the corporate bankruptcy. It is also observed that logistic regression showed superior results than MDA. The major limitation of the study is that it is restricted only to the Indian manufacturing companies. Future research may extend it further to the other sectors of the economy.

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