A Comparative Study of Default Prediction Models

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Abstract

This study developed two credit risk models using MDA and Logistic regression to predict the default of 600 BSE Listed Indian companies (300 defaulting and 300 non-defaulting) for the period of 15 years from April 1, 2004 to March 31st, 2019. Paper further, examined the robustness of both the models by analysing various statistical measures. The developed models were examined and compared for both in-sample and out-sample firms year cases with regard to accuracy rate, type I and type II error to the Altman's (1968) model, calibrated Altman model and to each other. Paper draw a conclusion that in respect of classification perfection rate and robustness the logistic model exhibited more proficiency than the discriminant model followed by Altman's calibrated model.

Keywords:

Default, Bankruptcy, Default Prediction, Logistic regression, Multiple Discriminant Analysis, Logit, MDA, Insolvency.

Introduction

As on December 31, 2019, sixty Indian Listed firms reported approximately seventy-five thousand cumulative defaults, where the majority of the default pertain to Reliance group of companies namely Reliance Infrastructure, Reliance Power and Reliance Communications. Other willful defaulters were JaypeeInfratech, Religare Enterprises, Suzlon Energy and Bombay Rayon Fashions (The hindu, 2020). As per the analysis of credit ratios performed by Reuters that the Asian companies are gradually drifting towards grey zone due to outbreak of coronavirus pandemic. Reuters reported the highest Debt to EBIT ratio since 2014 which implies that companies shall take a long period to repay the loan. Moreover, the study also gave the snapshot of the worst-hit sectors namely Airlines, Real estate, Travel and which might enter into the group of potential defaulters (news18.com, 2020).

Predicting the firm's insolvency is in the best interest of not only the company itself rather to its stakeholders, economists and regulators to take remedial actions and bring necessary reforms. Prediction of credit risk is pervasive in all the areas of finance for ascertaining risk attached to the financial instruments, mutual funds, loan(Casserley, 1993) and to price them accordingly (Altman & Narayanan, 2001)(Shumway, 2001). There is an indirect cost attached to the default made by the firms which can be gauged using two yardsticks, first constantly eroding sales value, the elevated cost of capital and the firm's droppingprofitability (Altman, 1984).

Since 1932 numerous scholars developed various models for predicting bankruptcy. Primarily, the concept of default prediction is being conceived by(Fitzpatrick, 1932), (Beaver, 1966) and (Altman, 1968) by integrating the statistical tool accompanied financial ratios of the entities and achieved quite satisfactory results which opened the scope for the further study. Beaver (1966) used Univariate Discriminant Analysis (UDA) tool that had some shortcomings which were overcome by (Altman, 1968) introducing Multiple Discriminant Analysis (MDA). Latter, Ohlson (1980) advanced the study of insolvency prediction with the development of logistic regression (Logit). Logit model predicts the bankruptcy using Binary response (0&1), unlike MDA which computes credit score (Z score) thereafter provide the probability of default. Subsequently, alternate modelswere proposed by different scholars such as structural model by (Black & Scholes, 1973), (Merton, 1976) which diagnose the financial status of companies by examining its market value of assets and their outside liabilities. According to the BSM model firm default when it's MVA reaches to zero or become less than its book value of debts. Then the hazard model was propounded by (Campbell, Hilscher, & Szilagyi, 2008), it is purely a statistical model which incorporates changes in the value of variables according to the time. This model is also called as hybrid model since it incorporates both accounting and market-based variables for estimating the risk of default.

Research Gap

There are few studies that dealt with the development of credit risk model for the Indian entities namely (Bandyopadhyay, 2006) and (Sharma, Singh, & Upadhyay, 2014) however; the sample included in the paper was very less and the study mainly focused into either one or two Indian corporate sectors. Thereby it refrain the scholars to generalize the result of their study into the other unexplored sectors. Past studies concentrated on the prediction of the manufacturing and non-service sector only such as(Singh & Mishra, 2016)(Altman, 1968), (Sajjan, 2016). Edward I Altman (2007) compared the Z score and Logit model using qualitative variables and (Desai & Joshi, 2015) developed a model for measuring the financial performance of the firms using only financial ratios. None of the studies till date had incorporated the set of different variables namely Accounting, Market, Economic and qualitative Variables.

