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Research Paper

Determination of Significant Default Predictors For Indian Corporate Sector Using MDA And LOGIT Model

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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 2 default prediction methods namely Multiple Discriminant Analysis, and Logistic Regression for predicting the default probability of 13 sectors namely Chemicals, Construction and Engineering, Electronics, Hotels, Infrastructure, Pharmaceuticals, Plastic & Fibre, Realty, Software, Steel, Sugar, Textile and Miscellaneous. The study used accounting, market, economic variables to determine the default prediction of selected sectors. The findings of the study depicted that the most significant predictor of the default are NI/TA, WC/TA, EBIT/TA, TBD/TA, RE/TA for MDA models and WC/TA, Y, NI/TA, RE/TA and Log (TA/GNP) for logit model with satisfactory prediction accuracies.

Keywords: *Logit, MDA, NPA, Default, Accounting ratios, Default Predicting Variables*.

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I. Introduction

The loan can classify into the bad loan and good loan using statistical methods (Durand, 1941). Earlier, human judgement was prevalent to evaluate the repayment capacity of the borrowers which was found to be erratic and replaced by default prediction models (Khandani et al., 2010).

The adoption of Basel II by RBI made it mandatory for all Indian commercial banks to establish an internal default prediction mechanism including the development of credit risk models to facilitate the bankers, economists, and regulators like RBI. This credit evaluation model has 3 categories which have been segregated into 3 generations first, second and third (Boris & Tomas, 2014).

Guidelines of RBI and shortcomings of rating agencies have paved the way for the implementation of credit risk models implementation. The major contribution of the default prediction model is to categorise the good and bad loans of the commercial banks as well as to apprise the stakeholders about the potential corporate failures.

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).

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.

Logit Model was propounded by Martin (1977) that provides a dichotomous result i.e. 0 or 1 which directly declares the defaulting position of an entity. Avery & Hanweck (1984) applied the Logit model to predict the default probability of 100 defaulting and 1190 non-defaulting banks, result of which was consistent with Martin (1977). Consequently, Barth, Beaver, & Landsman (2001) after examining 12 financial ratios concluded that in the logistic model the most appropriate predictor of insolvency is liquidity. A study was conducted to find the most suitable predictors by applying the Logit function on 23 financial ratios. The result of the study concluded that ratios pertinent to liquidity, earnings, capital adequacy and assets are the most significant predictors of default (Andersen, 2008).

MDA and Logit function is predominantly based upon corporate-specific financial information. Nevertheless, Dietrich & Kaplan (1982) advocated the role of non-financial variables as the significant predictors of default. As the financial information data is computed using financial statements which are historical. Hence, scholar considered the changing market value of the assets that too play a crucial role in examining the financial robustness of the corporate. Altman (1968) is the most popular and used default prediction model which was applied across the various countries over different sectors by integrating diverse financial ratios which covers the liquidity, leverage, profitability, solvency and growth aspects of the firm.

Some of the scholars supported the Basel II accord and integrated it with the default prediction model to encourage research prospects in the area of insolvency prediction. Loss Given Default (LGD) prediction can be performed using statistical tools in collaboration with financial ratios such as MDA, Z-Score models (Asquith et al., 1989). Altman & Sabato (2007) used Logit and MDA models in the light of Basel accord recommendation to lower the capital requirement of the bank that sanctioned loans to SMEs and to evaluate the financial position of SMEs.

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.

Variables generally used in default prediction model are

- Accounting Ratios
- Market Variables
- Economic Variables
- Industry effects

The accounting ratios encompass leverage, activity, profitability, liquidity and debt coverage ratios. The classification of the financial ratios used for the bankruptcy prediction has been stated in Altman (1968). Carlos Gonzalez Aguado Bluecap (2012) argued in favour of WC/TA, RE/TA, TL/TA and Standard deviation of firm stock return as the most significant predictor of the bankruptcy event. Keasey & Watson (1987) advocated the use of financial and non-financial variables for default prediction. Beaver (1966) supported Cash /Total debt as the key predictor of default. The size of the firm variable has direct correlation to the bankruptcy risk ((Altman, 1968), (Agarwal & Taffler, 2008) & (Fama & French, 1992)). Chen & Chan (1991) advocated that the high leverage and cash crunch trigger the default. The accounting ratios selected by the various authors for default prediction must convey the pivotal attributes of the financial statements of the selected firms namely Leverage, Growth, and Liquidity that play a vital role in determining the default status of any firm.

