PREDICTING BANKRUPTCY OF INDIAN MANUFACTURING COMPANIES

A Thesis submitted during 2016 to the University of Hyderabad in partial fulfillment of the award of a Ph.D. degree in Economics

By

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Dean of the School

Dedicated
To
My Mother

SITA DEVI

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Bhanu Pratap Singh

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ABBREVIATIONS

ADB: Asian Development Bank

ANN: Artificial Neural Network

AUC: Area Under Curve

AUROC: Area Under ROC

BCBS: Basel Committee on Banking Supervision

BIFR: Board for Industrial and Financial Reconstruction

BIS: Bank of International Settlement

BSE: Bombay Stock Exchange

BVEBVD: Book Value of Equity/ Book Value of Total Debt

CACL: Current Assets/ Current Liabilities

CAP: Capital Assessment Process

CAR: Capital Adequacy Ratio

CARE: Credit Analysis and Research Ltd.

CASL: Current Assets/ Sales

CATA: Current Assets/ Total Assets

CCB: Capital Conservation Buffer

CCB: Countercyclical Capital Buffer

CCPs: Central Counterparty Clearing House

CDOs: Collateralized Debt Obligation

CET: Common Equity Tier

CFOT: Cash Flow from Operations/ Total Assets

CFTD: Cash Flow from Operations/ Total Debt

CLCA: Current Liabilities/ Current Assets Profitability

CLTA: Current Liabilities / Total Assets

CRISIL: Credit Rating Information Services of India Limited

CSFP: Credit Suisse Financial Products

CVA: Credit Value Adjustment

DA: Discriminant Analysis

DCR: Digital Content Ratings

DD: Distance to Default

DEA: Data Envelopment Analysis

DM: Default mode models

DMUs: Decision Making Units

D-SIBs: Domestic Systemically Important Banks

EAD: Exposure at Default

EBITA: Earnings Before Interest and Taxes/ Total Assets

ECA: Effective Capital Adequacy

EDF: Expected default frequency

FLIS: Fuzzy Logic Inference System

FUTL: Fund Provided by Operations to Total Liabilities Liquidity

GA: Genetic Algorithm

GM: General Motors

GMLS: Global Minimum Liquidity Standard

GNP: Gross National Product

GNPA: Gross Non-performing Asset

G-SIBs: Global Systemically Important Banks

ICAP: Internal Capital Assessment Process

ICRA: Investment Information and Credit Rating Agency of India Limited

IRB: Internal Rating Based

IRB-A: Internal Rating Based-Advanced

IRBD: International Bank for Reconstruction and Development

IRB-F: Internal Rating Based-Foundation

ISO: International Organization for Standardization

IT/ITES:InformationTechnology/Information Technology-enabled services

ITEs: Intra-group Transaction and Exposure

KNN: K-nearest Neighbour

LABs: Local Area Banks

LCR: Liquidity Coverage Ratio

LGD: Loss Given Default

LPM: Linear Probability Model

LR: Leverage Ratio

LTDTA: Long-term Debt/ Total Assets

LVQ: Learning Vector Quantization

MANOVA: Multivariate Analysis of Variance

MDA: Multiple Discriminant Analys

MLE: Maximum Likelihood Estimation

MTM: Market-to-Market

MVEBVD: Market Value of Equity/Book value of Total Liabilitie

NIC: National Industrial Classification

NINW: Net Income/ Net Worth

NISL: Net Income/ Sales

NITA: Net Income/Total Assets

NITL: Net Income/ Total Liabilities Turnover

NN: Neural Networks

NPAs: Non-performing Assets

NPV: Negative Predictive Value

NSFR: Net Stable Funding Ratio

NWTA: Net Worth/ Total Assets

OCC: Office of the Comptroller of Currency

OECD: Organization for Economic Co-operation and Development

OTC: Over-the-counter

PD: Probability of Default

PPV: Positive Predictive Value

RBI: Reserve Bank of India

RETA: Retained Earnings/ Total Assets

ROC: Receiver Operating Characteristic

RR: Recovery Rate

RRB: Regional Rural Banks

RWA: Risk Weighted Assets

S&P: Standard & Poor's

SCBs: Schedule Commercial Banks

SENSEX: Stock Exchange Sensitive Index

SLTA: Sales/ Total Assets

SMERA: SMERA Ratings Ltd

SMEs: Small and Medium-sized Enterprises

SREP: Supervisory Review and Evaluation Process

SVMs: Support Vector Machines

TDNW: Total Debt/ Net Worth

TDTA: Total Debt/ Total Assets

TLNW: Total Liabilities/ Net Worth

TLTA: Total Liabilities/ Total Assets

UFCE: Unhedged Foreign Currency Exposure

VaR: Value at Risk

WCNW: Working Capital/ Net Worth

WCSL: Working Capital/ Sales

WCTA: Working Capital/ Total Assets

Chapter 1

Background, Issues, and Objectives of the Study

1.1 Introduction

The change in the attitude towards financial leverage as means of economic prosperity led to credit explosion all over the world. Polonius, a character in Shakespeare's 17th century play Hamlet says, "Neither a borrower nor a lender be", but he was voicing perception of his time (Lamb 2000, p. 52). In the modern times, since Schumpeter (1911), there is a long-standing debate on the role of finance contributing to economic growth. Some believe that finance promotes growth (Goldsmith, 1969; McKinnon, 1973; Shaw, 1973; King and Levine, 1993 a, 1993 b, 1993 c): few do not find it worth discussing (Lucas, 1988). Others assert that real sector development itself creates demand for financial development (Robinson, 1952; Singh and Mishra, 2014, 2015). In spite of the differences in the views of economists on the finance-growth nexus, all believe finance works as a facilitator in the economic system and reduces transaction and information cost. Earlier, being a borrower or debtor brought misery and shame. Now the perception of people has changed, and the debtor is seen as a person using financial leverage and entitlement. The use of credit has become a major factor in economic prosperity of countries as well, and there is a significant increase in the leverage by individuals and corporations all over the world.

The financial system plays a pivotal role by facilitating surplus fund from savers to investor. A well-developed financial sector mobilize savings, which increases productive investment and therefore, leads to economic growth. For companies, investment funds are needed to support the production of goods and services. Governments often borrow to finance short-term and long-term shortfalls between expenditures and revenues. Borrowing is often a means to finance long gustation capital projects which requires lumpy investment whose returns spread over generations. Households equally borrow from the financial sector to fund large purchases that exceed their current incomes.

Banks and other financial institutions work in a diversified manner, and offer multiple products and services to multiple individuals, corporates, financial institutes, government authorities, high net worth customers, etc. They use innovative delivery channels, sophisticated technology, and automate certain activities for speedy execution and timely delivery of services, in order to sustain business in the face of strong national and international competition. In the context of banks and other financial institutions, financial risk is defined as an exposure to an adverse situation that could result into financial loses. Financial risk directly affects the financial position of an individual or an organization. Depending on the nature of lending activities and credit-worthiness of borrowers, financial institutions are exposed to various types of risks, namely - credit risk, market risk, operational risk, strategic risk, reputational risk, liquidity risk, etc. Amongst them credit risk is the primary and major risk that these institutions face frequently. Credit risk can be defined as a risk, in a credit transaction, the borrowing entity willingly or unwillingly not following its contractual obligations. It directly affects the financial position of the financial institutions, including banks. If not managed properly, it can lead to disastrous consequences in the economy affecting real sector and financial sector development. For a developing country like India, it will have serious implications for economic growth.

The financial risk can be managed by taking an informed decision. It is for this reason that the financial regulators of different countries, including banking regulators and Bank for International Settlement (BIS) globally, focus primarily on three types of risks, namely, credit, market and operational. The maiden encounter of the Basel Committee on Banking Supervision (BCBS) took place and Basel I (1988) Accord came into existence. From Basel I (1988) to Basel III (2009) credit risk is the heart of all Basel Accords and plays vital importance in the regulatory and supervisory role of the banks. In Basel II, operational risk is put into consideration along with credit and market risk. The new accord came with a motive to promote financially sensible and cautious policies in the banking and financial sectors to build the capacity to absorb shocks, irrespective of the source. It also enhances the banking and financial systems’ shock-absorbing capability.

The World Economy at the start of 21st century began with the financial crisis, which led to emphasis on modeling and evaluation of credit risk. The factors behind the shift in the trend are the rapid growth of the credit derivative market, rise in the bankruptcy and emergence of credit risk literature. 'Black Monday', i.e. August 24, 2015, was the historical day for Chinese and other emerging market economies (Times of India Aug 25, 2015). In a single day Chinese stock plunged down by 5 percent and Indian Bombay Stock Exchange (BSE) SENSEX slumped nearly 6 percent. Huge capital outflow was registered in emerging economies all over the world. Such volatility in the market had critical implications for India and China, which have witnessed the highest growth in the past two decades. Financial stability in this region is very crucial because of the interconnectedness of world market and the contagion effect. The 'Black Monday' and failure of rating agencies (Moody's, Standard and Poor's) to predict the fall of giant manufacturing companies like Chrysler, GM, LyondellBasell Industries, Excide Technologies, etc. alarmed the need to revisit risk management framework worldwide after global financial crisis of 2007.

The term 'bankruptcy' is used in the default prediction studies of US. In India, there is no bankruptcy law, like US and UK. The country has embarked upon a new bankruptcy legislation. Bankruptcy is a legal event which takes place at a definite point of time. It is unquestionably a conclusive evidence of firm or a borrowing entity having failed to perform. In practice, bankruptcy is the result of failure. In the economic sense, failure occurs prior to the event of bankruptcy. Industrial sickness in India is beyond bankruptcy. Here, the industrial sickness refers to the firms persistently making losses and surviving. India has coined her own terminology as 'industrial sickness' or 'corporate sickness'. According to Sick Industries Companies (SICA) Repeal Act, 2003, a sick company refers to an industrial company whose accumulated losses at the end of financial year exceeded 50 percent of peak net worth during the last four years. A company can also be said to be sick industrial unit if it failed to repay instalment of its debt or default in obligation to creditors for 3 consecutive quarters. Any of the condition mentioned above is sufficient to consider a company sick. Due to lack of bankruptcy prediction law and systematic data on default, credit risk analysis is very difficult in India. Notwithstanding these difficulties, we procced with our analysis, using Board of Industrial and Financial Reconstruction (BIFR) reference as an indicator for identifying distressed firms. The scope of the study is restricted to Indian manufacturing firms because of two reasons: First, majority of companies registered with BIFR during the period 2006-2014 are manufacturing firms. Second, the report of Ministry of Commerce & Industry, Department of Industrial Policy & Promotion (2014) shows there is rise in the trend of sick and closed units in India. The study uses 'sickness' and 'bankruptcy' interchangeably.

Since Beaver (1966), a substantial literature on bankruptcy prediction has developed to assess the financial health of companies. Models have been developed based on different theoretical approaches and have used different types of information to assess bankruptcy. Three notable and most cited accounting-based bankruptcy models in the literature of accounting research are Altman (1968), Ohlson (1980) and Zmijewski (1984) (Grice and Dugan, 2001). In the bankruptcy prediction literature academic and accounting practitioners have articulated differing views on the power of these models to address the sensitivity of time periods and financial conditions (cross-country heterogeneity, market structure, business cycle, etc.).

Begley et al. (1996) re-estimates and compares the performance of original Altman's and Ohlson's models using US data for 1980's. The major finding of the study suggests that Altman's and Ohlson's original models led to better predictive accuracy as compared to the re-estimated models. Both the re-estimated models - Altman's and Ohlson's - have higher classification errors compared to the original models. In line with Begley, Boritz et al. (2007), studying bankruptcy in Canada found that the predictive accuracy of Altman's and Ohlson's original models are higher than the re-estimated models. They also compared the accuracy of alternative models developed for Canadian firms, namely, Springate (1978), Altman and Levallee (1980), and Legault and Veronneau (1986). The study concludes that the Canadian models are simpler and require fewer data. All models have a stronger performance with the original coefficients than the re-estimated coefficients.

On the contrary, there are several studies questioning the construct validity of the original models with respect to change in time periods and financial conditions. Grice and Ingram (2001) analysed the sensitivity of Altman's Z-score model for US companies. The study suggests that the coefficients of the models are sensitive to change in the financial environment and time period. The re-estimated model with the most recent information gives better predictive accuracy. Grice and Dugan (2001) conducted study on US companies and found that predictive accuracy of re-estimated Altman's and Ohlson's model is higher than the original models. Timmermans (2014) analysed the sensitivity of Altman's, Ohlson's and Zmijewski's models on US companies. The major finding of the study suggests the re-estimated model have a higher predictive accuracy than the original models. Avenhuis (2013) conducted study on Dutch companies. The study re-estimates and compares performance of Altman's, Ohlson's and Zmijewski's original models. The major finding of the study is that the re-estimation of the model with specific and bigger sample gives better predictive accuracy.

According to Platt and Platt (1990) the economic environment of two periods may differ because of three reasons: First, change in the relationship between bankruptcy (dependent variable) and financial ratios. Second, change in the range of financial ratios (independent variables). And third, change in the relationship among financial ratios. They also find that changes in the economic environment lead to changes in the corporate strategy, competitiveness of market, business cycle, and technology adoption. In the context of the Indian market, Bandyopadhyay (2006), Bhumia and Sarkar, (2011) and Shetty et al. (2012) developed industry-specific models for Indian corporate bond sector, pharmaceutical companies, and Information Technology/ Information Technology Enabled Services (IT/ITES) industries respectively. Chudson (1945) mentions that industry specific models are more appropriate than general models. Similar evidence is also found in the study of Avenhuis (2013).

As outlined in the first part of this thesis, the major aim of this study is threefold: First, to develop a new bankruptcy prediction model for Indian manufacturing companies based on accounting data pertaining to a large sample. Second, to revisit and re-estimate Altman (1968), Ohlson (1980) and Zmijewski (1984) models to examine the sensitivity of these models towards change in financial conditions and time periods. Finally, to choose the best model for prediction of financial distress of Indian manufacturing companies. The current study differs from earlier studies in terms of three perspectives: Firstly, the study uses larger data set sampled over a longer period (sample size 208 and with data for 2006-2014) than in previous studies on Indian market which increases the statistical power of the model. Second, the new bankruptcy prediction model is proposed with a unique combination of financial ratios measuring leverage, profitability, and turnover of the Indian manufacturing companies. Third, in the Indian market, there has been no attempt made to compare the sensitivity of Altman's, Ohlson's and Zmijewski's models together towards change in time period and financial conditions. In the latter part of this thesis, Black-Sholes-Merton (BSM) model is used to generate risk neutral probabilities of the firms going for BIFR reference. The current study is an humble attempt to bridge lacuna in the relevant research literature.

1.2 Objectives of the Study

There is significant development in the credit risk literature world-wide. Researchers and accounting practitioners use various credit risk models to assess credit worthiness of a borrower or group of borrowers. Some of the most cited accounting-based models for credit risk modeling are Altman's Z-score, Ohlson's logit and Zmijewski's probit models. On the contrary, the most- cited market-based model is BSM. All the above-mentioned models use a unique combination of ratios and different methods to analyze and predict bankruptcy. The present study focuses on three aspects of credit risk modeling. First, re-estimation of accounting-based models. Second, develop new bankruptcy prediction model and third, to calculate risk neutral probability of Indian manufacturing companies. The objectives of the study may be spelled out more specifically as follows:

1. To re-estimate bankruptcy prediction models such as Altman (1968), Ohlson (1980) and Zmijewski (1984) for Indian manufacturing companies.
2. To examine the construct validity of Altman, Ohlson, and Zmijewski models with change in time period and economic environment.
3. To propose a new bankruptcy prediction model for Indian manufacturing companies.
4. To compare and choose the best model to predict bankruptcy for Indian manufacturing companies.

5. To estimate risk neutral probabilities on larger samples of Indian listed companies in a BSM framework.

1.3 Methodology

This study deals with the measurement of credit risk where specific econometric methods are applied to calculate default probabilities or bankruptcy of the firms. Altman's Z-score model is based upon multivariate discriminant analysis (MDA) technique. In MDA, a linear combination of dependent variables, which can best discriminate between defaulted and non-defaulted groups, is used. The Z-score for each of the company is calculated using the linear discriminant model. The cutoff value for Z-score model is decided where total sum of errors is minimum. The total sum of errors is defined as sum of Type I and Type II errors. Type I error occurs when model incorrectly classifies a defaulted firm as non-defaulted, whereas Type II error occurs when a non-defaulted firm is classified as defaulted firm. Two Z-score models are estimated using data one year and two years prior to bankruptcy respectively and the predictive accuracy of these models is compared.

Ohlson's model for default prediction is based on a logit model. In this model, dependent variable is binary in nature and takes value 1 for defaulted and 0 for non-defaulted groups. A logistic cumulative density function is used to combine financial and non-financial independent variables with the dependent variables. The estimated logit model yields a score, which can be interpreted as probability of default and ranges between 0 and 1. Again the cutoff value for logit model is decided where total sum of errors is minimum. The two logit models are estimated using financial data one year and two years before bankruptcy respectively.

Zmijewski's model for bankruptcy prediction is based on a probit model, where the dependent variable is binary in nature. The dependent variable takes value 1 for defaulted and 0 for non-defaulted groups. The normal cumulative density function is used to combine financial ratios or independent variables with the dependent variables. The estimated probit model yields a score, which can be interpreted as probability of default and ranges between 0 and 1. Again the cutoff value for probit model is decided where total sum of errors is minimum. The two probit models are estimated using financial data one year and two years prior to bankruptcy respectively.

Before developing new bankruptcy prediction model for Indian manufacturing companies, Altman's, Ohlson's and Zmijewski's original models are tested on Indian manufacturing companies. Using the same coefficients and cutoff values in the original model, the scores are obtained for individual companies.

The new bankruptcy prediction model for Indian manufacturing companies is developed using logit methodology. Four steps are followed to develop the new bankruptcy prediction model for Indian manufacturing firms. First, analysis of variables in which 25 financial ratios are chosen on the basis of past empirical literature and analysed by using mean, standard deviation and T-test for equality in mean, between defaulted and non-defaulted groups. Second, in a stepwise regression logistic forward selection and backward elimination methods are applied. Different combinations of the ratios which significantly differ in mean by T-test are tested. The final set of ratios are selected on the basis of the statistical significance of the estimated parameters, the sign of each variable's coefficient and the model's classification power. Third, in order to capture inter-industry effects, 14 industrial dummies were included in the model, but none of them are significant. Finally, all the financial ratios which are found to be statistically significant have been chosen for the model.

The estimated logit model yields a score, which can be interpreted as probability of default and ranges between 0 and 1. The cut-off value for the new model is decided where total sum of errors is minimum.

The study also examines predictive ability of the Black-Scholes-Merton (BSM) model. Unlike the accounting-based models of Altman and Ohlson and Zmijewski, BSM model uses market-based information such as market value of equity, equity return volatility, market value of assets and asset volatility. This approach is based on the fact that the firm's capital structure is based on option-like payoff where the value of a firm's equity and debt are contingent on the market value of its assets.

1.4 Nature and Sources of the Data

The study uses various financial ratios to model bankruptcy of companies used in the original and newly developed models. Financial ratios used in these models represent liquidity, profitability, leverage, solvency, activity/size and growth of the companies. Unlike USA and UK, in India, the data on bankruptcy prediction is not systematically available because of absence of bankruptcy law. However, the study identifies distressed firms from the list of firms registered in Board for Industrial & Financial Reconstruction (BIFR) as sick firms during 2006 to 2014. BIFR reference is also used in the studies of Bandyopadhyay (2006), Ramkrishnan (2005), Kulkarni et al. (2005), and Varma and Raghunathan (2000). A set of matched non-distressed companies are identified randomly on the basis of asset size and industry type. More than 600 sick companies are registered with BIFR during this period. The study shortlisted 104 sick companies on the basis of availability of reliable financial data (balance sheet and profit and loss data). A total of 130 companies comprising distressed and non-distressed firms are used in the estimation sample. Data for 78 companies are used for the purpose of model validation. However, for Black-Scholes-Merton (BSM) model, the study uses data for a total of 80 companies comprising distressed and non-distressed firms, since historical stock data on some of the distressed companies are not available. The balance sheet and income statements of the companies at the end of each year are collected from their respective websites. The data on stock prices of the listed companies are taken from Bombay Stock Exchange (BSE). Information related to risk-free return and Gross National Product (GNP) are collected from Reserve Bank of India (RBI) publications. The estimated and holdout sample have been classified into 14 industry categories, matching with their economic activities with reference to the National Industrial Classification Code (NIC), 3 digit classification of 2008 (Table 1.1).

Table: 1.1 Distribution of Firms for the Study as per NIC Classification 2008

NIC Code	Sector	Estimation Sample	Holdout Sample	Total
107	Manufacturer of other food products	14	6	20
131	Spinning, weaving and finishing of textiles	34	16	50
170	Manufacturer of paper and paper products	4	10	14
201	Manufacturer of basic chemicals, fertilizer and nitrogen compounds, plastics, synthetic rubber in primary form	18	6	24
210	Manufacturer of pharmaceuticals, medicinal chemical, and botanical products	6	2	8
221	Manufacturer of rubber products	4	4	8
231	Manufacturer of glass and glass products	4	2	6
239	Manufacturer of non-metallic mineral products n.e.c.	2		2
243	Casting of metals	16	6	22
261	Manufacturer of electronic components	6	16	22
271	Manufacturer of electric motors, generators, transformers and electricity distribution and control apparatus	4		4
291	Manufacturer of motor vehicles	8	6	14
310	Manufacturer of furniture	4		4
492	Other land transport	6	4	10
	Total	130	78	208

Source: Author's compilation

1.5 Organization of Thesis

The study is organized into eight chapters. The first chapter introduces the study. It gives an overview of thesis, role of financial leverage as means of economic prosperity and importance of financial stability and credit risk management. It spells out the scope and objectives, methodology, data sources and sample period.

The second chapter discusses global regulatory framework and various theoretical approaches to asses credit risk. First part of this chapter brings light on the various Basel Accords passed by Bank of International Settlement (BIS) for a resilient financial system. Second part of the chapter discusses about different theoretical approaches to model default risk.

The third chapter covers empirical literature on credit risk measurement. The chapter extensively covers literature related to parametric and non-parametric approaches to model credit risk. Under parametric models, accounting and market-based models are covered, whereas under non-parametric models Artificial Neural Networks (ANN), Hazard Models, Fuzzy Models, Genetic Algorithms (GA) and Hybrid Models, or models in which several of the former models are combined are covered.

The fourth chapter revisits Altman (1968) model and re-estimates the model to predict corporate bankruptcy in the Indian manufacturing context. Two Z-score models are developed using data one and two year prior to bankruptcy. The Z-score one year prior model has higher classification power on both estimation and holdout sample. The major finding of the study suggests that movement in the asset value and cumulative profitability are the most significant variables to predict corporate bankruptcy. The most recent year financial information is found to be more helpful in predicting bankruptcy.

The fifth chapter models default probabilities of the Indian companies using logit and probit approaches. The chapter revisits Ohlson's (1980) logit and Zmijewski's (1984) probit model and re-estimates the model to predict corporate bankruptcy. For both logit and probit, two models are developed using data one and two years prior to bankruptcy. The major finding of the study suggests the most recent year financial information is more helpful in predicting bankruptcy. The mean Probablity of Default (PD) estimated by logit model is higher than probit model.

Chapter six, dealing with construct validity of various models, is divided into two parts. In the first part, new bankruptcy prediction model for Indian manufacturing companies is developed. In the later part construct validity of Altman, Ohlson, and Zmijewski models with change in time period and economic environment in the Indian setting is analyzed. The major findings from the chapter suggest that the coefficients of Altman, Ohlson, and Zmijewski models are sensitive towards change in time period and economic environment. Out of all contesting models newly proposed hybrid, four step model outperforms all the other models.

The risk neutral estimates using BIFR reference under BSM framework for 80 manufacturing companies are covered in chapter seven. Summary, conclusion, and scope for the future research is covered in chapter eight. It is hoped that this research will assist companies and regulators to estimate parameters relating to bankruptcy. The newly proposed bankruptcy law in India will require objective methods to assess the fiscal health of companies. This research is step in that direction.

CHAPTER 2

CREDIT RISK MEASUREMENT: BASEL ACCORDS AND THEORETICAL UNDERPINNINGS

2.1 Introduction

Economic crisis of 70's and 80's compelled the regulators of the G-10 nations to take proactive measure to safeguard the banks from financial risks. Basel Committee on Banking Supervision (BCBS) was formed to make guidelines on financial supervision for internationally active banks. The first capital measurement system was introduced in the year 1988, commonly known as Basel I Accord. The Basel I Accord was primarily focused on credit risk. Later, the accord was supplemented with requirements for exposures to market risk. More recently, the issue of financial stability in the wake of economic integration and globalization, as highlighted by the global financial crisis of 2007. Basel III Accord emerged on the eve of global financial system. Before reviewing literature on credit risk modeling, various approaches to model credit risk under different Basel Accords and theoretical underpinnings to model different approaches of credit risk are discussed in the current chapter.

The reminder of the chapter is organized as follows: Section 2.2 deals with Basel Accords and credit risk measurement. Theoretical underpinnings to model credit risk under different approaches are covered in section 2.3. Section 2.4 covers Merton (1974) Model and different Credit Value at Risk models. The chapter concludes with section 2.5.

2.2 Basel Accords and Credit Risk Measurement

From Basel I (1988) to Basel III (2009) credit risk is the heart of all Basel Accords and plays a vital part in the regulatory and supervisory role of the banks. In this setting, the major motivation of the chapter is to explore the preparedness of Indian banks to enforce the Basel accords, especially when Basel III document was released in September 2010. This also assumed importance when the new cap and liquidity measures were supported at the G20 Leaders Summit in Seoul and subsequently agreed at the Basel committee meeting in November 2010.

2.2.1 Basel Accord I (1988)

Introduction of novel financial instruments exposed the financial system to more risk. This led to maiden encounter of the Basel Committee on Banking Supervision (BCBS) and thus Basel I (1988) Accord came into existence. Bank of International Settlement (BIS) published the Accord with the title, "International Convergence of Capital Measurement and Capital Standards" in July 1988 and initial document was mailed to all member countries for their remarks. After change and alternations in the initial bill of exchange, the final draft was put out and supported by the group of ten central bank regulators.

In July 1988, under the chairmanship of W.P. Cooke, the Basel I Accord was endorsed by 12 countries (all G-10 countries plus Luxembourg and Switzerland) (Bardos, 1988). Since many banks were undercapitalized, a target of 7.25 percent was set to be achieved by the end of 1990, and the 8 percent requirement was to be accomplished by the end of 1992. Since then, under a consultative framework, the Basel Accord has been subjected to several amendments and has been evolving. The major goal of the Accord was to set a minimum regulatory capital standard for the commercial banks and bring financial stability and solvency in the banking sector. The minimum regulatory capital is determined as the minimum capital which should be kept away to meet adverse circumstances in future. In Basel I Accord, Capital Adequacy Ratio (CAR), which is the proportion of total assets to risk-weighted asset was defined as 8%. But in India, it was set at 9% by RBI. The CAR depends upon two components, capital of the bank and risk-weighted assets. The capital of the bank is further separated into two groups: core capital (equity capital) and supplementary capital. The risk-weighted assets were determined as the product of risk weights to the value of the assets. There were five broad classes of weight, namely, 0, 10, 20, 50, and 100%. Credit risk was the primary focus of Basel I, which was bettered in the year 1996 through inclusion of market risk.

A uniform system of capital adequacy standard was established in Basel I, which came into effect from January 1993. The recommended formula under Basel I is stated bellow:

$$Capital\ Ratio\ (Minimum\ 8\%) = \frac{Capital(Tier\ 1 + Tier2)}{Risk\ Weighted\ Assets} \tag{2.1}$$

Capital: The capital of banks was divided into Tier 1 and Tier 2 capital. Tier 1 capital was considered as most important which consists of paid-up share of capital and disclosed reserves. Tier 2 capital is the supplementary capital of the banks which comprises undisclosed reserves, loan loss allowances/reserves, asset revaluation reserves, hybrid capital instruments (such as mandatory convertible debt, and so on) and subordinated debt. In the accord, the Tier 1 capital was set at 50% of the entire capital.

Risk weighted assets: On balance sheet and off balance sheet assets were assigned different weights under Basel I. The risk weighting for on balance and off balance sheet assets under Basel I is reported in the Table 2.1 and Table 2.2 respectively:

Table 2.1: Risk weighting for On-balance Sheet Assets

	Risk weights			
Counterparty assets	0%	20%	50%	100%
Cash, central bank, and government exposure	✓			
OECD Govt debt/claims guaranteed by central banks	✓			
Multilateral development banks (ADB, IBRD, etc.)		✓		
Banks in OECD/claims guaranteed by them		✓		
Residential mortgage backed loans			✓	
Private sector entities				✓

Source: Joseph, C. (2013) p. 286 and BCBS

Table 2.2: Risk weighting for Off-balance Sheet Assets

	Risk weights			
Off balance sheet risks	0%	20%	50%	100%
Transaction related contingencies (bid bond, etc.)			✓	
Direct credit substitutes – Guarantee of indebtedness				✓
Letters of Credit, collateralized by underlying shipments		✓		
Certain commitments that are cancellable Unconditionally	✓			

Source: Joseph, C. (2013) p. 287 and BCBS

Criticism of Basel I

Basel I was the revolutionary step towards resilient banking and financial system but had following limitations:

(i) Basel I accord put more stress over credit risk and ignored other important risks, namely - market risk, operational risk, systematic risk, etc. After 1996, with partial amendments, banks were directed to allocate capital to cover market risk.

(ii) The accord was very simple and worked as a thumb rule in which 8% of capital adequacy ratio is set; irrespective of differences in industry and the country in which the bank is operational.

(iii) The rules were rigid and unrealistic in some instances. For instance, private counterparties have to draw 100% weight regardless of their underlying strength. Corporate lending to the counterparty with credit rating AAA to B were assigned same 100% weighting, whereas it is very much clear that AAA is less risky than B.

(iv) The different weighting gave an opportunity to banks to find ways to bypass the rules, which is likewise recognized as ‘regulatory capital arbitrage.' This contributes to reduction of bank capital without reducing their corresponding risk.

(v) The accord gave scope for dysfunctional behavior because it failed to check concentration risk, which in turn encouraged banks to manage their risk by diversification.

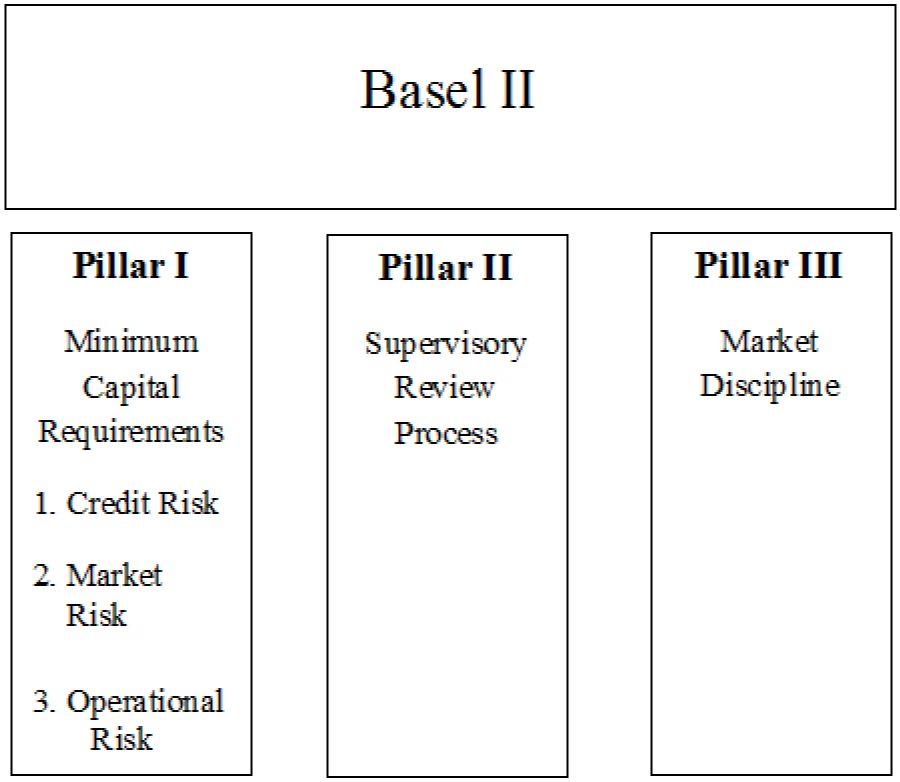
The above shortcomings seem to have distorted the conduct of banks, and this made it much more complicated to monitor them. Nevertheless, it is not yet clear whether higher capital ratios observed since the debut of this novel kind of capital regulation necessarily lowered risks.

2.2.2 Enhancements of Basel II (2006) over Basel I

With a more risk-sensitive approach, in the summers of 1988, BIS proposed to revise Capital Adequacy Ratio (CAR). The last draft of revised CAR was published after a long consultation process with all member countries in July 2004 (BIS, 2004). The comprehensive version of the document was published in 2006, which adopted the form of Basel II and was expected to be carried out by the member countries by 2007. The new framework was applied to internationally active banks, domestic banks, securities firm and insurance companies. In Basel II, operational risk is put into consideration along with credit and market risk. Under this approach bank can figure out the capital charge for credit, market and operational risk to make it at minimum CAR.

Basel II under three pillar approach presented more sophisticated method for the computation of minimum regulatory capital. In this approach economic capital was used along with regulatory capital.

Figure 2.1: Schematic Diagram of Basel II



Source: Author's compilation

Pillar-I Minimum Capital Requirement

The Pillar-I under Basel II Accord deals with calculation of total minimum capital requirement against risk-weighted assets. The CAR of banks is counted using risk-weighted assets for credit risk and capital charge for market and operational risks. Following is the recommended formula under Basel II:

$$Capital\ Adequecy\ Ratio\ (Minimum\ 8\%) = \frac{Capital(Tier\ 1 + Tier2)}{RWA(Credit, Market\ and\ Operational)} \quad (2.2)$$

The new rules allowed banks to apply more advanced methods to calculate credit, market and operational risks in determining capital levels. Banks were allowed to use

Internal Rating Based (IRB) methods, in contrast to conventional standardized approach. It gave banks the flexibility to travel for an approach that best fits their size, activities, level of sophistication and risk profile.

Pillar-II Supervisory Review

The Supervisory Review process deals with the risks not covered in Pillar I. The compliance of Pillar II is to ensure that banks and investment firms make arrangements to ensure that they have enough capital to hide all their risks. It also enables the regulator to set the capital requirements calculated under Pillar I. The supervisors were required to judge how robust the risk measurement techniques of banks are and to mark off how they are outfitted to distribute with the capital needs about their risks. If supervisors found any flaws in the risk measurement framework of the banks, it can intervene, and direct banks take prompt and decisive action to cut down risk or restore capital when deficiencies are identified. The Basel II stresses the importance of Internal Capital Assessment Procedures (CAP) of the banks, which correlates with their particular risk profile and control environment. If supervisors find the capital levels maintained are insufficient, they can drive banks to directly raise their capitals. Hence, banks are encouraged to maintain a buffer layer of capital above the minimum levels.

Pillar-III Market Discipline

The market discipline is complementary to Pillar I and Pillar II, and the market discipline is affected by public disclosures. Public disclosure here refers to non-confidential information, which is freely available to all market participants. Pillar III makes mandatory disclosure of numerous information by the banks, which is required for market discipline. It also provides market participants a better understanding of the banks' capital positions and their portfolio risk profiles. Further, this also gives information of a bank's methodology to calculate capital adequacy and risk management framework. According to Basel document, "the Committee proposes to encourage market discipline by getting a set of disclosure requirements which will allow market participants to assess key pieces of info on the scope of application, capital, risk exposures, risk assessment processes, and hence the capital adequacy of the institution. The commission thinks that such disclosures have particular relevance under the fabric, where reliance on internal methodologies gives banks more discretion in assessing capital requirements (BCBS, 2006)." It also gave awareness to the essentials of several national accounting standards by providing timely and transparent information, which in turn enabled market to better understand the business and the respective risks of banks.

In brief, following are the four principles for supervisory review process:

(i) There should be an Internal Capital Adequacy Process (ICAP) based upon solid risk management and control framework.

(ii) Pillar III reviews the Supervisory Review and Evaluation Process (SREP) in which ICAP assessment is again reviewed. The SREP also deals with compliance of minimum solvency requirements and requirements on internal control.

(iii) The dialogue on capital adequacy between the institutions and the supervisors.

(iv) If required; the supervisory measures should be used.

Approaches of Credit Risk Measurement under Basel II

Credit risk remains at the center of Basel II, and there are three approaches of risk measurement suggested, namely - standardized approach, foundation internal rating based approach and advanced internal rating-based approach.

Standardized approach

Conceptually, it is same as Basel I, where exposures are grouped into series of categories. Under Basel I each category was assigned a fixed risk weight, whereas in Basel II they are grouped into the loan to sovereigns, corporations, and banks, and their risk weighting was determined by external credit rating assigned to the borrower. Table 2.3 summarieses the risk weights under Basel II.

Table 2.3: Risk weights under Basel II

Counterparty	Unrated	Assessment based upon the external rating agency AAA to AA-	A+ to A-	BBB+ to BBB	BB+ to B-	Below B-
Sovereigns	100%	0%	20%	50%	100%	150%
Banks (Note 1)	100%	20%	50%	100%	100%	150%
Corporates	100%	20%	50%	100%	100%	150%
Retail-mortgage	35%					
Other retail	75%					

Source: Joseph, C. (2013) p. 290 and BCBS

In Basel II, the counterparties receive the risk weights ranging from 20% to 150% by external rating agencies. The unrated counterparties continue with a 100% risk weights. The risk CAR under Basel II vary from 1.6% to 12%, depending upon the risk weight. In Basel I it was kept fixed at 8%. Effective Capital Adequacy (ECA) ratio for different risk weights are reported in Table 2.4.

Table 2.4: Effective Capital Adequacy Ratios for different Risk weights

Risk weight	20% weight	100% weight	150% weight
Capital adequacy	1.60%	8%	12%

Source: Joseph, C. (2013) p. 291 and BCBS

Internal Ratings Based Approach- Foundation (IRB-F)

The major goal behind setting Internal Ratings Based (IRB) approach is to align more accurately capital requirements with the intrinsic amount of credit risk to which a bank is exposed. This approach allows banks to use their own internal risk estimate to calculate capital requirements subject to approval from their supervisors. The standardized approach is mandatory, but the bank can go for foundation internal rating based approach by approval from their supervisors (Central Banks). In foundation IRB approach banks calculate PD using their internal rating method and utilize a predetermined estimate of Loss Given Default (LGD), Exposure at Default (EAD) and a factor for maturity provided by the regulators.

Internal Ratings Based Approach- Advanced (IRB-A)

Under this approach, the PD, LGD, and EAD are estimated by the banks subject to regulatory satisfaction. Banks with their model subject to regulatory approval, get estimates of PD, LGD and EAD which use sophisticated risk management techniques and data.

