MODELING CREDIT AND OPERATIONAL RISKS OF INDIAN COMPANIES AS PER BASEL II NORMS

A Thesis submitted during 2014 to the University of Hyderabad in partial fulfillment of the award of a Ph.D. degree in Economics

By

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CERTIFICATE

This is to certify that the thesis entitled "**Modeling Credit and Operational Risks of Indian Companies as per Basel II Norms"** submitted by **Nilambar Mishra** bearing Regd. No. 04SEPH14 in partial fulfilment of the requirements for the award of Doctor of Philosophy in Economics is a bonafide work carried out by him under my supervision and guidance. The thesis has not been submitted previously in part or in full to this or any other university or institution for the award of any degree or diploma.

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DECLARATION

I hereby declare that the thesis entitled "**Modeling Credit and Operational Risks of Indian Companies as per Basel II Norms**" submitted by me under the supervision of **Prof. Vathsala Narasimhan** is a bonafide research work. I also declare that it has not been submitted previously in part or in full to this university or any other university or institution for the award of any degree or diploma.

Date:

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Dedicated
To
My Parents

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Nilambar Mishra

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ABBREVIATIONS

A-D: Anderson-Darling
AMA: Advanced Measurement Approach
ASA: Alternative Standardized Approach
BBL: Basel Business Line
BCBS: Basel Committee on Banking Supervision
BEICF: Business Environment and Internal Control Factor
BIA: The Basic Indicator Approach
BIFR: Board for Industrial & Financial Reconstruction
BIS: Bank for International Settlement
BSE: Bombay Stock Exchange
BSM: Black-Schole-Merton
BVE: Book Value of Equity
CAR: Capital Adequacy Ratio
CDF: Cumulative Distribution function
DD: Distance to Default
EAD: Exposure at Default
EBITDA: Earnings before Interest, Taxes, Depreciation, and Amortization
EC: Economic Capital
ECAI: External Credit Assessment Institutions
EDA: Exploratory Data Analysis
EDF: Expected Default Frequency
EI: Exposure Indicator
EVT: Extreme Value Theory
GNP: Gross National Product
GOF: Goodness-of-Fit
GPD: Generalized Pareto Distribution
IID: Independently and Identically Distributed
IRB: Internal Rating Based Approach
KRI: Key risk Indicator
K-S: Kolmogorov-Smirnov
LDA: Loss Distribution Approach
LGD: Loss Given Default
MDA: Multivariate Discriminant Analysis
MEP: Mean Excess Plot
MLE: Maximum Likelihood Estimation
MVE: Market Value of Equity
NSE: National Stock Exchange
OCC: Office of the Comptroller of the Currency
OECD: Organisation for Economic Co-operation and Development
OpVaR: Operational Value at Risk
ORC: Operational Risk Category
ORM: Operational Risk Management
ORRC: Operational Risk Regulatory Capital
OTC: Over the Counter
PD: Probability of Default
POT: Peak over Threshold
P-P: Probability-Probability
PSE: Public-Sector Entity
Q-Q: Quantile-Quantile
RBI: Reserve Bank of India
RCSA: Risk and Control Self Assessment
RE: Retained Earnings
RR: Recovery Rate
RWA: Risk Weighted Asset
SME: Small and Medium Enterprises
TA: Total Assets
TL: Total Liabilities
TSA: The Standardized Approach
UGD: Usage Given Default
WC: Working Capital

CHAPTER 1

INTRODUCTION, BACKGROUND AND OBJECTIVES OF THE STUDY

1.1 Introduction

In the context of finance, risk can be defined as exposure to an adverse situation that could lead to a financial loss. Risk cannot be defined as a single concept; its meaning varies depending on the environment where it is used. Every activity in our day to day life involves certain amount of risks, whether financial or non-financial in nature. Financial risk is something which directly affects the financial position of an individual or an organization. Individuals manage their risks through taking informed decisions before performing any activity. However, an institution, by its very definition of being an aggregation of individuals, must manage risks in a somewhat different manner: it must adopt the 'take-informed-decisions-before-performing-any activity' principle in a systematic way. This approach to risk management, especially for a financial institution, is also driven by the fact that it deals with public funds and works under a regulated environment.

Banks, especially, are highly leveraged financial institutions that take money in the form of deposits from individuals to further their goals of giving loans and investing. Therefore, it is their prime responsibility to safeguard their depositors' money under any adverse circumstance. For banking institutions, since they deal with the most important 'commodity' that fuels the entire economy - 'money' - risk management therefore becomes paramount. The impact of any adverse situation faced by the banking industry can be large and affect all the other industries - retail trade, wholesale trade, services, infrastructure, construction, transportation, agriculture etc. This underscores the tremendous importance of risk management to the banking sector/ industry. Thus, the highest responsibility is cast on banks, and their national regulator, to have a robust risk management system in place to address unforeseen adverse situations. For this reason, regulators attribute great importance to the effectiveness and stability of risk management in banks.

In comparison with non-banking-institutions (like fast-moving consumer goods (FMCG), oil exploration, trading, shipping manufacture, real estate, commodities, etc.), the pace of seamless interconnectedness of every activity and industry in the economy on the one hand and the banking industry on the other hand is very high. Today, with a high degree and fast rate of technological development lead by the internet and mobile revolution, national borders are irrelevant and the movement of money and creation of credit is instantaneous. Consequently, banks getting into risky situations in one country or continent can have a cascading effect in many countries across the globe. This provides another overriding rationale for adoption of the best practices in risk management by banking institutions

Banks work in a diversified manner, and offer multiple products and services to multiple individuals, corporates, financial institutes, 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 in the business, given the presence of a strong global competition. These activities and processes expose banks to various risks, namely, credit risk, market risk, operational risk, strategic risk, reputational risk, liquidity risk, etc. Amongst them, credit, market and operational risks are the primary and major risk types that bank faces frequently. These primary risks directly affect the financial position of the banks and if not managed properly, can lead to a disastrous situation for the bank. It is for this reason that the banking regulators of different countries globally and Bank for International Settlement (BIS)[1], focus primarily on these three types of risks. One of the significant measures that the Basel Committee had introduced during late '80s for solvency of the banks is to maintain minimum regulatory capital, which is otherwise known as capital adequacy ratio (CAR)[2]. The capital adequacy ratio for the bank considers these three types of risks.

The Basel Committee on Banking Supervision (BCBS), which is also known in short as Basel Committee, formulates guidelines for commercial banks and regulators for an effective

[1] BIS was established on 17 May 1930 to serve central banks in their pursuit of monetary and financial stability, to foster international cooperation in those areas and to act as a bank for central banks. The head office of BIS is in Basel, Switzerland.

[2]CAR is the minimum capital to risk weighted asset ratio that every bank is required to maintain as per the regulatory direction. As per Basel II Accord, CAR is 8%.

risk management framework. BCBS has been continuously trying to formulate various measures in consultation with the central banks of its member countries to monitor and control different risks faced by the banks. The first guideline of BCBS pertaining to credit risk management was circulated in 1988, which was known as Basel I Accord. This Accord primarily focused on measurement and monitoring of only credit risk. It prescribed a CAR of 8%. The Accord defined different weights for different types of credit exposure to arrive at risk weighted asset (RWA). Subsequently, market risk was included in the computation of minimum CAR of the bank as per the amendment made to the Accord during '90s.

Some of the high profile risk events during '90s, which posed challenges to the risk management framework in the banks, and emergence of new types of risk, forced the committee to revisit the existing approaches. After a series of meetings and consultations, the Basel committee came up with a new Accord in 2004, which is popularly known as Basel II Accord. The new Accord addressed various limitations of the old Accord and most importantly, it included operational risk management in the ambit of minimum CAR for the bank. Hence, as per the Basel II Accord, banks are required to maintain minimum CAR considering credit, market and operational risks. The new Accord increased capital requirement for the bank, which is indeed good for the customers and shareholders, since a higher capital buffer will minimize the chance of being insolvent. Subsequent to the circulation of Basel II guideline, the Reserve Bank of India (RBI) notified all the commercial banks in India to implement Basel II Accord within a stipulated timeframe.

The first pillar of the three pillar based Basel II Accord is the estimation of minimum capital requirement for credit, operational and market risks. The other two pillars are supervisory review process and market discipline. Credit risk arises when the counterparty fails to meet its financial contractual debt obligation towards the bank. In simple language, when the customer of a bank does not repay principal or interest of a loan, it leads to a credit loss to the bank. Market risk arises due to changes in market related variables such as interest rate, foreign exchange rate, price level, etc. Operational risk is faced by each organization, both financial and non-financial. This type of risk arises due to failed or inadequate process, people and system, or from external events. The ambit of operational risk is broader than credit and market risk, since it covers all activities of the bank unlike the other two types of risks. Measuring these risks is crucial for an effective risk management framework, since it has direct implications for the capital buffer that the bank should maintain to remain solvent during unforeseen adverse circumstances. Hence the modeling of credit, operational and market risks is the foremost activity of the banks for a better risk management framework.

Basel II Accord defines a set of risk measurement methods starting from standard approaches to advanced approaches. For credit risk, it defines Standardized and Internal Rating Based (IRB) approaches. IRB approach is the most risk sensitive approach. For operational risk measurement, the Accord defines three approaches: The Basic Indicator Approach, the Standardized Approach and the Advanced Measurement Approach (AMA). AMA is the most risk sensitive approach since it uses actual losses of the bank, whereas the other two approaches use gross income of the bank to compute operational risk capital charge. For market risk, it defines standardized approach and internal rating based approach.

After the implementation of Basel II Accord, there has been felt a growing importance of modeling credit, operational and market risks. The inter-dependence of the world of finance with the entire economy of countries was forcefully proved in 2007-08 with the collapse of Lehman and the sub-prime crisis, the effect of which reverberated around the globe impacting all types of countries and political affiliations viz. rich or developed, or poor or emerging, communist or democratic or monarchies. The impact so wide spread that new words like ‘contagion’ were coined and the BIS was shaken up once again and started re-looking at Basel II and thus Basel III was born.

Banks are continuously trying to use sophisticated modeling techniques to predict probability of default of a borrower, which is one of the major components of credit risk modeling, before sanctioning any credit. The traditional approach of measuring probability of default of a customer was based on expert judgment and qualitative assessment. The further development in modeling techniques came up by using various statistical models, starting from accounting based models and going on to market based models. Accounting based models use financial information of a company available in the balance sheet and income statement of the company, to predict probability of default; whereas, market based models use various market information related to stock data, bond data along with financial information, to predict probability of default.

However, while the modeling for credit and market risks continued to evolve over the years, modeling operational risk was a relatively new concept for banks. Though there is no clear regulatory direction as far as operational risk modeling is concerned, banks globally are adopting various modeling techniques to compute operational risk capital based on advanced measurement approach. There is no published literature available on operational risk management and modeling techniques used for operational risk in India. None of the Indian banks so far have implemented AMA for operational risk capital computation; hence there is an urgent need to have literature on the practical aspects, challenges in the modeling techniques. This study tries to carry out a detailed analysis of modeling aspects and statistical techniques used for it, and is therefore, an humble attempt towards making up for this lacuna.

1.2 Objectives of the Study

Given the significance of risk management in the banking sector, there has been a continuous development of research and modeling techniques for measuring various risks. Researchers are focusing on the correct measurement of those risks using alternative measurement techniques. The two most significant risks in the banking sector are credit and operational risks. There are different models used to measure the probability of default of a company, i.e., the credit risk. There are accounting based models, such as Altman's Z-score model, and Ohlson's logit model; and there is also the well-known market based model due to Black, Schole and Merton. However, modeling for operational risk is still a relatively grey area. The present study focuses on two types of risks namely credit and operational. It applies different models to measure the credit risk, and compares their predictive ability. It also presents a study of the AMA for computing capital charge for operational risk. The objectives of the study may be spelt out more specifically as follows:

1. To predict corporate bankruptcy of Indian companies using two well-known and widely used accounting based models namely, Altman's Z-Score model and Ohlson's logit model.

2. To compare default predictive ability of the Altman model and Ohlson model. Also, to examine model predictive ability using data one year and two years prior to bankruptcy.

3. To predict probability of default of Indian companies using the market based model developed by Black, Schole and Merton.

4. To analyze operational risk management framework as per Basel II Accord as prescribed by Basel Committee on Banking Supervision (BCBS) and explicate various methods used for computing operational risk capital requirement.

5. To compute operational risk capital charge using Advanced Measurement Approach (AMA). Since, unlike credit and market risks operational risk management in the banking sector is comparatively new and evolving, the study aims to analyze AMA in detail along with presenting the computational process using a sample loss database.

1.3 Methodology of the Study

Since the study deals essentially with measurement, the methodology is econometric. The particular method used is specific to each model. Altman’s Z-Score model for bankruptcy prediction is based on multivariate discriminant analysis (MDA). MDA is based on the linear combination of some of the dependent variables that will discriminate best between default and non-default groups. The Z-score for each of the firms are obtained from the linear discriminant model and compared with the cut off value. Then, a particular firm will be classified as distressed or non-distressed depending on the value of the Z-score. Cut off value for Z-Score model is decided where sum of type I and type II errors are minimum. Two Z-Score models are estimated using data one year prior to bankruptcy and two years prior to bankruptcy respectively and the predictive ability of these models is compared.

