RESEARCH ARTICLE
Vol.9.Issue.4.2022
Oct-Dec.

Impact Factor 6.853 SJIF

IJBMAS
www.ijbmas.in

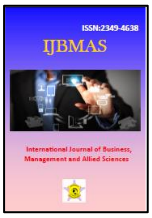
ISSN INTERNATIONAL STANDARD SERIAL NUMBER INDIA
2349-4638

INTERNATIONAL JOURNAL OF BUSINESS, MANAGEMENT AND ALLIED SCIENCES (IJBMAS)

A Peer Reviewed and refereed Journal

TESTING ALTMAN MODEL AND CALIBRATED MODEL TO MDA MODEL IN THE CURRENT SCENARIO FOR SELECTED SECTORS

Dr. Deepika Verma
Assistant Professor
Sri Aurobindo College (Eve)
Delhi University
Email: deepika.delhiuniversity@gmail.com
DOI: 10.33329/ijbmas.9.4.1



ABSTRACT

The present study has attempted to predict the default events of selected Indian corporate from selected 13 sectors. The total sample firms included in the study are 580 (320 Non-defaulted, 260 Defaulted) firms listed in the Indian stock exchange. The period of research commences from 1st April 2004 and ends at 31st March 2019. The study incorporated 3 default prediction methods namely Multiple Discriminant Analysis, Altman Original and Calibrated. The study developed models for each selected sector using MDA. The firm-specific sample data is collected from the 13 Indian sectors namely Chemicals, Construction and Engineering, Electronics, Hotels, Infrastructure, Pharmaceuticals, Plastic & Fibre, Realty, Software, Steel, Sugar, Textile, Miscellaneous sector and complete sample. The classification result of in-sample data demonstrated that the MDA model attained satisfactory predictive accuracies for Chemicals, Steel, Pharmaceuticals, Plastic & Fibre, Hotels and Electronics which range from 90% to 87% in conjunction with troublesome values of Type II Errors. The validation accuracy obtained by MDA model did not provide acceptable results except for Electronics and Sugar sectors that are 76% and 74% respectively. The Altman model classified groups of Software sector with 29% accuracy rate which is highest amongst the accuracies achieved by Altman in other selected sectors.

Keywords: Altman model, Multiple Discriminant Analysis, Revised Altman model, Calibrated model, Default prediction, Credit risk model, Bankruptcy.

Introduction

David Durand (1941) attempted the classification process of solvent and insolvent firms. Since then numerous studies have been widely conducted in developed and emerging economies using diverse credit risk models. Credit risk models have been crucial for making strategic decisions on credit risk assessment (Huang et al., 2004). Earlier the human judgment was considered as the tool to evaluate the default probability of the borrower which were generating inaccurate predictions. Therefore, the need for such credit risk evaluation techniques was felt that contains different types of algorithm to accomplish high predictive accuracy (Khandani et al., 2010). However, credit rating agencies namely S&P, Moody's, Fitch, CRISIL are also committed for providing solvency information of the firms by allotting them credit ratings.

Beaver (1966) defined failure as "Failure is defined as the inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account or non-payment of preferred stock dividend" (Beaver, 1966). Financial distress is also a sort of failure in which the company's assets begin depleting, outside liabilities escalates and firm faces severe losses.

The corporate default has a snowball effect on the economy that initiates from the steep growth of NPA of Indian commercial banks. After the financial crisis, the Indian banks have started practising "Provisioning" by setting aside the amount to compensate the credit default that eroded the capital of the banks and put them into losses. The swelling NPA and stressed assets disrupts the credit supply channel in the economy this will discourage the investment in large projects. The retail loan will also be negatively affected which will reduce the aggregate demand and culminates the lower GDP growth. The problem of NPA does not persist in isolation rather it impacts the whole economy from lower aggregate demand to lower GDP growth to higher unemployment rate to lower credit supply. It has a ripple effect on every single element of the economy. Therefore, few stringent provisions have to be made; internal vigilance system has to be set up in the form of Corporate Governance and internal credit risk management committee at the banks and corporate level.

Credit risk models are also used to ascertain the price of risky bonds, debenture, derivatives, portfolio risk, diagnosing the solvency of firms and to determine the optimum capital structure with minimum cost of capital (Duffie et al., 2007). Since there are indirect costs also attached to the corporate failure such as the decline in profit which pushes downsizing that create unemployment & threatens the economic unrest (Huang et al., 2004).

Beaver (1966) and Altman (1968) developed a credit scoring model using Linear Discriminant Analysis (LDA) and Multiple Discriminant Analysis (MDA) respectively to classify the companies according to their credit risk exposure. Credit risk models compute Z scores which determine the financial position of firms and group them accurately. Altman (1968) applied MDA on the paired sample of 33 defaulting, 33 non-defaulting manufacturing firms and classified the firms into 3 categories according to their Z score. Firms having a Z score more than 2.99 belong to the safe group, firms with Z score less than 2.99 but more than 1.80 are grouped into grey zone and firms having Z score less than 1.80 are termed as distressed.

Due to the high classification accuracy results, MDA was used by many authors to develop the credit risk models. However, it has some drawbacks too, MDA function is based on few assumptions that were often violated and criticized by various scholars. Hence, it became difficult to generalize the result of MDA over divergent firm's data. To conquer these weaknesses O score or Logistic regression model was introduced by Ohlson (1980) to predict bankruptcy prediction.

The financial information is used in the credit risk models are of two kinds accounting ratios and cash flow-based. Wilcox (1971) describes accounting ratios as the significant predictors of bankruptcy followed by Kaminski, Wetzel, & Guan (2004), whereas Casey & Bartczak (1985) which validated the cash flow variables as the pivotal element to discriminate companies into defaulting and non-defaulting.