The market variables are generally used in the Structural Model which integrates the information pertinent to the market value of the asset of the firms and its volatility. Market variables also include index return and equity return. Merton (1974) in his Structural Model emphasis the use of market information which overcomes the limitations of accounting ratios and gives more accurate & practical results. Nevertheless, it can only be used in the default prediction of listed firm.

The economic variables consist of GDP growth, GNP growth, and Industrial Production Index. Antunes, Ribeiro, & Antao (2005) supported macroeconomic indicators over accounting variables. On the contrary Gonz & Moral-benito (2012) documented the inability of the GDP growth and Industrial Production to predict the default through the findings of empirical results (Gonz & Moral-benito, 2012).

II. Literature Review

Literature review is divided into 2 categories. One category dicusses the literature according to prediction models and second category covers the literature pertinent to independent variables used in the default prediction.

Multiple Discriminant Analysis

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 (Li, 2014)

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).

The study used Z score model to examine the existing MDA model and to develop the new mda model for predicting the default of 30 defaulted and 30 non-defaulted Indian non-financial firms. The sectors included in the study are Paper, Paints, Pharmaceuticals, Textiles, Machinery, Consumer Food & Sugar, Cement & Metal, and others. The study found that the predictive accuracy of developed mda model is higher than the Altman MDA model that predicted the default one year prior. The used financial ratios which included ratios of Altman model (Jay & Nisarg, 2015).

Study used MDA and Logit model to predict the default of 236 Slovakia (118 defaulted and 118 non-defaulted) firms. The significant variables obtained in the study are ni/ta, ca/cl, cl/ta. The recommended artificial intelligence over mda and logistic regression due to its statistical inconvenience that violated the assumption of normality etc. (Mihalovič, 2016).

The study conducted a credit default prediction of banking market in Bosnia, Herzegovina to classify the firms into defaulted and non-defaulted using Logit and MDA model. Study found Return on Asset ratio as the most significant preditor for both MDA and Logit model (Memic, 2015).

The study is conducted to select the most parsimonious mda model for predicting the default of wood industry of Poland. The study examined 10 mda models namely Altman Gajdka and stos, hadasik, holda, jagiello, maczynska, Poznan, prusak, prusak 2 and Wierzba. (Adamowicz & Noga, 2017).

The study used Z score to find the default probability of Indian Firms. The independent variable considered in the study are current ratio, debt/equity ratio, operating margin, wc/ta, ebit/ta, net worth/debt, and asset turnover ratio. The study developed three model for 112 indian firms which belong to Chemical, Food, Textile, breweries and distilleries, pharmaceuticals, electronics and miscellaneous etc. The study obtained 82% and 57% accuracy with current ratio and debt to equity ratio which are the most used and significant predictors of the study. The sample data of defaulters was collected from bank of india, sbi, cbi, bob, pnb as stated by CIBIL. (Jayadev, 2006).

The study was conducted to develop the default prediction model for predicting the default of 145 (73 defaulted and 72 operating) Lithuanian private ltd firms using MDA model. The model provided 89% classification accuracy (Šlefendorfas, 2016).

The study developed default prediction model for 195 SMEs of Tunisia using MDA and Logit function. The data was collected for the period from 2012 to 2014 for the sectors namely Trade, agriculture, industry, service and tourism. The found that the both the developed models are statistically significant and provided 76.7% and 76.4% default prediction accuracy (Khemais et al., 2016).

The study developed a default prediction models for the Indian Manufacturing firms. The sample data is divided into two part : in sample data contained 130 firms and hold out sample data contained 78 firms that is used to examine the developed models. The industry included in the study are manufacturing firms of food, spinning, paper, chemical, pharmaceutical, rubber, glass, non-metallic, metal, electronic, motors and furniture etc. The statistical models used for the study are Altman z score, ohlson Y score, zmijewski me x score. The study found that the accuracy level of original and hold out model got increased when its coefficients were re estimated. The study recommended to develop industry specific default prediction models along with new combination of financial ratios (Singh & Mishra, 2016).