Objectives of the study

Study shall develop the two default prediction models using Multiple Discriminant Analysis (MDA) and Logistic regression. The developed model will be evaluated with regard to its predictive accuracy, statistical robustness and Type I and Type II errors on in-sample data and hold-out sample data. A Comparative analysis of the study shall also be performed while examining the models against the Edward I Altman (1968) model, recalibrated Edward I Altman (1968) model and to each other.

Literature Review

The first-ever study published in the area of default prediction was(Fitzpatrick, 1932)followed by(Altman, 1968)that was treated as the milestone study in the area ofcredit risk modelling. The study used Multiple Discriminant Analysis for categorising the firms into solvent and insolvent by applying the method on the matched sample of 33 manufacturing firms. Later on Altman (1984), Zmijewski (1984), Shumway (2001) &Hillegeist (2004).Prior to Altman (1968)(Beaver, 1966) conducted the study including financial ratios to explore the predictive capacity of the 30 financial ratios by applying Univariate Discriminant model to provide the true financial position of the firms and to determine the predictive accuracy of the financial ratios for the period from 1954 to 1964. Study concluded that the most pertinent variable in the default prediction is cash flow to total debt ratio. However, Edward I Altman (1968) imposed certain assumptions on the application of MDA function such as Normality of sample data, equality in covariance-variance group mean. These assumptions criteria was criticised and violated by many scholars that made the application of MDA function limited.To conquer this (Ohlson, 1980) presented the Logistic regression model for predicting default of the firms using financial ratios. The logistic model stood out against the MDA model.Vandana Gupta (2014) Compared the original Altman model to Z score model for predicting the default of Indian listed firms the study found that the Z score model outperform the (Altman, 1968) in terms of classification accuracy rate. Cornelius Casey (1984) advocated that instead of cash flow analysis the MDA performs better in the accrual-based system of accounting. Z score model is helpful in generating a prediction, risk-adjusted sales, income, and return on assets using financial information and outperform the market-based prediction model(Agarwal & Taffler, 2008).Duffie, Saito, & Wang (2007) introduced a model to estimate the survival probability of corporate by applying conventional accounting ratios with time-varying independent variables. MDA and Logit model gives different result even if the independent variables are same. Ciampi&Godini (2013) applied both MDA and Logit on the sample of SME firms. Findings of the study revealed that both the function performed well and that there must be a separate model to predict the financial position of SMEs. Altman &Sabato(2007) supported Logit model for estimating the likelihood of default of SMEs companies over MDA. The Logit regression was applied for estimating the bankruptcy for 1 to 5 years prior and got the result similar to (Ohlson, 1980) i.e. 92% accuracy. Integrating economic variables into the Logit model increased its discriminatory power when applied to the matched sample of manufacturing companies (Daraseh, Waples, & Tsoukalas, 2003). MDA and logistic models were also used to predict the bankruptcy of Indian listed firms by (Bandyopadhyay, 2006), (Upadhyay, 2019) where both the models performed quite well nevertheless, z score showed high accuracy in recognising credit risk. In order to bring more accuracy, less Type I and Type II error is required(Bandyopadhyay, 2007). Bandyopadhyay (2007) also emphasised to use the information generated from the structural model which followed by (Sharma, Singh, & Upadhyay, 2014) in which scholar revealed the significance of volatility of assets value as the main predictor of insolvency. Dr Radha Ganesh Kumar (2012) presented a comparative study of Z score, O-score model, and Zmijewski's models. The model developed for the sample from 2006 to 2010 which was validated for the period 2011-2014. Paper concluded that O-score performed better amongst all (Kumar & Kumar, 2012). Subsequently, Castagnolo (2014) and Hasan (2016) confirmed the findings by revealing the superiority of O-score amongst Z score, Campbell and structural model. Models were applied on a sample of firms from 1990 to 2010 by incorporating accounting, market and economic variables.

Charles Kwofie (2015) developed a model for the micro finance company using Logisitic regression to predict the default of retail customers using qualitative variables. Study unveiled that duration of business and its capital base do impact the financial stability of the firms(Kwofie, Ansah, & Boadi, 2015).

DeniMemic (2015) compared the predictive accuracy of both MDA and Logit model while predicting the default of banking market of Bosnia and Herzegovina for the year 2011 of 1148 companies. Result showed similar accuracy with ROA as a significant predictor of the bankruptcy (Memic, 2015).

