IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Predicting default of Pharmaceuticals sector using MDA, Altman, Calibrated, logit and Structural model

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Abstract

An attempt has been made in the present study to predict the default occurrence of selected pharmaceutical sector firms using MDA, Logit function and structural model. Study developed 2 models using MDA and Logit model, further study also evaluated the Altman original model and calibrated model by applying it on sample data of selected textile sector. The developed models have also been validated on the out-of-sample data. The study obtained satisfactory statistical results pertaining to the MDA and Logit developed models but not from Structural Model and Altman Z score model. Additionally, the classification results witnessed the following accuracies for MDA, Calibrated, Altman, Logit and Structural model such as 88%, 80%, 19%, 90% and 25%. The validation accuracies obtained by mda, calibrated and logit models are 37%, 37% and 92%.

Keywords: Altman Z score, Multiple Discriminant Analysis, Logistic Regression, Structural Model, Default Prediction, Bankruptcy Prediction, NPA, and Corporate Default.

Introduction

According to the annual report published during 2020-2021 by department of pharmaceuticals, Govt of India the Indian pharmaceuticals sector is the 3rd largest in the world and a leading supplier and manufacturer of DPT, generic drugs and Measles vaccines across the countries (India, 2022) (Pharmaceuticals annual report, 2021). Currently indian pharmaceuticals sector has a domestic market of US $42 billion during 2021 which will grow 3 times to reach US $ 120-130 billion in 2030 (Economic Survey, 2021).

Despite of growing global market for Indian pharmaceutical firms, the pharma sector has been facing multiple challenges such as business risk, market risk, high dependence on imported ingredients of drug, regulatory compliances, perpetual R&D, and Financial risk. Since, the pharma sector required extensive and perpetual research to innovate and discover affordable drugs for several diseases which is quite a capital intensive task. Due to excess need of capital there is always need to raise funds from various sources such as bonds, bank loan etc. In April 2022 Govt of India announced the new alternative of credit line for Indian pharmaceuticals firms i.e. loan against IPR.

Secondly, the high dependence of Indian pharma firms on the imported raw material of drug reduces their margins which impact the profitability and net income of the firms. Hence, the firms tend to default in the repayment of their loans. Firms namely Sun Pharma, Glenmark, Torrent pharma are amongst the most debt ridden Indian listed pharmaceutical sector firms. Further, there are plenty of listed Indian Pharmaceuticals firm which default in their loan repayment some of them are Advik Laboratory ltd, Avon life sciences ltd, bilcare ltd, parabolic drugs ltd, zenotech laboratories ltd, venus remedies ltd etc.

Therefore, the need of advanced default prediction arises. The future default can be predicted by using various statistical and non-statistical methods. The study of bankruptcy prediction is extensively conducted in the accounting and finance literature for categorizing solvent and insolvent firms. The is a significant role of financial distressed prediction methods for providing a guidance to the regulators, accountants, managers and other stakeholders of the firm for taking remedial measures in advance. There are mainly 3 statistical tools used to develop default prediction model i.e. MDA, probit and logit.

The bankruptcy problem is not limited to any sector or any country rather it's a global epidemic. The compulsory winding up of any firm due to bankruptcy has both economic and social costs (Edward I Altman, 1968). The default prediction and bankruptcy have a two way approach it impacts economy in one way and also get impacted due to reducing GDP rate, accelerating unemployment etc.

The evolution of credit risk model has been a continuous process which initiated during 1930's and still going on. The early studies such as FitzPatrick, 1932, Smith and Winakor, 1935 used univariate models for default prediction using single financial ratio. However, it did not predict default correctly. Later few pioneering works have been conducted using Z score, O-score models by Altman (1968), Ohlson (1980), Zmijewski (1984) and Shumway (2001). Where, Altman (1968) applied MDA for predicting failed and non-failed US firms by using 5 financial ratios which is followed by Deakin (1972), Altman (1973), Blum (1974), and Libby (1975).

Subsequently, Ohlson (1980) used O-score Logit technique in default prediction using firm-specific financial ratios which is followed by Mensah (1984). Similarly Zmijewski (1984) applied probit analysis using firm-specific financial indicators for predicting default prediction of U.S firms. Whereas, Shumway (2001) deployed dynamic analysis for default prediction and classification of failed and non-failed firm. Further, studies such as Hardle (2005), Chen (2011) applied support vector machines for default prediction of firms.

The present study is divided into 4 sections for predicting the default of indian pharmaceuticals sector firms. The first section includes introduction, literature review, objectives and hypotheses of the default prediction models. The second section included research methodology in which study described the sources of data, default prediction models used in the present study, variables used in the default prediction models. The third section depicts the empirical results pertaining to the developed models and existing models. The fourth section explained in detail the conclusion of the study with reference to the obtained results of the models.

Literature Review

MDA (Multiple Discriminant Analysis)

Altman (1968) presented MDA for credit risk modeling by including five financial ratios such as WC/TA, RE/TA, EBIT/TA, MVE/BV and Sales/TA. The study used the paired sample of the 33 defaulted and 33 non-defaulted manufacturing firms. The model categorised the firms with 90% accuracy. MDA has been extensively applied by numerous scholars across countries and sectors such as Altman (2006), Bandyopadhyay (2006), Chijoriga (2011), Khaddafi, Falahuddin, Heikal, & Nandari (2017). Agarwal & Taffler (2008) had advocated that MDA outperform the market-based BSM model, further, Casey & Bartczak (1985) too recommended MDA over UDA.

MDA Model

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 (W. H. Beaver, 1966).

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 (T. 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 (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 present study attempts to apply mixed-effects models for predicting Loss Given Default of US corporate bonds referred from Moody's using STAT. The analysis shows that model is capable to decode the unobservable heterogeneity and predict more accurately than the linear regression and fractional response regression (Yao, 2014).

Ariesta (2015) evaluated whether the Z score is feasible to predict the financial soundness of 42 listed and 15 delisted banks of Indonesia. The sample data included share price information that was accessed from the Indonesian stock exchange and financial ratios. The study concludes that some of the delisted banks are in the safe zone and few are in the grey zone which signifies that the listed companies do not all the time have a sound financial situation (Ariesta, 2015).

A paired sample data for the span of 2007-2013 of 145 Lithuanian companies were examined using MDA. The empirical results of the model presented 89% accuracy in the classification of the firms into defaulted and non-defaulted (Šlefendorfas, 2016).

The prediction probability of the default and the financial profitability of Kuwait firms are examined to test the profitability of these firms for investment purposes. This study developed Altman Z score and Zmijewski models for 196 firms for the period 2009-2014. The sample data was obtained from annual reports & financial statements available on the Kuwait stock exchange website. The study concluded that the Altman Z score grouped the firms into safe, distressed, & grey zone accurately than the Zmijewski model which provides results that was contrary to Altman (1968) (Chadha, 2016).

Edward I Altman (2017) aimed to review the efficiency of the Altman Z score and Z" score model and its applications in predicting bankruptcy of both manufacturing & non-manufacturing companies. Earlier, the Model applied to only small and middle-sized US manufacturing firms and subsequently, on different industries across the countries. The study reviewed 34 scientific papers (2000), 32 European and 3 non-European Papers. The model performed both effectively and ineffectively in different papers. There was no single study that can be used to generalize the result. The study concluded that the prediction accuracy improved when the model was developed particularly for a specific country (Altman et al., 2017).

