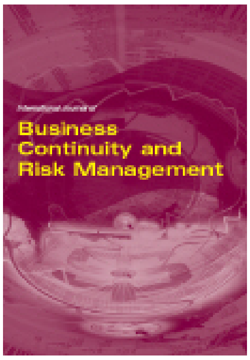

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Prediction of financial distress in the Indian corporate sector: an improvement over Altman's Z-score model

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Abstract: Financial distress is the situation when a firm faces difficulty regarding the payment of its financial obligations on due time which may result into business failure. Prediction of financial distress at an early stage can be used as a warning signal to take corrective actions and to avoid the future bankruptcy. Altman's Z-score model is widely used in practice to measure financial distress. This study has re-estimated the coefficients of Altman's model using recent data and has also developed a new model using logistic regression to predict financial distress. The accuracy of the two models is compared using testing sample and receiver operating characteristic (ROC). The results reveal that the newly developed model has achieved higher predictive accuracy than re-estimated Altman's model and hence can be more suitable to predict financial distress and to avoid future bankruptcy.

Keywords: Altman's model; business failure; financial distress prediction; financial ratios; logistic regression; receiver operating characteristic; ROC curve.

JEL codes: G01, G32, G33.

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1 Introduction

Financial statements are prepared with the aim to provide the information related to financial health of the company. Financial analysis of these statements provides useful information to all interested parties especially to investors. Apart from the information provided by financial statements investors should also keep in mind the probability of failure of the company. There are number of reasons like higher costs, ineffective sales, mismanagement, and faulty credit policy which results into business failure. Despite of this, financial distress is the initial stage in which a company faces problems regarding cash inflows which leads to business failure (Senbet and Wang, 2012). Financial distress is the situation when a company becomes unable to repay its financial obligations on time. Earlier signs of financial distress include poor profits and a company raises finance externally which increases the financial risk and lowers the creditworthiness of the company. A distressed firm also faces many problems like decrease in market value, cancellation of orders by customers and suppliers avoid credit terms and insist on cash on delivery terms (Baimwera and Muriuki, 2014). Prediction of financial distress is necessary because of its negative consequences for company, investors and also for economy. Early prediction of financial distress is also required to avoid the bankruptcy because financial distress results into the emergence of business failure.

Several models have been developed from time to time to predict the probability of failure and among these models Altman's Z-score model is commonly used in practice. Many studies have been conducted to develop the financial distress prediction models after the development of Altman's model. These models are used to predict whether a company faces any financial problem and will become bankrupt in nearest future or not. A financial distress prediction model is not only used to calculate the probability of failure of a company but can also be used as an early warning signal to avoid the situation of bankruptcy (Celli, 2015).

The predictive power of these financial distress prediction models depends upon the data sample and methodology used. A developed model can be applied only to a specific set of firms that possess similar characteristics as the firms used to develop the model. Due to the difference in macroeconomic conditions, capital structure, political and legal system a model developed in one country cannot be directly applied to another country. Many studies applied Altman's model to test its predictive accuracy in recent times and it is observed that Altman's model is still effective in predicting financial distress (Agarwal and Taffler, 2005; Celli, 2015). However, its predictive accuracy can be enhanced by re-estimating its coefficients by using recent data or by adding new variables (Grice and Ingram, 2001; Agarwal and Taffler, 2005; Karamzadeh, 2013; Micvdova, 2013; Thai et al., 2014; Karas and Rezankova, 2015; Singh and Mishra, 2016).

The relationship of the variables used in models may also vary from one country to another due to the difference in accounting and taxation system which may result into the obsolescence of the coefficients of the variables. Thus, it is better to re-estimate the model rather than directly applying the model. The purpose of this study is to re-estimate the original Altman's model and to develop improved model by introducing the additional variables to Altman's model. For this purpose, the widely used logistic regression is used to identify the best combination of the ratios which can be used to discriminate between distressed and non-distressed firms.

2 Review of literature

Business failure depresses the economy because of its negative consequences to various stakeholders like investors, creditors, lenders and government. Every business faces number of events before it becomes bankrupt. Hence it is very necessary to identify the various indicators of financial distress that can be used as early warning signals to predict the financial distress situation and to avoid the business failure. Literature related to financial distress prediction exists since 1930's. Several studies have been done from time to time to develop the financial distress prediction model. Pioneer studies related to corporate failure prediction (Beaver, 1966; Altman, 1968; Ohlson, 1980; Mensah, 1984) have been done in the pre-1990's era. Many studies have been done to compare the ratios of distressed and non-distressed firms and reported that net worth to debt (Fitz-Patrick, 1932), current assets to total assets (Smith and Winakor, 1935), working capital to total assets (Smith and Winakor, 1935; Merwin, 1942; Jackendoff, 1962), net worth to total assets (Merwin, 1942) and current ratios (Merwin, 1942; Jackendoff, 1962) are some important ratios that can be used to discriminate between distressed and non-distressed firms.