Ohlson’s model for bankruptcy prediction is based on logit model, where the dependent variable is binary in nature. The dependent variable takes value 1 in case of distressed firms and 0 in case of non-distressed firms. The estimated logit model yields a score between zero and one for each of the firms, which can be interpreted as probability of default. The study estimates two logit models using financial data one year prior to bankruptcy and two years prior to bankruptcy, to examine distress predictive ability of the two models. Like in the Altman model, the cutoff point is identified where sum of type I and type II errors is minimum. The predictive ability of the Altman and Ohlson models are compared by estimating sum of type I and type II errors and correct prediction percentage.

The study also examines predictive ability of the Black-Schole-Merton (BSM) model. Unlike the accounting based models of Altman and Ohlson, 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.

Operational risk capital charge under Advanced Measurement Approach (AMA) is calculated using Loss Distribution Approach (LDA). Monte-Carlo simulation technique is used to simulate loss frequency and severity to arrive at aggregated loss distribution. Separate statistical distributions are fitted to frequency and severity data. Distributions used to model severity data are identified on the basis of available literature. A set of continuous distributions like Lognormal, Weibull, Exponential and Gamma are tested to model severity data, while a discrete distribution, namely the Poisson distribution is used to model severity data. Graphical exploratory data analysis like Quantile-Quantile (Q-Q) plot and Probability-Probability (P-P) plot and goodness-of-fit test like Kolmogorov-Smirnov (K-S) test are used to identify the best-fit distribution.

The study uses Extreme Value Theory (EVT) to model tail events. In the presence of extreme events in the database, one single statistical distribution may not be a good fit for the entire database. In such a case, body and tail should be modeled separately. The study uses Peak over Threshold Approach (POT) to model tail events. An EVT threshold is identified using Mean Excess Plot (MEP), above which losses are modeled through Generalized Pareto Distribution (GPD). Single loss approximation method is used in the study to model operational risk category where the presence of a single extreme event causes major changes in the estimate of the parameters of the distribution. In such a case, simulation based Operational Value at Risk (OpVaR) may not provide a correct estimate of operational risk capital. Modeling tail events using a closed form solution like single loss approximation method will provide a better result.

1.4 Nature and Sources of Data

In order to examine bankruptcy predictive ability of Altman's Z-Score model and Ohlson's logit model, the study uses various financial ratios used in the original models. Financial ratios used in these models represent liquidity, profitability, leverage, solvency, activity/size and growth of the companies. Bankruptcy data in India is not systematically available unlike in the US or UK. However, the study identified distressed firms from the list of firms registered in Board for Industrial & Financial Reconstruction (BIFR) as sick firms during 2006 to 2012. A set of matched non-distressed companies are identified randomly on the basis of asset size and industry type. More than 500 sick companies are registered in BIFR during this period. Amongst them, the study shortlisted 62 sick companies on the basis of availability of financial data (balance sheet and profit and loss data) for historical period. A total of 124 companies comprising distressed and non-distressed companies are used for accounting based models. However, for Black-Schole-Merton (BSM) model, the study uses a total of 80 companies comprising distressed and non-distressed companies, since historical stock data of some of the distressed companies are not available.

Financial information of the companies is collected from their balance sheet and profit and loss statement. Balance sheet and income statements of the companies at the end of each year are collected from Bloomberg, Money Control, Rediff Money and from other online sources. Stock prices of the listed companies are collected from Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) website and Money Control website. Gross National Product (GNP) data used in logit model is collected from the Economic Survey 2010-11 report. Information related to risk free return is collected from RBI publication.

In order to study the computational aspects of AMA capital for operational risk, the study uses hypothetical loss data for four operational risk categories (ORCs). Actual loss data of the banks due to operational risks are very confidential information for the bank, which is not available publicly. Also in India, there is no publicly available external database, which can be used for the analysis by the researchers. Due to the difficulty in obtaining actual losses of banks, the study created a hypothetical database, which follows a similar pattern that a typical loss database should follow. The period of the study is considered as 1-Apr-2008 to 31-Mar-2011.

The loss data used for the analysis in four ORCs represent behavior and nature of operational losses that banks usually experience.

1.5 Organization of the Study

The study is organized into eight chapters including the present one. The present chapter introduces the study, briefs the scope and objectives, various methodology used and nature and source of data used for the study. Chapter 2 discusses the elements of Basel II Accord and how it evolved, and how it addresses various major risks faced by the banks. It also briefly discusses different types of risks that a bank faces.

Chapter 3 discusses Basel II and credit risk management and various credit risk models used by the bank briefly. It details three bankruptcy prediction models used in this study. We have also reviewed some of the important studies conducted by researchers and academicians related to credit risk modeling.

The estimation procedures and empirical results obtained from credit risk models are presented in Chapter 4. We have discussed statistical and econometric tools used to estimate these models and the resultant output is compared to study predictive ability of various models to predict corporate bankruptcy. We have also estimated probability of default for a set of both distressed and non-distressed companies using BSM model of distress prediction.

Chapter 5 of the study deals with operational risk management framework as per the Basel II norms. Various components of operational risk management and methods prescribed by the Basel Committee to compute operational risk capital charge are discussed in this chapter.

Chapter 6 discusses Advanced Measurement Approach (AMA) in detail for operational risk management. It discusses the modeling aspects involved in computation of AMA capital for a bank. Various modeling techniques used to compute operational risk capital charge, and back testing of models, are discussed here. The chapter also deals with modeling of tail events, scenario analysis and qualitative adjustment of capital estimates. We have also reviewed some of the relevant literature, which shows the operational risk management practices followed by various banks and research work on modeling of operational risk.

Chapter 7 empirically examines the modeling techniques that can be used to compute operational risk capital charge under Advanced Measurement Approach, using loss data of four operational risk categories (ORCs). This chapter discusses the details of the statistical tools used for distribution fitting, and results obtained from various ORCs, using different modeling techniques. Finally, chapter 8 concludes the thesis with a summary of the study followed by limitations of the study and scope for further research.

CHAPTER 2

RISK MANAGEMENT AND BASEL ACCORDS

2.1 Introduction

Rising global competition, multi-fold business expansion and innovative delivery channels have exposed banks to various risks, both financial and non-financial. Banks deal with number of risks during the day to day activities carried out by them. It can be credit risk, market risk, liquidity risk, operational risks (people and/or process related risk, technology risk, external risk), reputational risk, strategic risk, etc. Of these, the major risks faced by the banks are credit, market and operational risks. These risks can put a bank in a very difficult situation if they are not managed - identified, assessed, measured & monitored - on an ongoing basis. On occasion, a bank may even be forced to shut down its business. With the global economic interdependence between countries, bank failures can have a large scale cascading impact on the economic health of countries beyond their borders. Both banks and regulators are therefore, required to take prompt and appropriate measures to address these critical risks. A bank's prime responsibility thus becomes management of these risks. The bank should have a dedicated risk management unit in place to take care of risk assessment and risk management activity. Regulators of each country are also proactively involved in it and circulate various guidelines for the management of these risks to ensure public confidence, protect depositors' money, ensure stability of the financial system and reduce chances of profitability and sustainability of the bank being adversely affected. The central bank and commercial banks of various countries have been concerned to analyse the causes of such risks and arrive at the steps to be taken for its mitigation.

The present chapter is organized as follows. Section 2 discusses the Basel I and Basel II Accords, improvement of Basel II over Basel I Accord and risk management framework defined in Basel II Accord. Section 3 deals with the Basel III Accord and capital requirement. Section 4 discusses the types of risks faced by the bank followed by conclusion in section 5.

2.2 Basel II Accord

The Bank for International Settlement (BIS) had undertaken an initiative under the guidance of Basel Committee on Banking Supervision (BCBS), (known as Basel Committee in short) to formulate guidelines to measure and manage the risks mentioned above with the help of a well documented framework incorporating the best practices, and sound principles of risk management. This risk management framework or guideline is commonly referred as the “Basel Accord”, named after the city of Basel in Switzerland where the BIS is headquartered.

2.2.1 Overview of Basel I Accord

The first meeting of BCBS was held in the year 1988 and resulted in “Basel Accord- I”. Initially, the Basel Committee consisted of representatives from central banks and regulatory authorities of the G10 countries. The framework was progressively introduced in member countries gradually. Currently, central banks of over 25 countries including the Reserve Bank of India (RBI) are members of BIS and have adopted the Basel accords in varying degrees, depending on the specific requirements, and relevance to their respective economies.

The first document published by Basel Committee in July 1988 was “International Convergence of Capital Measurement and Capital Standards”. This report presented the outcome of the Committee’s work over several years to secure international convergence of supervisory regulations governing the capital adequacy of international banks. The final document agreed to by the member countries was arrived at by taking into account expert comments of regulatory authorities of all member countries. The document presents details of the agreed framework for measuring capital adequacy and minimum standards to be achieved in terms of its implementation by the member countries. The framework and the standard have been endorsed by the Group of Ten Central Bank governors.

The aim of the committee was to maintain stability and solvency in banking sectors. A bank is solvent if it has sufficient capital reserves to meet unforeseen adverse circumstances. If the loan portfolio of the bank worsens due to degradation of credit worthiness of the counterparty, as a result of which default arises, it should have sufficient capital to withstand the adverse situation. The basic principle of the Basel I Accord is to define a minimum regulatory capital[3] standard for the commercial banks. Minimum regulatory capital is obtained as a prescribed ratio, of total capital to risk weighted assets, and is referred as "Capital Adequacy Ratio (CAR)". As per Basel I Accord, CAR is set at 8%, but in India RBI has however, set the CAR for banks in India as 9%.

Minimum capital requirement obviously depends upon the riskiness embedded in asset portfolio. By assigning appropriate weights to different asset class and by multiplying the value of assets with these weights, the "Risk weighted assets" measure was derived. The committee had defined that the assets had to be assigned risk weights depending on the broad categories of relative riskiness that the assets possess. There were only five weights defined in the Accord - 0, 10, 20, 50, and 100%. Basel I Accord also classified capital into two broad categories: core capital (equity capital) and supplementary capital. The details of the constituents of these two types of capital are discussed in the following sections. The main focus of Basel I Accord was credit risk (counterparty failure) as the credit activity was the main source of risk that the banking sectors were exposed to. In 1996 the committee enhanced the scope by introducing an amendment to the existing Accord requiring banks to measure and apply capital charge for market risk in addition to credit risk. Market risks include the risks originating from interest related instruments and equities in the trading books of banks; and constitutes interest rate risk, equity risk, foreign exchange risk and commodities risk.

2.2.2 Journey from Basel I to Basel II Accord

Eight years after the Basel I Accord came into effect, based on continuing studies and research by the BIS and member central banks, global developments, experience of loss events, and a host of related factors, a number of refinements were made to the framework, the most significant one being inclusion of market risk for the calculation of CAR. Despite these amendments, however, the Basel I Accord suffered certain fundamental limitations, for instance:

[3] The minimum regulatory capital is defined by the regulators. It is the minimum capital that a bank should keep aside to meet adverse scenarios in future.

(i) The Accord lacked flexibility in assigning risk weights since it assigned a single (uniform) risk weight to various assets categories, irrespective of the asset quality.

(ii) Definition of Regulatory capital was restricted only to credit and market risks, while Operational risk, which is one of the major sources of risk faced by the financial institutions was not recognized

(iii) Scope of Regulatory capital estimation was confined at bank level, while ignoring capital requirement at granular levels, for instance at business line or unit level.

The Basel committee felt the need for a more risk sensitive approach; as a result of which the committee issued a proposal for revising the capital adequacy framework in June 1998. An extensive consultative process was set up among all member countries and the proposals were also circulated to supervisory authorities worldwide. The Committee subsequently released additional proposals for consultation in January 2001 and April 2003 and furthermore conducted three quantitative impact studies related to its proposals. As a result of these efforts, many valuable improvements were made to the original Basel I accord. The final version published in June 2004[4] was agreed to by all its member countries. By June 2006, the final version of the revised Basel I accord post a series of refinements, underwent a comprehensive change. This revised framework, which is more flexible and risk sensitive, is known as Basel II Accord. This framework is applicable to internationally active banks, domestic banks and securities firms and insurance companies. The Basel committee expected that the banks should implement the new Accord by end of 2007.

Unlike the Basel I Accord, the refined version, the Basel II Accord for the first time, categorically recognized a third type of risk, viz. operational risk, into the risk management framework in addition to credit and market risks. Banks were required to calculate capital charge for credit, market and operational risks to arrive at minimum CAR. The new framework also incorporated lot of flexibility in terms of application of various techniques to estimate capital requirement for these risks and provided a range of options for calculating capital for credit and

[4] "International Convergence of Capital Measurement and Capital Standards: A Revised Framework", Bank for International Settlement (BIS), June 2004

operational risks to allow banks and supervisors to select the approaches that are more appropriate and suitable for them.

Adopting the Accords, the Reserve Bank of India issued a draft guideline in March 2007 on the implementation of the new capital adequacy framework, and asked foreign banks operating in India and Indian banks having foreign operational presence to migrate to the new Basel Accord with effect from March 31, 2008; all other scheduled commercial banks were required to migrate by March 31, 2009.