The original study of MDA was conducted by the Altman (1968) in which a set of 5 financial ratios were investigated to predict the insolvency of the firm. The sample data for the period 1946-1965 contains the paired sample of 66 firms concerning the financial ratios that cover the various aspects of the company's financial position such as liquidity, profitability, leverage, solvency and activity ratios. The ratios collaborated in the model were WC/TA, RE/TA, EBIT/TA, MV OF EQUITY/BOOK VALUE OF DEBT, S/TA. The developed model accomplished the prediction process with 95% accuracy (Altman, 1968) lately, Mohammed & Soon (2013) supported the original Z score model followed by Babatunde, Akeju, & Malomo (2017) who has applied the Z score on the sample data of 10 Nigerian listed firms. The Z score model can be used in the pricing of bonds and can be utilized by regulators, auditors for checking the bankruptcy risk (Altman, 2018).

The study aimed to evaluate the financial management capacity of the firms using Z and Zem scores to measure their bankruptcy risk. The study concluded that the poor financial management results in bankruptcy and ROE impacts the most on the prediction accuracy of the Model (Basovníková et al., 2018).

MDA vs Other models

Studies such as Mihalovic (2016), Hassan, Zainuddin, & Nordin (2017), Gurny & Gurny (2013), Sirirattanaphonkun & Pattarathammas (2012) suggested Logit model over MDA. On the contrary Jaffari & Ghafoor (2017), Memic (2015) supported MDA. Liang Q. (2003) revealed that though Logit is more accurate but it has poor classification skills. Djamaluddin, Putridan, & Ali (2017) compared the prediction capacity of Z score, Ohlson Y score and Zmiejewsi X score model, the result of which indicates that Ohlson Y score stood out amongst other models followed by Z score and Zmijewski. The survival probability of the Shinkin Bank was estimated by using the Z score, Kaplan Meier method and Cox model hazard model. The study concluded that the Z score is one of the efficient models which can be used to analyse the survival probability (Iwamoto & Mori, 2011). Gupta (2017) supported the Z score in comparison to the original Altman Z scores for predicting the credit risk of an emerging market. Agarwal & Taffler (2008) concluded that accounting-based models such as the Z score defeated the market-based models in the prediction of bankruptcy reason being Z-score is popular amongst banks for making lending decisions. Pang & Kogel (2013), Muminovic (2013) asserted to apply sector-specific models rather than a generic model Z score model. Altman, Haldeman and Narayanan (1977) documented an advanced version of the Z score model called Zeta models that incorporated variables from Altman (1968) original model which provided the higher accuracy than the earlier Altman (1968) model. Altman (2007) developed two credit risk models Z-score and Zeta 1977, study used F test to figure out the main indicator of the default risk. The result indicated that the

Zeta score predicted the default probability accurately for 5 years whereas the Z score predicted the default risk for 2 years only.

The comparative study of the MDA and Logit model was conducted by Altman & Sabato (2005) for developing a one-year default prediction model. The study documented the higher accuracy for Logit model and further advocated to apply the separate model for SMEs for improving the prediction capacity. Ali (2015) prepared 3 credit risk models namely Altman (1968) Z score, Zeta and Z3 model for mapping the drift of private and public firms of Iraq for the period 2004 to 2013 towards bankruptcy and to group them into various categories. However, the study did not achieve the desired results like the Al-Dalayeen (2016). The study reviewed the original Z score, Z' and Z" over the listed Colombian firms for the period from 1986 to 1997. The findings of the study recommended using Z score over the other models (Samarakoon, Lalith; Hasan, 2003). This study developed 3 models namely structural, accounting-based and hybrid model that incorporates the properties of former models. The study suggested using the hybrid model because it complements the limitation attached to the accounting and market-based models (Baixauli et al., 2012).

William Gang Li (2014) applied the Altman bankruptcy model to predict the financial distress of the Construction industry in North America. The sample data encompasses 108 defaulted and non-defaulted entities for the period during 1985-2013. Alongside, the study also compared the accuracy of the Altman model by developing a new calibrated model by adding few more variables. Numerous classification tests have been conducted using techniques such as Naive Bayes, Logit Regression, SVM, K N_Neighbors, Grid search. The result of all the techniques was similar except the SVM and Grid search that outperformed other default prediction models. Additionally, the result stated that there is no considerable difference between the performance of the original Altman and calibrated model (W. G. Li, 2014)

Logistic Regression

Ohlson (1980) developed a credit risk model using statistical method called the Conditional Logit model that does not need to meet the assumptions required for MDA. The model attained 88% accuracy on the sample data of 105 listed firms (Zvaríková & Majerová, 2014). The Logit model was introduced by Martin (1977) that classified the distressed and non-distressed banks. Later on Andersen (2008) applied the Logit approach to determine the most appropriate predictors of Norwegian bank failure. The study incorporated 23 financial and non-financial variables out of which 6 variables are found to be the best fitting.

The assumptions of MDA such as the normal distribution of variables and equal variance and covariance matrices of defaulted and non-defaulted firms have been violated in many studies which paved a way for the Logit or O-score model (Ohlson, 1980). According to Thomas, Edelman, & Cook (2002) Logit is the most used statistical method in the field of prediction of default where the dependent variable is binary. The binary result of the conditional Logit model describes the default probability and provides a list of significant variables (Balcaen & Ooghe, 2006). Studies that used the Logit model are Kwofie, Ansah, & Boadi (2015), Bartual, Garcia, Guijarro, & Romero-Civera (2012), Bewick, Cheek, & Ball (2005), Bandyopadhyay (2007).

Thereafter, the Multi-period Logit framework was brought up by Shumway (2001) which included time-varying variables for predicting failure. This model stood out against the single period Logit model.

Jones & Hensher (2004) & Train (2002) advocated the use of the Mixed Logit model to label the firms into non-failed, insolvent firms, and the firms filed for bankruptcy. This Model grouped the firms with high accuracy, result of the model shows that the mixed Logit model stood out in the prediction and classification of firms into appropriate categories. The Mixed Logit is the most recently developed technique. Wooldridge (2009) criticized the Logit model for over prediction of the bankruptcy risk.

Logit model

A corporate failure prediction study of 105 bankrupted and 2058 non-bankrupted firms was conducted using a conditional Logit model. The study developed 3 models where, the first model predict bankruptcy within one year, the second within 2 years, the third model predicted the bankruptcy within one or two years for the period 1970-76. The study denoted the size of the firm as the key predictor of financial distress. The findings of the study unearthed that financial factors surge the predictive power of the model. Further, the results of the study was validated by Memic & Rovcanin (2012) (Ohlson, 1980).

Lau (1987) develops a model which can predict the probability that a firm shall enter into every five financial states such as 0: financial stability; 1: Omitting and reducing dividend payments; 2: technical default and default on loan payment; 3: protection under chapter X or XI of the bankruptcy act; and 4: bankruptcy and liquidation. The result of the study exhibits that the Multinomial Logit model is robust to perform the estimation (Lau, 1987)

The default risk of Norwegian limited companies that belongs to the Agriculture, Construction, Industry and Service sector for the period 1995-1999 was estimated using Logistic regression by integrating financial ratios into the model. The findings inferred that model is static, helpful for a short time horizon only (Westgaard & Van der Wijst, 2001).