The present study is broadly classified into 5 sections. Section one encapsulates the introduction and literature review of the study. The second section encompasses the objectives, research methodology where in the section includes sources of data, sector-wise description of selected Indian firms, and the description of selected default prediction functions. The third section of the study depicted the obtained empirical results for in-sample and out-of-sample data and it further, explains the sector-wise analysis of the default prediction accuracies and misclassifications. The last section the study comprises of the conclusion that summarises the entire study and provided the inference of the obtained empirical results.

Literature Review

The default prediction models have been used universally to determine the insolvency status of firms across the world in various sectors. However, after the implication of Basel II and escalating cases of default in the USA it became customary for all the banks and financial institutions to maintain an internal credit risk mechanism for ascertaining Loss Given Default in advance (E I Altman & Hotchkiss, 2006). Subsequently, the global financial calamity of 2008 drew the attention of all the credit rating agencies and financial institutions towards bank loan defaults.

The credit risk models were developed using three versions of the original Z score model for the default prediction using both financial and non-financial information by Bandyopadhyay (2006). Thereafter, Bhunia & Sarkar (2011), Upadhyay (2019), Verma & Raju (2019), Sharma, Singh, & Upadhyay (2014), and Verma (2019) applied MDA, Structural and Logit model for predicting insolvency of Indian Listed firms by including financial ratios, non-financial and market-based ratios in the model.

Ambika (2015) developed Z score model to diagnose the financial efficacy of both public and private Indian firms by integrating financial ratios for the period 1999 to 2012 (Ambika.T & A, 2015). The financial profitability of the Indian firms was gauged using the Z score model over the period from 2000 to 2005 (Kannadhasan, 2015). The MDA model was applied to the Indian Pharmaceuticals companies for the sample data from 2000 to 2012 to group them according to their profitability status (Selvi & Dheenadhayalan, 2014). Arab, Masoumi, & Barati (2015) examined the financial health of the Indian Steel sector using ratios that cover liquidity, solvency, and activity and profitability aspects of the firm with MDA function that performed quite well for showing the true snapshot of the firm. The default probability of SAIL was computed using the Z score during the period from 2005 to 2010 in the study Sinku & Kumar (2014) & Pal (2013) in which the profitability of two public listed companies namely SAIL and RINL were compared using the Z score. Studies namely Varma & Raghunathan (2000) & Kulkarni, Mishra, & Thakker (2008) had predicted default risk by using the data of Sick industries published by BIFR.

Generally, the financial ratios depict the gradual drift of an entity towards insolvency. The insolvency occurred either when the assets of the firm become zero or when firm is running out of liquidity. Accordingly, the ratios of solvent and insolvent firms are in contrast to each other (Wilcox, 1971). Hence, one can predict the solvency status of the firm by employing credit risk models.

Beaver, W. (1966) predicted the distress using a Univariate model based on 30 financial ratios for the 79 pair of distressed and non-distressed firms. The study found that WC/TA ratio and NI/TA ratio are the best discriminators for the distress prediction (Beaver, 1966).

The used the sample of 66 listed manufacturing companies to predict the default using financial ratios. The author selected the sample in 2 groups, group I consists of 25 paired sample firms and group II included 14 firms from diversified asset size. The financial ratios incorporated into the study are WC/TA, RE/TA, EBIT/TA, MVE/BOOK VALUE OF TOTAL DEBT, SALES/TA. The profitability ratio contributed the most in the default prediction of the study followed by SALES/TA ratio. Study obtained accuracy of 95% with only 6% and 3% Type I and Type II errors respectively. The study also the bankruptcy prediction 2 years prior in which study obtained 72% accuracy (Edward I. Altman, 1968).

The study investigates the use of discriminant analysis for multi-level classification on large datasets. This study unveils that the discriminant analysis gives a fast, effective and accurate alternative for multi-level classification. The result achieved using LDA is comparable to SVM and less time consuming than the other approaches (Li et al., 2006).

An internal credit scoring system was developed to rate the external bonds and to assess the probabilities of default. Z-score model was applied along with financial ratios, which was later validated on Steel companies that provided 85-90 % accuracy. The study concluded that the model is accurate, simple, accessible, however not perfect since it has Type II Errors (Edward I. Altman, 2006).

Suzzane Hayes (2010) aimed to develop Z score for public sector retail bankrupt companies for up to 2 succeeding years. Altman's Z score successfully predicted all companies' financial health except 2 but its accuracy is lower than Z". Study states that Z" score is effective for public non-manufacturing firms unlike Altman's Z (Hayes et al., 2010).

Abdul Rashid (2011) attempts to identify which financial ratios are important predictors of bankruptcy in the non-financial sector of Pakistan. The sample selected from the companies that went insolvent and delisted from the Karachi stock exchange during 1996-2006. The study used 24 financial ratios which reflect the following features of the firm such as profitability, liquidity, leverage, and turnover. The ratios were assessed for 5 years before insolvency. The result draws the inference that the ratios namely Sales/TA, EBIT/CL, and cash flow ratio were identified as better predictors of bankruptcy (Rashid, 2011).

An investigation was conducted to check whether the inclusion of risk assessment variables in the MDA model improved the bank's ability to classify customers and predict the firm's financial performance. The study was based on the recent financial calamity of 2009. The financial information was gathered for the period 1985-1994 of 100 customers from the National Bank of Commerce. The outcome of the model signifies that the MDA model has higher predictive and classification accuracy when the model integrates both qualitative and quantitative variables (Mvula Chijoriga, 2011).

Micudova (2013) gauged the capability of Z score to discriminate companies and to identify which independent variable play a significant role to misclassify the companies. The research was based on 47 firm's accounting data from 2008 to 2010. The study demonstrates that the Z score is competent to classify companies and the asset turnover ratio has a remarkable impact on misclassification (Mičudová, 2013).