Beaver in 1966 analysed the usefulness of financial ratios in predicting the financial distress by applying univariate analysis and reported that cash flows to total debt ratio showed higher predictive power. Beaver's study is one of the initial contributions in the field of business failure prediction. Main drawback of the Beaver's study was that it used univariate analysis which serves as a base for the development of multivariate model of financial distress prediction.

Altman (1968) developed the multivariate model based on multiple discriminant analysis which produces a single score known as Z-score that can be used to discriminant between distressed and non-distressed firms. These studies used financial ratios as important predictors of the financial distress and there are several studies (Ganesalingam and Kumar, 2001; Agarwal and Taffler, 2005; Bandyopadhyay, 2006; Karami et al., 2012; Thai et al., 2014) which validates the usefulness of financial ratios in predicting the financial distress. Agarwal and Taffler (2008) investigated the performance of accounting-based models and market-based models and reported that accounting-based models found to be superior to market-based models. Lin et al. (2012) found that profit related variables, employee efficiency ratios and growth ratios are most important ratios to discriminate between distressed and non-distressed firms. Gu and Gao (2000) developed the failure prediction model composed of five ratios (total liabilities to total assets, earnings before interest and taxes to current liabilities, gross profit ratio, long-term liabilities to total assets and sales to fixed assets) by using multiple discriminant analysis. Bandyopadhyay (2006) developed the model based on multiple discriminant analysis by using financial and non-financial variables and reported that all the financial ratios of non-distressed firms were better than the ratios of distressed firms.

Earlier studies focused on the application of multiple discriminant analysis which requires the assumption of normality of data. Ohlson (1980) developed the business failure prediction model by using logistic regression and concluded that logistic regression overcomes the problems of multiple discriminant analysis and also showed higher predictive power than multiple discriminant analysis. It was also reported that size is the most important factor which affects the likelihood of business failure. Ohlson's study can be considered as a milestone in the studies related to corporate failure prediction. After the application of logistic regression in the development of financial distress prediction model many researchers like Mensah (1984), Aziz and Lawson (1989), Daily and Dalton (1994), Liang (2003), Grice and Dugan (2003), Pindo et al. (2008), Lin (2009), Xu and Wang (2009), Andreica et al. (2010), Campbell et al. (2011), Lin et al. (2012), Tinoco and Wilson (2013) and Oz and Yelkenci (2017) used logistic regression to develop the financial distress prediction model.

Few studies have also been done to analyse the effectiveness of cash flow-based information in predicting financial distress and concluded that higher classification accuracy can be achieved by using the cash flow-based ratios (Gombola et al., 1987; Aziz and Lawson, 1989). Non-financial variables have been also used along with financial variables in studies like Bandyopadhyay (2006) and Sun (2007) and studies like Liang (2003) and Desai and Joshi (2015) combined the financial variables with market-based variables to develop the financial distress prediction models. Financial ratios can be considered as integral part of the financial distress prediction models as used in many studies like Beaver (1966), Altman (1968), Ganesalingam and Kumar (2001), Agarwal and Taffler (2005), Bandyopadhyay (2006), Thai et al. (2014), and reported that financial ratios can be used to develop the corporate failure prediction model. Predictive accuracy of the model can be enhanced by combining the financial ratios with market-based ratios (Liang, 2003; Desai and Joshi 2015) or by using non-financial variables (Bandyopadhyay, 2006; Sun, 2007) also.

Altman's model is developed by taking the sample of 66 US companies equally divided into manufacturing and non-manufacturing companies. Altman's model has better predictive power and can be used to predict the corporate failure or financial distress as evidenced from the studies like Moyer (1977), Grice and Ingram (2001), Micvdova (2013), Thai et al. (2014), Celli (2015), Desai and Joshi (2015) and Almamy et al. (2016). Although these studies highlight the predictive power of the Altman's model but a model developed in advanced countries cannot be directly applicable to emerging countries like India due the difference in legal, political, accounting and taxation systems. Secondly, the coefficients of these models may become obsolete with time. Grice and Dugan (2001) and Singh and Mishra (2016) tested the validity of models by applying the various models (Altman, Ohlson and Zmijewski) to different time periods and to different industries. It is concluded that overall accuracy of the model decreases when applied to different time period and industry and hence, the predictive accuracy of the models can be increased by re-estimating the coefficients by using recent data and further an industry specific model should be developed to predict the business failure. Altman's model can be used to predict the business failure or financial distress but its accuracy can be increased by re-estimating the model by using recent data or by adding new variables to it (Grice and Ingram, 2001; Agarwal and Taffler, 2005; Karamzadeh, 2013; Micvdova, 2013; Thai et al., 2014; Celli, 2015; Karas and Rezenakova, 2015; Desai and Joshi, 2015; Almamy et al., 2016).