This study has reviewed various tests of logistic regression namely the hosmer lemeshow test, R square test, wald test which examines the goodness of fit, the utility of the model and measures the importance of individual coefficients. The model was applied to medical research to investigate that how death and survival of patients can be predicted by logistic regression which provides binary outcomes i.e 0 and 1 (Bewick et al., 2005).

Zeitun (2007) attempts to explore the role of cash flow on the financial distress of 167 listed Jordan companies for the period 1989-2003 in an emerging market using panel data of the paired sample by employing the Logit function. The findings of the study were: the capital structure determines the probability of default, cash flow is a significant indicator of default & the financial position of the firm directly impacts the management practice (Zeitun et al., 2007).

Lieu (2008) proposed an early warning model using Logit regression for 116 (58 distressed and 58 non-distressed) listed Taiwanian firms for the horizon of 5 years from 2002 to 2007. The model provided the risk probability for 1-3 years before the event using financial ratios. The financial ratios are found to be key indicators of credit risk modeling. The result of the study is consistent to Holian & Joffe (2013) (Lieu et al., 2008).

Frade (2008) aims to create a model which can predict that 186 US issuers shall default within a year. The study used financial ratios and value of equity as the independent variables that incorporated Logistic, Altman Z score, Barclay's & bond score CRE default model. The data related to financial and market information was collected for the period 1996-2008. It is evident from the findings of the model that all the market variables are not significant predictors in a logistic regression model (Frade, 2008).

A binary logistic model was developed for examining the Chinese SMEs from the year 2004 to 2007. The study concluded that only financial indicators are not enough to predict insolvency therefore, it’s imperative to include qualitative indicators for eg the Type of ownership that would accelerate the model’s accuracy (Wang & Zhou, 2011).

The study applied the regularization approach along with Logit to develop a default predicting model for South-Asian companies and to identify the significant predictors of default. The outcome of the study does highlight that the higher accuracy, depicts that the regularization approach is well capable to forecast and to select the default predictors for Indonesia, Singapore, and Thailand countries (Härdle & Prastyo, 2013).

A credit risk model was developed for predicting the distress of the listed manufacturing firms of Tehran using the Logit function. The financial data was accessed from 2001 to 2008. The robustness of the model was examined using the AUROC curve which illustrated the acceptable results (Moghadas & Salami, 2014).

This study focused on predicting the default of Hong Kong firms by incorporating the logistic and jackknifes functions along with the variables that are retrieved from financial, non-financial firm-specific & economic information of the firm. The findings suggested the high robustness of the model coupled with the significant contribution of all deployed variables (Hu & Sathye, 2015).

Kwofie (2015) evaluates the model developed for default prediction of financial companies. The independent variables considered in the study were age, marital status, gender, number of years of education, number of years in business and base capital. The study found that marital status, number of years in business and base capital were significant predictors of default. However, the model failed to provide an accurate prediction (Kwofie et al., 2015).

These studies aimed to increase the predictive power of the LDA and Logistic regression model using principal component analysis. A set of 200 applicants of the Bank of Nigeria was selected as a sample. The result exhibits that the principal component used as input that enhances the predictive capability of LDA and logistic regression ((Suleiman & Usman, 2014) & (Mcdonald & Maloy, 2015)).

Manjusha Senapati (2016) builds a model for predicting the probability of insolvency of non-financial listed firms and to anticipate the distressed bank debt. The sample data for the span of 2006 to 2014 integrated into multivariate logistic regression along with financial ratios namely Debt/TA, OP/TL, and CA/CL. The model was found competent to diagnose the failure, illness of the companies. Findings of the study outlined that the model identified the distressed bank debt one year before the bankruptcy (Senapati & Ghosal, 2016).

The study developed a model for predicting financial distress in advance by integrating logistic regression with panel data of Brazilian listed firms from the year 2011 to 2014. The independent variables included in the model were financial and macroeconomic variables. The variables are found statistically significant. Results further demonstrated that about 96% of the firms were financially distressed. The study displayed the important predictors namely quick ratio, asset turnover, and NE/TL (Rezende et al., 2017).

A Multiple Logistic regression model was developed to recognize the major indicators of student loan default in Kenya. The study used ANOVA test for measuring the statistical strength of the developed model. The sample data was accessed from the 5100 Kenyan student loan account for 2009 to 2014. The covariates incorporated in the study are loan amount, overdue days, age, interest rate, employer, gender, marital, father's education. The result signifies that the model performed well and the major indicator of loan default was the loan amount itself (Kamau, Muthoni, & Odhiambo, 2018).

The credit risk model was developed for the US banks using logistic regression for the time horizon from 1 to 5 years by integrating the financial ratios in the forward stepwise selection method. The result indicated a high classification power of the model for one year only (Tong, 2015).

Logistic Regression vs Other Models

Since 1980 scholars namely Ohlson (1980), Lennox (1999) developed a default prediction Logit model using 9 independent variables and achieved considerable accuracy for predicting bankruptcy up to 2 years before the bankruptcy event. Altman & Sabato (2005), Abid, Masmoudi, & Ghorbel (2016), Khemais, Nesrine, & Mohamed (2016) conducted a comparative study of different models for developing a credit risk model of SMEs and confirmed that the logistic regression outperformed MDA. Lennox (1999) advocated that the Logit model overcome the limitation of the MDA function. Theodossiou (1991) also recommended Logit over Probit.

Castagnolo & Ferro (2014), Hasan (2016) & Kumar & Kumar (2012) examined the predictive capacity of O-score, Z-score, Hazard model, and Merton's distance to default model. The result disclosed that the O score surpasses the Z score but couldn't supersede Hazard, Merton's DD model and SVM model. Nehrebecka (2008) depicted that the logistic regression outshines over SVM while predicting credit risk in contrast to (Dima & Vasilache, 2016) who favoured the artificial neural network. Soureshjani & Kimiagari (2013) supported both Logit and Neural Network. Reza Raei (2016) developed a hybrid model consisting of Logit and Neural network for default estimation of the Tehran firms. The empirical results of the study unfolded that the hybrid model is best fitting than the individual Logit model and neural network model (Raei et al., 2016). Shah (2014), Berardi, Ciraolo, & Trova (2004) used Logit and Reduced-form model for predicting the default risk, measuring the impact of the portfolio's risk and returns of expected changes on the default probability of the US market bond for the year from 1997 to 2001. The findings of the study suggested the higher predictive capacity of the Logit over Reduced Form model.

Structural Model

Off lately, the Structural Model is the most relevant function used for the credit risk modeling that incorporates the market-based information unlike the credit scoring models ((Vassalou & Xing, 2004), (Kealhofer, 2003)). Several leading authors contributed to the literature of structure models namely Vasicek (1984), Longstagg & Schwartz (1995), Hull & White, Collin-Dufresne & Goldstein (2001), and Duffie, Saita, & Wang (2005) that highlighted the higher accuracy of the Structural Model in the default prediction process. The Structural Model was incepted by Black & Scholes (1973) & Merton (1974). The Structural Model is based on option pricing approach in which a firm's equity is treated as a call option value of firm's assets (Geske, 2016).