Risk Weighted Assets (RWA) and Capital Adequacy

The technique used in standardized approach to calculate RWA is quite similar to Basel I, but IRB-F and IRB-A use sophisticated techniques to get these estimates. Under IRB-A and IRB-F the components which should be calculated are PD, LGD, and EAD. Then it is adjusted for correlation and maturity of the portfolios, lastly computation of capital requirement (K) is done. The formula to calculate K is given by:

$$K = \left[LGD \times N \left\{ \sqrt{\frac{1}{1-R}} G(PD) + \sqrt{\frac{1}{1-R}} \times G(0.999) \right\} - LGD \times PD \right] \times \frac{1 + (M - 2.5) \times b(PD)}{1 - 1.5 \times b(PD)} \qquad (2.3)$$

Where, N: normal distribution variable, R: correlation, G (PD): inverse of cumulative normal distribution variance for the PD value, G (0.999): inverse of cumulative normal distribution variance of 99.9% statistical confidence (or 3.09), M: maturity or term of the credit, asset, b (PD): maturity adjustment with PD. After getting the value of K, we can calculate RWA with the following formula:

WA=12. 5×K×EAD

Limitations of Basel II

(i) Basel II has given insufficient attention to check liquidity risk. The collapse of Lehman Brothers in the 2007 financial crisis was because of a liquidity crisis.

(ii) The risk profile of banks changes in the business cycle under the internal rating based system, which will lead to pro-cyclical behaviour of banks in the business cycles. It will allow banks to leverage and make them less capitalize and more vulnerable in a downswing.

(iii) The correlation value of the assets considered to be static in Basel II, but practically, it is dynamic and affected by innovations and changes in the economic system. The global financial crisis of 2007 is an example of such a credit crisis.

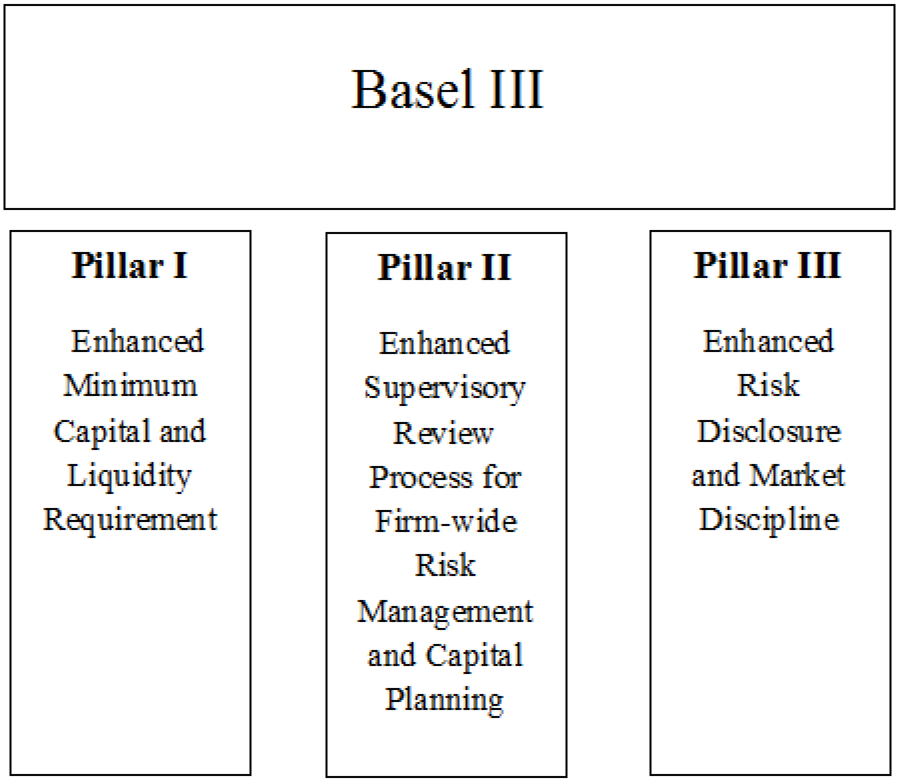
(iv) The over reliance of banks on external rating affects capital adequacy because according to Basel II rules, securities rated AAA require less capital as compared to securities rated AA. This will contribute to alterations in the portfolio of banks, and the bank will pass for such securities which have higher ratings. But in some cases, higher rated securities were also found to be very risky, example Collateralized Debt Obligations (CDOs).

(v) It has also provided scope for inattentive banks to systemically underestimate their risk and loss adjustments. This will lead to knock-on effect on capital adequacy.

2.2.3 Post-crisis Regulatory response and Basel III (2009)

The global financial crisis of 2007 warranted the urgent demand to strengthen the regulatory system for banks and other financial firms. Inaugural meeting in this regard of G-20 leaders was held in September 2009. BCBS published a comprehensive document in this regard in December 2010, titled "Basel III: A global regulatory framework for more resilient banks and banking systems." The new accord came with a motive to promote financially sensible and cautious policies in the banking and financial sectors to build the capacity to absorb shocks, despite the source. It also enhances the banking and financial systems' shock absorbing capability. The new regulations prescribe more liquidity measures and buffers along with more stringent control on leverage. There is no substantial dispute in the risk measurement approach in Basel III compared to Basel II. Basel III has suggested three new pillars such as Pillar I: Enhanced Minimum Capital and Liquidity Requirement; Pillar 2: Enhanced Supervisory Review Process for Firm-wide Risk Management and Capital Planning; Pillar 3: Enhanced Risk Disclosure and Market Discipline.

Figure- 2.2: Schematic Diagram of Basel III



Source: Author’s compilation

To overcome the pitfall in Basel II, following modifications are made in Basel III:

Capital Standards: The Capital base is increasing to bring consistency and transparency in the capital base disclosure of the banks. The capital standards are invoked to check off balance sheet items and derivatives exposures. It is for the first the Credit Value Adjustment (CVA) is presented. CVA is the adjustment to the value of derivative products to account credit risk of the counterparty. In the new rules, it is made mandatory for the banks to hold regulatory capital against their CVA positions. The accounting valuation method varies across the banks, but banks use following formula to calculate CVA:

$$CVA = (LGD_{MKT}) \sum_{i=1}^{T} Max\left[0; \exp\left(-\frac{S_{i-1}}{LGD_{MKT}}\right) - \exp\left(\frac{S_i t_i}{LGD_{MKT}}\right)\right]\left(\frac{EE_{i-1}.D_{i-t}+EE_i.D_I}{2}\right) \quad (2.4)$$

Where,

t: the time of the i-th revaluation time bucket, starting period t_0: 0

t_T: the longest contractual maturity across the netting set with the counterparty

S: the credit spread of the counterparty at tenort_i. Whenever Credit Default Swap (CDS) spread is available, it should be applied. If not, then proxy spread based on the rating, industry and region of the counterparty should be applied.

LGD: Loss Given Default of the counterparty based upon the spread of the market instrument of the counterparty.

EE_i: Expected exposure to the counterparty at revaluation time t_i.

The first element represents an estimate of the market implied marginal probability of default occurring between time $t_{i-1} and\ t_i$, within the sum, also known as risk neutral probability. This represents market price of buying protection against default and in general, is different from the remainder of the world likelihood of a default.

Introduction of stress tested Probability of Default estimates: Stress tested PD estimates are given vital importance in Basel III. The access to calculate PD will be same as which is used in IRB-F and IRB-A with a slight modification in the sense that along with usual PD estimate, stress tested PD estimates will be used to take care of adverse scenario. It will make banks more strong to absorb shocks.

Strengthening Capital Requirement against Credit Risk: The risks generated from off balance sheet items are also given vital importance in Basel III to control risk by raising capital charge. The additional economic capital that the banks need to keep with them to hold in unexpected loss is not captured in conventional credit risk estimates. Formula for credit risk is presented as:

$$Credit\ Risk = Max\{EL - UL, 0\} \qquad (2.5)$$

Credit risk is a part, where we maximize the difference of Expected Loss (EL) and Unexpected Loss (UL), which accepts a positive turn. EL is calculated from on balance sheet items, whereas UL is calculted from off balance sheet items and exogenous economic factors. EL can be expressed as:

$$EL = PD * LGD * EAD \tag{2.6}$$

Tightening control on Over-the-Counter (OTC) trading: OTC refers to the trading activities between two parties without any oversight. Such actions have more vulnerability to risk because there is no disclosure of trading action. In Basel III there are stricter regulations to curb OTC trading.

Flesh out the instances where Credit Risk is Miscalculated: In examples where credit risk is miscalculated, the exposure to the counterparty are highly correlated. In such instances the PD estimates are found to be really high where it should be really low. The new patterns call for care of miscalculation of credit risk.

Leverage Ratio (LR): The LR is introduced to bring guardianship of 'credit crunch'. It helps banks to check them build up leverage. The introduction of LR is also in lieu of 2007 global financial crisis because major default event in 2007 was a result of liquidity shortage and the credit crunch.

Pro-cyclicality: The extra buffer is preserved in order to share with pro-cyclicality events. The PD estimates are calculated subject to EL of banks' portfolios. The extra buffer will run to banks forward looking behaviour to check adverse situations.

Global Minimum Liquidity Standards (GMLS): GMLS were made mandatory for the internationally active banks to maintain 30-day Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). This will lead to uniformity in the liquidity of internationally active banks and also enable regulators to supervise and help the banks to minimize their exposure to various risks.

Nevertheless, in India, Basel III capital regulation commenced from April 1, 2013. This is expected to be implemented in phases and by March 31, 2019 it will be fully implemented, close to internationally agreed time. The transitional arrangements for the carrying out of Basel III norms in India for Scheduled Commercial Banks (SCBs) are described in Table 2.5.

Table 2.5: Transitional arrangements of Basel III norms in India

Transitional Arrangements-SCBs*						
Minimum capital ratios	April 1,2013 (%)	March 31,2014 (%)	March 31,2015 (%)	March 31,2016 (%)	March 31,2017 (%)	March 31,2018 (%)
Minimum common Equity Tier 1 (CET1)	4.5	5	5.5	5.5	5.5	5.5
Capital conservation buffer (CCB)	-	-	0.625	1.25	1.875	2.5
Minimum CET1+ CCB	4.5	5	6.125	6.75	7.375	8
Minimum Tier 1 capital	6	6.5	7	7	7	7
Minimum Total Capital*	9	9	9	9	9	9
Minimum Total Capital +CCB	9	9	9.625	10.25	10.875	11.5
Phase-in of all deductions from CET1 (in %) #	20	40	60	80	100	100

* excluding LABs and RRBs

Source: Reserve Bank of India

From the above table (Table 2.5) the difference of the total minimum capital requirement (9%) and Tier 1 requirement will be met by Tier 2 and other higher forms of capital. The major features of transitional arrangement of Basel III by RBI are as follows:

Tier I Capital Leverage Ratio: Tier I capital is the primary capital of the banks. In Basel III, BCBS have proposed Tier I capital leverage ratio at 3%, whereas, RBI had set it at 4.5% in the parallel run period from January 1, 2013 to January 1, 2017.

Pillar III Disclosure requirements: In order to improve transparency in regulatory capital and market discipline, Pillar III disclosure requirement is enhanced and expected to be effective from September 30, 2013.

Comprehensive liquidity coverage ratio (LCR): The BCBS have issued LCR guidelines on November 7, 2012. The modified guidelines were issued in January 2013, and the RBI is still in the process to finalize LCR.

Central Counterparty Clearing House (CCP's) exposures Capital Requirement: The RBI released issued guidelines on CCP's exposures capital requirement on July 2, 2013, which is effective from January 1, 2014. This will provide incentives to banks to clear, standardized OTC derivatives contracts through qualified central counterparties.

Framework to deal with Domestic- Systemically Important Banks (D-SIBs): From India, none of the banks are listed in the Global- Systemically Important Banks (G-SIB's). Systematically important banks are those banks which take in higher exposure to default because of its size, complexity and systemic interconnectedness. A draft framework to deal with D-SIBs has been published on December 2, 2013. This involves an additional common equity capital requirement to a D-SIBs with highest systemic importance with 0.8% of RWAs.

Guidelines on Securitization: In May 2012, the guidelines on securitisation were revised. The norms of the minimum holding period, minimum retention ratio, and standard for due diligence to align the interest of the originators and investors, and induce 'Skin in the Game' concept to discourage 'Originate to Distribute' models were also introduced.

Un-hedged Foreign Currency Exposures (UFCE): UFCE will also be taken into consideration because it poses risk to individual, corporate and then to the entire financial system.

Concentration of Credit Risk: Sensible measure is taken to check Intragroup Transactions and Exposures (ITEs) to avoid concentration of credit risk and large losses. In this line RBI has prescribed regulatory guidelines on February 11, 2014. It puts both quantitative limits for the financial ITEs and sensible standards for the non-financial ITEs.

A Framework for Revitalizing NPAs and Distressed Assets: The rising NPAs are a concern for both financial and real sector. In this regard, a framework is implemented with effect from April 1, 2014, for revitalizing distressed assets in the economic system.

Countercyclical Capital Buffer (CCB) Framework: For Indian banks, the RBI has proposed to create a CCB framework. This is based on credit-to-GDP gap in conjunction with Gross Non-Performing Assets (GNPA) growth. The CCB will increase linearly from 0 to 2.5 % of the risk-weighted assets (RWA) of the banks. This will be based on the position of the gap between 3 percentage points and 15 percentage points.

Countercyclical Provisioning: In case of a downturn, RBI is also ready to bring countercyclical provisioning buffer to the banking system. This buffer will be maintained with the idea to save profits made in the peak of the business cycle to deal during downturns.

2.3 Theoretical Underpinning

The credit risk measurement depends upon the likelihood of default of a firm on its contractual obligations. Probability of default is the dominant source of uncertainty in the lending decision; that's why models used in credit risk measurement mostly focus on probability of default. Credit risk models are developed through different stages from traditional to modern (new) approaches. This section covers major credit risk models used by banks and financial institutions. Credit risk models can be broadly classified into expert system, rating system, credit scoring models, logistic and probit regression models, structural models, reduced-form models and credit value at risk models.

2.3.1 Expert System

It is one of the most traditional ways of assessing credit worthiness of counterparty. In an expert system, the decision to extend credit is left to the local or branch lending officer. The lending officer's expertise, skill set, subjective judgment, and weighting of certain key factors are the most important determinants in the decision to grant credit. There can be infinite number of factors a lending officer could look at but five most common factors looked by an expert are called five 'Cs' . The five Cs are: character, capital, capacity, collateral, and cycle or (economic) conditions of borrowers. The expert gives certain weights to each factor to arrive at a credit decision**.**

- **Character-** It is subjective and can be judged by reputation of the firms, willingness to repay and credit history. Age factor is considered to be a good proxy for organization repayment reputation.
- **Capital Structure-** The leverage is considered to be most important predictor of bankruptcy probability and debt to equity ratio is more commonly used leverage ratio. High leverage ratio suggests greater probability of bankruptcy than low leverage.
- **Capacity-** Capacity refers to the ability of repayment; it also reflects the volatility of borrower earnings. If repayments on debt contracts show a constant stream over time, but earnings are volatile, the probability is high that the firm's capacity to repay debt claims is at risk.
- **Collateral-** In the event of default, a lender has claims on the collateral pledged by the borrower. The greater the priority of this claim and greater the market value of the underlying collateral, the lower the exposure risk of the loan.
- **Cycle or Economic Conditions-** The state of business cycle is an important element in determining credit risk exposure, especially for cycle-dependent industries. For example, the infrastructure sectors like metal industries, construction, etc. tend to be more cycle dependent than goods sectors like food, retail, and services etc.

2.3.2 Rating Systems

One of the oldest rating systems for loans was developed by the US Office of the Comptroller of the Currency (OCC). The US regulators and bankers have used this system to assess the adequacy of their loan loss reserves (Gallati , 2003). The OCC ratings system places an existing loan portfolio into five categories: four low-quality rating and one high-quality rating. Regulator defines certain percentage of loss reserve for various rating buckets, which is maintained by the banks. Over the period, banks have extended the OCC rating system by developing internal rating systems that more finely subdivide the pass/performing rating category.

There are various US rating agencies namely, Moody's, Standard and Poor's, Fitch IBCA, etc., which assign different ratings to commercial credit. In India, the credit rating agencies are Credit Rating Information Services of India Limited (CRISIL), Investment Information and Credit Rating Agencies of India (ICRA), Credit Analysis and Research Limited (CARE), Duff and Phelps Credit Rating India Private Ltd. (DCR India), ONICRA credit rating agency of India Ltd., SME Rating Agency of India Ltd (SMERA) etc.

Rating agencies specialize in evaluating the creditworthiness of corporate, municipal and sovereign debt securities. Their job is to inform investors about the likelihood that they will receive all principal and interest payments as scheduled for a given security. This is implied from the rating states which the security has got. Rating agencies use a system of letter grades that show the credit quality of issuer from the highest to lowest grades. For example, S&P uses symbols such as AAA, AA, A, BBB, BB, B, CCC, CC,… and D to classify credit quality. AAA is the highest and D is the lowest quality of credit. Similarly, Moody's uses symbols such as Aaa, Aa, A, Baa,…, Ca. Rating agencies consider different factors when they assign different ratings. S&P explains that in rating an industrial bond, it focuses on areas such as industry characteristics, competitive position (marketing, technology, and efficiency), management, financial characteristics, financial policy, profitability, capital structure, cash flow protection, financial flexibility.

2.3.3 Scoring System

Altman (1968) Z-score model is one of the pioneer work on scoring models for credit risk analysis. This model is based on Multivariate Discriminant Analysis (MDA). MDA is based on linear combination of two or more independent variables that will best discriminate between a priori defined groups: the default from non-default firms (Benos et.al. 2005). It weights the independent variables (financial ratios and accounting variables) and generates a single composite discriminant score. The score is then compared to a cutoff value, which determines the group that the firm belongs to. Scoring models identify certain key factors that determine probability of default. Key factors are combined with certain weights to compute risk scores. These scores are used to classify borrowers into a good or bad group.

Multivariate Discriminant Analysis (MDA)

The crucial assumption of MDA[1] is that variance-covariance matrices of the two groups are statistically identical. The weights of the discriminant function are the difference of the mean vectors of the explanatory variables for the defaulted and non-defaulted groups. In the MDA model, our purpose is two folds: The first one is to look for predictors (financial ratios) that lead to lower misclassification rates within the sample and the second one is to get improved prediction accuracy in an un-estimated holdout sample.

The discriminant analysis (DA) model involves linear combinations of the following form:

$$Z = \sum_{i=0}^{k} a_i x_i \tag{2.7}$$

Where, Z: overall index (discriminate function)

a_0: a constant

a_i's: the discriminate coefficients or the weight of that dependent variable

x_i's: the set of independently normally distributed random variables.

i:1 to k

The weights can be defined as[2]:

$$a = (\mu^1 - \mu^2)\Sigma^{-1} \tag{2.8}$$

Where μ^1 and μ^2 are the mean vectors of the explanatory variables of the two groups, in the current context distressed and non-distressed. Σ Signifies variance-covariance matrix of the two group which is assumed to be equal[3]. More formally:

$$x^1 \sim N(\mu_1, \Sigma) \tag{2.9}$$

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[1] For details on MDA, see Everitt BS, Dunn G (1991) Applied Multivariate Data Analysis. Edward Arnold, London

[2] For details, see Anderson (1984)

[3] In order to obtain a linear discriminant function the assumption of equality of variance-covariance matrix of the two groups in necessary. Otherwise the function will become quadratic (Altman, 1993).

$$x^2 \sim N(\mu_2\ , \sum) \quad (2.10)$$

Meaning that x is a k*1 multivariate normally distributed random variables with parameter μ_1 and $\sum$ for group one and parameter μ_2 and $\sum$ for group two.

The equation 1 is similar to the linear regression equation; wherein V(s) are the unstandardized discriminant coefficient analogous to the coefficient B(s) in the regression equation.

The discriminant coefficients (v's) maximize the distance between the categories; namely - defaulted and non-defaulted in the present context. Good predicting variables have larger weights. The function maximizes the distance between the categories will be one less than the number of groups. Hence, it reduces analyst space dimensionality. If there is a set of K explanatory variables that classify observations into G groups (K≥G), it will yield G-1 discriminant functions. The objective of the DA analysis to combine variables in such a way so that single composite variable can be obtained and have best classifying power. Following are the assumptions of DA analysis:

1. The observations used are independent.
2. X's are normally distributed
3. In the initial classification, each of dependent categories is correctly classified
4. There should be minimum two groups which are mutually exclusive and collectively exhaustive.
5. The group sizes of the defendant should not be grossly different and should be at least five times the number of independent variables.

Following statistical tests are carried out to check if the two groups are statistically different:

Wilks' Lambda (Λ[4]) is one of the widely used test statistic of multivariate mean differences. It is also the first MANOVA test statistic developed which is the direct

[4] For details on derivation, see Bernstein (1987) Applied Multivariate Analysis, p. 328-331.

measure of the proportion of the variance in the combination of dependent variables that is accounted for by the independent variable. If a large proportion of the variance is accounted then, the test suggests there is an effect from the grouping variable i.e. the groups have different mean values.

Wilks' lambda = $\Lambda = \frac{|SS_w|}{|SS_t|}$

$|SS_w|$ is the determinant of the within group sum of squares and

$|SS_t|$ is the determinant of total group sum of squares.

Intuitively, a small Λ signifies, a small proportion of the total variance of the constituent variables ($|SS_t|$) is accounted for within group dispersion ($|SS_w|$), while the larger proportion of total variance is explained by the squared deviation of the group means from their polled means ($|SS_b|$).The quantity (1 - Λ) is interpreted as the proportion of variance in the dependent variables explained by the model effect. Thus, we will reject the null hypothesis if Wilks' lambda is small (close to zero).However, this quantity can be biased and quite misleading in small samples.

F-statistic[5]: It is used to check the statistical significance of the equality of the mean of the two groups. If the p-value is less than 0.05, we can conclude that the corresponding function explains the group membership well, which means a greater chance for the null of equal means to be rejected.

Under the null hypothesis, the means of both the groups are equal i.e. H_O ($\mu_1 = \mu_2$) and the F-statistic can be defined as:

[5] The F test relates the difference between the average values of the ratios in each group to the variability of values of the ratios within each group (Altman, 1968). The null hypothesis used for F test is means of variables in both distressed and non-distressed group are equal. The lower value of Wilks' lambda and the higher value of F statistic indicate greater chance for the null hypothesis being rejected.

$$F\,(p, n_1+n_2\text{-}p\text{-}1)=\frac{1-\Lambda}{\Lambda}\left[\frac{n_1+n_2-p-1}{p}\right] \quad (2.11)$$

Where,

$\Lambda=\frac{|SS_w|}{|SS_t|}$

n_1 is the number of observation in group one,

n_2 is the number of observation in group two,

p is the number of explanatory variables that achieves the classification,

Chi-square test is conducted to check how well the discriminant function classifies the groups.

Altman (1968) has found 22 potentially helpful variables (ratios) out of a large number of significant variables, which are indicators of corporate problems and complied for evaluation of the firm. Again, the 22 variables are classified into five standard ratios categories, including liquidity, profitability, leverage, solvency and activity. The ratios are chosen on the basis of their popularity in the literature and their potential relevancy to the study. From the original 22 variables, five are selected as doing the best overall job together in the prediction of corporate bankruptcy. The figures in parentheses indicates F-statistics of the equality in mean between defaulted and non-defaulted firms (2.12). Using linear discriminant analysis, the Altman's scoring model was defined as:

$$Z = 1.2WCTA + 1.4RETA + 3.3EBITA + 0.6MVEBVD + .99SLTA \quad (2.12)$$

(32.60) (58.86) (26.56) (33.26) (2.84)

Where, WCTA: working capital/total assets,

RETA: retained earnings/total assets,

EBITA: earnings before interest and taxes/ total assets,

MVEBVD: market value of equity/book value of total liabilities,

SLTA : sales/total assets, and

Z: overall index.

WCTA (Working Capital/Total Assets) ratio: It is a measure of the net liquid assets of the firm about the total capitalization which measures the firm's ability to manage its short-term capital position. Along with liquidity, the size characteristics are also explicitly considered in the ratio. A high value of ratio signifies that the firm can retain a large proportion of its current assets as a proportion of its total assets after meeting its current liabilities. In general, the firms experiencing consistent operating losses will have shrinking current asset about its total assets and the firms is having positive and high ratio is not going to default on its short-term commitments. Hence, for failing firms, this ratio will be negative, and it is expected to have positive influence on discriminant score.

RETA (Retained Earnings/Total Assets): Retained earnings is the account which reports the total amount of retained earnings and losses of a firm over its entire life. This is also referred as earned surplus. The high positive ratio signifies the firms' better preparedness or ability during downturn in the business activity. This means it can meet its debt service payments by running down its earned surplus or reserves. The age of a firm is implicitly considered in this ratio. For example, a relatively young firm probably shows a low RETA ratio because it has not had time to build up its cumulative profit. The RETA ratio also measures the leverage of a firm. The firms with low or negative RETA ratio will have higher exposure to leverage which shows larger portion of the firm asset is financed by high-risk capital (other person money). The ratio is expected to have positive effect on discriminant score.

EBITA (Earnings before Interest and Taxes/Total Assets): This ratio is a measure of the true productivity of the firm's assets which is independent of any tax or leverage factors. The higher and positive ratio signifies the firm is more efficiently using its total assets to generate surplus. If the share of surplus generated is higher then there are greater chances that firm will not default on its debt obligations. The firm's ultimate existence is based on the earning power of its assets; this ratio appears to be particularly appropriate for studies dealing with corporate failure. The ratio is expected to have positive effect on discriminant score.

MVEBVD (Market Value of Equity/Book value of Total Debt): The firms' equity is measured by the combined market value of all shares of stocks, preferred and common, whereas liabilities includes both current and long term. The ratio explains how much the firm's asset can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets, and the firm becomes bankrupt. It appears to be a most effective predictor of bankruptcy than a similar, more commonly used ratio: net worth/ total book value of debt. It is found that the larger proportion of changes in the average Z-score is due to dramatic changes in stock price and its impact on MVEBVD. The ratio is expected to have positive effect on discriminant score.

SLTA (Sales/Total Assets): This is a key variable for the measurement of the size of the firm. The capital turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capability in dealing with competitive conditions. This ratio ranks second in its contribution to the overall discriminating ability of the model. The ratio is expected to have positive effect on discriminant score. Here one of the major pitfall of the model is that the Z-score model is linear whereas the path of bankruptcy may be non-linear. The accounting ratios used in the model may be discrete which may be based upon historic and book value accounting principles. Some of the major developments in credit risk analysis use neural network techniques which are non-linear in nature and take care of the problem.

There are certain issues to be looked at. First, the Z-score model is linear whereas the path to bankruptcy may be highly nonlinear (the relationship between the X's is likely to be nonlinear). Second, the model is essentially based on accounting ratios. In most countries, accounting data appears only at discrete intervals (e.g. quarterly) and are generally based on historic or book value accounting principles. It is argued that the recent application of nonlinear methods such as neural networks to credit risk analysis shows promise of improving upon older vintage credit-scoring models (Saunders, 1999).

2.3.4 Logistic Model for Credit Risk

In some of the default studies based on MDA models, authors have pointed out that two basic assumptions of MDA are often violated when applied to the default prediction problems[6]. Apart from that, in MDA models, the standardized coefficients cannot be interpreted like the slope of a regression equation and hence do not indicate the relative importance of different variables (Altman and Sabato, 2007). Considering the problem with MDA models, Ohlson (1980), for the first time, applied the conditional logit model to the default prediction's study. The advantages of the logit methodology are that it does not require the restrictive assumptions of MDA and allows working with disproportional samples.

Logit Model

If a dependent variable is binary and is a function of a set of independent variables, the Linear Probability Model (LPM) can be written as:

$$P_i = E(Y = 1|X_i) = \beta_1 + \beta_2 X_i \tag{2.13}$$

Where, P_i represents probability, X_i represents various financial ratios of the firms and Y is the dependent variable. Y=1 means the firm is failed. β_1 and β_2 are slope coefficients.

The intrinsic defects of LPM gave birth to logit and Probit models. In LPM (2.13) the probability of Y can exceed the limit of 0 and 1. Hence, the useful way to solve the problem is to transform

$X_i(s)$ and β (s) into a probability with function F that translates Xβ into number between 0 and 1.

---

[6] MDA is based on two restrictive assumptions: (1) the independent variables included in the model are multivariate normally distributed; (2) the group dispersion metrics (or variance-covariance metrics) are equal across the failing and the non-failing group.

$$prob(y_i = 1) = F(X_i\beta) \tag{2.14}$$

Where F is cumulative density function.

Choosing F to be the logistic distribution yields one of the ways to limit $prob(y_i = 1)$ between 0 and 1. This is called the logit model.

$$prob(y_i = 1) = \Lambda(X_i\beta) = \frac{expX_i\beta}{1 + expX_i\beta} \tag{2.15}$$

In the context of default prediction study, the logit model is used to classify whether a company is defaulted or non-defaulted by using accounting-based financial ratios.

Ohlson's (1980) logit model is used for distress prediction in the present study. A brief overview of the Ohlson's model is discussed here. Ohlson (1980) identified some of the problems in Z- score model: (i) certain statistical requirements imposed on the distributional properties of the predictors. For example, the variance-covariance matrices of the predictors should be the same for both groups (failed and non-failed firms), (ii) The output of the application of an MDA model is a score which has little intuitive interpretation, since it is basically an ordinal ranking (discriminatory) device, (iii) There are also certain problems related to the "matching" procedures which have typically been used in MDA. Failed and non-failed firms are matched according to criteria such as size and industry, and these tend to be somewhat arbitrary. All these problems can be avoided in the logit model.

Ohlson (1980) employed a logit technique with less restrictive assumptions than those taken in the MDA approach to model bankruptcy. The model uses nine predictive variables which measure firms' size, leverage, liquidity, and performance. The estimated model consists of 105 bankrupt and 2,058 non-bankrupt industrial firms for the period 1970–1976. The original model is shown in equation (2.16):

$$\underset{(-0.970)}{Y = -1.3} - \underset{(-3.78)}{0.4SIZE} + \underset{(6.61)}{6.0TLTA} - \underset{(-1.89)}{1.4WCTA} + \underset{(0.761)}{0.1CLCA} - \underset{(-2.450)}{2.4OENEG} - \underset{(-1.85)}{1.8NITA} + \underset{(-2.36)}{0.3FUTL} - \underset{(0.812)}{1.7INTWO} - \underset{(-2.21)}{0.5CHIN} \tag{2.16}$$

Where, Y is the overall index based upon logistic function which determine the probability of firms' membership in default or non-default group. Based upon total error minimization criterion for the given data, firms with Y > 0.5 are classified defaulted firm, otherwise classified as non-defaulted (Ohlson 1980, p. 120). The figures in parentheses indicates T-statistics.

The nine financial ratios used by Ohlson to predict bankruptcy are as follows:

SIZE: It is log of total assets to GNP price-level index. 2011-12 is taken 100 as a base value for GNP. The total assets are in Indian rupee. The index year for respective company is taken as the year prior to the year of the balance sheet date. The log transformation has very important implications, if two firms, X and Y, have balance sheet date in the same year, then the sign of Px – Py will be independent of price-level index.

TLTA: It is the ratio of total liabilities to total assets which captures leverage of a firm which measures financial structure.

WCTA: It is the ratio of working capital to total assets which is a measure of current liquidity.

CLCA: Current liabilities divided by current assets is also a measure of current liquidity. WCTA and CLCA jointly can be considered as a measure of current liquidity.

OENEG: This is a dummy and; it takes value 1 if total liabilities exceed total assets, 0 otherwise. It is used as a discontinuity correction for TLTA. The positive sign is the signal of certain bankruptcy whereas negative sign is also signal of bad financial position but better than positive.

NITA: It is the ratio of net income to total assets which is a measure of performance.

FUTL: It is the ratio of funds provided by operations to total liabilities which is also a measure of performance.

INTWO: It takes value 1, if net income was negative for the last two years, 0 otherwise.

CHIN: It can be defined as (NIt NIt1)/(|NIt| + |NIt1|), where NIt is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.

Ohlson's population boundaries were restricted by (i) the period from 1970 to 1976; (ii) the equity of the company had to be traded on some stock exchange or OTC market; (iii) the company must be classified as an industrial firm. He ended up with 105 failed firms which were used for his study. He mentioned in his paper that no attempt was made to select predictors by rigorous theory. The first six predictors were partially selected simply because they appear to be the ones most frequently mentioned in the literature.

Three sets of estimates were computed for the logit model using the predictors above. Model 1 predicts bankruptcy within one year, Model 2 predicts bankruptcy within two years, given that the company did not fail within the subsequent year; Model 3 predicts bankruptcy within one or two years.

2.3.5 Probit Model

A probit model is similar to logit model, but instead of using the cumulative logistic distribution, a probit model uses the cumulative normal distribution to limit $prob(y_i = 1)$ between 0 and 1.

$$prob(y_i = 1) = \phi(X_i\beta) = \int_{-x}^{X_i\beta} \frac{1}{\sqrt{2\pi}} exp\left(\frac{-z^2}{z}\right) dz \tag{2.17}$$

The standard normal transformation $\phi(.)$ limit the probability to lie between 0 and 1.

or,

$$\lim_{z\to+\infty} \emptyset(z) = 1 \qquad \text{and} \qquad \lim_{z\to-\infty} \emptyset(z) = 0$$

Zmijewski (1984) adopts a probit method to model bankruptcy which uses financial ratios measuring firm's performance, leverage, and liquidity. The ratios were selected by their performance in the previous studies. The model uses 40 bankrupt and 800 non-bankrupt industrial firms' data for the period 1972–1978. Equation (2.18) represents the original model estimated by Zmijewski (1984):

$$X = -4.3 - 4.5NITL + 5.7TLTA - .004CACL \tag{2.18}$$

$$(0.00) \quad (0.00) \qquad (0.00) \qquad (0.00)$$

Where, X is the overall index based upon probit function which determines the probability of firms' membership in bankrupt and non-bankrupt group. Again based upon total error minimization criterion firm with $X > 0.5$ is classified as a bankrupt firm otherwise non-defaulted (Zmijewski 1984, p. 72). The figures in parentheses indicates p-value. NITL, TLTA, and CACL are the variables used in the model.

Following are the description of the variables used in the probit model:

NITL: It is the ratio of net income to total assets. The ratio measures return on asset which is the measure of firm's performance

TLTA: It is the ratio of total debt to total assets. The ratio measures the leverage of the firms.

CACL: It is the ratio of current assets to current liabilities. The ratio measures liquidity of the firms.

2.3.6 Structural Credit Risk Models

Altman (2006) has discussed about the development of various credit risk models for the past thirty years. According to him, these models can be classified into (i) credit pricing models, and (ii) portfolio credit value-at-risk (VaR) models. Again credit pricing models are divided into first generation structural-form, second generation structural-form and reduced-form models. Now we concisely discuss some of the models stated in his paper.

First Generation Structural-form Models

These models are based upon the original framework developed by Merton (1974) based on the option pricing theory of Black and Scholes (1973). These models adopt the contingency claim analysis, where the corporate liabilities are taken as contingent claims on assets of the firm. In this framework, the default process of a firm is determined by the value of a firm's total assets. Therefore, the risk of a firm's default is explicitly linked to the variability of the firm's asset value. The basic intuition of the model is that default takes place when the value of a firm's asset is lower than its liabilities.

Assuming if firm's debt is completely denoted by zero-coupon bond and if at maturity the value of the firm is higher than the face value of the bond, then bond holder gets back the face value of the bond. In case, if the firms value is lower than the face value of the bond, the bond holder gets back the market value of the firm and shareholders get nothing. On the same principle, Merton developed an explicit formula for risky bonds which can be used both to estimate the probability of default (PD) of a firm and can also be used to estimate the yield differential between a risky bond and a default-free bond. The derivation of model and calculation of PD is discussed in details in the forthcoming section on Merton model. In this setting, a firm can default on its debt obligation only at the time of maturity. Later, some extension is done by allowing default to occur before the date of maturity. These models were introduced by Black and Cox (1976), Lonfstaff and Schwartz (1995), Leland and Toft (1996), etc.

Second Generation Structural-form Models

Later, some extension is done in Merton model by allowing default to occur before the date of maturity. In these models default may occur anytime between the issuance and maturity of the debt and that default is triggered when the value of the firm's assets reaches a lower threshold level. These models were introduced by Lonfstaff and Schwartz (1995), Leland and Toft (1996), etc. Under these approaches, the RR (Recovery Rate) in the event of default is exogenous and independent of the firm's asset value. It is defined as fixed ratio of the outstanding debt value and is, therefore, independent of the PD.

Although second generation models are improved versions of first generation models but they had following limitations:

(i) The models still need estimates for the parameters of a company's asset value, which is non-observable.

(ii) These models integrate credit-rating changes that occur quite frequently for default-risky corporate debt.

(iii) Most of these models assume that the value of the firm is continuous in time. As a result, the time of default can be predicted just before it happens and hence there is no 'sudden surprise'.

Reduced form Model

In structural form, models are based on some unrealistic assumptions on the calculation of value of firms. To overcome these limitations, reduced form models were developed. In contrast to structural form models, reduced form models are not conditioned upon default on the value of the firm. In these models parameters related to the firm's value need not be estimated to implement them (Altman, 2006). The reduced-form models also introduce separate explicit assumptions on the dynamics of both PD and RR. In these models, an exogenous RR is independent of PD.

The reduced form models fundamentally differ from typical structural form models in the degree of predictability of the default as they accommodate defaults that are sudden surprises (Atman, 2006). In a typical reduced form model, it is assumed that an exogenous random variable drives default and that the probability of default over any time interval is nonzero. The event of default takes place when the random variable undergoes a discrete shift in its level. Under these models defaults are treated as unpredictable poison events.

This approach was first introduced by Jarrow and Turnbull (1995) and further extended by Duffie and Singleton (1999) and Lando (1998). All these models differ from each other by the manner in which the RR is parameterized. Some models allow for a random RR that depends on the pre-default value of the bond. Other models assume that bonds of the same issuers, seniority and face value have the same RR at defaults, regardless of the remaining maturity.

2.4 Merton (1974) and Credit Value at Risk Models

This section deals with modelling Black-Scholes-Metron (1974) model. The credit VaR approach to model risk is also discussed here.

2.4.1 Merton Model

The BSM model is based on the option pricing theory of Black and Scholes (1973). In the model, the value of the equity of firms' assets is modeled as a call option, with the face value of debt as exercise price and debt maturity as the option's time to maturity, and the value of the debt is modelled as a put option. This model is based on certain assumptions: (i) The firm only defaults at the time of maturity T. (ii) Firm's asset value follows lognormal distribution. (iii) The firm's assets V is financed by equity, E, and debt F, where the total value of the firm's debt (D) consists of one non-callable zero-coupon bond with face value F. Hence, if at maturity T, the firm's asset value V is enough to pay back the face value of the debt F, i.e. if $V > F$, the firm does not default and the shareholders receive $V - F$. Otherwise, if $V < F$, the firm defaults, bondholders take control of the firm, and the shareholders receive nothing.