2.2.3 Overview of Basel II Accord

One of the central themes running through the Basel II framework is the “Three Pillar Approach”.

Pillar 1- Minimum Capital Requirements

Basel II framework requires the minimum capital for the bank, also defined as regulatory capital, to be based on credit, market and operational risks. The CAR is calculated using RWA for credit risk and capital requirements for operational and market risks. Pillar I describes in detail the actual calculation of total minimum capital requirement for credit, market and operational risks.

Basel II prescribed two broad methods for calculation of risk weighted assets for credit risk: (1) The Standardized Approach; (2) The Internal Rating Based (IRB) Approach. The internal rating based approach is again bifurcated into Foundation Internal Rating Based Approach and Advanced Internal Rating Based Approach. The IRB approach is the most sophisticated approach. These approaches are discussed in more details in the forthcoming chapters.

The approaches defined by the Basel II Accord for calculating capital charge for market risk can be classified into: (1) The Standardized Approach; (2) The Internal Model Based Approach.

The inclusion of operational risk for minimum regulatory capital requirement is one of the important and remarkable steps that the Basel Committee has taken as part of Basel II Accord.

As per the new Accord banks were required to measure both expected and unexpected losses due to operational risk over a one year time horizon, and maintain capital accordingly. To measure operational risk capital charge, the new Accord has recommended three approaches. These are: (1) The Basic Indicator Approach (BIA); (2) The Standardized Approach (TSA); (3) The Advanced Measurement Approach (AMA). The detailed description of these approaches is presented in the subsequent chapters.

Pillar 2- Supervisory Review Process

Pillar 2 of Basel II framework is the supervisory review process. As mentioned in the Basel II document, "The supervisory review process of the Framework is intended not only to ensure that banks have adequate capital to support all the risks in their business, but also to encourage banks to develop and use better risk management techniques in monitoring and managing their risks. The supervisory review process recognizes the responsibility of bank management in developing an internal capital assessment process and setting capital targets that are commensurate with the bank's risk profile and control environment. In the Framework, bank management continues to bear responsibility for ensuring that the bank has adequate capital to support its risks beyond the core minimum requirements (BCBS, 2006)".

Pillar 2 also envisages supervisors to evaluate the robustness of the risk management framework of banks and to determine how well banks have assessed their capital needs relative to their risks. Where deficiencies in the bank's risk management framework are identified, supervisors are expected to intervene and interact with the banks and may even force the bank to take prompt and decisive action to reduce risk or restore capital.

The supervisory review process is further buttressed by four key principles: (1) Banks should have a process for assessing their overall capital adequacy in relation to their risk profile and a strategy for maintaining their capital levels; (2) Supervisors should review and evaluate banks' internal capital adequacy assessments and strategies, as well as their ability to monitor and ensure their compliance with regulatory capital ratios and take appropriate supervisory action if they are not satisfied with the result of this process; (3) Supervisors should expect banks to operate above the minimum regulatory capital ratios and should have the ability to require banks to hold capital in excess of the minimum; (4) Supervisors should seek to intervene at an early stage to prevent capital from falling below the minimum levels required to support the risk characteristics of a particular bank and should require rapid remedial action if capital is not maintained or restored.

Pillar 3- Market Discipline

The third pillar of Basel II framework is market discipline or market disclosure by way of transparency that would help the market participants and the public at large to have a better understanding of the bank's risk profiles and adequacy of their capital position, the methodology adopted by the bank to calculate capital adequacy and the risk management framework adopted by the bank. Market discipline would complement the minimum capital requirement and supervisory review process. As per the Basel document, "the Committee aims to encourage market discipline by developing a set of disclosure requirements which will allow market participants to assess key pieces of information on the scope of application, capital, risk exposures, risk assessment processes, and hence the capital adequacy of the institution. The Committee believes that such disclosures have particular relevance under the Framework, where reliance on internal methodologies gives banks more discretion in assessing capital requirements (BCBS, 2006)".

2.2.4 Regulatory vs. Economic Capital

The main thrust of Pillar 1 is calculation of minimum regulatory capital. As per the Basel II Accord, the minimum capital requirement ratio is 8%. This capital ratio is commonly referred as Capital Adequacy Ratio (CAR)[5] of the bank. CAR is calculated using the following formula.

$$CAR = \frac{Tier1Capital + Tier2Capital + Tier3Capital}{RWA + 12.5 * C_{mr} + 12.5 * C_{or}}$$

The components in the numerator refer to the regulatory capital, and will be discussed in depth in the following sections. The components of the denominator, RWA is the risk weighted asset for credit risk, C_{mr} is capital requirements for market risk and C_{or} is capital requirements for operational risk. The ratio which was defined in 1988 did not include Tier 3 capital, capital

[5] CAR as per Basel I Accord is also 8%.

requirement for market and operational risks. The methods to calculate risk weighted assets for credit risk and capital requirement for operational risk are discussed in the subsequent chapters. However, this study does not analyze computational technique for market risk capital requirement since it is not within the scope of the study.

Components of Regulatory Capital

The constituents of capital for the purpose of calculating capital adequacy, as shown in the previous paragraph are tier 1, tier 2 and tier 3 capital. These are detailed as follows:

Tier 1 capital is the Core Capital, consisting of mainly shareholders' equity and disclosed reserves. It includes paid up purchase price of stock (or shares) usually termed as par value, capital reserves (surplus from sale proceeds of fixed assets), disclosed free reserves and innovative perpetual debt instruments. Regulators have also allowed other instruments, other than common stock, to be counted as tier one capital. These instruments are unique to each national regulator, but are always close in nature to common stock viz. being perpetual in nature. These are also referred to upper tier one capital.

Tier 2 capital is known as Supplementary Capital, which includes undisclosed reserves, revaluation reserves, general provisions/ loan-loss reserves, hybrid instruments and subordinated term debt. Undisclosed reserves include only reserves which, though unpublished, have been passed through the profit and loss account and which are accepted by the bank's supervisory authorities. Revaluation reserves are reserves created when a company has an asset revalued and an increase in value is brought to account. The increase would be added to the revaluation reserve. If general provisions/ loan loss reserves are not attributable to the actual diminution in value or identifiable potential loss in any specific asset and are available to meet unexpected losses, this can be included in Tier 2 capital. Hybrid instruments- Banks in India are allowed to recognize funds raised through debt capital instrument which has a combination of characteristics of both equity and debt, as Upper Tier 2 capital provided the instrument complies with the regulatory requirements. Subordinated term debts also eligible for inclusion in Tier 2 capital, provided the instrument is fully paid-up, unsecured, subordinated to the claims of other creditors, free of restrictive clauses, and should not be redeemable at the initiative of the holder or without the consent of the Reserve Bank of India. They often carry a fixed maturity.

Finally, Tier 3 Capital is comprised of Short-term subordinated debt covering market risk. As defined in the Basel document (BCBS, 2006), for short-term subordinated debt to be eligible as Tier 3 capital, it needs, if circumstances demand, to be capable of becoming part of a bank's permanent capital and thus be available to absorb losses in the event of insolvency. It must, therefore, at a minimum, be unsecured, subordinated and fully paid up, have an original maturity of at least two years, not be repayable before the agreed repayment date unless the supervisory authority agrees, and be subject to a lock-in clause which stipulates that neither interest nor principal may be paid (even at maturity) if such payment means that the bank falls below or remains below its minimum capital requirement.

Economic Capital

In contrast to Regulatory Capital, Economic Capital (EC) is the amount of capital that a bank or financial institution needs in order to protect itself with a chosen level of certainty against insolvency due to unexpected losses over a given time period at a specified confidence level. EC can also be considered as that capital which the top management or shareholders would choose to hold in the absence of regulation considering the cost and benefit of holding optimum capital. EC is a more forward looking requirement as it is based on an assessment of potential future losses. It is a number which summarizes the current risk profile across all risks - inclusive market, credit, operational - for a financial institution.

The calculation of economic capital depends on the level of certainty with which a bank wishes to protect itself against various risks including that of insolvency. In short, the higher the chosen level of certainty, the greater the amount of economic capital to be set aside. A second factor, viz. the time horizon also plays an important role in the estimation of economic capital. The longer the time period, in which losses are expected to accumulate, the greater would be the amount of economic capital needed. An incorrect estimation of either of the factors would result in an inaccurate depiction of the of the bank's risk profile, ultimately resulting in erosion in value of shareholders' investments or, at worst lead the institution to insolvency. A widely used model for computation of economic capital for operational risk is based on Value at Risk (VaR) approach, where bank estimates both expected and unexpected loss at a given level of confidence over a specified period (say, one year). Calculation of economic capital is usually based on unexpected losses that a bank could in a worst case scenario experience over the specified period.

2.2.5 Improvements of Basel II over Basel I

The shortcomings of Basel I Accord described above were resolved in Basel II Accord, while simultaneously making the new Accord more risk sensitive. Some of the significant improvements the new Accord brought-in vis-a-vis the old Accord are:

1. Basel I Accord initially focused solely on credit risk and subsequently added market risk into the framework. But it completely ignores operational risk, which is one of the major sources of risks that most of the financial institutions are facing. By recognizing Operational risk, Basel II Accord brought comprehensiveness to the Accord. The capital adequacy ratio as per the new Accord is based on all these three types of risks.

2. Basel I Accord focussed on uniform risk measure to maintain regulatory capital ratio, while the new Accord incorporates a broader risk management framework by the three pillar approach that included all stakeholders in the risk management arena viz, the bank's own internal risk measurement and management methodologies, supervisory review and market disclosure.

3. In terms of risk measure the earlier Accord focuses on single risk measure, without considering asset quality, whereas the new Accord is more risk sensitive and assigns risk weights as per the quality of the assets.

4. The Basel I Accord has been described as a "one size fits all" policy. Virtually all loans to counterparties are subjected to 8 percent capital ratio, irrespective of the size of the loan, its maturity, and the credit quality of the borrowing counterparty. Thus, capital requirement for loans to a firm near bankruptcy is treated on par with loans to a prime (Triple-AAA rated) borrower. The new Accord resolves this static approach by proposing the Internal Rating Based (IRB) approach, banks are not required to maintain same amount of capital for low quality and high quality assets. The capital requirement is based on the probability of default and loss given default associated with the assets.

5. As per the old Accord, the capital requirement is additive across all the loans and securities. It does not allow banks to maintain lower capital requirements because of a greater degree of diversification in the portfolio. The New Accord allows bank to consider the diversification effect in the portfolio for estimating capital requirements, using advanced approach for credit, market and operational risks.

2.3 Basel III and Capital Requirement

In the aftermath of the 2008 financial crisis that impacted many countries the Basel Committee on Banking Supervision (BCBS) revisited the Basel II guidelines and issued revised guidelines in December 2010[6]. The modified version of Basel II thus became Basel III. In India, the Reserve Bank of India adopted the Basel III guidelines and published them in May 2012[7]. Basel III incorporates lessons from the financial crisis into a more comprehensive reform package. This resulted in a set of significant changes to capital/ liquidity requirements and related areas of banking supervision. The Basel III guideline lays greater emphasis on raising quality, quantity and transparency of capital base, enhancing risk coverage, reducing leverage, reducing procyclicality and promoting countercyclical buffers. A key feature of the Basel III approach is supplementing the risk-based capital requirement with a leverage ratio, addressing systemic risk and interconnectedness, thereby introducing a global liquidity standard on which both the Basel I and Basel II Accords were silent.

Some of the major changes outlined in the new guideline are: The minimum common equity requirement will increase from 2% to 4.5%, warranting significant additional capital requirements for banks. In addition to this a capital conservative buffer of 2.5%, which will be met with common equity is introduced. This will increase the total common equity requirement to 7%. The concept of Counter-cyclical capital requirement is also introduced in the latest Accord, which means the capital requirements should be higher during stable economic conditions and comparatively lower during downturns. The purpose of countercyclical capital buffer is to achieve the broader macro-prudential goal of protecting the banking sector from

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[6] "Basel III: A global regulatory framework for more resilient banks and banking systems", Basel Committee on Banking Supervision (BCBS), December 2010, June 2011 (Revised)

[7] "Guidelines on implementation of Basel III capital regulation in India", Reserve Bank of India, May 2012

periods of excess aggregate credit growth. For any given country, this buffer will only be in effect when there is excess credit growth that results in a system-wide build-up of risk. This would achieve the purpose of “leaning against the wind” and slowing lending activities when the situation overheats and encouraging lending when times are challenging.

In India, the RBI guidelines have stated that a countercyclical capital buffer within a range of 0 - 2.5% of RWAs in the form of common equity or other fully loss absorbing capital will be implemented according to national circumstances. It has prescribed a set of guidelines as far as capital ratios are concerned. Following table shows a summary of ratios and capital requirements for the Indian banks after full implementation new capital ratios and capital conservation buffer[8].