The study attempts to discriminate sample data collected from 20 listed firms of Bucharest stock exchange into solvent and default. MDA has been applied on the sample data for the period 2005-2013. The result stated that MDA classifies companies with 90% accuracy (Stancu & Stancu, 2014).

The used MDA and Logistic regression to predict the default of 139 Chinese firms belong to Metal, machinery, medicines, manufacturing, real estate, electrical equipment, food beverages, paper and printing, petroleum and other chemicals etc. Study used 25 financial ratios categorised into profitability, liquidity, solvency, potentiality, activity, capital market, capital structure. significant ratio for the logit model is net income to ta and the ratios found significant for MDA model are net sales to ta, ebit to ta, and growth rate to ta. The classification accuracies of both developed models for 1 year prior is 98% and 80% for 2 to 3 years prior. However, the logistic model outperformed the mda by providing least % of Type I and Type II errors (Liang, 2003).

This study used Altman, Taffler and logistic regression credit score model to examine the default prediction of 105 SMEs (75 non-defaulted and 30 defaulted) of European emerging economy during the period of 2009. The results obtained were in line with the existing literature where the logistic regression outperformed mda. The study used 14 financial ratios. (Smaranda, 2014).

The study conducted a comparative analysis of MDA and Logit model with respects to their advantages and disadvantages. The study summarized the contribution of past studies about the default prediction achievements of MDA and Logistic regression. Study concluded that these models are beneficial for the financial regulators, bankers and policy makers to regulate the firms and take prior corrective actions and making policies (Hassan et al., 2017).

The study examined the sample data of 300 USA listed firms for the varied period from 1962 to 1992 using the market driven information along with dynamic logit or hazard model. The study advocated the usage of market driven variables with non-static models (Shumway, 2001).

Study used 4980 non-bankrupt and 229 bankrupt Australian listed firms for 2001 to 2003 by including multinomial logit which found to be successful (Jones & Hensher, 2004).

The study predict the default prediction of 40 pvt ltd firms of Turkey form the period 1994 to 2001 using MDA, Principal component, probit, and logit model. The study found principal Component analysis as the best predictor in combination with other 3 models to help turkis banks to predict default (Canbas et al., 2005).

Study predicted the bankruptcy of 40 Korean manufacturing firms for one year from 1997 to 1998 using Logit model. Model obtained classification accuracy of 80.4% (Hoo-Ha & Jinn Taehong, 2000).

The study applied MDA model on 52 non financial Pakistani company using 24 financial ratios for the year 1996 to 2006. The model obtained 76.9% prediction accuracy. The mda model was found parsimonious along with sale/ta, ebit/cl, cash flow ratios (Rashid & Abbas, 2011).

The bankruptcy prediction study is conducted on 22 bankrupt and 22 non-bankrupt listed Jordan companies of saudi Arabia for the period from 2000 to 2003 using MDA along with 11 financial ratios. The financial ratios covered the liquidity, profitability, leverage, solvency, and activity aspects of the firms. The study found that the WC/TA, CA/CL, MVE/BOOK VALUE OF DEBTS, RE/TA, SALES/TA are significant predictors. However, the WC/TA is the most significant bankruptcy predictor (Almansour, 2015).

The objective of this study is to develop the default prediction model using MDA and logit analysis for Moroccan agricultural firms. The sample data of 75 solvent and 75 non-solvent firms was collected for the span from 2011 to 2013. The 10 financial ratios were used in the study to predict bankruptcy. Study concluded that the logit model outperforms mda model with higher accuracy of 82% whereas the mda obtained only 71%. The study reported that the for MDA debt/asset, ca/cl, sales/wc, and ni/asset as the significant predictors. For logit model asset/cl, debt/asset, sales/wc, and stock/sales are found to be efficient predictors (El-Ansari & Benabdellah, 2017).

The study used mda and logit regression to study the default prediction of Pakistani firms. The sample data of listed 35 bankrupt and 35 non-bankrupt firms was collected for the period from 1996 to 2012. Study obtained 80% and 78.6% predictive accuracy for Logistic regression and mda model respectively. The significant variables for logit model identified in the study are equity/debt, ebit/cl, re/ta. The variables found relevant for mda are ebit/cl, sales/ta, sales/quick assets. The study recommended to use logit model for future bankruptcy prediction (Jaffari, 2017).

Objective of the Study

- To develop default prediction model using MDA function for the selected sectors and complete sample

- To Predict default probability of the selected sectors and complete sample using Altman original model and Calibrated model.
- Validate the calibrated model and developed MDA model on out-of-sample data.
- To assess the competency of Altman original model on present sample by comparing its predictive accuracy to MDA developed model and Calibrated model.

Research Methodology

The present study developed the credit risk models for selected 13 corporate sectors of India namely Chemicals, Construction and Engineering, Electronics, Hotels, Infrastructure, Pharmaceuticals, Plastic & Fibre, Realty, Software, Steel, Sugar, Miscellaneous and Textile and one for Complete Sample that amalgamates the sample cases. study developed 14 MDA models and applied the Calibrated and Altman Original model to check the relevance of Altman (1968) in the present sample data collected for the period from 1 April 2004 to 31st March 2019. Present study compared the classification results of developed MDA model, Altman Original and calibrated model. The developed and calibrated model is validated over out-of-sample data as well.

Sample Data and Study Period

The sample data has been collected from the selected firms belong to 13 Indian corporate sectors namely Chemicals, Construction and Engineering, Electronics, Hotels, Infrastructure, Pharmaceuticals, Plastic & Fibre, Realty, Software, Steel, Sugar, Miscellaneous and Textile. The study included total of 580 (260 Defaulted and 320 Non-Defaulted) Indian listed firms. The sample data is collected from the various sources given below for the period of 15 years from 1st April 2004 to 31st March 2019.