The Structural Model has been criticized by Jones, Mason, & Rosenfeld (1984), Franks & Torous (1994), Sarig & Warga (1989), Ogden (1987) which asserted that real risk exposure is considerably higher than the model risk exposure. Eom, Helwege, Huang (2003) & Hillegeist, Keating, Cram, & Lundstedt (2004) specified that the lower leverage and volatility of firm are the main causes of underprediction of default. Therefore, the following studies advised to insert accounting-based variables namely Shumway (2001), Chava & Jarrow (2004) and Baixauli, and Alvarez, & Modica (2012) to build a default prediction model of 8000 listed companies of US and Canada and achieved substantial accuracy. Bharath & Shumway (2008) stated that the Merton model is not a sufficient method to explain the default and drivers of default. Further, Altman & Saunders (1998) condemns its inapplicability on Pvt Firms.

Longstagg & Schwartz (1995) and Leland & Toft (1996) extended the Structural Model by suggesting stochastic interest rates to be included in the Structural Model and considering the impact of cost of default and taxes on the prediction model that made the model more flexible and pragmatic. To overcome the limitation of the BSM model Moody's KMV (2004) revised the Structural Model called the Vasicek-Kealhofer (VK) model by introducing a concept of Distance to Default (DtD) to predict the default frequency. Moody's KMV approach has 4 steps: Estimating asset value and volatility, ascertain default boundary, compute DD & convert DD to default probability. The KMV model assumes the strike price of the option is equal to the face value of the total debt. The distance to default has been suggested by Bharath & Shumway (2008), Benos & Papnastasopoulos (2007) & Duffie, Saito, & Wang (2007) as a significant predictor.

Falkenstein et. Al (2000) applied Moody's KMV model for computing the distressed risk of private firms data consist of a sample data of 28104 non-distressed and 1604 distressed firms. The empirical findings unveiled that by analysing balance sheet data accompanied by market variables escalates the prediction power of public listed firms for a time horizon of 1 to 5 years (Falkenstein et al., 2000).

Moody's KMV 2003 computed the expected default frequency of 250000 company years data including default firms data of 4700-year firms by including variables such as firms asset value, default point, the book value of debts, & volatility of assets at time T. The study adhered to the assumption of BSM that the firm triggers to default when its net worth becomes zero (Kealhofer, 2003).

Hayne E Leland (2004) predicted the default probability of corporate bonds rated by Moody's for the period commences from 1970 to 2000. The model did perform the prediction quite accurately for the long term bonds than the short term bonds. The study also examined the exogenous and endogenous default boundary and its implication on the capital structure and rating methods (Leland et al., 2004).

The Merton-model approach was applied to predict the bankruptcy of individual UK companies and a group of bankrupt companies during 1990-2001. The study stated the advantages of the model for indicating failure one year prior. The study compared the model to Reduced Form model and proclaims that the Structural Model outshines the Reduced Form model for a horizon of 1 year. On the contrary the Reduced Forms model outperforms when prediction is conducted marginally (Tudela & Young, 2005).

The study employed a Structural Model for describing financial distress. The sample data was collected from 420 failed US firms from 1986 to 2001. The result signifies that a firm's volatility is the best determinant of bankruptcy for 5 years prior. Besides this, D2D is also a significant indicator of bankruptcy. The distances to default (d2d) and the probability of default at maturity (-d2) were found as the significant predictors of default (Charitou & Trigeorgis, 2005).

This study proposes an econometric method for forecasting the term structure of default probabilities for multiple future periods. The sample data comprised of 2700 US-listed companies for 1980-2004. The sample data of the bankruptcy firms was collected from Moody's default risk service and CRSP. The empirical result unveiled that the Structural Models along with macroeconomic variables can provide better estimation (Duffie et al., 2007).

This study investigates the performance of the indicators generated using the Merton Model to predict the bankruptcy of corporate in Australia for the period 1990-2003 by applying a multiperiod Logit model. The sample data of the failed companies was obtained from www. Delisted.com. The study exhibits that the Merton model significantly predicts bankruptcy. The study revealed that the TL/TA ratio and idiosyncratic standard deviation of stock returns are remarkable indicators of the failure (Tanthanongsakkun et al., 2010).

Tarashev (2011) attempts to examine the performance of various Structuralcredit risk models. The study recommends that leverage ratio, default recovery rate and risk-free ROR impacts the prediction power of model. The findings suggest that the appropriate model to predict the default is an endogenous model group that provides impartial prediction. This study also substantiate that the Structural Model unveils material information about the time pattern of default rates (Tarashev, 2011).

Ahmad & Wahab (2012) documented some of the distinguished attributes and assumptions of Moody's Structural Model such as the default triggers when a firm's asset drops below the threshold limit or when the firm's net worth reached zero even before the maturity of the debt. The default position of the firm also get impacted by the market variables like market value asset of the firm; its equity, its market volatility etc. The study further exemplified the role of macroeconomic variables and their interdependence for instance recession brings more default occurrence than the boom. The 2008-09 financial crises is the classic example that ends up spreading the epidemic of bankruptcies which culminate into the growth of NPAs (Ahmad & Wahab, 2012).

The study aims to assess the performance of credit scoring and Merton based model for predicting insolvency of 246 UK SMEs from 2001 to 2004. The performance of the models was tested for 4 years using AUROC. The Merton model is used to calculate DD and EDF in the study. The credit scoring model performed better with the sample group by incorporating a sufficient number of bankrupt firms consequently, the Merton performed quite well with higher acceptance rates (Lin et al., 2012).

The study employed a hybrid model which is an amalgamation of option and accounting-based models. The sample data consists of financial information collected from Compustat annual file for the span from 1970 to 2006. This study witnessed that the option-based model performed better than the accounting-based model for discriminating companies. The hybrid model defeated both option based and the accounting-based model (Tsai et al., 2012).

The study inscribed that according to the theoretical framework of Structural Models default occurs when the market value of assets of the firm drops down a certain solvency boundary. Nevertheless, they would be wrong in prediction and classification. Hence the study evidence that the application of the empirical parameters is advantageous to boost the model's predictive competency remarkably. The sample comprises of bond issuers who defaulted from 1997 to 2005 (Davydenko, 2013).

Dwyer (2004) developed a default prediction model for private firms by incorporating Moody's KMV (2003) approach. The purpose of the study is to facilitate the commercial banks to earn profitability by correctly computing the risk associated with the debt of private firms using innovative techniques of default prediction. The developed model outpaced the earlier developed models (Kmv et al., 2015).

The study develops a model using the KMV model which applied a genetic algorithm and also compares it to the KMV model. The samples were selected from bankrupted companies listed in the Tehran stock exchange for the period from 2009 to 2014. The result indicates that the developed model is well capable to predict bankruptcy and discriminate the firms better than the KMV model (Hasanzadeh & Yazdanian, 2017).

The study prepares a default predicting model using the Black Scholes formula for the european call option. This study describes the indicators of default namely firm value, FV of debt, expected return, time, and volatility. The findings advised that the probability of default reduces when firm value enhances. Whereas, probability of default escalates if future value of debt hike, expected return increases, time period extends, and volatility rises (Ahmad Dar et al., 2017).

This study explores the performance of the Merton model by employing the implied volatility and implied cost of capital for predicting defaults. The outcome of the models is compared with predictions obtained from another popular model. The result unveiled that the Merton model performed pretty well in comparison to the other models with 89% accuarcy (Miao et al., 2018).

