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Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies

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Abstract

Background: The suitability and performance of the bankruptcy prediction models is an empirical question. The aim of this paper is to develop a bankruptcy prediction model for Indian manufacturing companies on a sample of 208 companies consisting of an equal number of defaulted and non-defaulted firms. Out of 208 companies, 130 are used for estimation sample, and 78 are holdout for model validation. The study reestimates the accounting based models such as Altman EI (Journal of Finance 23: 19189–209, 1968) Z-Score, Ohlson JA (Journal of Accounting Research 18:109–131, 1980) Y-Score and Zmijewski ME (Journal of Accounting Research 22:59–82, 1984) X-Score model. The paper compares original and re-estimated models to explore the sensitivity of these models towards the change in time periods and financial conditions.

Methods: Multiple Discriminant Analysis (MDA) and Probit techniques are employed in the estimation of Z-Score and X-Score models, whereas Logit technique is employed in the estimation of Y-Score and the newly proposed models. The performance of all the original, re-estimated and new proposed models are assessed by predictive accuracy, significance of parameters, long-range accuracy, secondary sample and Receiver Operating Characteristic (ROC) tests.

Results: The major findings of the study reveal that the overall predictive accuracy of all the three models improves on estimation and holdout sample when the coefficients are re-estimated. Amongst the contesting models, the new bankruptcy prediction model outperforms other models.

Conclusions: The industry specific model should be developed with the new combinations of financial ratios to predict bankruptcy of the firms in a particular country. The study further suggests the coefficients of the models are sensitive to time periods and financial condition. Hence, researchers should be cautioned while choosing the models for bankruptcy prediction to recalculate the models by looking at the recent data in order to get higher predictive accuracy.

Keywords: Bankruptcy prediction, Indian manufacturing companies, MDA, Logit, Probit, Unstable coefficient, Predictive accuracy, Receiver operating characteristic, Long range accuracy

JEL Classification Codes: G 33

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Background

The World Economy at the start of 21st century begin with the financial crisis, which led to shift emphasis on modeling and evaluation of credit risk. The factors behind the shift in the trend are the rapid growth of the credit derivative market, rise in the bankruptcy and developing credit risk literature. The failure of rating agencies (Moody's, Standard and Poor's) to predict the fall of giant manufacturing companies like Chrysler, GM, LyondellBasell Industries, Excide Technologies alarmed the need to revisit risk management framework worldwide.

The current study proposes a new bankruptcy prediction model for Indian manufacturing companies. Since Beaver (1966), a substantial literature on bankruptcy prediction is developed to assess the financial health of companies. These models were based upon different theoretical approaches and types of information to model bankruptcy. Three notable and most cited accounting based bankruptcy models in the literature of accounting research are Altman (1968), Ohlson (1980) and Zmijewski (1984) (Grice and Dugan, 2001). The suitability and performance of these models in the new era is an empirical question due to change in time periods and financial conditions in which it was originally developed. The study re-estimates and compares these models with the newly proposed model.

In the bankruptcy prediction literature academician and accounting, practitioners have differed in the opinion on the power of these models to address the sensitivity of time periods and financial condition (cross-country heterogeneity, market structure, business cycle, etc.).

Begley et al. (1996) re-estimates and compares performance of original Altman's and Ohlson's models using US 1980's data. The major finding of the study suggests Altman's and Ohlson's model outperforms re-estimated model. Both the re-estimated model have higher classification errors. Out of four contesting models, Ohlson's original model outperforms other three contesting models. In line with Begley, Boritz et al. (2007) studying bankruptcy in Canada founds predictive accuracy of Altman's and Ohlson's original models are higher than re-estimated model. They also compared the accuracy of models developed for Canadian firms, namely, Springate (1978), Altman and Levallee (1980), and Legault and Veronneau (1986). The study concludes the Canadian models are being simpler and requiring less data. All models have stronger performance with the original coefficients than the re-estimated coefficients.

On the contrary, there are ample of studies questioning construct validity of the models to original models towards the change in time periods and financial conditions. Grice and Ingram (2001) analysed the sensitivity of Altman's Z-score model for US companies. The study suggests the coefficients of the models are sensitive to the change in the financial environment and time period. The re-estimated model with the most recent information give better predictive accuracy. Grice and Dugan (2001) conducted study on US companies founds predictive accuracy of re-estimated Altman's and Ohlson's model is higher than the original models. Timmermans (2014) analysed the sensitivity of Altman's, Ohlson's and Zmijewski's models on US companies. The major finding of the study suggests the re-estimated model have a higher predictive accuracy than the original models. Avenhuis (2013) conducted study on Dutch companies. The study re-estimates and compares performance of Altman's, Ohlson's and Zmijewski's original models. The major finding of the study suggests re-estimation of model with specific and bigger sample give better predictive accuracy.

According to Platt and Platt (1990) the economic environment of two periods may change because of three reasons: First, change in the relationship between bankruptcy (dependent variable) and financial ratios. Second, change in the range of financial ratios (independent variables). And third, change in the relationship among financial ratios. They also suggested these changes attribute to bring change in the corporate strategy, the competitive nature of market, business cycle and technology. In the Indian market Bandyopadhyay (2006), Bhumia and Sarkar, (2011) and Shetty et al. (2012) developed Industry specific models for Indian corporate bond, pharmaceutical, and Information Technology/Information Technology Enabled Services (IT/ITES) industry respectively. Chudson (1945) mentions industry specific models are more appropriate than general models. The similar evidence is also found in the study of Avenhuis (2013).

In the light of above discussion the major aim of the paper is threefold: First, to develop a new bankruptcy prediction model for Indian manufacturing companies on Indian sample. Second, to revisits and re-estimate Altman (1968), Ohlson (1980) and Zmijewski (1984) models to examine the sensitivity of these models towards change in financial conditions and time periods. Finally, to choose the best model for prediction of financial distress of Indian manufacturing companies. The current study differs from prior study in three perspectives: Firstly, the study uses larger data set sampled over a longer period (Sample size 208) than in previous studies on Indian market which increases statistical power of the model. Second, the new bankruptcy prediction model is proposed with a unique combination of financial ratios measuring leverage, profitability and turnover of Indian manufacturing companies. Third, in the Indian market, there is no attempt is made to compare the sensitivity of Altman's, Ohlson's and Zmijewski's models together towards change in time period and financial conditions.

The major findings of the study reveal that the overall predictive accuracy of all the three models improves on estimation and holdout sample when the coefficients are re-estimated. Amongst the contesting models, the new proposed model outperforms while predicting bankruptcy for Indian manufacturing companies. The study further suggests the coefficients of the models are sensitive to time periods and financial conditions. The relation between financial ratios and bankruptcy and the comparative importance of the financial ratios are also not constant over the time periods. The findings are in line with past studies of Grice and Ingram (2001), Grice and Dugan (2001), Timmermans (2014) and Avenhuis (2013). Hence, researchers should be cautioned while choosing the models for bankruptcy prediction to recalculate the models by looking at the recent data in order to get higher predictive accuracy. The remainder of this paper is organized as follows. Survey of literature is covered in section 2. Section 3 discusses considered models for the study. Section 4 deals with sample and development of new bankruptcy prediction models for Indian manufacturing companies. Re-estimations of models, results and discussion and evaluation of the model is done in section 5. The study concludes with section 6 which discusses the implications of those findings for users of the models.

Survey of literature

The formal studies on credit risk started in the 1930's (Altman, 1968). The early studies were univariate in nature, and single financial ratios were used to assess the financial position of the borrower. These studies set the platform for the further development of credit risk models. Some of the important univariate studies are Fitzpatrick (1932), Smith and Winaker (1935), Merwin (1942), Chudson (1945), Jackendoff (1962) and Beaver (1966). After seven decades of credit risk measurement, there is extensive development in the credit risk literature. The credit risk models can be classified into the following categories (Fejer-Kiraly, 2015):

1. Parametric Models (Accounting and market-based models) and
2. Non-parametric Models (Artificial Neural Networks (ANN), Hazard models, Fuzzy Models, Genetic Algorithms (GA) and Hybrid models, or models in which several of the former models are combined)

Parametric models

The parametric models could be univariate and multivariate in nature which uses mainly financial ratios and focuses on the symptoms of bankruptcy (Andan & Dar, 2006). Sometimes these models uses non-financial information (Ohlson, 1980; Bandyopadhyay, 2006). Balcaen and Ooghe (2004) and Bellovary et al. (2007) are the most cited paper in literature of bankruptcy prediction. Both the papers focused on the problems of parametric models. These problems are related to assumptions on the dichotomous variable, the sampling method, stationarity assumptions, data instability, selection of independent variables, use of accounting information and the time dimension (Balcaen & Ooghe, 2004). Further, parametric models can be classified into two categories: accounting based and market-based models. Market-based models are again divided into two parts structural and reduced form models.