The study examine the sample data of listed Bangladeshi Pharmaceuticals firms to predict financial distress using Altman Z score. The model successfully classified non-distressed and distressed firms along-side study also concluded that market value of equity does not provide the fundamental information of the firms (Mizan A.N.K et al., 2011).

Study used Altman original and Revised z score model to assess the financial health and bankruptcy risk of Kingfisher Airlines ltd. The financial information is collected for the period from 2005 to 2012. The study found satisfactory classification accuracy for both the models (Kumar & Anand, 2013).

The study analysed the financial statement of 385 Greek bankrupted and 385 non bankrupted firms belong to trade and manufacturing sector for the period 2003 to 2014. In which period is divided into pre global crisis and post global crisis. The used MDA and Logit model. The study reported that for the period from 2003 to 2008 mda and logit model depicted least accuracy for the 1 prior to the actual default which in contrast to the early studies which concludes that the financial statement are altered using strategic accounting methods. In contrast the predictive accuracy for the period from 2009 to 2014 increased during the last year of the default which leads to the fact that the accounting statements are not being altered during crisis (Arnis et al., 2019).

The study assessed the financial statement of 122 listed manufacturing firms for the period from 1999 to 2007 using logit and mda. The study found that the models are competent to predict default one year prior with profitability, financial structure, liquidity ratios. Further, the net profit/ta is found most significant predictor for both the models. The mda and logit model found 84% accuracy for one year and 80% accuracy for 2nd year (Vuran et al., 2009).

Study attempted to predict the credit risk of 3 Indian Cement firms for the periof from 2001 to 2010 using liquidity, working capital, solvency ratios along with Altman Z score model. study concluded that the Z score model can make an indication to the managers to take remedial action pertinent to proper planning, management style, sales forecasting, technology advancement (Venkataramana et al., 2012).

Logistic Regression

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.

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).

Independent Variables

Accounting Ratios

The financial ratios help to obtain the financial status and performance of the corporate (Muresan & Wolitzer, 2005). Accounting ratios are still relevant for default prediction as it was recommended by Beaver (1966) that used 30 financial ratios into UDA model to predict the corporate failure (Beaver et al., 2005). Casey and Bartczak (1985) supported the MDA model accompanied with accrual-based ratios than the Univariate analysis model. Altman, Haldeman, & Narayanan (1977), Ohlson (1980) and Lennox (1999) applied financial ratios in Zeta & Logit model. Begley et al. (1996) compared the performance of the accounting variable by combining them with MDA and Logit model, the result of the study demonstrated the outperformance of Logit over MDA.

Memic & Rovcanin (2012) used ROA that impacted the most on the credit risk prediction. Subsequently, Santosuosso (2014) documented that the cost of the debt might trigger growth but also increases the probability of default. The accelerated value of working capital results in higher profitability that mitigates the risk of default (Jouault & Featherstone, 2011).

The Multivariate Logit Model was used to predict the bankruptcy probability of 22 Jordian Companies for the period 2000 to 2003. It was found that WC to TA, CA to CL, MVE to BVD, RE to TA and SALES to TA are best indicator of probability of bankruptcy (Almansour, 2015). Soo (2001) recommended Sales/CA, CA/CL and % change in NI as the significant predictors of default followed by Bhimani (2013) that asserted to amalgamate macroeconomic variables with accounting variables for higher predictive accuracy.

Market Variables

The financial ratios cannot individually comprehend the true snapshot until it is incorporated with the market variables. The accounting ratios are historical data that upgrades only quarterly in contrast to market-based information that gets updated on daily basis. The future cash flow and volatility can only be estimated using market variables (Agarwal & Taffler, 2008).

The most commonly used market variables are stock return and stock volatility. The higher stock return directly correlates to higher bankruptcy risk in small size firms (Chava & Jarrow, 2008). Prior studies suggested that by including market information in the model does not predict default risk (Crossen & Zhang, 2011). On the contrary, Vassalou & Xing (2004) documented that the market-based information is more significant than accounting-based information to gauge the default prediction.

The Structural Models namely Black & Scholes (1973) & Merton (1974) have used market-based information to predict the likelihood of default. According to the option-based model, bankruptcy occurrence depends on the volatility of MVA and strike price. Frade (2008) incorporated market information in Logistic regression and successfully predicted the default risk. Afterwards, Shumway (2001) supported market-based information over accounting variables. The hazard models by using the combination of accounting and market-driven variables provide more accurate prediction than Merton' DTD and multivariate model (Charalambakis C.Evangelos, 2014).