Structural Model vs Other models

Patel and Pereira (2005) and Wang & Suo (2006) examined the Merton (1974), Black & Cox (1976), Longstagg & Schwartz (1995) and Leland & Toft (1996), Ericsson and Reneby (1998) and Collin-Dufresne and Goldstein (2001) models for predicting the expected default probabilities. The selected models provided consistent results yet the misclassification occurred because of special company management and/or regulatory circumstances (Patel & Pereira, 2007) that is contrary to Wang & Suo (2006) that supported Merton (1974). VK (Vasicek- Kealhofer) model performed significantly better than other models however, in the case of multiple bonds the Reduced Form model turned out as the best predicting model (Crossen & Zhang, 2011). The option-based models perform pretty well than the Z score model, it also ranked the firms as per their financial health (Gharghori et al., 2006). On the contrary Agarwal & Taffler (2008), Hillegeist, Keating, Cram, & Lundstedt (2004), Miller (2009) recommended the BSM model over MDA and Logit since it is based upon market variables data.

Other Models

The motive of this study is to build a model for estimating bankruptcy more effectively and accurately using a hybrid model accompanied with independent variables namely the firm’s age, Altman variables, Zmijewski's variables, and market information. Findings of the study recommended that the hazard model outperformed the static models when it is integrated with market size, past stock returns, and idiosyncratic returns variation (Shumway, 2001).

Du (2003) intends to employ a hazard model to quantify the credit rating and its variability. This study confirms that a Multiple hazard model can be developed using standard logistic models. The study evidenced that the hazard model outperformed the traditional models in the area of prediction probability. The study also proved that the duration effect and momentum effect influence the probability of credit rating variability (Du, 2003).

The study used Reduced Form model to measure the probability of default of global bonds of 12 emerging markets for the period 1997-2001, to recognize the impact of the probability of default on portfolio risks and returns of different default probability expectations. The study demonstrates that a key indicator of default probability is capital market variables. The study reveals that the predicted default likelihood is close to the original data observed during the same period (Berardi et al., 2004).

William H. Beaver (2005) examined the capacity of financial statement data for predicting the bankruptcy by incorporating ROA, ETL, and LTA ratios together with market-based variables into the hazard model. The results demonstrated that the ratios are core predictors that substantiate the prediction accuracy. Nonetheless, the study unveils that the combination of both market and accounting ratios are no longer significant for prediction during the period from 1962-2002 (W. Beaver et al., 2005).

Beaver, Mc Nichols, & Rhie (2005) advocated that market-based variables provide more information than the accounting-based variables. Hence, Shumway (2001) and Beaver, Mc Nichols, & Rhie (2005) recommended combining both sorts of variables to get more accurate and unbiased prediction.

The Reduced Form model works on the different assumption that contrasts to the earlier developed static models. The Reduced Form model has an assumption that default is exogenous and it is a random event that can occur at any point in time without declining the value of assets (Jarrow & Turnbull, 1995). The Reduced Form model has been introduced by Jarrow & Turnbull (1995) and followed by Duffie & Singleton (1999), Jarrow, Lando, & Turnbull (1997).

Cox (1972) originated the proportional hazard model to diagnose the default risk of debt. It is an advanced method of default prediction which discloses the time of failure accompanied by the status of the default position of the firm (Cox, 1972). Successively, Lane, Looney, & Wansley (1986) compared the accuracy level of the hazard model against MDA. Findings of the study suggested that the performance of both the models were comparable for one-year prediction, however, the hazard model stood out against MDA when the time horizon increased to 2 years. Whalen (1991) had also witnessed similar results and concluded that the hazard model has emerged as an outstanding early warning approach of default prediction having least Type I and Type II Errors. The hazard model successfully ascertains the most appropriate predictors of failure Wheelock & Wilson (2000). The Reduced Form model is better than the Structural Model because it does not require information regarding the capital structure of the firm (Bharath & Shumway, 2011) (Duffie & Singleton, 1999). This model can predict the corporate default over multiple periods (Duan, Sun, & Wang, 2012). The Hazard models surmount the drawbacks of earlier models since it calibrates itself according to the time, information and best fitting for validation purpose (Shumway, 2001).

According to Jarrow & Turnbull (1995), Duffie & Singleton (1999) the Reduced Form Model does not based on the condition that default is determined by the value of the firm, asset volatility and leverage, instead of determining the default, the hazard models attempt to ascertain the survival time of a credit event. Therefore, along with predicting the probability of default, the model can also approximate the time of default, the model also relaxes the assumption regarding the distribution of independent variables (Whalen, 1991).

Luoma & Latitinen (1991) criticized the hazard model by stating that prediction of default time can be affected by the period when information gets released. One of the drawbacks of the Reduced Form model is when it is being employed by observant variables it provides underestimated default prediction (Koopman et al., 2009).

The study develops a credit distressed testing method that incorporates a bottom-up default prediction model which translates shocks into covariates to get the risk of default of a particular portfolio. The study included 7 macroeconomic variables into the hazard model that are found as the key indicators of default. The findings elucidated that model is significant for the in-sample testing but insignificant for the out-of-sample data test (Duan & Wang, 2012).

The study develops an early warning model to predict default by incorporating Forward Intensity Model. Study depicted that the banks in distress might exit through various modes for instance acquisition and nationalization instead of default. The result of the model conveys that by including distressed exits as a variable the prediction accuracy can be enlarged and the prediction can be conducted for 5 years (Chen & Laere, 2012).

This study has recommended a hazard model over static model. The hazard model encapsulates an accounting-based and Structural Model. The static model does not consider the information of non-defaulted companies which leads to bankruptcy in the future years. In contrast hazard model provides an adjusted result that was found more rigorous (Foster et al., 2013).

This white paper is the outcome of a Credit Research Initiative that applied a Forward Intensity Model for predicting the probability of default of public listed firms by examining its financial, market, and economic data. The result delineates that this model is more efficacious in measuring credit risk from 1 month to 5 years' time horizon (The Credit Initiative, 2019).

Pharmaceuticals

This study evaluated the Pharmaceutical firms namely Dr Reddy's Lab, Cipla, Sun Pharma, Ranbaxy, Lupin Ltd, Aurobindo, Cadila health care etc by applying Altman's Z score together with a set of financial ratios for 1 year from 2013 to 2014. The concluding remarks given in the study were: firm's capital structure is a combination of both debt & equity hence; the firm must use different models which are best fitting in the sample data to predict financial health and take remedial actions (T & M, 2015).

Behera (2016) used Altman Z score to examine the financial distress of 6 BSE listed Pharmaceuticals firms namely Cipla, Lupin Aurobindo Pharma, Aarti drugs, JB Chemicals and Indoco for the period from 2005 to 2014. The calculated Z score of 6 companies was approximately 2.9 that suggest that the firms are financially stable and secured. Nonetheless, Aarti drugs went into the grey zone from 2006 to 2008 but will not get bankrupted in the next 2 years. Therefore, it is required for the company to take proactive measures to enhance the liquidity and funds of the firms (Behera, 2016).

The study categorises Pharmaceutical firms into healthy, grey and bankrupt groups using Z score. The study concluded that the firms should focus on expanding the assets, reducing the liabilities to improve the financial position and for the growth of the firms. Moreover, study stated that if firms experience declining assets and increasing liabilities for long period it can cause bankruptcy (Geethalakshmi & Jothi, 2017).

A study was conducted on the 4 Indian Pharma companies during period from 2012-2017 for the prediction of default probability using Z score model. The result reveals that the Z score is 5.90 which is far above the threshold of 1.8, this indicates that the firms are financially healthy and not going to default in near future. The drawback of the study is that the findings of the study is based upon the small data of a single sector of one country only , that hinders the generalization of the findings for the other countries and sectors (Panigrahi, 2019).