The study concluded that using the set of accounting, macro-economic and market variables increase the predictive capacity of the default prediction model. Where, paper demonstrated 85% accuracy on the overall set of variables while 80% for the individual group of variables(Tinoco, Holmes, & Wilson, 2015).

This Article has used Option pricing models for examining the financial distress of US firms for the span of 1986-2001. Paper revealed that amongst all firms volatility has the substantial role in the describing the bankruptcy 5 years prior to the event (Charitou & Trigeorgis, 2004).

Study applied multi-period Logit model on the public companies of Australia during the year 1990 to 2003. Information collected from the financial statements of the firms and from Merton model. Result indicate that the developed model effectively classify bankrupt and delisted firms (Tanthanngsakkun, Pitt, & Treepongkaruna, 2009).

Data& Methods

Sample in this study comprises of 600 (300 Defaulting and 300 non Defaulting) BSE listed firms belong to various Indian corporate sectors namely Chemicals, Hotel, Infrastructure, Packaged food, Paper, Pharmaceuticals, Plastic &Fibre, Realty, Software, Steel, Sugar, Textile and others for the period from 1st April 2004 to 31st March 2019. Accounting information collected from the financial statements companies fetched from their individual websites. Information regarding Market price of shares of the sample firms collected from BSE website. GDP data for the 15 years accessed from the database maintained by World Bank. The study developed two models using MDA and Logistic regression. Total no of cases used for both the models were 5777 which reduced to 5558 after removing outlier cases using Mahalanobis Statistics. For the validation purpose, 2833 cases in MDA and 1321 cases were included. The study further included a calibrated model to compare it with MDA, Logistic and Altman's Model. The study include set of 21 variables consists of Accounting, Market and economic variables.

Multiple Discriminant Analysis

Developed Model

Study computed Z score model consist of 4 significant variables. Where, WC/TA and NI/TA were documented as the best fitting variables to discriminate the groups by (Beaver, 1966).

$$Z=-0.141+1.428*WC/TA+5.432*RE/TA+0.344*EBIT/TA-1.709*NI/TA$$

Calibrated Model

$$Z=-0.688+1.675*WC/TA+2.978*RE/TA+0.827*EBIT/TA+0*MVE/TBD+2.404*SALES/TA$$

Altman Model

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

Where

WC/TA = Working Capital to Total Assets

RE/TA = Retained Earnings to Total Assets

EBIT/TA = Earnings before Interest and Taxes to Total Assets

NI/TA = Net Income to Total Assets

MVE/TBD = Market value of equity to Total book value of debts

SALES/TA = Sales to Total Assets

Logistic Regression

L score has been calculated with 9 significant variables.

Developed Model

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/GDP)+0.596*X+2.052*Y

Where

GRTA = Growth to Total Assets

LOG(TA/GDP) = Log value of ratio of Total Assets to GDP Index

X = it will be 1 if Total Liabilities > Total Assets and

It will be 0 if Total Liabilities < Total Assets.

Y = it will be 1 if Average net profit of two years < 0 and

It will be 0 if Average net profit of two years > 0.

Data Analysis & Result

Multiple Discriminant Analysis

Table 1 : Test of equality of Group Means

Particulars	Sample firms data		
	Wilks' Lambda	F	Sig.
WC/TA	.963	211.722	.000
RE/TA	.975	142.465	.000
EBIT/TA	.979	119.906	.000
MVE/TBD	.999	6.748	.009
Sales/TA	.997	14.450	.000
CA/CL	1.000	.305	.581
NI/TA	.951	287.993	.000
NP/TE	.997	14.126	.000
TBD/TA	.997	18.996	.000
EBIT/Int	.996	22.971	.000
OCFR	.998	13.914	.000
GRTA	.994	34.195	.000
Inv. Turn.	1.000	.074	.785
FAT	.998	8.998	.003
MP/EPS	.998	11.996	.001
MP/BV	.999	2.823	.093
D/E	.999	3.678	.055
TL/TA	.995	28.210	.000
Log(TA/GDP)	1.000	2.086	.149
Sales Growth	.999	5.337	.021
SG/GNP Growth	1.000	.512	.474

Source: Output obtained from SPSS 23

Table 1 depicts that there are 15 significant variables having p-value < .05. Additionally, it also satisfies one of the assumptions of MDA i.e. there is a significant difference between the groups on each of the group of the independent variable mean. Lennox(1999) presented some of the assumptions of MDA out them equality of a group is important to get the accurate result.