Table- 2.1: Basel III and Capital Requirement

	Regulatory Capital	As % to Risk Weighted Assets (RWAs)
(i)	Minimum Common Equity Tier 1 ratio	5.5
(ii)	Capital conservation buffer (comprised of Common Equity)	2.5
(iii)	Minimum Common Equity Tier 1 ratio plus capital conservation buffer [(i)+(ii)]	8.0
(iv)	Additional Tier 1 Capital	1.5
(v)	Minimum Tier 1 capital ratio [(i) +(iv)]	7.0
(vi)	Tier 2 capital	2.0
(vii)	Minimum Total Capital Ratio (MTC) [(v)+(vi)]	9.0
(viii)	Minimum Total Capital Ratio plus capital conservation buffer [(vii)+(ii)]	11.5

Source: Guidelines on implementation of Basel III capital regulation in India, Reserve Bank of India, May 2012

The Basel Committee had largely ignored liquidity in the past, leaving it discretion of the national regulators. The Basel III document has introduced guidelines to strengthen liquidity management.

2.4 Types of Risks

Risks faced by financial institutions in their day to day business can be classified as financial and non-financial risks. As defined in Investopedia, financial risk is “the risk that a company will not have adequate cash flow to meet financial obligations. Financial risk is the

[8] RBI has prescribed transitional arrangements in the guideline for smooth migration to these capital ratios

additional risk a shareholder bears when a company uses debt in addition to equity financing. Companies that issue more debt instruments would have higher financial risk than companies financed mostly or entirely by equity." Key risks coming under this category include Credit risk, Market risk, Operational risk, and Liquidity risk.

Non-financial risks, generally termed as business risks. These risks arise due to flawed management decisions, faulty business strategies. These types of risks are also classified as Reputational and Strategic risks, Concentration risk, and Country risk. These different types of risk are discussed below.

2.4.1 Credit Risk

Credit risk is the risk of loss to the bank due to failure of counterparty to meet its financial contractual debt obligation towards the bank. This risk arises when counterparty is unable to pay loan principal and/ or interest amount. If the creditworthiness of the counterparty or borrower decreases, it gives a sign of default. Effect of credit risk is measured by the cost of replacing cash flows if the counterparty defaults. Creditworthiness of the counterparty deteriorates due to various factors such as, falling of volume of business, decreasing of profit, increasing of cost of production in relation to selling price and some economic factors like falling in demand of the products. There are various forms of credit risks. As defined in Jorion (2007), some of them are mentioned here. Credit risk should be defined as the potential loss in mark-to-market value that may be incurred due to the occurrence of credit event. A credit event occurs when there is a change in the counterparty's ability to perform its obligations. Thus changes in market prices of debt owing to changes in credit ratings or in the market's perceptions of default can be viewed as credit risk, which creates some overlap between credit and market risk. Another form of credit risk is sovereign risk. This occurs, for instance, when countries impose foreign exchange controls that make it impossible for counterparties to honour their obligations. Default risk by its nature is company-specific, whereas sovereign risk is country-specific. There is another type of credit risk, which is known as settlement risk, which occurs when two payments are exchanged the same day. This risk arises when the counterparty defaults after the institutions have already made the payment. Settlement risk is very real in case of foreign exchange transactions, which involve exchange of payments in different currencies at different time.

2.4.2 Market Risk

Market risk is defined as the possibility of loss to a bank due to change in the market variables such as, interest rate, price level, foreign exchange rates etc. or, as the Basel Committee defines, “market risk is the risk of losses in on and off-balance-sheet positions arising from movements in market prices. The risks subject to this requirement are (i) the risks pertaining to interest rate related instruments and equities in the trading book; (ii) foreign exchange risk and commodities risk throughout the bank (BCBS, 2006).” Thus market risk is the risk of loss to the bank arising due to change in interest rates or prices of the securities, foreign exchange rates, commodities and equities, as well as volatilities of those prices.

Basel Committee on Banking Supervision (BCBS) had made an amendment in the year 1996 to include market risk in bank’s minimum capital requirement. Hence capital requirement for market risk was part of Bank’s CAR. The objective in introducing this amendment to the capital Accord was to provide an explicit capital cushion for the losses arising from price volatility; particularly those arising from trading activities. Basel Committee has classified market risk is into following categories:

1. Interest rate risk, which is the risk of holding or taking positions in debt securities and other interest rate related instruments in the trading book. Interest rate risk arises due to adverse movement in prices of debt securities. The instruments covered under interest rate risk measurement include all fixed and floating rate debt securities and instruments that behave like them, including non-convertible preference shares.

2. Equity position risk, which arises due to change in prices of equities in trading book of the bank. If the equity prices change adversely, it will result in a loss in the bank’s trading activities. Equity position risk arises from long and short positions in all instruments that exhibit market behaviour similar to equities. The instruments covered include common stocks, irrespective of voting rights, convertible securities that behave like equities, and commitments to buy or sell equity securities.

3. Foreign exchange risk that is the risk due to change in exchange rate of position held by the bank in foreign currencies including gold. Gold is to be dealt with as a foreign exchange position rather than a commodity because its volatility is more in line with foreign currencies and banks manage it in a similar manner to foreign currencies. Banks incur loss if there is an adverse change in foreign exchange rate of the securities or instruments held by them.

4. Commodities risk, which as defined in the Basel Accord, refers to the risk of holding or taking positions in commodities, including precious metals, but excluding gold (which is treated as foreign currency). A commodity is defined as a physical product that is traded on a secondary market, e.g. agricultural products, minerals (including oil) and precious metals. Risk arises due to change in spot prices or future prices of commodities. Change in supply and demand in the commodity market has significant effect on the price and volatility, as a result of which risk arises.

2.4.3 Operational Risk

Operational Risk is the risk of loss resulting from inadequate or failed internal processes, people and system, or from external event. This risk was not considered for minimum capital requirement framework of the banks as per Basel I Accord. Although operational risk losses have been taking place for many years, even before Basel Accords, it was only in the late 1990s a growing number of high profile operational risk loss events worldwide caught the attention of the regulators. These losses were huge and occasioned by adoption of sophisticated technology for product development, distribution, sales/ marketing and day to day operation. This led banks and regulators to intensively view operational risk management as an integral part of risk management activity of the banks. As a result, BIS included operational risk along with credit and market risk for capital adequacy purpose and considered it as an integral part of banks' risk management framework in its Basel II Accord. Unlike credit and market risks, operational risk events with high severity may lead to collapse of an organization. Two prominent bank failures were: (a) the collapse of the Barings Bank, which was the oldest investment bank in UK. The bank collapsed due to trading and accounting fraud through aggressive trades in equity futures and options, by a rogue trader, who was a star trader in the bank and had unfettered access to the back office also thus enabling him to manipulate the internal system to hide his massive losses that bordered on very big bets on across cross border stock exchanges; (b) fraud in the Paris based financial giant, 'Society Generale Bank', which led to a loss of more than $7 billion again, from losses due to massive unauthorized trading positions in futures contracts on European equity indices by a rogue trader. He circumvented and manipulated system security restrictions & controls. The positions undertaken by the trader were believed to be fraudulent transactions. In both these headline cases, during investigations it became clear that that deficiencies in the Bank's internal auditing and risk management practices was the primary cause for the well-concealed frauds.

BCBS defines operational risk as the risk of loss resulting from inadequate or failed internal processes, people and system, or from external event. This definition includes legal risk, but excludes strategic and reputational risk. The definition of operational risk is based on four basic causes/ sources of risk: internal process, people, system and external events.

Process risk arises when the laid down process is inadequate or not followed properly, or if the process itself is flawed. Inadequate or failed process can cause breakdowns in information, transaction processing, delays/ errors in settlement systems, problems in back-office operations, which deal with the recording of transactions and reconciliation. If settlement is not done within the time, or if a cheque is not cleared within the stipulated time the bank has to bear loss in the form of interest/compensation to the customers or counterparties. Model risk is part of inadequate internal process. This risk refers to the risk of losses owing to the fact that the valuation models may be flawed.

People risk refers to the risks that arise due to intentional or unintentional error or mistake or fraud done by the staff. This includes internal fraud, such as fraud, forgeries, cheating and theft; misuse of internal information by the staff to make profit; data entry error, maintenance error; rogue trading, etc.

System risk arises due to failure of systems in place to perform certain activities or if there is inadequate system in place. System risk includes system down time, accounting error in the system, hardware or software failure, utility outrage/ disruption. In this globalized era, with increasing use of internet and mobile phones, most banking activities are conducted remotely, online-often on real time basis - 24x7 - with a high degree of flexibility. Core banking activities, treasury activity, ATM activity and clearing activity are mostly dependent on various systems. A small error in the system or downtime is likely to lead to a huge loss to the bank. Hence most of the leading banks have their disaster management in place.

External events could also cause loss to the bank and include man made activities such as fraud by an external party, terrorism and vandalism, natural calamities such as, flood, earthquake, fire, etc. Losses faced by the institutions due to external events include external fraud, damage to physical assets (building, office premises, fixed assets, etc.), human losses, and losses due to business disruption.

As per the definition, operational risk includes legal risk, which arises from fines, penalties, or punitive damages resulting from supervisory actions and private settlements. Legal risk arises if customer sues a bank for harassing him or not performing certain activities and claims compensation; or if the institutions do not abide by the regulations outlined by the regulators. Non-compliance by the institutions will force regulators to impose penalties.

2.4.4 Liquidity Risk

Liquidity risk refers to the risk of not having sufficient liquidity with the bank to meet its day to day requirement. Generally, it arises when the payments due from borrowers are delayed leading to severe cash shortages and the bank is unable to cope with. The usual contributory factor for liquidity risk is a decline in deposits. Managing liquidity risk is vital for effective operations of commercial banks. Analysis of liquidity risk involves the measurement of not only the liquidity position of the bank on an ongoing basis but also examining how funding requirements are likely to be affected under crisis scenarios. This risk is related to credit risk in the sense that if the credit rating of a bank undergoes downgrade, the bank is likely to experience large scale unexpected cash outflow due to loss of confidence by the public, ultimately leading to paucity of reliable funding. Severe liquidity risk manifestation resulting from the loss of confidence is called “run on the bank”.

As mentioned in Jorion (2007), liquidity risk takes two forms: asset liquidity risk and funding liquidity risk. Asset liquidity risk, also known as market/ product-liquidity risk, arises when a transaction cannot be conducted at prevailing market prices owing to the size of the position relative to normal trading lots. This risk varies across categories of assets and across time as a function of prevailing market conditions. Market/ product-liquidity risk can be managed by setting limits on certain markets or products and by means of diversification.

Funding-liquidity risk, also known as cash flow risk, refers to the inability of the bank to meet payments obligations, which may force early liquidation, thus transforming paper losses into realized losses. Cash-flow risk interacts with product-liquidity risk if the portfolio contains illiquid assets that must be sold at less than fair market value. Compared to the former, Funding-risk has more serious implication, but can be controlled by proper planning of cash-flow needs, which can be controlled by setting limit on cash-flow gaps, by diversification, and by consideration of how new funds can be raised to meet cash shortfalls.

2.4.5 Reputational and Strategic Risks

Banks are required to consider reputational and strategic risk in the Pillar II framework of Basel II Accord. Reputational risk causes indirect loss to the bank as they by themselves do not normally lead to any loss. Trust that consumers and clients put in financial institutions is the main asset, which help them run a profitable business. Nobody with reasonable information level would trust their savings to an institution that is rumoured to be in poor financial conditions, and have unreliable employees.

Financial institutions may fail due to severe reputational risk. The severity of reputational risk differs from industry to industry. For example, if a manufacturing company faces financial problems caused by poor management but the quality of product produced is of good quality, a customer will not think of the situation caused by the financial problem and continue to buy the product manufactured by them. For a financial institution or a bank on the other hand, trust is of paramount need to even conduct business.

Reputational risk can arise due to a number of factors. Strategic risk could be one of the factors that affect the reputation of a financial institution. Strategic risk is related to crucial changes made by the executive board of an institution that can put danger to its value. Merger and acquisition, research and development are some of the factors responsible for strategic risk.

Changes in the strategies of financial institutions are in general announced and analyzed by the market, and transformed into a rise or fall in the share price (in other words it changes the value of the institutions).

Strategies badly perceived or poorly communicated to the market provoke a reduction in the price. Some business may be more sensitive to reputational events than others. For example, a rogue trader in a fund management would probably have a much more serious impact on reputational losses than losses in a lower profile department such as shipping finance.

It is usual business situation to decide between two or more strategy keeping in mind the growth of the business. Sometimes a well thought out decision anticipating a positive return would result in a negative return. The classic example of this kind of strategic risk is the case of NatWest.

2.4.6 Concentration Risk

Like reputational and strategic risks, concentration risk is treated under Pillar II framework of Basel II Accord. Concentration risk can be interpreted in a number of different ways in risk management, depending on the context in which the term is used. For example, those concerned with evaluating the level of credit risk in an organization see concentration risk arising from the point of view of low or diminishing diversification across industrial sectors, geographical regions, etc. in a loan portfolio. From a risk and stability perspective, this concentration can be a serious problem. If a particular sector in which a bank is excessively exposed experiences economic hardship, this can result in serious financial problems for the bank.