Objectives

- To develop models using MDA and Logit function for selected pharmaceuticals sector
- To predict default of Indian pharmaceuticals sector firms using Altman, Calibrated and Structural model.
- To Validate developed MDA and developed Logit model on out-of-sample data of selected Indian pharmaceuticals sectors.
- To compare the statistical and default prediction significance of developed and existing model.

Hypotheses of MDA Model are:

Hypothesis 1:

H_0: The covariance matrices are equal in both the groups namely defaulted and non-defaulted made by dependent variables of the developed models.

H_1: The covariance matrices are not equal in both the groups namely defaulted and non-defaulted made by dependent variables of the developed models.

Hypothesis 2:

H_0: There is no discriminating power in the independent variables of the developed models.

H_1: There is a discriminating power in the independent variables of the developed models.

Hypothesis 3:

H_0: The mean of each independent variable between the defaulted and non-defaulted groups of developed models are equal.

H_1: The mean of each independent variable between the defaulted and non-defaulted groups of developed models are not equal.

Hypotheses of Logit model:

Hypothesis 1:

H_0: The independent variables of the developed models have no significant impact on its dependent variable.

H_1: The independent variables of the developed models have significant impact on its dependent variable.

Hypothesis 2:

H_0: The developed models are correctly specified and best fitting.

H_1: The developed models are not correctly specified and best fitting.

Hypothesis 3:

H_0: The corresponding coefficient to each independent variable of each developed model is zero.

H_1: The corresponding coefficient to each independent variable of each developed model is not zero.

Research Methodology

The study incorporated the sample data for 15 years' time horizon from 1st April 2004 to 31st March 2019 to develop the credit risk models and to predict the default probability. The sample contains data of Indian BSE listed Pharmaceuticals firms collected. **In-Sample data** is used to develop the model and second part of the sample data called **out-of-sample** is used to validate the developed models.

Table No 1 Description of Sample Data for Pharmaceutical Sector

S.No	Sector	Total no of Defaulted Firms	Total no of Non-Defaulted Firms
1	Pharmaceuticals	15	19

Data Sources

The study collected the company specific information such as the accounting, market and macroeconomic data of the selected Indian firms from various sources. The accounting data was fetched from the individual financial statements of each selected firm and share price information was retrieved from the BSE website. The macroeconomic data such as interest rate and GNP index were collected from the database maintained and uploaded on the websites of RBI and World Bank. The information about the default status of selected firms is sourced from the audited annual reports of all selected firms for 15 years from 1 April 2004 to 31st March 2019. The sample data of the proxy interest rate of 91 days Treasury bill is collected from the database maintained by Reserve Bank of India on its website. The information about the daily average price of shares, return on the shares, BSE index and return on BSE index of the selected firms is collected from the BSE website.

Default Prediction Methods used in the study

In light of the previous literature review, the study selected 5 default prediction methods to predict the default status of the selected firms namely MDA (Multiple Discriminant Analysis), Calibrated, Altman Original model, Logistic Regression, and Structural Model to provide the comparative analysis of the Classification results of these function. The conceptual frameworks, mathematical processes of each applied method have been discussed in detail below.

Independent Variables used in MDA Model

The present study has used 21 independent variables for predicting the default probabilities that belong to accounting, market and economic variables.

Table No 2 Description of Independent Variables of MDA

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		

Independent Variables Used in the Logit Model

This model has incorporated 23 independent variables to predict the default probability. The Independent variables are comprised of accounting variables, market variables, economic and categorical variables. Logit model incorporated 2 qualitative variables namely X and Y along with 21 accounting, market and economic variables that are integrated into the MDA model.

Categorical Variables

1. **X**= 1, TL >TA and **X**= 0, TA>TL

2. **Y**=1, Avg NP for 2 years < 0 and **Y**=0, Avg NP for 2 years >0

Independent Variables of Structural Model

The variables employed in the Structural Model are the Market Value of the firm's Assets, book value of the outside liability and drift rate that is used to calculate the probability of default which has been accessed from the financial statement and market-driven information.

Empirical Results

Models developed using MDA

Z = -0.074-5.789*EBIT/TA-7.802*NI/TA-2.746*WC/TA+1.726*TBD/TA+10.259*RE/TA

Models developed using Calibrated Model

1.24-2.501* WC/TA +10.884* RE/TA -12.904* EBIT/TA +0* MVE/TBD +11.217*SALES/TA

Models Developed Using Altman

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

Description of Sample Data

Table No 3 Summary of Cases processed from Pharmaceuticals Sector for MDA model

Sector	In-sample	Out-of–sample
Pharmaceuticals		
• Total cases	383	119
• Cases considered	345	118
• Cases removed	38	1

Empirical Results of MDA Model

Log Determinant

Table No 4 Log Determinant

Non-Defaulted	Defaulted	Pooled Within-groups
9.956	-9.738	12.078

One of the assumptions of the discriminant function is to have homogeneity of covariance matrices between the groups. The relatively equivalent log determinant values of the groups recommend that the covariance matrices of these groups are homogenous. Besides, homogeneity, proximity in the log determinants values of non-defaulted, defaulted and pooled with-in group indicates the robustness of the developed prediction model. The log determinant values of selected chemical sector firm are neither equivalent nor close to defaulted, non-defaulted and pooled within group. Log determinant also enumerates that for selected chemical sector the log determinant values for the non-defaulted groups and pooled within-groups are closer to each other yet, this is quite distant from the defaulted groups due to the existence of higher Type II Error in the prediction results of selected chemical sector firm.

Coefficients of MDA Model

Table No 5 Coefficient of MDA Model

Box's M	Sig. Value of Box M	Eigenvalue	Canonical Correlation	Wilks' Lambda	Sig value of Wilk's lambda
1613.9	0	0.489	0.573	0.672	0

Box's M Test

To evaluate the Multiple Discriminant Analysis function's assumptions about the equality of variance-covariance matrices in dependent variable's groups (defaulted and non-defaulted) the study used Box's M Test.

Hypothesis 1

H_0: The covariance matrices are equal in both the groups namely defaulted and non-defaulted made by dependent variables of the developed models.

The significant P-value of the box's M test of selected Pharmaceuticals sector as depicted in Table No 5 Coefficients contravenes the basic assumptions of the MDA function. The large sample data produces a higher value of the Box's M which generally results in a significant value of the box's M test in such instances the assumption is tested using the Log Determinants test. The Box' M value of selected pharmaceuticals is 1613.9 as displayed in Table No 5 Coefficients in conjunction with significant sig-value of Box's M test i.e. <.05. This is an unpleasant result that conveys the violation of the assumption of MDA. Hence, the H_0 will be rejected; this finding of the study about the Box's M test is consistent with the findings of Bandyopadhyay (2006), Altman (2000) and contrary to Suleiman (2014) and Memic (2015). However, the developed model was found robust even if it violates the box' M test condition because of the large number of sample cases considered in the study that makes the Box's M test less relevant for the default prediction.

Eigen Value

The eigenvalue denotes the variation in the dependent variable that can be explained by the MDA model. Primarily the Eigenvalue is a ratio between explained and unexplained variance. The higher eigenvalue recommends the greater discriminatory power of MDA function that explains the variation in the dependent variable. The strong discriminant function has a higher eigenvalue i.e. close to 1. The present study found .489 eigen value for selected pharmaceuticals sector as depicted in Table No 5 Coefficients that conveys the lower prediction power of the developed models. Further, it reflects that the variation in the dependent variable of the models of selected pharmaceuticals sector is explained by the developed model by 48% only.