Above discussions showed that many studies supported that Altman's model showed higher classification power and still effective in predicting the financial distress or business failure. Earlier 1990's the focus was on development of the bankruptcy prediction model but after this several trends have been observed in the area of corporate failure prediction regarding the use of variables and methodology. As it is highlighted in the literature that a model developed in one country should not be applied directly to another country. The work related to financial distress prediction model is not much encouraging in Indian context. The majority of Indian studies focused on the application of existing models to predict the financial distress. In this study an attempt is made to re-estimate the original Altman's model and also to develop an improved model by adding new variables to Altman's model. For this purpose, logistic regression is used because it is found to be superior technique which is widely used to develop financial distress prediction models.

3 Data and methodology

Initially the total sample of 164 manufacturing companies (48 distressed companies and 116 non-distressed) was selected. Finally, the sample of 117 Indian listed companies comprising of 42 distressed and 75 non-distressed companies was selected after matching by assets size and industry classification. The sample was further divided into two sub samples, one was estimation sample composed of 78 companies (including 28 distressed and 50 non-distressed companies) and other was the testing sample composed of 39 companies (including 14 distressed and 25 non-distressed companies). Estimation sample is used to re-estimate the Altman' model and testing sample is used to validate the newly developed model. The classification of companies into distressed and non-distressed group is done by using credit ratings given by CRISIL, ICRA and CARE in the year 2015–2016. 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. The selected companies are from seven different industries (Appendix A).

To re-estimate the Altman's model, financial ratios are selected on the basis of their importance in literature. These ratios are further divided into profitability ratios, liquidity ratios, solvency ratios, cash flow-based ratios, turnover ratios and growth ratios. Companies grouped into distressed and non-distressed group may differ in the size. In order to capture the size effect log of market capitalisation is introduced as control variable. A list of all financial ratios is given in Appendix B.

Shapiro-Wilk test is used to examine the normality of data and Mann-Whitney test is used to find out the variables that can be used to discriminate between distressed and non-distressed companies. To re-estimate the model logistic regression is used.

Logistic regression is the statistical technique which is applied when the dependent variable is categorical variable coded as 0 or 1. Application of logistic regression does not require the assumption of normality regarding the data and it is also found to be superior to traditional methodologies as supported in many studies (Ohlson, 1980; Liang, 2003; Lin, 2009; Chen, 2011). Hence logistic regression is applied to re-estimate the model and to find out the best combination of the predictors. A simple linear regression equation can be written as:

$$Y = \delta + \pi_1 x_1 + \pi_2 x_2 + \ldots + \pi_n x_n \tag{1}$$

where δ is the intercept and $\pi_1 \rightarrow \pi_n$ represents the coefficients of n explanatory variables.

Logistic regression predicts the probability of happening of event Y, $p(Y = 1)$ instead of predicting the value of Y and probability of happening of event (p) may vary from 0 to 1. Ratio of happening of an event to the probability of non-happening of an event is known as odds ratio is the ratio expressed as:

$$\left(\frac{p}{1-p}\right)$$

Logistic transformation of odds ratio or logit(*p*) is nothing but the log of *p* (to base *e*), which ranges from negative to positive infinity which normalise the distribution. Symbolically it can be written as:

$$\operatorname{logit}(p) = \ln\left(\frac{p}{1-p}\right)$$

The logistic regression can be expressed as:

$$\ln\left(\frac{p}{1-p}\right) = \delta + \pi_1 x_1 + \pi_2 x_2 + \ldots + \pi_n x_n \quad (2)$$

In above equation δ is the intercept and $\pi_1 \rightarrow \pi_n$ represents the coefficients of *n* explanatory variables.

The probability of happening of an event can be calculated by using following formula:

$$p = \frac{\exp\left(\delta + \pi_1 x_1 + \pi_2 x_2 + \ldots + \pi_n x_n\right)}{1 + \exp\left(\delta + \pi_1 x_1 + \pi_2 x_2 + \ldots + \pi_n x_n\right)}$$

or

$$p = \frac{1}{1 + e^{-y}}$$

where p lies between 0 to 1 ($0 < p > 1$).

y is nothing but the dependent variable. It indicates that as the value of *y* increases value of *p* will move towards 1 which means with increase in the value of *p* probability of happening of an event ($Y = 1$) will increase. In other words, the value of *y* greater than cut off rate indicates that company is defaulted and the value of *y* lower than the cut off rate implies the company is non-defaulted.