Sources of Data

The accounting information was collected from the audited financial statement of the selected Indian listed firms that are accessed from each firm's websites. The share price information of each selected firm is collected from the BSE website. The information about the default position of the selected Indian firms has been attained from the audited annual reports of the firms. The Indian GNP data for the period 1st April 2004 to 31st March 2019 was obtained from the database maintained by the World Bank.

Independent Variables

Altman Original Model and Calibrated Model

As depicted in Table No 1 Independent Variable the Alman Original (1968) and Calibrated Model have taken only 5 financial ratios as independent variables to compute the Z score model.

Table No 1 Independent Variables

Accounting Variables	Market Variables
WC/TA	MVE/TBD
RE/TA	
EBIT/TA	
SALES/TA	

Multiple Discriminant Analysis

In contrast to Altman original and calibrated model the study selected 21 financial, market and economic variable to calculate the Z score. The model shall be developed using MDA function only by taking the significant independent variables.

Table No 2 Independent Variables

Accounting Variables	Market Variables	Economic Variables
WC/TA	MP/EPS	LOG(TA/GNP)
RE/TA	MP/BV	SALES GROWTH/GNP GROWTH
EBIT/TA	MVE/TBD	
SALES/TA		
CA/CL		
NI/TA		
NP/TE		
TBD/TA		
EBIT/INT		
OCFR		
GRTA		
INVENTORY TURN		
FAT		
D/E		
TL/TA		
SALES GROWTH		

Sector-Wise Description of Selected Indian Listed Firms

Table No 3 Sector-Wise Description of selected Firms

S.No	Sectors	Total no of Defaulted Firms	Total no of Non-Defaulted Firms
1	Chemicals	18	29
2	Construction and Engineering	13	13
3	Electronics	22	19
4	Hotels	9	8
5	Infrastructure	29	6
6	Pharmaceuticals	15	19
7	Plastic & Fibre	7	11
8	Realty	11	10
9	Software	15	8

10	Steel	33	48
11	Sugar	12	4
12	Textile	30	34
13	Miscellaneous	46	111
14	Complete Sample	260	320

Default Prediction Methods used in the study

Altman Original

The Altman Original is the model developed and applied by Altman in his paper Titled "Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy" that was Published in The Journal of Finance in the year 1968 in which the author developed the bankruptcy model using discriminant analysis function. The Altman (1968) is a trailblazer study that has been applied by numerous studies till date in the area of bankruptcy and default prediction research. The popular credit rating agencies namely CRISIL, CARE, FITCH are also the user of the Altman Model that evaluates solvency or default status of the firms using Altman (1968) model.

The Altman (1968) had provided a slab of Z score based upon the outcomes of the study that determine the default position of firm. Since then, the scholars, credit rating agencies, banks and firms examine the solvency of business by considering the Z score of firms. Hence, the Z score slab is given below that has been used in the present study to compute the probability of default of selected firms.

Z score < 1.81: "Distress Zone"

1.81 < Z score < 2.99: "Grey Zone"

Z score > 2.99: "Safe Zone"

Source: "Financial Ratios, Discriminant Analysis and The Prediction of Corporate Bankruptcy" Altman (1968)

Therefore, the present study applied the Altman Original model on In-Sample data cases that are processed using Microsoft Excel. The Altman model equation will remain the same for all 13 sectors and Complete Sample for predicting default.

Calibrated Model

The study applied the Calibrated model as well on the selected firm's sample data. The Calibrated Model is the revised version of the Altman original (1968) discriminant analysis function that considers the same independent variables to develop the default prediction model that was originally used by Altman in his pioneer paper in 1968 yet the corresponding weights of each of the independent variables are derived by processing the sample cases on IBM SPSS version 22.

Multiple Discriminant Analysis

Fisher (1936) introduced the MDA function that categorises the observations into distinguished groups. The fundamental aim of the MDA is to minimise the spread between cases within a group and maximise the spread between cases in different groups. The MDA has two assumptions: first, the independent variables employed in the model are normally distributed second, the group variance-covariance are equal across the groups. However, there are some arguments about these assumptions; some people thought they are critical.

The Multivariate Discriminant Analysis is a statistical technique that has been used in various disciplines since 1930. The MDA is predominantly used to predict the categorical/nominal dependent variable e.g. bankrupt or non-bankrupt and male or female. The dependent variables can be grouped into more than two groups. The discrimination equation generates Z score that classifies the observations into different groups. The DA examines the independent variables by integrating the weights assigned to each variable that are labelled as discriminant coefficients (Rencher, 2002).

The equation of the MDA is as follows which calculate the Z score:

$$Z = \beta_1 x_1 + \beta_2 x_2 + \cdots \ldots \ldots . \beta_n x_n$$

Where Z is the overall score, $\beta_1 x_1 + \beta_2 x_2 + \cdots \ldots \ldots \ldots \beta_n$ is discriminant coefficient, $x_1, x_2, \ldots \ldots . . x_n$ are independent variables. Z score determines the bankruptcy risk of any firm. The lower value of Z score indicates a higher risk of bankruptcy.

Empirical Analysis

Models developed using Altman model

1. **Altman model for every 13 sectors and the Complete Sample developed using Altman's (1968) original model.**