Canonical Correlation

The Canonical Correlation gauges the association between the groups of dependent variable and discriminant function, the value of canonical correlation lies between 0 to 1. The large value of canonical correlation implies a strong association between the groups of dependent variable and developed models. Further, it signifies the high classification accuracy of the developed model. The discriminant function with a high value of canonical correlation value i.e. close to 1 is an acceptable discriminant function model. The square of Canonical Correlation is similar to R square which explains the variation in the dependent variable. When the squared value of the Canonical Correlation is more than 50% it conveys the high competence of the discriminant function. The canonical correlation values as exhibited in Table of selected Pharmaceutical sectors is >.50 i.e. .573. The higher canonical correlation values substantiate the good classification ability of the developed models as found in the present study.

Wilk's Lambda

Wilk's lambda describes the discriminatory power of the discrimination function together with independent variables incorporated in the developed model. The Wilk's lambda ranges from 0 to 1, the smaller value signifies the higher classification accuracy of the model coupled with the significant contribution of each independent variable. Wilk's lambda always works in contrast to the canonical correlation, the higher value of the canonical correlation will lead to a lower value of Wilk's lambda which is a desirable situation for any robust model. Table No 5 Coefficients exhibit the value of the wilk's lambda for selected pharmaceuticals i.e. .672 which is not significant for any developed model. Hence the developed model is having average discriminatory power.

Hypothesis 2

H_0: There is no discriminating power in the independent variables of the developed models.

The sig value of Wilk's lambda for each sector is <.05 that substantiates that there is a significant difference between defaulted and non-defaulted group of the dependent variable, also that the independent variables are contributing significantly well for discriminating the defaulted and non-defaulted group of dependent variable. Hence the H_0 hypothesis will be rejected, these findings of the present study concerning the hypothesis test result of each developed model and wilk's lamda value obtained for each selected sector and Complete Sample are consistent with Altman (2000), Altman (1968) and Memic (2015).

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

Table No 6 In-Sample Classification Result

Models	Accuracy Rate	Type I Error	Type II Error
Developed model	88%	10%	24%
Calibrated Model	80%	18%	30%
Altman's Original	19%	93%	0%

Findings and Discussion

The developed model outperformed with 88% accuracy rate in pharmaceuticals sector followed by calibrated and Altman model. The Calibrated model attained 80% accuracy rate whereas, the Altman model classification results did not show impressive classification accuracy for the selected Pharmaceuticals sector which is only 19% along with 93% type I error which is troublesome for any prediction model. Developed model depicted less type I and type ii errors which substantiates better prediction accuracy than calibrated and altman model.

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

Table No 7 Validation Results

Models	Accuracy Rate	Type I Error	Type II Error
Developed model	37%	62%	100%
Calibrated Model	37%	62%	80%

Findings & Discussion

Table No 7 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 only 37% prediction accuracy for both developed and calibrated model which is not appropriated for any discriminate model. Further the developed model obtained 100% type ii error followed by calibrated model that obtained 80% type ii error, this conveys that model cannot predict defaulted cases with higher accuracy. The type I error acquired by developed and calibrated model are showing 62% rate which is better than the rate obtained under type ii errors for selected pharmaceuticals sector.

Model Developed using Logit Function

$$L = -4.0408-3.856*WC/TA+14.014*RE/TA+16.186* SALES/TA+1.583*Y$$

Description of Sample Data

Table No 8 Summary of Cases Processed for Logit Model

Sector	In-sample	Out-of–sample
Pharmaceuticals		
• Total cases	382	119
• Cases considered	344	118
• Cases removed	38	1

Empirical Results of Logit Model

Table No 9 Coefficient of Logit Model

Omnibus tests of the model coefficient (Chi-Square)	Sig Value of Omnibus tests	-2 Log likelihood	Cox & Snell R Square	Nagelker R Square	Hosmer and Lemeshow Test	Sig. value of Hosmer and Lemeshow test
123.189	0	147.47	0.301	0.553	10.243	0.248

Omnibus Test

The Omnibus Test evaluates the significance of each independent variable of the model for predicting the default risk of the firm, for recognising the best fitting independent variables of the model, and for assessing the overall robustness of each developed model. The small value of chi-square with sig value <.05 specify the higher predictive accuracy of the developed model.

Hypothesis 1

H_0: The independent variables of the developed models have no significant impact on the dependent variables.

Since the sig- values for all selected sectors in the Omnibus test given in the table are less than .05, hence it suggests the rejection of the null hypothesis. The findings of this hypothesis test are consistent with Suleiman, Suleman, Usman and Salami (2014) and Kwofiew (2015).

-2 Log likelihood

-2 Log Likelihood test examines the robustness of the model. The large values of the -2 log-likelihood depict the high robustness of the developed model. The value of -2 log-likelihood indicated the greater classification ability of the developed model for the pharmaceutical sector.

Cox & Snell R Square Test

The Cox & Snell R square test provides the measure to examine the variation in the dependent variable that can be explained by the developed model. Cox & Snell R Square test, this signifies that the developed model explained the variations in the dependent by only .30%.

Negelker R square

Negelker R square is a Pseudo R square of the Logit model which assesses the variation in the dependent variable of the model that can be explained by the independent variables included in the logistic regression model. The study found 0.55 Negelker R square value for for selected pharmaceutical sector that is an average value. This result demonstrated that the variation in the dependent variable of pharmaceutical is explained by the independent variables by 55% accuracy.

Hosmer and Lemeshow Test (Goodness-of-Fit Test)

The Hosmer and Lemeshow test evaluates the goodness of fit of the sample data for predicting the default probabilities. This test also indicates whether the model is specified or not which implies that how perfectly the groups of dependent variables can be classified according to the predicted probabilities. The hosmer lemeshow test is similar to the chi-square goodness of fit test of the regression. The small value of the Hosmer and Lemeshow test suggests the good fit of the sample data into the model. The insignificant sig-value value i.e. P value >.05 recommends that the data is best fitted into the specified model.

Hypothesis 2

H_0: The developed models are correctly specified and best fitting.

Table No 9 coefficients present that the sig-value of hosmer lemeshow test of each model developed for each selected sector is non-significant i.e. P-value is > .05 hence; the developed model is specified and best fitting into the sample data to predict the default probability. Therefore, the study fails to reject the null hypothesis. This finding about the hypothesis test is consistent with Kwofie (2015).

In-sample classification result of the Logit model

Table No 10 In-Sample Classification Result

Accuracy Rate	Type I Error	Type II Error
90%	3%	52%

Findings and Discussion

Table No 9 In-sample Classification Results presents the empirical results of Logit Model developed for selected Pharmaceutical sector. The accuracy rate of the Logit model is 90% in conjunction with 3% Type I and 52% Type II error. The obtained results of the developed model are better than the results achieved by developed MDA model.

Validation of Model (out-of-sample classification result) of the Logit Model

Table No 11 Validation Results

Accuracy Rate	Type I Error	Type II Error
92%	6%	100%

Findings & Discussion

Table No 11 validation results displays the validation result of the out-of-sample data that is employed in the study to check the validity of the developed Logit model. T The validation result shows higher accuracy rate i.e. 92% alongwith 6% Type I Error and 100% Type II Error. The acquired accuracy rate and error rates have outperformed the in-sample results of logit model for pharmaceutical sector. However, the 100% type II error is troublesome which is not commendable.