To perform logistic regression distressed companies are coded as 1 and non-distressed companies as 0 in the dependent variable. To divide a company in defaulted or non-defaulted zone a cut off rate of 0.5 is used where the value greater than 0.5 indicates that the company is defaulted company and value less than 0.5 indicates that the company is non-defaulted company.

To validate the model two diagnostic tests, viz., testing sample and receiver operating characteristic (ROC) curve are used. Testing sample is used as hold out sample to test the predictive power of the model. ROC curve is a graphical plot in which area under the curve (AUROC) is used to measure the classification accuracy of the model. In ROC curve true positive rate (sensitivity) and false positive rate (1-specificity) are taken at various threshold values. *Sensitivity* and *specificity* can be expressed as:

$$sensitivity = \frac{number\ of\ true\ positives\ (TP)}{number\ of\ true\ positives\ (TP) + number\ of\ false\ negatives\ (FN)}$$

$$specificity = \frac{number\ of\ true\ negatives\ (TN)}{number\ of\ true\ negatives\ (TN) + number\ of\ false\ positives\ (FP)}$$

where

TP number of distressed companies classified as distressed

FN number of distressed companies classified as non-distressed

FP number of non-distressed companies classified as distressed

TN number of non-distressed companies classified as non-distressed.

ROC curve minimises the both, that is, false negative rate and false positive rate. Area under the curve equals to 1 represents that the model is perfect and an area of 0.5 represents the model is worthless or null.

4 Results and discussion

To re-estimate the Altman's model, 40 financial ratios as additional variables are selected on the basis of their importance in the literature. Shapiro-Wilk test is used to examine whether data is normally distributed or not. Results of Shapiro-Wilk test are presented in Table 1.

Results of the test showed that all the variables are not normally distributed except five variables namely S_TA, CA_TA, INT_TD, LN_MCP and LN_TA. As the results of Shapiro-Wilk test indicated that the majority of the variables violates the assumption of normality, hence Mann-Whitney test, a non-parametric test, is used to find out the variables that can be used to discriminate between distressed and non-distressed companies (see Table 2).

Results of Mann-Whitney test proved that all the Altman's ratios, profitability ratios cash flow-based ratios and turnover ratios along with control variable size are able to discriminate between distressed and non-distressed companies. Three variables (C_TA, CA_TA and INV_TA) from liquidity ratios, two variables (LTD_EQ and LTD_SF) from solvency ratios and two variables (GR_PAT and GR_EQ) from growth ratios are not found to be significant hence these cannot be used to differentiate between distressed and non-distressed companies. Variables found to be insignificant on the basis of the results of Mann-Whitney test are excluded and remaining 33 financial ratios including one control variable (LN_MCP) are used to re-estimate the Altman's model.

Logistic regression is used to re-estimate the Altman's model and to find out the best discriminators between distressed and non-distressed companies. Re-estimation of the Altman's model is done in two phases firstly, re-estimation of original Altman's model is done. Secondly, an attempt is made to develop an improved model by introducing new variables to Altman's variables. Hence, present study is focused on developing two different models by employing logistic regression which are:

Model_1 Re-estimated model by using variables used in Altman's model.

Model_2 Re-estimated model by introducing new variables in addition to the variables used in Altman's model.

Table 1 Results of Shapiro-Wilk test

Altman's ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
WC_TA	0.782	0.000	MVE_TL	0.535	0.000
RE_TA	0.832	0.000	S_TA	0.982	0.340*
EBIT_TA	0.597	0.000			
Profitability ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
PAT_TA	0.579	0.000	GP_S	0.434	0.000
ROE	0.577	0.000	EBIT_S	0.423	0.000
ROA	0.579	0.000	CP_TA	0.569	0.000
PAT_S	0.435	0.000	EPS	0.943	0.002
Liquidity ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
QA_CL	0.911	0.000	WC_S	0.586	0.000
QA_S	0.415	0.000	WC_EQ	0.622	0.000
C_TA	0.364	0.000	INV_TA	0.919	0.000
CA_TA	0.973	0.096*			
Solvency ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
TD_EQ	0.842	0.000	EBIT_EBT	390	0.000
LTD_EQ	0.592	0.000	EBIT_TD	0.827	0.000
TD_TA	0.840	0.000	CP_TD	0.843	0.000
TTL_SF	0.290	0.000	EBIDTA_IN	0.676	0.000
PAT_TD	0.865	0.000	INT_TD	0.985	0.495*
Cash flow-based ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
CF_TD	0.855	0.000	CF_TL	0.600	0.000
CFFO_TD	0.954	0.007	CFFO_TA	0.915	0.026
CFFO_CL	0.950	0.004	CF_CL	0.924	0.000
Turnover ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
FATR	0.762	0.000	EQTR	0.875	0.000
ITR	0.492	0.000	DTR	0.795	0.000
Growth ratios					
Variable	*Statistic*	*P-value*	*Variable*	*Statistic*	*P-value*
GR_PAT	0.093	0.000	GR_S	0.949	0.003
GR_TA	0.141	0.000	GR_EQ	0.093	0.000
Size					
Variable	*Statistic*		*P-value*		
LN_MCP	00.972		00.089*		

Note: *$p > 0.05$ which indicates that data is normally distributed.