Table 2: Log Determinants

Z	Rank	Log Determinant
0	21	67.260
1	21	54.894
Pooled within-groups	21	68.855

Source: Output obtained from SPSS 23

Table No 2 shows the large values of log determinants for both the categories which make the discriminant functions significant. Here, the Rank column denotes the number of independent variables included in the study i.e. 21.

Table 3: Box's M Result

Box's M		19041.013
F	Approx.	81.691
	df1	231
	df2	6718566.477
	Sig.	0.000

Source: Output obtained from SPSS 23

Box's M assesses the equality of covariance across the groups and between the groups which according to which the significant value of the Box's M must be > .05 however, its table 3 show sig. value 0.000 which make the discriminant function non- efficient for classifying the groups correctly.

Table 4: Eigen Values

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	0.107	100.0	100.0	.311

Source: Output obtained from SPSS 23

For the effective discriminant function, the eigenvalue must be => 1 and canonical correlation close to 1, but according to Table 4, its 0.107 and .311 respectively. This ascertains that function is incapacitated to explain the variance in the dependent variable and there is a weak association between discriminant function and classification groups.

Table 5: Wilk's Lambda

Test of Function(s)	Wilks Lambda	Chi-square	df	Sig.
1	.904	562.695	21	.000

Source: Output obtained from SPSS 23

Wilk's Lambda examines the predictive power of the independent variables. Table 5 denotes the high value of Wilk's lambda which is not desirable for the developed model's performance yet the sig. value of the Chi-square <.05 which indicates high discriminatory power of the model.

Table 6: Standardized Canonical Discriminant Function

Particularly	Sample Firms Data
WC/TA	.533
RE/TA	1.078
EBIT/TA	.103
MVE/TBD	.045
Sales/TA	1.017
CA/CL	-.020
NI/TA	-.240
NP/TE	.127
TBD/TA	-.128
EBIT/Int	.027
OCFR	.105
GRTA	.191
Inven.Turn	.000
FAT	.080
MP/EPS	.075
MP/BV	-.017
D/E	-.007
TL/TA	-.140
Log(TA/GDP)	-.110
Sales Growth	.057
SG/GNP Growth	-.003

Source: Output obtained from SPSS 23

Wilcox(1971) elucidated how certain accounting variables are more significant in discriminating firms correctly than the others which were followed by (Casey & Bartczak,

1984) which documented cash flow ratios as the important predictors. Table 6 reflects that RE/TA has the highest coefficient value i.e. 1.078 which indicates that RE/TA has the highest discriminatory power amongst all the independent variables. On the other hand, NI/TA has the lowest value at -0.24, it has the lowest discriminatory power.

Table 7: Structure Matrix

Particulars	Sample Firms Data
NI/TA	.697
WC/TA	.597
RE/TA	.490
EBIT/TA	.450
GRTA	.240
TL/TA	.218
EBIT/Int	.197
TBD/TA	-.179
Sales/TA	.156
NP/TE	.154
OCFR	.153
MP/EPS	.142
FAT	.123
MVE/TBD	.107
Sales Growth	.095
D/E	-.079
MP/BV	.069
Log(TA/GDP)	-.059
SG/GNP GROWTH	.029
CA/CL	-.023
INVET. TURN	-.011

Source: Output obtained from SPSS 23

Structure Matrix table provides the list of the variables which contributes to the development of the model. Table 7 indicates that there are only top 4 variables which are used for developing the model.

Table: 8 Canonical Discriminant Function Coefficients

WC/TA	1.428
RE/TA	5.432
EBIT/TA	.344
MVE/TBD	.000
Sales/TA	5.229
CA/CL	.000
NI/TA	-1.709
NP/TE	.077
TBD/TA	-.033
EBIT/Int	.000
OCFR	.084
GRTA	.132
Inventory Turnover	.000
FAT	.003
MP/EPS	.001
MP/BV	-.001
D/E	-.001
TL/TA	-.265
Log(TA/GDP)	-.054
Sales Growth	.012
SG/GNP Growth	.000
(Constant)	-.141

Source: Output obtained from SPSS 23

Table 8 presents the value of significant independent variables which shall be used to arrive at Z score.