From the above underlying assumptions, the value of equity in the Black-Scholes-Merton (BSM) framework is given by:

$$E = \max(0, V - F) \tag{2.19}$$

Apart from other parameters to calculate distance to default (DD) and Probability of Default (PD), we need to find out the total market value of the firm and its volatility. The total market value of the firm is defined as the sum of the market value of the firm's debt and the value of its equity. Market equity values are readily available, whereas reliable data on market value of debt is unavailable. The BSM model solves this problem by assuming that the total value of a firm follows a geometric Brownian motion:

$$dV = \mu V dt + \sigma_V V dZ \tag{2.20}$$

Where, V is the total value of the firm,

μ is expected continuously compounded return on V,

σ_V is volatility of firm value

dZ is a standard Wiener process.

Again, by Black-Scholes formula equity value of a firm as a call option is given as:

$$E = VN(d_1) - Fe^{-rT} N(d_2) \tag{2.21}$$

Where,

$$d_1 = \frac{\ln(V/F) + (r + \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \tag{2.22}$$

$$d_2 = \frac{\ln(V/F) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \tag{2.23}$$

Or, $d_2 = d_1 - \sigma_V \sqrt{T}$

r and *T* are risk-free rate and time to maturity respectively. *N ( )* is the cumulative standard normal distribution function.

Under the risk neutral probability measure, the default probability (PD) is given by:

$$N(-d_2) = N\left[-\frac{\ln(V/F) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \right] \tag{2.24}$$

If the risk-free interest rate *r* is replaced in (2.24) with the expected return on the asset value or the ‘drift’ of the asset value, μ_V, the distance to default measures can be obtained, which is:

$$DD = \frac{\ln(V/F) + (\mu_V - \sigma_V^2/2)T}{\sigma_V\sqrt{T}} \tag{2.25}$$

And the corresponding probability of default (PD) of the firm as per Black-Scholes-Merton (BSM) model is:

$$N(-\hat{d}_2) = N\left[-\frac{\ln(V/F) + (\mu_V - \sigma_V^2/2)T}{\sigma_V\sqrt{T}}\right] \tag{2.26}$$

The equation (2.26) shows the probability of bankruptcy as a function of the distance between the current values of the firm's assets and face value of its liabilities (V/F) adjusted for the expected growth in asset values $(\mu_V - \sigma_V^2/2)$ about asset volatility (σ_V). The state of default occurs when, at maturity, the value of the firm is below the face value of debt, that is when $V \leq F$. Equation (2.21) is derived under the assumption of risk-neutrality where all assets are expected to grow at the risk-free rate, hence PD based on the risk-free rate will provide the risk neutral probability of default as shown in equation (2.24). However, the probability of bankruptcy depends upon the actual distribution of future asset values, which is a function of the expected return on asset values (μ_V). When the objective is to assess credit risk of various positions, and not to price contingent claims, the objective or 'real' default probability has to be used. Hence, the prime objective of credit risk model is to find the real or objective probabilities of default.

Equation (2.26) includes three unknowns, namely, V, σ_V and μ_V. We need to find all three parameters to obtain an estimate of (2.26). To identify the above unknowns, the model invokes the Wiener process to model equity value, E.

$$E = \mu_E E dt + \sigma_E E dZ \tag{2.27}$$

Where , μ_E is the expected continuously compounded return on E, σ_E is the volatility of equity value, and *dz* is a standard Wiener process. By Ito's lemma, we can also represent the process for equity as:

$$dE = \left(\frac{\partial E}{\partial t} + \mu_V V \frac{\partial E}{\partial V} + \frac{1}{2} \sigma_V^2 V^2 \frac{\partial^2 E}{\partial V^2} \right) dt + \sigma_V V \frac{\partial E}{\partial V} dZ \tag{2.28}$$

Since the diffusion terms in the equity process in (2.27) and (2.28) are equal, we can write the following relationship:

$$\sigma_E E = \sigma_V V \frac{\partial E}{\partial V} = \sigma_V V N(d_1) \tag{2.29}$$

Equation (2.21) and (2.29) complete the system of two simultaneous nonlinear equations with two unknowns, *V* and σ_V ; and the k parameters are *E*, σ_E , *r*, *F* and *T*. Hence the above two unknowns can be obtained by solving the two equations (2.21) and (2.29) simultaneously using the solver routine in Microsoft Excel.

Having found asset value *V*, and its volatility σ_V , the next step is finding the drift of asset value, which is expected market return on asset (μ_V). μ_V is estimated from market value of asset of current year estimated by solving equation 2.21 and 2.29 and market value of asset of previous year. In many cases, the actual return on assets is negative. As mentioned in Hillegeist et al. (2004), since expected returns cannot be negative, we can set the expected growth rate equal to the risk-free rate in such cases. Hence, he suggested that μ_V can be calculated as:

$$\mu_v(t) = \max\left[\frac{V(t) - V(t-1)}{V(t-1)}, r \right] \tag{2.30}$$

Now using the known parameters (*E*, σ_E , *r*, *F* and *T*) and estimated unknown parameters (*V*, σ_V and μ_V), one can estimate real or objective probability of default using equation (2.26).

2.4.2 Credit Value at Risk Model

In late nineties, bank started developing models based upon Value at Risk (VaR) framework to measure credit risk. This was the result of growing importance of credit risk measurement, and which was the heart of new Basel Accords as well. In general, VaR models are used to measure market risk of portfolio assets. In the new accord, it is prescribed that banks can use its internal credit risk models, and regulators should be convinced with 'concentration risk,' 'spread risk,' 'default risk' and 'downgrade risk'.

The spread risk is associated with both credit and market risk. It fluctuates either because of change in equilibrium conditions in the capital market, which affects credit spread of all credit ratings. The spread can also fluctuate because of improvement or deterioration in the credit quality of obligor, or both the conditions simultaneously (Crouhy et.al. 2000). Downgrade risk can be defined as the pure credit spread risk. In case of default risk, it is a special case of downgrade risk at a level in which credit quality is deteriorated at which obligor cannot serve its debt obligations. The adequate VaR model for credit risk should address both the migration risk, i.e., default risk and credit spread risk in an integrated and consistent framework.

As discussed above, the VaR models for credit risk address the issue of credit risk due to change in the credit quality. Credit VaR models are divided into two categories: (1) Mark-to-Market (MTM) models and (2) Default mode models (DM). In case of DM models, binomial approach is adopted, and credit risk is identified with default risk. Whereas, in case of MTM, only two possible events are taken into consideration: default and survival. The credit losses arise only when default takes place in DM models, whereas MTM models are multinomial, and losses can arise when negative credit migration takes place. Some of the notable industry sponsored credit VaR models are:

(i) KMV's Credit Portfolio Manager
(ii) Credit Suisse Financial Products' (CSFP) CreditRisk+
(iii) J. P. Morgan's CreditMetrics
(iv) Kamakura's Risk Manager
(v) McKinsey's CreditPortfolioView

KMV Corporation developed both Expected Default Frequency (EDF) model and Portfolio Manager Model based upon asset value model developed by Merton (Merton, 1974). The EDF measures the probability a company will default over a specific period. For that market value of asset, book value of debt and volatility of market value of asset data are used. KMV introduced Portfolio Manager Model in 1993. This tool is used to manage credit portfolio risk, and it is also based upon VaR principle. The corporation has also developed various models for default probabilities, loss distribution, and migration risk.

In the year 1997, JP Morgan first published CreditMetrics. This approach is based upon credit migration. In this approach, we see the default probabilities of moving from one credit quality to another. This also includes default within given time horizon which is often taken as an year. In CreditMetrics models full forward distribution of the values of loan portfolio or bond, for example, a year at which change in values, are associated to credit migration only and interest rates are guaranteed to change in a deterministic fashion (Couhy et al., 2000). In a similar fashion, Credit-VaR of portfolio is then derived to estimate market risk. It is percentile of distribution matching with the desired confidence level.

Later in the year 1997, Credit Suisse Financial Products (CSFP) published a new approach, CreditRisk+, which only emphasizes on default risk. The model assumes default for loans or individual bonds follow a poisson process. In this analysis credit migration risk is not explicitly modeled. In its place, CreditRisk+ permits for stochastic default rates which partly account, though not rigorously, for migration risk.

Like CreditRisk+, McKinsey developed its model known as CreditPortfolioView, which only measures default risk. CreditPortfolio View is a discrete time multi-period model in which default probabilities are a function of macro-economic variables. These variables are unemployment, government expenses, foreign exchange rates, the level of interest rates and the growth rate of the economy, which drive up to a large extent credit cycles.

Risk Manager a software of Kamakura Corporation, world's premier providers of risk management software. The software offers a combined solution of market risk, credit risk, asset and liability management and performance measurement. It also provides credit-adjusted valuation, measurement for default probability, VaR, etc.

2.5 Conclusion

The current chapter discussed emergence of Basel Accord and shift in the approaches to assess various types of risk under the different accords. In Basel I (1988), credit risk was the only focus which later in Basel II (2006) and Basel III (2009) was supplemented by market and operational risk. Limitations of one accord gave birth to others with more promising stable and resilient banking system. Basel III Accord emerged on the eve of global financial crisis. Many new changes are introduced in lieu of innovated financial products and their exposure to various types of risks. The chapter also discusses various approaches to assess credit risk in lieu of global regulatory framework and different approaches to model credit risk in the new accords. The later chapters will review empirical literature and deal with modeling and other aspects of credit risk modeling.

CHAPTER 3

SURVEY OF LITERATURE

3.1 Introduction

The Basel Accords and theoretical models of credit risk were covered in the second chapter. The current chapter extensively surveys the literature on credit risk modeling. The formal studies on credit risk started in the 1930's **(Altman, 1968)**. The early studies were univariate in nature, and single financial ratios were used to assess financial position of borrowers. These studies have set the platform for the development of credit risk models. Some of the important univariate studies are **Fitzpatrick (1932)**, **Smith and Winaker (1935)**, **Merwin (1942)**, **Chudson (1945)**, **Jackendoff (1962)** and **Beaver (1966)**. After seven decades of credit risk measurement, there been extensive development in the credit risk literature. The credit risk models can be classified into following categories **(Fejer-Kiraly, 2015)**:

1. Parametric Models (Accounting and Market-based models) and
2. Non-parametric Models (Artificial Neural Networks (ANN), Hazard models, Fuzzy Models, Genetic Algorithms (GA) and Hybrid models, or models in which several of the former models are combined)

The remainder of the chapter is organized as follows. Section 3.2 provides information on parametric models. Non-parametric models are covered in section 3.3. The chapter concludes with section 3.4.

3.2 Parametric Models

The parametric models could be univariate or multivariate in nature which use mainly financial ratios and focus on the symptoms of bankruptcy **(Andan & Dar, 2006)**. Sometimes these models use non-financial information (**Ohlson, 1980**; **Bandyopadhyay, 2006**). **Balcaen and Ooghe (2004)** and **Bellovary et al. (2007)** are the most cited papers in literature of bankruptcy prediction. Both the papers focused on the problems of parametric models. These problems are related to the assumptions of the dichotomous variable, the sampling method, stationarity assumptions, data instability, selection of independent variables, use of accounting information and the time dimension **(Balcaen & Ooghe, 2004)**. Further, parametric models can be classified into two categories: accounting based and market-based models. Market-based models are again divided into two parts - structural and reduced form models.

3.2.1 Accounting based Models

Beaver (1966) with his univariate default prediction study on US firms revolutionized the practice of credit risk assessment. The study compares the mean values of 30 financial ratios of 79 failed and 79 non-failed firms in 38 industries. The study steps further to test the ability of individual financial ratios to classify between bankrupt and non-bankrupt firms. Four financial ratios were found to have highest classification power, namely - net income to total debt (92%), net income to net worth (91%), cash flow to total debt (90%), and cash flow to total assets (90%). For future research, the study suggest multiple ratios to be considered simultaneously could have higher predictive ability than single ratios. The study creates a platform for multiple ratio models.

Altman (1968) developed a first multivariate discriminant model for default prediction for US companies. The model used five financial ratios to predict bankruptcy of the firms. The model can predict bankruptcy with 95% of accuracy for the initial sample one year before bankruptcy. **Altman et al. (1977)** developed a model for US manufacturing and retailers, which had the effective classifying ability from 5 years before default. Since **Altman (1968)**, discriminant analysis used by many researchers by making changes in financial ratios, study sample, and change in business culture. Some of the notable studies are **Deakin (1972)**, **Blum (1974)**, **Springate (1978)** and **Fulmer et al. (1984)**.

Deakin (1972) developed bankruptcy prediction model using MDA technique. In the **Altman (1968)** study, he used matched sample of defaulted and non-defaulted firms, whereas Deakin applied random selection method and selected 11 defaulted and 23 non-defaulted firms to develop bankruptcy prediction model. The classification error of the model was found to be low up to three years prior to bankruptcy (3-4.5%) and high for fourth and fifth year prior to bankruptcy (21-17%).

Springate (1978) estimated a bankruptcy prediction model for Canadian manufacturing companies using a sample of 20 failed companies matched with 20 non-failed companies. The study applied four financial ratios and used MDA techniques to model bankruptcy. The major finding of the study suggests the model correctly classifies 90% of failed and 95% of non-failed firms.

Fulmer et al. (1984) developed bankruptcy prediction model for small firms. The study used nine financial ratios and MDA technique to model bankruptcy. The model correctly classified 96 % of bankrupt and 100% of non-bankrupt firms before one year. The predictive accuracy was reduced to 70% for bankrupt and 93% for non-bankrupt firms before two years of bankruptcy.

Izan (1984) conducted study on Australian firms using MDA technique. The study utilized five financial ratios to model bankruptcy of the firms. The model has 100% predictive accuracy before one year and accuracy reduced to 70% to 40% before two and three years of bankruptcy respectively.

Casey and Bartczak (1985) developed bankruptcy prediction model using MDA and logit techniques. Both the models used nine financial ratios to predict bankruptcy of the firms. The accuracy of MDA model to predict defaulted firms varied from 57% to 90% and for non-defaulted firms 47% to 87%. In case of logit model, the classification varied from 13% to 63% for bankrupt firms and 95% to 98% for non-bankrupt firms.

Levitan and Knoblett (l985) developed bankruptcy prediction model for general firms using MDA technique. The model used 26 financial ratios to predict bankruptcy of the firms. The model correctly classified 95% before one year and 91% before two years of bankruptcy respectively.

Rose and Kolari (1985) conducted a study and developed bankruptcy prediction models for banks. The model used 23 financial ratios in a MDA framework to model bankruptcy of the firms. The model correctly classified 76% of failed banks and 69% of non-failed banks before one year. The predictive accuracy of the model declined and it correctly classifies 77% of failed banks and 71% of non-failed banks before two years of bankruptcy.

Keasey and Watson (l986) developed bankruptcy prediction model for small UK firms. The model used five financial ratios in a MDA framework to model bankruptcy of the firms. The model correctly classified 70% of failed and 80% of non-failed firms.

Gombola, Haskins, Ketz and Williams (1987) conducted bankruptcy prediction study and developed model for general firms. The model used nine financial ratios in a MDA framework to model bankruptcy of the firms. The model correctly classified 85-89% of firms before one year. The accuracy declined and model correctly classified 67-70% of firms two years prior to default.

Pantalone and Platt (1987b) developed bankruptcy prediction model using MDA technique. The model used nine financial ratios to predict bankruptcy of the firms. The model correctly classified 85.71% of failed and 96% of non-failed firms respectively.

McNamara, Cocks and Hamilton (1988) conducted study on private Australian firms using MDA framework. The model used six financial ratios to predict bankruptcy of the companies. The model correctly classified 86.4% of defaulted and 83.3% of non-defaulted firms respectively.

Laitinen (l991) conducted study on small and medium-size Finnish firms. The study developed bankruptcy prediction model using six financial ratios in an MDA framework. The model correctly classified 90% of bankrupt and 87.5% of non-bankrupt firms before one year. The predictive accuracy declined to 72.5% and 65% for defaulted and non-defaulted firm before two years respectively.

Rujoub, Cook and Hay (1995) developed bankruptcy prediction model for general firms using MDA technique. The study used 14 financial ratios to model bankruptcy of the firms. The model correctly classified 45% to 82% bankrupt firms and 52% to 100% of non-bankrupt firms respectively.

Gardiner, Oswald and Jahera (1996) developed bankruptcy prediction models for hospitals using MDA techniques. The model used 12 financial ratios to predict bankruptcy of the firms. The model correctly classified 96% to 89% of failed hospitals and 99% to 91% of non-failed hospitals respectively.

McGurr (1996) developed bankruptcy prediction model for retail firms. The model used seven financial ratios in a MDA framework to model bankruptcy of the firms. The predictive accuracy of the model varied from 69.7% to 75.26% on holdout samples.

Zordan (1998) conducted study on retail, wholesale and manufacturing firms. The model used 30 financial ratio in a MDA framework to model bankruptcy of the firms. The model correctly classified 78.7% to 85.2% failed and 66.7% to 68.5% of non-failed firms respectively.

Gao (1999) conducted study on hospitality firms and developed bankruptcy prediction model. The model used five financial ratio in an MDA framework to model bankruptcy of the firms. The model correctly classified 52% to 88% of bankrupt and 96% to 100% of non-bankrupt firms.

Patterson (2001) conducted bankruptcy prediction study on casinos. The study developed bankruptcy prediction model using 12 financial ratios in an MDA framework. The model correctly classified 100% of failed and 89% of non-failed firms.

Grice and Ingram (2001) in their notable study found that the credit risk models are sensitive towards change in time period and financial environment in which it was originally developed. The major finding of their study revealed re-estimation of Altman's Z-score model gives better predictive accuracy rather relying on the coefficient estimated in Altman's (1968) original model.

Charitou, Neophytou, and Charalambous (2004) conducted study on UK public industrial firms. The major finding of the study suggested that a parsimonious model which included three financial variables, namely - financial leverage, profitability and cash flow, gives better predictive accuracy. The model correctly classified 83% of firms one year before failure. The logit model outperformed Altman model in the study and operating cash flows is found to be most significant variable to predict bankruptcy of UK companies.

Sori, Hamid and Nassir (2006) examined the corporate failure of three emerging market economies such as Malaysia, Singapore, and Thailand. The study examined corporate failure in this region prior to 1997. Using MDA technique, the study developed bankruptcy prediction model on the sample of 33 Malaysian, 17 Singaporean and 52 Thailand failed firms and similar number of non-failed firms in the respective countries as a control sample for the period 1980 to 1996. The major finding of the study suggests the overall correct prediction for Malaysian, Singaporean and Thailand firms is found to be 86%, 82%, and 71% respectively.

Chowdhury and Barua (2009) conducted study on default prediction for Dhaka Stock Exchange (DSE) Z category companies. In case of 90% firms, it is found that poor management capability and operating inefficiency are the prominent reasons for financial distress of these firms. The Altman's Z-score model is applied, and it has proved its strong validity and correctness in predicting distressful status of the Z category companies. The study also suggested Altman Z-score (1968) model was not good to predict the financial distress of publicly traded manufacturing firms.

Gerantonis, Vergos and Christopoulos (2009) examined the efficacy of Altman Z-score model to predict the corporate failure up to three years before bankruptcy. The major finding of the study suggested the model correctly classified firms' distress up to 2 years before bankruptcy as it matched both accounting data and market value.

Angelina (2009) conducted a study on Indian textile industry and developed corporate failure model in an MDA framework considering 70 textile companies out of which 39 were distressed and 31 were non-distressed firms for the period 1996 to 2006. The study uses 25 financial ratio and BIFR reference is used to identify distressed firms. The study found that in case of isolated data set, the discriminant model correctly classifies 76.9%, 87.2% and 89.7% on failed and 83.9%, 80.6%, and 83.9% on non-failed firms for first, second and third years prior to bankruptcy respectively.

Hlahla (2010) developed a bankruptcy prediction model using MDA technique for South African companies listed in the Johannesburg Stock Exchange. The study was conducted on the sample of 14 failed and 14 non-failed companies. The study used total 64 financial ratios to assess credit worthiness of firms. The major finding of the study suggested working capital to turnover ratios, times interest earned and cash to debt ratios are significant ratios to foretell bankruptcy. The overall predictive accuracy of the model was found to be 75.3 %.

Yap, Yong, and Poon (2010) developed a bankruptcy prediction model for Malaysian companies using matched sample of 32 defaulted and 32 non-defaulted firms in an MDA framework. The study used 16 financial ratios to classify between distressed and non-distressed companies. Finally, seven financial ratios were used in a discriminant function. The major finding of the study revealed the predicative accuracy of the model on estimation and holdout sample is 90% and 89% respectively. The result also showed profitability and liquidity were the most significant indicators to foretell bankruptcy.

Kosmidis, Venetaki, Stavropoulos and Terzidis (2011) conducted study on the sample of 27 failed and 27 non-failed companies using MDA and logit technique. The study used 41 financial ratios to assess financial position of the companies. The major finding of the study suggested logit model has better predictive accuracy as compared to MDA model.

Rashid and Abbas (2011) developed a bankruptcy prediction model for Pakistani non-financial firms for the period 1996 to 2006. The matched sample of defaulted and non-defaulted firms were used for the respective period. Appling T-test for equality in means, it was found that there was significant difference in the mean of market value of equity to book value of debt, EBIT to total assets, and equity to long-term debt for defaulted and non-defaulted groups. The default prediction model was developed using MDA technique using 24 financial ratios. The overall predictive accuracy of the model is found to be 76.9 %.

Uchenna and Okelue (2012) using MDA technique conducted study on 11 Nigerian manufacturing firms. The study used parametric t-test to test the hypothesis if there is no significant difference between the failure/success factor (Z) of Nigerian manufacturing firms. The major finding of the study suggested there was no significant difference between the failure/success factors (Z) of Nigerian manufacturing firms.

As noted earlier, due to some of the inherent limitations of MDA model, the logistic regression model was developed, and made popular by **Ohlson (1980)**. He used logit model to predict bankruptcy using 105 bankrupt and 2058 non-bankrupt companies from 1970 to 1976 using financial ratios of the companies. Ohlson identified nine dependent variables based on their frequent use in the bankruptcy prediction literature. The dependent variable was binary in nature; it takes value 1 for bankrupt firms and 0 for non-bankrupt companies. He estimated three models- Model 1 predicts bankruptcy within one year; Model 2 predicts bankruptcy within two years and Model 3 predicts bankruptcy within one or two years. He found that all the variables were statistically significant in Model 1 except three variables namely - WCTA, CLCA and INTWO. He identified the cutoff probability value, which minimized sum of type I and type II errors. The predictive ability of Model 1 is found to be greater than that of the other two models.

After **Ohlson**, **Mensah (1983)** developed bankruptcy prediction model using both MDA and logit technique on manufacturing firms. Both the model used 32 factors to model bankruptcy of the firms. The model correctly classified 18% to 55% of bankrupt and 80% to 86% of non-bankrupt firms.

Zavgren (1985) developed bankruptcy prediction model for manufacturing firms using logit technique. The model used seven variables to model bankruptcy of the firms. The model correctly classified 69% on firms of holdout sample before one year of bankruptcy. The accuracy remained constant (69%) from 1 to 5 years prior to bankruptcy on secondary sample.

Dambolena and Shulman (1988) re-estimated logit model using financial ratios used in the Altman's (1968) and Gentry et al. (1985) models for 25 bankrupt and 245 non-bankrupt firms. The study founds net liquid balance of non-bankrupt firms improved the predictive accuracy of both the models. The predictive accuracy of Gentry et al. (1985) model is found to be higher than Altman's (1968) model.

Aziz, Emanuel and Lawson (1988) in their study developed a bankruptcy prediction model applying logit technique using six financial ratios. The predictive accuracy of the model was found to be 85.7%, 85.7%, 79.6%, 81.3% and 84.8% for 1st, 2nd, 3rd, 4th and 5th year prior to default respectively.

Gilbert et al. (1990) on two types of samples: 52 defaulted and 208 non-defaulted firms for the period 1974-83 examined the predictive abilities of bankruptcy prediction models. For model validation secondary sample was used. The study used 14 financial ratios of which three were cash flow ratios. In a stepwise logit regression, it was found that cash flow from operations to total liabilities was significant in classifying bankrupt and non-bankrupt firms and cash flow from operations to current liabilities was significant in classifying bankrupt and distressed firms. The study concluded that cash flow ratios add significantly to predictive accuracy of the models.

Sulaiman, Jili and Sanda (2001) developed a bankruptcy prediction model for Malaysian companies that did and those that did not seek court protection from their creditors in a logit framework. The financial ratios found to be most significant in default prediction were total asset turnover ratio, interest coverage and debt ratio. The overall predictive accuracy of the model on estimation and holdout sample was found to be 80.7% and 74.4 % respectively.

Wang (2004) developed bankruptcy prediction model for internet firms using logit technique. The model used eight financial ratios to model bankruptcy of the firms. The model correctly classified 26.7% of bankrupt firms and 90.8% of non-bankrupt firms respectively.

Further, **Zmijewski (1984)** performed a bankruptcy prediction model using a probit model on a sample of 40 bankrupt and 800 non-bankrupt US firms for the period 1970 - 1978, where the dependent variable (1 for bankrupt and 0 for non-bankrupt companies) was binary in nature and the independent variables were: ratio of net income to total liabilities, ratio of total liabilities to total assets and ratio of current assets to current liabilities.

Gentry, Newbold, and Whitford (1985) conducted a default prediction study and found that the adding of cash-based funds flow components to the traditional financial ratios to discriminate between defaulted and non-defaulted firms resulted in significantly improved predictive accuracy. A matched sample of 33 failed and 33 non-failed companies were chosen on the basis of size and industry classification. The three techniques were applied, namely - linear discriminant, logit, and probit analysis. The major finding of the study suggested that the predictive accuracy of MDA was higher than the logit and probit model.

Mohamed, Li, and Sanda (2001) in their study compared MDA and logit model on a sample of 79 distressed and 79 non-distressed companies. The result showed that in the case of MDA model, debt ratio and total assets turnover were most significant indicators to foretell bankruptcy, whereas in case of logit model interest coverage is found to be most significant indicator and leverage ratio has more importance in a default prediction. The predictive accuracy of logit model for estimation and holdout sample was found to be 80.7 % and 74.4 % respectively, whereas in case of MDA model predictive accuracy was found to be 81.1 % and 75.4 % respectively.

Bandyopadhyay (2006) conducted a study to predict probability of default of Indian corporate bonds using Z-score and logistic regression models. He identified 52 defaulted firms and 52 matched solvent firms from period 1998 to 2003 for his analysis. The matched samples were identified on the basis of asset size, year and industry affiliation. Information on defaulted firms was collected from CRISIL's annual rating of long-term bonds issued by the companies. Three Z-score models were estimated: the first model was estimated using variables of Altman's original model; the second model was the revised form of Altman's emerging market model; the third model was developed by the author, and comprises of five dependent variables. He tried to examine the predictive accuracy of the third model using data of 1 to 5 years prior to default. The performance of the models was also tested using holdout sample. The author has examined predictive ability of the models by considering 148 distressed manufacturing firms which were registered as sick with BIFR. He found that the predictive ability of the models to predict default falls as one moves from one year prior to default to five years prior to default. He has compared the default prediction ability of three logit models using the same set of firms; Model 1 and 2 use both financial and non-financial (industry dummy, dummy related to age of the company, dummy for ISO certification etc.) factors to predict default, whereas model 3 uses only financial ratios to predict probability of default. The results suggested that the younger firms were at more risk of default than the older firms, and the ISO dummy indicates that the firms that maintain a quality management system have less chance of default since a negative relationship was established between ISO dummy and probability of default.

Another study on bankruptcy prediction of Indian companies was conducted by **Ramakrishnan (2005)** using discriminant analysis and logistic regression model. He identified sick and failed firms using the criteria which are made for BIFR reference. Firms which satisfy conditions to be registered as sick company in BIFR were treated as distressed in his study. Financial data of distressed and non-distressed companies for four years spanning from 1996 to 1999 was used to model bankruptcy. The results of Z-score models showed that the predictive ability of the model improved as the model used more recent data, which means predictive ability of the model based on data one year prior to distress was greater than the model used on the data four years prior to bankruptcy. Logistic regression model was found to reduce misclassification error (Type I error) significantly. Similar to Z-score model, the logistic regression model indicated that the predictive ability of the model and Type I error were increased when data of one year prior to bankruptcy was used in comparison to model which used data four years prior to bankruptcy. The author concluded that his models were capable of predicting distress with minimum error, one year in advance.

Abdullah, Halim, Ahmed and Rus (2008) conducted a study on predicting corporate failure of Malaysian companies. They compared performance of multiple discriminant analysis and logit model to identify distressed companies using 36 distressed and 36 matched non-distressed companies. The MDA model provided an overall accuracy rate of 80.8% and 85% for the estimation and the holdout sample respectively, whereas logit model could correctly predict 82.7% and 80% of the respective estimation and holdout sample. The study also compared performance of hazard model to predict bankruptcy.

Bhumia and Sarkar (2011) in another study on Indian pharmaceutical industry developed model for corporate failure using MDA technique. The study chooses 16 financial ratios based upon past empirical literature measuring profitability, solvency, liquidity and efficiency of the firms.

Datta (2011) developed bankruptcy prediction model for Indian companies using logit and MDA technique. The study used panel data of 50 defaulted and 50 non-defaulted firms. The MDA model correctly classified 97%, 95%, 93%, 90% and 86% before one, two, three, four and five years before bankruptcy respectively. The logit model correctly classified 97% of firms.

A number of studies attempted making comparison between logit, probit, and MDA techniques. In case of Thailand, **Pongsatat et al. (2004)** examined predictive capabilities of Ohlson's and Altman's models. The study concludes Altman model outperforms Ohlson model on the basis of predictive accuracy. Likewise, **Ugurlu and Aksoy (2006)** developed bankruptcy prediction model for Turkish firms using **Altman's (1968)** and **Ohlson's (1980)** statistical techniques. Further, **Gu (2002)** developed MDA model for estimating the failure of USA restaurant firms.

3.2.2 Market-based Models

The market-based models are classified into structural and reduced form models.

Structural form Models

Structural models can further be classified into two groups, namely - first generation models (Merton Approach) and second generation structural-based models.

The first generation models were developed on the principle of **Merton (1974)** model. In such models default process of a firm was dependent upon the value of a firm's assets. The default risk therefore explicitly associated with the changeability of the companies' asset value. The basic principle behind the approach was simple: the default event takes place when the market value of the firm's assets was lower than its total liabilities.

The first generation models include models developed by **Black and Cox (1976)**, **Geske (1977)** and **Vasicek (1984)**. Each of these studies tried to refine the original Merton model by eliminating one or more of the naïve assumptions. In the study of **Black and Cox (1976)** with subordinated debt more complex capital structures was introduced. Interest-paying debt was introduced in the study of **Geske (1977)**. The distinction between long-term and short-term debt was introduced in the study of **Vasicek (1984)**.

Some of the notables studies on structural based credit risk models were **Agarwal and Tafller (2008)**, **Wu, Gaunt and Gray (2010)**, **Hillegeist et al. (2004), Kulkarni et al. (2005)** and **Bharath and Shumway (2008)**.

Agarwal and Taffler (2008) conducted a study on UK non-financial companies and compared the performance of market-based and accounting models. The study used two market-based models, namely - a model suggested by **Hillegeist et al. (2004)** and naïve market-based model defined by **Bharat and Shumway (2004)** and UK based Z-score model defined by **Taffler (1984)**. The study found that neither market-based model nor accounting based model was sufficient for default prediction. Both the models carry unique information about the firm's failure.

Wu, Gaunt and Gray (2010) did a comparative analysis of different bankruptcy prediction models, namely - Altman's model, Ohlson's logit model, Shumway's hazard model and market-based model of **Hillegeist et al. (2004)**. The major finding of the study suggested **Shumway (2001)** hazard model which considers both market and accounting based information outperforms models that use accounting data only and BSM type model suggested by **Hillegeist et al. (2004)**.

Hillegeist, Keating, Cram and Lundsted (2004) had defined the market-based model based on the BSM contingent claims approach. The study identified limitations of accounting based models: (i) the probability of default estimates were for future, based on the financial data used for the estimation of the model, were designed to measure past performance and hence, may not be very informative about the future position of the company; (ii) asset volatility was one of the crucial variables for bankruptcy prediction, but accounting based models do not incorporate this variable; (iii) difficulty in extracting probability of default related information from the stock prices in case of accounting based models. They assessed the prediction accuracy by comparing the sum of Type I and Type II errors for each alternative model and the model with the lowest total error was defined as the best model to predict bankruptcy.

Kulkarni et al. (2005) conducted a study on the predictive ability of Merton model in assessing credit risk using data of Indian companies. They computed both objective probability of default and risk neutral probability of default and compared results with default rate reported by CRISIL's average one-year rating transition data and results from Altman's Z-score model. Financial data of Indian companies, which included both distressed and top rated solvent companies from period 1998 to 2004, weree used for the study. Companies which were registered with BIFR were considered as distressed companies for the study. They computed default probability and credit spread for both default and non-default companies as on March every year for the entire sample period. Their results indicated that the probability of default estimated using Black-Scholes-Merton model was much higher in case of firms filed with BIFR than the probability of default estimated for top rated firms. They also found that the PD estimates were sensitive to the equity volatility experienced during the period of study. The results obtained from Merton model were found to be similar to the results obtained from Z-score model and CRISIL's average one-year average rating transition matrix.

Bharath and Shumway (2008) used market-based model to predict bankruptcy of the US firms. The study concluded that the KMV probability was marginally useful to forecast default, but not a sufficient indicator of default.

Reduced-Form Models

The inherent limitation of structural form models led the development of reduced form models. Some of the notable studies on reduced form models are **Litterman and Iben (1991)**, **Jarrow and Turnbull (1995)**, **Madan and Unal (1993)**, **Jarrow et al. (1997)**, **Duffie and Singleton (1999)** and **Duffie (1998)**.

In reduced form models, the default process was not conditioned upon the value of firm. This approach introduces explicit assumptions on the dynamics of both PD and RR.

From the structural features of the firms both the variables were modeled independently. The model assumes an exogenous RR, which was independent of PD. There was a probability a firm can default on its debt obligations at each instant. Through the time, both PD and RR can vary stochastically in the event of default. The price of credit risk was determined by theses stochastic processes.

There were limited evidence regarding reduced-form models. **Duffie and Singleton (1999)** study found that reduced form models have trouble in explaining the pragmatic term structure of credit spreads across companies of diverse credit risk qualities. Specifically, reduced form models have trouble in creating both fairly flat yield spreads when companies have low-credit risk, and steeper yield spreads when companies have higher credit risk.

Zhou (2001) made a recent attempt to combine the benefits of structural-form models. This was done by modeling the development of company's value as a jump diffusion process. This model also links RR to a company's value at default. The variation in RR was endogenously generated and the correlation between RR and credit ratings was reported in **Altman (1989)** and **Gupton et al. (2000)**.

3.3 Non-parametric Models

The non-parametric models are heavily dependent on computer technology and mainly multivariate in nature **(Andan and Dar, 2006)**. Some of the well-known non-parametric models are artificial neural networks (ANN), fuzzy models, genetic algorithms (GA) and DEA models.

3.3.1 Artificial Neural Network (ANN)

The ANN models can learn and adapt, form a data set, and have the ability to capture non-linear relationships between variables, which are all advantages of these models. The main shortcomings of these model are that they fail to explain causal relationships among their variables, which restrict their application to practical management problems **(Lee and Choi, 2013)**. **Kirkos (2015)** in a survey paper, published between 2009 and 2011, focuses mainly on artificial intelligence models.

Since multilayer networks are the dominant approach of NN, majority of the bankruptcy prediction studies are based on this approach. One of the first default prediction studies based on NN is done by **Odom and Sharda (1990)**. They have used **Altman (1968)** financial ratios as inputs and applied NN method on a sample of 128 US firms. They have also compared results of NN model with MDA. The NN correctly classifies in the range of 77.8% to 81.5% of defaulted and 78.6% to 85.7% non-defaulted firms depending on the training setup. In case of MDA, the model correctly classifies in the range of 59.3% to 70.4% defaulted and 78.6% to 85.7% non-defaulted firms respectively.

Tam and Kiang (1991, 1992) conducted study on bank failure prediction. The study compared different methods, namely - LR, K-nearest neighbor (KNN), MDA, ID3 (a decision tree classification algorithm), multilayer network and single-layer network. Major finding of the study suggested for one year before, the multilayer network was the best method, whereas in the case of two years before, LR was the best method.

Salchenberger et al. (1992) in their study examined the problem of predicting thrift failures. The study compared LR with NN. The empirical findings showed NN outperforms LR. The predictive accuracy of LR models in the range 18 month ahead was found to be 83.3–85.4%, whereas NN achieves 91.7% respectively.

Coats and Fant (1993) conducted a comparative study on NN and MDA models. The major finding of the study suggested the classification accuracy of NN depends on the time horizon and was found to be in the range of 81.9% to 95.0%, whereas for MDA in the range of 83.7% to 87.9%.

Kerling and Poddig (1994) in their study compared NN with MDA on a database of French companies. The predictive accuracy for NN was in the range of 85.3–87.7% as compared to 85.7% for MDA.

Altman et al. (1994) conducted study on a larger database of 1000 Italian firms using NN and MDA techniques. The major finding of the study suggested no complete winner. However, MDA was considered somewhat better technique.

Boritz and Kennedy (1995) conducted a comparative study of NN, LR and MDA techniques using indicators chosen by Altman (1968) and Ohlson (1980). The result was found to be inconclusive.

Fernandez and Olmeda (1995) conducted a comparative study using NN, MDA, LR, MARS and C4.5 (methods based on the CART decision tree algorithm) on Spanish banks. In this study, no horizon was specified. The major finding of the study revealed 82.4% accuracy as compared to other models which were in the range of 61.8–79.4%.

Alici (1995) conducted a study using principal component analysis. In the input selection phase, self-organizing maps were used. In the last phase with principal component analysis and self-organising maps, NN was applied. The major finding of the study showed NN model achieves accuracy in the range of 69.5% to 73.7% as compared to 65.6% for MDA and 66.0% for LR on a database of UK companies.

Leshno and Spector (1996) organized a study using novel NN architectures. The model has both cross-terms and cosine terms. The major finding of the study showed predictive accuracy of the model two years ahead was found to be in the range of 74.2–76.4% as compared to 72% for the linear perceptron network.

Lee et al. (1996) conducted study and proposed a hybrid model. The study tested combinations of the models MDA, ID3, self-organizing maps, and NN for default prediction for Korean firms.