Accounting based models

Beaver (1966) with his univariate default prediction study on US firms revolutionize the practice of credit risk assessment. The study compares the mean values of 30 financial ratios of 79 failed and 79 non-failed firms in 38 industries. Further, the study tests the ability of individual financial ratios to classify between bankrupt and non-bankrupt firms. Four financial ratios were found to have highest classification power, namely, net income to total debt (92 %), net income to net worth (91 %), cash flow to total debt (90 %), and cash flow to total assets (90 %). For future research, the study suggested multiple ratios considered simultaneously may have higher predictive ability than single ratios which created a platform for multiple ratio models.

Altman (1968) developed a first multivariate discriminant model for default prediction for US companies. The model uses five financial ratios to predict bankruptcy of the firms. The model can predict bankruptcy with 95 % of accuracy for the initial sample one year prior to bankruptcy. Altman et al. (1977) developed a model for US manufacturing and retailers, which had the effective classifying ability from 5 years prior to default. Since Altman (1968), discriminant analysis is used by many researchers by making changes in financial ratios, study sample, and change in business culture. Some of the notable studies are Deakin (1972), Blum (1974), Springate (1978) and Fulmer (1984).

The limitations of discriminant analysis created space for the development of logit model. Ohlson (1980) introduced a logit model in the literature of bankruptcy prediction. The assumptions of logit model were different from Z-score models. Ohlson identified nine independent variables (financial and non-financial) based upon their frequent use in the bankruptcy prediction literature. The model was developed with the sample of 2163 companies (105 defaulted and 2058 non-defaulted) for the period 1970-1976. In line with Ohlson, Abdullah et al. (2008), applied the logistic model to foretell corporate failure of Malaysian firms. Further, Zmijewski (1984) applied probit technique using data of 40 bankrupt and 8000 non-bankrupt US firms for the period 1970-1978.

After logit and probit models, the number of studies attempted making comparison between logit, probit, and MDA analysis. In case of Thailand, Pongsatat et al. (2004) examines predictive capabilities of Ohlson's and Altman's models. The study concludes Altman model outperforms Ohlson model on the basis of predictive accuracy. Likewise, Ugurlu and Aksoy (2006) developed bankruptcy prediction model for Turkish firms using Altman's (1968) and Ohlson's (1980) statistical techniques. Further, Gu (2002) develops MDA model for estimating the failure of USA restaurant firms. In the Indian market, Bandyopadhyay (2006) develops a bankruptcy prediction model for the Indian corporate bond sector using MDA and logistic technique. Bhumia and Sarkar, (2011) developed a corporate failure model for the Indian pharmaceutical company based upon MDA technique. Ramkrishnan (2005) used discriminant and logistic model to foretell bankruptcy for Indian companies.

Market-based models

The market-based models are classified into structural (Merton 1974; Agarwal and Taffler 2008; Wu, Gaunt and Gray 2010; Hillegeist et al. (2004) and Bharath and Shumway 2008) and reduced (Jarrow and Turnbull 1995; Duffie and Singleton 1999 and Lando 1994) form models.

Black and Scholes (1973) option pricing theory which was extended by Metron (1974) is applied to model default in structural based models. In these models firms can default on its debt obligation only at the time of maturity. Later, some models were developed by extension to allow a default to occur before the date of maturity. These models were familiarized by Black and Cox (1976), Lonfstaff and Schwartz (1995), Leland and Toft (1996). On the other hand, reduced form models focus over modeling default explicitly as an intensity or compensator process. Some of the notable market-based studies in the Indian market based upon Board of Industrial and Financial Reconstruction (BIFR) reference are Varma and Raghunathan (2000), Kulkarni et al. (2005).

Non-parametric models

The non-parametric models are heavily dependent on computer technology and mainly multivariate in nature (Andan & Dar, 2006). Some of the well-known non-parametric models are artificial neural networks (ANN), hazard models, fuzzy models, genetic algorithms (GA) and hybrid models, or models in which several of the former models are combined.

The ANN models can learn and adapt, from a data set, and they have the ability to capture non-linear relationships between variables which are also advantages of these models. The main shortcomings of the model are that they fail to explain causal relationships among their variables which restricts their application to practical management problems

(Lee & Choi, 2013). Kirkos (2015) in a survey paper on credit risk, which focuses mainly on artificial intelligence models published between 2009 and 2011. The information technology revolution in the 1990's helped artificial intelligence and managerial systems to grow and develop. This led to the development of a new set of bankruptcy prediction models known as neural networks. The study of Messier and Hansen (1988) is linked to the use of neural networks in bankruptcy prediction. This is followed by number of studies (Bellovary et al. 2007) such as Raghupathi et al. (1991), Coats and Fant (1993), Guan (1993), Tsukuda and Baba (1994), and Altman, Marco, and Varetto (1994).

Apart from neural network, there are other non-parametric models, namely, hybrid model. The hybrid models are use of two models either parametric or non-parametric (Lee et al. 1996). Genetic algorithm is also one of the prominent other non-parametric models which work as a stochastic search technique to find out a company goes bankrupt or not (Varetto, 1998). Other widely used non-parametric models are: genetic programming (Etemadi et al., 2009), models based on "rough test" theory (Dimitrias et al. 1999), Bayesian, Fuzzy, Hazard and Data Envelopment Analysis (DEA).

After 2005, the artificial intelligence-based models became more famous and widely used. Premachandra et al. (2009) compares LR and DEA models and concluded DEA models have a better predictive accuracy to predict bankrupt firms (between 84 % and 89 %), but the LR is more accurate in predicting healthy firms (between 69.3 % and 99.47 %). Verikas et al. (2010) conducted a study which reviews hybrid models and ensemble-based soft computing techniques applied in default prediction. Fuzzy logic approach is used by Korol and Korodi (2011). The model is based upon the financial data of 132 companies (107 non-bankrupt and 25 bankrupt). Gupta et al. (2014) conducted study which uses discrete-time hazard model on the data base of 385,733 non-bankrupt and 8,162 bankrupt SMEs. The study develops three hazard models for micro-, small-, and medium-sized firms. The study further suggests the financial reports do not provide sufficient information about the default of the micro-firms.

Shetty et al. (2012) develops early warning system for Indian IT/ITES using Data Envelopment Analysis (DEA). Kumar and Rao (2015) develops non-linear new Z-score model based upon Person Type-3 distribution for Indian companies.

Methods

Considered models

Over the past four decades, various credit risk models were developed based upon alternative approaches to model bankruptcy. Use of accounting ratios is always dominated the literature of bankruptcy prediction because of its simplicity and larger applicability to the firms. The current study examines three well-known accounting based bankruptcy prediction models. They are:

(i) Altman (1968) Z-score model based upon Multiple Discriminant Analysis (MDA)
(ii) Ohlson (1980) Y-score model based upon Logit Analysis
(iii) Zmijewski (1984) X-score model based upon Probit Analysis

Altman (1968) developed a bankruptcy prediction model which uses financial ratios that measures liquidity, profitability, leverage and solvency of the firm. The model uses

MDA framework to model bankruptcy on 33 defaulted and 33 non-defaulted US manufacturing firms for the period 1946-1965. Equation (1) represents the original model estimated by Altman (1968):

$$Z = 1.2WCTA + 1.4RETA + 3.3EBITA + 0.6MVEBVD + .99SLTA \tag{1}$$

Where Z is the overall index used to determine the membership of firms in defaulted or non-defaulted groups. The firm with $Z \geq 2.675$ is classified as non-bankrupt, whereas firm with $Z < 2.675$ is classified as bankrupt firms. WCTA to SLTA are accounting variables used in the model whose description is given in Table 1.

Ohlson (1980) employed a logit technique with less restrictive assumptions than those taken in the MDA approach to model bankruptcy. The model uses nine predictive variables which measures firms' size, leverage, liquidity, and performance. The estimated model consist 105 bankrupt and 2,058 non-bankrupt industrial firms for the period 1970–1976. The original model is shown in equation (2):

$$\begin{aligned} Y = & -1.3 - 0.4SIZE + 6.0TLTA - 1.4WCTA + 0.1CLCA - 2.4OENEG - 1.8NITA \\ & + 0.3FUTL - 1.7INTWO - 0.5CHIN \end{aligned} \tag{2}$$

Where, Y is the overall index based upon logistic function which determine the probability of firms' membership in default or non-default group. Based upon total error minimization[1] criterion for the given data firm with $Y > 0.5$ is classified defaulted firm otherwise non-defaulted (Ohlson 1980, page 120). The description of variables is provided in Table 1.