Economic Variables

Corporate default has straightway economic impacts. Consequently, it is in the interest of regulators, and corporate stakeholders to practice the early-warning approach. Hitherto several scholars reported the higher predictive accuracy of the financial ratios through the optimum combination has not been found yet (Sarlija & Jeger, 2011).

Simon & Rolwes (2009) proclaimed that the contribution of macroeconomic variables cannot be trivialized against the market and financial variables. It's been evident for decades that the occurrence of corporate failure is more frequent during recession period. The model which collaborates with financial, market and economic variables are termed as hazard model (Chan-Lau, 2006).

The macroeconomic models explain the changes in the default concerning the macroeconomic condition. The most commonly used macroeconomic variables are GDP growth, interest rates, & financial market information (Chan-Lau, 2006). Antunes, Ribeiro, & Antao (2005) supported macroeconomic indicators over accounting variables.

Industry effects variables

Hu & Sathye (2015) advocated the significance of Industry-specific financial, non-financial and macroeconomic variables for the credit risk modeling. The industry-specific variables play a pivotal role in the prediction of default risk (Kale & Shahrur, 2007) which is supported by Opler & Titman (1994) and study also explains the impact of volatility on the national market (for instance financial reforms, revision in industrial policies, varied level of competition and different accounting conventions) on the probability of default Nishant (2001), Chava & Jarrow (2004). Every industry has its industry-specific attributes which tend to change over time and impact the default probability and recovery rate (Acharya et al., 2005).

According to Kayo & Kimura (2011) industries having enough resources are tend to grab more opportunities, consequently, have profitable results. The Construction and financial firms are likely to default more than paper, Chemicals, Metal and the transport and retail industries. These industries are most vulnerable that tend to get bankrupted (Platt & Platt, 1991).

Wang & ZHOU (2011), Hu & Sathye (2015) and Agarwal, Chomsisengphet, & Liu (2007) revealed that the industry-specific variables such as type of ownership, facilitate the estimation of bankruptcy along with financial and macroeconomic variables. Ohlson (1980) too conducted the pioneering study using size, capital structure and liquidity position of a firm for default prediction. Study concluded that the size of the firm was found to be significant predictor.

III. Research Methodology

The research methodology comprises of the sample data, study period, source of data, kinds of sample data, and method of default prediction. This section discusses about every vital elements of the research methodology of the present study herewith.

Sample Selection & Period of Study

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 firms collected from 13 Indian selected sectors. The sample data is divided into two parts.

Sector-Wise Description of Selected Indian Listed Firms

Table No 1 Sector wise description of 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

In light of the previous literature review, the study selected 2 default prediction methods to predict the default status of the selected firms namely MDA (Multiple Discriminant Analysis) and Logistic Regression 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.

Multiple Discriminant Analysis

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.

Logistic Regression

The equation of the logistic function is:

$$f(x) = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_i)}}$$

The linear probability model is

$$P_i = E(Y = 1|X_i) = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_i)}}$$

This can be written as

$$P_i = \frac{1}{1+e^{-Z}} = \frac{e^Z}{1+e^Z}$$

Where $Z_i = \beta_1 + \beta_2 X_i$

P_i is the probability of default therefore, $(1 - P_i)$ is the probability of non - default. Where P_i is denoted by $\frac{e^z}{1+e^z}$.

Therefore, the equation for non-default shall be:

$$1 - P_i = \frac{1}{1 + e^z}$$

This can be rewritten as:

$$\frac{P_i}{1 - P_i} = \frac{1 + e^z}{1 + e^{-Z}} = e^z$$

After taking the natural log the equation shall be:

$$L_i = \ln\left(\frac{1}{1 + e^z}\right) = Z_i = \beta_1 + \beta_2 X_i$$

Log of odds ratio L is linear both in X as well as in parameter. Where L is termed as Logit.

Variables

The study used two kinds of variables, dependent & Independent variables to predict the default probability of each selected sector.

Dependent Variable of MDA Model

Z score: it is a credit rating score that is calculated using the independent variables. The Z score categorises the sample cases into defaulted and non-defaulted groups. For categorising purpose the study shall use the centroid value of each group namely defaulted and non-defaulted. The centroid values of each group of each selected sector have been calculated after processing the sample cases on IBM SPSS Software version 22.

