© 2015 IJEDR | Volume 3, Issue 4 | ISSN: 2321-9939

A Proposed Model for Industrial Sickness

[1]Dr. Jay Desai, [2]Nisarg A Joshi
[1]Assistant Professor, [2]Assistant Professor
[1]Shri Chimanbhai Patel Institute of Management & Research, Ahmedabad, India
[2]Shri Chimanbhai Patel Institute of Management & Research, Ahmedabad, India

***Abstract* - The objective of this study is to examine the performance of default prediction model: the Z- score model using discriminant analysis, and to propose a new prediction model on a dataset of 30 defaulted and 30 solvent companies. Financial ratios obtained from corporate balance sheets are used as independent variables while solvent/defaulted company (ratings assigned) is the dependent variable. The predictive ability of the proposed Z score model is higher when compared to both the Altman original Z-score model and the Altman model for emerging markets. The research findings establish the superiority of proposed model over default discriminant analysis and demonstrate the significance of accounting ratios in predicting default.**

***Index Terms* - industrial sickness, discriminant analysis, ratio analysis**

I. INTRODUCTION

Every company commences a variety of operational activities in the business. There are some activities of the business whose outcomes are unpredictable. This launches an element of risk for every business. Among the different risks that an organization is faced with, default risk is possibly one of the ancient financial risks, though there have not been many instruments to manage and hedge this type of risk till recently. Earlier, the focus had been primarily on market risk & business risk and bulk of the academic research was determined on this risk. On the other hand, there has been an increase in research on default risk with increasing emphasis being given to its modelling and evaluation.

Default risk is spread through all monetary transactions and involves a wide range of functions from agency downgrades to failure to service debt liquidation. With the improvement in new financial instruments, risk management techniques and with the global meltdown, default risk has assumed utter importance. Risk of default is at the center of credit risk: implying failure on the part of a company to service the debt obligation. Credit rating agencies (CRAs) have been the major source for assessing the credit quality of borrowers/businesses in developing economies like India. Since improvement and deterioration of ratings can impact the price of debt and equity being traded, market participants are interested in developing good forecasting models. With the implementation of Basel III norms globally, banks are increasingly developing their own internal ratings-based models; developing internal scores. However, a credit rating or a credit score is not as directly as estimating the probability of default.

Despite a plethora of mathematical models available, there has been little effort, specifically in an emerging market economy such as India to develop a default prediction model. Thus, a default prediction model that can quantify the default risk by predicting the probability that a corporate default in meeting the financial obligation can be specifically useful to the lenders. Traditionally the credit risk literature has taken two approaches to measure default on debt. One is the structural approach which is based on market variables, and the second is the statistical approach or the reduced approach which factors in information from the financial statements.

This paper attempts to evaluate the predictive ability of two default prediction models for listed companies in India: a Z-score model using discriminant analysis and a proposed model using discriminant analysis. Discriminant analysis is used for two reasons. Firstly, there is prior empirical evidence of the models being used to forewarn against defaults in the developed countries. Secondly, through this study, we can judge to what extent accounting-based models can predict default risk from information available in the public domain. By using Z score, banks and financial institutions can assess the solvency status for companies.

II. REVIEW OF LITERATURE

Important research studies having relevance to the present work have been reviewed under broad categories viz. studies on accounting models. Accounting-based models have been developed from information contained in the financial statements of a company. The first set of accounting models were developed by Beaver (1966, 1968) and Altman (1968) to asses the distress risk for a corporate. Beaver (1966) applied a univariate statistical analysis for the prediction of corporate failure. Altman (1968) developed the z-score model using financial ratios to separate defaulting and surviving firms. Subsequent z-score models were developed by Altman et al. (1977) called ZETA and Altman et al. (1995) in the context of corporations in emerging markets. Altman and Narayanan (1997) conducted studies in 22 countries where the major conclusion of the study was that the models based on accounting ratios (MDA, logistic regression, and probit models) can effectively predict default risk.

Ohlson's O-Score model (1980) selected nine ratios or terms which he thought should be useful in predicting bankruptcy. Martin (1977) applied logistic regression model to a sample of 23 bankrupt banks during the period 1975-76. Other accounting-based models developed were by Taffler (1983, 1984) and Zmijewski (1984). Bhatia (1988) and Sahoo, et al. (1996) applied the multiple discriminant analysis technique on a sample of sick and non-sick companies using accounting ratios. Several other studies used financial statement analysis for predicting default.