Table 11: In sample classification result

Case wise		Developed Model (MDA)			Calibrated Model			Altman's Model		
		Non-Defaulting	Defaulting	Cases	Non-Defaulting	Defaulting	Cases	Non-Defaulting	Defaulting	Cases
	Non-Defaulting	3826	909	4735	4317	51	4368	167	4681	4848
	Defaulting	313	511	824	712	51	763	4	847	851
	Total			5559			5131			5699
Percentage wise	Non-Default	81%	19%	100%	99%	1%	100%	3%	97%	100%
	Default	38%	62%	100%	93%	7%	100%	0%	100%	100%
Overall		78%			85%			18%		

Source: Output obtained from SPSS 23

Table 11 sign exhibits the classification result of Developed, Calibrated and Altman's Original Model. The accuracy rate of Non-default groups is highest in the calibrated model but which reduced to 85% for the overall result owing to 93% Type II error, and for Default group Altman's Model outperforms the others and overall it performed poorly. MDA's overall accuracy rate also not quite good nevertheless similar (Altman &Sabato, 2007) but less than (Chijoriga, 2011) because of a higher Type II error.

Table 12: Validation of models on out sample firms data

Cases wise		Developed model (MDA)			Calibrated Model		
		Non-Defaulting	Defaulting	Cases	Non-Defaulting	Defaulting	Cases
	Non-Defaulting	1913	747	2660	295	184	479
	Defaulting	102	71	173	20	68	88
	Total			2833			567
Percentage wise	Non-Defaulting	72%	28%	100%	62%	38%	100%
	Defaulting	59%	41%	100%	23%	77%	100%
Overall		70%			64%		

Source: Output compiled by authors

Model's validation result is being depicted in Table 12. MDA model discriminated firms with higher accuracy than the Calibrated model. Result obtained in the present study is not as satisfactory as (Bandyopadhyay, 2006) in which validated the developed Z score model with 92% accuracy.

Logistic Regression

Table 13: Omnibus Test of Model Co-efficient

	Chi-square	df	Sig.
Sample Firms Data	1017.879	23	.000

Source: Output obtained from SPSS 23

The omnibus test examines the role of the independent variable in predicting default and their impact on dependent variables. As the significant value of the chi-square is <.05 in table 13 which implies that the independent variables included in the study do impact the dependent variables and contribute to the prediction model.

Tale 14: Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	3650.023	.167	.295

Source: Output obtained from SPSS 23

The model summary is helpful in assessing the robustness of the developed model. Nagelkereke R square denotes that how much variation in the default prediction is being explained by the developed model, the value depicted in Table 14 is .295 i.e. only 29% of the variation is being explained by the model which is not desirable. Likewise the value of Cox & snell R square is very less which makes the model less robust. On the contrary, the value of -2 Log-likelihood is quite high which proves the model is significant for the prediction purpose.

Table 15: Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	13.101	8	.108

Source: Output obtained from SPSS 23

Hosmer and Lemeshow test provides information about the goodness of fit. Here, it tells whether the data included in the model is the best fitting into the model to predict the default of the loan. To prove the goodness of fit the p-value of the chi-square must be greater than the critical value, which is evident from Table 15. Hence, the data is the best fitting into the model.

Table 16: Variables in equation

Particulars	Sample Firms Data (Cases)		
	B	Wald	Sig.
WCTA	-.313	6.805	.009
RETA	-1.758	11.594	.001
EBITTA	-.167	.588	.443
MVETBD	-.004	5.393	.020
Sales/TA	-1.663	10.857	.001
CACL	.000	.151	.698
NITA	1.925	9.877	.002
NPTE	-.023	1.001	.317
TBDTA	.010	1.520	.218
EBIT/Int	.001	1.880	.170
OCFR	-.012	.111	.739
GRTA	-.153	5.866	.015
INV.TUR	.000	.130	.718
FAT	.000	.035	.851
MPEPS	.001	2.998	.083
MPBV	.001	.418	.518
DE	-.002	.118	.731
TL/TA	.099	1.620	.203
Log (TA/GDP)	.100	20.252	.000
SalesGrowth	-.013	.500	.480
SG/GNP GROWTH	.000	.135	.713
X	.596	32.581	.000
Y	2.052	378.281	.000
Constant	-3.425	480.675	.000

Source: Output obtained from SPSS 23

Wald test exhibited in Table 16 explain the predictive power of the independent variables. The high value of the Wald test implicates the higher predictive power of variables. It is witnessed from the table that variable Y has the highest contribution in terms of predicting the default of the loan and variable Fixed Asset turnover has the least.