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.

Accounting Variables

The study used 16 accounting ratios for the development of MDA model. The accounting variables identify the financial profitability or risk on the business or on the firm aggregately. The following ratios are incorporated in the present study:

WC/TA, RE/TA, EBIT/TA, SALES/TA, CA/CL, NI/TA, NP/TE, TBD/TA, EBIT/INT, OCFR(OPERATIONG CASH FLOW), GRTA(GROWTH TO TOTAL ASSETS), INVENTORY TURNOVER, FIXED ASSET TURNOVER, D/E, TL/TA, SALES GROWTH.

Market Variables

The market variables of any firm are the market price of share, price earning capacity of its share, the market value assets, market value of equity. The study considered the most vital variables that can predict the default probability accurately. Hence, the following ratios have been selected that can reflect the drift of the firm towards default.

MP/EPS (P/E ratio), MP/BV, MVE/TBD

Economic Variables

Economic variables like GNP, GNP Growth, and inflation impact the performance of businesses, their finance and risk of getting bankrupt. Present study has included two macroeconomic variables to quantify the impact of these factors on the default probability of the firm.

Log (TA/GNP), Sales Growth/GNP Growth

Dependent Variable of Logit Model

L Score: The L score is also a credit rating score but unlike MDA the determination of the L score is based upon simple criteria i.e. if the inverse of exponent of L score is <.5 then the firm is non-defaulted & vice versa. That's why the logistic model is called as binary Logit model because the dependent variable of the provide dichotomous result i.e. 0 and 1.

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

X: X is a categorical independent variable; X is 1 if the total liabilities of the firm are more than its total assets and 0 if the total assets of the firm are more than its total liabilities.

Y: Y is a categorical independent variable that shall be 1 when the average net profits of the firm for previous two years are less than zero and 0 when the average net profits of previous 2 years of the firm are more than zero.

Empirical Results

Models developed using MDA

Table No 2 Developed MDA Model

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
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

Models Developed using Logit Function

Table No 3 Developed Logit Model

Sectors	Logit Models
Chemicals	L =-0.77-0.214*FAT-0.282*LOG(TA/GNP)+2.582*Y
Construction and Engineering	L = 1.546-68.583*RE/TA-99.168*EBIT/TA-54.034*SALES/ TA+134.647*NI/TA-6.147*GRTA-0.662*LOG(TA/GNP)
Electronics	L =0.077-2.478*WC/TA+0.006*MP/EPS+2.179*Y
Hotels	L = -7.807-9.452*WC/TA+91.822*NI/TA+0.022*MP/EPS-1.32*MP/BV
Infrastructure	L = -0.905-2.398*GRTA+1.185*Y
Pharmaceuticals	L = -4.0408-3.856*WC/TA+14.014*RE/TA+16.186* SALES/TA+1.583*Y
Plastic & Fibre	L = -7.384-46.228*RE/TA-39.066*SALES/TA+55.379*NI/TA+6.497*TBD/TA-1.381*FAT-1.583*NP/TE
Realty	L = -4.097+11.521*WC/TA-1.011*CA/CL-30.564*NP/TE-3.482*OCFR+0.111*INVEN TURN.
Software	L = -0.702+8.199*WC/TA-1.684*OCFR-0.253*FAT-3.352*MP/BV
Steel	L = -3.683+1.711*WC/TA-11.539*RE/TA-0.737*MVE/TBD-14.771*SALES/TA+20.906*NI/TA+0.044*TBD/TA-1.436*GRTA+0.047*INVEN. TURN-0.303*FAT-1.854*TL/TA+0.375*LOG(TA/GNP)+1.91*Y
Sugar	L = 2.523-7.11*WC/TA-4.995*MVE/TBD-2.716*OCFR-0.848*LOG(TA/GNP)
Textile	L = -2.087-2.937*GRTA+0.004*MP/BV+1.22*X+1.049*Y
Miscellaneous	L = -3.281-9.277*EBIT/TA+9.619*NI/TA-.415*NP/TE-1.648*TBD/TA-.390*OCFR-.005*INVEN. TUR+.677*TL/TA-.796*SALES GROWTH+1.883*X+1.933*Y
Complete Sample	L = -3.425-0.313*WC/TA-1.758*RE/TA-0.004*MVE/TBD-1.663*SALES/TA+1.925*NI/TA-0.153*GRTA+0.1*LOG(TA/GNP)+0.596*X+2.052*Y