Table No 4 Models Developed Using Altman

0.012*WC/TA+0.014*RE/TA+0.033*EBIT/TA+0.006*MVE/TBD+0.999*SALES/TA

Source: Models developed using Altman's (1968) model

2. **Models Developed Using Calibrated Model**

Table No 5 Models Developed using Calibrated Model

Chemicals	-0.943+2.717* WC/TA +3.022* RE/TA +0.043* EBIT/TA + 0* MVE/TBD +4.81*SALES/TA
Construction and Engineering	-0.767-0.787* WC/TA +8.786* RE/TA +5.475* EBIT/TA + 0* MVE/TBD +4.18*SALES/TA
Electronics	-0.683+2.11* WC/TA +4.383* RE/TA +0.267* EBIT/TA +0.002* MVE/TBD +4.529* SALES/TA
Hotels	-0.438+2.345* WC/TA +3.506* RE/TA +1.1* EBIT/TA +0.002* MVE/TBD +3.452* SALES/TA
Infrastructure	0.633+0.001* WC/TA +20.224* RE/TA -15.387* EBIT/TA +0* MVE/TBD +18.722* SALES/TA
Pharmaceuticals	1.24-2.501* WC/TA +10.884* RE/TA -12.904* EBIT/TA +0* MVE/TBD +11.217*SALES/TA
Plastic & fibre	-0.643+0.983* WC/TA -0.714* RE/TA +8.291* EBIT/TA +0.083* MVE/TBD -3.222* SALES/TA
Realty	-0.959+1.257* WC/TA +29.744* RE/TA -13.215* EBIT/TA +0.019* MVE/TBD +31.867* SALES/TA
Software	-1.027+0.155* WC/TA +12.685* RE/TA -3.66* EBIT/TA -1* MVE/TBD +11.771*SALES/TA
Steel	-0.494+0.892* WC/TA +12.245* RE/TA -4.942* EBIT/TA +0.009* MVE/TBD +12.105* SALES/TA
Sugar	-1.158+4.41* WC/TA +4.384* RE/TA -0.764* EBIT/TA +0.222* MVE/TBD +6.707* SALES/TA
Textile	-0.707+1.89* WC/TA +5.684* RE/TA -0.635* EBIT/TA +0.002* MVE/TBD +2.966* SALES/TA
Miscellaneous	-.882+.429*WC/TA+9.012*RE/TA+2.695*EBIT/TA-.002*MVE/TBD+7.661*SALES/TA

Complete Sample	-0.688+1.675*WC/TA+2.978*RE/TA+0.827*EBIT/TA+0*MVE/TBD+2.404*SALES/TA

Source: Models Developed using the SPSS findings based on Secondary data

3. Model Developed Using Multiple Discriminant Analysis

Table No 6 MDA Models

Sectors	Model
Chemicals	Z = -1.515+0.648*WC/TA+0.115*CA/CL+0.555*NI/TA+1.199*NP/TE-1.647*TBD/TA+0.047*FAT
Construction and Engineering	Z = -1.469+0.103*WC/TA+4.848*RE/TA+13.55*EBIT/TA+0.191*CA/CL-15.19*NI/TA-2.076*TBD/TA+1.692*GRTA+0.05*MP/BV+0.959*TL/TA
Sectors	**Model**
Electronics	Z= -0.551+0.849*WC/TA-0.47*TBD/TA+0.056*INVEN.TURN+0.012*FAT+0.111*MP/BV
Hotels	Z = -0.709-3.459*WC/TA-0.593*NP/TE+0.134*D/E
Infrastructure	Z = -894+6.233*RE/TA-1.624*EBIT/TA+0.446*NI/TA+0.182*MP/BV-0.084*TBD/TA+0.732*GRTA
Pharmaceuticals	Z = -0.074-5.789*EBIT/TA-7.802*NI/TA-2.746*WC/TA+1.726*TBD/TA+10.259*RE/TA
Plastic & Fibre	Z = -1.226+3.418*TBD/TA-0.08*FAT-5.721*EBIT/TA+14.417*NI/TA-1.017*NP/TE
Realty	Z =0.351+9.626*NP/TE+9.34*EBIT/TA
Software	Z = -1.162+11.377*EBIT/TA+0.308*MP/BV-17.478*NI/TA+8.327*RE/TA+0.517*GRTA
Steel	Z = 0.392+11.68*EBIT/TA-24.905*NI/TA+0.044*FAT-0.159*LOG(TA/GNP)
Sugar	Z = -0.297+4.48*WC/TA+0.615*MVE/TBD-0.075*CA/CL+0.293*NP/TE+20.581*EBIT/INT+0.011*D/E
Textile	Z= -0.448+1.687*WC/TA+8.624*RE/TA-8.379*NI/TA-0.358*TBD/TA+1.253*GRTA
Miscellaneous	-.545+2.630*NI/TA+.430*EBIT/TA+4.620*RE/TA+.736*NP/TE-.476*TBD/TA+.002*EBIT/INT
Complete Sample	Z = -0.141+1.428*WC/TA+5.432*RE/TA+0.344*EBIT/TA-1.709*NI/TA

Sector wise Analysis of the Empirical Results of Developed MDA, Calibrated and Altman Original Model

In-Sample Classification Result of Developed MDA, Calibrated model and Altman's model

Table No 7 In-Sample Classification Results demonstrated the accuracy rate, Type I Error, and Type II Error of the developed MDA, Calibrated and Altman Original model applied on selected sector and Complete Sample. The given values of the accuracy rate, Type I Error and Type II Error are the results generated using IBM SPSS version 22, and MS-Excel. Table No In-sample classification results intimate the prediction results of the developed MDA, calibrated and the Altman original model for 13 selected sectors and Complete Sample. The accuracy rate indicates that how accurate the discriminant function is to categorise the dependent variable groups perfectly. The Type I and Type II Errors denotes the misclassification of the models. The higher accuracy rate in conjunction with lower Type I & Type II Error specifies the high robustness of the default prediction model.