From a market and operational risk viewpoint, concentration risk can be seen much more from the key personnel side. Concentration risk would be the risk that star producers, revenue generators or even efficient back officers leave the organization, therefore impacting the earnings and shareholder value of the organization by being an unexpected source of volatility of earnings. This would happen when the performance of trading desk and various key departments of the commercial banks depends heavily on a relatively few number of star traders or key/critical employees, Basel II Accord says that the concentration risk should be pro-actively managed and assessed by firms and concentrated positions should be routinely reported to senior management. To measure the concentration risk, the bank should identify three factors that contribute to overall level of risk, namely the gross income generated by the employee, the concentration of the income generation within that employee, and the probability of the employee leaving. Other such concentration factors could be one or two vendors in essential outsourcing such as telecom, processing, operational activity outsourcing, etc

2.4.7 Country Risk

"Investopedia" describes country risk as "a collection of risks associated with investing in a foreign country. These risks include political risk, exchange rate risk, economic risk, sovereign risk and transfer risk, which is the risk of capital being locked up or frozen by government action. Country risk varies from one country to the next. Some countries have high enough risk to discourage much foreign investment". This risk arises due to new policies or political upheavals, or major changes in the political events and actions including political instability that is likely to adversely impact the investments made by foreign entities in the country. For instance, during a favorable and stable political scenario, a bank in the US may choose to invest in a small country in a far away continent and suddenly there is a major revolution by the masses and a new political ideology starts ruling, whose first actions are to nationalize and expropriate the assets of the country or introduce a blanket ban of capital conversion thus preventing the overseas branch to remit the profits to its overseas principal. Country risk must be assessed properly before making investment in another country, as it can reduce the expected return. Some country risk cannot be hedged, whereas some risk like exchange rate risk can be protected against marginal potential loss. As the United States is generally considered as the benchmark for low country risk, most nations can measure country risk as compared to US. Country risk could be higher for the investment, which are not invested through a regulated market or exchange.

2.5 Conclusion

Various financial and nonfinancial risks were discussed in this chapter. Among all financial risks, credit, operational and market risks are identified as three major risks that a bank faces in its day to day activities. Strategic and reputation risks indirectly affect financial position of the banks. If a management's business strategy does not work as expected or if the reputation of the bank is at stake due to the prevalence of some adverse circumstances, then it will lead to financial loss since business volume will be adversely affected, customer base will be reduced, and there will be public fear to do business with such banks.

Risk management is one of the significant activities of any financial institution including banks. BCBS circulated various Basel Accords for an effective risk management of the banking sector across the globe. From the old Basel I Accord to the recent Basel III Accord, the committee has been bringing in a series of reforms to address risks faced by the banking sector, particularly credit, market, operational and liquidity risks. The Accord mandates central banks of various countries to direct their banks to maintain a minimum 8% of capital adequacy ratio. This chapter outlined a description of various Basel Accords and features of Basel II Accord. Basel II Accord is a three pillar based approach, wherein the first pillar talks about computation of minimum capital requirement, the second pillar is on supervisory review process and the third pillar talks about market disclosure. The Accord prescribed both standardized and advanced approaches to compute capital requirement for credit, operational and market risks. Subsequent to BCBS guideline on Basel II Accord, RBI issued various guidelines related to the implementation of Basel II Accord and risk measurement using advanced approaches for Indian banks.

In the aftermath of 2008 subprime crisis, BCBS revisited its Basel II guideline and came up with Basel III guideline, which prescribes a higher tier 1 capital requirement and introduced capital conservative buffer and countercyclical capital buffer to have a robust risk management process in the banks. This too was discussed in the chapter. However, the concern in the thesis is with looking at risk management from the Basel II perspective.

CHAPTER 3

CREDIT RISK MODELS: THEORY AND LITERATURE

3.1 Introduction

The recent financial crisis which affected the world economy emanated from default of credit exposures of the banks in the US, UK and Europe. Historically, from the earliest of times when banking as a concept in the world of finance evolved, credit risk always occupied the centre stage of risk management activity of the bank. But it has assumed special importance for banks and regulators after the Bank for International Settlement (BIS) came up with Basel I Accord. Basel I Accord of 1988 only focused on capital requirement for credit risk. Unlike the old Accord, which defined fixed weights for calculating risk weighted assets for credit risk, the new Accord (Basel II) wants banks to develop internal systems and models to measure and manage credit risk exposure.

As pointed out in Chapter 2, credit risk refers to the risk due to unexpected change in the credit quality of a counterparty or issuer. Credit worthiness of a potential borrower determines credit risk. Hence credit risk measurement depends on the likelihood of default of an individual or firm to meet its required or contractual obligations and if the obligation is not fulfilled, default occurs. Credit quality of an obligation refers to the counterparty's ability to perform on that obligation. This includes both the default probability of the obligation and anticipated recovery rate. Default probability refers to the likelihood that the counterparty will default on its obligation over the life of the obligation. Recovery rate is the fraction of the total exposure, which may be recovered, in the event of default through bankruptcy proceedings, legal recourse, or some other form of settlement. Credit exposure is the total outstanding obligation at the time default occurs.

This chapter sets out the credit risk management framework as per Basel II Accord and different approaches prescribed by the Accord for the measurement of credit risk in the next section. It further discusses various advanced models available for measuring credit risk as per Internal Rating Based Approach (IRB) and practices followed by banks worldwide in section 3.

In section 4, the study reviews some of the empirical literature on bankruptcy prediction based on these models and section 5 concludes.

3.2 Basel II and Credit Risk Management

The first Basel Accord, that is, Basel I Accord, was adopted by the banks worldwide during the early nineties. The Basel Committee on Banking Supervision (BCBS) felt that amongst different types of risks that a bank faces, the major risk is credit risk, which is known as counterparty failure. Hence the central focus of the Basel I framework was credit risk. As per the old framework, there were various weights used for different types of credit instruments to calculate risk weighted assets. The weights were kept as simple as possible and only five weights were used as mentioned in the previous chapter. The loans/ claims of a bank were classified into- (a) Claims on all foreign countries with various weights being defined for claims on the central governments within the OECD, claims on central governments and central banks outside the OECD, claims on banks incorporated within or outside the OECD; (b) Claims on non-central-government, public-sector entities (PSEs); (c) Collateral and guarantees; (d) Loans secured on residential property; and finally, (e) Off-balance-sheet engagements.

The Basel II Accord has defined a more risk sensitive approach for measuring credit risk and calculating risk weighted assets for credit risk. The committee permits banks to choose one of the following methodologies to compute capital requirements for credit risk.

(i) The Standardized Approach

(ii) The Internal Rating Based (IRB) Approach: this is further divided into two types- Foundation IRB approach and Advanced IRB approach.

3.2.1 The Standardized Approach

The standardized approach is used to measure credit risk in a standardized manner, supported by external credit ratings. The weights defined by Basel I for various exposures of the banks in their banking books, were revised in the Basel II Accord. Furthermore, the credit equivalent amount of Securities Financing Transactions (SFT) and OTC derivatives that expose a bank to counterparty credit risk[9] and exposure related to securitization are also included in the new Accord.

Basel II Accord has defined weights for different assets based on the ratings assigned by the external rating agencies. There are certain eligibility criteria listed by the BCBS for external credit assessment institutions (ECAI)[10]. The Accord states that "the assessments of ECAIs may be recognized on a limited basis, e.g. by type of claims or by jurisdiction. The supervisory process for recognizing ECAIs should be made public to avoid unnecessary barriers to entry (BCBS, 2006)".

Risk weights are assigned as per external rating and it varies according to exposure type. For example, for claims on sovereign entity and central banks, 0% weight is applicable for AAA to AA- rating; 20% for A+ to A-, 50% for BBB+ to BBB-, 100% for BB+ to B-, 150% for below B- and 100% for unrated claims. The Accord has classified claims into various categories: claims on sovereigns, claims on non-central government public sector entities (PSEs), claims on multilateral development banks (MDBs), claims on banks, claims on securities firms, claims on corporate, claims included in the regulatory retail portfolios, claims secured by residential property, claims secured by commercial real estate, past due loans, investments in equity or regulatory capital instruments issued by banks or securities firms and off-balance sheet items.

3.2.2 The Internal Rating Based Approach (IRB)

The IRB approach of Basel II Accord is more risk sensitive compared to the standardized approach and, more importantly, IRB approach does away with the dependency on ratings done by external agency. Rather it is based on the bank's own estimates of risk components in determining the capital requirement for a given exposure. The components used to estimate

[9] The counterparty credit risk as defined by the BCBS is "the risk that the counterparty to a transaction could default before the final settlement of the transaction's cash flows. An economic loss would occur if the transactions or portfolio of transactions with the counterparty has a positive economic value at the time of default. Unlike a firm's exposure to credit risk through a loan, where the exposure to credit risk is unilateral and only the lending bank faces the risk of loss, the counterparty credit risk creates a bilateral risk of loss: the market value of the transaction can be positive or negative to either counterparty to the transaction. The market value is uncertain and can vary over time with the movement of underlying market factors (BCBS, 2006)".

[10] Details of criteria mentioned in Para 91, BCBS document, 2006

expected loss as per IRB approach are Probability of Default (PD), Loss Given Default (LGD) and Exposure at Default (EAD). PD is also known as Expected Default Frequency (EDF) and indicates the default probability for a borrower over a one year period. It is the anticipated probability that a borrower will default on the debt obligation before its maturity. It is generally estimated based on the historical default result or changes in the ratings, especially down-grading of ratings. LGD, also known as Loss severity, is the expected amount of loss on a loan provided to the borrower, which will occur at the time of default. LGD and recovery are inversely related. Precisely, LGD is one minus recovery rate. EAD, also known as usage given default (UGD), is the amount the borrower owes to the bank at the time of default.

The IRB Approach is again divided into two types: Foundation IRB approach and Advanced IRB approach. Under Foundation IRB, banks are permitted to use their own internal risk rating system and own calculation of PD, but the LGD and EAD will be provided by the regulator. Under Advanced IRB approach banks are permitted to use their own calculated PD, LGD, EAD and the effective maturity.

3.3 Models Used for Credit Risk Measurement

Credit risk measurement depends on the likelihood of default of a borrower to meet its contractual obligations to creditors/ lenders. If the obligation is not fulfilled on the due date or as per the terms of the contract, a default would get triggered. Models used for credit risk measurement focus on the estimation of probability of default of borrowers, since it is the single most dominant source of uncertainty in the lending decision. Credit risk models have evolved through different stages starting from traditional approaches to new approaches. This section reviews various credit risk measurement models used by banks and financial institutions.

Credit risk models can be classified as: expert system, rating system, credit scoring models, logistic regression models, structural models, reduced-form models and credit value at risk models. It is not so easy to bifurcate between traditional and new approach to credit risk model, as many of the superior concepts of the traditional models are used in new models. Nevertheless, researchers classified traditional credit risk models into three categories: Expert Systems, Rating Systems and Credit-Scoring Systems. Edward Altman (1968) was the pioneer of credit scoring model. His model is known as Z-Score model. Structural models date back to

Merton (1974). Currently, there are a number of credit risk models which adopt the formulation of Merton's model, which, in turn is based on Black-Scholes (1973) option pricing theory. The structural models adopt the contingency claim approach, where the corporate liabilities (equity and debt) are contingent claims on the assets of the firms. The different models are discussed below. Both the credit scoring models and Merton's structural models, in particular, are discussed in detail in the following sections.

3.3.1 Expert System

The expert system that is even now followed is the traditional and oldest system that has been in existence since the start of lending where credit decision vests with the local or branch lending officer. His expertise, skill set, subjective judgment, and weighting of certain key factors are the most important determinants in the decision to lend. By its very nature expert systems involve a high degree of subjectivity and consequently, there are infinite number of expert systems a lending officer could look at. However, one of the common expert systems informally accepted as best practice is the use of five 'Cs' of credit - character, capital, capacity, collateral and cycle or (economic) conditions of borrowers. The expert assigns weights to each factor to arrive at a credit decision. Character is judged by the reputation of the firms, its willingness to repay, and its repayment (credit) history. It is commonly believed that vintage factor of an organization is a good proxy for its repayment reputation. Capital Structure, i.e., the debt to equity ratio (known as leverage), is viewed as a good predictor of bankruptcy probability. High leverage suggests greater probability of bankruptcy than low leverage, because a low level of equity reduces the ability to survive losses. Capacity is the ability to repay, which reflects the volatility of the borrowers' earnings; the cash flow generation from operations and related elements. Although, debt servicing may be timely, if earnings are volatile and there are mismatches in cash flow management, the likelihood of default in the near future may be high. 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. Finally, the external environment, the business cycle and related factors also form an important element in determining credit risk exposure, especially for industries whose business/ products growth driving the revenue generation are dependent on the economic cyclical/ seasonal factors. For example, the infrastructure sectors like metal industries, construction, etc. tend to be more dependent on macro level policy decisions by the government and regulators, than goods sectors like food, retail, and services.

Although many banks even today continue to use expert systems as part of their credit decision process, these systems face two main problems: (i) Consistency, i.e., what are the important common factors to analyze across different types of borrowers? (ii) Subjectivity, or, what are the optimal weights to apply to the factors chosen? The credit decision is influenced by the weights assigned to these factors. However, despite the existence and the evolving nature of sophisticated models and a host of objective factors, expert system is likely to be used as the final arbiter. The relevance of expert system therefore, cannot be underestimated and will have to be used as a complement to the other systems/models.