The In-sample classification results of MDA, Logistic Model

Table No 4 Classification Results

Particulars	MDA			Logistic		
Sectors	**Accuracy Rate**	**Type I Error**	**Type II Error**	**Accuracy Rate**	**Type I Error**	**Type II Error**
Complete Sample	78%	19%	38%	86%	3%	83%
Chemicals	90%	3%	69%	93%	1%	60%
Construction and Engineering	82%	20%	9%	92%	4%	28%
Electronics	85%	18%	9%	92%	5%	21%
Hotels	87%	10%	28%	91%	5%	30%
Infrastructure	79%	20%	25%	82%	10%	42%
Pharmaceuticals	88%	10%	24%	90%	3%	52%
Plastic & Fibre	88%	9%	31%	92%	3%	33%
Realty	80%	17%	34%	89%	2%	69%
Software	75%	25%	23%	89%	5%	29%
Steel	89%	2%	84%	91%	2%	62%
Sugar	76%	25%	23%	83%	11%	33%
Textiles	81%	14%	42%	86%	4%	62%
Miscellaneous	89%	2%	8%	89%	2.7%	74%

IV. Findings and Discussions

Model-wise Analysis of Findings

This table evident that the highest accuracy of 93% is achieved by Logit model for Chemical sector followed by Construction and Engineering, Electronics, and Plastic & Fibre sectors that witnessed 92% classification accuracy. The MDA model has provided moderate classification accuracy rates that are below accuracies obtained by Logit model. The MDA model classified the Chemicals sector with 90% accuracy which is highest amongst selected sectors for which the MDA models were developed. The MDA model secured acceptable prediction accuracy that fall between 85% to 90% in the sectors namely Engineering, Electronics, Hotels, Pharmaceuticals, Plastic & Fibre, Steel, Textile and Miscellaneous.

The developed models have few shortcomings as well concerning the misclassification which is exhibited by Type I and Type II Errors. The higher value of Type I and Type II Errors convey the weak predictive accuracy of the default prediction models. The MDA and Logit models accomplished good results about the Type I Errors. As the table demonstrated the MDA model endured only 2% Type I Error for Steel and Miscellaneous sectors followed by Chemicals sector. Whereas, the Logit model successfully achieved 1% Type I Error for Chemicals sectors followed by Steel, Realty, Pharmaceuticals, Plastic & Fibre and Textile sectors.

The Type II Error exhibited in the table states that the MDA model have encountered 84% Type II Error in the Steel sector followed by Logit model that encounter 83% and 74% Type II Error for Complete Sample and Miscellaneous sector. The remaining sectors demonstrated 60% to 34% Type II Errors for MDA and Logit Model.

Sector-wise Comparison

The sectors that acquire higher accuracy rates are Chemicals, Construction and Engineering, Electronics, Plastic & Fibre, Hotels, and Steel. Table displayed higher accuracies for Logit model followed by MDA model.

Interpretations of Complete Sample

Table No 4 Classification Results exhibits that the predictive accuracies obtained for the Complete Sample by MDA and Logit are 78% and 86% respectively which are average accuracy levels. The study also found moderate outcomes of Type I and Type II Errors for Complete Sample for MDA and Logistic.

Common Independent variables found to be significant for MDA and Logit Models across the Selected Sectors and Complete Sample.

Table No 5 Common Independent Variables displays the significant independent variable that are incorporated in the developed MDA and Logit models for predicting the default risk of selected Indian firms from the selected sectors.