In sample classification result

Table 17: Developed Model (Logistic)

Case wise	Sample Firms Data (Cases)			
		Non-Defaulting	Defaulting	Cases
	Non-Defaulting	4611	120	4731
	Defaulting	683	143	826
	Total			5557
Percentage wise	Non-Defaulting	97%	3%	100%
	Defaulting	83%	17%	100%
Overall	86%			

Source: Output obtained from SPSS 23

Table 17 exhibits the in sample classification result where firms grouped into the defaulting and non-defaulting categories with 86% accuracy, which equal to the accuracy obtained by (Sirirattanaphonkun & Pattarathammas, 2012). Type II error of the model is quite high that make to misclassify the firms.

Validation of Models

Table 18: Developed Model (Logistic)

		Non-Defaulting	Defaulting	Total
Case wise	Non-Defaulting	1157	28	1185
	Defaulting	122	14	136
	Total			1321
Percentage wise	Non-Defaulting	98%	2%	100%
	Defaulting	90%	10%	100%
Overall	89%			

Source: Output obtained from SPSS 23

Table 18 provide the information pertaining to the validation of the Logistic model, result yield in this table is 89% with 90% type II error and 2% type I error.

Comparative Results

This section compares the results of MDA, calibrated, Altman's and Logistic regression model for In sample firms cases.

Table 19: **In sample comparisons**

Particular	MDA	Calibrated Model	Altman's Original	Logistic Regression
Accuracy Rate	78%	85%	18%	86%
Type I Error	19%	1%	97%	3%
Type II Error	38%	93%	0%	83%

Source: Output compiled by authors

For accuracy rate Logistic regression outperforms with 86% rate however it is less than the accuracy achieved by(Verma, 2019) in which data of only 90 firms were undertaken for the period 2010 to 2014 and the study conducted on 32 listed firms for 2010-11 to 2015-16 by (Upadhyay, 2019). Type I error is least in Calibrated model having 85% accuracy which is proximately similar to (Verma & Raju, 2019). Whereas, Altman's model has 0% Type II error.

Table 20: **Validation of Models on out sample**

Particular	MDA	Calibrated Model	Logistic Regression
Accuracy Rate	70%	64%	89%
Type I Error	28%	38%	2%
Type II Error	59%	23%	90%

Source: Output compiled by authors

Table 20 demonstrated the validation result of the MDA, Calibrated and Logistic regression model. The Logistic stood out amongst others for grouping the companies correctly. Logit model generated 89% accuracy along with 90% Type II error which provides unacceptable results. The calibrated model showed the least Type II error with a 64% rate of classification accuracy. Type II error is costlier than Type I error as the study has misclassified the defaulting firm into non- defaulting which can cause loses to banks and investors (Carcello & Palmrose, 1994) (Krishnan & Krishan, 1997).

Conclusion and Discussion

Discrimination power of Developed Logit model and the calibrated Discriminant model shows quite indistinguishable results, yet Logit model outperformed the MDA with very high type II errors for in-sample classification result which is identical to(Hasan, 2016). Result of the study is consistent with the findings of Jayadev (2006), Sirirattanaphonkun&Pattarathammas (2012) and Altman &Sabato (2007). Accuracy of developed Z score model is quite higher than the Edward I Altman (1968) model which supported the conclusion of (Desai & Joshi, 2015).Additionally, study tested developed model and calibrated model on out-sample firm's year cases in which developed logistic found to be better than the other two, however, it has 90% type II error which makes the model inadequate for predicting defaults which is similar to (Singh & Mishra, 2016). After analysing the empirical results present study concludes that Developed Logistic regression model is more robust than the developed MDA model which is evident from the HosmerLemeshow test and Box M's result test. In the Discriminant function model, only accounting variables found to be significant with having RE/TA ratio is the most relevant predictor which validates the inference given by (Raei, Kousha, Fallahpour, & Fadaeinejad, 2016). Conversely, in the logistic model all categories of variables namely Accounting, Market, Economic and Qualitative played a pivotal role for developing the model. Besides, variable Y demonstrated high prediction capacity with highest Wald Test value.