Opler and Titman (1994) and Asquith et al. (1994) identified default risk to be a function of firm-specific idiosyncratic factors. Lennox (1999) concluded from their study that profitability, leverage, and cash flow; all three parameters have a bearing on the probability of bankruptcy on a sample of 90 bankrupt firms. Further studies were done by Shumway (2001), Altman (2002) and Wang (2004) and all these studies emphasized the significance of financial ratios for predicting corporate failure. Grunert et al. (2005) however, found empirical evidence in his study that the combined use of financial and non-financial factors can provide greater accuracy in default prediction as compared to a single factor. Jaydev (2006) emphasized on the role of financial risk factors in predicting default while Bandyopadhyay (2006) compared three z- score models.
Bandyopadhyay (2007) developed a hybrid logistic model based on inputs obtained from Black Scholes Merton (BSM) equity-based option model described in his paper, Part 1 to predict corporate default. Agarwal and Taffler (2007) emphasized on the predictive ability of Taffler's z-score model in the assessment of distress risk spanning over a 25-year period. Baninoe (2010) evaluated two types of bankruptcy models; a logistic model and an option pricing method and concluded from his research that distressed stocks generated high returns. Laitinen (2010) in his study assessed the importance of interaction effects in predicting payment defaults using two different types of logistic regression models. Kumar and Kumar (2012) conducted empirical analysis on three types of bankruptcy models for Texmo industry: (i) the Altman z-score; (ii) Ohlson's model; and (iii) Zmijewski's models to predict the probability that a firm will go bankrupt in two years.
Recently, Gupta (2014) had developed an accounting based prediction model using discriminant analysis and logit regression and compared the predictive ability of these models. For logistic regressions, an attempt was made to combine macro variables and dummy industry variables along with accounting ratios. The paper had analysed that the predictive ability of the proposed Z score model was higher when compared to both the Altman original Z-score model and the Altman model for emerging markets. The research findings establish the superiority of logit model over discriminant analysis and demonstrate the significance of accounting ratios in predicting default.
It is observed from the literature review above that several models have been developed based on accounting information (MDA, logit, probit). However, MDA which is applied to develop a z-score does not directly compute probabilities. Moreover, the model to be developed and the ratios may vary across regions. Thus, this paper examines the MDA to develop a Z-score and to evaluate which is a better model in its predictive ability that can be used by lenders to forewarn against a corporate default.

III. RESEARCH DESIGN AND METHODOLOGY

Research Design

As the objective of the research is to develop a default prediction model, secondary data has been used to carry out the analysis. The relevant secondary data on the financial statements of the companies has been primarily collected from ACE Equity database. A dataset of 60 companies is taken from the CRISIL database as the estimated sample which consists of 30 companies rated "D" by CRISIL (defaulted) and 30 companies rated "AAA" and "AA" (indicating highest safety thus 'solvent'). The solvent companies are chosen on a stratified random basis to match the defaulted list. Table 1 provides the industry classification and the number of companies in each industry.
The major component involves running discriminant analysis on the 60 companies in the dataset for estimated sample. Here the dependent variable is the solvent companies coded as "0" and defaulted companies coded as "1" and the financial ratios are taken as the independent variable. There are three models evaluated for their predictive ability using discriminant analysis. The first model is based on the five ratios included in the original Altman model. The second model is based on the ratios taken from the Altman model for emerging markets. The third model is developed in this study based on the ratios identified by the researcher as significant predictors.

Scope of the Study

The scope of this study covers listed companies in India. All the companies from the financial services sector have been removed from the database. The rationale for removing the companies in the financial services sector is that their financial statements broadly differ from those of non-financial firms. For ratings the focus of the research is on long-term debt instruments and structured finance ratings and short-term ratings.