Table No 5 Common Independent Variables

Sectors	MDA Model	Logistic Model
Complete Sample	WC/TA, RE/TA, EBIT/TA, and NI/TA	WC/TA, RE/TA, MVE/TBD, SALES/TA, NI/TA, GRTA, LOG (TA/GNP), X and Y
Chemicals	WC/TA, CA/CL, NI/TA, NP/TE, TBD/TA, FAT.	FAT, LOG (TA/GNP) and Y
Construction and Engineering	WC/TA, RE/TA, EBIT/TA, CA/CL, NI/TA, TBD/TA, GRTA, TL/TA and MP/BV	RE/TA, EBIT/TA, SALES/TA, NI/TA, GRTA and LOG (TA/GNP)
Electronics	WC/TA, TBD/TA, INVE.TURN, FAT and MP/BV	WC/TA, MP/EPS and Y
Hotels	WC/TA, NP/TE and D/E	WC/TA, NI/TA, MP/EPS, MP/BV
Infrastructure	RE/TA, EBIT/TA, NI/TA, MP/BV, TBD/TA, GRTA	GRTA and Y
Pharmaceuticals	EBIT/TA, NI/TA, WC/TA, TBD/TA, RE/TA	WC/TA, RE/TA, SALES/TA and Y
Plastic & Fibre	TBD/TA, FAT, EBIT/TA, NI/TA, NP/TE	RE/TA, SALES/TA, NI/TA, TBD/TA, FAT, NP/TE
Realty	NP/TE and EBIT/TA	WC/TA, CA/CL, NP/TE, OCFR, INVENT. TURN
Software	EBIT/TA, MP/BV, NI/TA, RE/TA and GRTA	WC/TA, OCFR, FAT, and MP/BV
Steel	EBIT/TA, NI/TA, FAT, and LOG (TA/GNP)	WC/TA, RE/TA, MVE/TBD, SALES/TA, NI/TA, TBD/TA, GRTA, INVENT TURN, FAT, TL/TA, LOG (TA/GNP) and Y
Sugar	WC/TA, MVE/TBD, CA/CL, NP/TE, EBIT/INT and D/E	WC/TA, MVE/TBD, OCFR, LOG (TA/GNP)
Textiles	WC/TA, RE/TA, NI/TA, TBD/TA, GRTA	GRTA, MP/BV, X and Y
Miscellaneous	NI/TA, EBIT/TA, RE/TA, NP/TE, TBD/TA and EBIT/INT	EBIT/TA, NI/TA, NP/TE, TBD/TA, OCFR, INVEN.TURN, TL/TA, SALES GROWTH, X and Y

Source: Prepared by Scholar by considering findings of the selected sectors

The table provided the independent variables that have been used in 28 developed MDA and developed Logit model for the selected Indian sectors. The analysis of the variables has been conducted model wise.

Significant Variable used in MDA Models

The outcome of the analysis of the above table conveys the most used, moderately used, once used and not used independent variables. Therefore, the most used variables which are incorporated in more than 6 models are WC/TA, RE/TA, EBIT/TA, NI/TA, TBD/TA, and NP/TE. Moreover, the NI/TA has been used for the development of 10 default prediction models. The moderately used variables are CA/CL, FAT, GRTA, MP/BV, D/E, and EBIT/INT. The variables which are used only once for the development of the model are TL/TA, LOG (TA/GNP), and MVE/TBD. The analysis found that there are few independent variables that did not contribute at all to the development of any model such as INVEN.TURN, OCFR, SALES GROWTH, SALES/TA, MP/EPS, and SALES GROWTH/GNP.

Significant Variables used in Logit Models

Similarly, the analysis of the Logit model also indicates the most used, moderately used, once used and not used independent variables. The most used variables in the Logit model are WC/TA, Y and NI/TA. The moderately used variables are RE/TA, EBIT/TA, NP/TE, TBD/TA, FAT, GRTA, TL/TA, MP/BV, INVEN.TURN, LOG (TA/GNP), MVE/TBD, OCFR, X, SALES/TA, and MP/EPS. The variables which have been used once are CA/CL and SALES GROWTH. The variables which have not contributed to any model development are D/E, EBIT/INT, and SALES GROWH/GNP.

V. Conclusion & Discussion

The MDA model developed for the Complete Sample has the highest numbers of the significant independent variables. The MDA model developed for the Construction and Engineering sector included 9 significant variables that is the maximum count of significant independent variables included for the model development.

The most frequent independent variables amongst all selected independent variables are NI/TA, WC/TA, EBIT/TA, TBD/TA, RE/TA and the variables which were used only once to develop the default prediction models are TL/TA, INVEN.TURN, Log (TA/GNP), MVE/TBD and EBIT/INT. These findings recommended the relevance of the accounting variables that reflects the Profitability, Liquidity, Solvency and Leverage of the firms that contribute the most to predict the default risk. This is inevitable from the findings that the market and economic variables are still not competent enough to predict the default firms accurately for the MDA model.