Table No 7 In-Sample Classification Results

Sectors	Models	Accuracy Rate	Type I Error	Type II Error
Chemicals	Developed model	90%	3%	69%
	Calibrated Model	87%	2%	88%
	Altman's Original	16%	94%	0%
Construction and Engineering	Developed model	82%	20%	9%
	Calibrated Model	80%	21%	14%
	Altman's Original	18%	98%	0%
Electronics	Developed model	85%	18%	9%
	Calibrated Model	82%	15%	30%
	Altman's Original	22%	98%	0%
Sectors	Models	Accuracy Rate	Type I Error	Type II Error
Hotels	Developed model	87%	10%	28%
	Calibrated Model	81%	15%	36%
	Altman's Original	19%	100%	0%
Infrastructure	Developed model	79%	20%	25%
	Calibrated Model	70%	25%	45%
	Altman's Original	28%	95%	0%
Pharmaceuticals	Developed model	88%	10%	24%
	Calibrated Model	80%	18%	30%
	Altman's Original	19%	93%	0%
Plastic & Fibre	Developed model	88%	9%	31%
	Calibrated Model	76	4%	79%
	Altman's Original	18%	100%	0%
Realty	Developed model	80%	17%	34%
	Calibrated Model	87%	1%	86%
	Altman's Original	14%	100%	0%
Sectors	Models	Accuracy Rate	Type I Error	Type II Error
Software	Developed model	75%	25%	23%
	Calibrated Model	81%	15%	33%
	Altman's Original	29%	98%	0%
Steel	Developed model	89%	2%	84%
	Calibrated Model	74%	24%	43%
	Altman's Original	11%	100%	0%

Sugar	Developed model	76%	25%	23%
	Calibrated Model	72%	27%	31%
	Altman's Original	27%	100%	0%
Textile	Developed model	81%	14%	42%
	Calibrated Model	87%	2%	73%
	Altman's Original	17%	100%	0%
Miscellaneous	Developed model	89%	3%	84%
	Calibrated Model	90%	2%	86%
	Altman's Original	13%	97%	1%
Sectors	Models	Accuracy Rate	Type I Error	Type II Error
Complete Sample	Developed model	78%	19%	38%
	Calibrated Model	85%	1%	93%
	Altman's Original	18%	97%	0%

Source: Prepared by Scholar using the default prediction results of MDA models obtained from SPSS and MS-Excel

Sector-wise Analysis of Findings

The developed model outperformed with 90% accuracy rate in Chemical sector followed by model developed for Textile and Miscellaneous sector that achieved 89% predictive accuracy. The Pharmaceutical & Plastic & Fibre sector's developed model showed 88% accuracy. The Calibrated model attained 90% accuracy rate for Miscellaneous sector followed by Chemicals and Textile sectors in which the calibrated model achieved 87% prediction accuracy. The Altman model classification results did not show impressive classification accuracies across the selected sectors. The Altman model classified groups of Software sector with 29% accuracy rate which is highest amongst the accuracies achieved by Altman in other selected sectors. The sectors specifically Sugar, Hotels, Plastic & Fibre, Textile, Realty, Steel have witnessed 100% Type I Error in the Altman model whereas, the calibrated model had displayed only 1% Type I Error for Complete Sample and Realty sector. The developed model has achieved 2% Type I Error in the Steel sector. The highest Type II Error of 93% is found in the calibrated model of Complete Sample and 0% Type II Error is obtained by Altman model for Sugar, Hotels, Plastic & Fibre, Textile, Realty, Steel, Software, Electronics, Construction and Engineering, Infrastructure, Chemicals, Pharmaceuticals sectors and Complete Sample. The developed model performed well concerning Type II Error in the Construction & Engineering and Electronics sectors. The model witnessed only 9% Type II Error.

Out-of-sample classification results of Calibrated and MDA Model

Validation of the Developed Model and Calibrated Model on out-of-sample data

Table No 8 Validation Results depicts the results obtained by applying the developed and calibrated model on out-of-sample data of selected sectors and Complete Sample. The study tested the validity of developed and calibrated model w.r.t accuracy rate, Type I Error & Type II Error, using MS-Excel.

Table No 8 Validation Results

Sectors	Models	Accuracy Rate	Type I Error	Type II Error
Chemicals	Developed model	16%	91%	11%
	Calibrated Model	78%	22%	0%
	Developed model	69%	33%	0%

Construction and Engineering	Calibrated Model	61%	45%	25%
Electronics	Developed model	76%	24%	27%
	Calibrated Model	82%	16%	38%
Hotels	Developed model	18%	85%	25%
	Calibrated Model	65%	43%	0%
Infrastructure	Developed model	19%	100	0%
	Calibrated Model	73%	22%	45%
Pharmaceuticals	Developed model	37%	62%	100%
	Calibrated Model	37%	62%	80%
Plastic & Fibre	Developed model	58%	40%	67%
	Calibrated Model	74%	26%	0%
Realty	Developed model	83%	17%	17%
	Calibrated Model	35%	75%	0%
Software	Developed model	33%	71%	0%
	Calibrated Model	37%	100%	0%
Steel	Developed model	27%	74%	20%
	Calibrated Model	59%	45%	5%
Sugar	Developed model	74%	24%	100%
	Calibrated Model	62%	41%	14%
Textile	Developed model	55%	45%	46%
	Calibrated Model	52%	51%	36%
Miscellaneous	Developed model	55%	48%	16%
	Calibrated Model	63%	41%	9%
Complete Sample	Developed model	70%	28%	59%
	Calibrated Model	64%	38%	23%

Source: Prepared by Scholar on MS-Excel using the results of Developed MDA models

Sector-wise Analysis of Findings

Table No 8 Validation Results summarises the results achieved by the study for validating the developed and calibrated model on the out-of-sample data of the selected firms. The out-of-sample classification results found in the study are very satisfactory. The study attained higher accuracies of 83% and 74% for Realty and Sugar sector. The developed model performed exemplary in the Realty sector by classifying the groups correctly with 83% accuracy followed by the calibrated model that derived 82% accuracy in the Electronic sector with least Type I Error. Further, the table depicted 100% Type I Error for Plastic & Fibre and Infrastructure sectors experienced by developed model. Similarly, the Software sector suffered 100% Type I Error in calibrated model. The study found 0% Type II Error in Construction & Engineering, Software, and Infrastructure sectors for developed model. The Plastic & Fibre, Hotels, Realty and Software sectors also witnessed 0% Type II Error in calibrated model.