Selection of Variables

Since the focus of the present study is to measure the default risk, it is imperative to choose a set of financial ratios which can be relevant in impacting the default risk of the company. In assessing creditworthiness, both business risks and financial risks have been factored. The criteria for choosing ratios are those that:
(i) have been theoretically identified as indicators for measuring default
(ii) have been used in predicting insolvency in empirical work before
(iii) and can be calculated and determined in a convenient way from the databases used by the researcher.
In all 24 accounting ratios as predictors of default risk spread across four categories were identified: liquidity, profitability, solvency, productivity (activity) ratios. The Altman ratios are also factored in as predictors. (Gupta et al, 2013). The four categories of ratios are as follows which are also shown in Table 2.

Table 1. Industry-wise list of companies in the dataset

Industry	**No. of Companies**
Paper & Paper Products	5

Paints	5
Pharmaceuticals	8
Textile	8
Machinery	8
Consumer Food & Sugar	10
Cement & Metals	10
Others	6
Total	60

1). Profitability ratios: High profitability margins reflect the company's ability to grow and also indirectly indicate the ability of the company to generate cash and thereby service its debt obligations. The ratios included under this classification are
(i) Profit after Tax/Capital Employed **(**PAT/CE)**;**
(ii) Profit After Tax /Sales (PAT/Sales);
(iii)Profit before interest and tax/Sales (PBIT/Sales);
(iv)Profits before depreciation, interest, tax and amortization/Total Income (PBDITA/TI).

2). Liquidity ratios: The liquidity position of a company reflects on the readily available cash of the company or the assets which can be liquidated. Since the purpose of identifying ratios is to determine which ones impact the creditworthiness of a company, liquidity plays a very important role as cash resources are necessary to service the debt obligations. The liquidity ratios taken for this study as independent variables to measure default risk are:
(i) Cash profits/ Total Assets;
(ii) Current ratio (CR);
(iii) Quick ratio (QR);
(iv) Cash flow from operations/Debt (CFO/Debt);
(v) Cash/Current Liabilities (Cash/CL);
(vi) Net working capital/Sales (NWC/Sales).
3). Solvency ratios: These ratios assess the ability of a company to meet long –term debt obligations. These ratios are:
(i) Interest coverage (INTCOV);
(ii) Debt/Equity (D/E).

4). Productivity ratios: Activity ratios measure the efficiency with which a company can utilize its resources. These ratios are:
(i) Cash/Cost of sales (Cash/COS);
(ii) Net working capital cycle (NWC cycle);
(iii) Debtor days;
(iv) Creditor days;
(v) Raw material cycle (RM cycle); (vi)Work in progress cycle (WIP cycle);
(vii) Finished goods cycle (FG cycle).

5). Altman Ratios: The Altman z-score model is the pioneer work in predicting bankruptcy and distress firms, and thus the original five ratios which constitute the Altman Z score model are also included. These are:
(i) Net working capital/Total Assets (NWC/TA);
(ii) Retained Earnings/Total Assets (RE/TA);
(iii) Profit before interest and tax /Total Assets (PBIT/TA);
(iv) Sales/Total Assets (Sales/TA);
(v) Market value of equity/ Book value of debt (MVE/BVD)

6) Altman Ratios for Emerging Markets: Altman had developed a model for predicting bankruptcy in emerging economies like India in the year 1995 and had included four ratios from his original model. He had removed Sales/Total Assets ratio from the model and taken Book Value of Equity rather than Market Value of Equity. These ratios are also included.
(i) Net working capital/Total Assets (NWC/TA)
(ii) Retained Earnings/Total Assets (RE/TA);
(iii) Profit before interest and tax /Total Assets (PBIT/TA);
(iv) Book value of equity/ Book value of debt (MVE/BVD)
Summary statistics on these variables are presented in Table 3. It is observed that the mean for explanatory variables in the defaulted group shows a poor performance when compared to the solvent group. The mean of profitability ratios for firms which are defaulted is with a negative sign whereas the average for solvent firms shows a higher average margin. Also, for the solvency ratios, namely the Debt/Equity, the ratios is less than 1 for solvent firms, indicating low leveraging whereas for defaulted firms the average is significantly higher than 1, mean interest coverage ratio is lower for defaulted companies than for solvent companies.