Zmijewski (1984) adopts a probit method to model bankruptcy which uses financial ratios measuring firm's performance, leverage, and liquidity. The ratios were selected on the basis of their performance in the previous studies. The model uses 40 bankrupt and 800 non-bankrupt industrial firms' data for the period 1972–1978. Equation (3) represents the original model estimated by Zmijewski (1984):

$$\mathrm{X} = -4.3 - 4.5\mathrm{NITL} + 5.7\mathrm{TLTA} - .004\mathrm{CACL} \tag{3}$$

Where, X is the overall index based upon probit function which determines the probability of firms' membership in bankrupt and non-bankrupt group. Again based upon total error minimization criterion firm with $X > 0.5$ is classified bankrupt firm otherwise non-defaulted (Zmijewski 1984, page 72). NITL, TLTA, and CACL are the variables used in the model which details are provided in Table 1.

The new bankruptcy prediction model for indian manufacturing companies

This section covers the development of new bankruptcy prediction model for Indian manufacturing companies. The new bankruptcy prediction model is developed on sample of 208 equal numbers of defaulted and non-defaulted Indian manufacturing firms for the period 2006-2014. Out of 208 companies 130 used for estimation sample and 78 holdout for model validation.

Sample

The analysis reported here used estimation and a hold-out sample, with each sample including distressed and non-distressed firms. The Board of Industrial and Financial Reconstruction (BIFR) reference is used to identify distressed firms from the list of

Table 1 Summary of Empirical Models Employed and Variables Employed

Models	Formula	Variables	Descriptions
Altman (1968) Multiple Discriminant Analysis	$Z = \beta^{l}X$ Where Z is the MDA score and X represent the variables listed. Cutoff value: $Z \geq 2.675$, classified as non-bankrupt $Z < 2.675$, classified as bankrupt	WCTA RETA EBITA MVEBVD SLTA	= Net Working Capital/Total Assets = Retained earnings/Total Assets = Earnings before interest and taxes/Total assets = Market value of equity/Book value of total liabilities = Sales/Total Assets
Ohlson (1980) Logit Model	$P = (1 + exp\ \{-\beta^{l}X\})^{-1}$ Where P is the probability of bankruptcy and X represents the variables listed. The logit function maps the value of $\beta^{l}X$ to a probability bounded between 0 and 1. Cutoff value: $Y > 0.5$, classified as defaulted otherwise non-defaulted.	SIZE TLTA WCTA CLCA OENEG NITA FUTL INTWO CHIN	= Log (Total assets/GNP price-level index). Index with a base 100 for 1968. = Total liabilities/Total Assets = Working capital/Total Assets = Current Liabilities/Current Assets = 1 If total liabilities exceed total assets, 0 otherwise. = Net income/Total assets = Funds provided by operations (income from operation after depreciation) divided by total liabilities. = 1 If net income was negative for the last 2 years, 0 otherwise. = $(NI_t - NI_{t-1})/(\lvert NI_t \rvert + \lvert NI_{t-1} \rvert)$ where, NI_t is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure the relative change in net income.
Zmijewski (1984) Probit model	$P = \phi\ (\beta^{l}X)$ Where, P is the probability of bankruptcy and X represents the variables listed, and ϕ (.) represents the cumulative normal distribution function. The probit function maps the value β^{l}X to a probability bounded between 0 and 1. Cutoff value: $X > 0.5$, classified as bankrupt, otherwise non-bankrupt.	NITL TLTA CACL	= Net income divided by total liabilities. = Total liabilities divided by total assets. = Current assets divided by current liabilities.

Note: The cutoff value of Ohlson (1980) and Zmijewski (1984) models are decided using total error minimisation criterion (Ohlson 1980 page 120; Zmijewski 1984 page 72)
Source: Author's compilation

firm's registered sick during 2006 to 2014. A set of matched non-distressed companies are identified randomly on the basis of asset size and industry type. A total of 130 companies comprising distressed and non-distressed companies are used for estimation sample. A sample of 78 companies' holdout for model validation. Financial information of the companies is collected from their balance sheet and income statements. The Balance sheet and income statements of the companies at the end of each year are collected from their respective websites. The estimated and holdout sample have been classified into 14 industry category matching with their economic activity with the National Industrial Classification Code (NIC) 3 digit classification of 2008 (See Table 2).

Selection of financial ratios

There is extensive literature on the use of financial ratios to predict bankruptcy of the firms. Since Beaver (1966), various financial ratios were tried to foretell bankruptcy, and they can be broadly classified into four categories, which measures firm's leverage, liquidity, profitability and turnover. Bellovary et al. (2007), in a survey paper on bankruptcy prediction list 42 financial ratios which is used in more than five financial studies on bankruptcy prediction.

In the Indian market, Bandyopadhyay (2006) develops bankruptcy prediction model based upon MDA and logistic technique for Indian corporate bond sector. The ratios used in his study measures liquidity, leverage, productivity, turnover and other financial variables which measures age, group ownership, ISO Quality Certification and inter-industry effects of the firms. Bhumia and Sarkar (2011) in other study on Indian pharmaceutical industry developed model for corporate failure using MDA technique. The study chooses 16 financial ratios based upon past empirical literature measuring

Table 2 Distribution of Firms as per NIC Classification 2008

NIC Code	Sector	Estimation Sample	Holdout Sample	Total
107	Manufacturer of other food products	14	6	20
131	Spinning, weaving and finishing of textiles	34	16	50
170	Manufacturer of paper and paper products	4	10	14
201	Manufacturer of basic chemicals, fertilizer and nitrogen compounds, plastics, synthetic rubber in primary form	18	6	24
210	Manufacturer of pharmaceuticals, medicinal chemical and botanical products	6	2	8
221	Manufacturer of rubber products	4	4	8
231	Manufacturer of glass and glass products	4	2	6
239	Manufacturer of non-metallic mineral products n.e.c.	2		2
243	Casting of metals	16	6	22
261	Manufacturer of electronic components	6	16	22
271	Manufacturer of electric motors, generators, transformers and electricity distribution and control apparatus	4		4
291	Manufacturer of motor vehicles	8	6	14
310	Manufacturer of furniture	4		4
492	Other land transport	6	4	10
	Total	130	78	208

Source: Author's compilation

profitability, solvency, liquidity and efficiency of the firms. Shetty et al. (2012) develops early warning system for Indian IT/ITES using Data Envelopment Analysis (DEA). Based upon the past empirical studies ten financial ratios measuring firm's liquidity, leverage, productivity, and turnover. Kumar and Rao (2015) develops non-linear new Z-score model based upon Person Type-3 distribution for Indian companies. In addition to Altman (1968) variables, the study uses two other non-financial variables measuring industry effects and rating of the companies. Based upon the past empirical literature and our own analytical judgment, we have chosen 25 financial ratios measuring firm's leverage, liquidity, profitability, and turnover. In most of studies on global or Indian market, they found leverage, liquidity, profitability and turnover are the major financial ratio which predicts corporate failure.

Out of four major financial ratio leverage is considered to be one of the important ratios to assess financial position of the firms. According to Argenti (1976) in his study, he founds high indebtedness of the firms is one of the major reason leading a firm to bankruptcy. Similarly, Jensen (1989) argues leverage is an invitation to bankruptcy, and high debt ratios are not good for firms. In the Indian market Bandyopadhyay (2006), Bhumia and Sarkar (2011), Shetty et al. (2012) and Kumar and Rao (2015) acknowledges the importance of leverage ratio and uses different leverage indicators to assess bankruptcy. Except Bhumia and Sarkar (2011) all other studies (Bandyopadhyay (2006), Shetty et al. (2012) and Kumar and Rao (2015)) on Indian market have taken market value of equity to book value of total debt as ratio measuring leverage of the firms. In lieu of past empirical literature and importance of the indicators including market value of equity to book value of total debt, 11 leverage ratios are chosen out of 25 financial ratios.

Liquidity is also considered to be one of the important ratio to assess credit worthiness of firms. Beaver (1966) in his study found the firms with lower liquid assets are more prone to bankruptcy. In line with Beaver (1966), Altman, Haldeman and Narayana (1977), Charalambrus, Charitiu and Kaourou (2000) and Platt and Platt (2002) also gets the similar findings. In the Indian market Bandyopadhyay (2006), Bhumia and Sarkar (2011), Shetty et al. (2012) and Kumar and Rao (2015) all have used liquidity indicator including working capital to total assets as a common liquidity indicator used in all the four empirical studies. In the current study including working capital to total assets, four liquidity indicators are used out of 25 financial ratios.