Zhang et al. (1999) in a comparative study between NN and LR models employed a five-fold cross-validation procedure on a sample of manufacturing firms. The study used **Altman's (1968)** financial ratios plus the ratio current assets/current liabilities. The major finding of the study suggested NN outperformed LR with accuracy of 88.2% as compared to 78.6%.

Martinelli et al. (1999) conducted study on Brazilian firms and compared between two decision tree algorithms (C4.5 and CN2) and NN. The major finding of the study revealed C4.5 outperforms the other methods.

McKee and Greenstein (2000) conducted study on US firms. The study developed method using decision tree, and the results were compared with NN and MDA models. Major finding of the study showed for Type II error the new method outperforms NN and MDA. But it underperforms in case of Type I error.

Fan and Palaniswami (2000) developed a method using Support Vector Machines (SVMs) for foretelling bankruptcies of Australian firms. The new method was compared with NN, MDA and Learning Vector Quantization (LVQ). The major finding of the study reveals SVM obtained the best results in the range of 70.35%–70.90%, followed by NN 66.11%–68.33%, LVQ 62.50%–63.33% and MDA 59.79%–63.68% respectively.

3.3.2 Fuzzy Models

Automated credit risk system plays a vital role to reduce human error and attain faster accuracy in the credit valuation process. In order to examine transparency and accuracy of credit-scoring models, **Lahsasna (2009)** conducted study on the firms of Australia and Germany. The study used two fuzzy models. To conduct extra analysis, different modeling approaches were proposed in the study.

In order to model dependencies between variables, **Matsatsinis at el. (2003)** conducted study and developed a bankruptcy prediction model using fuzzy rules. In the data mining phase, the rules were used to model bankruptcy.

Cheng at el. (2006) conducted a study and claimed the observed value may be better considered as a fuzzy phenomenon rather random. Thus, they used an interval as an alternative of a single value for financial variables. Using fuzzy regression they developed an early-warning model for firm's failure.

Li at el. (2011) developed model using a linear fuzzy programing method to assess classification problem with soft computing constraints in order to solve classification problem of credit card holder.

Cherubini and Lunga (2001) found that in the process of pricing contingent claims the probability measures were not precisely known. Hence, a class of fuzzy models were applied to take care of this problem. Further, this approach was used to quantify liquidity risk in the presence of illiquid markets.

A multi-criteria decision analysis tool was developed using fuzzy set theory by **Yu et al. (2009)** for credit risk evaluation. At inception, in the form of the fuzzy opinions the tool was developed to ascribe results got from other contending credit assessment approaches.

Reveiz and Leon (2009) studied operational risk using the Fuzzy Logic Inference System (FLIS). This method is used to account for nonlinearity and complex interaction of inputs. The FLIS allows to apply quantitative and qualitative inputs in effective and convenient way.

3.3.3 Genetic Algorithms (GA)

GA as a method to foretell bankruptcy of the firms became possible because of advances in the high-speed computing technology. The GA technique largely puts emphasis on volatility stretches which bounds even the high-powered computers. In the GA method, the main objective is to redo the way in which genes are passed from one generation to the next. The remaining genes produce models that form the most durable and effective offspring.

According to **Mitchell (1998)** there was no prescribed answer for the use of GA technique for a particular application. Nevertheless, if the space to be searched is large and the space was not perfectly smooth and unimodal GA will have a decent chance of being reasonable.

Bernstein (1998) suggested some of the theoretical shortcomings of GA technique. In the GA approach it incorporates vital intuitions into the complexity of reality but in practice, there was no proof of cause and effect in the acknowledgment of forms that head the advent of other forms ranging from financial events to the spin of a roulette wheel.

There are several advantages of GA technique. The benefits include being able to diminish some of the adverse effects of Simpson's Paradox and corollary's which state that a connotation between two variables can be reversed upon inclusion of a third variable.

Thus, the GA enables some important enhancements for model development. Further, sign of this is described by **Ong et al. (2005)**. One of the advantage is that it reduces significantly model development time by 50 to 74%.

Fogarty and Ireson (1993/4) conducted a study on a sample of fifty thousand accepted credit card applications. The GA driven Bayesian classifier with decision rules was compared with various techniques, namely - a decision tree, a nearest neighbor clustering algorithm, and a simple Bayesian classifier. The major finding of the study suggested GA derived classifier did better than other methods.

Desai et al. (1997) conducted study looking three-way classification problems, namely - good, poor or bad payers. The major finding of the study suggested GA approach was marginally good as compared to linear discriminant analysis, logistic regression and a variety of neural network models.

Yobas et al. (2000) in their study found that GA model outperformed neural networks and decision trees models on the development sample. All the three models, namely - GA, neural network and decision tree outperform MDA model. In this study GA method was again explored, but combines various features that distinguish it from previous studies.

3.3.4 DEA Models

In order to assess relative efficiency of 'Decision-Making Units (DMUs),' DEA approach was developed by **Charnes et al. (1978)**. In the late 1990's, it was introduced for credit risk evaluation. Some of the notable studies were **Simak (2000)**, **Troutt et al. (1996)**; **Cielen and Vanhoof (1999) Emel et al. (2003)**, **Cielen et al. (2004) and Paradi et al. (2004).**

In the DEA method**,** a unit-free single performance index was formed as a ratio of aggregated outputs to aggregated inputs. Theoretically, every DMUs output was compared in DEA to establish an efficient frontier by identifying relative 'best practices.' The degree of efficiency of individual DMUs was measured by the efficient frontier. Hence, DEA offers a platform which was more flexible and powerful to traditional credit scoring methods.

There were ample of studies including **Keasey and Watson (1987), Zavgren (1985) and Becchetti and Sierra (2003)** which emphasized on the importance of non-financial data to model firms' bankruptcy**. Zavgren (1985)** said that econometric models that exclusively depend on financial statement data will not predict correctly business failures. **Becchetti and Sierra (2003)** applying a stochastic frontier model as a measure of efficiency found that productive inefficiency was an important ex-ante indicator of firms' failure**. Keasey** and **Watson (1987)** in their study found non-financial information were more significant to predict small business failures.

In the Indian market **Shetty et al. (2012)** developed early warning system for Indian IT/ITES using Data Envelopment Analysis (DEA). Based upon the past empirical studies ten financial ratios measuring firm's liquidity, leverage, productivity, and turnover were used.

3.4 Conclusion

The current chapter extensively surveyed literature on default prediction. In the chapter credit risk models are broadly classified into parametric and non-parametric models. Parametric models can further be divided into accounting and market-based models. There are huge range of accounting based models which have been surveyed from Beaver (1966) univariate, Altman's (1968) MDA, Ohlson's (1980) logit, Zmijewski (1984) probit models, etc. Under market-based models, there are broadly two types of models -structural form and reduced form models. The chapter also covers extensively non-parametric models such as Artificial Neural Networks (ANN), Hazard models, Fuzzy Models, Genetic Algorithms (GA) and Hybrid models, or models in which several of the former models are combined.

In the past six decades, extensive credit risk literature is developed based upon different techniques and financial ratios used to foretell bankruptcy. There are several papers addressing the performance of alternative models on one market. Some studies also point out the construct validity of original model towards change in period and financial environment in which it was originally estimated. The next chapter will try to take some of the issues discussed in the review of literature and specifically mentioned in the objectives of the study.

CHAPTER 4

BANKRUPTCY PREDICTION USING ALTMAN'S Z-SCORE MODEL

4.1 Introduction

In the previous chapters Basel Accords, theoretical models, and empirical literature on credit risk modeling were discussed in detail. The first objective of the study is to re-estimate bankruptcy prediction models such as Altman (1968), Ohlson (1980) and Zmijewski (1984) on Indian manufacturing companies' data. The current chapter re-estimates Altman (1968) Z-score model on the data of Indian manufacturing companies. The Multiple Discriminant Analysis (MDA) technique is employed to estimate weights of financial ratios using 130 firms' data consisting equal number of distressed and non-distressed firms and a sample of 78 firms holdout for model validation. In order to check the prognostic power of the models three diagnostic checks are employed, namely - holdout sample test, Receiver Operating Characteristics (ROC) and long-range accuracy test. Two Z-score model; Z-score 1 and Z-score 2 are estimated using data one year and two years prior to default. While the model used in the current chapter is already discussed in Chapter 2 (Section 2.3.3), this chapter will detail and analyze results obtained by using this model to predict distressed firms in India.

The remainder of the chapter is organized as follows. Section 4.2 provides information on methodology. Data and descriptive statistics are covered in section 4.3. In detail, section 4.4 and 4.5 deals with results and model validation of Z-score models respectively. The chapter concludes with section 4.6.

4.2 Methodology

Multiple Discriminant Analysis (MDA) is a statistical technique used for the classification of groups on the basis of certain information. This technique is used when the dependent variables are categorical, and there are two or more categories of dependent variables. This technique is applied in finance to classify between distressed and non-distressed firms on the basis of financial ratios. The crucial assumption of MDA is that variance-covariance matrices of the two groups are statistically identical. The weights of the discriminant function are the difference of the mean vectors of the explanatory variables for the distressed and non-distressed groups. In the MDA model our purpose is two folds: The first one is to look for financial ratios that lead to lowest misclassification rates within the sample and the second one is to get improved prediction accuracy in an un-estimated holdout sample.

The Discriminant Analysis (DA) model specifies linear combinations of the following form:

$$Z = v_0 + v_1 X_1 + v_2 X_2 + v_3 X_3 + ... + v_i X_i \quad (4.1)$$

Where, Z: overall index (discriminate function)

v_0 : a constant

v's: the discriminant coefficients or the weight for that independent variable

X's: independent variable

The above function is similar to the linear regression equation; wherein v's are the unstandardized discriminant coefficient analogous to the coefficient b's in regression equation. The discriminate coefficients (v's) maximises the distance between the categories; namely - distressed and non-distressed in the present context. Good predicting variables have larger weights. The function maximises the distance between the categories. In classification problem, the number of discriminating function will be used, which will be one less than number of groups. The objective of MDA analysis to combine variables in such way so single composite variable should be obtained and have best classifying power. Following are the assumptions of MDA analysis:

(i) The observations are independent.

(ii) X's are normally distributed.

(iii) In the initial population, each of the dependent categories are correctly classified.

(iv) There should be minimum two groups which are mutually exclusive and collectively exhaustive.

(v) The group sizes of the dependent variables should not be grossly different and should be at least five times the number of independent variables.

Following statistical tests are carried out to check the two groups are statistically different:

(i) Chi-square test is conducted to check how well the discriminant function classifies the groups.

(ii) Wilks' Lambda tests the significant contribution of variables in the discriminant function. The closer Wilks' lambda is to 0, the more the variable contributes to the discriminant function.

(iii) F-statistic checks the significance of Wilks' Lambda. If the p-value is less than 0.05, we can conclude that the corresponding function explains the group membership well, which means a greater chance for the null of equal means to be rejected.

4.3 Variable Descriptions and Data

The study uses Board of Industrial and Financial Reconstruction (BIFR) reference to identify distressed firms from the list of firms registered sick during 2006 to 2014. BIFR reference is also used in the studies of Bandyopadhyay (2006), Ramkrishnan (2005), Kulkarni et al. (2005) and Varma and Raghunathan (2000). A set of matched non-distressed companies are identified randomly on the basis of asset size and industry type. More than 600 sick companies are registered with BIFR during this period. The study shortlisted 104 sick companies on the basis of availability of financial data (balance sheet and profit and loss data). A total of 130 companies comprising distressed and non-distressed companies are used for estimation sample. The 78 companies holdout for model validation. Financial information of the companies are collected from their respective balance sheets and income statements. The audited balance sheet and income statements of the companies at the end of each year are extracted from their respective websites. The estimated and holdout sample have been classified into 14 industry categories matching with their economic activity as per National Industrial Classification Code (NIC) 3 digit classification of 2008 (Table 1.1 Chapter 1).

All the variables used in the current study are similar to Altman (1968) model except market value of equity to book value of total liabilities. In the current study, in place of market value of equity to book value of total liabilities, book value of equity to book value of total liabilities is taken. This is because current study comprises of both publicly and privately held firms and calculation of market value of equity requires stock price data (Altman, 1993). The stock price data for privately held firms are not available because the shares of such companies are not traded in the secondary market. However, the same model can also be used for publicly traded companies. The description of variables used in the Z-score models is provided in Table 4.1. All these above variables have been discussed in detail in Chapter 2 (Section 2.3.3).

Table 4.1: Description of the Variables of Altman's Z-score Model

Variables	Definition
WCTA (Working Capital/Total Assets)	It is a measure of the net liquid assets of the firm about the total capitalization which measures the firm's ability to manage its short-term capital position.
RETA (Retained Earnings/Total assets)	It is measure of cumulative profitability and leverage of a firm.
EBITA (Earnings Before Interest and Taxes/ Total Assets)	This ratio is a measure of the true productivity of the firm's assets which is independent of any tax or leverage factors.
BVEBVD (Book Value of Equity/Book Value of Total Liabilities)	The ratio explains how much the firm's asset can decline in value before the liabilities exceed the assets, and the firm becomes bankrupt.
SLTA (Sales/Total Assets)	The ratio illustrating the sales generating ability of the firm's assets.

Source: Author's compilation

4.3.1 Descriptive Statistics

Table 4.2 reports mean and standard deviation of the variables used in the Z-score model one and two years prior to bankruptcy. Here, the year before bankruptcy represents the financial statements reported in the year prior to the year of bankruptcy. Since the non-distressed firms have no year of bankruptcy, their means are reported for their respective year. The financial variables shows there is difference in the mean of distressed and non-distressed firms. For distressed firm the financial variables start deteriorating as the date of bankruptcy approaches closer.

From Table 4.1, the mean of working capital to total assets (WCTA) for the non-distressed firms are found to be 1.632 for two years prior and 0.553 for one year prior respectively. On other hand the mean WCTA for the distressed firms are found to be 0.319 for two years prior and 0.215 for one year prior to bankruptcy respectively. In case of retained earnings to total assets (RETA), the mean value for the non-distressed firms are found to be 0.281 for two years prior and 0.034 for one year prior to bankruptcy respectively. In case of distressed firms the values are found to be -0.199 for two years prior and -0.295 for one year prior to bankruptcy. The variables is found to be negative for distressed and positive for non-distressed firms.

Table 4.2: Descriptive Statistics

Panel- A (one year prior)				
	Distressed firms		Non-distressed firms	
Variable	Mean	Standard deviation	Mean	Standard deviation
WCTA	0.215	0.538	0.553	0.788
RETA	-0.295	0.322	0.034	0.080
EBITA	-0.100	0.260	0.152	0.140
BVEBVD	-0.157	0.200	0.481	0.300
SLTA	0.984	1.041	2.013	2.966
Panel-B (two years prior)				
WCTA	0.319	0.417	1.632	9.165
RETA	-0.199	0.235	0.281	2.018
EBITA	-0.070	0.179	0.602	3.716
BVEBVD	0.038	0.238	0.522	0.417
SLTA	1.153	1.061	15.306	109.097

Source: Author’s estimation

The mean of earnings before interest and taxes to total assets (EBIT) for non-distressed firms are found to be 0.602 for two years prior and 0.152 for one year prior respectively, whereas for distressed firms the mean are found to be -0.070 for two years prior and -0.100 for one year prior to bankruptcy. The variable is found to negative for distressed firms and the values declines as the date of bankruptcy approaches closer. The book value of equity to book value of total liabilities (BVEBVD) mean for non-distressed firms are found to be 0.522 for two years prior and 0.481 for one year prior respectively, whereas for distressed firms it is found to be 0.038 for two year prior and -0.157 for one year prior to bankruptcy respectively. The variable is found to be negative for distressed and positive non-distressed firms. In case of sales to total assets (SLTA) the mean for non-distressed firms are found to be 15.306 for two years prior and 2.013 for one year prior respectively, whereas for distressed groups means are found to be 1.153 for two years prior and 0.984 for one year prior to bankruptcy respectively. The result shows mean values of the variables of distressed firms declines as the year of bankruptcy approaches closer.

In many past empirical studies, it is found that the financial information closer to the date bankruptcy are the best predictor of bankruptcy (Bandyopadhyay 2006, Ramkrishnan 2005). Table 4.2 summarizes that there is a significant difference between the means of distressed and non-distressed firms for one year and two years prior to bankruptcy. Hence, MDA technique can be applied to classify between distress and non-distress firms.

4.4 Results

Based upon the methodology discused in the earlier section, two Z-score models are estimated using the accounting data on one year and two years prior to bankruptcy respectively. The five financial ratios used in the studies measure liquidity, profitability, leverage and solvency of the firms.

Table 4.3 reports the results of the Z - score model 1 (equation 4.2) using financial data one year prior to default. All the coefficients in the model are positive except constant and EBITA.

Table 4.3: Results of Z-score Model 1

Variable	Estimate	Wilks' Lambda for the difference in mean	F- Statistics for the difference in mean
WCTA	0.076	0.940	8.157*
RETA	1.464	0.667	63.912*
EBITA	-0.630	0.731	47.181*
BVEBVD	3.474	0.386	203.754*
SLTA	0.028	0.948	6.964*
Constant	-0.425		
Wilks' lambda for the discriminant function as a whole			0.369
Chi-square value (χ^2)			125.082 (0.000)

Note- * indicates significant at 1% level of significance. Figures mentioned in the parentheses against χ2 test is the significance level at which null hypothesis can be rejected.
Source: Author's estimation

Following is the estimated model:

$$Z = -0.425 + 0.076WCTA + 1.464RETA - 0.630EBITA + 3.474BVEBVD + 0.027SLTA \tag{4.2}$$

The Z score can be obtained by substituting the values of the explanatory variables in the above equation. It is observed from the Table 4.3, the magnitude of Wilks' Lambda and F-statistic of the individual variables suggests that it is highly unlikely the means of non-distressed and distressed groups to be equal.

From Table 4.3 book value of equity to book value of total liabilities (BVEBVD) and retained earnings to total assets (RETA) are the most effective predictors in the Z-score model 1. The Wilks' Lambda for BVEBVD and RETA are found to be 0.385 and 0.667 respectively. All the variables significantly contribute to discriminant function in the model 1. On the basis of Wilks' Lambda test BVEBVD ranks 1st, RETA ranks 2nd, EBITA ranks 3rd, WCTA ranks 4th and SLTA ranks 5th to contribute in the model 1. The F- test is conducted for each of the variable and all variables are found to be statistically significant at 1 percent level of significance. Hence, the null hypothesis that the means of the variables in both the groups are equal can be rejected in case of the all the financial variables as a predictor used in Z-score model 1.

The Wilks' Lambda for overall Z-score model 1 is found to be 0.369, which is close to 0 and signifies 63 percent variation in Z-score is explained by discriminant function. A chi-square test ($\chi 2$) test is performed to test the overall significance of the discriminant function (Z-score model 1). The chi-square test shows that the null hypothesis can be rejected at a very low level of significance (less than 1% level of significance). Hence, it can be concluded that the discriminant function mentioned in the Table 4.3 is highly significant.

Likewise, Z-score model 2 (equation 4.3) is estimated using financial data two years prior to bankruptcy. Following is the estimated model:

$$Z = 0.488 + 0.187WCTA + 0.821RETA + 3.336EBITA + 2.009BVEBVD - 0.143SLTA \tag{4.3}$$

Table 4.4 represent that most of the variable's weights in Z-score model-2 are found to be insignificant except BVEBVD and RETA, which are the ratios of movements in the asset value and cumulative profitability or leverage.

Table 4.4: Results of Z-score Model 2

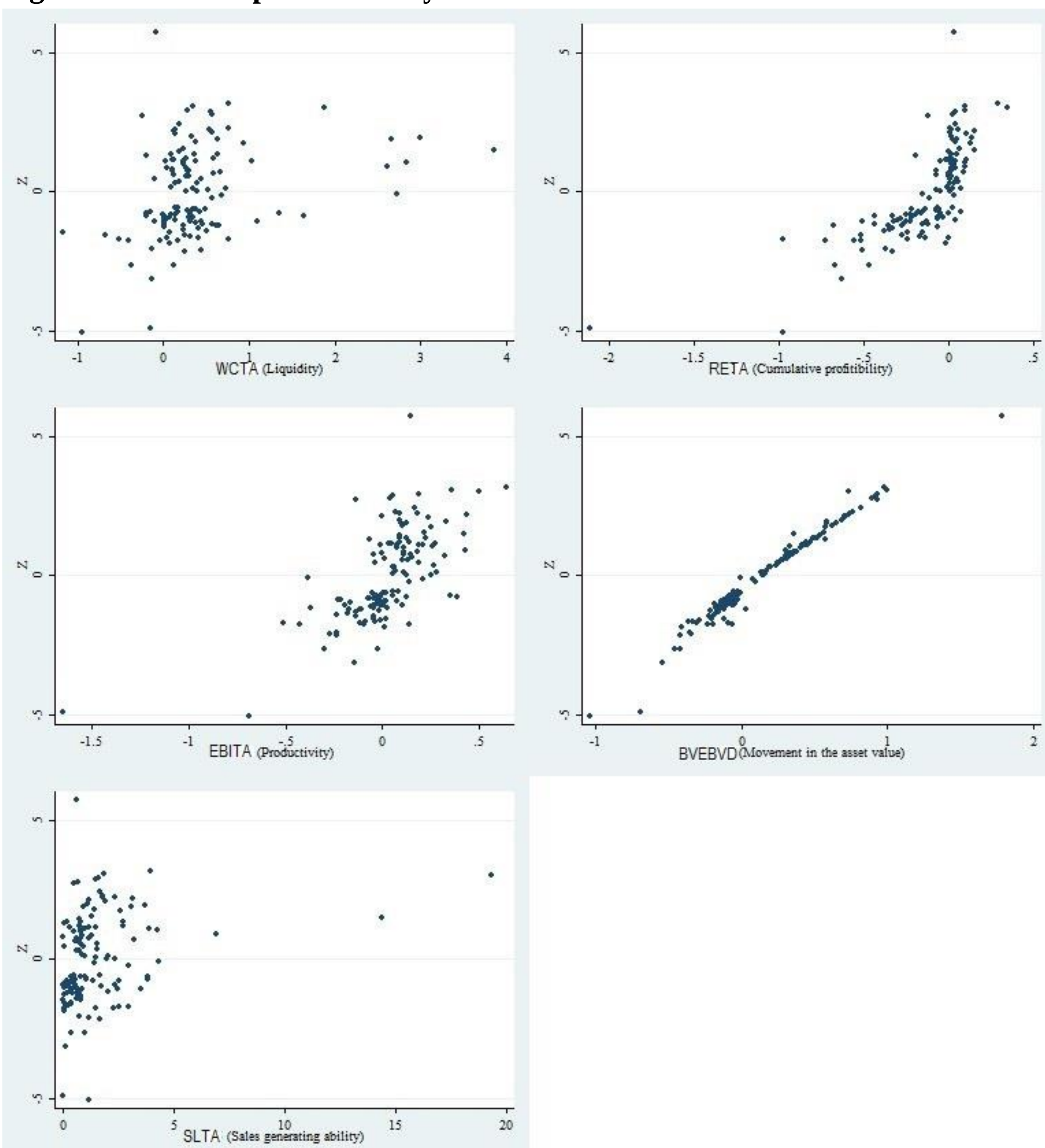
Variable	Estimate	Wilks' Lambda for the difference in mean	F- Statistics for the difference in mean
WCTA	0.187	0.989	1.332
RETA	0.821	0.972	3.638**
EBITA	3.336	0.984	2.125
BVEBVD	2.009	0.660	65.939*
SLTA	-0.143	0.991	1.094
Constant	-0.488		
Wilks' lambda for the discriminant function as a whole			0.539
Chi-square value (χ^2)			77.375 (0.000)

Note- * and ** indicates significant at 1% and 5% level of significance respectively. Figures mentioned in the parentheses against $\chi 2$ test is the significance level at which null hypothesis can be rejected.
Source: Author's estimation

The result is consistent with the Z-score model 1 which had the higher discriminating power to classify distressed and non-distressed firms.

After estimating both the Z-score models, a scatterplot is constructed for Z-score and individual financial ratios for both the years.

Figure 4.1: Scatter plot of the key Variables and Z-score of Model 1



Source: Author's estimation

This exercise is carried out to check the correlation between estimated Z-score and the respective financial ratios used in each of the models. Figure 4.1 plots the scatter plot of Z-score and other financial ratios used in Z-score model 1. The result shows there is a strong linear association between BVEBVD and Z-score. The defaulted firms have both the negative Z-score and BVEBVD ratio. As discussed in the earlier section BVEBVD is the movement in the asset value and it is defined as a book value of equity to book value of total liabilities. The book value of equity is the difference between total assets and total liabilities. If the book value of equity is negative, meaning that total assets are not sufficient enough to pay back total liabilities, it will result into firms' bankruptcy.

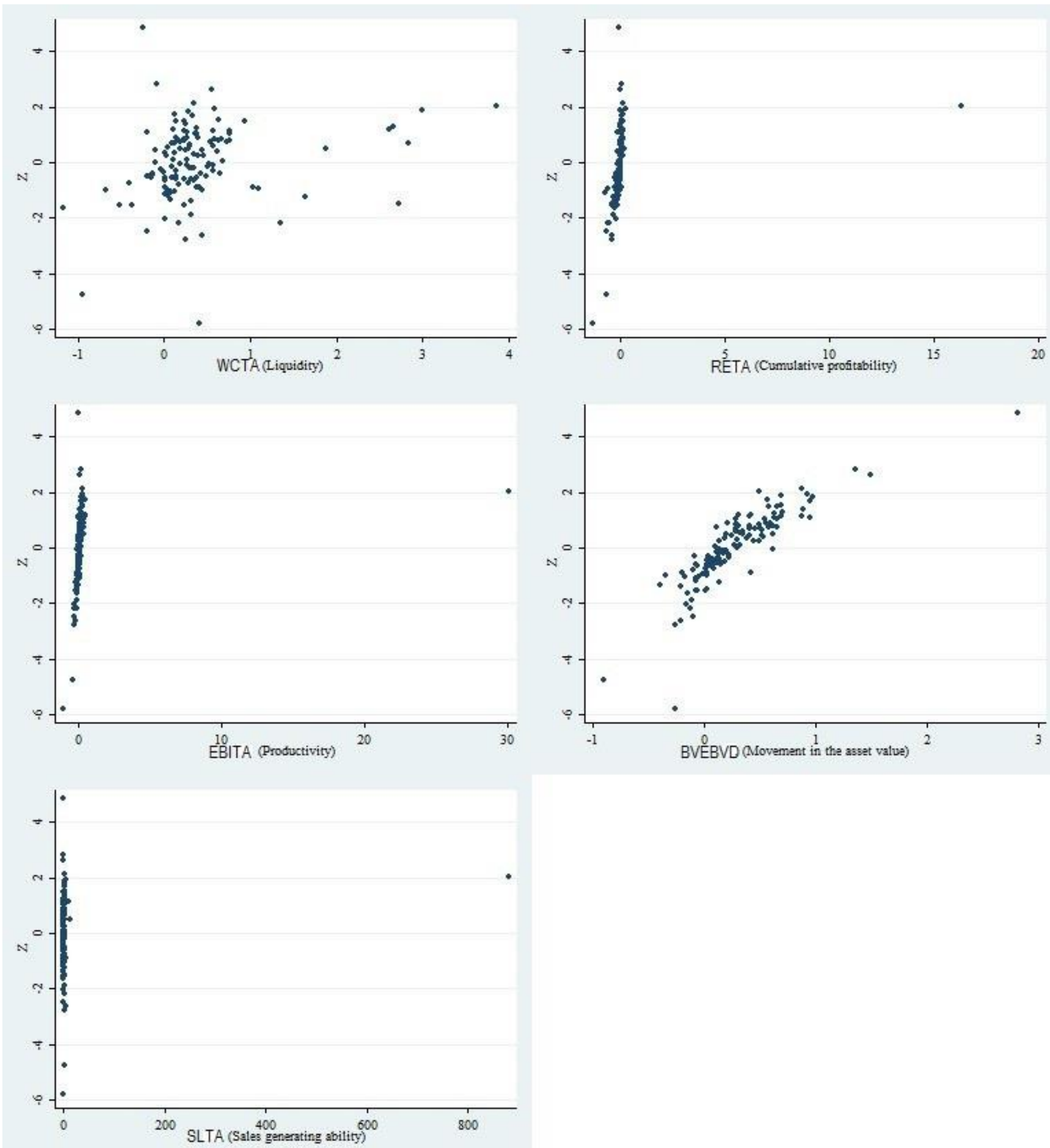
In the case of RETA there is weak but positive linear association between Z-score and RETA. The defaulted firms have both the negative Z-score and RETA ratios, whereas non-defaulted firms have both the positive Z-score and RETA ratios. As discussed in the earlier section negative cumulative profitability is the signal of the firm's bankruptcy. From figure 4.1 no clear pattern can be observed between Z-score and WCTA, EBITA and SLTA. In case of SLTA, defined as the sales generating ability of the firms, larger value of this ratio implies that the firm has a larger market share and thus is more competitive. Figure 4.1 shows defaulted firms have both positive Z-score and SLTA ratios, whereas non-defaulted firms have negative Z-score and low but positive SLTA ratios. SLTA is a sufficient but not necessary condition for bankruptcy. In case of EBITA the coefficient estimated in the Z-score model 1 is negative and there is no clear pattern observed in figure 4.1. It can be because of multicollinearity between RETA and EBITA. In case of WCTA there is no clear pattern because of high standard error in the ratio.

Similarly, a scatter plot of Z-score and other key variables are plotted for the data two years prior to default shown in figure 4.2.

In case of Z-score model 2 the result is similar with model 1. Figure 4.2 shows BVEBVD and RETA are the only ratios which are positively linearly associated with Z-score. The weights of discriminant model 1 and 2, their respective Wilks' Lambda and scatter plot shows movements in the asset value and cumulative profitability, which are the most important variables to predict bankruptcy. The firms having negative cumulative profitability (RETA) and BVEBVD ratios have a higher likelihood to bankruptcy and most recent year information is more helpful in forecasting bankruptcy.

The next section deals with evaluating performances of both the models. The distress predictive ability of Z-score model 1 and 2 are tested by using principle of total error minimization.

Figure 4.2: Scatter plot of the key Variables and Z-score of Model 2



Source: Author's estimation

4.4.1 Distress Prediction by Z-score Model

The current section covers identification of cutoff points and evaluation of model performance. The total error minimization principle is applied to obtain cutoff value.

Various cutoff values are tested (some are reported in Table 4.5 and Table 4.6 for Z-score model 1 and 2 respectively) and the final cutoff value is decided where the sum of Type I and Type II errors are minimized.

The costs associated with Type I and Type II errors are different. Type I errors are much more costly than Type II errors. Bortiz et al. (2007) summarizes "the costs of Type I errors as company management may not be aware of the seriousness of the situation and therefore, may not be motivated to take corrective action early; investors may not have sufficient warning of the imminent liquidation and therefore, can lose part or all of their investment; and, auditors may face a loss of reputation and the possibility of litigation which can result in financial penalties. The costs of Type II errors include the 'self-fulfilling prophesy,' where the model's prediction actually causes a healthy company to fail, and excessive investigation costs incurred by auditors as a result of the 'false positive."

Table 4.5 shows Type I and Type II errors at various cutoff points and resultant total errors, and overall correct prediction obtained from Z-score model 1. The cutoff points which are not mentioned in the results table gives a higher total error than the values reported in the table and overall prediction is lower than the reported figures.

It can be seen from the Table 4.5 that the sum of Type I and Type II errors at 0 cutoff is the lowest (6.154 %) among other cutoff points. At this cutoff, 64 distressed firms are predicted correctly out of 65 and 62 non-distressed firms are predicted correctly out of 65. Both Type I and Type II errors are minimum at this cutoff. Hence the cutoff point 0 is considered for model evaluation. Companies with Z-scores less than 0 are predicted to be distressed and companies with Z-scores greater than or equal to 0 are predicted to be non-distressed.

The overall correct prediction is the ratio between the total number of correct predictions and total number of firms considered for the study. In the case of Z-score model 1 the overall correct prediction percentage is higher (96.923 %) at 0 cutoff.

Table 4.5: Distress Classification rate of Z-score Model 1

Cutoff point	Correct classification as per model: Distressed	Non-distressed	Type I error (%)	Type II error (%)	Total error (%)	Overall correct prediction (%)
0.0	64	62	1.538	4.615	6.154	96.923
0.2	64	56	1.538	13.846	15.385	92.308
0.3	64	55	1.538	15.385	16.923	91.538
0.4	64	53	1.538	18.462	20.000	90.000

Source: Author's estimation

Table 4.6 represents the overall correct prediction of Z-score model 2. Applying the same principle of total error minimization, the cutoff point of Z-score model 2 is selected. In case of Z-score model 2 again the sum of Type I and Type II errors at 0 cutoff is the lowest (23.077 %) among all cutoff points. At this cutoff point, 58 distressed firms are predicted correctly out of 65 and 57 non-distressed firms are predicted correctly out of 65. Hence, the cutoff point 0 is considered for model evaluation. Companies with Z-scores less than 0 are predicted to be distressed and companies with Z-scores greater than or equal to 0 are predicted to be non-distressed. The overall correct prediction percentage is higher (88.462 %) in case of 0 cutoff in comparison to the overall correct prediction percentage obtained from other cutoff points.

Table 4.6: Distress Classification rate of Z-score Model 2

Cutoff point	Correct classification as per model: Distressed	Non-distressed	Type I error (%)	Type II error (%)	Total error (%)	Overall correct prediction (%)
0	58	57	10.769	12.308	23.077	88.462
0.2	58	54	10.769	16.923	27.692	86.154
0.3	60	47	7.692	27.692	35.385	82.308
0.4	61	51	6.154	21.538	27.692	86.154

Source: Author's estimation

The cutoff point 0 is selected for both the Z-score model 1 and 2, since the total errors are minimum at this cutoff point.

4.5 Z-score Model Validation

In order to judge the correct prediction power of the discriminant function, the model needs to be tested. Following are the tests applied to check the robustness of the model.

4.5.1 Holdout Sample test

The holdout sample validation perhaps constitutes one of the best tests to validate the discriminant function. The holdout sample of total 78 equally defaulted and non-defaulted firms of similar asset size and industry is taken for the period 2006 to 2014.

Table 4.7 shows an overall correct prediction of Z-score model 1 on the holdout sample. The overall correct prediction at cutoff 0 similar with the original model is found to be 88.158 %. At this cutoff, the model correctly classifies 34 out of 39 distressed and 35 out of 39 non-distressed firms.

Table 4.7: Distress Classification rate of Z-score Model 1 on Holdout Sample

	Correct Classification as per model					
Cutoff point	Distressed	Non-Distressed	Type I Error (%)	Type II Error (%)	Total Error (%)	Overall correct prediction (%)
0	34	35	13.158	10.526	23.684	88.158

Source: Author's estimation

Likewise, the exercise is repeated for Z-score model 2. At cutoff 0, the Z-score model 2 correctly classifies 25 out of 39 and 34 out of 39 distressed and non-distressed firms respectively (Table 4.8). The overall correct prediction is found to be 75 %.

Table 4.8: Distress Classification rate of Z-score Model 2 for Holdout Sample

	Correct Classification as per model					
Cutoff point	Distressed	Non-Distressed	Type I Error (%)	Type II Error (%)	Total Error (%)	Overall correct prediction (%)
0	25	34	36.842	13.158	50.000	75.000

Source: Author's estimation

Hence, from the above results, we can conclude that the accuracy of the Z-score model 1 is higher as compared to Z-score model 2 and overall significance of the model improves as we get information closer to the date of bankruptcy. Therefore Z-score model 1, which is based on the data one year prior to distress, is better than the Z-score model 2, which is based on the data two years prior to distress for the prediction of bankruptcy.

4.5.2 Receiver Operating Characteristic (ROC[7]) Curve

An ROC curve is one of the widely used diagnostic checks for model evaluation to visualize the performance of a binary classifier. Area Under the ROC (AUROC) is the best way to summarize its performance in a single number. The accuracy of the test depends upon how well it classifies between the groups. An ROC with AUROC 1 represents the perfect test, whereas AUROC with 0.5 represents worthless test. The benefit of using an ROC curve to evaluate a classifier instead of a simpler metric such as misclassification rate is that an ROC curve visualizes all possible classification thresholds, whereas the misclassification rate only represents error rate for a single threshold.

The sensitivity or Positive Predictive Value (PPV) of a diagnostic test is the proportion of firms for whom the outcome is positive that are correctly identified by the test. In other words it is the probability that a firm has a positive outcome given that they have a positive test result. Similarly, the specificity or Negative Predictive Value (NPV) is the probability that a firm has a negative outcome given that they have a negative test result.

The ROC is the graph of specificity against 1 - sensitivity by which the impact of choice is understood. A fairly excellent test has good balance between sensitivity and specificity. The decision to set the classification threshold to predict out-of-sample data depends upon the business decision.

Figure 4.3 shows AUROC for Z-score model 1 on (a) estimation and (b) holdout sample respectively. The total AUROC for Z-score model 1 on estimation and holdout sample are

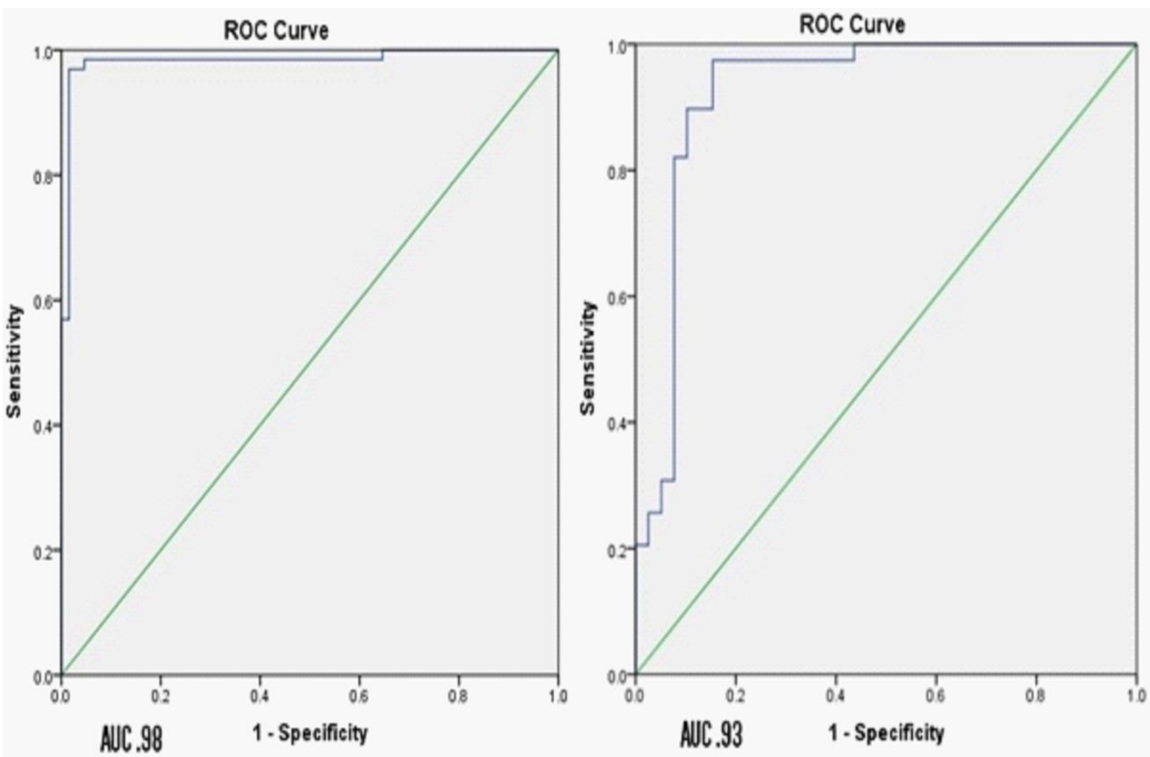
[7] For details, see Hanley, J.A. & McNeil, B.J. (1982)

.98 and.93 respectively, which is in between 0.9 to 1. Hence, the test is excellent on both the data sets for Z-score model 1 which have a good balance of specificity and sensitivity.