3.3.2 Rating System

One of the earliest 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, R. R., 2003). The OCC ratings system places an existing loan portfolio into five categories: four types of portfolios under low quality rating and one type of portfolio under high quality rating. Regulators define certain percentage of loss reserve for various rating brackets that is maintained by banks. Over the period, banks have extended the time tested OCC rating system by developing internal rating systems that is more split into either pass or performing rating category.

There are various US rating agencies namely, Moody's, Standard and Poor, Fitch IBCA etc., which assign different ratings to commercial credit. In India, some of 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. and SME Rating Agency of India Limited (SMERA).

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 their own system of letter grades that shows the credit quality of issuer from the highest to lowest grades. Rating agencies consider different factors when they assign different ratings. S & P explains that in rating an industrial bond, it focuses on the areas such as, industry characteristics, competitive position (marketing, technology, and efficiency), management, financial characteristics, financial policy, profitability, capital structure, cash flow protection, financial flexibility.

3.3.3 Scoring System

Altman (1968) Z-Score model is one of the pioneering works 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 discriminate best between a priori defined groups: the default from non-default firms (Benos et.al. 2005). It weights the independent variables (financial ratios) and generates a single composite discriminant score. The score is then compared to a cut-off 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 safe or distressed groups.

Altman (1968) has found 22 potentially helpful variables (ratios) out of a large number of significant variables, which are indicators of corporate problems for evaluation of the firm. The 22 variables are classified into five standard ratio categories: 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. Using linear discriminant analysis, the Altman's scoring model was defined as:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \qquad \ldots(3.1)$$

Where, the variables are defined as follows:

X_1, Working Capital/Total Assets (WC/TC) ratio, which is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities.

X_2, Retained Earnings/Total Assets (RE/TS): Retained earnings is the account which reports the total amount of retained earnings and/or losses of a firm over its entire life. This is also referred as earned surplus. The firm's vintage is implicitly considered in this ratio. For example a relatively younger firm is more likely to show a low RE/TA ratio because the smaller time frame to have built-up of cumulative profit. The RE/TA ratio also measures the leverage of a firm. Firms with high RE, relative to TA, would indicate that the firm would have financed its assets through retention of profits and not through borrowings. Consequently, debt would be relatively lower for such firm.

X_3, Earning before Interest and taxes/Total Assets (EBIT/TA): This ratio is a measure of profitability of the firm prior to outgo on taxation and debt servicing. Since a 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.

X_4, Market Value of Equity/Book Value of Total Liabilities (MVE/TL): Equity is measured by the combined market value of all shares of stocks, preferred and common, while liabilities include both current and long term. The measure shows 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 insolvent. It appears to be a more effective predictor of bankruptcy than a similar, more commonly used ratio: Net worth/ total book value of debt.

X_5, Sales/Total Assets (S/TA): This is a key variable for the measurement of size of the firm. The capital turnover ratio is a standard financial ratio illustrating the revenue generating ability of the firm's assets. It serves as a 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. It is one measure of management's capacity to deal with competitive conditions.

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 as well). Second, the model is essentially based on accounting ratios. In most countries, accounting data appear 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 on the older vintage credit-scoring models (Saunders, 1999).

3.3.4 Logistic Regression Model

In some of the default studies based on MDA models, authors have pointed out that the two basic assumptions of MDA are often violated when applied to the default prediction problems[11]. 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 E. I. and G. Sabato, 2007). Considering the problem with MDA models, Ohlson (1980), for the first time, applied the conditional Logit model to the study of default prediction. The advantages of the Logit methodology are that it does not require the restrictive assumptions of MDA and allows working with disproportional samples.

Logistic regression models such as Logit and Probit are predictive models where target variable or dependent variable is a categorical variable. From a statistical point of view, Logit regression seems to fit well the characteristics of the default prediction problem, wherein the dependent variable is binary (default/ non-default) and with the groups being discrete, non-overlapping and identifiable. The Logit model yields a score between zero to one which conveniently gives the probability of default. Also, the estimated coefficients can be interpreted separately to know the importance or significance of each of the dependent variables in the explanation of the estimated PD. Altman, E. and Sabato G. have used Logit model for default prediction for SMEs in US market. They have considered some of the accounting ratios as independent variables. The dependent variable is binary in nature, which means it takes two values (1 or 0) for default and non-default states.

Since Ohlson Logit model is one of the models used for distress prediction in the present study, a brief overview of the Ohlson model is discussed here. Ohlson (1980) identified some problems in Z-Score model: (i) certain restrictive statistical requirements are imposed on the distributional properties of the predictors. For example, the variance-covariance matrices of the

[11] 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.

predictors should be the same for both groups (failed and non-failed firm); (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) for the first time used logit model to predict failure of the US firms. He selected nine independent variables that he thought should be helpful in predicting bankruptcy, but did not provide any theoretical justification for the same. He used the following logit model for bankruptcy prediction:

$$P = \left(1 + \exp(-\beta' X)\right)^{-1} \qquad \ldots(3.2)$$

Where, P is the probability of bankruptcy and X represents the independent variables used in the model. Value of the P will lie between 0 to 1. The dependent variable is binary in nature- either 1 in case of bankrupt or 0 in case of non-bankrupt.

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

1. SIZE = log(total assets/GNP price-level index). The index assumes a base value of 100 for 1968. Total assets are as reported in dollars. The index year is as of the year prior to the year of the balance sheet date.

2. TLTA = Total liabilities divided by total assets.

3. WCTA= Working capital divided by total assets.

4. CLCA= Current liabilities divided by current assets.

5. OENEG = One if total liabilities exceeds total assets, zero otherwise.

6. NITA= Net income divided by total assets.

7. FUTL = Funds provided by operations divided by total liabilities.

8. INTWO = One if net income was negative for the last two years, zero otherwise.

9. CHIN= (NIt - NIti)/(|NIt| + |NIt-i|), 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 have been traded on some stock exchange or over the counter (OTC) market; (iii) the company must be classified as an industrial. 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 on the basis of rigorous theory. The first six predictors were partially selected simply because they appear to be the ones most frequently mentioned in the literature.

In Ohlson's study, three sets of estimates were computed for the logit model using the aforementioned predictors. 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.

3.3.5 Structural Credit Risk Models

Altman, E. I. (2006) has discussed the development of various credit risk models during the last thirty years. He has classified these models into (i) credit pricing models, and (ii) portfolio credit value-at-risk (VaR) models. Credit pricing models are further divided into first generation structural-form models, second generation structural-form models and reduced-form models. Here, we briefly discuss some of the models mentioned in his paper.

First Generation Structural-Form Models

First generation structural-form models are structural models completely based on the original framework developed by Merton (1974) using the principles of option pricing (Black and Scholes, 1973). Structural models adopt the contingency claim analysis, wherein the corporate liabilities are considered as contingent claims on the asset of the firm. In the Merton framework, the default process of a company is driven by the value of the company's total assets and the default risk originating in the firm is therefore explicitly linked to the variability of the firm's asset value. The fundamental intuition of Merton model is default occurs when the value of a firm's asset (the market value of the firm) is lower than its liabilities.

Assuming that the company's debt is entirely represented by zero-coupon bond, if the value of the firm's assets at maturity is greater than the face value of the bond, then the bond holder gets back the face value of the bond. However, if the value of the firm's assets is less than the face value of the bond, the shareholders would get nothing while the bond holder is more likely to get back the market value of the liquidated firm. The payoff at maturity or on insolvency, to the bondholder is therefore, equivalent to the face value of the bond minus a put option on the value of the firm's assets, with a strike price equal to the face value of the bond and a maturity equal to the maturity of the bond. Following this basic intuition, Merton derived an explicit formula for risky bonds that can be used both to estimate the probability of default (PD) of a firm and to estimate the yield differential between a risky bond and a default-free bond. Under Merton's theoretical framework, PD and Recovery Rate tend to be inversely related. The derivation of the Merton model and calculation of PD is discussed in details in section 3.3.6 below.

Second Generation Structural-Form Models

Since the first generation models were based on some unrealistic assumptions, an alternative approach was developed which, while continuing to adopt the original Merton framework as far as the default process is concerned, removed one of these unrealistic assumptions; namely, that default can occur only at maturity of the debt. Instead, in Second Generation models, it is assumed that 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 vis-à-vis the liabilities. Under these models, the Recovery rate (RR) in the event of default is exogenous and independent from the firm's asset value. It is generally defined as fixed ratio of the outstanding debt value and is therefore independent from the PD.

Despite the improvements with respect to the original Merton's framework, second generation structural-form models continue to suffer from some drawbacks: (i) they still require estimates for the parameters of the firm's asset value, which is non-observable; (ii) structural-form models cannot incorporate credit-rating changes that occur quite frequently for default-risky corporate debt, (iii) most structural-form 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, firm’s default depends on the value of the firm’s assets and the calculation of default is based on certain unrealistic assumptions. To overcome the drawbacks of structural-form models, new models known as reduced-form models, were developed by the researchers. Unlike structural form models, reduced-form models do not postulate default occurrence based on the value of the firm’s assets and the parameters related to the value of the firm’s assets, need not be estimated to implement them (Altman, 2006). In addition, reduced-form models introduced explicit assumptions on the dynamics of both PD and RR. Reduced-form models assume an exogenous RR that is independent from PD and take as basic the behaviour of default-free interest rates, the RR of bonds that would face default, as well as a stochastic process for default intensity (Altman, 2006).

3.3.6 Black-Schole-Merton Model

Since the Black-Schole-Merton model is studied in this thesis, its derivation is worked out here. Merton (1974) in his seminal paper on the valuation of corporate debt, proposed a contingency claim approach to value corporate liabilities, using Black and Schole’s (1973) option pricing theory. Merton model was later modified by different authors and corporate service providers like, KMV Corporation, Black and Cox (1976) and Longstaff and Schwartz (1995), and many more. Merton’s approach is referred to as the ‘structural approach’ because it relies entirely upon the capital structure of the firm (debt and equity) for modeling credit risk. This approach, as mentioned earlier, 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. Thus the value of equity can be modeled as a call option on the firm’s assets, 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 can be modeled as a put option.

The Merton model is used to calculate probability of default of corporate debt. This model is based on certain assumptions: (i) The firm can default only at maturity at time T. (ii) Firm's asset values follow lognormal distribution. (iii) The value of the firm's assets V is financed by equity, E and debt F, where the total value of 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 share holders receive nothing. This shows that the firm's equity is treated as a call option and therefore Black-Schole pricing formula is applied for its pricing.

From above assumptions, it is clear that the value of equity in the Black-Schole-Merton (BSM) framework is given by:

$$E = \max(0, V-F)$$

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 apart from other known parameters. The total market value of the firm is simply the sum of the market value of the firm's debt and the value of its equity. Calculation of PD would be an easy task if both of these quantities are readily available. While equity values are readily available, reliable data on market value of debt is generally unavailable. The Merton model helps to solve this problem. Merton model assumes that the total value of a firm follows geometric Brownian motion:

$$dV = \mu V dt + \sigma_V V dZ \qquad \ldots(3.3)$$

Where, V is 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, equity value of a firm as a call option is given by Black-Schole formula:

$$E = VN(d_1) - Fe^{-rT} N(d_2) \quad \ldots(3.4)$$

Where, $$d_1 = \frac{\ln(V/F) + (r + \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \quad \ldots(3.5)$$

$$d_2 = \frac{\ln(V/F) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \quad \ldots(3.6)$$

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:

$$N(-d_2) = N\left[-\frac{\ln(V/F) + (r - \sigma_V^2/2)T}{\sigma_V \sqrt{T}}\right] \quad \ldots(3.7)$$

If we replace the risk free interest rate *r* in (3.6) with the expected return on the assets value or the 'drift' of the asset value, μ_V, we get the distance to default measures, which is:

$$DD = \frac{\ln(V/F) + (\mu_V - \sigma_V^2/2)T}{\sigma_V \sqrt{T}} \quad \ldots(3.8)$$

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

$$N(-\hat{d}_2) = N\left[-\frac{\ln(V/F) + (\mu_V - \sigma_V^2/2)T}{\sigma_V \sqrt{T}}\right] \quad ...(3.9)$$

The equation (3.9) shows that the probability of bankruptcy is 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 $(\mu_V - \sigma_V^2/2)$ relative to 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 (3.4) is derived under the assumption of risk-neutrality where all assets are expected to grow at the risk-free rate, hence PD based on risk free rate will provide risk neutral probability of default as shown in equation (3.7). However, the probability of bankruptcy depends upon 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 (3.9) includes three unknowns, namely, V, σ_V and μ_V. We need to find all three parameters in order to obtain an estimate of (3.9). In order to identify the above unknowns, the model invokes the Weiner process to model equity value, *E*.

$$E = \mu_E E dt + \sigma_E E dZ \qquad \ldots(3.10)$$

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

$$dE = \left(\frac{\partial E}{\partial t} + \mu_V V \frac{\partial E}{\partial V} + \frac{1}{2} \sigma_V^2 V^2 \frac{\partial^2 E}{\partial V^2} \right) dt + \sigma_V V \frac{\partial E}{\partial V} dZ \qquad \ldots(3.11)$$

Since the diffusion terms in the equity process in (3.10) and (3.11) are equal, we can write the following relationship:

$$\sigma_E E = \sigma_V V \frac{\partial E}{\partial V} = \sigma_V V N(d_1) \qquad \ldots(3.12)$$

Equation (3.4) and (3.12) complete the system of two simultaneous nonlinear equations with two unknowns, *V* and σ_V; and the known parameters are *E*, σ_E, *r*, *F* and *T*. Hence the above two unknowns can be obtained by solving two equations (3.4) and (3.12) simultaneously using 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, which is estimated by solving equation (3.4) and (3.12) and market value of asset of previous year. In many cases, the actual return on assets is negative. As mentioned in Hillegeist (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:

$$\mu_v(t) = \max\left[\frac{V(t) - V(t-1)}{V(t-1)}, r\right] \qquad \ldots(3.13)$$

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 (3.9).