Profitability ratios measures the performance of the firms. The ratio explains how efficient and effective utilization of its assets and management of its expenditure to produce adequate earnings for its shareholders. According to Gu (2002), unprofitable firms are more likely to default. Izan (1984), Maricca and Georgeta (2012) also got similar findings in their respective studies. In the Indian context Bandyopadhyay (2006) uses operating profits to total assets as the proxy for profitability indicator. Kumar and Rao (2015) and Bhumia and Sarkar (2011) uses retained earnings to total assets as a proxy for profitability indicator. In the current study out of 25 financial ratio, 7 profitability ratios are chosen.

Turnover ratio measures efficiency of firms in utilizing their assets. Eljilly (2001) argues high efficiency leads to company profitable and less chance of bankruptcy and vice-versa. It measures the ability of companies to generate sales by the capital invested. Molinero and Ezzamel (1991) and Laitnen (1992) also founds the similar results. In the

Indian market, Bandyopadhyay (2006) and Kumar and Rao (2015) have chosen Sales to Total Assets as proxy for turnover ratio. In the present study including Sales to Total Assets, 2 other turnover ratios are taken out of 25 ratios. The profile of variables used in the study is reported in Table 3. To check industry specific effects, the sample firms have been divided into 14 industry dummies based upon major economic activity as per NIC classification (Table 5).

Following steps are followed to select final profile of the ratios:

Step-I: Analysis of Variables: We have chosen 25 financial ratios on the basis of past empirical literatures on Indian market. Analyses on these ratios are carried out in two broad steps. First, mean and standard deviation of bankrupt and non-bankrupt firms are analysed. Second, *T*-test for equality in means of bankrupt and non-bankrupt groups are analysed.

Table 3 Profile of Financial Ratios

Sl No.	Financial Ratio	Calculations
	Leverage Ratios	
1	TDTA	Total Debt/Total Assets
2	BVEBVD	Book Value of Equity/Book Value of Total Debt
3	CFOTA	Cash Flow from Operations/Total Assets
4	CLTA	Current Liabilities/Total Assets
5	CFTD	Cash Flow from Operations/Total Debt
6	LTDTA	Long-term Debt/Total Assets
7	NWTA	Net Worth/Total Assets
8	TDNW	Total Debt/Net Worth
9	TLNW	Total Liabilities/Net Worth
10	TLTA	Total Liabilities/Total Assets
11	FUTL	Fund Provided by Operations to Total Liabilities
	Liquidity	
12	CACL	Current Assets/Current Liabilities
13	WCTA	Working Capital/Total Assets
14	CATA	Current Assets/Total Assets
15	CLCA	Current Liabilities/Current Assets
	Profitability	
16	NITA	Net Income/Total Assets
17	RETA	Retained Earnings/Total Assets
18	EBITA	Earnings Before Interest and Taxes/Total Assets
19	NINW	Net Income/Net Worth
20	CASL	Current Assets/Sales
12	NISL	Net Income/Sales
22	NITL	Net Income/Total Liabilities
	Turnover	
23	SLTA	Sales/Total Assets
24	WCSL	Working Capital/Sales
25	WCNW	Working Capital/Net Worth

Source: Author's compilation

Step-II: Step-wise regression: Forward logistic selection and backward elimination methods are applied and different combinations of the ratios which are significantly different in mean by *T*-test are tested and the final set of ratio are selected on the basis of the statistical significance of the estimated parameters, the sign of each variable's coefficient and the model's classification results.
Step-III: Inclusion of industry dummy: In the next step along with four financial ratios 14 industrial dummies were included in the model but none of them are found to be significant. This is also tested trough through stepwise regression model. However, the results are unchanged.
Step-IV: Final profile of the ratios: Finally, all the financial ratios which are found to be statistically significant chosen for the model.

Analysis of variables

This sections covers analysis of mean and standard deviation of defaulted and non-defaulted firms. *T*-test for equality in mean is employed to check weather defaulted, and non-defaulted groups have significantly different in their respective means. It is well-known from past empirical studies that the bankrupt companies have higher indebtedness, lower liquidity, poor profitability and turnover ratios. Also from Table 4, out of three turnover ratios, WCSL mean is not found to be statistically different. For defaulted groups it is found to be negative (WCSL and WCNW) and lower (SLTA) than the defaulted groups. In case of profitability indicators, out of 7 financial ratios all means are found to be significant expect CASL and NISL. For most of the profitability indicators, the ratio is found to be negative (NITA, RETA, EBITA, and NITL) for defaulted groups except NINW. For liquidity indicators out of 4, 2 turned to be statistically different means (WCTA, CLCA) and others are insignificant (CACL, CATA). In case of leverage indicators, all indicators are statistically different in mean except CLTA. For defaulted groups the ratios are found to be negative for all indicators except TDTA and TLTA. From the analysis on variables, in general, most of ratios are grouped under liquidity, profitability and turnover ratios have shown negative signs and declining for bankrupt companies.

T-test for equality in means for defaulted and non-defaulted groups shows out of 25 financial ratios chosen for the model, 19 ratios have statistically different in mean between defaulted and non-defaulted groups.

Step-wise regression

In a step-wise regression, logistic forward selection and backward elimination methods were applied and different combinations of the ratios (19 ratios) which had significantly different in their respective means are tested. The selections of the final set of the variables are based upon statistical significance and sign of the each of the variable coefficients. The model classification power also took into consideration. The similar method is also used by Neophytou et al. (2001) conducting study for Netherland firms. The final set of ratios and their statistical significance is reported in third column (Model 2) of Table 7. From Table 7 all the set of financial ratios are significant at 1 % to 10 % level of significance, and LR ratio shows the overall significance of the model.

Table 4 Descriptive Statistics of the Financial Ratios

Sample	Statistic	NITA	CACL	WCTA	RETA	EBITA	SLTA	TDTA	CATA	NINW
Distressed	Mean	−0.290	2.519	0.215	−0.295	−0.100	0.984	1.151	0.714	2.257
	SD	0.321	3.951	0.538	0.322	0.26	1.041	0.651	0.833	3.946
Non-Distressed	Mean	0.044	3.496	0.553	0.034	0.152	2.013	0.723	0.961	0.054
	SD	0.094	6.428	0.788	0.08	0.14	2.966	0.627	1.058	0.185
	P-Value	0.000	0.299	0.005	0.000	0.000	0.009	0.000	0.142	0.000
Sample	Statistic	MVEBVD	CFOTA	CLTA	CFTD	CASL	NISL	LTDTA	NWTA	TDNW
Distressed	Mean	−0.157	−0.159	0.499	−0.205	39.016	−23.170	1.151	−0.287	−14.589
	SD	0.200	0.262	0.571	0.409	250.959	114.765	0.651	0.485	40.268
Non-Distressed	Mean	0.481	0.104	0.407	0.132	0.861	0.012	0.723	0.48	1.858
	SD	0.300	0.128	0.436	0.999	1.830	0.447	0.627	0.420	1.835
	P-Value	0.000	0.000	0.307	0.013	0.223	0.106	0.000	0.000	0.001
Sample	Statistic	TLNW	WCSL	WCNW	TLTA	CLCA	FUTL	NITL		
Distressed	Mean	−23.578	−41.127	−5.685	1.681	0.821	−0.091	−0.191		
	SD	76.339	342.421	29.01	0.982	0.693	0.116	0.230		
Non-Distressed	Mean	2.859	0.305	1.094	1.150	0.560	0.129	0.360		
	SD	2.451	1.060	0.932	0.873	0.427	0.371	2.586		
	P-Value	0.006	0.331	0.062	0.001	0.011	0.000	0.089		

Source: Author's estimation

Table 5 Industry Dummies for Sample Companies

Industry Dummy	Industry Type	No of Firms
D1	Manufacturer of other food products	14
D2	Spinning, weaving and finishing of textiles	34
D3	Manufacturer of paper and paper products	4
D4	Manufacturer of basic chemicals, fertilizer and nitrogen compounds, plastics, synthetic rubber in primary form	18
D5	Manufacturer of pharmaceuticals, medicinal chemical, and botanical products	6
D6	Manufacturer of rubber products	4
D7	Manufacturer of glass and glass products	4
D8	Manufacturer of non-metallic mineral products n.e.c.	2
D9	Casting of metals	16
D10	Manufacturer of electronic components	6
D11	Manufacturer of electric motors, generators, transformers and electricity distribution and control apparatus	4
D12	Manufacturer of motor vehicles	8
D13	Manufacturer of furniture	4
D14	Other land transport	6
	Total	130

Source: Author's compilation

Inclusion of industry dummy

To capture the industry specific effects, our sample is characterized into 14 major industries based upon NIC 3 digit industrial classification code (Table 5). In the Indian case, similar kind of approach was adopted by Bandyopadhyay (2006), and Kumar and Rao (2015). Again along with four financial ratios 14 industrial dummies are included in the model, but none of them are found to be significant. Even different combination of specific industry dummies is tried but none of the turned to be significant. Finally, we have decided to drop dummies and go with only financial ratios (Table 7, Model 2).