Analysis of Results

Multiple Discriminant Analysis

The model for the Pharmaceutical sector is purely developed upon the financial ratios namely EBIT/TA, NI/TA, WC/TA, TBD/TA, and RE/TA. The study included 345 and 118 sample observations to prepare and to test the model. The log determinant values depicted in the table were not similar for the defaulted and pooled within-group however; the values were relatively same for the Non-Defaulted and the pooled within-group. This advises that the covariance matrices of the model differ, which hampers the classification accuracy of the prediction model and inhibits the model's robustness. The values of the Eigenvalue, Canonical Correlation and Wilk's Lambda unveiled in Table No 5 coefficients are beneath the acceptable threshold; this culminates the insignificant accuracy, higher level of misclassification and the lower association between the dependent variable and discriminant function. The developed model highlighted the higher level of accuracy than calibrated and Altman's original model for the In-sample classification results. However, the validation test results of the developed and calibrated model depicted identical accuracies and Type I Errors but differed from Type II Errors; the Type II Error obtained in the calibrated model was 80%.

Logit Model

This model incorporated the financial ratios and dummy variables such as WC/TA, RE/TA, SALES/TA and Y. The sample cases included in the study for training and testing the model are 344 and 118 respectively. Table No 9 Coefficients provides the results of the tests conducted on IBM SPSS version 22 namely Omnibus, -2 log-likelihood, cox and snell r square, Nagelker R Square, Hosmer and Lemeshow test. The values obtained for each test are 123.296; 0,147.47, 0.301, 0.553, 10.243, 0.248 respectively. The result advocates that the independent variables of the models were significant, the sample data included in the model is best-fitting. Nevertheless, the model and its independent factors did not explain the variation in dependent variable accurately. The model discriminated the defaulted and non-defaulted group with 90% accuracy for in-sample cases. Model obtained 92% accuracy for the out-of-sample data along with considerably low Type I and Type II Errors.

Structural Model

Case Summaries

Table No 12 Cases Processed

Sector	Cases Processed
Pharmaceuticals	400

Classification Results of Structural Model

Table No 13 Classification Results of Structural Model

	NON-DEFAULTED	DEFAULTED	Total
NON-DEFAULTED	54	293	347

DEFAULTED	8	45	53
Accuracy Rate		25%	400
Type I Error	84%		
Type II Error	15%		

Findings & Discussion

The found results depicted in Table No 13 Classification Result of structural model pharmaceutical sector depicted that the structural model performed quite well for classifying defaulted cases than non-defaulted cases. As it's reflected in the table that out of total 53 defaulted cases structural model correctly classified 45 cases that amounts to 85% accuracy. Nonetheless, for overall accuracy the structural model provided only 25% accuracy due to higher level of Type I error. The Type I Error is the most troublesome error found in the Structural Model; due to the high percentage of Type I Error the classification accuracy of the model becomes smaller. The higher value of Type I Error also signifies that the structural model is most compatible to classify the defaulted cases than non-defaulted cases.

Conclusion

The classification rate of Altman's original model depicted a lower accuracy level for the selected pharmaceutical sector. This accuracy rate substantiates the irrelevance of the Altman (1968) Original model. The calibrated model performed considerably well for both In-sample and Out-of-sample data. The validation results elaborated that the calibrated model performed similar to the developed MDA model concerning the accuracy rate. This indicates that the independent variables used by Altman (1968) are still relevant. The developed model performed satisfactorily well for the In-sample data than the Out-of-sample data. The out-of-sample classification results did not show the pleasant accuracy rates.

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 but it is worrisome for out-of-sample classification results.

The classification accuracy of the developed Logit model for In-sample data for the selected pharmaceutical sector is 90%. This is significantly high in comparison to the developed MDA, calibrated and Altman's original model. There is no acute misclassification problem with the Logit model specifically rate of Type I Error. The validation results of the Logit model are also remarkable i.e. 93%. Nonetheless, the values depicted for the Type II Errors are quite high both for in-sample and out-of-sample data which is 52% and 100% respectively.

The classification results of the Structural Model witnessed undesirable results since the overall accuracy attained by the Structural Model is at the lower side in contrast to the default events probabilities discussed in the immediately above point. The overall accuracy of the selected pharmaceutical sector is 25% only. This signifies that the Structural Model is competent to predict defaulted cases accurately. However, it misclassifies the non-defaulted cases as defaulted due to which its overall accuracy drops. The Type II Errors secured by this substantiates that the Structural Model is not robust enough to recognise the non-defaulted cases.

The developed MDA and developed Logit model 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), Arlov, Rankov & Kotlica (2013), Jaffari & Ghafoor (2017). The Logit model also used one economic and one qualitative variable for credit risk modeling that was supported by Hu & Sathye (2015). 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 obtained accuracy rates of MDA model are similar to the results depicted in the following past studies such as Mahadevan, & Kulkarni (2012), Zvaríková & Majerová (2014), Agrawal & Maheshwari (2019), Verma (2019), Verma & Raju (2019), Upadhyay (2019), Rashid & Abbas (2011), Slefendorfas (2016), Jaffari & Ghafoor (2017), Abid, Masmoudi, & Ghorbel (2016), Altman E. I. (2006), Memic (2015), Liang Q. (2003), Hassan, Zainuddin, & Nordin (2018). However, the obtained accuracy rates of the developed MDA model are less than the level of accuracy acquired by Sharma, Singh, &Upadhyay (2014), Pang & Kogel (2013), Salehi & Abedini (2009), Desai & Joshi (2015), Chijoriga (2011), Kumar &Rao (2014).

The developed logistic model outperformed the developed MDA model that attained higher predictive accuracy for selected pharmaceutical sector. These accuracy rates are reasonably good for any robust model. The achieved accuracy rates of the developed Logit model are close to Ohlson (1980), Bandyopadhyay (2006), Agrawal & Maheshwari (2019), Sheikhi, Shams, & Sheikhi (2012), Upadhyay (2019), Ong, Yap, & Khong (2011), Moghadas & Salami (2014), Gurny & Gurny (2013). Nonetheless, higher than the accuracy obtianed by Khemais, Nesrine, & Mohamed (2016), Mihalovic (2016), Memic (2015), Kwofie, Ansah, & Boadi (2015).

The overall predictive accuracies of the Structural Model attained for selected pharmaceuticals sector is not satisfactory due to the high level of Type I Error. However, the Type I Error was not as costly as the Type II Error according to the previous studies, yet it drops the overall classification accuracy of the model. The higher rate of Type I Error is also observed by Rao Atmanathan, Shankar, & Ramesh (2013) in the Structural Model. The results signify that the Structural Model did classify the defaulted cases with elevated accuracy but failed to recognise the non-defaulted cases in all selected sectors. The prediction accuracies acquired by the Structural Model in the present study are less than the predictive accuracies obtained by previous studies such as Karthik, Subramanyam, Srivastava, & Joshi (2018), Duan, Miao, & Wang (2014), Sharma, Singh, &

Upadhyay (2014), Ko, Blocher, & Lin (1986), Mileris (2010), Hasanzedeh & Yazdanian (2017) and Bandyopadhyay (2007).

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