Table 2 Results of Mann-Whitney test

Category	*Variables*	*Mean rank*		*P-value*
		Non-defaulted	*Defaulted*	
Altman's ratios	WC_TA	46.20	27.54	0.000**
	RE_TA	50.26	20.29	0.000**
	EBIT_TA	51.30	18.43	0.000**
	MVE_TL	52.52	16.25	0.000**
	S_TA	45.42	28.93	0.002*
Profitability ratios	PAT_TA	51.54	18.00	0.000**
	ROE	50.82	19.29	0.000**
	ROA	51.54	18.00	0.000**
	PAT_S	49.96	20.82	0.000**
	GP_S	46.52	26.96	0.000**
	EBIT_S	48.62	23.21	0.000**
	CP_TA	52.48	16.32	0.000**
	EPS	51.40	18.25	0.000**
Liquidity ratios	QA_CL	45.66	28.50	0.001**
	QA_S	35.02	47.50	0.020*
	C_TA	41.30	36.29	0.349
	CA_TA	40.70	37.36	0.532
	WC_S	46.38	27.21	0.000**
	WC_EQ	45.36	29.04	0.002*
	INV_TA	40.62	37.50	0.560
Solvency ratios	TD_EQ	45.50	28.79	0.002*
	LTD_EQ	38.27	41.70	0.522
	TD_TA	28.76	58.68	0.000**
	LTD_SF	38.53	41.23	0.613
	PAT_TD	51.62	17.86	0.000**
	EBIT_EBT	45.38	29.00	0.002*
	EBIT_TD	51.54	18.00	0.000**
	CP_TD	52.46	16.46	0.000**
	EBIDTA_INT	51.92	17.32	0.000**
	INT_TD	34.32	48.75	0.007*
Cash flow-based ratio	CF_TD	52.30	16.64	0.000**
	CFFO_TD	50.36	20.11	0.000**
	CFFO_CL	50.20	20.39	0.000**
	CF_TL	52.46	16.36	0.000**
	CFFO_TA	49.26	22.07	0.000**
	CF_CL	52.12	16.96	0.000**

Notes: ** and * indicate significance at 0.01 and 0.05 levels respectively.

Table 2 Results of Mann-Whitney test (continued)

Category	*Variables*	*Mean rank*		*P-value*
		Non-defaulted	*Defaulted*	
Turnover ratios	FATR	44.00	31.46	0.019*
	ITR	44.62	30.36	0.008*
	EQTR	49.68	21.32	0.000**
	DTR	44.08	31.32	0.017*
Growth ratios	GR_PAT	40.42	37.86	0.632
	GR_TA	47.20	25.75	0.000**
	GR_S	49.06	22.43	0.000**
	GR_EQ	39.50	39.50	1.00
Size	LN_MCP	50.48	19.89	0.000**

Notes: ** and * indicate significance at 0.01 and 0.05 levels respectively.

The results of logistic regression are presented in Table 3.

Table 3 Results of logistic regression

Variables	*Model_1 (coefficients)*	*Model_2 (coefficients)*
WC_TA	–3.310	
RE_TA	11.160	
EBIT_TA	–12.012	
MVE_TL	–6.954**	
S_TA	–1.228	
QA_CL		–10.407**
QA_S		6.076**
CFFO_TA		–21.127*
GR_S		–10.209**
SIZE		–10.209**
Intercept	3.432**	15.578**
Chi-square statistic	68.679***	81.454***
Nagelkerke R^2	0.803	0.889
–2LL	33.162	20.386

Notes: ***, ** and * indicate significance at 0.01, 0.05 and 0.10 levels respectively.

A significant value of chi-square statistic indicates that the overall model is statistically significant and inclusion of the variables as predictors to constant only model significantly contributes to the model fit and both the estimated models are significant improvement over the constant only model. Nagelkerke R-square is used because it is an improved version of Cox and Snell R-square. Nagelkerke R-square of Model_2 is found to be higher than Model_1 which indicates that the inclusion of additional variables to Altman's model significantly improves the predictive accuracy of the model. –2log likelihood ratio also decreases in case of Model_2 which also indicates that the model estimated by adding additional variables to Altman's model is significant improvement over the Altman's model. The Wald statistic of each individual predictor in the Model_2 is found to significant which indicate that all the variables significantly contribute to the model, whereas in case of Model_1 only one variable (MVE_TL) is found to be significant.