Final profile of the ratios

The final profile of the financial ratios used in the model are:

BVEBVD (Book Value of Equity/Book value of Total Liabilities): This indicator measures leverage of the firms. The similar ratio is also used in the study of Altman (1968) on US manufacturing companies. In the current study market value of equity is replaced by book value of equity. The current study uses data of both publicly and privately held firms. In order to calculate market value of equity, stock price data (Altman, 1993) is required. The same principle is employed while re-estimating Altman's model. The ratio is found to be most effective predictor of bankruptcy than a similar, more commonly used ratio: net worth/total book value of debt. The indicator explains how much the firm's asset can decline in value before the liabilities exceed the assets, and the firm becomes bankrupt. In the Indian case of India, Bandyopadhyay (2006), Shetty et al. (2012) and Kumar and Rao (2015) uses this indicator to predict bankruptcy.
SLTA (Sales/Total Assets): It is one of the widely used turnover ratio of firms. It measures efficiency and effectiveness of the firm's assets to generate profit. This is a

key variable for the measurement of the size of the firm. The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capability in dealing with competitive conditions. It is used in the study of Altman (1968) and Bandyopadhyay (2006) and Kumar and Rao (2015), used in the Indian market.

NITA (Net Income/Total Assets): It is the ratio of net income to total assets which is a measure of performance of the firms. It measures profitability and also used in the study of Ohlson (1980) on US manufacturing companies.

NITL (Net Income/Total Liabilities): It is the ratio of net income to total liabilities. The ratio measures return on asset which is the measure of firm's performance and profitability. The ratio is also used in the study of Zmijewski (1984).

Broadly all the ratios used in the current study are from the studies of Altman (1968), Ohlson (1980) and Zmijewski (1984). The first two ratio's BVEBVD and SLTA measuring leverage and turnover of the firms are also used in the Study of Altman (1968). Third ratio NITA measures profitability of the firms is used in the study of Ohlson (1980), and fourth NITL measures profitability of firm is also applied in the study of Zmijewski (1984). The new bankruptcy prediction model uses ratios measuring leverage, profitability, and turnover of the firms. The model is also considered to be comprehensive model because it uses variables from all three major accounting based bankruptcy prediction model mentioned above. By 'Common Sense' and past studies all the variables are expected to have negative sign (Ohlson 1980, page 119).

Table 6 reports descriptive statistics of the variable used in the new model. The mean BVEBVD for non-defaulted group for both estimation (0.481) and holdout (3.359) sample respectively are found to be positive for non-defaulted and negative for defaulted groups. SLTA measures the firms' market size. For non-defaulted groups, the size is larger on both estimation (2.013) and holdout (2.522) whereas for defaulted groups its value is smaller on both estimation (0.984) and (1.521) holdout samples respectively. NITA is a ratio which measures firms' performance. The ratio deteriorates and found to be negative for bankrupt companies on estimation (-0.289) and holdout (-0.843) sample, whereas it is positive for non-bankrupt firms. NITL measures return on asset which is a measure of firm performance. For defaulted groups it is negative on both

Table 6 Descriptive Statistics of the Final Profile of the Financial Ratios

Sample	Statistic	BVEBVD	SLTA	NITA	NITL
Estimation					
Distressed (N = 65)	Mean	−0.157	0.984	−0.289	−0.191
	SD	0.200	1.040	0.321	0.230
Non-Distressed (N = 65)	Mean	0.481	2.013	0.044	0.360
	SD	0.299	2.965	0.094	2.586
Holdout					
Distressed (N = 39)	Mean	−0.157	1.521	−0.843	−0.192
	SD	0.264	1.919	1.863	0.602
Non-Distressed (N = 39)	Mean	3.359	2.522	0.110	0.094
	SD	7.173	3.111	0.169	0.160

Source: Author's estimation

estimation (-0.191) and holdout (-0.192) sample, whereas the ratio is found to be positive for non-bankrupt firm on both estimation (0.360) and holdout (0.094) sample respectively.

Logit model: estimation procedure

The logistic regression method is used to investigate the relationship between binary response variable (1 for bankrupt and 0 for non-bankrupt groups) and financial ratios (explanatory variables). The Maximum Likelihood Estimation (MLE) procedure is applied to estimate parameters. The objective of the logit regression is to evaluate the role of accounting variables in predicting bankruptcy for Indian manufacturing firms and also to arrive at an estimate of probability of default for a firm using them.

Logit model

If a dependent variable is binary and is a function of set of independent variables, the Linear Probability Model (LPM) can be written as:

$$P_i = E(Y = 1|X_i) = \beta_1 + \beta_2 X_i$$

Where, Pi represents probability, X_i represents various financial ratios of the firms and Y is the dependent variable. Y = 1 means the firm is failed. β_1 and β_2 are slope coefficients.

The intrinsic defects of LPM given birth to Logit and Probit models. In LPM (1) the probability of Y can exceeds the limit of 0 and 1. Hence, the useful way to solve the problem is to transform X_i'*s* and *β's* into a probability with function F that translates Xβ into number between 0 and 1.

$$prob(y_i = 1) = F(X_i\beta)$$

Where F is cumulative density function.

Choosing F to be the logistic distribution yields one of the ways to limit *prob* ($y_i = 1$) between 0 and 1. This is called the logit model.

$$prob(y_i = 1) = \Lambda(X_i\beta) = \frac{expX_i\beta}{1 + \exp X_i\beta}$$

In the context of default prediction study, the logit model is used to classify whether a company is defaulted or non-defaulted by using accounting-based financial ratios.

Estimation results

In the logit regression, dependent variables is defined as a binary variable taking value 1 for defaulted and 0 for non-defaulted groups. The balanced sample for 130 campiness consisting equal number of defaulted and non-defaulted groups for the period 2006 to 2014 has been used to run logit model. In a stepwise logistic regression applying forward and backward elimination method is used, and finally, we obtained two models (Table 7). In Model 1 along with significant financial ratios all the dummies are incorporated to check industry effects but all financial ratios and dummies turned to be insignificant. Model 2 is taken as final model which uses only financial variable. In case of model 2 all variables are significant and preserves expected sign. From Table 7, in case of Model 2 BVEBVD is negatively significant at 1 % level on default probability. NITA and NITL are negatively significant (5 % level) with default probabilities. In case of SLTA, it is also negatively significant at 10 % level of significance.

Table 7 Results of Logit Model 1 and 2

	Model 1	Model 2
Variables	Coefficients	Coefficients
MVEBVD	−39.907	−13.8597[a]
SLTA	−4.488	−1.11303[c]
NITA	−72.776	−18.760[b]
NITL	−107.685	−34.354[b]
C	−7.012	−0.604
D1	13.256	
D2	6.277	
D3	−14.496	
D4	Dropped	
D5	−2.311	
D6	8.592	
D7	10.97	
D8	Dropped	
D9	3.865	
D10	15.956	
D11	Dropped	
D12	−1.563	
D13	Dropped	
D14	7.767	
LR Ratio	172.219	164.956
p-Value	0.000	0.000

Note: [a], [b] and [c]signifies the level of significance at 1 %, 5 %, and 10 % respectively and LR is log likelihood ratio
Source: Author's estimation

LR ratio tests the overall significance of the model. In case of final model (Model 2) the LR ratio is found to be 164.956 and statistically significant at 1 % level of significance. The Model 2 can be directly used to find PDs of firms to assess credit risk.

Model re-estimations

This section covers re-estimation of Altman, Ohlson and Zmijewski models using estimation sample of 130 Indian firms consisting equal numbers of defaulted and non-defaulted firms. The statistical methodologies are the same used in the original models and discussed in section 2. The stability of the coefficients of original models is tested by comparing it from re-estimated models. The original and re-estimated coefficients are reported in Table 11. The coefficients of original and re-estimated models are compared to test the stability of coefficients to the time periods and change in the financial conditions. The overall predictive accuracy of model is tested on estimation and holdout sample to test whether change in coefficients (re-estimated) with recent data set improves the predictive accuracy of the model. The newly proposed model is compared with original and re-estimated models. By overall predictive accuracy, ROC, long-range accuracy test and the method to model bankruptcy, it is summarised that the newly proposed model for Indian manufacturing sectors outperforms other competitive models.