The independent variables which were not used in any of the developed models are SALES/TA, MP/EPS, OCFR, SALES GROWTH, SALES GROWTH/GNP GROWTH. These independent variables denoted the firm-specific sales, cash flow, market and economic variables. This suggests that the economic and cash flow ratios were peripheral for the credit risk modeling of the firms in the context of MDA model.

The developed MDA model performed satisfactorily well for the In-sample data than the Out-of-sample data. The chemical sector's default prediction has been correctly conducted by the developed model with 90% accuracy followed by Construction and Engineering, Electronics, Hotels, Plastic & Fibre, Steel and Miscellaneous sectors that attained the accuracies in the range of 89% to 80%. The out-of-sample classification results did not show the pleasant accuracy rates for Chemicals, Hotels, Infrastructure, Steel and Miscellaneous sectors. The study found that only Realty sector depicted the acceptable prediction accuracy in validation results i.e. 83%. 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.

Out of 23 independent variables deployed in the Logit function to develop the Logit model, there are 19 predictors that contributed variably in all the developed models, This includes qualitative independent variables also.

The factors that have been frequently used in the developed Logit models are WC/TA, Y, NI/TA, RE/TA and Log (TA/GNP). These factors belong to the accounting, economic and qualitative category of variables. The independent variables which did not contribute at all in any of the developed Logit models are EBIT/INT, INVEN. TURN, SALES GROWTH, SALES GROWTH/GNP. This advocates that the sales growth, inventory turnover has no impact on the default status of the firms.

The classification accuracy of the developed Logit model for In-sample data for the selected sectors and Complete Sample is between 93% to 86%, 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 attained by all developed models for selected sectors and Complete Sample is at minimum level. However, the study witnessed substantially high rate of Type II Error for few selected sectors namely Realty, Textile, Miscellaneous and the Complete Sample i.e. 69%, 62%, 74% and 83% respectively.

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), 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 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 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 Karthik, Subramanyam, Srivastava, & Joshi (2018), Bandyopadhyay A (2006), Sheikhi, Shams, & Sheikhi (2012), Sharma, Singh, &Upadhyay (2014), Pang & Kogel (2013), Salehi & Abedini (2009), Desai & Joshi (2015), Chijoriga (2011), Kumar &Rao (2014).

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 developed logistic model outperformed the developed MDA model that attained higher predictive accuracies across the selected sectors and Complete Sample. The in-sample classification accuracy rates of the Logit model arrayed from 83% to 93%. 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).

- Out of the total 23 independent variables the study recommends using the following variables for the accurate default prediction.
  - The significant independent variables that are compatible with both developed MDA and developed Logit model are WC/TA, NI/TA, EBIT/TA, FAT, GRTA, MP/BV, RE/TA, and TBD/TA.
  - The independent variables that are best fitting into the developed MDA model are WC/TA, RE/TA, EBIT/TA, NI/TA, TBD/TA and NP/TE, followed by CA/CL, D/E and EBIT/INT.
  - The variables that can predict the default risk accurately with Logit function are WC/TA, Y, NI/TA, followed by TL/TA, INVE.TURN, LOG (TA/GNP), MVE/TBD, OCFR, X, SALES/TA and MP/EPS.

Hence, the outcome of the default prediction result conveys the relevance of accounting variables over market, and economic variables particularly for the developed MDA model. However, in the Logit model all four categories of the independent variable (accounting, market, economic and qualitative) performed significantly well for default prediction. Further, the study found that the market variables are significant for the developed MDA and developed Logit model. Consequently, study found that the economic variables are found significant only for developed Logit model. Further, the study also recommends and emphasised the particular accounting variable which is emerged as the true outcome of the study, and that can be used in future studies to predict the default risk of any listed firm. The accounting variable is NI/TA i.e. Net Income to Total Assets because this ratio is used in more than 10 developed MDA models and more than 6 developed Logit models. The crux of these findings is that this ratio is the most used independent variable of the study. NI/TA reflects the return on assets that indicates the profitability, and efficiency of the firm. Thus, it can be said that for evaluating the solvency of any firm the users are required to check its profitability and efficiency ratios using NI/TA along with either developed MDA or developed Logit model.

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