Whereas, developed models of Sugar and Pharmaceuticals sectors displayed 100% Type II Error. The Miscellaneous sectors and Complete Sample have exhibited average results for both developed and calibrated models concerning the classification accuracy and errors.

Conclusion

The classification rate of Altman's original model depicted a lower accuracy level for all selected sectors which ranges from 11% - 22%. This accuracy rate substantiates the irrelevance of the Altman (1968) Original model. Whereas, the calibrated model performed considerably well for both In-sample. The accuracy rate for In-sample data ranges from 70% to 90%. The study found the highest accuracy rate in Miscellaneous, Chemicals, Realty, Textile sectors followed by Complete Sample. The validation results elaborated that the calibrated model outperformed the developed MDA model concerning the accuracy rate for sectors such as Chemicals, Electronic, Hotels, Infrastructure, Plastic & Fibre, and Steel. The accuracy rate of the Calibrated model is 82% for Electronics sector that is highest amongst selected sectors. This indicates that the independent variables used by Altman (1968) are still relevant.

The developed, calibrated and Altman's original models have experienced a considerable amount of misclassifications that are quantified as Type I and Type II Errors. Altman's original model has encountered maximum Type I Error for in-sample data. However, Altman original model experienced minimum Type II Error; this suggests that Altman's original model misclassifies the non-defaulted cases as defaulted.

The misclassification problem was not severe in the calibrated model as depicted by In-sample and out-of-sample classification results. However, the sectors namely Chemicals, Textiles, Miscellaneous and Complete Sample had plagued with Type II Errors which were 88%, 73%, 85% and 93% respectively for in-sample classification results. The Type I Error is below 20% for the in-sample data. The Type II Error is minimum for the out-of-sample data of all selected sectors except Pharmaceuticals sector that demonstrated 80% Type II Error. Nonetheless, the Type I Error ranges from 22% to 75% for the out-of-sample cases.

The Type I Error values are negligible in the developed model for the In-sample classification results. However, there are considerable rate of Type II Error found in the study for few selected sectors such as Steel and Chemicals that witnessed 84% and 69% Type II Error. The values of Type I Error for the out-of-sample data cases for sectors namely Chemicals, Hotels, Software, Steel are 71%, 85%, 75%, 74% respectively. The Type II Errors values for the validation cases are quite low for all the selected sectors except Complete Sample.

The developed MDA predicted the default event of the firms using the accounting variables such as NI/TA, WC/TA, EBIT/TA, RE/TA, TBD/TA which are consistent with Aguado & Benito (2013), Zmijewski (1984), Ohlson (1980), Altman (1968, 1993), While Chen and Shimerda (1981), (Casey & Bartczak, 1985), Shimerda (1981), Arlov, Rankov & Kotlica (2013), Jaffari & Ghafoor (2017). The market variable was incorporated to develop the MDA model for the Sugar sector this advocates the impact of market variants on the default prediction as stated by Chava and Jarrow (2001) and Hillegeist et al (2004).

The MDA model developed for Hotels and Plastic & Fibre sectors were most robust amongst all developed MDA models. The in-sample accuracy rate of the MDA model ranges between 70-90% which is commensurated with the accuracy levels achieved by Slefendorfas (2016), Jaffari & Ghafoor (2017), Abid, Masmoudi, & Ghorbel (2016), Altman E. I. (2006), Memic (2015), Liang Q. (2003), Hassan, Zainuddin, & Nordin (2018).

The Type I and Type II Errors for the In-sample classification results are at the lower side this interprets that the developed MDA models have less misclassification problem. The Type I and Type II Errors showed satisfactory predictive faculty of the developed model. These findings are in congruence with the predictive accuracies attained by Upadhyay (2019), Chen & Hu (2006), Liang Q.

(2003), Chijoriga (2011), However, it is contrary to Sheikhi, Shams, & Sheikhi (2012), Verma & Raju (2019), Altman E. I. (2006). The empirical results of the out-of-sample data were displayed with high Type I Errors for few selected sectors.

Altman's original model displayed poor accuracy rates across the selected sectors which is contrary to the predictive accuracy rates obtained in the studies namely Rayalaseema and Muhammad (2012), Altman et al. (2014), Celli (2015), Karamzadeh (2013), Verma & Raju (2019), Hayes, Hodge, & Hughes (2010).

References

Almansour, B. Y. (2015). Empirical Model for Predicting Financial Failure. American Journal of Economics, 1(3), 113–124. http://www.publicscienceframework.org/journal/ajefmhttp://creativecommons.org/licenses/by-nc/4.0/

Altman, E I, & Hotchkiss, E. (2006). Corporate financial distress and bankruptcy : Predict and Avoid Bankruptcy, Analyze and invest in Distressed Debt: Vol. null.

Altman, Edward I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy (pp. 589–609).

Altman, Edward I. (2006). Estimating Default Probabilities of Corporate Bonds over Various Investment Horizons. CFA Institute Conference Proceedings Quarterly, 23(1), 65–71. https://doi.org/10.2469/cp.v23.n1.3549

Altman, Edward I., Haldeman, R. G., & Narayanan, P. (1977). ZETATM analysis A new model to identify bankruptcy risk of corporations. Journal of Banking and Finance, 1(1), 29–54. https://doi.org/10.1016/0378-4266(77)90017-6

Ambika.T, & A, S. (2015). Determinants of Profitability of Selected Fertilizer Companies In India. 2015(09), 1–239.

Beaver, W. H. (1966). of Failure Financial Ratios as Predictors. Journal of Accounting Research, 4(1966), 71–111.