Similarly, Figure 4.4 shows the AUROC curve of Z-score model 2 on (a) estimation and (b) holdout sample respectively. The AUROC for Z-score model 2 for estimation and holdout sample are .95 and.84 respectively. The test is fairly excellent on estimation sample and good for holdout sample. Hence, the test is fairly good for Z-score Model 2 and have presented a good balance between specificity and sensitivity.

Figure 4.3: AUROC: Estimation and Holdout Sample of Z-score Model 1

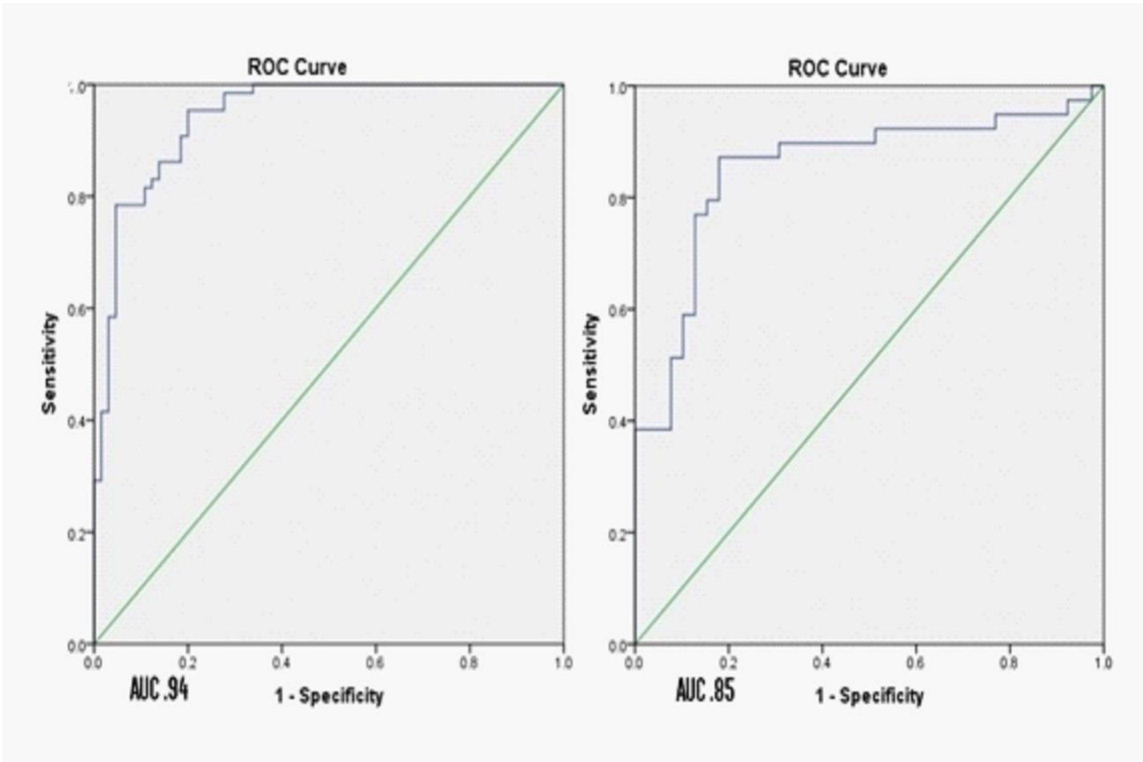
(a) **(b)**



Source: Author's estimation

Figure 4.4: AUROC: Estimation and Holdout Sample of Z-score Model 2

(a) (b)



Source: Author's estimation

4.5.3 Long Range Accuracy

The long range accuracy test is only conducted for Z-score model 1 because backward data is not readily available in the study two years prior to bankruptcy. The results are reported in Table 4.9.

The long range accuracy of Z-score model 1 on estimation sample are 96.92% and 84.46% for one year prior to default and two years prior to default respectively. On the holdout sample, it is 88.46% and 84.62% for one year and two years prior to default respectively. The long range accuracy results are fairly good and satisfactory.

Table 4.9: Long Range Accuracy of Z-score Model 1

Years prior to distress	Estimation sample (%)	Holdout sample (%)
1	96.920	88.460
2	84.460	84.620

Source: Author's estimation

The result shows the predictive accuracy of model decreases as we go more backward from the year of distress. Hence, the most recent information is helpful in foretelling bankruptcy with higher accuracy which is in line with the findings of Bandyopadhyay (2006) and Ramkrishnan (2005).

4.6 Conclusion

Using sample of 208 equal number of defaulted and non-defaulted firms, a Z-score model is developed which can accurately predict bankruptcy one year in advance using accounting based information. The Z-score 1 model has high classification power within the sample (96.92 per cent), and high predictive power in terms of its ability to detect bad firms in the holdout sample (with 88.46 percent accuracy). In case of Z-score model 2 most of the weight of financial ratios are found to be insignificant except RETA and BVEBVD. Hence, model 2 underperforms model 1. Moreover, the Z-score model 1 can predict corporate bankruptcy in two years prior to financial distress with an accuracy rate of 84.46 percent and 84.62 percent for estimation and holdout sample respectively. The major findings of the chapter suggests, Altman's (1968) Z-score model gives better predictive accuracy on Indian manufacturing companies data, when re-estimated and new cutoff values are used. The movements in the asset value and cumulative profitability are found to be the most significant variables to predict corporate bankruptcy. The most recent year financial information is also found to be helpful in predicting bankruptcy.

CHAPTER 5

PREDICTING CORPORATE BANKRUPTCY USING OHLSON'S LOGIT AND ZMIJEWSKI'S PROBIT MODEL

5.1 Introduction

In the previous chapter Altman's Z-score model is re-estimated for Indian manufacturing companies. The first objective of the study is to re-estimate bankruptcy prediction models such as Altman (1968), Ohlson (1980) and Zmijewski (1984) on Indian manufacturing companies' data. In line with the first objective, the current chapter deals with re-estimation of Ohlson (1980) and Zmijewski (1984) models. The logit and probit techniques are employed to estimate coefficients of Ohlson's and Zmijewski's models respectively, using 130 firms' data consisting equal number of distressed and non-distressed firms and a sample of 78 firms holdout for model validation. In order to check the prognostic power of the models the diagnostic checks such as holdout sample test, Receiver Operating Characteristics (ROC) and long-range accuracy test are employed. The two logit and probit models are estimated using the data on one year and two years prior to bankruptcy.

The remainder of the chapter is organized as follows. Section 5.2 presents the methodology. Data and descriptive statistics is covered in section 5.3. In section 5.4 the results are analyzed. The diagnostic tests of the models are examined in the section 5.5. The chapter concludes with section 5.6.

5.2 Methodology

The logit and probit model utilize the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable. In the context of bankruptcy prediction study, the logit and probit models are used to classify whether a company is distressed or non-distressed by using its financial ratios. The dependent variable in a logit and probit model is binary in nature, *i.e.*, it takes values either 1 or 0. The function used in the logit and probit analysis are known as the logistic and probit function. The details of the logit and probit models have already been discussed in chapter 2 section 2.3.4 and 2.3.5 respectively. Hence, we are not making an attempt to discuss these techniques once again here.

5.3 Variable Description and Data

The default probabilities of the Indian companies are modelled using BIFR reference to identify distressed firms from the list of firm's registered sick during 2006 to 2014. A matched sample of non-distressed companies is identified randomly on the basis of asset size and industry type. Between 2006 and 2014 more than 600 companies registered with BIFR. On the basis of the availability of financial data, 104 companies were shortlisted. The study uses a total of 130 companies consisting equal number of distressed and non-distressed firms for estimation sample. Financial information of the companies is extracted from their balance sheets and income statements. The Balance sheet and income statements of the companies at the end of each year are collected from their respective websites. The estimated and holdout sample have been classified into 14 industry category matching with their economic activity with the National Industrial Classification Code (NIC) 3 digit classification of 2008 (Table 1.1 Chapter 1).

Logit and Probit can be seen as an advancement in the traditional discriminant analysis in the sense that it produces direct PD estimates, which is more helpful for banks to calculate credit capital and model default in a non-linear fashion. It uses both financial and non-financial information to model bankruptcy. The summary of the variables considered for the estimation is briefly presented in the Table 5.1. The logit model uses financial, non-financial and macro-economic variables to model bankruptcy, whereas probit model uses only accounting based financial information. All these above variables have been discussed in detail in Chapter 2, section 2.3.4 and 2.3.5 respectively.

Table 5.1: Description of the Variables of Logit and Probit Model

Variables	Definition
	Logit model
SIZE	It is log of total assets to GNP price-level index. The 2011-12 is taken 100 as a base value for GNP.
TLTA	It is the ratio of total liabilities to total assets which captures leverage of a firm which measures financial structure.
WCTA	It is the ratio of working capital to total assets which is measure of current liquidity.
CLCA	Current liabilities divided by current assets is also a measure of current liquidity.
OENEG	This is a dummy variable and defined as; it takes value 1 if total liabilities exceeds total assets, 0 otherwise.
NITA	It is the ratio of net income to total assets which is a measure of performance.
FUTL	It is the ratio of funds provided by operations to total liabilities which is also a measure of performance.
INTWO	It takes value 1, if net income was negative for the last two years, 0 otherwise.
CHIN	It can be defined as (NIt NIt1)/(|NIt| + |NIt1|), where NIt is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure change in net income.
	Probit model
NITL	It is the ratio of net income to total assets. The ratio measures return on asset which is the measure of firm's performance
TLTA	It is the ratio of total debt to total assets. The ratio measures the leverage of the firms.
CACL	It is the ratio of current assets to current liabilities. The ratio measures liquidity of the firms.

Source: Author's compilation

5.3.1 Descriptive Statistics

The descriptive statistics of the variables used in both logit and probit models are reported in Table 5.2 and 5.3 respectively.

Table 5.2: Descriptive Statistics of the Variables used in the Logit Model

Sample	Statistic	SIZE	TLTA	WCTA	CLCA	OENEG	NITA	FUTL	INTWO	CHIN
Pane-A (one year prior)										
Estimation										
Distressed	Mean	0.615	1.681	0.215	0.821	0.938	-0.290	-0.091	0.615	-0.117
	SD	1.289	0.982	0.538	0.693	0.242	0.321	0.116	0.490	0.627
Non-distressed	Mean	0.638	1.150	0.553	0.560	0.338	0.044	0.129	0.077	0.057
	SD	1.121	0.873	0.788	0.427	0.477	0.094	0.371	0.269	0.503
	p-value	0.915	0.001	0.005	0.011	0.00	0.00	0.00	0.000	0.084
Holdout										
Distressed	Mean	-0.587	3.145	0.634	1.116	0.949	-0.843	-0.153	0.590	-0.236
	SD	1.219	3.282	1.917	1.197	0.223	1.863	0.209	0.498	0.682
Non-distressed	Mean	-0.501	1.113	1.089	0.796	0.385	0.110	0.183	0.128	0.048
	SD	1.343	1.200	1.406	2.685	0.493	0.169	0.516	0.339	0.476
	p-value	0.767	0.001	0.236	0.499	0.000	0.002	0.00	0.000	0.037
Panel-B (two years prior)										
Estimation										
Distressed	Mean	0.855	1.392	0.319	0.576	0.600	-0.191	-0.089	0.431	-0.342
	SD	1.316	0.791	0.417	0.458	0.494	0.230	0.103	0.499	0.570
Non-distressed	Mean	0.555	3.255	1.632	0.544	0.338	0.360	0.089	0.154	0.027
	SD	1.385	17.650	9.165	0.409	0.477	2.586	0.106	0.364	0.549
	p-value	0.208	0.397	0.251	0.677	0.003	0.089	0.000	0.000	0.000
Holdout										
Distressed	Mean	-0.321	2.884	1.235	0.703	0.667	-0.192	-0.048	0.538	-0.215
	SD	1.259	4.519	2.833	0.799	0.478	0.602	0.191	0.505	0.662
Non-distressed	Mean	-0.356	0.990	0.816	0.819	0.308	0.094	0.243	0.179	-0.052
	SD	1.365	0.965	0.963	2.644	0.468	0.160	0.309	0.389	0.413
	p-value	0.908	0.012	0.385	0.795	0.001	0.005	0.000	0.001	0.197

Source: Author's estimation

Table 5.2 represents descriptive statistics of the variables on estimation and holdout sample used in the logit model. Panel A of Table 5.2 shows descriptive statistics of the variables one year prior to default and Panel B reports descriptive statistics of the variables two years prior to default.

In the logit model SIZE is the log of total assets to GNP price-level index. The mean SIZE for both distressed and non-distressed groups are not significantly different on both estimation and holdout sample in one year prior to default. The mean of SIZE on estimation sample for distressed and non-distressed groups is found to be 0.615 and 0.638 respectively. On the other hand that mean of SIZE on holdout sample for distressed and non-distressed groups are found to be 0.587 and 0.501 respectively. The group mean of SIZE on estimation and holdout sample for one year prior to bankruptcy is not significantly different. The group mean of SIZE variable for bankrupt and non-bankrupt firms on estimation sample two years prior to bankruptcy are found to be 0.855 and 0.555 respectively. For holdout sample the group mean of distressed and non-distressed groups are found to be -0.321 and -0.356 respectively. For both the years on estimation and holdout sample the group means of the SIZE is not significantly different and the standard deviation of the series is more than 1 for all the groups. Hence, in the current model the indicator is not much significant to differentiate between distressed and non-distressed firms.

TLTA measures the leverage of the firms. In Panel A both on estimation and holdout sample the ratio is found to be higher for defaulted and lower for non-defaulted firms. The mean values of TLTA for defaulted and non-defaulted firms on estimation sample are 1.681 and 1.150 respectively, whereas on holdout sample it is found to be 3.145 and 1.113 respectively. In Panel B the mean of TLTA for defaulted (1.392) groups is lower than non-defaulted (3.255) groups on estimation sample, whereas it is found to be higher for defaulted (2.884) groups than non-defaulted (0.990) groups respectively on holdout sample for two years prior. The mean of TLTA of defaulted and non-defaulted groups on estimation sample both one year prior to default is also significantly different, whereas for two years prior the mean is statistical different for estimation sample but not for holdout sample.

WCTA measures the current liquidity of the firms. The ratio deteriorates for the firms facing financial difficulty. In Panel A the ratio is found to be lower for distressed groups on both estimation and holdout sample for one year prior. The mean WCTA for distressed and non-distressed groups are 0.215 and 0.533 respectively on estimation sample, whereas 0.634 and 1.089 respectively on holdout sample. In Panel B the ratio on estimation sample is consistent with one year prior result but on holdout sample distressed firms (1.235) is greater than non-distressed firms (0.816). On estimation sample for both one and two years prior the ratio deteriorates in higher magnitude when default date comes closer. For distressed firms two year prior the ratio is 0.319 and deteriorates to 0.215 one year prior to default.

CLCA again measures the current liquidity of the firms. The ratio is expected to be higher for firms facing financial difficulty and lower for healthy firms. In Panel A the mean of CLCA for distressed and non-distressed groups are 0.821 and 0.560 respectively on estimation sample, whereas 1.116 and 0.796 on holdout sample respectively. Again on estimation sample in Panel B for two years prior for defaulted group (0.576) is higher than the mean of CLCA in non-defaulted group (0.544). The ratio increases from 0.576 (two year prior) to 0.821 (one year prior) on estimation sample. The ratio exhibits the defaulted firms have higher CLCA ratio because for defaulted groups current liabilities exceeds current assets. OENEG is a dummy used for discontinuity correction for TLTA.

The performance of the firm is measured by NITA. The ratio is expected to preserve negative sign for the firms facing financial difficulty because their net income becomes negative. On all estimation and holdout sample the ratio is found to be negative for distressed and positive for non-distressed groups. On estimation sample for both one and two years prior the ratio deteriorates from -0.191 to -0.290.

FUTL again is one of the performance measures of the firm. The ratio is similar to NITA. The mean of FUTL for distressed groups is found to be negative and positive for non-distressed groups. On estimation sample for both one and two years prior, the ratio deteriorates from -0.089 to -0.091.

INTWO is a dummy which takes value 1, if net income was negative for last two years, 0 otherwise. The change in the net income of the firm is measured by CHIN. In Panel A for one year prior on estimation and holdout sample the mean of CHIN are -0.117 and 0.057 respectively, whereas on holdout sample -0.236 and 0.048 respectively. For two year prior, the mean of CHIN on estimation sample for defaulted and non-defaulted groups are -0.342 and 0.027 respectively, whereas -0.215 and -0.052 on holdout sample respectively.

Table 5.3 reports descriptive statistics of the variable on estimation and holdout sample used in the probit model. Panel A of Table 5.3 shows descriptive statistics of the variables one year prior and Panel B reports descriptive statistics of the variables two years prior.

Table 5.3: Descriptive Statistics of the Variables used in the Probit Model

Panel-A (one year prior)				
Sample	Statistic	NITL	TLTA	CACL
Estimation				
Distressed	Mean	-0.185	1.649	2.519
	SD	0.167	0.958	3.980
Non-distressed	Mean	0.057	1.131	3.496
	SD	0.195	0.861	6.428
	p-value	0.083	0.001	0..299
Holdout				
Distressed	Mean	-0.309	3.054	2.603
	SD	0.572	3.173	2.925
Non-distressed	Mean	0.175	1.043	4.693
	SD	0.301	1.205	6.526
	p-value	0.005	0.011	0.503
Panel-B (two years prior)				
Estimation	Mean	-0.130	1.365	2.560
Distressed	SD	0.135	0.785	1.752
	Mean	0.039	3.131	3.682
Non-distressed	SD	0.081	16.878	8.210
	p-value	0.089	0.401	0.283
Holdout	Mean	-0.094	2.825	4.483
Distressed	SD	0.180	4.415	6.107
	Mean	-0.091	0.935	6.918
Non-distressed	SD	0.181	0.956	21.751
	p-value	0.221	0.012	0.301

Source: Author’s estimation

NITL measures return on asset which is measure of firms' performance. The ratio is found to be negative for defaulted and positive for non-defaulted groups for both one and two year prior. Again, TLTA is similar to TLTA discussed in the logit model. The ratio is explained already in the earlier section. CACL measures the liquidity of the firms. In Panel A on estimation sample for defaulted and non-defaulted groups the mean of CACL are 2.519 and 3.496 respectively, whereas on holdout sample 2.603 and 4.693 respectively. In Panel B for two year prior on estimation sample for distressed and non-distressed groups the mean CACL value is found to be 2.560 and 3.682 respectively, whereas on holdout sample 4.483 and 6.918 respectively. The mean CACL for non-distressed group is higher for both one year and two year prior to bankruptcy.

5.4 Results

This section covers development and the analysis of results of logit and probit models. Both logit and probit models are developed on the data one and two years prior to default.

5.4.1 Development of Logit Model

Based upon the methodology and variables discussed in the previous sections the logit model is developed on the data of one and two year prior to default using the sample of 130 Indian companies consisting of equal numbers of defaulted and non-defaulted firms.

Table 5.4: Signs of the Variables of Logit and Probit Model

Expected sign					
Ohlson's (1980) model			Zmijewski (1984) model		
Positive	Negative	Indeterminate	Positive	Negative	Indeterminate
TLTA CLCA INTWO	SIZE WCTA NITA FUTL CHIN	OENEG	TLTA	NITL CACL	-

Source: Author's compilation

Table 5.4 shows expected sign of logit and probit models. On the basis of 'Common Sense' and past studies the same expected signs of the variables are suggested by Ohlson (p. 119, 1980).

Table 5.5 reports the results of the logit models for one and two year prior to bankruptcy. From Table 5.5, the NITA, OENEG, CLCA are significant at both 1 and 5 percent level of significance respectively. WCTA and CHIN are significant at 10 percent level of significance and all other variables are found to be insignificant. The log-likelihood ratio for logit model one year prior is -15.952, which is significant at 1 percent level of significance.

The coefficient of SIZE is found to be positive and insignificant which is in contrast to the suggested sign by Ohlson (1980). TLTA is found to be insignificant but preserves similar sign suggested as above. In case of WCTA, it preserves similar sign and the variable is significant at 10 percent level. CLCA is significant at 5 percent level, but differs in expected sign. OENEG serves as a discontinuity correction for TLTA whose sign is indeterminate. For current sample it is found to be significant at 5 percent level and have a positive sign. NITA is significant at 1 percent level and preserves negative sign consistent with past empirical studies. For FUTL the coefficients are insignificant but consistent with sign suggested as above. INTWO is found to be insignificant but preserves expected sign. CHIN is significant at 10 percent level but differs in sign. The change in sign of the variables can be because of change in the financial environment and time periods in which it was originally estimated (Platt and Platt, 1990)

Table 5.5: Results of Logit Models

	one year prior		**two years prior**	
Variables	Estimate	p-value	Estimate	p-value
SIZE	0.079	0.853	0.224	0.357
TLTA	1.623	0.162	1.465	0.170
WCTA	-5.216	0.073	-1.679	0.158
CLCA	-2.973	0.046	-1.714	0.046
OENEG	2.836	0.049	-0.087	0.935
NITA	-29.676	0.007	-10.502	0.068
FUTL	-2.559	0.761	-11.823	0.018
INTWO	0.337	0.783	0.303	0.702
CHIN	1.730	0.093	0.366	0.464
Constant	-2.454	0.093	-0.545	0.550
Log- likelihood ratio	-15.952	0.000	-41.411	0.000

Source: Author’s estimation

Again for logit two years prior model (Table 5.5) all the coefficients are found to be insignificant except CLCA, NITA and FUTL. The log-likelihood ratio for the model is found to be -44.411 which is significant at 1 percent level of significance. Out of all significant variables in the logit model two years prior, NITA and FUTL preserve similar signs mentioned as above but CLCA differs in sign. Out of insignificant variables only WCTA and INTWO preserve expected sign and rest of all differ in sign. Most of the variables for logit model two years prior are found to be insignificant and differ in sign because of high standard error in the series. The result shows the more recent year information gives more significant and consistent parameters.

5.4.2 Development of Probit Model

Based upon the methodology and variables discussed in the earlier sections the probit model is developed on the data one and two year prior using the sample of 130 Indian companies which comprises of equal number of defaulted and non-defaulted firms. Table 5.6 reports the results of the probit model one and two years prior to default. Expected sign of the variable is reported in Table 5.4. From Table 5.4, Zmijewski (1984) suggested the default probabilities are decreasing function of return of asset, i.e., NITL is expected to preserve negative sign. Financial leverage (TLTA) is increasing function of default probabilities and expected to have positive sign. In case of CACL (Liquidity), it is decreasing function of default probabilities and expected to have negative sign (Zmijewski, p. 76,1984)

From Table 5.6, for probit model one year prior all variables are significant at 1 percent level of significance except CACL. The log-likelihood ratio for probit model one year prior is -33.296 at 1 percent level of significance.

For probit model one year prior all the variables are significant and preserve similar signs suggested by Zmijewski (1984) except CACL.

Again for probit model two years prior (Table 5.6) all the coefficients are found to be insignificant except NITL. The log-likelihood ratio for the model is found to be -48.621 at 1 percent level of significance. Most of the variables for probit two years prior model are found to be insignificant and differ in sign because of high standard error in the series.

The result again confirms the more recent year information gives more significant and consistent parameters.

Table 5.6: Results of Probit Models

	one year prior		two years prior	
Variables	Estimate	p-value	Estimate	p-value
NITL	-13.797	0.000	-11.124	0.000
TLTA	0.586	0.013	0.197	0.427
CACL	0.010	0.708	-0.007	0.841
C	-1.522	0.000	-0.624	0.035
Log- likelihood ratio	-33.296	0.000	-48.621	0.000

Source: Author's estimation

5.4.3 Distress Prediction by Logit and Probit Model

This section covers identification of cutoff value and model evaluation for logit and probit models. The cutoff values for each of the models are arrived based upon total error minimization principle. The same principle is applied by Ohlson and Zmijewski in their original models (Ohlson 1980 p. 120; Zmijewski 1984 p.72).

Table 5.7 reports overall correct prediction, Type I and Type II errors for logit model one year and two years prior on various cutoff values. For logit model one year prior the Type I and Type II error is found to be minimum at 0.4 cutoff value. At 0.4 cutoff value the Type I and Type II errors are 6.15 and 3.08 percent respectively. The overall correct prediction at 0.4 cutoff value is 95.38 percent. Similarly, for logit two year prior model the Type I and Type II errors are minimum at 0.4 cutoff value. At 0.4 cutoff value Type I and Type II errors are 15.38 and 13.85 percent respectively. The overall correct prediction at 0.4 cutoff value is 85.38 percent.

For logit models the predictive accuracy increases when more recent year information is used to obtain parameters of the models. The predictive accuracy of logit two years prior model is 85.38 percent which increases to 95.38 percent for logit one year prior model.

Table 5.7: Distress Classification rate of Logit Models

Cutoff	one year prior			two years prior		
	Overall correct prediction (%)	Type I error (%)	Type II error (%)	Overall correct prediction (%)	Type I error (%)	Type II error (%)
0.7	93.85	3.08	9.23	86.15	4.62	23.08
0.6	94.62	4.62	6.15	84.62	10.77	20
0.5	94.62	6.15	4.62	85.38	12.31	16.92
0.4	95.38	6.15	3.08	85.38	15.38	13.85
0.3	93.85	9.23	3.08	85.38	20.00	9.23
0.2	93.08	10.77	3.08	85.38	27.69	1.54

Source: Author's estimation

Table 5.8 reports overall correct prediction, Type I and Type II errors for probit one and two years prior model on various cutoff values. For both the probit models the overall correct prediction is higher and Type I and Type II errors are minimum at 0.5 cutoff value. For probit one year prior model the Type I and Type II errors at 0.5 cutoff value are 9.23 and 12.31 percent respectively. The overall correct prediction at 0.5 cutoff value is 89.23 percent. Similarly, for probit model two years prior the Type I and Type II errors at 0.5 cutoff value are 10.77 and 21.88 percent respectively. The overall correct prediction at 0.5 cutoff value is 83.85 percent.

Table 5.8: Distress Classification rate of Probit Models

Cutoff	one year prior			two years prior		
	Overall Correct Prediction (%)	Type I Error (%)	Type II Error (%)	Overall Correct Prediction (%)	Type I Error (%)	Type II Error (%)
0.7	86.15	3.08	24.62	83.85	3.08	29.69
0.6	85.38	4.62	24.62	82.31	9.23	26.56
0.5	89.23	9.23	12.31	83.85	10.77	21.88
0.4	88.46	13.85	9.23	83.85	13.85	18.75
0.3	87.69	16.92	7.69	86.92	18.46	7.81
0.2	86.92	21.54	4.62	76.92	44.62	1.56

Source: Author's estimation

Even in case of probit models the predictive accuracy increases when more recent year information is used to obtain parameters of the models. The predictive accuracy of probit two years prior model is found to be 83.85 percent which increases to 89.23 percent for logit one year prior model.

5.4.4 Comparison of Probability of Default (PD)

This section deals with Probability of Default (PD) comparison of all logit and probit models. Table 5.9 reports default probabilities of logit and probit models one and two years prior. The mean PD for distressed companies by logit and probit one year prior are 92.60 and 83.57 percent respectively. For two years prior model the mean PD for distressed groups for logit and probit models are 80.29 and 85.43 percent respectively. On the other hand mean PD for non-distressed companies for logit and probit models one year prior are 7.39 and 15.65 percent respectively. For two years prior the mean PD from logit and probit model on non-distressed firms are 19.70 and 12.90 percent respectively.

Table 5.9: Probability of Default (PD) Comparison of all Logit and Probit Models

Models	**Distressed**				**Non-Distressed**			
	Logit Model		Probit		Logit Model		Probit	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
One Year Prior	92.605	18.056	83.571	26.901	7.395	18.552	15.658	20.629
Two Years Prior	80.294	24.966	85.432	30.484	19.706	23.983	12.909	25.558

Source: Author's estimation

The average PD for distressed companies is predicted higher by logit one year prior model. The mean PD predicted by logit model one year prior is 92.60 percent, which is higher than 83.57 percent predicted by probit model. For two years prior model the mean PD predicted by probit model is 85.43 percent which is higher than 80.29 percent predicted by logit model but the standard deviation is found to be higher in case of probit model (30.48 percent) than logit model (24.96 percent).

The mean PD for non-distressed group is predicted lower by logit one year prior model as compared to probit model. For non-distressed companies the mean PD predicted by logit one year prior model is 7.39 percent which is lower than 15.65 percent predicted by probit model. For two years prior model the probit model predicts lower (12.90 percent) mean PD than logit (19.70 percent) model but the standard error is again higher in case of probit model (25.55 percent) as compared to logit model (23.98 percent).

The average PD predicted by logit one year prior model is better than probit model for both distressed and non-distressed companies. For two years prior model `the probit model predicts better PD than logit model but has a higher standard deviation. Hence, it can be concluded that logit models predicts better average PD than probit models on more recent year information.

5.5 Diagnostic Checks

This section deals with the diagnostic checks for logit and probit models. The holdout and ROC tests are applied as the diagnostic checks for the models.

5.5.1 Holdout Sample test

The holdout or secondary sample test is one of the widely used test to validate binary classifier models. The secondary sample of 78 equal number of defaulted and non-defaulted firms are considered taken for the period spanning from 2006 to 2014.

Table 5.10: Holdout Sample test for Logit and Probit One Year Prior Models

	Logit Model			Probit		
Models	Overall correct prediction (%)	Type I error (%)	Type II error (%)	Overall correct prediction (%)	Type I error (%)	Type II error (%)
one year Prior	89.744	12.821	7.692	87.179	7.692	10.256
two years Prior	80.769	23.077	15.385	89.744	17.949	14.103

Source: Author's estimation

Table 5.10 shows an overall correct prediction for logit and probit models on holdout sample. The overall correct prediction by logit one year prior model is 89.74 percent. The Type I and Type II errors on holdout sample by logit one year prior model are 12.82 and 7.69 percent respectively. For two years prior model the overall accuracy is found to be 80.76 percent. The Type I and Type II errors by logit two year prior model are 23.07 and 15.38 percent respectively.

The overall correct prediction by probit one year prior model is 87.17 percent. The Type I and Type II errors are 7.69 and 10.25 percent respectively. For two years prior model the overall accuracy is 89.74 percent. The Type I and Type II errors are 17.94 and 14.10 percent respectively.

The overall accuracy on holdout sample by one year prior model is higher in case of logit (89.74 percent) model than probit (87.17 percent) model. For two years prior model it is higher for probit model (89.74 percent) than logit model (80.76 percent). The overall accuracy increases from 80.76 to 89.74 percent when more recent information is used on logit model but it is opposite in case of probit model.

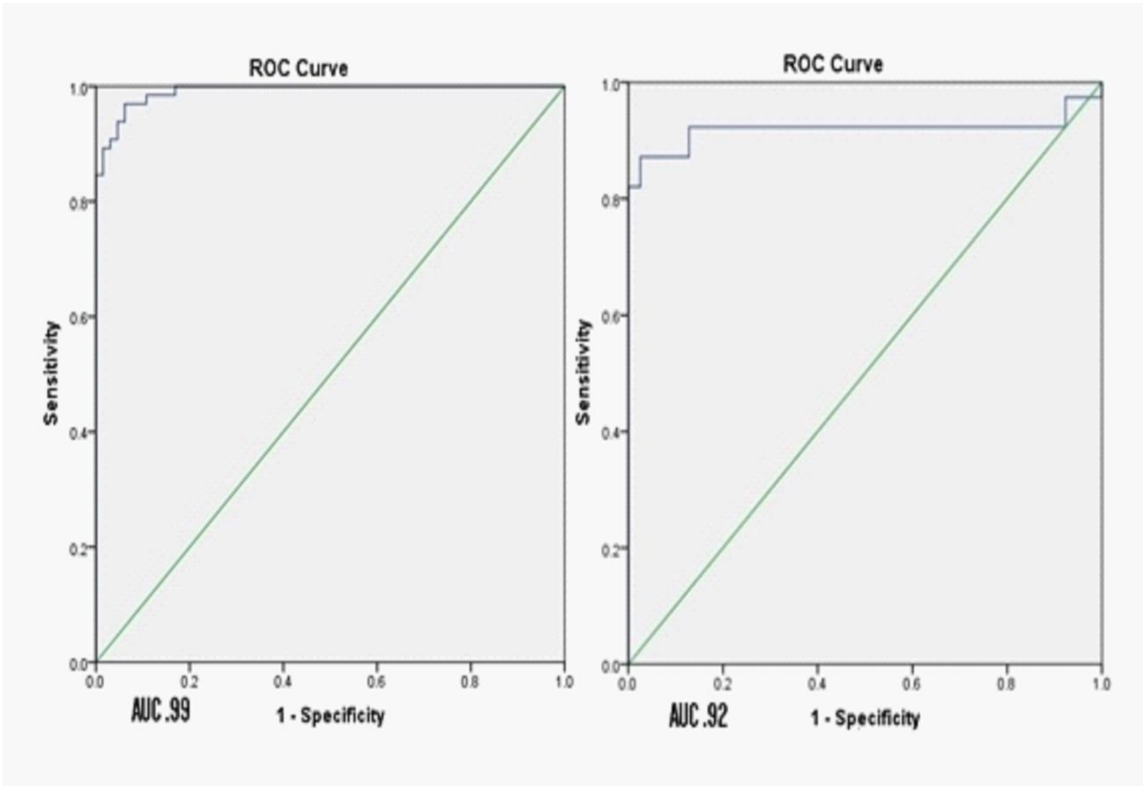
5.5.2 ROC test

This section deals with ROC test for all the logit and probit models.

Figure 5.1 shows the AUROC curve of logit one year prior model on (a) estimation and (b) holdout sample respectively. The total AUROC for logit one year prior model on estimation and holdout sample are 0.99 and 0.92 respectively, which is in between 0.9 to 1. Hence, the test is excellent on both the logit models which have good balance of specificity and sensitivity.

Figure 5.1: AUROC: Estimation and Holdout Sample of Logit one year prior Model

(a) (b)

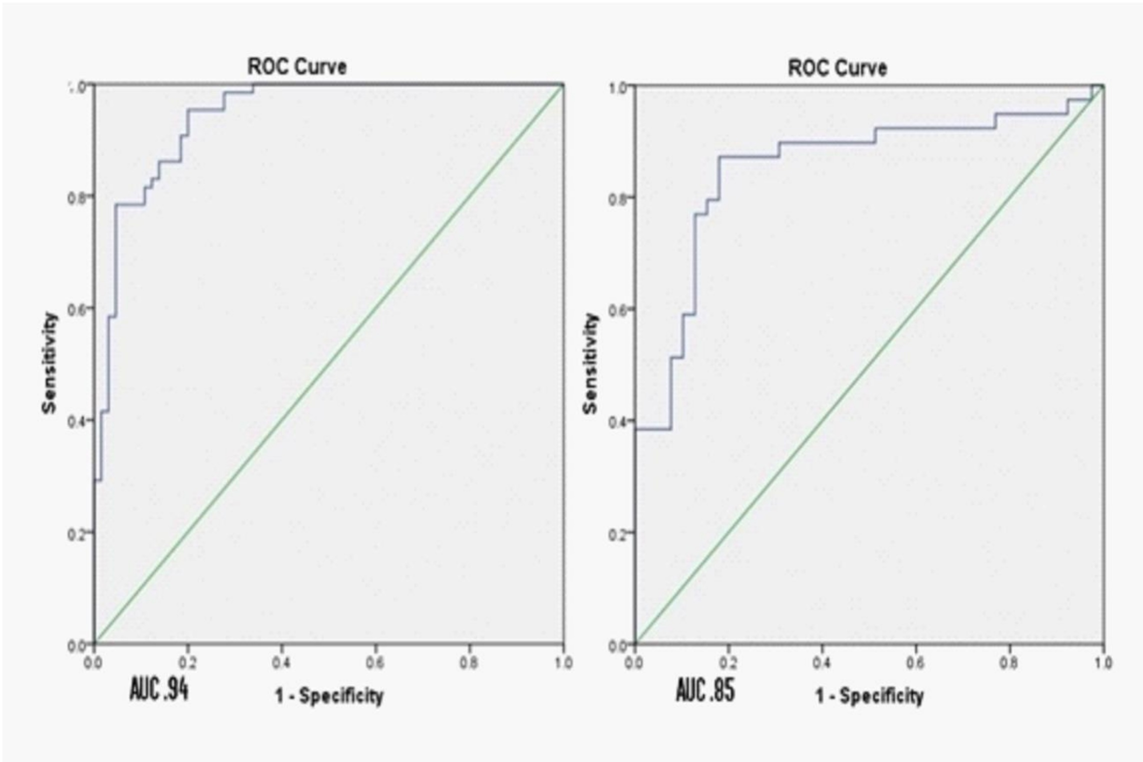


Source: Author's estimation

Similarly, Figure 5.2 shows the AUROC curve of logit two years prior model on (a) estimation and (b) holdout sample respectively. The total AUROC for logit two years prior model for estimation and holdout sample are 0.94 and 0.85 respectively. The test is fairly excellent and has good balance between specificity and sensitivity.