References

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting -based bankruptcy prediction models . Journal of Banking & Finance, 32(8), 1541-1551.

Altman, E. I. (1968, September). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. The Journal of Finance , 23(4), 589-609.

Altman, E. I. (1984, September). A Further Empirical Investigation of the Bankruptcy Cost Question. Journal of Finance, 39(4), 1067-1089.

Altman, E. I., & Narayanan, P. (2001, December 26). An International Survey of Business Failure Classification Models. Wiley Online Library.

Altman, E. I., & Sabato, G. (2007, September). Modeling Credit Risk for SMEs: Evidence from the US Market. A Journal of Accounting, Finance and business studies, 43(3), 332-357.

Bandyopadhyay, A. (2006). Predicting Probability of Default of Indian Corporate Bonds: Logistic and Z-score model Approaches. The Journal of Risk Finance, 7(3), 255-272.

Bandyopadhyay, A. (2007). Mapping corporate drift towards default part 2 : a hybrid credit scoring model . the journal of risk finance, 8(1), 46-55.

Beaver, W. H. (1966). Financial Ratio as Predictors of failure. Journal of Accounting Research, 4, 71-111.

Black, F., & Scholes, M. (1973, May-June). The pricing of optons and corporate liabilities. The journal of Political Economy, 81(3), 637-654.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008, December). In Search of Distress Risk. The Journal of Finance, 2899-2939.

Carcello, J. V., & Palmrose, Z. V. (1994). Auditor Litigation and Modified Reporting on Bankrupt Clients. Journal of Accounting Research, 32, 1-30.

Casey, C., & Bartczak, A. N. (1984). Using Operating Cash Flow Data to Predict Financial Distress: Some Extension. Journal of Accounting Research, 23(1), 384-401.

Casserley, D. (1993). Facing to the Risks: How Financial Institutions can survive and prosper. USA, USA: Wiley.

Castagnolo, F., & Ferro, G. (2014). Models for predicting default: towards efficient forecasts. The journal of risk finance, 15(1).

Charitou, A., & Trigeorgis, L. (2004, 12 1). EXPLAINING BANKRUPTCY USING OPTION THEORY. SSRN Electronic Journal, 1-44.

Chijoriga, M. M. (2011). Application of multiple discriminant analysis (MDA) as a credit scoring and risk assessment model. International journal of Emerging MArkets, 6(2), 132-147.

Ciampi, F., & Godini, N. (2013, January). Small Enterprise Default Prediction Modeling Through Artificial Neural Network: An Empirical Analysis of Italian Small Enterprise. Journal of small Business Management.

Daraseh, M., Waples, E., & Tsoukalas, D. K. (2003, September). Corporate failure for manufacturing industries using firms specifics and economic environment with logit analysis. Managerial Finance, 29(8), 23-36.

Desai, D. J., & Joshi, N. A. (2015). A Proposed Model for Industrial Sickness. International Journal of Engineering Development and Research , 3(4), 754-760.

Duffie, D., Saito, L., & Wang, K. (2007). Multi-period corporate default prediction with stochastic covariates. Journal of Financial Economics, 83, 635-665.

Fitzpatrick, P. (1932). A comparison of the ratios of successful industrial enterprise with those of failed companies. . The Accountants Publishing .

Gupta, V. (2014, Aug 22). An Empirical Analysis of Default Risk for Listed companies in India: A Comparison of two prediction Models. International Journal of Business and Management, 9(9), 223-234.

Hasan, K. R. (2016). Development of a Credit Scoring Model for Retail Loan Granting Financial Institutions from Frontier Markets. International Journal of Business and Economics Research, 5(5), 135-142.

Hillegeist, S. A., Keating, E. K., Cram, D. P., & Lundstedt, K. G. (2004, March). Assesing the Probabiltiy of Bankrutpcy. Review of Accounting Studies, 9, 5-34.

Jayadev, M. (2006, July-September). Predictive Power of Financial Risk Factors: An Empirical Analysis of Default Companies. Vikalpa, 31(3), 45-56.

Khemais, Z., Nesrine, D., & Mohamed, M. (2016, March 25). Credit scoring and Default Risk Prediction : A comparative Study between Disciminant Analysis & Logistic Regression. International Journal of Economics and Finance, 8(4), 39-53.

Krishnan, J., & Krishan, J. (1997, October). Litigation Risk and Auditor Resignations. The Accounting Review, 72(4), 539-560.