Table 2: Accounting Ratios Category wise as Predictors

LIQUIDITY	PROFITABILITY	SOLVENCY	PRODUCTIVITY	ALTMAN RATIOS
Current Ratio (CR)	Net profit margin (PAT/SALES)	Debt/Equity D/E)	Cash/Cost of sales (CASH/COS)	NWC/TA
Quick Ratio (QR)	Operating profit margin (PBIT/Sales)	Interest coverage (INTCOV)	Raw material Cycle (RMCYCLE)	RE/TA
Cash profits	Profit before interest, dep (PBDITA/Sales)		Work-in progress cycle (WIPCYCLE)	PBIT/TA
Cash/current liabilities (CASH/CL)	PAT/Capital employed (PAT/CE)		Finished Goods Cycle (FGCYCLE)	Sales/TA
Cash flow from operations/Debt (CFO/DEBT)			NWC Cycle (NWCCYCLE)	MVE/BVD
NWC/Sales (NWC/SALES)			Debtor Days	
			Creditor Days	

Table 3: Descriptive Statistics for Ratios

RATIO	Solvent Firms		Insolvent Firms	
	MEAN	**STD. DEV.**	**MEAN**	**STD. DEV.**
WC/TA	0.302065	0.07254	0.196317	0.136845
RE/TA	0.242317	0.128604	-0.00043	0.599231
C.R.	2.834205	1.295321	3.527936	4.616937
Q.R.	2.026087	0.973536	2.456866	3.992333
I.C.R.	125.0084	319.8243	43.75943	519.1784
DEBT/EQ.	0.433508	2.047059	2.669984	8.951126
SALES/TA	1.137232	0.191678	0.785547	0.323731
EBIT/TA	0.155909	0.053599	0.062639	0.050182
PAT/TA	0.104941	0.051552	0.018016	0.13294
PAT/SALES	0.114522	0.087616	-0.09616	1.45969
PBDITA/SALES	0.196796	0.040765	0.097517	0.418706
PBIT/SALES	0.165158	0.04403	0.007062	1.280789
MVE/BVL	1.373223	0.734843	0.607935	1.258045
BE/BVL	0.552433	0.062186	0.26883	0.436553
DEBT/TA	0.157998	0.06601	0.451856	0.289925
FC/TA	0.252166	0.04396	0.138215	0.041694
OCF/SALES	0.111473	0.088201	0.146293	1.679495
CL/TA	0.283191	0.041127	0.32732	0.136009
PAT/CE	0.158127	0.079822	0.104949	1.264399
EBIT/TTA	1.24033	1.300447	0.659092	6.229918
SALES/TTA	7.087613	5.115992	4.142872	9.714137

Discriminant Analysis

Multiple Discriminant Analysis (MDA) is a statistical technique where the dependent variable appears in a qualitative form. The discriminant function takes the following form:

$$Z = X_0 + W_1 X_1 + W_2 X_2 + W_3 X_3 + \dots\dots\dots + W_n X_n \qquad (1)$$

Z = Discriminant Score, X_0 = Constant,
W_1 = Discriminant Weight for Variable i, X_1 = Independent Variable i

For the purpose of identifying significant ratios the following are considered (Bandopadhyay 2006).

- F and Wilk's Lambda statistics. Wilk's Lambda tells us the variance of dependent variable that is not explained by the discriminant function.
- Chi-square statistic as check for the overall significance of various discriminant functions.
- The canonical correlation is the most useful measure in the table, and it indicated the degree of association between the dependent variable and the explanatory variables.

Table: 4 Canonical Correlation and Wilk's Lambda

	With 21 Parameters	**With 12 Parameters**
Canonical Correlation	**0.83**	**0.77**
Wilk's Lambda	**0.31**	**0.41**

For the purpose of identifying the key predictors, we have calculated the canonical correlation and Wilk's Lambda. As a result, we found that while taking all 21 ratios, the canonical correlation is 0.83 while for 12 ratios is 0.77. So there is difference of 0.06 and we can interpret that most of the information is covered by these 12 ratios. While calculating Wilk's Lambda for 21 and 12 ratios, we get F value as 0.31 and 0.41 respectively which also signifies there is no much difference in the variance of the dependent variables that is not explained by the discriminant function. Therefore we have identified 12 ratios for proposed discriminant function.

Model Validation

For validating the model, the model was tested on a sample that has not been used for estimation. A sample of 36 companies is considered as hold out sample for the FY2014 and tested. For any model, its performance is validated by the extent of Type I and Type II errors. This is based on the classification accuracy for the hold out sample. This accuracy is expressed as Type I accuracy— the accuracy with which the model identified the failed firms as weak. Type II accuracy is the accuracy with which the model identified the healthy firms as such.