Figure 5.2: AUROC: Estimation and Holdout Sample of Logit two years prior Model

(a) **(b)**



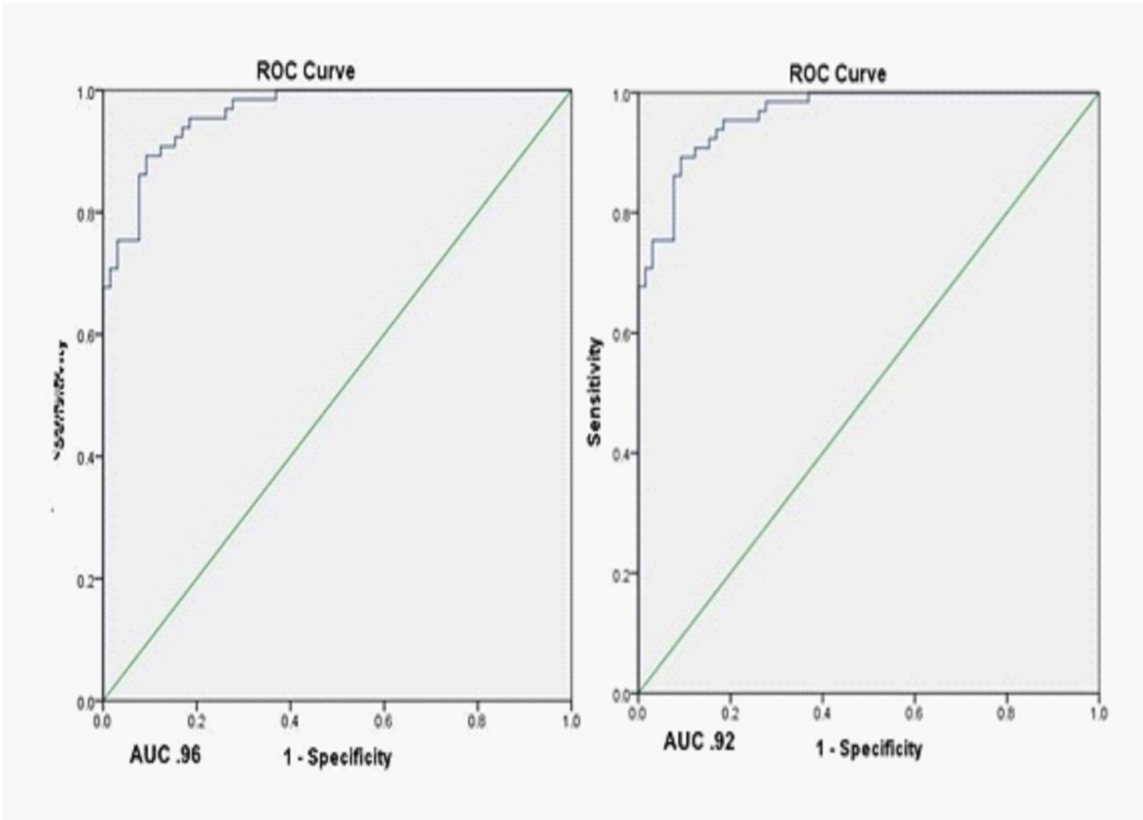
Source: Author's estimation

Figure 5.3 shows the AUROC curve of probit one year prior model on (a) estimation and (b) holdout sample respectively. The total AUROC for logit two years prior model for estimation and holdout sample are 0.96 and 0.92 respectively. The test is fairly excellent and has good balance between specificity and sensitivity.

Figure 5.4 shows the AUROC curve of probit two years prior model on (a) estimation and (b) holdout sample respectively. The total AUROC for probit two years prior model for estimation and holdout sample are 0.917 and 0.877 respectively. The test is fairly excellent and has good balance between specificity and sensitivity.

Figure 5.3: AUROC: Estimation and Holdout sample of Probit one year prior Model

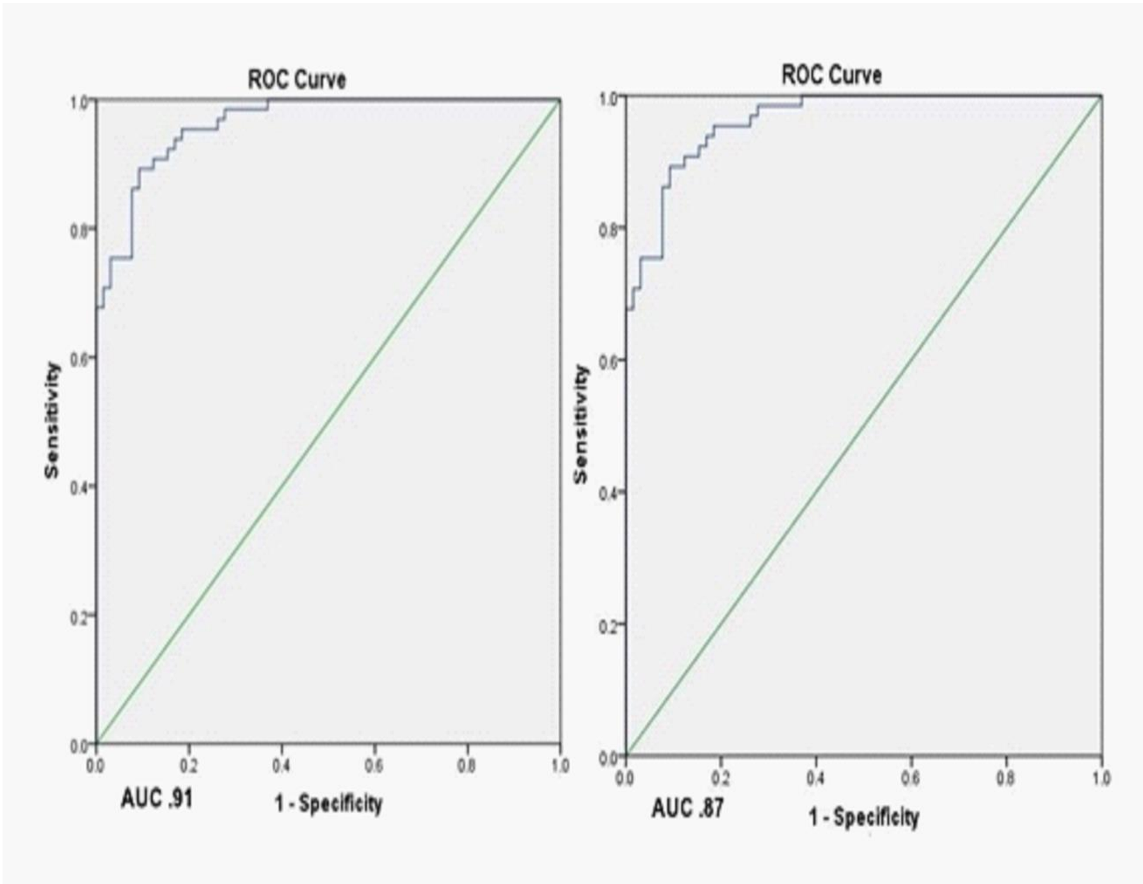
(a) **(b)**



Source: Author's estimation

Figure 5.4: AUROC: Estimation and Holdout sample of Probit two years prior Model

(a) **(b)**



Source: Author's estimation

5.6 Conclusion

The chapter models default probabilities for 208 Indian companies for the period 2006 to 2014 using logit and probit framework. The overall predictive accuracy on estimation sample of logit one and two years prior model is found to be 95.38 and 85.38 percent respectively. On the other hand overall predictive accuracy of probit one and two years prior model on estimation sample are 89.23 and 83.85 percent respectively. On holdout sample the overall predictive accuracy of logit one and two years prior model are 89.74 and 80.76 percent respectively. For probit two years prior model the overall accuracy is 87.17 and 89.74 percent respectively.

The mean PD estimated by logit one and two years prior model for defaulted firms are 92.60 and 80.29 percent respectively. For non-distressed firms the mean PD calculated by logit one year and two years prior model are 7.39 and 19.70 percent respectively. In case of probit model the mean PD calculated for defaulted groups by one and two years prior probit model are 83.57 and 85.43 percent respectively. For non-distressed groups the mean PD calculated by one and two years prior probit model are 15.65 and 12.90 percent respectively.

The major findings of the chapter show the overall predictive accuracy and mean PD estimates of logit one year prior model is better than probit one year prior model on both estimation and holdout sample. Probit model gives better results for two years prior model in terms of average PD but has a higher standard deviation. For both logit and probit models the one year prior model gives higher predictive accuracy, better average default estimates and robust coefficients. The predictive accuracies of both the models increase when the most recent financial information is used.

CHAPTER 6

HYBRID BANKRUPTCY PREDICTION MODEL AND COMPARISONS WITH ALTERNATIVE ACCOUNTING BASED MODELS

6.1 Introduction

In chapters 4 and 5 alternative accounting based models such as Altman's (1968) Z-score, Ohlson's (1980) Y-score and Zmijewski's (1984) X-score models are re-estimated on Indian manufacturing companies data. As noted earlier the suitability and performance of the bankruptcy prediction models is an empirical question. There are empirical studies which believe original coefficients give better performance than re-estimated ones. A couple of examples of these studies are Begley et al. (1996) and Boritz et al. (2007). On the contrary there are studies which question the construct validity of the models to original models towards the change in time periods and financial conditions. The studies which support this hypothesis are Grice and Ingram (2001), Grice and Dugan (2001), Timmermans (2014) and Avenhuis (2013).The second objective of the study is to check the construct validity of Altman, Ohlson and Zmijewski models with change in time period and economic environment. In line with second objective the current chapter tests the construct validity of the original models towards the change in time periods and financial conditions. Chudson (1945) mentions that industry specific models are more appropriate than general models. A similar evidence is also found in the study of Avenhuis (2013). The third objective of the study is to propose a new bankruptcy prediction model for Indian manufacturing companies. In the current chapter new bankruptcy prediction model is developed with a unique combination of financial ratios measuring leverage, profitability and turnover of Indian manufacturing companies. The fourth objective of the study is to compare and choose best model to predict bankruptcy for Indian manufacturing companies. In the current chapter all the original, re-estimated and hybrid models are assessed on predictive accuracy, significance of parameters, long-range accuracy, secondary sample and Receiver Operating Characteristic (ROC) tests.

The remainder of the chapter is organized as follows. The Altman's, Ohlson's and Zmijewski's original models are explained in section 6.2. The development of hybrid model of bankruptcy prediction is explained in section 6.3.Section 6.4 deals with re-estimations of models. Section 6.5 and 6.6 cover results and discussion and diagnostic checks for the model. The study concludes with section 6.7 which discusses the implications of those findings for users of the models.

6.2 Considered Models

Over the past four decades, various credit risk models were developed based upon alternative approaches to model bankruptcy. The use of accounting ratios has always dominated the literature of bankruptcy prediction because of its simplicity and larger applicability to the firms. The current study examines three well-known accounting based bankruptcy prediction models. They are:

(i) Altman (1968) Z-score model based upon MDA analysis

(ii) Ohlson (1980) Y-score model based upon logit analysis

(iii) Zmijewski (1984) X-score model based upon probit analysis

Altman (1968) developed a bankruptcy prediction model which uses financial ratios that measures liquidity, profitability, leverage and solvency of the firm. The model uses MDA framework to model bankruptcy on 33 defaulted and 33 non-defaulted US manufacturing firms for the period 1946-1965. Equation (6.1) represents the original model estimated by Altman (1968):

$$Z = 1.2WCTA + 1.4RETA + 3.3EBITA + 0.6MVEBVD + .99SLTA \tag{6.1}$$

(32.60) (58.86) (26.56) (33.26) (2.84)

Where Z is the overall index used to determine the membership of firms in defaulted or non-defaulted groups. Firms with Z $\geq$ 2.675 are classified as non-bankrupt, whereas firms with Z $<$ 2.675 are classified as bankrupt firms. The figures in parentheses indicates F-statistics of the equality in mean between defaulted and non-defaulted firms. The result shows the F-statistics is significant at 1 percent level of significance for all the coefficients, except SLTA. WCTA to SLTA are accounting variables used in the model whose descriptions are given in Table 6.1.

Ohlson (1980) employed a logit technique with less restrictive assumptions than those taken in the MDA approach to model bankruptcy. The model uses nine predictive variables which measures firms' size, leverage, liquidity, and performance. The estimated model uses 105 bankrupt and 2,058 non-bankrupt industrial firms for the period 1970–1976. The original model is shown in equation (6.2):

$$\underset{(-0.970)}{Y = -1.3} - \underset{(-3.78)}{0.4SIZE} + \underset{(6.61)}{6.0TLTA} - \underset{(-1.89)}{1.4WCTA} + \underset{(0.761)}{0.1CLCA} - \underset{(-2.450)}{2.4OENEG} - \underset{(-1.85)}{1.8NITA} + \underset{(-2.36)}{0.3FUTL} - \underset{(0.812)}{1.7INTWO} - \underset{(-2.21)}{0.5CHIN} \tag{6.2}$$

Where, Y is the overall index based upon logistic function which determines the probability of firms' membership in default or non-default group. Based upon total error minimization criterion for the given data, firms with $Y > 0.5$ are classified as defaulted firms, otherwise non-defaulted (Ohlson 1980, p. 120). The figures in parentheses indicates T-statistics. The description of variables are provided in Table 6.1.

Zmijewski (1984) adopts a probit method to model bankruptcy which uses financial ratios measuring firm's performance, leverage, and liquidity. The ratios were selected on the basis of their performance in the previous studies. The model uses 40 bankrupt and 800 non-bankrupt industrial firms' data for the period 1972–1978. Equation (6.3) represents the original model estimated by Zmijewski (1984):

$$\underset{(0.0)}{X = -4.3} - \underset{(0.00)}{4.5\mathrm{NITL}} + \underset{(0.00)}{5.7\mathrm{TLTA}} - \underset{(0.00)}{.004\mathrm{CACL}} \tag{6.3}$$

Where, X is the overall index based upon probit function which determines the probability of firms' membership in bankrupt and non-bankrupt group.

Table 6.1: Summary of Empirical Models along with Variables used

Models	Formula	Variables	Descriptions
Altman (1968) Multiple Discriminant Analysis	$Z = \beta^{I}$X Where Z is the MDA score and X represent the variables listed. Cutoff value: Z ≥2.675, classified as non-bankrupt Z<2.675, classified as bankrupt	WCTA RETA EBIT MVEBVD SLTA	= Net Working Capital/TotalAssets = Retained earnings/Total Asset =Earnings before interest and taxes/Total assets =Market value of equity/Book value of total debt =Sales/Total Assets
Ohlson (1980) Logit Model	$P = (1 + exp\{-\beta^{I}X\}^{-1}$ Where P is the probability of bankruptcy and X represents the variables listed. The logit function maps the value of $\beta^{I}X$ to a probability bounded between 0 and 1. Cutoff value: Y>0.5, classified as defaulted otherwise non-defaulted.	SIZE TLTA WCTA CLCA OENEG NITA FUTL INTWO CHIN	=Log (Total assets/GNP price-level index). Index with a base 100 for 1968. =Total liabilities/Total Assets =Working capital/Total Assets =Current Liabilities/Current Assets = 1 If total liabilities exceed total assets, 0 otherwise. = Net income / Total assets = Funds provided by operations (income from operation after depreciation) divided by total liabilities. = 1 If net income was negative for the last 2 years, 0 otherwise. =$(NI_{t} - NI_{t-1})/(\lvert NI_{t}\rvert + \lvert NI_{t-1}\rvert)$ where, NI_{t} is net income for the most recent period. The denominator acts as a level indicator. The variable is thus intended to measure the relative change in net income.
Zmijewski (1984) Probit model	$P = \phi(\beta^{I}X)$ Where, P is the probability of bankruptcy and X represents the variables listed, and $\phi(.)$ represents the cumulative normal distribution function. The probit function maps the value β^{I}X to a probability bounded between 0 and 1. Cutoff value: X>0.5, classified as bankrupt, otherwise non-bankrupt.	NITL TLTA CACL	= Net income divided by total liabilities. = Total liabilities divided by total assets. = Current assets divided by current liabilities.

Note: The cutoff value of Ohlson (1980) and Zmijewski (1984) models are decided using total error minimisation criterion (Ohlson 1980 p. 120; Zmijewski 1984 p. 72).
Source: Author's compilation

Again based upon total error minimization criterion, firms with $X > 0.5$ are classified as bankrupt, otherwise non-defaulted (Zmijewski 1984, p. 72). The figures in parentheses indicates p-value. NITL, TLTA and CACL are the variables used in the model whose details are provided in Table 6.1.

6.3 Hybrid Bankruptcy Prediction Model for Indian Manufacturing Companies

This section covers the development of hybrid bankruptcy prediction model for Indian manufacturing companies. The hybrid bankruptcy prediction model is developed on sample of 208 equal numbers of defaulted and non-defaulted Indian manufacturing firms for the period 2006-2014. Out of 208 companies 130 have been used for estimation sample and 78 for holdout sample.

6.3.1 Sample

The analysis reported here uses estimation and a holdout sample, where each sample includes distressed and non-distressed firms. The Board of Industrial and Financial Reconstruction (BIFR) reference is used to identify distressed firms from the list of firms registered as sick during 2006 to 2014. A set of matched non-distressed companies are identified randomly on the basis of asset size and industry type. A total of 130 companies comprising of distressed and non-distressed companies are used for estimation sample. A sample of 78 companies holdout for model validation. Financial information of the companies are collected from their balance sheets and income statements. The Balance sheet and income statements of the companies at the end of each year are collected from their respective websites. The estimated and holdout sample have been classified into 14 industry categories matching with their economic activity with the National Industrial Classification Code (NIC) 3 digit classification of 2008 (Table 1.1, Chapter 1).

6.3.2 Selection of Financial Ratios

There is extensive literature on the use of financial ratios to predict bankruptcy of the firms. Since Beaver (1966), various financial ratios are tried to foretell bankruptcy, and they can be broadly classified into four categories, which measure a firm's leverage, liquidity, profitability and turnover. Bellovary et al. (2007) in a survey paper on bankruptcy prediction list 42 financial ratios which are used in more than five financial studies on bankruptcy prediction.

In the Indian market, Bandyopadhyay (2006) develops bankruptcy prediction model based upon MDA and logistic technique for Indian corporate bond sector. The ratios used in his study measure liquidity, leverage, productivity, turnover. Other non-financial variables are used which measure age, group ownership, ISO Quality Certification and inter-industry effects of the firms. Bhumia and Sarkar (2011) in another study on Indian pharmaceutical industry developed model for corporate failure using MDA technique. The study chose 16 financial ratios based upon past empirical literature measuring profitability, solvency, liquidity and efficiency of the firms. Shetty et al. (2012) develop early warning system for Indian IT/ITES industry using Data Envelopment Analysis (DEA).

Based upon the past empirical studies ten financial ratios measuring a firm’s liquidity, leverage, productivity, and turnover, Kumar and Rao (2015) develop of a non-linear new Z-score model based upon Pearson Type-3 distribution for Indian companies. In addition to Altman (1968) variables, the study uses two other non-financial variables measuring industry effects and rating of the companies. Based upon the past empirical literature and our own analytical judgment, we have chosen 25 financial ratios measuring firm’s leverage, liquidity, profitability, and turnover. Most of studies on global or Indian market found leverage, liquidity, profitability and turnover to be major financial ratios which predict corporate failure.

Out of four major financial ratios leverage is considered to be one of the most important ratios to assess financial position of the firms. According to Argenti (1976), high indebtedness of the firms is one of the major reason leading a firm to bankruptcy. Similarly, Jensen (1989) argues leverage is an invitation to bankruptcy, and high debt ratios are not good for firms. In the Indian market Bandyopadhyay (2006), Bhumia and Sarkar (2011), Shetty et al. (2012) and Kumar and Rao (2015) acknowledge the importance of leverage ratios and use different leverage indicators to assess bankruptcy. Except Bhumia and Sarkar (2011) all other studies (Bandyopadhyay (2006), Shetty et al. (2012) and Kumar and Rao (2015)) on Indian market have taken market value of equity to book value of total debt as ratio measuring leverage of the firms. In lieu of past empirical literature and importance of the indicators including market value of equity to book value of total debt, 11 leverage ratios are chosen out of 25 financial ratios.

Liquidity is also considered to be one of the important ratios to assess credit worthiness of firms. Beaver (1966) in his study found that the firms with lower liquid assets are more prone to bankruptcy. In line with Beaver (1966), Altman et al. (1977), Charalambrus et al. (2000) and Platt and Platt (2002) also get similar findings. In the Indian market Bandyopadhyay (2006), Bhumia and Sarkar (2011), Shetty et al. (2012) and Kumar and Rao (2015) all have used liquidity indicators. Working capital to total assets is the common liquidity indicator which has been used in all the above four empirical studies. The current study in addition to used working capital to total assets apart from four other liquidity indicator which are namely- current asset to current liability (CACL), current asset to total assets (CATA) and current labilities to current assets from the list of 25 financial ratios.

Profitability ratios measure the performance of the firms. The ratios explain how efficient and effective utilization of its assets is and management of its expenditure to produce adequate earnings for its shareholders. According to Gu (2002), unprofitable firms are more likely to default. Izan (1984), Georgeta and Georgia (2012) also get similar findings in their respective studies. In the Indian context Bandyopadhyay (2006) uses operating profits to total assets as the proxy for profitability indicator. Kumar and Rao (2015) and Bhumia and Sarkar (2011) uses retained earnings to total assets as a proxy for profitability indicator. The present study chooses seven profitability ratios.

Turnover ratios measures efficiency of firms in utilizing their assets. Eljilly (2001) argues high efficiency leads to high profitability and less chance of bankruptcy and vice-versa. It measures the ability of a company to generate sales by the capital invested. Molinero and Ezzamel (1991) and Laitnen (1992) also finds similar results. In the Indian market, Bandyopadhyay (2006) and Kumar and Rao (2015) have chosen sales to total assets as a proxy for turnover ratio. The present study in addition to sales to total assets incorporates two other turnover ratio. The profile of variables used in the study are reported in Table 6.2. To check industry specific effects, the sample firms have been divided into

14 industry dummies based upon major economic activity as per NIC classification (Table 6.4).

Table 6.2: Definition of Financial Ratios

Sl No.	Financial Ratio	Definition
	Leverage Ratios	
1	TDTA	Total Debt/ Total Assets
2	BVEBVD	Book Value of Equity/ Book Value of Total Debt
3	CFOTA	Cash Flow from Operations/ Total Assets
4	CLTA	Current Liabilities / Total Assets
5	CFTD	Cash Flow from Operations/ Total Debt
6	LTDTA	Long-term Debt/ Total Assets
7	NWTA	Net Worth/ Total Assets
8	TDNW	Total Debt/ Net Worth
9	TLNW	Total Liabilities/ Net Worth
10	TLTA	Total Liabilities/ Total Assets
11	FUTL	Fund Provided by Operations to Total Liabilities
	Liquidity	
12	CACL	Current Assets/ Current Liabilities
13	WCTA	Working Capital/ Total Assets
14	CATA	Current Assets/ Total Assets
15	CLCA	Current Liabilities/ Current Assets
	Profitability	
16	NITA	Net Income/Total Assets
17	RETA	Retained Earnings/ Total Assets
18	EBITA	Earnings Before Interest and Taxes/ Total Assets
19	NINW	Net Income/ Net Worth
20	CASL	Current Assets/ Sales
12	NISL	Net Income/ Sales
22	NITL	Net Income/ Total Liabilities
	Turnover	
23	SLTA	Sales/ Total Assets
24	WCSL	Working Capital/ Sales
25	WCNW	Working Capital/ Net Worth

Source: Author's compilation

Following steps are followed to select final profile of the ratios:

Step-I: **Analysis of Variables**: We have chosen 25 financial ratios on the basis of past empirical literature on Indian market. Analysis on these ratios are carried out in two broad steps. First, mean and standard deviation of bankrupt and non-bankrupt firms are analysed. Second, T-test for equality in means of bankrupt and non-bankrupt groups are analyzed.

Step-II: **Step-wise Regression**: Forward logistic selection and backward elimination methods are applied. Different combinations of the ratios which are significantly different in mean by T-test are tested. The final set of ratios are selected on the basis of the statistical significance of the estimated parameters, the sign of each variable's coefficient and the model's classification results

Step-III: **Inclusion of Industry Dummy**: In the next step along with four financial ratios 14 industrial dummies were included in the model but none of them are found to be significant. This is also tested through stepwise regression model. However, the results are unchanged.

Step-IV: **Final Profile of the Ratios**: Finally, all the financial ratios which are found to be statistically significant have been chosen for the model.

6.3.3 Analysis of Variables

This sections covers analysis of mean and standard deviation of defaulted and non-defaulted firms. T-test for equality in mean is employed to check whether defaulted, and non-defaulted groups have significant difference in their respective means. It is well-known from past empirical studies that the bankrupt companies have higher indebtedness, lower liquidity, poor profitability and turnover ratios. Also from Table 6.3, out of three turnover ratios, WCSL mean is not found to be statistically different. For defaulted groups WCSL and WCNW are found to be negative and low SLTA value. In case of profitability indicators, out of 7 financial ratios all means are found to be significant expect CASL and NISL. For most of the profitability indicators, the ratios are found to be negative (NITA, RETA, EBITA, and NITL) for defaulted groups except NINW. For liquidity indicators out of 4, 2 turned out to have statistically different means (WCTA, CLCA), while others are insignificant (CACL, CATA). In case of leverage indicators, all indicators are statistically different in mean except CLTA. For defaulted groups the ratios are found to be negative for all indicators except TDTA and TLTA.

Table 6.3: Descriptive Statistics of the Financial Ratios

Sample	Statistic	NITA	CACL	WCTA	RETA	EBITA	SLTA	TDTA	CATA	NINW
Distressed	Mean	-0.290	2.519	0.215	-0.295	-0.100	0.984	1.151	0.714	2.257
	SD	0.321	3.951	0.538	0.322	0.26	1.041	0.651	0.833	3.946
Non-Distressed	Mean	0.044	3.496	0.553	0.034	0.152	2.013	0.723	0.961	0.054
	SD	0.094	6.428	0.788	0.08	0.14	2.966	0.627	1.058	0.185
	P-Value	0.000	0.299	0.005	0.000	0.000	0.009	0.000	0.142	0.000
Sample	Statistic	BVEBVD	CFOTA	CLTA	CFTD	CASL	NISL	LTDTA	NWTA	TDNW
Distressed	Mean	-0.157	-0.159	0.499	-0.205	39.016	-23.170	1.151	-0.287	-14.589
	SD	0.200	0.262	0.571	0.409	250.959	114.765	0.651	0.485	40.268
Non-Distressed	Mean	0.481	0.104	0.407	0.132	0.861	0.012	0.723	0.48	1.858
	SD	0.300	0.128	0.436	0.999	1.830	0.447	0.627	0.420	1.835
	P-Value	0.000	0.000	0.307	0.013	0.223	0.106	0.000	0.000	0.001
Sample	Statistic	TLNW	WCSL	WCNW	TLTA	CLCA	FUTL	NITL		
Distressed	Mean	-23.578	-41.127	-5.685	1.681	0.821	-0.091	-0.191		
	SD	76.339	342.421	29.01	0.982	0.693	0.116	0.230		
Non-Distressed	Mean	2.859	0.305	1.094	1.150	0.560	0.129	0.360		
	SD	2.451	1.060	0.932	0.873	0.427	0.371	2.586		
	P-Value	0.006	0.331	0.062	0.001	0.011	0.000	0.089		

Source: Author’s estimation

From the analysis of variables, in general, most of ratios grouped under liquidity, profitability and turnover have shown negative signs and a declining trend for bankrupt companies. T-test for equality in means for defaulted and non-defaulted groups shows out of 25, financial ratios chosen for the model, 19 ratios have statistically different mean for defaulted and non-defaulted groups.

6.3.4 Step-wise Regression

In a step-wise regression, logistic forward selection and backward elimination methods are applied and different combinations of the ratios (19 ratios), which had significant differences in their respective means, are tested. The selection of the final set of the variables are based upon statistical significance and sign of the each of the variable's coefficients. The model also takes into consideration the classification power. A similar method is also used by Neophytou et al. (2001) conducting a study on Netherland firms. The final set of ratios and their statistical significance is reported in third column (Model 2) of Table 6.7. From Table 6.7 all the set of financial ratios are significant at 1 percent to 10 percent level of significance, and LR ratio shows the overall significance of the model.

6.3.5 Inclusion of Industry Dummy

To capture the industry specific effects, our sample is cateogrized into 14 major industries based upon NIC 3 digit industrial classification code (Table 6.4). In the Indian case, similar kind of approach was adopted by Bandyopadhyay (2006) and Kumar and Rao (2015). Again along with four financial ratios 14 industrial dummies are included in the model, but none of them are found to be significant. Even different combinations of specific industry dummies are tried but none of them turned to be significant. Finally, we have decided to drop dummies and go with only financial ratios (Table 6.7, Model 2).

6.3.6 Final Profile of the Ratios

The final profile of the financial ratios used in the model are:

BVEBVD (**Book Value of Equity/Book value of Total Debt**): This indicator measures leverage of the firms. The similar ratio is also used in the study of Altman (1968) on US manufacturing companies. In the current study market value of equity is replaced by book value of equity. The current study uses data of both publicly and privately held firms. In order to calculate market value of equity, stock price data (Altman, 1993) is required. The same principle is employed while re-estimating Altman's model. The ratio is found to be most effective predictor of bankruptcy than a similar, more commonly used ratio: net worth/ total book value of debt. The indicator explains how much a firm's asset can decline in value before the liabilities exceed the assets, and the firm becomes bankrupt. In the Indian case, Bandyopadhyay (2006), Shetty et al. (2012) and Kumar and Rao (2015) use this indicator to predict bankruptcy.

Table 6.4: Industry Dummies for Sample Companies

Industry Dummy	Industry Type	No of Firms
D1	Manufacturer of other food products	14
D2	Spinning, weaving and finishing of textiles	34
D3	Manufacturer of paper and paper products	4
D4	Manufacturer of basic chemicals, fertilizer and nitrogen compounds, plastics, synthetic rubber in primary form	18
D5	Manufacturer of pharmaceuticals, medicinal chemical, and botanical products	6
D6	Manufacturer of rubber products	4
D7	Manufacturer of glass and glass products	4
D8	Manufacturer of non-metallic mineral products n.e.c.	2
D9	Casting of metals	16
D10	Manufacturer of electronic components	6
D11	Manufacturer of electric motors, generators, transformers and electricity distribution and control apparatus	4
D12	Manufacturer of motor vehicles	8
D13	Manufacturer of furniture	4
D14	Other land transport	6
	Total	130

Source: Author's compilation

SLTA (**Sales/Total Assets**): It is one of the widely used turnover ratio of firms. It measures efficiency and effectiveness of a firm's assets to generate profit. This is a key variable for the measurement of the size of the firm. The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. It is one measure of management's capability in dealing with competitive conditions. It is used in the studies of Altman (1968), Bandyopadhyay (2006) and Kumar and Rao (2015).

NITA (**Net Income/ Total Assets**): It is the ratio of net income to total assets which is a measure of performance of the firms. It measures profitability and also used in the study of Ohlson (1980) on US manufacturing companies.

NITL (**Net Income/ Total Liabilities**): It is the ratio of net income to total liabilities. The ratio measures return on asset which is the measure of firm's performance and profitability. The ratio is also used in the study of Zmijewski (1984).

Broadly all the ratios used in the current study are from the studies of Altman (1968), Ohlson (1980) and Zmijewski (1984). The first two ratio's BVEBVD and SLTA measuring leverage and turnover of the firms are also used in the study of Altman (1968). Third ratio NITA measures profitability of firms and is used in the study of Ohlson (1980), and fourth NITL measures profitability of firm and is also applied in the study of Zmijewski (1984). The hybrid bankruptcy prediction model uses ratios measuring leverage, profitability, and turnover of the firms. The model is also considered to be comprehensive model because it uses variables from all three major accounting based bankruptcy prediction model mentioned above. By 'Common Sense' and past studies all the variables are expected to have negative sign (Ohlson 1980, p. 119).

Table 6.5 reports descriptive statistics of the variable used in the new model. The mean of BVEBVD for non-defaulted group for both estimation (0.48) and holdout (3.35) sample respectively are found to be positive for and negative for defaulted groups. SLTA measures the firms' market size. For non-defaulted groups, the size is larger on both estimation (2.01) and holdout (2.52) samples, whereas for the defaulted group its value is smaller on both estimation (0.98) and (1.52) holdout samples respectively. NITA is a ratio which measures firms' performance. The ratio deteriorates and found to be negative for bankrupt companies on estimation (-0.28) and holdout (-0.84) sample, whereas it is positive for non-bankrupt firms. NITL measures return on asset which is a measure of a firm's performance. For the defaulted group it is negative on both estimation (-0.19) and holdout

(-0.19) samples, whereas the ratio is found to be positive for non-bankrupt firms on both estimation (0.36) and holdout (0.09) samples respectively.

Table 6.5: Descriptive Statistics of the Final Profile of the Financial Ratios

Sample	Statistic	BVEBVD	SLTA	NITA	NITL
Estimation					
Distressed(N=65)	Mean	-0.157	0.984	-0.289	-0.191
	SD	0.200	1.040	0.321	0.230
Non-Distressed (N=65)	Mean	0.481	2.013	0.044	0.360
	SD	0.299	2.965	0.094	2.586
Holdout					
Distressed (N=39)	Mean	-0.157	1.521	-0.843	-0.192
	SD	0.264	1.919	1.863	0.602
Non-Distressed (N=39)	Mean	3.359	2.522	0.110	0.094
	SD	7.173	3.111	0.169	0.160

Source: Author's estimation

An important issue in application of logit model can be the problem of multicollinearity among the independent variables. The problem of multicollinearity in the estimated model causes inefficiently estimated parameters and high errors, which results in insignificant variables and high explanatory power of the estimated model. In order to control this problem we have decided to use matrix of Pearson's Correlation coefficients, where the correlation coefficient is higher than 0.8 (Pervan et al. 2011) indicates multicollinearity problem.

Table 6.6: Correlation Matrix of the Final Profile of the Financial Ratios

Variables	BVEBVD	SLTA	NITL	NITA
BVEBVD	1			
P-vale				
SLTA	0.227	1		
P-vale	(0.009)			
NITL	0.100	0.517	1	
P-vale	(0.255)	(0.000)		
NITA	0.629	0.278	0.114	1
P-vale	(0.000)	(0.001)	(0.197)	

Source: Author's estimation
Note: Figures in the parentheses ( ) represents the p-values.

Table 6.6 reports matrix of Pearson's correlation coefficients, which reveal that in our analysis many financial ratios have very low correlation coefficients. Only in the case of BVEBVD and NITA the correlation coefficient is found to be 0.62 which is also less than 0.8. The correlation matrix shows that the independent variables are free from multicollinearity problem.

6.3.7 Logit Model: Estimation Procedure

The logistic regression method is used to investigate the relationship between binary response variable (1 for bankrupt and 0 for non-bankrupt groups) and financial ratios (explanatory variables). The Maximum Likelihood Estimation (MLE) procedure is applied to estimate parameters. The objective of the logit regression is to evaluate the role of accounting variables in predicting bankruptcy for Indian manufacturing firms and also to arrive at an estimate of probability of default for a firm using them.

6.3.8 Estimation Results

In the logit regression, dependent variables is defined as a binary variable taking value 1 for defaulted and 0 for non-defaulted group. The balanced sample for 130 campiness consisting equal number of defaulted and non-defaulted groups for the period 2006 to 2014 has been used to run the logit model. In a stepwise logistic regression, forward and backward elimination method is applied. Finally we obtain two models (Table 6.7).

In Model 1 along with significant financial ratios all the dummies are incorporated to check industry effects but all financial ratios and dummies turned out to be insignificant. Model 2 is taken as final model which uses only financial variables. In case of model 2 all variables are significant and preserves expected sign. From Table 6.7, in case of Model 2, BVEBVD is negatively significant at 1 percent level on default probability. NITA and NITL are negatively significant (5 percent level) with default probabilities. In case of SLTA, it is also negatively significant at 10 percent level of significance.

Table 6.7: Results of Logit Model 1 and 2

	Model 1	Model 2
Variables	Coefficients	Coefficients
BVEBVD	-39.907	-13.8597*
SLTA	-4.488	-1.11303***
NITA	-72.776	-18.760**
NITL	-107.685	-34.354**
C	-7.012	-0.604
D1	13.256	
D2	6.277	
D3	-14.496	
D4	Dropped	
D5	-2.311	
D6	8.592	
D7	10.97	
D8	Dropped	
D9	3.865	
D10	15.956	
D11	Dropped	
D12	-1.563	
D13	Dropped	
D14	7.767	
LR Ratio	172.219	164.956
p-Value	0.000	0.000

Note: *, ** and *** signifies the level of significance at 1%, 5%, and 10% respectively and LR is log likelihood ratio.
Source: Author's estimation

LR ratio tests the overall significance of the model. In case of final model (Model 2) the LR ratio is found to be 164.956 and statistically significant at 1 percent level of significance. The Model 2 can be directly used to find probability of default (PD) of firms to assess credit risk.

6.4 Model Re-estimations

This section covers re-estimation of Altman, Ohlson and Zmijewski models using estimation sample of 130 Indian firms consisting of equal numbers of defaulted and non-defaulted firms. The statistical methodologies are the same used in the original models and discussed in section 2. The stability of the coefficients of original models is tested by comparing it from re-estimated models. The original and re-estimated coefficients are reported in Table 6.8. The coefficients of original and re-estimated models are compared to test the stability of coefficients to the time periods and changes in the financial conditions. The overall predictive accuracy of the model is tested on estimation and holdout samples to test whether change in coefficients (re-estimated) with recent data set improves the predictive accuracy of the model. The newly proposed model is compared with original and re-estimated models.

6.5 Results and Discussion

This section analyzes the findings of the original, re-estimated and newly proposed models on estimation and holdout samples. The stability of their coefficients and their predictive accuracies are also tested. This section also evaluates which of the three models best suited in the Indian context.

6.5.1 Stability of Coefficients

Table 6.8 reports the coefficients of original and re-estimated models. It is needless to mention over here that the coefficients of all the considered models can not be compared as because the dependent as well as independent variables across the models are different. Therefore, the sensitivity of the models towards the change in the economic environment and time periods is analysed by comparing the overall predictive accuracy of the corresponding models. This is explained in the next section.

Table 6.8: Summary of the Coefficients of different Models

Statistic	Altman's model		Ohlson's model		Zmijewski's model		Hybrid Model
	Original Model	Re-estimated Model	Original Model	Re-estimated Model	Original Model	Re-estimated Model	
WCTA	1.2*	0.076*	-1.4**	-5.216***			
RETA	1.4*	1.464*					
EBITA	3.3*	-0.63*					
MVEBVD/BVEBVD	0.6*	3.474*					-13.86*
SLTA	0.99	0.028*					-1.113***
SIZE			-0.4*	0.079			
TLTA			6.03*	1.623	5.7*	0.586*	
CLCA			0.1**	-2.973**			
OENEG			-2.4*	2.836**			
NITA			-1.8**	-29.676*			-18.76**
FUTL			0.3*	-2.559			
INTWO			-1.7	0.337			
CHIN			-0.5*	1.73***			
NITL					-4.5*	-13.797*	-34.354**
CACL					0.004**	0.01	
Constant		-0.425	-1.3	-2.454***	-4.3*	-1.522*	-0.604
LR			0.839†	-15.952	203.78	-33.296	164.956
P-value			0.000	0.000	0.000	0.000	0.000

Note: *, ** and *** signifies the level of significance at 1%, 5% and 10% respectively.† Likelihood ratio index and LR is log likelihood ratio. The (*) indicates the statistical significance of F-statistic in the difference of mean in case of Altman's model.
Source: Author's estimation

6.5.2 Predictive Accuracy

Predictive accuracy of all the original, re-estimated and newly proposed hybrid models on estimation and holdout samples is reported in Table 6.10. In the earlier section, we have mentioned that based upon total error minimization principle, cutoff value is taken for all the three models.