3.3.7 Credit Value at Risk Models

Basel II Accord has already been implemented in many developed countries. During the late nineties, banks started using models based on Value at Risk (VaR) framework to measure credit risk. This was mostly motivated by the growing importance of credit risk measurement, which took an important place in new Basel Accord. Generally, VaR model is used to measure market risk of the asset portfolio. The new Accord has prescribed that banks are free to use credit risk models developed internally. To qualify as an internal model for specific risk, the regulator should be convinced that ‘concentration risk’, ‘spread risk’, ‘downgrade risk’, and ‘default risk’ are all appropriately captured.

Spread risk is related to both market risk and credit risk. Spreads fluctuate either because equilibrium conditions in capital market changes, in turn affecting credit spreads across all credit ratings, or because the credit quality of the obligor has either improved or deteriorated; or because both conditions have occurred simultaneously (Crouhy et al 2000). Downgrade risk is purely a credit spread risk. Default is just a special case of downgrade, when the credit quality has deteriorated to a point where the obligor is unable to service its debt obligations anymore. An adequate credit-VaR model should therefore address both migration risks, i.e. credit spread risk, and default risk in a consistent and integrated framework. Concentration risk may arise when too much of money is lent out to certain categories of borrowers. An example of concentration risk is: if the entire mortgage lending of a bank is confined to a particular neighborhood of a city, the bank would face major risks if some sort of disaster hits that neighborhood; all the customers of the bank will be affected by the event and bank will not be able to recover its money.

Credit VaR models address the issues of credit risk due to change of credit quality, either improvement or deterioration or default. Altman (2006) has divided the credit VaR models into two categories: (1) Default mode models (DM) and (2) Mark-to-Market (MTM) models. In the former, credit risk is identified with default risk and a binomial approach is adopted. Therefore, only two possible events are taken into account; default and survival. The latter includes all possible changes of the borrower creditworthiness, technically called "credit migrations". In DM models, credit losses only arise when a default occurs. On the other hand, MTM models are multinomial, in that losses arise also when negative credit migration occur. Some of the industry sponsored credit VaR models are: (i) J. P. Morgan's CreditMetrics; (ii) Credit Suisse Financial Products' (CSFP) CreditRisk+; (iii) KMV's Credit Portfolio Manager; (iv) McKinsey's CreditPortfolioView; (v) Kamakura's Risk Manager

CreditMetrics from J. P. Morgan was first published and well publicized in 1997. CreditMetrics approach is based on credit migration analysis i.e. the probability of moving from one credit quality to another, including default within a given time horizon, which is often taken arbitrarily as 1 year. CreditMetrics models the full forward distribution of the values of any bond or loan portfolio, say 1 year forward, where the change in values are related to credit migration only, while interest rates are assured to evolve in a deterministic fashion (Couhy et al, 2000). Credit-VaR of portfolio is then derived in a similar fashion as for market risk. It is simply the percentile of distribution corresponding to the desired confidence level.

At the end of 1997, Credit Suisse Financial Products (CSFP) released a new approach, CreditRisk+, which only focuses on default. CreditRisk+ assumes that default for individual bonds, or loans follow a Poisson process. Credit migration risk is not explicitly modeled in this analysis. Instead, CreditRisk+ allows for stochastic default rates which partially account, although not rigorously, for migration risk.

KMV Corporation, a firm specialized in credit risk analysis, has developed different models and extensive data base to assess default probabilities and the loss distribution related to both default and migration risk. KMV developed both Expected Default Frequency (EDF) model and Portfolio Manager model. EDF was developed to measure the probability that a company will default over a specified period of time using the current market value of a firm, book value of debt and volatility of the market value of the asset. This model is based on asset value model developed by Merton (Merton, 1974). In 1993, KMV introduced Portfolio Manager model, a tool for managing credit portfolio risk. KMV Portfolio Manager model is based on VaR principle.

McKinsy, a consulting firm, developed its own model, CreditPortfolioView, which, like CreditRisk+, measures only default risk. It is a discrete time multi-period model, where default probabilities are a function of macro-economic variables such as unemployment, the level of interest rates, the growth rate in economy, government expenses, foreign exchange rates, which also drive, to a large extent, credit cycles.

Kamakura Corporation is one of the world's premier providers of risk management software. Its Risk Manager is the first software package in the world that offers combined solution for credit risk, market risk, asset and liability management and performance measurement. It provides measurement for default probability, credit-adjusted valuation and VaR etc.

3.4 Literature Review

The earlier sections of the chapter discussed various popular models used widely in the credit risk model literature. The current section will detail some of the empirical literature on bankruptcy prediction published and available in the public domain. The development of bankruptcy prediction models dates back to 1960s, during which the first bankruptcy prediction model was developed by Beaver (1966) using financial ratios. Beaver's credit risk model was a univariate model developed to predict bankruptcy, which was followed by a wide range of credit risk models which include multivariate discriminant analysis, logistic model variants and variants of Black-Schole models.

Probably this was the first model developed to predict corporate bankruptcy using financial information. Beaver used individual financial ratios to predict bankruptcy using 79 failed firms and 79 non-failed firms. The non-failed firms were matched on the basis of industry type and asset size. By using a wide range of financial ratios spanning from 1954 to 1964, he found that the total cash flow to total debt ratio has excellent explanatory power to predict bankruptcy. Other variables which were found to be significant are net income to total assets and total debt to total assets. He also found that not all ratios predict equally well and the ratios could not predict failed and non-failed firms with the same degree of success. The Beaver study was the base study on bankruptcy prediction model using financial ratios. Subsequent to this study, Altman and Ohlson developed their bankruptcy prediction models using multivariate discriminant analysis and logit model, which have occupied a significant place in the credit risk modeling literature.

Two years post-Beaver, Altman (1968) developed a bankruptcy prediction model using financial ratios of US companies. The set of ratios used in Altman’s Z-Score model was different from ratios used by Beaver. Altman tried to predict bankruptcy using multivariate discriminant analysis (MDA). Altman's model was discussed in detail earlier in section 3.3. He used financial ratios of 33 distressed firms and 33 non-distressed firms for the period spanning from 1946 to 1964. The matched non-distressed firms were identified on the basis of industry type and their asset size. Non-failed firms were identified from the same industry the failed firms belonged to and the asset size was matched to failed firms. Altman identified 5 variables for the study from 22 potentially helpful financial ratios, on the basis that they were significant in predicting bankruptcy. Some of the key ratios used in his study are: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to book value of total debt and sales to total assets.

Altman performed F test to test the discriminating ability of the individual variables. He found 4 out of five variables to be significant, indicating significant differences in the variables between groups. Z-Score was determined using MDA and the cut-off point was found to be 2.675, which discriminates best between bankrupt and non-bankrupt firms. Hence the firms with Z-Scores less than 2.675 are predicted to be bankrupt and those whose Z-Scores are greater than 2.675 are predicted as non-bankrupt. However, Altman found that all firms having a Z-Score of greater than 2.99 clearly fall into the non-bankrupt group, while all firms having Z-Score below 1.81 fall into bankrupt group. The area between 1.81 and 2.99 is defined as the zone of ignorance or the gray area. He found that the predictive ability of his MDA model is very high at 95% one year prior to failure. Subsequent to his 1968 study, Altman identified another bankruptcy prediction model. The revised Z-Score model was estimated by substituting book value of equity for the market value of equity used in the previous model. All the coefficients and cut-off points in the revised model were changed. An obvious advantage of the revised Z-Score model is that it can be used for predicting bankruptcy of the firms where market value of equity is not available.

As noted earlier, due to some of the inherent limitations of MDA model used in the literature of bankruptcy prediction, 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 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 cut-off probability value, which minimizes sum of type I and type II errors. The predictive ability of Model 1 was found to be greater than that of other two models.

After the development of Altman Z-Score and Ohlson logit models, a number of research studies and publications have been carried out to predict bankruptcy using similar methodology of MDA and logit model. One of them is Bortiz, Duane, Kennedy and Sun (2007). This study evaluated the performance of Altman and Ohlson models against three Canadian bankruptcy prediction models using data of Canadian companies. Model performance was evaluated using type I and type II errors as well as overall accuracy rate. The study used both original models of Altman and Ohlson and compared their performance with the re-estimated models applied to the actual Canadian firms' data. They found that all the models have stronger performance with the original coefficients than the re-estimated coefficients. Wang and Campbell (2010) applied Ohlson model to predict bankruptcy of Chinese companies. Consistent with Ohlson's original model, they estimated three models; model 1 predicts bankruptcy within one year, model 2 predict bankruptcy within two years and model 3 predicts bankruptcy within one or two years.

Abdullah, Halim, Ahmed and Rus (2008) had 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 provides 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. Charitou, Neophytou and Charalambous (2004) developed a failure prediction model for UK public industrial firms using a sample of companies spanning from 1988 to 1997 with the help of neural network and logit model. They tried to explore the incremental information content of operating cash flows in predicting the probability of business failures. Their data set includes 51 matched pairs of bankrupt and healthy UK companies. Their result showed that both neural network model and logit model can be viable alternatives for bankruptcy prediction.

After the development of Beaver and Altman Z-Score models Deakin (1978) in his study used both these models to predict corporate bankruptcy. He used a similar dichotomous classification test to what Beaver has used considering data of 32 failed firms spanning from 1964 to 1970. He also performed discriminant analysis by using 14 financial ratios which are used in Beaver’s model. He tried five models by using financial data of the companies from 1 year prior to failure to five years prior to failure. The significance of each of the discriminant functions was measured using Wilks' lambda statistic, which is used to test the hypothesis that the mean of the ratio vectors for each group are equal. Taffler (1982) used linear discriminant analysis to predict company failure of UK by using financial ratios of the companies from period 1968 to 1973. Zmijewski (1984) performed a bankruptcy prediction model using a probit model, where the dependent variable (1 for bankrupt and 0 for non-bankrupt companies) is binary in nature and the independent variables are: ratio of net income to total liabilities, ratio of total liabilities to total assets and ratio of current assets to current liabilities.

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 comprised 5 dependent variables. He tried to examine the predictive accuracy of the third model using data of 1 to 5 years prior to default. The model performance was also tested using holdout sample. The author has examined predictive ability of the models by considering 148 distressed manufacturing firms who registered as sick with BIFR (Board for Industrial and Financial Reconstruction). He found that the predictive ability of the models to predict default falls as one moves from one year prior to default to six 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 are 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 were made for BIFR reference. Firms which satisfy conditions to be registered as sick company in BIFR are treated as distressed in his study. Financial data of distressed and non-distressed companies for 4 years spanning from 1996 to 1999 was used to model bankruptcy. The results of Z-Score models show that the predictive ability of the model improves as the model uses more recent data, which means predictive ability of the model based on data one year prior to distress is 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.

Kulkarni, Mishra 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 result 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 include both distressed and top rated solvent companies, from period 1998 to 2004 are used for the study. Companies which are registered with Board for Industrial and Financial Reconstruction (BIFR) are 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 indicate that the probability of default estimated using Black-Scholes-Merton model is 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 result obtained from Merton model was found to be similar to the results obtained from Z-score model and Crisil's average one-year average rating transition matrix.

Varma and Raghunathan (2000) carried out a study to analyze credit rating migrations in Indian corporate bond market to bring a better understating of its credit risk. Their study based on the data consists of ratings of debentures of manufacturing companies by the Credit Rating and Information Services of India Ltd (CRISIL). Ratings for 426 companies were collected for 24 quarters from January 1993 to October 1998. They found that ratings below A- behave very differently from ratings of A- and above. Bonds rated A- or above are almost never upgraded by more than two notches, while lower rated bonds are often subject to larger upgrades. For bonds rated A- or better, the rating downgrades tend to be smaller and there is a large probability that the downgrade is by only one or two notches.

Shumway (2001) developed a hazard model to predict bankruptcy of firms at each point in time. The estimation of hazard model is similar to the estimation of the logit model since the hazard model has same likelihood function and same asymptotic variance-covariance matrix as the logit model. He has used a different set of dependent variables, which includes both accounting variables and market-driven variables during the period 1962 to 1992. The accounting variables include ratio of net income to total assets and the ratio of total liabilities to total assets, whereas market-driven variables included market size, past stock returns and the idiosyncratic standard deviation of the stock returns. The Hazard model uses company-year data. The dependent variable in the hazard model is the time spent by a firm in the healthy group. Dependent variable takes value 1 if the company fails and 0 otherwise. For example, if a company has been in existence for 5 years and declared as bankrupt in the fifth year and during previous four years it was healthy, then the dependent variable for fifth year will have the value as 1 and for other four years it will have value as 0. He estimated the hazard model using logit program. Shumway found from his study that some of the financial ratios used in the earlier studies were found to be insignificant to predict bankruptcy and some of the market driven variables were strongly related to bankruptcy probability.