Descriptive statistics

Tables 8, 9 and 10 reports the descriptive statistics of the variables used in estimation and holdout sample for Altman, Ohlson, and Zmijewski models respectively.

Table 8 shows the profile of variables used in Altman model on estimation and holdout sample. WCTA measures the liquidity of the firm; the mean WCTA for non-distressed group is higher than distressed group in both the sample. RETA measures the earned surplus of the firm. The average RETA for distressed group on both estimation (-0.295) and holdout sample (-0.843) is found to be negative whereas for non-distressed group it is positive on both estimation (0.034) and holdout sample (0.086) respectively.

EBITA measures the true productivity of the firm assets. For defaulted group the mean EBITA is negative for both estimation (-0.100) and holdout (-0.550) and positive for non-defaulted group. BVEBVD is measure of the leverage of the firm. The mean BVEBVD for non-defaulted group for both estimation (0.481) and holdout (3.359) sample is found to be positive for non-defaulted and negative for defaulted groups. SLTA measures the firms' market size. For non-defaulted groups, the size is larger on both estimation (2.013) and holdout (2.522) whereas for defaulted groups its value is smaller on both estimation (0.984) and (1.521) holdout sample respectively.

Table 9 reports the descriptive statistics of the variable used in Ohlson model. SIZE is defined as log of total assets to GNP price-level index. The year 2011-12 is taken 100 as a base value. The mean SIZE for defaulted (0.615) and non-defaulted (0.638) groups is positive and not significantly different on estimation sample. Similarly, mean SIZE for defaulted (-0.587) and non-defaulted (-0.501) is negative and not significantly different from estimation sample. TLTA measures the leverage of firm. For the distressed companies the ratio is higher on both estimation (1.681) and holdout (3.145) sample as compare to non-distressed companies which have lower ratio on both estimation (1.150) and holdout (1.113) sample respectively. The higher ratio for defaulted groups indicates higher leverage.

WCTA is a measure of the current liquidity of the firm. The ratio deteriorates for distressed firms on both estimation (0.215) and holdout (0.634) sample as compare to non-defaulted firms' ratio on estimation (0.553) and holdout sample (1.089) respectively. CLCA is also measure of firm current liquidity. As expected the ratio is higher

Table 8 Descriptive Statistics for Altman Model

Sample	Statistic	WCTA	RETA	EBITA	BVEBVD	SLTA
Estimation						
Distressed (N = 65)	Mean	0.215	−0.295	−0.100	−0.157	0.984
	SD	0.538	0.322	0.260	0.200	1.041
Non-Distressed (N = 65)	Mean	0.553	0.034	0.152	0.481	2.013
	SD	0.788	0.080	0.140	0.299	2.966
Holdout						
Distressed (N = 39)	Mean	0.634	−0.843	−0.550	−0.157	1.521
	SD	1.917	1.863	1.405	0.264	1.919
Non-Distressed (N = 39)	Mean	1.089	0.086	0.214	3.359	2.522
	SD	1.406	0.136	0.230	7.173	3.111

Source: Author's estimation

Table 9 Descriptive Statistics for Ohlson Model

Sample	Statistic	SIZE	TLTA	WCTA	CLCA	OENEG	NITA	FUTL	INTWO	CHIN
Estimation										
Distressed (N = 65)	Mean	0.615	1.681	0.215	0.821	0.938	−0.289	−0.091	0.615	−0.117
	SD	1.289	0.982	0.538	0.693	0.242	0.321	0.116	0.490	0.627
Non-Distressed (N = 65)	Mean	0.638	1.150	0.553	0.560	0.338	0.044	0.129	0.077	0.057
	SD	1.121	0.873	0.788	0.427	0.477	0.094	0.371	0.269	0.503
Holdout										
Distressed (N = 39)	Mean	−0.587	3.145	0.634	1.116	0.949	−0.843	−0.153	0.590	−0.236
	SD	1.219	3.282	1.917	1.197	0.223	1.863	0.209	0.498	0.682
Non-Distressed (N = 39)	Mean	−0.501	1.113	1.089	0.796	0.385	0.110	0.183	0.128	0.048
	SD	1.343	1.200	1.406	2.685	0.493	0.169	0.516	0.339	0.476

Source: Author's estimation

for defaulted firms on both estimation (0.821) and holdout (1.116) sample as compare to non-defaulted firm which have lower ratio on both estimation (0.560) and holdout (0.796) sample respectively. The defaulted firms always expected to have higher ratio because their current liabilities will be always higher than current assets. OENEG is a dummy used for discontinuity correction for TLTA. It takes value 1 if total liabilities exceed total assets, 0 otherwise. NITA is a ratio which measures firms' performance. The ratio deteriorates and found to be negative for bankrupt companies on estimation (-0.289) and holdout (-0.843) sample, whereas it is positive for non-bankrupt firms. FUTL measures the performance of firms'. The result is similar to NITA. The ratio deteriorates and found to be negative for bankrupt companies on estimation (-0.091) and holdout (-0.153) sample where as it is positive for non- bankrupt firms. INTWO is a dummy which takes value 1, if net income was negative for the last two years, 0 otherwise. CHIN measures the change in the net income of the firm. The CHIN is negative for defaulted groups on both estimation (-0.117) and holdout (-0.236) sample, whereas it is found to be positive for non-defaulted groups on both estimation (0.057) and holdout (0.048) sample respectively.

Table 10 reports descriptive statistics of the variable used in Zmijewski model. NITL in the Table 10 measures return on asset which is measure of firm performance. For

Table 10 Descriptive Statistics for Zmijewski Model

Sample	Statistic	NITL	TLTA	CACL
Estimation				
Distressed (N = 65)	Mean	−0.191	1.649	2.519
	SD	0.230	0.958	3.980
Non-Distressed (N = 65)	Mean	0.360	1.131	3.496
	SD	2.586	0.861	6.428
Holdout				
Distressed (N = 390	Mean	−0.192	3.054	2.603
	SD	0.602	3.173	2.925
Non-Distressed (N = 39)	Mean	0.094	1.043	4.693
	SD	0.160	1.205	6.526

Source: Author's estimation

defaulted groups it is negative on both estimation (-0.191) and holdout (-0.192) sample, whereas the ratio is found to be positive for non-bankrupt firm on both estimation (0.360) and holdout (0.094) sample respectively. TLTA is the debt ratio which measures the leverage of the firms. The distressed firms have higher leverage on both estimation (1.649) and holdout sample (3.054) respectively. CACL measures the liquidity of the firms. The non-distressed firm have higher liquidity ratio on both (3.496) and holdout (4.693) sample as compared to distressed groups.

The profile analysis of the samples used in all the three models shows there is significant difference in the mean ratios of the defaulted and non-defaulted groups. The ratios deteriorates for bankrupt groups as compared to non-bankrupt groups.

Results and Discussion

This section analyzed the findings of the original, re-estimated and newly proposed models on estimation and holdout samples. The stability of their coefficients and their predictive accuracies are also tested. This section also evaluates out of three models which outperforms in the Indian setting.

Unstable coefficients

Table 11 reports the coefficients of original and re-estimated models. If the models are stable, then their re-estimated coefficient should be also similar. The coefficients of original and re-estimated Altman model are reported in the Table 11.

The result shows there is significant difference in the coefficients of original and re-estimated model except RETA. In case of RETA the original (1.4) and re-estimated (1.464) coefficients is found to be very close. For WCTA original coefficient was 1.2, and it ranks third with respect to relative importance of the variable to contribute in the overall index. In the re-estimated model the coefficient (0.076) significantly changes but still its ranks third in term of its relative importance in the overall index. In the original model EBITA, coefficient was 3.3, and it ranks first to contribute in the overall index, whereas re-estimated coefficient (-.063) becomes negative and ranks fifth. In case of BVEBVD, the original coefficient was 0.6 and re-estimated coefficient is 3.474 which is significantly different. For SLTA, the original coefficient was 0.99 and re-estimated coefficient is 0.028. The * indicates the statistical significance of F-statistic in the difference of mean. For both the Altman original and re-estimated models, the F-statistics is significant, meaning that both the groups defaulted and non-defaulted have significantly different means. The finding suggests the coefficients of Altman (1968) model are not stable, and they are sensitive to time periods.