IV. Empirical Findings and Discussion

Results of Discriminant Analysis

By running discriminant analysis, three reduced form equations based on the original Altman model, the Altman model for emerging markets and the model proposed by the author are presented below in Table 4.

For Model 1, the five ratios taken are the ones of Altman's original z-score model. These five ratios used in the original Altman model. The empirical findings reveal the coefficients of these variables using the above data. For Model 2, the four variables from the Altman's Emerging Market Score Model (1995) are identified. Altman model for emerging markets dropped the ratio Sales/Total Assets and the remaining four ratios of the original model were taken. Model 3 is what is proposed and tested for the research study. This model is based on a set of ratios which reflect the profitability, liquidity, solvency as parameters. Since the scope of the study is manufacturing sector, productivity ratios are significant. In addition to these four categories, the original Altman ratios are also included. It is observed from Table 4 below that although the classification of prediction for Model 1 and Model 2 is high; the predictive ability of Model 3 is significantly higher than the other two models, for both types of firms. The classification accuracy is around 97% for all the firms put together on the proposed model.

Table 5: Model for Multi Discriminant Analysis (MDA)

		Correct Classifications – Solvent Firms	**Correct Classifications – Solvent Firms**	**Overall Correct Classifications**
Model 1	$1.2\ X_1 + 1.4\ X_2 + 3.3\ X_3 + 0.6\ X_4 + 0.99\ X_5$	73.33%	76.67%	75%
Model 2	$6.56\ X_1 + 3.26\ X_2 + 6.72\ X_3 + 1.05\ X_4$#	93.33%	30%	61.67%
Model 3	0.1198 – 0.2201 D/E – 14.4404 DEBT/TA – 0.1287 PAT/CE + 16.734 PAT/TA + 3.2906 SALES/TA + 81.9494 PBDITA/SALES– 8.8728 RE/TA – 0.7724 QR – 98.6097 PBIT/SALES+ 28.9782 PAT/SALES+ 0.252 CR+ 0.0079 INTCOV	96.67%	80%	88.33%

The output of discriminant analysis is further analysed for the three models. The F-test and Wilk's Lamba are used for conducting the analysis. It is observed from Tables 5- 7 that the means of the ratios for solvent and defaulted companies differs. The profitability ratios are negative for the defaulted firms but positive for the solvent firms. A high value of the F-statistic means a greater chance for the null of equal means to be rejected. A small Lambda denotes that of the total variance of the variables, only a small proportion is accounted by the within groups' dispersions. (Bandyopadhyay, 2006)

Table 6: Results for Multi Discriminant Analysis for Proposed Model

Parameter	Total Firms	Solvent Firms	Default Firms
No. of Training samples	36	18	18
No. of Testing samples	24	12	12
Correctly Classified Companies for Training	32	17	15
Correctly Classified Companies for Training in %	88.89%	94.44%	83.33%
Correctly Classified Companies for Testing	21	12	9
Correctly Classified Companies for Testing in %	87.50%	100%	75%
Overall (Training + Testing)	53	29	24
Overall %(Training + Testing)	88.33%	96.67%	80%

V. CONCLUSION

This paper evaluates the predictive ability of the z-score model using discriminant analysis on a sample of 60 Indian listed companies. In the first model, discriminant analysis is applied to develop a z-score model by taking accounting information one year prior to the ratings assigned as defaulted/non defaulted. The proposed model exhibits significantly higher predictive ability when compared with the two Altman models: the original Altman model, and the Altman model for emerging markets, as evident by the classification accuracy. The z-score model developed can be used by financial institutions and banks in determining the solvency status for companies based on financial information of companies available in the public domain.

The conclusion drawn from the research findings are that though accounting–based models are not sufficient in themselves, they can identify financially distressed companies from the information disclosed in the financial statements.