5 Profile of the variables selected in the newly developed model

In order to find out the best combination of the financial ratios to discriminate between distressed and non-distressed firms' logistic regression with stepwise procedure is applied. As a result, the reported final model composed of five variables (QA_CL, QA_SL, CFFO_TA, GR_SL and LN_MCP) indicating the liquidity and cash flow position of the firm in relation to its size. All the variables included in the model are found to be significant from 5% to 10% significant level. First variable selected in the model is quick assets to current liabilities (QA_CL) which is indicator of firm's short-term liquidity position. Quick assets are calculated after deducting inventory and prepaid expenses from current liabilities. Hence this ratio composed of most liquid assets and reflects the capacity of the firm to meet its short-term obligations. Quick assets to current liabilities (QA_CL) are found to be negatively related to the financial distress which indicates that higher the ratio and better will be the position of the company and lower will be the probability of failure.

Second variable is quick assets to sales (QA_S) that is also found to have significantly contributed to the model. Normally the higher proportion of quick assets in relation to sales is considered to be better. But the estimated model reports positive coefficient of the quick assets to sales (QA_S) ratio which indicate that higher the ratio higher will the level of financial distress. Quick assets generally composed of trade receivables plus cash and cash equivalents. Quick assets to sales (QA_S) ratio is analysed by segregating into trade receivables to sales and cash and cash equivalents to sales to find out the reason for positive coefficient. It was observed that quick assets composed major portion of trade receivables and trade receivable to sales ratio was found to be significant. If the proportion of cash and cash equivalents is found to be higher than the trade receivables in quick assets then the high quick assets to sales may be considered as good. But in case of distressed companies' quick assets majorly composed of trade receivables than cash and cash equivalents. Higher proportion of trade receivables indicates the growth of credit sales which is not a good sign for the company. Higher trade receivables to sales ratio indicates that customers are not paying and risk of delay or default in payments is high. A company should be aware about the growth of trade receivables because it also increases the working capital requirements which results into additional finance cost when company arranges finance externally. Hence increase of trade receivables in relation to sales indicates that a company faces problem regarding receivables collection, which is the sign of danger for the company. It was found that the quick assets of 95% distressed companies included in the estimation sample include more than 90% of trade receivables. This may be the possible reason for the positive relationship of quick assets to sales ratio with financial distress because the growth of trade receivables in relation to sales is not a good indicator as discussed above. Hence higher the quick assets to sales (QA_S), higher will be the level of financial distress provided the quick assets comprise major portion of trade receivables.

Cash flows from operations to total assets (CFFO_TA) is the third variable included in the model. This ratio measures the efficiency of a company to generate operating cash flows for every rupee invested in assets. Cash flows from operations to total assets (CFFO_TA) is similar to cash return on assets (ROA) which is calculated by cash flows from operations to total assets. For calculating cash ROA, net income used in return on assets (ROA) ratio is replaced by cash flow from operations. Cash flows from operations to total assets (CFFO_TA) is a financial metric which indicates how company utilises the amount invested in assets to generates cash flows. A low cash flows from operations to total assets (CFFO_TA) ratio indicates that a company generate less cash flows in relation to total assets which is the sign of inefficiency. Thus, higher the cash flows from operations to total assets (CFFO_TA) ratio, lower will be the level of financial distress.

Fourth variable which significantly contributes to the financial distress prediction model is growth rate of sales (GR_SALES) which indicates the increase of sales as compared to previous year. Growth of sales is very necessary for survival of company and to increase profitability of company. Growth rate of sales (GR_SALES) is found to be negatively related to financial distress which indicates that increase in sale reduces the level of financial distress. Growth of sales results into increase in profitability of the company which may result into payment of more dividends to shareholders. High payment of dividend can also positively affect the stock prices. Thus, low growth of sales is a bad sign for the company which may affect the survival and profitability of the company. Lastly log of market capitalisation (LN_MCP) is reported in the model which is taken as a measure of size. Log of market capitalisation (LN_MCP) is found to be negatively related to the financial distress. It indicates that the large companies are less prone to financial distress situation as compared to small companies. The reason for this is that large companies have larger resources and can easily access to outside funding due to greater credibility whereas small companies face difficulty to access funding from outside.