The results of Ohlson original and re-estimated models are also reported in Table 11. In the original model, all the variables were significant except CLCA, INTWO and constant whereas in the re-estimated model all the variables are significant except SIZE, TLTA, FUTL and INTWO. The coefficients which are significant in both the original and re-estimated models are WCTA, OENEG, NITA, and CHIN. In case of WCTA, the original coefficient was -1.43 and re-estimated coefficient is -5.216 which is significantly different. For OENEG the original coefficient was -1.72 and re-estimated coefficient is 2.836 which is different in value as well as in sign. There is huge difference in the value of NITA coefficient for original (-2.37) and re-estimated (-29.676) model. In

Table 11 Coefficient Comparison of Different Models

Statistic	Altman (1968) Model	Re-estimated Model	Ohlson (1980) Model	Re-estimated Model	Zmijewski (1984) Model	Re-estimated Model	New Model
WCTA	1.2[a]	0.076[a]	−1.4[b]	−5.216[c]			
RETA	1.4[a]	1.464[a]					
EBITA	3.3[a]	−0.63[a]					
BVEBVD	0.6[a]	3.474[a]					−13.86[a]
SLTA	0.99	0.028[a]					−1.113[c]
SIZE			−0.4[a]	0.079			
TLTA			6.03[a]	1.623	5.7[a]	0.586[a]	
CLCA			0.1[b]	−2.973[b]			
OENEG			−2.4[a]	2.836[b]			
NITA			−1.8[b]	−29.676[a]			−18.76[b]
FUTL			0.3[a]	−2.559			
INTWO			−1.7	0.337			
CHIN			−0.5[a]	1.73[c]			
NITL					−4.5[a]	−13.797[a]	−34.354[b]
CACL					0.004[b]	0.01	
Constant		−0.425	−1.3	−2.454[c]	−4.3[a]	−1.522[a]	−0.604
LR			0.839[d]	−15.952	203.78	−33.296	164.956
P-value			0.000	0.000	0.000	0.000	0.000

Note: [a], [b] and [c] represents the level of significance at 1 per cent, 5 per cent and 10 per cent respectively. d is the Likelihood Ratio Index and LR is the Log Likelihood Ratio
Source: Author's estimation

case of CHIN, the original (-0.5) and re-estimated (1.73) coefficient are not only different in value but also in sign. The result shows the coefficients of Ohlson (1980) model is sensitive to time period and not stable.

Finally, the result of Zmijewski model is again reported in Table 11. In the original model, all the coefficients are significant whereas in the re-estimated model all the variables are significant except CACL (Current assets to current liabilities). Rest other coefficients preserve similar sign but different in the magnitude. In case of TLTA, the original coefficients were 5.7 and re-estimated is 0.586 which is significantly different in magnitude. For NITL the original coefficients was -4.5 and re-estimated co-efficient is -13.797. The constant term in both the original (-4.3) and re-estimated (-1.222) is different in values. The result shows the coefficients of Zmijewski (1984) model is sensitive to time period and not stable. The results of newly proposed model are reported in the last column of Table 11. All the variables are significant except intercept.

The results reported in Table 11 shows coefficient of all the three accounting based models are not similar. They are unstable and sensitive to time period. The findings are in line with the studies of Grice and Ingram (2001), Grice and Dugan (2001), Timmermans (2014) and Avenhuis (2013). Empirically it is found in the context of Indian manufacturing sector the coefficients are unstable and sensitive to time periods.

Predictive accuracy

Predictive accuracy of all the original, re-estimated and newly proposed models on estimation and holdout sample is reported in Table 12. In the earlier section, we have mentioned based upon total error minimization principle, cut-off value is taken for all the three models. The cut-off value for original Altman (1968), Ohlson (1980) and Zmijewski (1984) models were 2.675, 0.5 and 0.5 respectively (Ohlson 1980 page 120; Zmijewski 1984 page 72). In the re-estimated model based upon the same principle the cut-off value for Altman, Ohlson and Zmijewski model is taken 0, 0.4 and 0.5 respectively. For the newly proposed model same principle of total error minimization criterion is followed and 0.6 is taken cut-off value for the model (Appendix 1, Table 14).

Panel-A of the Table 12 reports the predictive accuracy of original, re-estimated and newly proposed models on estimation sample. The predictive accuracy of original Altman model on estimation sample is 67.692 % which correctly classify 92.308 % of distressed and 43.077 % of non-distressed firm. The Type II error is very high in case of Altman original model on estimation sample. The overall accuracy of Altman re-estimated model on estimation sample is 96.923 which correctly classify 98.462 % of distressed and 95.385 % of non-distressed firms. For Ohlson original model the overall predictive accuracy is 48.462 % on estimation sample which correctly classifies 95.385 % of distressed firms and 1.538 % of non-distressed firms. The Type II error in the case of Ohlson original model on estimation sample is close to 100 %. On the other hand, overall predictive accuracy of re-estimated Ohlson model is 95.385 which correctly classifies 96.923 % of defaulted and 93.846 % of non-defaulted firms. In case of Zmijewski original model, the overall predictive accuracy is 71.538 %. The model correctly classify 98.462 % of distressed and 44.615 % of non-distressed firms. The overall predictive accuracy of re-estimated Zmijewski model on estimation sample is found to be 89.231 which correctly classify 87.692 % of defaulted and 90.769 % of non-defaulted firms. In case of newly proposed model, the predictive accuracy on estimation sample is found to be 98.46 which correctly classify 98.46 % of distressed and 98.46 % of non-distressed firm. The Type I and Type II error in case of new model is found to be equal. Panel-A of Table 12 shows predictive accuracy of re-estimated models is higher than original model on estimation sample. The newly proposed model have highest (98.46) predictive accuracy with minimum and equal Type I and Type II errors. Type II error

Table 12 Comparison of Predictive Accuracy of the Models

	Panel-A (Estimation Sample)					
	Original model Accuracy			Re-estimated model Accuracy		
Model	Overall	Distressed	Non-Distressed	Overall	Distressed	Non-Distressed
Altman	67.692	92.308	43.077	96.923	98.462	95.385
Ohlson	48.462	95.385	1.538	95.385	96.923	93.846
Zmijewski	71.538	98.462	44.615	89.231	87.692	90.769
New Model	98.460	98.460	98.460	NA	NA	NA
	Panel-B (Holdout Sample)					
	Original model Accuracy			Re-estimated model Accuracy		
	Overall	Distressed	Non-Distressed	Overall	Distressed	Non-Distressed
Altman	61.538	25.641	97.436	88.462	87.179	89.744
Ohlson	64.103	97.436	30.769	89.744	87.179	92.308
Zmijewski	79.487	97.436	61.538	76.923	61.538	92.308
New Model	87.179	82.051	92.308	NA	NA	NA

Source: Author's estimation

is found to be more than 50 % in all the three original models. In case of original Ohlson model, the Type II error is close to 100 %. All the three re-estimated models have higher predictive accuracy and low Type I and Type II errors compared to original models.

Panel-B of Table 12 reports the predictive accuracy of original, re-estimated and newly proposed models on holdout sample. The overall accuracy on holdout sample also constitutes diagnostic test for the estimated models. The overall accuracy of Altman original model on holdout sample is 61.538 % which correctly classifies 25.641 % of defaulted and 97.436 % of non-defaulted firms. The Type I error in case of Altman original model on holdout sample is very high and close to 75 %. On the other hand, overall predictive accuracy of Altman re-estimated model is 88.462 % which correctly classifies 87.179 % of defaulted and 89.744 % of non-defaulted firms. In case of Ohlson original model, the overall predictive accuracy is found to be 64.103 % which correctly classify 97.436 % of distressed and 30.769 % of non-distressed firms. The Type II error in the case of Ohlson original model on holdout sample is close to 70 %. On re-estimated Ohlson model, the overall predictive accuracy is 89.744 % which correctly classifies 87.179 % of defaulted and 92.308 non-defaulted firms. The predictive accuracy of Zmijewski original model on holdout sample is 79.487 % which correctly classifies 97.436 % of distressed and 61.538 % of non-distressed firms. The Type II error in case of original Zmijewski model on holdout sample is close to 40 %. The overall predictive accuracy of re-estimated Zmijewski model on holdout sample is 79.487 % which correctly classifies 97.436 % of distressed and 61.538 % of non-distressed firms. On holdout sample, the Type II error is again high for original models except Altman model. The Type II error in case of both Ohlson and Zmijewski original model is more than 50 %. In case of all the re-estimated models both the Type I and Type II errors are minimum except Zmijewski model. In case of new model the overall predictive accuracy on holdout sample is found to be 87.179 % which correctly classifies 82.051 % of defaulted and 92.307 % of non-defaulted firms. The Type I error in case of new model is found to be 18 % and Type II error close to 8 %.