Kumar, D. R., & Kumar, K. (2012, April). A Comparison of Bankruptcy Models. International Journal of Marketing, Financial Services & Management Research, 1(4), 76-86.

Kwofie, C., Ansah, C. O., & Boadi, C. (2015, November 25). Predicting the probability of loan - Default : An Application of Binary Logistic Regression . Research journal of Mathematics and statitics , 7(4), 46-52.

Lennox, C. (1999). Identifying failing companies: A re-evaluation of the logit, probit and DA approaches. Journal of Economics and Business, 51(4), 347-364.

Memic, D. (2015, January 12). Assessing credit default using logistic regression and multiple discriminant analysis: empirical evidence from bosnia and herzegovina. Interdiscplinary description of complex system , 13(1), 128-153.

Merton, R. C. (1976). Option pricing when underlying stock return are discontinuous . Journal of Financial Economics, 3, 125-144.

news18.com. (2020, June 8). https://www.news18.com/news/business. Retrieved October 10, 2020, from https:// www.news18 .com /news: https://www.news 18.com/news /business/ asian- companies-at-higher-risk-of-default-this-year-amid-pandemic-2658947.html

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, 18(1), 109-131.

Raei, R., Kousha, M. S., Fallahpour, S., & Fadaeinejad, M. (2016, June 18). A hybrid model for estimating the probability of default of corporate customers. Iranian Journal of Management Studies , 9(3), 651-673.

Sajjan, P. R. (2016, April). Predicting Bankruptcy of Selected firms by applying Altman's Z score Model. International Journal of Research Granthaalayah, 4(4), 152-158.

Sharma, D. C., Singh, D. K., & Upadhyay, R. K. (2014, December). Predicting Probability of Default. Primax international journal of commerce and management research, II(3), 5-13.

Shimko, D. C., Tejima, N., & Van Deventer, D. R. (1993). The pricing of Risky Debt When Interest Rates are Stochastic. The Journal of Fixed Income , 3(2), 58-65.

Shumway, T. (2001, January). Forecasting Bankruptcy More Accurately: A Simple Hazard Model. The Journal of Business, 74(1), 101-124.

Singh, B. P., & Mishra, A. k. (2016). Predicting probability of default of Indian companies: A market based approach. Theoretical and Applied Economics, XXIII(3), 197-204.

Sirirattanaphonkun, W., & Pattarathammas, S. (2012, December). Default Prediction for Small - Medium Enterprise in Emerging Market: Evidence from Thailand. Seol Journal of Business , 18(2), 26-54.

Soureshjani, M. H., & Kimiagari, A. M. (2013, april 28). Calculating the Best cut off point using Logistic regression and neural network on credit scoring problem- A Case study of a commercial bank. African journal of business management, 7(16), 1414-1421.

Tanthanngsakkun, S., Pitt, D., & Treepongkaruna, S. (2009, April). A Comparison of Corporate Bankruptcy Models in Australia: the Merton vs Accounting-based Models. 1-33.

The hindu. (2020, January 10). www.thehindu.com. Retrieved October 9, 2020, from https:// www.thehindu.com/business: https:// www.thehindu.com/business/60-listed-firms-disclose-75000-cr-default/article30526706.ece

Tinoco, M. H., Holmes, P., & Wilson, N. (2015, January). Polytomous Response Financial Distress Models: the role of Accounting, Market and Macroeconomic Variables.

Upadhyay, R. K. (2019, December). Predicting Default by Indian Firms using Statistical Methods. J-GIBS, 11(1), 89-94.

Verma, D. (2019). Predicting the Probability of Corporate Default using Logistic Regression. CASS , 3(1), 161-173.

Verma, D., & Raju, D. M. (2019, October). Predicting Corporate Defaults Using Multiple Discriminant Analysis. CASS, 3(2), 1-19.

Wilcox, J. W. (1971). A simple theory of financial ratios as predictors of failure. Journal of Accounting Research, 9(389-85).

Zavgren, C. V. (1985). Assessing the vulnerability to failure of american Industrial Firms: A Logistic Analysis. Journal of Business Finance & Accounting , 12(1).

Zmijewski, E. M. (1984). Methodological Issues Related to the estimation of financial distress prediction models . Journal of Accounting Research , 22, 59-82.