Table 6.9: Identification of Cuttoff Value for Re-estimated and Hybrid Models

Cutoff	Overall Correct Prediction	Type I Error	Type II Error
	Altman's re-estimated Model		
0	96.923	1.538	4.615
0.2	92.308	1.538	13.846
0.3	91.538	1.538	15.385
0.4	90.000	1.538	18.462
	Ohlson's re-estimated Model		
0.7	93.850	3.080	9.230
0.6	94.620	4.620	6.150
0.5	94.620	6.150	4.620
0.4	95.380	6.150	3.080
	Zmijewski's re-estimated Model		
0.7	86.150	3.080	24.620
0.6	85.380	4.620	24.620
0.5	89.230	9.230	12.310
0.4	88.460	13.850	9.230
	Hybrid Model		
0.7	98.460	3.080	0.000
0.6	98.460	1.540	1.540
0.5	97.690	1.540	1.540
0.4	97.690	1.540	3.080

Source: Author's estimation

The cutoff value for original Altman (1968), Ohlson (1980) and Zmijewski (1984) models were 2.675, 0.5 and 0.5 respectively (Ohlson 1980, p. 120; Zmijewski, 1984, p. 72). In the re-estimated model based upon the same principle the cutoff value for Altman, Ohlson and Zmijewski model are 0, 0.4 and 0.5 respectively. For the newly proposed hybrid model, the same principle of total error minimization criterion is followed and 0.6 is taken as the cutoff value for the model (Table 6.9).

Panel-A of the Table 6.10 reports the predictive accuracy of original, re-estimated and newly proposed hybrid models on estimation sample. The predictive accuracy of original Altman model on estimation sample is 67.69 percent which correctly classifies 92.30 percent of distressed and 43.07 percent of non-distressed firm. The Type II error is very high in case of Altman original model on estimation sample. The overall accuracy of Altman re-estimated model on estimation sample is 96.92 which correctly classifies 98.46 percent of distressed and 95.38 percent of non-distressed firms. For Ohlson original model the overall predictive accuracy is 48.46 percent on estimation sample which correctly classifies 95.38 percent of distressed firms and 1.53 percent of non-distressed firms. The Type II error in the case of Ohlson original model on estimation sample is close to 100 percent. On the other hand, overall predictive accuracy of re-estimated Ohlson model is 95.38 which correctly classifies 96.92 percent of defaulted and 93.84 percent of non-defaulted firms. In case of Zmijewski original model, the overall predictive accuracy is 71.53 percent. The model correctly classify 98.46 percent of distressed and 44.61 percent of non-distressed firms. The overall predictive accuracy of re-estimated Zmijewski model on estimation sample is found to be 89.23 which correctly classify 87.69 percent of defaulted and 90.76 percent of non-defaulted firms. In case of newly proposed hybrid model, the predictive accuracy on estimation sample is found to be 98.46 which correctly classify 98.46 percent of distressed and 98.46 percent of non-distressed firms. The Type I and Type II errors in case of new hybrid model is found to be equal. Panel-A of Table 6.10 shows that predictive accuracy of re-estimated models is higher than the original models on estimation sample. The newly proposed model has the highest (98.46) predictive accuracy with minimum and equal Type I and Type II errors. Type II error is found to be more than 50 percent in all the three original models. In case of original Ohlson model, the Type II error is close to 100 percent.

Table 6.10: Comparison of Predictive Accuracy of the Models

	Panel-A (Estimation Sample)					
	Original model Accuracy			Re-estimated model Accuracy		
Models	Overall	Distressed	Non-Distressed	Overall	Distressed	Non-Distressed
Altman	67.692	92.308	43.077	96.923	98.462	95.385
Ohlson	48.462	95.385	1.538	95.385	96.923	93.846
Zmijewski	71.538	98.462	44.615	89.231	87.692	90.769
Hybrid Model	98.460	98.460	98.460	NA	NA	NA
	Panel-B (Holdout Sample)					
	Original model Accuracy			Re-estimated model Accuracy		
	Overall	Distressed	Non-Distressed	Overall	Distressed	Non-Distressed
Altman	61.538	25.641	97.436	88.462	87.179	89.744
Ohlson	64.103	97.436	30.769	89.744	87.179	92.308
Zmijewski	79.487	97.436	61.538	76.923	61.538	92.308
Hybrid Model	87.179	82.051	92.308	NA	NA	NA

Source: Author's estimation

All the three re-estimated models have higher predictive accuracy and low Type I and Type II errors compared to original models.

Panel-B of Table 6.10 reports the predictive accuracy of original, re-estimated and newly proposed models on holdout sample. The overall accuracy on holdout sample also constitutes diagnostic test for the estimated models. The overall accuracy of Altman original model on holdout sample is 61.53 percent which correctly classifies 25.64 percent of defaulted and 97.43 percent of non-defaulted firms. The Type I error in case of Altman original model on holdout sample is very high and close to 75 percent. On the other hand, overall predictive accuracy of Altman re-estimated model is 88.46 percent which correctly classifies 87.17 percent of defaulted and 89.74 percent of non-defaulted firms. In case of Ohlson original model, the overall predictive accuracy is found to be 64.10 percent which correctly classifies 97.43 percent of distressed and 30.76 percent of non-distressed firms. The Type II error in the case of Ohlson original model on holdout sample is close to 70 percent. On re-estimated Ohlson model, the overall predictive accuracy is 89.74 percent which correctly classifies 87.17 percent of defaulted and 92.30 non-defaulted firms. The predictive accuracy of Zmijewski original model on holdout sample is 79.48 percent which correctly classifies 97.43 percent of distressed and 61.53 percent of non-distressed firms. The Type II error in case of original Zmijewski model on holdout sample is close to 40 percent. The overall predictive accuracy of re-estimated Zmijewski model on holdout sample is 79.48 percent which correctly classifies 97.43 percent of distressed and 61.53 percent of non-distressed firms. On holdout sample, the Type II error is again high for original models except Altman model. The Type II error in case of both Ohlson and Zmijewski original model is more than 50 percent. In case of all the re-estimated models both the Type I and Type II errors are minimum except in Zmijewski model. In case of new hybrid model the overall predictive accuracy on holdout sample is found to be 87.17 percent which correctly classifies 82.05 percent of defaulted and 92.30 percent of non-defaulted firms. The Type I error in case of new model is found to be 18 percent and Type II error close to 8 percent.

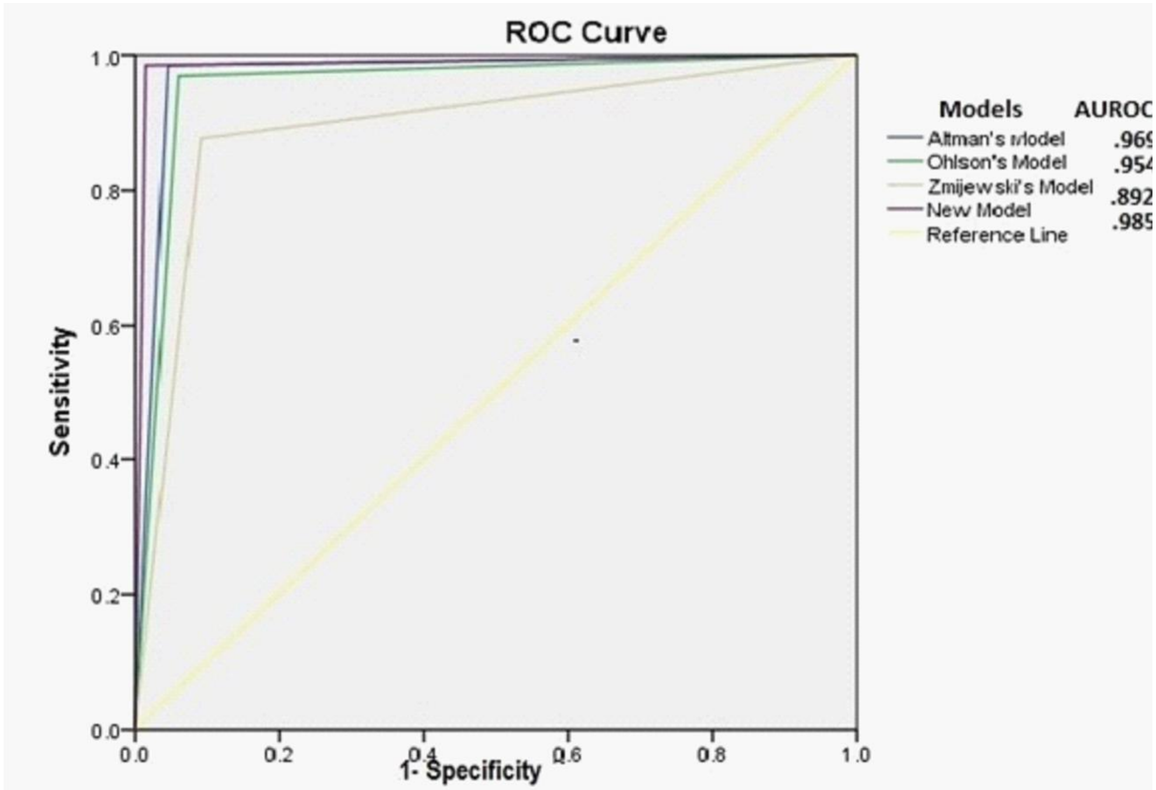
From the results reported in Panel-A and B of Table 6.10 on estimation and holdout samples, it can be summarized that the predictive accuracy of re-estimated models are significantly higher than the original models on both estimation and holdout sample. Except in Altman model the Type II error is very high for all the original models on both estimation and holdout samples. The result shows the model applied on the recent data set gives higher predictive accuracy on both estimation and holdout samples. Out of contesting accounting based models, the new hybrid model outperforms because of its overall predictive accuracy on estimation sample and fairly good accuracy on holdout sample for Indian manufacturing firms. The overall predictive accuracy of re-estimated Ohlson model is 95.38 and 89.74 on estimation and holdout samples respectively. The overall predictive accuracy of Altman re-estimated model is also close to new model, but new model is better than Altman model because it gives direct probability estimates and model bankruptcy in a non-linear fashion which is in line with local and global regulatory framework. In the next section, we will apply other diagnostic checks to check the stability of newly proposed hybrid model. The results are in line with the studies of Grice and Ingram (2001), Grice and Dugan (2001), Timmermans (2014) and Avenhuis (2013). Empirically it is found in the context of Indian manufacturing sector that the coefficients are unstable and sensitive to time periods.

6.6 Diagnostic Tests for the New Hybrid Model

This section deals with two diagnostic tests for newly proposed hybrid model - ROC and long-range accuracy test.

Figure 6.1 shows the comparison of AUROC for re-estimated and newly proposed models for bankruptcy prediction. From the results, it is summarized the hybrid model shows the best results when compared to other contesting models. The AUROC for new model is 0.985 which is higher than the other contesting models. Hence, we can say this model is the most appropriate model amongst the contesting models for prediction of the corporate failure for Indian manufacturing firms.

Figure 6.1: Comparison of AUROC for Re-estimated (Altman's, Ohlson's and Zmijewski's) and New Hybrid Model



Source: Author's estimation

Table 6.11 reports the long-range accuracy results of new hybrid model on estimation and holdout samples. The long range accuracy of new hybrid model on estimation sample is 98.46 and 86.92 percent for one year before bankruptcy and two years before bankruptcy respectively. On the holdout sample, it is 89.74 and 70.51 percent for one year and two years before default respectively.

Table 6.11: Long Range Accuracy of Hybrid Model

Years before Distress	Estimation sample	Holdout sample
1	98.460	89.743
2	86.923	70.513

Source: Author's estimation

The long range accuracy results are fairly good and satisfactory. The result shows the predictive accuracy of new hybrid model decreases as we go more backward from the year of distress. Hence, the most recent information is most helpful in predicting default with higher accuracy.

6.7 Conclusion

The chapter proposed a new hybrid model to predict the bankruptcy of Indian manufacturing sector and also examines the sensitivity of Altman's (1968), Ohlson's (1980) and Zmijewski's (1984) models to the sample of 208 equal numbers of defaulted and non-defaulted firms for the period 2006 to 2014 in the Indian context. The result shows the overall accuracy of the model improves when the coefficients are re-estimated. The overall accuracy of Altman (1968), Ohlson (1980) and Zmijewski (1984) original models in the estimation sample are 67.69, 48.46 and 71.53 percent respectively. When all the models are re-estimated the accuracy improves to 96.92, 95.38 and 89.23 percent respectively. On holdout sample, the overall accuracy of Altman's (1968), Ohlson's (1980) and Zmijewski's (1984) original models are 61.53, 64.10 and 79.48 percent respectively. The accuracy improves to 88.46, 89.74 and 76.92 percent when the models are re-estimated. The predictive accuracy of new model on estimation and holdout sample is found to be 98.46 and 87.17 percent respectively. Therefore, the new model is found to be a more robust model in comparison to Altman's , Ohlson's and Zmijewski's models. The major finding of the study suggests the coefficients of the Altman's (1968), Ohlson's (1980) and Zmijewski's (1984) models are sensitive to time periods and financial condition. The predictive accuracy of the models increase when more recent data are used in the estimation samples. The change in the financial environment leads to change in the relation between financial distress and financial ratios. This also alters the comparative importance of the ratios to predict default. Hence, researchers should re-estimate the original models to get higher predictive accuracy. In case of Indian manufacturing companies, out of all competitive accounting based models, the new model outperforms regarding predictive accuracy, ROC, and long-range accuracy test.

CHAPTER 7

MODELING DEFAULT PROBABILITIES IN BSM FRAMEWORK: A MARKET BASED APPROACH

7.1 Introduction

In the earlier chapters, all the models were accounting-based default prediction models since they use accounting variables of a firm to predict bankruptcy. On the other hand, BSM model uses market-based information, namely- market value of equity, equity return volatility, market value of assets, etc. As noted earlier, the Black-Scholes-Merton (BSM) model for bankruptcy prediction uses the option pricing principle of Black and Scholes (1973), subsequently fine-tuned by (Kealhofer, McQuown and Vasicek) KMV Corporation and various financial institutes to predict company bankruptcy. The final objective of the study is to calculate risk neutral probabilities of Indian manufacturing companies using BSM approach. The current chapter deals with estimation of risk neutral probability of Indian manufacturing firms using BIFR reference under BSM approach.

The rest of the chapter is structured as follows. Section 7.2 discusses about the BSM model. The data used in the model is explained in section 7.3. Empirical results and model validation is covered in section 7.4 and the chapter concludes with section7.5.

7.2 The Model

The Contingent Claims Approach gained much prominence in credit risk literature. This approach was first introduced in the seminal work of Merton (1974) on the valuation of corporate debt. The Black-Scholes (1973) option pricing theory is extended in the credit risk evaluation of a firm by characterising a company's equity as a call option on its asset. On the other hand, the debtholders of the company might be seen as holding a short put position on the company's assets. This approach relies on the capital structure of a company. Hence, it is referred as 'structural approach'. It shapes a structure within which credit events are caused by changes in the company's value subject to some pre-defined threshold.

The model considers that a firm has an equity. The equity consist of zero coupon debt, which will be due at a future timeT_1. There is a no dividend for equity. The Black-Scholes-Merton approach is an inventive application of Black and Sholes option pricing theory to predict bankruptcy but the performance of the approach depends upon how realistic are the assumptions. Following restrictions could challenge the model efficiency:

(a) The company can default only at the time of maturity, i.e. T and not before.

(b) The company's assets values follows a log-normal distribution.

(c) Default probabilities for private companies can be valued only by accomplishment of some comparability investigation based on accounting data.

(d) The model is not able to differentiate among various types of debt based on their collaterals, seniority, covenants or convertibility.

(e) The model is "static" in the sense that it assumes debt structure is unchanged even if the company's assets have improved.

(f) The model infers a 'shrink' in the default probability and credit spreads as the debt approaches maturity.

(g) The stock market may not efficiently consolidate all freely available information about default probability into the equity prices.

(h) The constant and flat term structure of interest rates is other important criticism of the model.

At a given point in time BSM model generates probability of default (PD) for each company in the sample. To calculate PD, face value of company's existing debt is subtracted from the company's estimate of future market value and divided to the estimate of the volatility of the firm. The resultant score, which is stated as the distance to default, is then replaced into a cumulative density function to compute the probability that the value of the company will be below the face value of debt at the forecasting horizon. The sum of the market value of the firm's debt and the value of its equity is referred to be market value of the firm. The estimation of default probabilities would be easy if the value of market value of the firm's debt and the value of its equity are readily observable. Data on equity values are freely available while consistent data on the market value of debt is usually unavailable. The two important assumptions of the Merton model are: First, total value of a firm is supposed to follow geometric Brownian motion,

$$dV = \mu V dt + \sigma_V V dZ \tag{7.1}$$

Where, V is the total value of the firm, μ is expected continuously compounded return on V, σ_V is volatility of firm value, dZ is a standard Wiener process. The incremental changes in ln V follow a generalized Wiener process with drift,

$$\mu_V - \sigma_V^2 / 2$$

$$d \ln V_T \approx \left[\left(\mu_V - \sigma_V^2 / 2 \right) \mathrm{T} \sigma \sqrt{T} \right] \tag{7.2}$$

V_T is log normally distributed because the logarithm of V_T is normal,

At time T, value of the firm's assets is given by,

$$V_T = V_o exp \left[\left(\mu_V - \sigma_V^2 / 2 \right) \mathrm{T} + \sigma \sqrt{T Z_r} \right] \tag{7.3}$$

The main feature of the model is that over time firm's value drifts upward (in the risk neutral world of option pricing at the risk-free rate), and its leverage falls. The second crucial assumption of the model is that the company has issued just one discount bond maturing at time T. At time T, the firm defaults if promised debt repayment is greater than value of its assets. With a strike price equivalent to the face value of the debt with maturity T, the equity of firm is a European call option on the assets of firms. The model can be applied to calculate risk neutral probability of the company to default on its debt obligations. The volatility of the firm's assets, current value of the firm's assets, the debt maturity, and the outstanding debt are used as inputs in Merton's model. One has to calculate current value and volatility of the firm's assets from the market value of the firm's equity and equity's instant volatility to make the model logically controllable. In some way debt maturity date and debt payments are mapped into a single payment on the debt maturity date. The other imbedded assumptions are the absence of bankruptcy costs, transaction costs, complications with indivisibilities of assets or taxes, unrestricted borrowing, continuous time trading, no restrictions on the short selling of the assets, lending at a constant interest rate r, etc.

If E is defined as a value of the company's equity, V as the value of company's assets as of today (t=0). Let V_T and E_T be the value of company's equity and asset at time T when the debt matures with face value F. Under Merton framework, at time T the value of equity is given by:

$$E_r = \max(0, V_T - F) \tag{7.4}$$

The value of equity will follow partial differential equation under option pricing theory:

$$\frac{\partial E}{\partial t} + rV\frac{\partial E}{\partial V} + 1/2\sigma^2 V^2 \frac{\partial^2 E}{\partial V^2} - rE = 0 \tag{7.5}$$

Subject to below boundary condition,

$$E_r = \max(0, V_T - F) \tag{7.6}$$

Representatively, the Merton model specifies that the equity value of a company fulfils the subsequent equation contained by risk-neutral framework,

$$E = VN(d_1) - Fe^{-rT}N(d_2) \tag{7.7}$$

Where r is instant risk-free rate, and $N(\cdot)$ is cumulative standard normal distribution function, d1 is given by

$$d_1 = \frac{\ln(V/F) + (r + \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \tag{7.8}$$

$$d_2 = \frac{\ln(V/F) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \tag{7.9}$$

On or before the date of maturity T, equation (7.7) will hold good regardless of equity holders exercise their call option. It is because under option pricing theory early exercise of call option is suboptimal. Therefore, the price of a call option is equal no matter whether it is American. Or European.

Default probability at time zero is given by,

$$= \Pr(V_T \leq F) \tag{7.10}$$

$$= \Pr(lnV_O + (r-1)/2\sigma^2)T + \sigma\sqrt{T}\, Z_T \leq lnF) \tag{7.11}$$

$$= \Pr(-\frac{\ln(V_0\,/F)+(r-1/2\sigma^2)T}{\sigma\sqrt{T}} \geq Z_r) \tag{7.12}$$

The default probability under risk-neutral probability measure is given by,

$$N(-d_2) = N\left[-\frac{\ln(V/F) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}}\right] \tag{7.13}$$

In the Merton formula, the “probabilities” do not signify the real probability of being below or above the strike price at the date of expiration. It does not really drift at the risk-free rate if the underlying asset is risky. If the risk-free interest rate, r, is replaced in equation (7.13) with ‘drift’ of the asset value, μ, we get an objective probability measure:

$$N(-d_2) = N\left[-\frac{\ln(V/F) + (\mu - \sigma_V^2/2)T}{\sigma_V \sqrt{T}}\right] \tag{7.14}$$

The risk-neutral default probabilities serve as upper bound to objective default probabilities in the study of Deliandes and Geske (2003).Though objective and risk neutral distributions of company's value have similar diffusion terms, even though, the objective distribution must usually have a mean larger than risk-free rate. It follows that risk neutral distribution suggests a higher default probability. Nevertheless, it is well-known that expected returns on equities are calculated with significant error term. Since risk neutral probabilities of default can be estimated without calculating the company's expected return, they may be more correctly calculated than objective default probabilities.

Equation (7.7) contains two unknowns V and volatility of V, i.e., σ_E. The model uses the Wiener process to identify two unknowns with two equations. The value of equity, i.e., E under Wiener process can be written as,

$$E = \mu_E E dt + \sigma_E E dZ \tag{7.15}$$

Where μ_E is expected continuously compounded return on E, σ_E is volatility of equity value, and dZ is a standard Wiener process. By Ito's lemma, we can also exemplify process for equity as:

$$dE = \left(\frac{\partial E}{\partial t} + \mu_V V \frac{\partial E}{\partial V} + \frac{1}{2}\sigma_V^2 V^2 \frac{\partial^2 E}{\partial V^2} \right) dt + \sigma_V V \frac{\partial E}{\partial V} dZ \tag{7.16}$$

Where,

$$EquityDelta\Delta^E = \frac{\partial E}{\partial V} = N(d1) > 0 \tag{7.17}$$

$$EquityGamma\tau^E = \frac{\partial^2 E}{\partial V^2} = \frac{n(d1)}{V\sigma\sqrt{T}} > 0 \tag{7.18}$$

$$EquityTheta\theta^E = \frac{\partial E}{\partial T} = -\frac{V_n(d1)\sigma}{2\sqrt{T}} - rDe^{-rT}N(d2) \leq 0 \tag{7.19}$$

Subsequently, diffusion terms in equity process in equation (7. 15) and (7.16) are equal. Thus we can write,

$$\sigma_E E = \sigma_V V \frac{\partial E}{\partial V} = \sigma_V V N(d_1) \tag{7.20}$$

Equations (7.7) and (7.20) complete a system of two simultaneous nonlinear equations. In the system two unknowns and two parameters need to be estimated. The system can be very well solved using Microsoft Excel Solver routine7. Likewise, the drift terms of equations (7.10) and (7.12) can be compared and solved for asset drift μ,

$$\mu_E E = \frac{\partial E}{\partial T} + \mu V \frac{\partial E}{\partial V} + \frac{1}{2}\sigma^2 V^2 \frac{\partial^2 E}{\partial V^2} \tag{7.21}$$

$$\mu_E E = \theta^E + \mu V \theta^E + \frac{1}{2}\sigma^2 V^2 \tau^E \tag{7.22}$$

$$\mu = \frac{\mu_E E - \theta^E - \frac{1}{2}\sigma^2 V^2 \tau^E}{V\Delta^E} \tag{7.23}$$

The method mentioned here assumes that expected return of equity μ_E or the drift of equity can be estimated from the stock market price data. To estimate μ_E, CAPM pricing model can be applied. Having found V, σ and μ, we can now calculate the objective probability of default using (7.14).

7.3 Data

Modeling credit risk for Indian firms is very difficult job on the account of the lack of reliable data. Notwithstanding these difficulties, we procced with our analysis based on the data for selected companies using BIFR reference to identify distressed firms from the list of firms registered as sick firms during 2006 to 2014. The study uses a total of 80 companies comprising 30 distressed and 50 non-distressed firms. Financial information of the companies are collected from their balance sheets and income statements at the end of each year from their respective websites. The data on stock prices of the listed companies are taken from Bombay Stock Exchange (BSE). Information related to risk-free return is collected from Reserve Bank of India (RBI) publication.

Since the accounting year runs from 1st April to 31st March for Indian firms, we compute the default probability for the aforementioned corporates as on 31st March every year during the sample period. Consistent with prior literature and KMV methodology, face value of debt (F) is calculated as the sum of short-term debt plus 50% of long-term debt as suggested by Bharath & Shumway (2008). The “debt due in one year” comprises of current liabilities and provisions, commercial papers outstanding, deferred tax payments, short-term bank borrowings and also current portion of long-term debt reported in Prowess database. “Long-term debt” is set equal to total long-term debt less the current portion of long-term debt. We calculate the equity return volatility σ_E as the annualized standard deviation of daily returns during the given year. The market value of equity (E) is calculated as the product of closing price at the end of the fiscal year and the number of shares outstanding (Bharat & Shumway, 2008; Hillegeist et al., 2004). ‘The yield on a government security with one year remaining to maturity constitutes the discrete risk-free rate of return. This rate is converted into continuously compounded rate for further analysis. Equity returns volatility is ‘de-levered’ to generate a seed value for asset volatility. The de-levered equity returns volatility implies σ_E E= σ V where N (d1) =1, implying zero debt. Market value of the firm V is proxied by the sum of market value of equity and book value of debt. Based on these initial estimates, we perform iterations with the Solver routine to generate final values for V and σ which serve as inputs for computing risk-neutral default probability’ (Kulkarni el al. 2005).

7.4 Empirical Results

The Black-Scholes-Merton (BSM) model predicts bankruptcy of Indian firms, with the use of primary market data. Table 7.1 to 7.3 report summary statistics for all the variables used in the BSM model and probability of default computed using BSM model. Market value of equity (E), face value of debt (F). risk-free rate of return (r) is measured as the 10-year government securities yield. Equity return volatility (σ_E) is calculated as the annualized standard deviation of daily returns during the given year.

Table :7.1 BSM Model Summary- All Companies

Variable	Mean	Standard deviation	Minimum	Maximum
Market value of equity (E)	196.752	478.733	1.742	3141.926
Face value of debt (F)	260.686	350.815	7.080	1760.195
Risk free rate (r)	0.077	0.004	0.071	0.084
Equity return volatility (σE)	0.667	0.349	0.279	3.360
Market value of firm asset (V)	457.437	695.076	16.439	4675.481
Asset volatility (σ_V)	0.272	0.294	0.029	2.480
Expected return on asset (μ_V)	0.208	0.291	0.071	1.529
Probability of Default (PD)	5.111	11.762	0.000	98.960

Source: Author's estimation

It is clear from Table 7.1 that wide range of firms are considered in the study in terms of their market value of equity and face value of debt. The firms with maximum and minimum market value of equity and face value of debt are 3141.96 and 1760.195, and 1.742 and 7.080 respectively. Market value of equity, face value of debt and market value of a firm assets are found to be highly volatile. The mean objective PD for all firms is 5.111 with 0.000 minimum and 98.960 maximum values respectively.

Table 7.2 and 7.3 show default probabilities for firms registered with BIFR and non-distressed firms respectively. From Table 7.2, the firms filed with BIFR or defaulted firms have higher PD than non-defaulted firms. The average PD reported for defaulted group is 10.439 with 2.990 minimum and 98.960 maximum values respectively. Even in case of distressed group market value of equity, face value of debt and market value of firm asset is found to be highly volatile.

Table 7.2: BSM Model Summary- Distressed Companies

Variable	Mean	Standard deviation	Minimum	Maximum
Market value of equity (E)	20.329	22.068	1.742	100.3254
Face value of debt (F)	279.402	378.137	14.640	1760.195
Risk free rate (r)	0.078	0.004	0.071	0.084
Equity return volatility (σE)	0.751	0.458	0.545	3.360
Market value of firm asset (V)	299.731	391.730	16.439	1801.563
Asset volatility (σ_V)	0.072	0.049	0.013	0.194
Expected return on asset (μ_V)	0.078	0.004	0.071	0.084
Probability of Default (PD)	10.439	16.053	2.990	98.960

Source: Author's estimation

From Table 7.3 the non-defaulted firms have mean objective PD of 0.752 with 0.000 minimum and 3.910 maximum values respectively. Again in the case of non-distressed firms market value of equity, face value of debt and market value of firm asset is found to be highly volatile.

From Table 7.2 and 7.3 it can be seen that mean value of PD for distressed companies (10.44%) is significantly higher than the non-distressed companies (0.75%).The result shows that the healthy firms have very less likelihood of default. Hence, as expected, the BSM model predicts a higher PD for distressed companies and lower PD for non-distressed companies.

Table 7.3: BSM Model Summary- Non-distressed Companies

Variable	Mean	Standard deviation	Minimum	Maximum
Market value of equity (E)	341.097	610.973	11.827	3141.926
Face value of debt (F)	245.372	330.438	7.080	1533.555
Risk free rate (r)	0.079	0.005	0.0712	0.084
Equity return volatility (σE)	0.543	0.114	0.256	0.783
Market value of firm asset (V)	586.469	851.382	19.906	4675.481
Asset volatility (σ_V)	0.116	0.061	0.457	0.557
Expected return on asset (μ_V)	0.314	0.359	0.071	1.529
Probability of Default (PD)	0.752	1.091	0.000	3.910

Source: Author's estimation

Table 7.4 reports results for sample distressed firms using BSM approach. The PD for all defaulted firms calculated using BSM model is reported in Appendix 2. From Table 7.4 the risk-neutral PD for Shamken Cotsyn Ltd registered sick in the year 2006 is found to be 13.41. The return volatility (σE), market value of firm asset (V), asset volatility (σ_V) and expected return on asset (μ_V) for Shamken Cotsyn Ltd is reported as 0.773, 67.581, 0.028 and 0.071 respectively. For Shamken Multifab Ltd. registered sick in the year 2006**,** the PD**,** σE, V, σ_V and μ_V are found to be 7.79, 0.669, 158.394,0.026 and 0.071 respectively. From Table 7.4 the risk-neutral PD for other sample distressed firms such as Kunststoffe Industries, Rathi Ispat Ltd., Nachmo Knitex Ltd., Hanjer Fibres Ltd., Triveni Glass, Nova Petrochemicals Ltd., Ganesh Benzoplast Ltd, Gem Spinners India, Gupta Synthetics, Stelco Strips, Gangotri Textiles Ltd., Euro Ceramics Ltd., Murli Industries Ltd. and Empee Sugar & Chemicals Ltd are reported as 29.46, 12.75, 16, 7.03, 5.36, 11.37, 98.96, 13.88, 9.95, 10.11, 9.27, 7.26, 9.36 and 8.66 respectively. In case of all sample, distressed firms risk-neutral default probabilities are found to be higher in the BSM model for the firms registered with BIFR.

Table 7.4: Results of Distressed Companies Sample Firms

Company Name	Market value of equity (E)	Face value of debt (F)	Risk-free rate (r)	Equity return volatility (σE)	Market value of firm asset (V)	Asset volatility (σ_V)	Expected return on asset(μ_V)	Probability of default (PD)
Shamken Cotsyn Ltd.	2.481	65.1	0.071	0.773	67.581	0.028	0.071	13.41
Shamken Multifab Ltd.	6.049	152.345	0.071	0.669	158.394	0.026	0.071	7.79
Kunststoffe Industries	1.742	15.685	0.071	1.021	17.427	0.102	0.071	29.46
Rathi Ispat Ltd.	9.429	148.32	0.078	0.763	157.749	0.046	0.078	12.75
Nachmo Knitex Ltd.	4.584	38.88	0.078	0.824	43.464	0.087	0.078	16
Hanjer Fibres Ltd.	3.313	24.07	0.079	0.661	27.383	0.08	0.079	7.03
Triveni Glass	27.509	96.44	0.079	0.646	123.949	0.143	0.079	5.36
Nova Petrochemicals Ltd.	35.1	146.805	0.076	0.769	181.905	0.148	0.076	11.37
Ganesh Benzoplast Ltd.	4.978	183.99	0.076	3.36	188.968	0.089	0.076	98.96
Gem Spinners India	17.583	57.3	0.076	0.829	74.883	0.195	0.076	13.88
Gupta Synthetics	4.044	168.375	0.084	0.736	172.419	0.017	0.084	9.95
Stelco Strips	3.796	46.775	0.084	0.719	50.571	0.054	0.084	10.11
Gangotri Textiles Ltd.	7.143	204.125	0.082	0.709	211.268	0.024	0.082	9.27
Euro Ceramics Ltd.	14.861	361.16	0.082	0.665	376.021	0.026	0.082	7.26
Murli Industries Ltd.	61.292	972.475	0.082	0.703	1033.767	0.042	0.082	9.36
Empee Sugar & Chemicals Ltd.	21.826	416.985	0.084	0.692	438.811	0.034	0.084	8.66

Source: Author’s estimation

Table 7.5 reports results for sample non-distressed firms using BSM approach. The PD for all non-defaulted firms calculated using BSM model is reported in Appendix 2. From Table 7.5, the risk-neutral PD for Chettinad Cement for the year 2006 is found to be 0.00. The return volatility (σE), market value of firm asset (V), asset volatility (σ_V) and expected return on asset (μ_V) for Chettinad Cement is reported as 0.518, 1297.913, 0.394 and 0.957 respectively. For Siyaram Silk Mills Ltd the risk-neutral PD**,** σE, V, σ_V and μ_V for year 2006 are found to be 0.00, 0.621, 458.573, 0.443 and 1.529 respectively. From Table 7.5 the risk-neutral PD for other sample non-distressed firms such as ECE Industries, Hinduja Foundries, Sumeet Industries, Atul Auto, Mahindra Ugine Steel Company, Sutlej Textiles and Industries, Shasun Pharmaceuticals, Usher Agro, Shasun Pharmaceuticals, Salona Cotspin, Cords Cable Industries, Manjushree Technopack, Real Strips, Syschem India, Kajaria Ceramics, Sanwaria Agro Oils, Alembic Pharma and Redington are reported as 0.00, 0.00, 0.00, 0.00,0.11, 0.03, 0.20,0.00, 0.00, 0.05, 0.07, 0.00, 0.01, 0.39, 0.00, 0.00, 0.00 and 0.01 respectively.

In case of all sample, non-distressed firms risk-neutral default probabilities are found to be lower and close to 0 under BSM model.

Table 7.5: Results of Non-distressed Companies Sample Firms

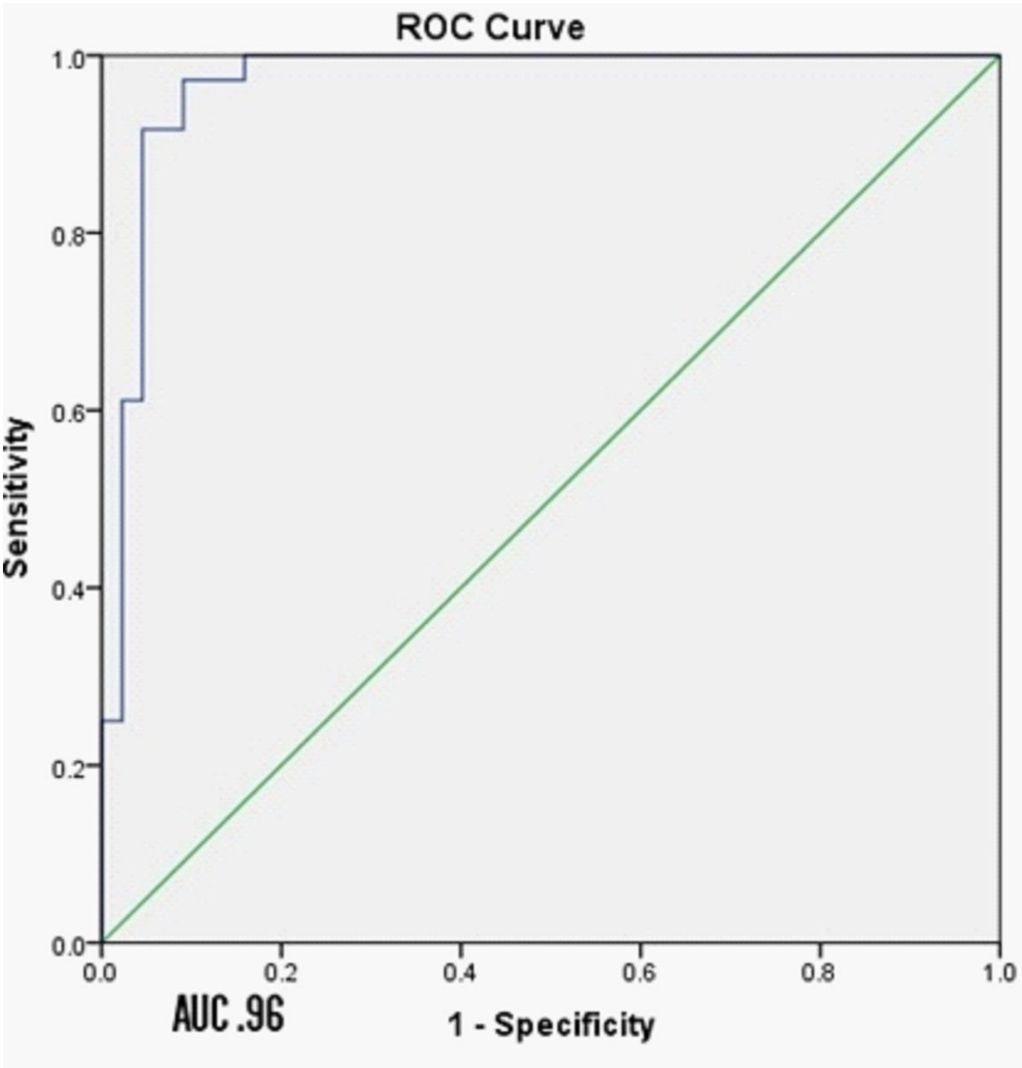
Company Name	Market value of equity (E)	Face value of debt (F)	Risk-free rate (r)	Equity return volatility (σE)	Market value of firm asset (V)	Asset volatility (σ_V)	Expected return on asset (μ_V)	Probability of Default (PD)
Chettinad Cement	986.138	311.775	0.071	0.518	1297.913	0.394	0.957	0.00
Siyaram Silk Mills	327.688	130.885	0.071	0.621	458.573	0.443	1.529	0.00
ECE Industries	209.856	68.34	0.078	0.545	278.196	0.411	1.168	0.00
Hinduja Foundries	237.404	151.745	0.078	0.497	389.149	0.303	0.122	0.00
Sumeet Industries	24.757	81.325	0.076	0.783	106.082	0.183	0.675	0.00
Atul Auto	26.188	29.485	0.072	0.526	55.673	0.247	0.221	0.11
Mahindra Ugine Steel	216.337	423.195	0.072	0.606	639.532	0.205	0.411	0.03
Sutlej Textiles	121.234	545.005	0.072	0.504	666.239	0.092	0.144	0.20
Usher Agro	390.485	201.6	0.079	0.315	592.085	0.208	1.229	0.00
Shasun Pharmaceuticals	252.191	286.52	0.079	0.549	538.711	0.257	0.079	0.00
Salona Cotspin	14.234	40.015	0.079	0.607	54.249	0.159	0.333	0.05
Cords Cables	36.798	140.02	0.079	0.465	176.818	0.097	0.16	0.07
Manjushree Technopack	105.674	119.825	0.084	0.306	225.499	0.143	0.147	0.00
Real Strips	74.003	79.26	0.084	0.386	153.263	0.186	0.113	0.01
Syschem India	27.207	19.495	0.082	0.677	46.702	0.394	0.337	0.39
Kajaria Ceramics	1414.652	401.575	0.082	0.256	1816.227	0.199	0.082	0.00
Sanwaria Agro Oils	941.475	508.115	0.082	0.517	1449.59	0.336	0.082	0.00
Alembic Pharma	1963.394	400.48	0.082	0.387	2363.874	0.322	0.796	0.00
Redington	3141.926	1533.555	0.084	0.428	4675.481	0.288	0.084	0.01

Source: Author's estimation

After estimating objective PD of the companies the Receiver Operating Characteristic (ROC) analysis is performed as a diagnostic check for the estimated PD by BSM model for defaulted and non-defaulted firms.