From the results reported in Panel-A and B of Table 12 on estimation and holdout sample, it can be summarized that the predictive accuracy of re-estimated models are significantly higher than original models on both estimation and holdout sample. Except Altman model the Type II error is very high for all the original models on both estimation and holdout sample. The result shows the model applied on the recent data set gives higher predictive accuracy on both estimation and holdout sample. Out of contesting accounting based models, the new model outperforms regarding its predictive accuracy on estimation sample and fairly good accuracy on holdout sample for Indian manufacturing firms. The overall predictive accuracy of re-estimated Ohlson model is 95.385 and 89.385 on estimation and holdout sample respectively. The overall predictive accuracy of Altman re-estimated model is also close to new model, but new model is better than Altman model because it gives direct probability estimates and model bankruptcy in a non-linear fashion which is in line with local and global regulatory framework. In the next section, we will apply other diagnostic check to check the stability of Ohlson re-estimated model. The results are in line with the studies of Grice and Ingram (2001), Grice and Dugan (2001), Timmermans (2014) and Avenhuis (2013). Empirically it is found in the context of Indian manufacturing sector that the coefficients are unstable and sensitive to time periods.

Diagnostics check for the New Model

This section deals with two diagnostics tests for newly proposed model, ROC and long-range accuracy test.

The ROC (Hanley and McNeil, 1982) is one of the important and widely used test to assess the performance of a binary classifier. The Area Under the Curve (AUC) summarizes the performance of a model in a single number. The accuracy of the test depends upon how well it classifies between the groups. In the present context, it is between bankrupt and non-bankrupt. The model ROC with AUC 1 shows the perfect test whereas the model with AUC 0.5 shows worthless test. As compare to a simple metric of misclassification rate, ROC visualizes all possible classification thresholds.

In the ROC test the sensitivity or positive predictive value (PPV) is defined as the proportion of firms for whom the outcome is positive that are correctly identified. Similarly, the specificity or negative predictive value (NPV) is the probability that a firm has a negative outcome given that they have a negative test result.

The ROC is the graph of specificity against 1-*senstivity* by which the impact of choice is understood. A fairly excellent test have good balance between sensitivity and specificity. The decision to set the classification threshold to predict out-of-sample data depends upon the business decision.

Figure 1 shows the AUROC for re-estimated and new proposed model for bankruptcy prediction. From the results, it is clear that new model shows the best results as compare to other contesting models in application to the control. The AUROC for new model is .985 which is higher than other contesting models. Hence, we can say this model is the most appropriate model among contesting models for prediction of the corporate failure for Indian manufacturing firms.

Table 13 reports the long-range accuracy results of new model on estimation and hold-out sample. The long range accuracy of new model on estimation sample are 98.46 and 86.92 % for one year before bankruptcy and two years before bankruptcy respectively. On the holdout sample, it is 89.74 and 70.51 % for one year and two years before default respectively.

The long range accuracy results are fairly good and satisfactory. The result shows the predictive accuracy of new model decreases as we go more backward from the year of distress. Hence, the most recent information is helpful in predicting default with higher accuracy.

Conclusion

The paper proposed a new model to predict the bankruptcy of Indian manufacturing sector and also examines the sensitivity of Altman's (1968), Ohlson's (1980) and Zmijewski's (1984) models to the sample of 208 equal numbers of defaulted and non-defaulted firms for the period 2006 to 2014 in the Indian context. The result shows the overall accuracy of the model improves when the coefficients are re-estimated. The overall accuracy of Altman (1968), Ohlson (1980) and Zmijewski (1984) original models in the estimation sample are 67.692, 48.462 and 71.538 % respectively. When all the models are re-estimated the accuracy improves to 96.923, 95.385 and 89.231 % respectively. On holdout sample, the overall accuracy of Altman's (1968), Ohlson's (1980) and Zmijewski's (1984) original models are 61.538, 64.103 and 79.487 % respectively. The accuracy improves to 88.462, 89.744 and

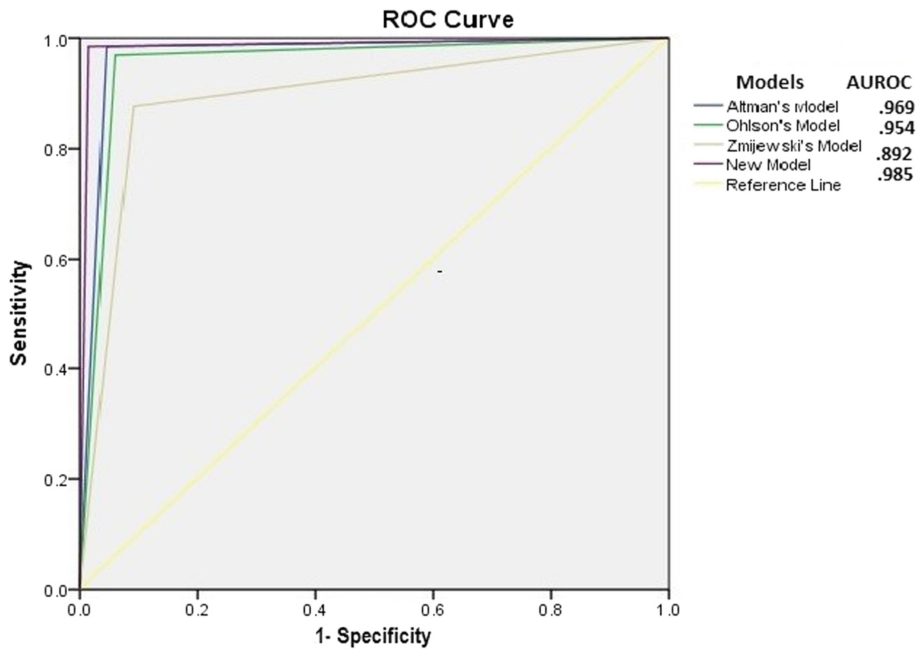

Fig. 1 Comparision of AUROC for re-estimated (Altman's Ohlson's and Zmijewski's) and new model

76.923 when the models are re-estimated. The predictive accuracy of new model on estimation and holdout sample is found to be 98.46 and 87.179 respectively. Therefore, the new model is found to be a more robust model in comparison to Altman's, Ohlson's and Zmijewski's models. The major finding of the study suggests the coefficients of the Altman's (1968), Ohlson's (1980) and Zmijewski's (1984) models are sensitive to time periods and financial condition. The predictive accuracy of the models increases when more recent data are used in the estimation samples. The change in the financial environment leads to change in the relation between financial distress and financial ratios. This also alters the comparative importance of the ratios to predict default. Hence, researchers should re-estimate the original models to get higher predictive accuracy. In case of Indian manufacturing companies, out of all competitive accounting based models, the new model outperforms regarding predictive accuracy, ROC, and long-range accuracy test.

The major limitation of the study is that it can be applied to only manufacturing firms and excludes financial firms. The study can also use larger data set applying various other parametric and non-parametric models to check validity of the model, robustness and stability of the parameters. Though, the results of Black-Scholes-Merton (BSM) model can't be directly compared with the proposed model but using Indian manufacturing data the same approach can be applied to develop model for Indian manufacturing companies.

Table 13 Long-range Accuracy of Newly Proposed Model

Years before distress	Estimation sample	Holdout Sample
1	98.460	89.743
2	86.923	70.513

Source: Author's estimation

Endnotes

[1]The total error minimization principle is applied to obtain cutoff value. Various cut-off values are tested and the final cutoff value is decided where the sum of Type I and Type II errors are minimized. Type I errors occur when a model incorrectly classifies a distressed company as non-distressed, while Type II errors occur when a model incorrectly classifies a non-distressed company as distressed.

Appendix 1

Table 14 Identification of Cutt-off Value for Re-estimated and Newly Proposed Model

Cut-off	Overall Correct Prediction	Type I Error	Type II Error
Altman's re-estimated Model			
0	96.923	1.538	4.615
0.2	92.308	1.538	13.846
0.3	91.538	1.538	15.385
0.4	90.000	1.538	18.462
Ohlson's re-estimated Model			
0.7	93.850	3.080	9.230
0.6	94.620	4.620	6.150
0.5	94.620	6.150	4.620
0.4	95.380	6.150	3.080
Zmijewski's re-estimated Model			
0.7	86.150	3.080	24.620
0.6	85.380	4.620	24.620
0.5	89.230	9.230	12.310
0.4	88.460	13.850	9.230
Newly proposed Model			
0.7	98.460	3.080	0.000
0.6	98.460	1.540	1.540
0.5	97.690	1.540	1.540
0.4	97.690	1.540	3.080

Source: Author's estimation

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
BPS collected the study material, design the concept, collected data, interpreted the results and drafted the manuscript. AKM participated in the study design, statistical analysis and interpretation of results and helped to draft the manuscript. Both authors read and approved the final manuscript.

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