Financial distress is the situation which can be defined as the inability of the firm to pay its obligations on time or a company faces the problem regarding the cash inflows. Variables selected in the model are majorly focused on liquidity, profitability and cash flows situation of the company. It can be concluded that higher quick assets to current liabilities (QA_CL), cash flows from operations to total assets (CFFO_TA) and growth rate of sales (GR_SALES) ratio is considered as better for the company. On the other hand, lower quick assets to sales (QA_SALES) ratio is considered as better to avoid the financial distress situation if major portion of quick assets includes trade receivables. These all variables are related to liquidity, cash flows and profitability situation of the company. Growth rate of sales (GR_SALES) indicates that increase in sales is better for a company but on the other hand trade receivables should not increase means a company should focus on cash sales to avoid the situation of financial distress.

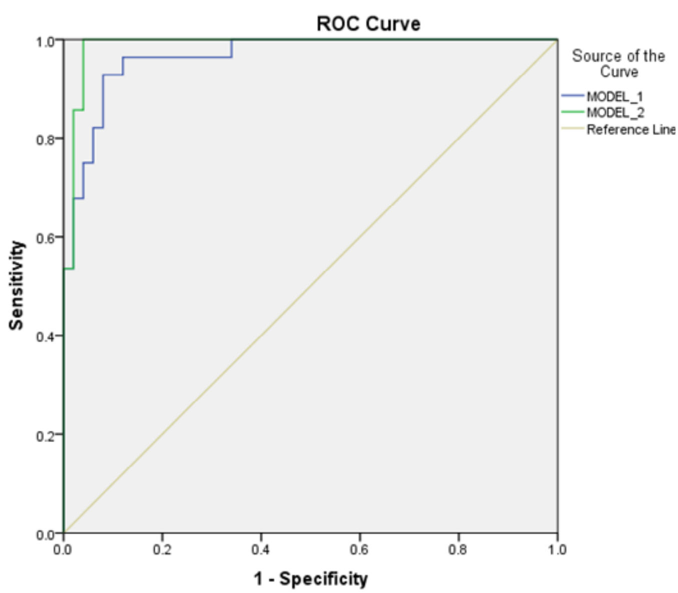
6 Validation of the models

To validate the accuracy of the newly developed model two diagnostic tests, that is, testing sample and ROC curve are used. Testing sample is used as hold out sample to test the predictive power of the model (see Table 4).

Table 4 Results of testing samples

Model_1						
Year	*Correct classification rate (number)*			*Correct classification rate (%)*		
	Defaulted	*Non-defaulted*	*Overall*	*Defaulted*	*Non-defaulted*	*Overall*
2011	08	16	24	57.14	64	61.54
2012	11	13	24	78.57	52	61.54
2013	11	13	24	78.57	52	61.54
2014	12	17	29	87.71	68	74.36
2015	13	21	34	92.86	84	87.18
Model_2						
Year	*Correct classification rate (number)*			*Correct classification rate (%)*		
	Defaulted	*Non-defaulted*	*Overall*	*Defaulted*	*Non-defaulted*	*Overall*
2011	04	21	25	28.57	84	64.10
2012	05	22	27	35.71	88	69.23
2013	06	23	29	42.86	92	74.36
2014	11	24	35	78.57	96	89.74
2015	13	22	35	92.86	88	89.74

Figure 1 ROC curve of Model_1 and Model_2 (see online version for colours)



Results of testing sample shows that the Model_1 achieved the overall accuracy rate of 87.18% in 2015 (92.86% in the case of distressed companies and 84% in case of non-distressed companies) and similarly it is found 89.74% (92.86% in the case of distressed companies and 88% in case of non-distressed companies) for Model_2. Further the overall accuracy of the Model_2 is found to be higher than Model_1 which indicates that inclusion of additional variables improves the predictive accuracy of Altman's model hence, Model_2 is a better model.

Results of the ROC curve (Figure 1) shows that the area under the ROC curve of the Model_1 and Model_2 is found to be 0.965 and 0.988 respectively. Results of ROC curve shows that newly developed model by adding new variables to Altman's model is found to be superior to the re-estimated Altman's model (see Figure 1).

Both diagnostic tests validate that the newly developed financial distress prediction model which is developed by adding new variables to Altman's model has achieved higher predictive power than re-estimated Altman's model on testing sample and the superior predictive ability of the newly developed model has also been proved by the statistical measure area under the ROC curve which is found significant.

7 Conclusions

The purpose of the study was to re-estimate the original Altman's model by using the recent data of Indian listed manufacturing companies and an attempt is made to develop an improved model by introducing new variables to Altman's model by using logistic regression. For this purpose, a final sample of sample of 117 Indian listed companies comprised of 42 distressed and 75 non-distressed companies after matching by assets size and industry classification is used. Further the sample is divided into estimation sample (including 28 distressed and 50 non-distressed companies) and testing sample (including 14 distressed and 25 non-distressed companies). Estimation sample is used to re-estimate the Altman's model and to develop the new model while testing sample is used to validate the accuracy of both models. Results of Shapiro-Wilk test shows that data is not normally distributed hence Mann-Whitney test is applied to find out the variables that can be used to discriminate between distressed and non-distressed companies. After excluding the variables rejected in Mann-Whitney test a final list of 33 financial ratios including one control variable (LN_MCP) are introduced as additional variables to Altman's variables and logistic regression is applied to develop the new model.