Figure 1 shows the AUROC curve for estimated PD from BSM model. The value of AUROC is .96, which is in between.9 to 1. Hence, the test is excellent for BSM model which has a good balance of specificity and sensitivity.

Fig 7.1: AUROC BSM Model



Source: Author’s estimation

7.5 Conclusion

The chapter calculates risk-neutral (and objective) probablities or indicator of credit risk that can be used to assess financial distress of firms based upon BSM framework. The empirical finding shows the mean PD estimated from BSM for distressed group (10.43 %) is higher than mean probability of default estimated from non-distressed (0.75 %) companies. The individual PD estimates are calculated using BSM model. The PD for firms registered sick with BIFR is found to have higher PD than non-registered firms. The ROC results show the BSM model calculates significantly higher PD for defaulted and lower PD for non-defaulted groups. The model can be applied to calculate direct PD estimates which can be used by investors and customers to take an informed decision on whether to do business with such companies which are about to default in the near future. Banks and the financial institutions can use the model to predict whether a company is going to default before sanctioning the credit.

CHAPTER 8

SUMMARY, CONCLUSION AND SCOPE FOR FURTHER RESEARCH

8.1 Summary of Study

The current research attempted to answer some of the important questions related to credit risk modeling. On the basis of the objective of the study, the thesis can be broadly classified into three parts. First, re-estimation of various accounting-based models such as Altman's Z-score, Ohlson's logit and Zmijewski's probit models using Indian manufacturing companies' data. The coefficients of original and re-estimated models are tested with reference to change in time period and financial environment. Second, the new bankruptcy prediction model is developed on Indian manufacturing companies' data with a unique combination of financial ratios measuring leverage, profitability and turnover of these companies. The newly proposed hybrid model is compared with original and re-estimated models to choose which model outperforms in the case of Indian manufacturing companies data. Third, the Black-Scholes-Merton (BSM) market-based approach is used to calculate risk neutral probabilities of Indian firms going in for Board for Industrial and Financial (BIFR) reference.

In chapter 2, various Basel Accords and shift in the approaches to assess various types of risk under these accords are discussed. The chapter also gives an idea about the preparedness of Indian regulators towards the new Basel norms. The chapter discusses about the plan of Reserve Bank of India (RBI) to implement Basel III in a phased manner. The various circulars issued by RBI to assess and address various types of risk are also discussed. Limitations of one accord gave birth to others with more promising, stable and resilient banking system. In every accord new changes are introduced in lieu of innovated financial products and their exposure to various types of risks. The later part of the chapter deals with theoretical models to assess credit risk. From time to time there are significant improvements witnessed in the credit risk modeling with improvements through the application of advanced statistical techniques and use of financial ratios, and innovation of new financial products. Different accounting-based and market-based approaches to model credit risk are discussed in detail. Every financial and economic crisis brought new challenges to the practice of risk measurement and management. BIS was formed to take informed decisions relating to management of expanding global financial market and exposure of innovative financial products in the globalized economy.

The literature on credit risk modeling is covered in chapter 3. The credit risk assessment practice is very old. By referring to the literature we can gauge back to 1930's (Fitzpatrick, 1932). In the earlier studies single accounting-based financial ratios were used to assess financial position of a borrower or group of borrowers. With the development of new statistical methods, univariate credit risk models were evolved, including discriminant analysis technique, which was later replaced by multivariate discriminant analysis method. Multivariate Discriminant Analysis (MDA) technique was made popular in the literature of credit risk by Altman (1968). The univariate study of Beaver (1966) is considered as the platform for the development of multivariate credit risk models with more sophisticated statistical techniques. Later logit and probit models were introduced by Ohlson and Zmijewski in the early 80's. All these models are accounting-based models because they use accounting based information to model bankruptcy of the firms. In contrast, various structural-based models were developed using accounting and market based information, e.g. BSM model. With the development of advanced computers various non-parametric models have been developed. These made the study of credit risk more interdisciplinary and uncovered various important dimensions of credit risk modeling. These models include ANN, GA, Hazard models, Fuzzy logic etc.

As regards the Indian market there have been very few studies which attempted to model bankruptcy of the firms. Unlike, US and UK there is no bankruptcy law in India. Hence, it is very difficult for Indian researchers and accounting practitioners to gather data on bankrupt firms. Sick Industrial Companies (Special Provisions) Act, 1985 gave the scope of credit risk modeling in the Indian market. After the formation of BIFR there are several studies which use BIFR reference to classify distressed firms. In the current study as well, BIFR reference is applied in both accounting based and market based models to predict bankruptcy. The survey of literature reveals that there is no study with a large sample size covering distressed and non-distressed firms in the Indian market. The current study has made a humble attempt to bridge the research gap by focusing on checking construct validity of accounting based bankruptcy prediction models such as Altman’s Z-score, Ohlson logit and Zmijewski’s probit models.

The Altman Z-score model is re-estimated using Indian manufacturing companies’ data in chapter 4. The two Z-score models were estimated using data one year and two years prior to bankruptcy. The Z-score model using data one year prior to default gave better predictive accuracy as compared to two years prior model. The overall predictive accuracy for Z-score model 1 is found to be 96.92 percent on estimation sample and 88.46 percent on holdout sample. On the other hand, overall predictive accuracy of Z-score 2 model is found to be 84.46 on estimation sample and 84.62 percent on holdout sample. In case of Z-score model 2 most of the weights of financial ratios were found to be insignificant except retained earnings by total assets (RETA) and book value of equity to book value to total debt (BVEBVD). The movements in the asset value and cumulative profitability were found to be the most significant variables to predict corporate bankruptcy. The most recent year financial information was also found to be most helpful in predicting bankruptcy.

Chapter 5 models default probabilities of Indian manufacturing companies using logit and probit approach. Ohlson’s logit and Zmijewski’s probit models were re-estimated using Indian manufacturing companies data to calculate default probabilities. Two logit and probit models were estimated using data one year and two years prior to default. The overall predictive accuracy for logit one year prior model was found to be 95.38 and 89.74 percent on estimation and holdout sample respectively, whereas for two years prior model it was found to be 85.38 and 80.76 percent on estimation and holdout sample respectively. On the other hand overall predictive accuracy of probit one year prior model was found to be 89.23 and 87.17 percent on estimation and holdout sample respectively, whereas for two years prior model it was found to be 80.76 and 89.74 percent on estimation and holdout sample respectively. The mean PD estimated by logit one and two years prior model for defaulted firms were found to be 92.60 and 80.29 percent respectively, whereas for non-distressed group it was found to be 7.39 and 19.70 percent respectively. The mean PD estimate by probit one year and two years prior model for distressed firms was found to be 83.57 and 85.43 percent respectively. Again in case of logit and probit models we found that most recent year financial information is more helpful in predicting bankruptcy.

In case of re-estimation of all the three accounting based models, we found that re-estimated models gave better predictive accuracy and the most recent year financial information is more helpful in predicting bankruptcy.

The sensitivity of all the three models was tested in chapter 6. This chapter can be broadly divided into three parts. First predicting financial distress of Indian manufacturing firms using all the three original models with original cutoff value and coefficients. Second part deals with development of new hybrid bankruptcy prediction model for Indian manufacturing firms. Third part of the chapter compares original, re-estimated and newly developed hybrid bankruptcy prediction model on the basis of overall predictive accuracy, ROC, secondary sample and long-range accuracy test.

In chapter 7, the risk neutral probability estimates using Board for Industrial and Financial Reconstruction (BIFR) reference were calculated using BSM model. The study was conducted for 80 Indian manufacturing companies consisting of 30 defaulted and 50 non-defaulted firms. The risk neutral probabilities were found to be higher for the firms registered with BIFR.

8.2 Major Findings

The major findings of the study suggest that accounting based models such as Altman's Z-score, Ohlson's logit and Zmijewski's probit models give better predictive accuracy when they are re-estimated with more recent financial information in terms of data. All the three models are sensitive towards change in time period and financial environment in which it was originally estimated. The parameters do not remain constant over a period of time and it supports Platt and Platt (1990) argument that the economic environment of two periods may differ because of change in the relationships between bankruptcy (dependent variable) and financial ratios, movements in the range of financial variables/ratios (independent variables) and changes in the relationship between financial variables/ratios. The study also develops a new hybrid bankruptcy prediction model for Indian manufacturing firms with a unique combination of financial ratios measuring leverage, profitability, and turnover of Indian manufacturing companies. The study found that the industry specific model should be developed with the new combinations of financial ratios to predict bankruptcy of the firms in a particular country. Amongst the contesting models, the new hybrid bankruptcy prediction model outperforms other models. The study further suggests that the coefficients of the models are sensitive to time periods and financial conditions. Hence, researchers should be cautious while choosing the models for bankruptcy prediction to re-estimate the models by looking at the recent data in order to get higher predictive accuracy.

The BSM model gives individual probability estimates for firms using accounting based and market based information. This model is better than other models because large number of Indian companies are not registered into stock exchanges. They trade in OTC market. Hence, market-based information is not available for these companies. Due to limited applicability of this model it cannot be used to calculate default probabilities of all the firms.

8.3 Limitations of Study and Directions for Future Research

This research has studied corporate bankruptcy prediction using data on Indian companies. It is a unique study in the context of Indian manufacturing companies.

Though the results are very encouraging in terms of prediction accuracy, the scope is limited due to certain data related constraints. Unlike USA or UK, where there is a provision to file for corporate bankruptcy with government citing data, which helps researchers to obtain information on default, India does not have such a provision for filing bankruptcy. However, the sick companies in India can register with Board for Industrial & Financial Reconstruction (BIFR) for assistance. Most of the default studies in India are either based on the data provided by BIFR or on information collected from the rating agencies in the absence of actual default related data. This study is limited to the distressed companies registered with BIFR.

Although the study compares distress predictive ability of Z-score model and logit model and estimates PD using BSM model, further research needs to be done to evaluate performance of other bankruptcy prediction models such as artificial neural network model and hazard model. Since macroeconomic factors have strong influence on the performance and financial situation of a firm, corporate bankruptcy can be profitably studied by using such variables. This may increase the predictive ability of the model. The accounting based models used in the study of default can be further enhanced by incorporation of some qualitative variables and macroeconomic parameters.

The current study deals with parametric models to estimate credit risk. It can be extended to non-parametric models such as stochastic, ANN, GA, Hazard, Fuzzy logic DEA etc. to uncover other facets of credit risk modeling and validate the results in a better fashion.

The copula-based modeling techniques can also be employed to estimate joint probability of credit and market risk because they both are interrelated to each other. The separate estimation of both the risks can give overestimated or underestimated value of credit and market risks which is not good for company. If the risk is overestimated, the banks and other corporations have to put larger capital against their exposures. If it is underestimated then those entities can be in trouble in the future because of credit losses.

8.4 Policy Implications of Study

The scope of the study is limited to Indian manufacturing firms because of two reasons: First, majority of companies registered with Board for Industrial and Financial Reconstruction (BIFR) during the period 2006-2014 are manufacturing firms. Second, the report of Ministry of Commerce & Industry Department of Industrial Policy & Promotion (2014) shows there is rise in the trend of sick and closed manufacturing units in India. The study uses ‘sickness’ and ‘bankruptcy’ interchangeably.

Corporate bankruptcy needs to be predicted well before the default time, using financial information of the companies and market variables, with the help of statistical models referred to in this research. The key financial ratios of the companies, which represent liquidity, profitability, solvency, leverage and activity, can be used as useful information to predict bankruptcy. Since bankruptcy can be predicted with the help of the suggested models, especially the new hybrid model, the banks and the financial institutions can predict whether a company is going to become bankrupt or not before sanctioning credit to them. Also, it will be helpful for the investors and customers to take an informed decision on whether to do business with such companies, which are likely to default in the near future. In addition to this, the companies themselves can use such models to predict corporate bankruptcy and estimate Probability of Default (PD) of their own companies as an early warning measure.

As India embarks upon a bankruptcy law which is under consideration by the Parliament, there will be need for highly objective methods to estimate bankruptcy parameters and predict bankruptcy well in advance to guide companies, banks, investors etc. While Altman, Ohlson and Zmijewski models, ANN, Fuzzy logic, non-parametric models need to be applied, the model suggested in this thesis can be a simple, yet robust approach to follow in an environment with constraints of data.

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APPENDIX 1

List of Companies used in Estimation Sample

Sl No.	**Year**	**Category**	**Name of the Company**	**Industry**
1	2006	Distressed	Saurashtra Cements Ltd.	Cement
2	2006	Distressed	Shree Rubber Industries	Miscellaneous
3	2006	Distressed	Gajra Bevel Gears Ltd.	Auto Ancillaries
4	2006	Distressed	Shree Rama Multi-Tech Ltd.	Packing
5	2006	Distressed	Duncans Industries Ltd.	Tea and Coffee
6	2006	Distressed	LML Ltd.	Automobiles
7	2006	Distressed	Shamken Cotsyn Ltd.	Textile-Processing
8	2006	Distressed	Shamken Spinners Ltd.	Textile-Spinning
9	2006	Distressed	Shamken Multifab Ltd.	Textile-Weaving
10	2006	Distressed	Kunststoffe Industries	Plastics
11	2007	Distressed	Sri Jayalakshmi Spinning Mills Ltd.	Textiles-Spinning
12	2007	Distressed	Hotline Glass Ltd.	Glass & Glass Product
13	2007	Distressed	BPL Engineering Ltd.	Electircals
14	2007	Distressed	Rathi Ispat Ltd.	Casting & Forgings
15	2007	Distressed	Nachmo Knitex Ltd.	Textiles-General
16	2007	Distressed	Rubfila International	Rubber
17	2008	Distressed	Indo Gulf Industries Ltd.	Chemicals
18	2008	Distressed	Lime Chemicals Ltd	Chemicals
19	2008	Distressed	Sarda Papers Ltd	Paper
20	2008	Distressed	Micro Forge (India) Ltd.	Casting & Forgings
21	2008	Distressed	Hanjer Fibres Ltd.	Textile-Spinning
22	2008	Distressed	Quantum Digital Vision (India) Ltd.	Packaging
23	2008	Distressed	Bharat Fertiliser Industries Ltd.	Fertiliser
24	2008	Distressed	NRC Ltd.	Textile-Manmade
25	2008	Distressed	Triveni Glass Ltd.	Glass & Glass Products
26	2009	Distressed	Prudential Sugar Corporation Ltd.	Sugar
27	2009	Distressed	Alumeco India Extrusion Ltd.	Aluminium
28	2009	Distressed	Polylink Polymers (India) Ltd.	Petrochemicals
29	2009	Distressed	Nova Petrochemicals Ltd.	Textile-Manmade
30	2009	Distressed	Ganesh Benzoplast Ltd.	Chemicals
31	2009	Distressed	Polar Pharma India Ltd.	Miscellaneous
32	2009	Distressed	Gem Spinners India	Textiles - Spinning - Cotton Blended
33	2010	Distressed	Scooters India Ltd.	Auto - 2 & 3 Wheelers

34	2010	Distressed	Shah Alloys Ltd.	Steel
35	2010	Distressed	Uniflex Cables Ltd.	Power
36	2010	Distressed	Alps Industries Ltd.	Textile
37	2011	Distressed	Agro Dutch Industries Ltd.	Food Processing
38	2011	Distressed	Marksans Pharma Ltd.	Pharmaceuticals
39	2011	Distressed	Amit Spinning Industries Ltd.	Textiles
40	2011	Distressed	NICCO Corporation	Cables - Power & Others
41	2012	Distressed	Abhishek Corporation Ltd.	Textile
42	2012	Distressed	Faze Three Ltd.	Textile-Spinning
43	2012	Distressed	Radha Madhav Corporation Ltd.	Packaging
44	2012	Distressed	Ramsarup Industries Ltd.	Steel
45	2012	Distressed	Gupta Synthetics	Textiles – Processing
46	2012	Distressed	Stelco Strips	Steel - Cr & Hr Strips
47	2013	Distressed	Tamilnadu Jai Bharath Mills Ltd.	Pesticides & Agro Chemicals
48	2013	Distressed	Websol Energy System Ltd.	Miscellaneous
49	2013	Distressed	Shree Bhawani Paper Mills Ltd.	Paper
50	2013	Distressed	Spentex Industries Ltd.	Textiles - Spinning - Cotton Blended
51	2013	Distressed	Gangotri Textiles Ltd.	Textiles - Spinning - Cotton Blended
52	2013	Distressed	SBEC Sugar Ltd.	Sugar
53	2013	Distressed	Indus Fila Ltd.	Textiles – Processing
54	2013	Distressed	Mawana Sugars Ltd.	Sugar
55	2013	Distressed	Euro Ceramics Ltd.	Ceramics & Granite
56	2013	Distressed	Murli Industries Ltd.	Edible Oils & Solvent Extraction
57	2013	Distressed	Surya Pharmaceutical Ltd.	Pharmaceuticals
58	2014	Distressed	Vishal Malleables Ltd.	Castings & Forgings
59	2014	Distressed	Regency Ceramics Ltd.	Ceramics & Granite
60	2014	Distressed	Shri Lakshmi Cotsyn Ltd.	Textiles – Processing
61	2014	Distressed	Moser Baer India Ltd.	Computers – Hardware
62	2014	Distressed	Hindustan Organic Chemicals Ltd.	Chemicals
63	2014	Distressed	Clutch Auto Ltd.	Auto Ancillaries
64	2014	Distressed	Empee Sugar & Chemicals Ltd.	Sugar
65	2014	Distressed	Facor Steels Ltd.	Steel – Large
66	2006	Non-distressed	Chettinad Cement	Cement

67	2006	Non-distressed	Indag Rubber	Miscellaneous
68	2006	Non-distressed	Remsons Industries Ltd.	Auto Ancillaries
69	2006	Non-distressed	Balmer Lawrie And Company	Packing
70	2006	Non-distressed	Assam Company	Tea & Coffee
71	2006	Non-distressed	Scooters India Ltd.	Automobiles
72	2006	Non-distressed	Weizmann Ltd.	Textile-Processing
73	2006	Non-distressed	Eurotex Industries And Exports	Textile-Spinning
74	2006	Non-distressed	Siyaram Silk Mills Ltd.	Textile-Weaving
75	2006	Non-distressed	National Plastic Technologies	Plastics
76	2007	Non-distressed	Amit Spinning Industries	Textiles-Spinning
77	2007	Non-distressed	Empire Industries	Glass & Glass Product
78	2007	Non-distressed	ECE Industries	Electircals
79	2007	Non-distressed	Hinduja Foundries	Casting & Forgings
80	2007	Non-distressed	Aunde India	Textiles-General
81	2007	Non-distressed	Cosco (India)	Rubber
82	2008	Non-distressed	Tanfac Industries Ltd.	Chemicals
83	2008	Non-distressed	National Oxygen	Chemicals
84	2008	Non-distressed	Kay Power And Paper	Paper
85	2008	Non-distressed	Hilton Metal Forging	Casting & Forgings
86	2008	Non-distressed	Salona Cotspin Ltd.	Textile-Spinning
87	2008	Non-distressed	Paramount Print Packing Ltd.	Packaging
88	2008	Non-distressed	Shiva Global Agro Industries	Fertiliser
89	2008	Non-distressed	Nirlon Ltd.	Textile-Manmade
90	2008	Non-distressed	Haldyn Glass	Glass & Glass Products
91	2009	Non-distressed	JK Sugar Ltd.	Sugar
92	2009	Non-distressed	Sacheta Metal Ltd.	Aluminium
93	2009	Non-distressed	Diamines And Chemicals	Petrochemicals
94	2009	Non-distressed	Sumeet Industries	Textile-Manmade
95	2009	Non-distressed	Alkyl Amines Chemicals Ltd.	Chemicals
96	2009	Non-distressed	Sun Pharma Advanced Research Company Ltd.	Miscellaneous
97	2009	Non-distressed	HP Cotton Textiles	Textiles - Spinning - Cotton Blended
98	2010	Non-distressed	Atul Auto	Auto - 2 & 3 Wheelers
99	2010	Non-distressed	Mahindra Ugine Steel Company	Steel
100	2010	Non-distressed	Cords Cable Industries	Power
101	2010	Non-distressed	Sutlej Textiles And Industries	Textile
102	2011	Non-distressed	Usher Agro	Food Processing
103	2011	Non-distressed	Shasun Pharmaceuticals	Pharmaceuticals
104	2011	Non-distressed	Salona Cotspin	Textiles

105	2011	Non-distressed	Cords Cable Industries	Cables - Power & Others
106	2012	Non-distressed	Amarjothi Spinning Mills	Textile
107	2012	Non-distressed	Kandagiri Spinning Mills	Textile-Spinning
108	2012	Non-distressed	Manjushree Technopack	Packaging
109	2012	Non-distressed	Varun Industries	Steel
110	2012	Non-distressed	Vijay Textiles	Textiles – Processing
111	2012	Non-distressed	Real Strips	Steel - Cr & Hr Strips
112	2013	Non-distressed	Syschem India	Pesticides & Agro Chemicals
113	2013	Non-distressed	Nitin Fire Protection Industries	Miscellaneous
114	2013	Non-distressed	Rama Paper Mills	Paper
115	2013	Non-distressed	Loyal Textiles	Textiles - Composite Mills
116	2013	Non-distressed	GTN Industries	Textiles - Spinning - Cotton Blended
117	2013	Non-distressed	Eastern Sugar Industries	Sugar
118	2013	Non-distressed	Mohit Industries	Textiles – Processing
119	2013	Non-distressed	Upper Ganges Sugar	Sugar
120	2013	Non-distressed	Kajaria Ceramics	Ceramics & Granite
121	2013	Non-distressed	Sanwaria Agro Oils	Edible Oils & Solvent Extraction
122	2013	Non-distressed	Alembic Pharma	Pharmaceuticals
123	2014	Non-distressed	Magna Electro Casting	Castings & Forgings
124	2014	Non-distressed	Restile Ceramic	Ceramics & Granite
125	2014	Non-distressed	Nakoda	Textiles – Processing
126	2014	Non-distressed	Redington	Computers – Hardware
127	2014	Non-distressed	Vishnu Chemicals	Chemicals
128	2014	Non-distressed	Talbros Automotive Components	Auto Ancillaries
129	2014	Non-distressed	Piccadilly Agro Industries	Sugar
130	2014	Non-distressed	Steel Exchange Of India	Steel – Large

List of Companies used in Holdout Sample

Sl No.	**Year**	**Category**	**Name Of The Company**	**Industry**
1	2006	Distressed	Unimin India Ltd.	Plastic

2	2006	Distressed	Digital Multiforms Ltd.	Printing & Stationary
3	2006	Distressed	Midland Plastics Ltd.	Plastic
4	2006	Distressed	Computerskill	Printing & Stationery
5	2006	Distressed	HMT	Auto – Tractors
6	2007	Distressed	Polar Industries Ltd.	Domestic Appliances
7	2008	Distressed	Gwalior Polypipes Ltd.	Chemicals
8	2008	Distressed	Oxford Industries Ltd.	Weaving
9	2008	Distressed	Arora Fibres Ltd.	Textile-Manmade
10	2009	Distressed	Scanpoint Geomatics Ltd.	Consumer Goods-Electronics
11	2009	Distressed	Tuticorin Alkali Chemicals & Fertilisers Ltd.	Chemicals
12	2009	Distressed	MP Telelinks Ltd.	Cables-Telephone
13	2009	Distressed	Rainbow Denim Ltd.	Readymade Apparels
14	2010	Distressed	Shree Ganesh Forgings	Castings & Forgings
15	2010	Distressed	Modern Syntex (India)	Textiles - Synthetic & Silk
16	2010	Distressed	Venus Sugar	Sugar
17	2011	Distressed	Modern Dairies Ltd.	Food Processing
18	2011	Distressed	KDL Biotech Ltd.	Pharmaceuticals
19	2011	Distressed	Blue Bird (India) Ltd.	Printing & Stationary
20	2011	Distressed	Grand Foundary	Steel - Medium & Small
21	2012	Distressed	Kanco Enterprises Ltd.	Textiles
22	2012	Distressed	Faze Three Ltd.	Textile-Spinning
23	2012	Distressed	Vikash Metal & Power Ltd.	Sponge Iron
24	2012	Distressed	Saffron Industries Ltd.	Paper

25	2012	Distressed	Kitply Industries	Miscellaneous
26	2012	Distressed	STL Global	Textiles – General
27	2013	Distressed	Excel Glasses Ltd.	Glass
28	2013	Distressed	AIMCO Pesticides Ltd.	Pesticides & Agro Chemicals
29	2013	Distressed	ENSO Secutrack Ltd.	Consumer Goods – Electronic
30	2013	Distressed	Avon Corporation Ltd.	Engineering
31	2013	Distressed	ICSA (India) Ltd.	Computers - Software
32	2013	Distressed	Shakti Press Ltd.	Printing & Stationery
33	2013	Distressed	Farmax India Ltd.	Trading
34	2014	Distressed	Mount Shivalik Industries Ltd.	Breweries & Distilleries
35	2014	Distressed	Hindustan Motors Ltd.	Auto - Cars & Jeeps
36	2014	Distressed	Kinetic Engineering Ltd.	Auto - 2 & 3 Wheelers
37	2014	Distressed	Zenith Computers Ltd.	Computers - Hardware
38	2014	Distressed	Jyoti Ltd.	Electric Equipment
39	2014	Distressed	Eastern Silk Industries Ltd.	Textiles - Synthetic & Silk
40	2006	Non-distressed	Peacock Industries Ltd	Plastic
41	2006	Non-distressed	Orient Press	Printing & Stationary
42	2006	Non-distressed	Tokyo Plast International	Plastic
43	2006	Non-distressed	Archies	PRINTING & STATIONERY
44	2006	Non-distressed	VST Tillers Tractors	Auto – Tractors
45	2007	Non-distressed	Panasonic Home Appliances India Company Ltd	Domestic Appliances
46	2008	Non-distressed	Jyoti Resins And Adhesives	Chemicals

47	2008	Non-distressed	Orbit Exports	Weaving
48	2008	Non-distressed	Zenith Fibres	Textile-Manmade
49	2009	Non-distressed	Photoquip (India) Ltd	Consumer Goods-Electronics
50	2009	Non-distressed	Chemfab Alkalies	Chemicals
51	2009	Non-distressed	Surana Telecom And Power	Cables-Telephone
52	2009	Non-distressed	Zodiac Clothing Company Ltd	Readymade Apparels
53	2010	Non-distressed	Akar Tools	Castings & Forgings
54	2010	Non-distressed	Shree Ram Urban Infrastructure	Textiles - Synthetic & Silk
55	2010	Non-distressed	Dhampure Specialty Sugars	Sugar
56	2011	Non-distressed	ADF Foods Industries	Food Processing
57	2011	Non-distressed	Celestial Labs	Pharmaceuticals
58	2011	Non-distressed	Navneet Publications	Printing & Stationary
59	2011	Non-distressed	Hindustan Wires	Steel - Medium & Small
60	2012	Non-distressed	Arrow	Textiles
61	2012	Non-distressed	Kandagiri Spinning Mills	Textile-Spinning
62	2012	Non-distressed	Tata Sponge Iron	Sponge Iron
63	2012	Non-distressed	Shreyans Industries	Paper
64	2012	Non-distressed	Bharatiya Global Infomedia	Miscellaneous
65	2012	Non-distressed	Sudar Industries	Textiles – General
66	2013	Non-distressed	Sezal Glass	Glass
67	2013	Non-distressed	Kilpest India	Pesticides & Agro Chemicals
68	2013	Non-distressed	Sharp India	Consumer Goods – Electronic
69	2013	Non-distressed	Virat Crane Industries	Engineering

70	2013	Non-distressed	Zensar Technologies	Computers - Software
71	2013	Non-distressed	Beckons Industries	Printing & Stationery
72	2013	Non-distressed	Visagar Polytex	Investment And Finance
73	2014	Non-distressed	Winsome Breweries	Breweries & Distilleries
74	2014	Non-distressed	Automobile Corporation Of Goa	Auto Ancillaries
75	2014	Non-distressed	Majestic Auto	Auto - 2 & 3 Wheelers
76	2014	Non-distressed	Allied Computers International (Asia)	Computers - Software Medium & Small
77	2014	Non-distressed	Modison Metals	Electrical Equipment
78	2014	Non-distressed	APM Industries	Textiles - Spinning - Synthetic Blended

APPENDIX 2

BSM Model Summary- All Distressed Companies

Company Name	**E**	**F**	**R**	**σE**	**V**	σ_V	μ_V	**PD**
Shree Rama Multi-Tech Ltd.	50.445	201.055	0.071	0.599	251.5	0.12	0.071	3.96
Duncans Industries Ltd.	100.325	903.085	0.071	0.545	1003.41	0.054	0.071	2.99
Shamken Cotsyn Ltd.	2.481	65.1	0.071	0.773	67.581	0.028	0.071	13.41
Shamken Spinners Ltd.	9.133	121.505	0.071	0.561	130.638	0.039	0.071	3.58
Shamken Multifab Ltd.	6.049	152.345	0.071	0.669	158.394	0.026	0.071	7.79
Kunststoffe Industries	1.742	15.685	0.071	1.021	17.427	0.102	0.071	29.46
Sri Jayalakshmi Spinning Mills Ltd.	5.856	36.11	0.078	0.841	41.966	0.117	0.078	16.45
Hotline Glass Ltd.	17.28	87.605	0.078	0.605	104.885	0.1	0.078	4.43
Rathi Ispat Ltd.	9.429	148.32	0.078	0.763	157.749	0.046	0.078	12.75
Nachmo Knitex Ltd.	4.584	38.88	0.078	0.824	43.464	0.087	0.078	16
Lime Chemicals Ltd	2.695	31.945	0.079	0.57	34.64	0.044	0.079	3.74
Micro Forge (India) Ltd.	9.928	26.85	0.079	0.604	36.778	0.163	0.079	3.45
Hanjer Fibres Ltd.	3.313	24.07	0.079	0.661	27.383	0.08	0.079	7.03
NRC Ltd.	60.982	292.82	0.079	0.624	353.802	0.107	0.079	5.02
Triveni Glass	27.509	96.44	0.079	0.646	123.949	0.143	0.079	5.36

Alumeco India Extrusion Ltd.	5.777	21.19	0.076	0.764	26.967	0.164	0.076	3.45
Polylink Polymers (India) Ltd.	1.799	14.64	0.076	0.627	16.439	0.069	0.076	5.71
Nova Petrochemicals Ltd.	35.1	146.805	0.076	0.769	181.905	0.148	0.076	11.37
Ganesh Benzoplast Ltd.	4.978	183.99	0.076	3.36	188.968	0.089	0.076	98.96
Gem Spinners India	17.583	57.3	0.076	0.829	74.883	0.195	0.076	13.88
ALPS Industries Ltd.	38.276	674.205	0.072	0.559	712.481	0.03	0.072	3.51
Agro Dutch Industries Ltd.	50.614	343.72	0.079	0.584	394.334	0.075	0.079	4.77
Amit Spinning Industries Ltd.	14.533	61.57	0.079	0.632	76.103	0.121	0.079	5.14
Gupta Synthetics	4.044	168.375	0.084	0.736	172.419	0.017	0.084	9.95
Stelco Strips	3.796	46.775	0.084	0.719	50.571	0.054	0.084	10.11
Tamil Nadu Jai Bharath Mills Ltd.	6.415	54.68	0.082	0.679	61.095	0.071	0.082	7.95
Websol Energy System Ltd.	15.93	427.8	0.082	0.569	443.73	0.02	0.082	3.42
Shree Bhawani Paper Mills Ltd.	14.279	142.205	0.082	0.655	156.484	0.06	0.082	6.97
Spentex Industries Ltd.	31.372	476.975	0.082	0.582	508.347	0.036	0.082	4.11
Gangotri Textiles Ltd.	7.143	204.125	0.082	0.709	211.268	0.024	0.082	9.27
Euro Ceramics Ltd.	14.861	361.16	0.082	0.665	376.021	0.026	0.082	7.26

Murli Industries Ltd.	61.292	972.475	0.082	0.703	1033.767	0.042	0.082	9.36
Surya Pharmaceutical Ltd.	23.316	1128.31	0.082	0.664	1151.626	0.013	0.082	6.17
Regency Ceramics Ltd.	5.791	153.17	0.084	0.649	158.961	0.024	0.084	6.39
Shri Lakshmi Cotsyn Ltd.	41.368	1760.195	0.084	0.603	1801.563	0.014	0.084	3.96
Empee Sugar & Chemicals Ltd.	21.826	416.985	0.084	0.692	438.811	0.034	0.084	8.66

BSM Model Summary- All Non-Distressed Companies

Company Name	**E**	**F**	**R**	**σE**	**V**	σ_V	μ_V	**PD**
Chettinad Cement	986.138	311.775	0.071	0.518	1297.913	0.394	0.957	0.00
Remsons Industries ltd	13.03	22.32	0.071	0.58	35.35	0.214	0.239	0.27
Balmer Lawrie and Company	948.741	283.485	0.071	0.449	1232.226	0.345	0.885	0.00
Scooters India Ltd	112.639	63.76	0.071	0.699	176.399	0.447	0.422	0.23
Weizmann Ltd	30.095	83.595	0.071	0.574	113.69	0.152	0.071	2.70
Eurotex Industries and Exports	35.394	84.515	0.071	0.474	119.909	0.14	0.071	0.71
Siyaram Silk Mills Ltd	327.688	130.885	0.071	0.621	458.573	0.443	1.529	0.00
Amit Spinning Industries	26.719	52.985	0.078	0.449	79.704	0.15	0.078	0.37
Empire Industries	178.2	64.355	0.078	0.614	242.555	0.451	0.091	0.25
ECE Industries	209.856	68.34	0.078	0.545	278.196	0.411	1.168	0.00
Hinduja Foundries	237.404	151.745	0.078	0.497	389.149	0.303	0.122	0.00

National Oxygen	12.826	7.08	0.079	0.71	19.906	0.457	0.079	1.97
Shiva Global Agro Industries	11.828	9.815	0.079	0.689	21.643	0.377	0.291	0.70
Nirlon Ltd	386.561	166.23	0.079	0.626	552.791	0.438	0.343	0.08
Haldyn Glass	36.254	43.445	0.079	0.667	79.699	0.303	0.23	1.05
Diamines and Chemicals	14.707	28.315	0.076	0.643	43.022	0.22	0.076	3.91
Sumeet Industries	24.757	81.325	0.076	0.783	106.082	0.183	0.675	0.00
Atul Auto	26.188	29.485	0.072	0.526	55.673	0.247	0.221	0.11
Mahindra Ugine Steel Company	216.337	423.195	0.072	0.606	639.532	0.205	0.411	0.03
Sutlej Textiles and Industries	121.234	545.005	0.072	0.504	666.239	0.092	0.144	0.20
Usher Agro	390.485	201.6	0.079	0.315	592.085	0.208	1.229	0.00
Shasun Pharmaceuticals	252.191	286.52	0.079	0.549	538.711	0.257	0.079	0.00
Salona Cotspin	14.234	40.015	0.079	0.607	54.249	0.159	0.333	0.05
Cords Cable Industries	36.798	140.02	0.079	0.465	176.818	0.097	0.16	0.07
Amarjothi Spinning Mills	27.675	65.755	0.084	0.581	93.43	0.172	0.084	2.75
Kandagiri Spinning Mills	29.445	79.125	0.084	0.577	108.57	0.156	0.084	2.67
Manjushree Technopack	105.674	119.825	0.084	0.306	225.499	0.143	0.147	0.00
Varun Industries	242.956	1237.115	0.084	0.57	1480.071	0.094	0.084	3.25
Real Strips	74.003	79.26	0.084	0.386	153.263	0.186	0.113	0.01
Syschem India	27.207	19.495	0.082	0.677	46.702	0.394	0.337	0.39
Nitin Fire Protection Industries	1299.057	148.315	0.082	0.449	1447.372	0.403	0.301	0.00
Loyal Textiles	74.768	452.33	0.082	0.434	527.098	0.062	0.082	0.62

Mohit Industries	58.331	62.17	0.082	0.513	120.501	0.248	0.738	0.00
Kajaria Ceramics	1414.652	401.575	0.082	0.256	1816.227	0.199	0.082	0.00
Sanwaria Agro Oils	941.475	508.115	0.082	0.517	1449.59	0.336	0.082	0.00
Alembic Pharma	1963.394	400.48	0.082	0.387	2363.874	0.322	0.796	0.00
Magna Electro Casting	27.675	28.475	0.084	0.566	56.15	0.279	0.084	0.99
Restile Ceramic	49.041	35.785	0.084	0.597	84.826	0.345	0.124	0.65
Nakoda	326.7	943.945	0.084	0.544	1270.645	0.14	0.136	0.83
Redington	3141.926	1533.555	0.084	0.428	4675.481	0.288	0.084	0.01
Vishnu Chemicals	102.497	225.165	0.084	0.616	327.662	0.193	0.084	3.38
Talbros Automotive Components	49.137	146.085	0.084	0.534	195.222	0.135	0.084	1.82
Piccadilly Agro Industries	104.953	135.245	0.084	0.738	240.198	0.323	0.298	1.43
Steel Exchange of India	297.414	854.765	0.084	0.524	1152.179	0.135	0.084	1.58