Begley, J., Ming, J., & Watts, S. (1996). Bankruptcy classification errors in the 1980s: an empirical analysis of altman's and ohlson's models. Review of Accounting Studies, 1(4), 267–284. https://doi.org/10.1007/BF00570833

Bhunia, A., & Sarkar, R. (2011). A Study of Financial Distress based on MDA. Journal of Management Research, 3(2). https://doi.org/10.5296/jmr.v3i2.549

Canbas, S., Cabuk, A., & Kilic, S. B. (2005). Prediction of commercial bank failure via multivariate statistical analysis of financial structures: The Turkish case. European Journal of Operational Research, 166(2), 528–546. https://doi.org/10.1016/j.ejor.2004.03.023

Duffie, D., Saita, L., & Wang, K. (2007). Multi-period corporate default prediction with stochastic covariates. Journal of Financial Economics, 83(3), 635–665. https://doi.org/10.1016/j.jfineco.2005.10.011

El-Ansari, F., & Benabdellah, P. M. (2017). Prediction of Bankruptcy: Evidence From Moroccan Agricultural Companies. The International Journal Of Business & Management, 3(6), 176–185.

Hassan, E. ul, Zainuddin, Z., & Nordin, S. (2017). A Review of Financial Distress Prediction Models: Logistic Regression and Multivariate Discriminant Analysis. Indian-Pacific Journal of Accounting and Finance, 1(3), 13–23. https://doi.org/10.52962/ipjaf.2017.1.3.15

Hayes, S. K., Hodge, K. A., & Hughes, L. W. (2010). A Study of the Efficacy of Altman's Z To Predict Bankruptcy of Specialty Retail Firms Doing Business in Contemporary Times. Economics & Business Journal, 3(1), 120–134.

Hoo-Ha, N., & Jinn Taehong. (2000). PDFlib PLOP : PDF Linearization , Optimization , Protection Page inserted by evaluation version Bankruptcy Prediction : Evidence from Korean Listed Companies during the. Journal of International Financial Management and Accounting, 11(3). https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-646X.00061

Huang, Z., Chen, H., Hsu, C. J., Chen, W. H., & Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: A market comparative study. Decision Support Systems, 37(4), 543–558. https://doi.org/10.1016/S0167-9236(03)00086-1

Jaffari, A. A. L. I. (2017). Predicting Corporate Bankruptcy in Pakistan A Comparative Study of Multiple Discriminant Analysis (MDA) and Logistic Regression. Research Journal of Finance and Accounting, 8(3), 81–100. https://core.ac.uk/download/pdf/234631944.pdf

Jones, S., & Hensher, D. A. (2004). Predicting firm financial distress: A mixed logit model. Accounting Review, 79(4), 1011–1038. https://doi.org/10.2308/accr.2004.79.4.1011

Kannadhasan, M. (2015). Retail investors' financial risk tolerance and their risk-taking behaviour: The role of demographics as differentiating and classifying factors. IIMB Management Review, 27(3), 175–184. https://doi.org/10.1016/j.iimb.2015.06.004

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking and Finance, 34(11), 2767–2787. https://doi.org/10.1016/j.jbankfin.2010.06.001

Lennox, C. (1999). Identifying failing companies: A reevaluation of the logit, probit and DA approaches. Journal of Economics and Business, 51(4), 347–364. https://doi.org/10.1016/s0148-6195(99)00009-0

Li, T., Zhu, S., & Ogihara, M. (2006). Using discriminant analysis for multi-class classification: An experimental investigation. Knowledge and Information Systems, 10(4), 453–472. https://doi.org/10.1007/s10115-006-0013-y

Liang, Q. (2003). CORPORATE FINANCIAL DISTRESS DIAGNOSIS IN CHINA : EMPIRICAL ANALYSIS USING CREDIT SCORING MODELS Author (s): Qi Liang Source : Hitotsubashi Journal of Commerce and Management , Vol . 38 , No . 1 (38) (October Stable URL : http://www.jstor.org/stable/. Hitotsubashi Journal of Commerce and Management, 38(1), 13–28.

Mičudová, K. (2013). Discriminatory Power of the Altman Z-Score Model. Ittera Scripta, 6(1), 95–106.

Mvula Chijoriga, M. (2011). Application of multiple discriminant analysis (MDA) as a credit scoring and risk assessment model. International Journal of Emerging Markets, 6(2), 132–147. https://doi.org/10.1108/17468801111119498

Ohlson, J. A. (1980). Ratios financieros y la predicción probabilística de la bancarrota. Journal of Accounting Research, 18(1), 109. https://www.jstor.org/stable/10.2307/2490395?origin=crossref

Rashid, A. (2011). Predicting Bankruptcy in Pakistan. Theoretical and Applied Economics, 18(9), 103–128.

Rashid, A., & Abbas, Q. (2011). Predicting Bankruptcy in Pakistan. Theoretical and Applied Economics, 18(9), 103–128.

Selvi, M. R., & Dheenadhayalan, V. (2014). An Analysis of Financial Health of Select Indian Bulk Drugs and Formulations Companies. Journal of Exclusive Management Science, 3(7), 1–14.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. Journal of Business, 74(1), 101–124. https://doi.org/10.1086/209665

Smaranda, C. (2014). Scoring Functions and Bankruptcy Prediction Models – Case Study for Romanian Companies. Procedia Economics and Finance, 10(14), 217–226. https://doi.org/10.1016/s2212-5671(14)00296-2

Stancu, & Stancu, D. A.-T. (2014). Predicting Company Performance By Discriminant Analysis. PROCEEDINGS OF THE 8th International Management Conference "Management Challenges For Sustainable Development," 1173–1180.

Wilcox, J. W. (1971). A Simple Theory of Financial Ratios as Predicators of Failure. 4, 71–111.

Zavgren, C. V. (1985). Assessing the Vulnerability To Failure of American Industrial Firms: a Logistic Analysis. Journal of Business Finance & Accounting, 12(1), 19–45. https://doi.org/10.1111/j.1468-5957.1985.tb00077.x