Results of logistic regression showed that in re-estimated Altman's model only one variable (MVE_TL) is found to be significant. In the new model, developed after adding new variables to Altman's model, five variables (QA_CL, QA_S, CFFO_TA, GR_S and SIZE) are selected. Chi-square statistic of both models is found to be significant which indicates that the overall model is statistically significant. Nagelkerke R-square of Model_2 is found to be higher than Model_1 which indicates that the inclusion of additional variables to Altman's model significantly improves the predictive accuracy of the model. –2log likelihood ratio also decreases in case of Model_2 which also indicates that the model estimated by adding additional variables to Altman's model is significant improvement over the Altman's model.

To validate the accuracy of both the models testing sample and ROC cure are used. Testing sample is used as holdout sample and results of testing sample shows that Model_2 achieved higher predictive power than Model_1 in all the years from 2011 to 2015. Similar results are also found when accuracy of the model is measured by area under the ROC curve. Area under the curve for Model_1 and Model_2 is found to be 0.965 and 0.988 respectively. Validation results of both diagnostic tests, i.e., testing sample and ROC curve proved that Model_2, that is, the model developed by adding new variables to Altman's model is found to be superior to the Model_1 which was developed by re-estimating Altman's model. It is found that Altman's model, which is widely used to predict the financial distress, was developed in US and its accuracy decreases when applied to the emerging countries like India. Hence it is better to re-estimate the coefficients of the model before applying it to predict the financial health of the firm. It is concluded that accuracy of the Altman's model can be increased by re-estimating the Altman's model by using recent data or by adding new variables to it.

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Appendix A

Table A1 Industry classification of companies

Industry	*Defaulted companies (number)*	*Non-defaulted companies (number)*
Chemical and chemical products	18	7
Construction materials	6	3
Foods and agro-based products	9	7
Metal and metal products	13	11
Miscellaneous manufacturing	6	4
Textile	9	8
Transport equipment	14	2
Total	75	42

Appendix B

Table B1 Financial ratios based on literature used as additional variables

Category	*Ratio*	*Formula*	*Code*
Profitability ratios	P1	Profit after tax / total assets	PAT_TA
	P2	Return on equity	ROE
	P3	Return on assets	ROA
	P4	Profit after tax / sales	PAT_S
	P5	Gross profit / sales	GP_S
	P6	EBIT / sales	EBIT_S
	P7	Cash profit / total assets	CP_TA
	P8	Earnings per share	EPS
Liquidity ratios	L1	Quick assets / current liabilities	QA CL
	L2	Quick assets / sales	QA S
	L3	Cash / total assets	C TA
	L4	Current assets / total assets	CA TA
	L5	Working capital / sales	WC S
	L6	Working capital / equity	WC EQ
	L7	Inventory / total assets	INV TA
Solvency ratios	S1	Total debt / equity	TD EQ
	S2	Long-term debt / equity	LTD EQ
	S3	Total debt / total assets	TD TA
	S4	Long-term debt / shareholder's fund	LTD SF
	S5	Total assets / total debt	TA TD
	S6	EBIT / EBT (leverage)	EBIT_EBT
	S7	EBIT / total debt	EBIT_TD
	S8	Cash profit / total debt	CP_TD
	S9	EBITDA / interest	EBITDA_INT
	S10	Interest / total debt	INT_TD
Cash flow-based ratios	C1	Cash flows / total debt	CF_TD
	C2	Cash flow from operations / total debt	CFFO_TD
	C3	Cash flow from operations / current liabilities	CFFO_CL
	C4	Cash flows / total liabilities	CF_TL
	C5	Cash flow from operations / total assets	CFFO_TA
	C6	Cash flows / current liabilities	CF_CL
Turnover ratios	T1	Sales / fixed assets (fixed assets turnover ratio)	FATR
	T2	COGS / average inventory (inventory turnover ratio)	ITR
	T3	Sales / equity (equity turnover ratio)	EQTR
	T4	Sales / average debtors (debtors turnover ratio)	DTR
Growth ratios	G1	Growth rate of PAT	GR_PAT
	G2	Growth rate of total assets	GR_TA
	G3	Growth rate of sales	GR_S
	G4	Growth rate of equity	GR_EQ
Size	S1	Log of market capitalisation	LN_MCP