REFERENCES

[1] Agarwal, V., & Taffler, R. J. (2008b). Does financial distress risk drive the momentum anomaly? Financial Management, 37(3), 461–484.
[2] Agarwal, V., & Taffler, R. J. (2007). Twenty-five years of the Taffler z-score model: Does it really have predictive ability? Accounting and Business Research, 37(4), 285–300.
[3] Agarwal, V., & Taffler, R. J. (2008a). Comparing the performance of market-based and accounting-based bankruptcy prediction models. Journal of Banking and Finance, 32(8), 1541–1551.
[4] Altman, E. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance, September, 189–209.
[5] Altman, E., Haldeman, R. G., & Narayanan, P. (1977). ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. Journal of Banking and Finance, 1(1), 29–54.
[6] Altman, E., Hartzell, J., & Peck, M. (1995). Emerging Markets Corporate Bonds: A Scoring System. Salomon Brothers, New York, NY.
[7] Asquith, P., Gertner, R., & Scharfstein, D. (1994). Anatomy of financial distress: an examination of junk bond issuers. Quarterly Journal of Economics, 625–658.
[8] Bandopadhyay, A. (2007). Mapping corporate drift towards default: Part 2: a hybrid credit- scoring model. Journal of Risk Finance, 8(1), 46–55.
[9] Bandyopadhyay, A. (2006). Predicting probability of default of Indian corporate bonds: logistic and Z-score model approaches. Journal of Risk Finance, 7(3), 255–272.
[10] Bandyopadhyay, A. (2007). Mapping corporate drift towards default: Part 1: a market-based approach. Journal of Risk Finance, 8(1), 35–45.
[11] Baninoe, R. (2010). Corporate Bankruptcy Prediction and Equity Returns in the U.K. Cranfield School of Management, Cranfield University.
[12] Basel Committee on Banking Supervision. (1999). Credit Risk Modeling: Current Practices and Applications. Report, Basle. June
[13] Beaver, W. H. (1966). Financial Ratios as Predictors of Failure. Journal of Accounting Research, 4(3), 179–192.
[14] Beaver, W. H. (1968). Alternative Accounting Measures as Predictors of Failure. Financial Ratios as Predictors of Failure. Journal of Accounting Research, 43(1), 113.
[15] Bhatia, U (1988). Predicting Corporate Sickness in India. Studies in Banking & Finance, 7, 57–71.
[16] Chava, S., & Jarrow, R. (2004). Bankruptcy prediction with industry effects. Review of Finance, 8(4), 537–569.
[17] Grunert, J., Norden, L., & Weber, M. (2005). The role of non-financial factors in internal credit ratings. Journal of Banking and Finance, 29, 509–531.
[18] Jayadev, M. (2006). Predictive Power of Financial Risk Factors: An Empirical Analysis of Default Companies. Vikalpa, 31(3).
[19] Kumar, R. G., & Kumar, K. (2012). A comparison of bankruptcy models. International Journal of Marketing, Financial Services and Management Research, 1(4).
[20] Laitinen, E. (2010). Financial and non-financial variables in predicting failure of small business reorganization: comparison of logistic regression analysis and survival analysis. International Journal of Accounting and Finance.

[21] Lennox, C. (1999). Identifying failing companies: a re-evaluation of the logit, probit and DA approaches. Journal of Economics and Business, 51, 347–364.
[22] Martin, D. (1977). Early warning of bank failure: a logit regression approach. Journal of Banking and Finance, 1, 249–276.
[23] Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research, 18(1), 109–131.
[24] Opler, T. C., & Titman, S. (1994). Financial distress and corporate performance. Journal of Finance, 49, 1015–1040.
[25] Sahoo, P. K., Mishra, K. C., & Soothpathy, M. (1996). Financial Ratios as the Forewarning Indicators of Corporate Health. Finance India, 10(4), 955–965.
[26] Shumway, T. (2001. Forecasting Bankruptcy More Accurately: A Simple Hazard Model. Journal of Business, 74(1), 101–24.
[27] Taffler, R. J. (1983). The assessment of company solvency and performance using a statistical model: a comparative UK-based study. Accounting and Business Research, 15(52), 295–307.
[28] Taffler, R. J. (1984). Empirical models for the monitoring of UK corporations. Journal of Banking and Finance, 8(2), 199–227.
[29] Wang, Z. (2004). Financial Ratio Selection for default-Rating Modeling: A Model-Free Approach and Its Empirical Performance. Journal of Applied Finance.