Agarwal and Taffler (2008) compared performance of market-based and accounting - based bankruptcy prediction models by using data of UK non financial companies. They have used two market-based models namely, the model suggested by Hillegeist et al (2004) and the naïve market based model defined by Bharat and Shumway (2004) and UK based Z-Score model defined by Taffler. Both these models are based on Black-Schole-Merton (BSM) model. They found that neither market based model nor the ratio based model is a sufficient statistic for failure prediction and both the models carry unique information about firm failure. There exists little difference between these models as far as predictive accuracy is concerned. Market based model suffers from some restrictive assumptions such as all liabilities only mature in one year, default triggered only at maturity, single class of zero coupon bond, assumption imposed on the measurement of total assets value and volatility of assets, etc. Agarwal and Taffler have given some arguments in favor of the accounting based model. The corporate failure is not a sudden event; it is the culmination of several years of adverse performance, which can be captured through the accounting information of the firm. They also point out that the loan covenants are usually based on accounting numbers and this information will be reflected in accounting based model. They concluded that the accounting based traditional models were robust and not dominated by KMV type bankruptcy prediction model and that accounting based bankruptcy prediction models have a significant advantage over the market based approach.

Wu, Gaunt and Gray (2010) compared five different key bankruptcy prediction models available in the literature. This includes both accounting based models like Altman's model, Ohlson's logit model, Shumway's hazard model and market based model of Hillegeist et al. (2004). Their sample includes listed companies spanning the period 1980 to 2006. They used a matched-pair sample based on total assets of the firms and two digit SIC industry classification code on a yearly basis. Their study identified cutoff points to classify a firm either in bankrupt group or in non-bankrupt group, based on minimization of sum of type I and type II errors. The cutoff point that minimizes sum of type I and type II errors is considered in the study. They found that the key accounting information related to profitability, liquidity and leverage. Altman model was found as a poor performer in relation to other accounting based models. Though Ohlson model's predictive ability was good during 1970, the performance has deteriorated over a more recent period. The hazard model of Shumway (2001), which considers both market data and accounting data, was found to outperform models that use accounting data only for bankruptcy prediction. The performance of BSM type model suggested by Hillegeist was also found to be inferior to the Shumway model in this study.

Hillegeist, Keating, Cram and Lundsted (2003) have defined a market based model based on the Black and Scholes (1973) and Merton (1974) contingent claims approach. They compared the performance of their market based model to predict bankruptcy with two accounting based models such as Altman's Z-Score and Ohlson's logit model using data of firms which filed for bankruptcy between 1980 and 2000. They identified some of the limitations of accounting based models: (i) the probability of default estimates are for future whereas, the financial data used for the estimation are designed to measure past performance and hence, may not be very informative about the future status of the company; (ii) asset volatility is 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 prediction accuracy by comparing the sum of type I and type II errors for each of the alternative models and the model with the lowest total error was defined as the best model to predict bankruptcy. Their study suggests that the market based model provides significantly more information about the probability of bankruptcy than the accounting based models used widely in the bankruptcy prediction literature.

Bharath and Shumway (2008) used a market based model to predict bankruptcy of the US firms. They developed a naïve model based on Black and Scholes (1973) and Merton (1974) contingent claims models, where equity is treated as a call option on the assets of the firms with strike price equal to the face value of the firms. Their study compares probability of default of their naïve model with probability of default of KMV-Merton model, considering default data from 1980 to 2003. The naïve model is much simpler to calculate and retains some of the functional forms of KMV-Merton model. The result suggests that the KMV-Merton model does not appear to be a sufficient statistic for default. Probability of default estimated from their naive model which captures both functional form and the same basic inputs of the KMV-Merton model performs quite well. They concluded that the KMV-Merton probability is a marginally useful default forecaster, but not a sufficient statistic for default.

Altman (1989) tried to measure corporate bond mortality and its performance using an alternative technique to measure default risk and utilized this measure to assess the performance of fixed income investment strategies over the entire spectrum of credit quality classes. His approach tries to measure the expected mortality of bonds and the consequent loss rates in a manner similar to the way actuaries assess mortality of human beings. The study computed mortality rate, adjusted for redemptions and defaults, for the period 1971-1987. The results of his study indicate the expected adjusted mortality rates and losses, cumulated for a number of years after issuance, for all bond-rating categories.

Altman and Sabato (2007) developed a distress prediction model for small and medium scale industries (SMEs) of USA. They developed a one- year default prediction model using a logit regression technique on panel data of 2010 USA SMEs including 120 default companies, spanning from the period 1994 to 2002. 1890 non-defaulted firms are selected randomly over the same period. The study identified five financial ratios, which represent the main aspects of a company’s financial profile like liquidity, profitability, leverage, coverage and activity. The financial ratios used in their model include short term debt to book value of equity, cash to total assets, EBITDA to total assets, retained earnings to total assets and EBITDA to interest expenses. A Wald test results indicated that each of the predictors is statistically significant in predicting default of the companies. Also the Log-likelihood test was found to be statistically significant, that shows that there is a significantly strong relationship between the selected predictors and the default event. The performance, in terms of prediction accuracy, of this model developed for SMEs is found to be almost 30 per cent higher than the performance of the generic corporate model (Z-Score model). The study also found that Multivariate Discriminant Analysis (MDA) default prediction models are likely to have a lower ability to discriminate between defaulted and non-defaulted companies than logistic models when the same variables are used as predictors.

Altman (2005) introduced a credit scoring model for emerging corporate bond, which was known as Emerging Market Score (EMS) model. The EMS model is an enhanced version of the statistically proven Z-Score model. The original Z-Score model was developed for publicly owned firms, whereas this model can be applied to manufacturing and nonmanufacturing companies and is also relevant for both private and public firms. Unlike the original Z-Score model where it is required that the firms should have publicly traded equity, the EMS model was developed by considering book value of equity instead of market value of equity. He applied EMS model to 30 Mexican corporations that had issued corporate bonds in the Eurobond market and estimated emerging market score for each of them.

Bandyopadhyay et al (2007) in their study had attempted to empirically calibrate the default and asset correlation of the large Indian companies and also examined its implication on capital estimates of the bank for credit risk. The study is based on CRISIL's annual ratings of long term bond issues by 542 Indian companies during July 1992 to January 2005. The main focus of the study was to estimate default correlation across all rating categories as well as across different industries. They found that the default events were correlated and the correlations are different for different rating grades. The default correlation between firms within each rating grade were found to increase as the rating grade worsens, which shows that the default correlation is positively related to the probability of default (PD) of firms. The highest default correlations were observed between companies within the same rating grades and within the same industry. The study did not find significantly smooth monotonic relationship between the probability of default and asset correlation.

Bandyopadhyay (2007) developed a credit scoring model for agricultural loan portfolio of large public sector bank in India using logistic regression model. He classified NPA, substandard assets, doubtful assets and loss assets as defaulted assets. Based on a sample of 800 accounts, he tried to find the major characteristics that decide the nature of agricultural loan. Using these parameters, he developed a credit scoring model for the agricultural loan portfolio that would help the bank to assess risk in such loan segment. There were around 63 data fields collected from the bank, which would reflect the borrower characteristics. The study used 36 independent variables to perform logistic regression analysis to develop the credit scoring model for agricultural loan portfolio.

Aziz and Dar (2006) conducted an extensive literature review on the credit risk modeling and provided a comprehensive analysis of the methodologies and empirical findings from these models. Their findings suggest that traditionally bankruptcy prediction studies use financial ratios to predict firm's failure. More than 60 percent of the studies used financial ratios (measuring liquidity, solvency, leverage, profitability, asset composition, firm size and growth etc) as the only explanatory variables. About 7 percent of the studies used cash flow information for default prediction while 33 percent used a mix of financial ratios and other variables including macroeconomic, industry-specific, location and other firm-specific variables. They found that the studies used different sample size ranging from 32 to 35,287 firms. Samples of less than 100 firms were used in about 42 percent of the reviewed studies, which suggests that small sample size is an inevitable limitation but this limitation need not necessarily hamper future research in this area. The review suggests that more than 30 percent studies used multivariate discriminant analysis model for bankruptcy prediction, while around 21 percent preferred logit model. This shows that the use of multivariate discriminant analysis and logit models dominate the research. Predictive accuracy was observed to be usually good across all models. The review also suggests that Artificial Intelligence and Expert System (AIES) and theoretical models have slightly better average predictive accuracy than statistical models; although this superior performance is based on a smaller number of studies. On the other hand, the consistently high predictive accuracy of MDA and Logit models and their low Type I and II error rate among all the models were achieved in a relatively large number of studies suggesting that these models may provide overall the most reliable methods of bankruptcy prediction.

After the development of Altman's Z-Score model, Altman et al (1977) developed another model for default risk prediction, which is popularly known as ZETA model, using financial ratios of the companies. The new model was developed using sample of bankrupt firms covering the period 1969 to 1975. The sample used for modeling consists of 53 bankruptcy firms and a matched sample of 53 non-bankrupt firms. The matched sample was identified on the basis of type, size and year of bankruptcy petition. The sample was equally divided into manufacturer and retailer groups. The ZETA model was found to be effective in classifying bankrupt companies up to five years prior to failure on a sample of corporations consisting of manufacturers and retailers. They concluded that the new model for bankruptcy classification appeared to be quite accurate for up to five years prior to failure with successful classification of well over 90% of their sample one year prior and 70% accuracy up to five years. They also observed that the ZETA model outperformed alternative bankruptcy classification strategies in terms of expected cost criteria utilizing prior probabilities and explicit cost of error estimates.

Premachandra et al (2009) tried to compare performance of data envelop analysis (DEA) in assessing corporate bankruptcy with logistic regression (LR) model. DEA is a non-parametric method that measures weight estimates (not parameter estimates) of a classification function for separating default and non-default firms. The study used data of 100 US firms spanning from period 1991 to 2004. There were nine financial variables used to predict bankruptcy. All the variables were computed at the end of the fiscal year immediately preceding the year of bankruptcy. Variables used for the study were cash flow to total assets, net income to total assets, working capital to total assets, current assets to total assets, earnings before interest and taxes to total assets, earnings before interest and taxes to interest expenses, total debt to total assets, current liabilities to total assets and market value of equity to book value of common equity. The results in this study suggest that the DEA model performs extremely well in correctly identifying the bankrupt firms compared to the LR model. However, LR model performs extremely well in correctly identifying the non-bankrupt firms in comparison to DEA model. The out of sample results suggest that the DEA model significantly outperforms the LR model in terms of total correct predictions.

3.5 Conclusion

Credit risk management has always occupied a significant position in the risk management framework of the bank. The first Basel Accord, which is known as Basel I Accord, had considered credit risk for minimum regulatory capital requirement. In Basel II Accord, BCBS prescribed advanced approach, namely, ‘internal rating based (IRB)’ approach for measuring credit risk. Under advanced approach banks are allowed to estimate their own PD, LGD and EAD. There are number of modeling techniques used by the banks globally to estimate probability of default (PD), starting from the traditional model to the most sophisticated statistical models and BSM model. Discriminant analysis and logit technique are two major techniques used by the researchers to study default prediction. Altman’s Z-score model is based on discriminant analysis, whereas, Ohlson’s distress prediction model is based on logit model. A detailed description of these accounting based and market based models for bankruptcy prediction was discussed in this chapter. The derivation of Black-Schole-Merton (BSM) model was presented in order to understand the calculation procedure of this model. Literature pertaining to bankruptcy prediction has also been reviewed. It was noted that though the discriminant model and logit model for bankruptcy prediction were developed during 1960s and 1980s, their relevance in the current scenario to predict bankruptcy cannot be ruled out and the predictive ability of these models are found to be significant even now.

CHAPTER 4

MODELING CREDIT RISK: EMPIRICAL ANALYSIS

4.1 Introduction

Some of the popular models used to predict corporate bankruptcy were discussed in the previous chapter. Literature on bankruptcy prediction based on both accounting based and market based models was also reviewed. The objective of our study is to examine predictive ability of some well known credit risk models in Indian context, and this chapter focuses on the empirical analysis of credit risk modeling. The study compares the performance of two widely used accounting based bankruptcy prediction models, namely, Altman’s Z-Score model and Ohlson’s logit model. Though these models were developed in 1960s and 1980s respectively, literature suggests that they are still relevant and perform significantly in the present scenario. The Black-Schole-Merton (BSM) model has also been studied to examine its predictive ability in Indian scenarios. As discussed in chapter 3, BSM model is a market based bankruptcy prediction model, wherein market variables pertaining to firms’ size, market behavior, and stock prices are used to predict bankruptcy. While the models used in our study were discussed at the theoretical level in the previous chapter, this chapter will detail the methodology, data used for the study and analyze results obtained by using these three bankruptcy prediction models to predict distressed firms in India. But it must be pointed out at the outset that there are a lot of challenges in obtaining bankruptcy data pertaining to Indian companies.

This chapter is organized as follows: the methodology and models are presented in the following section, section 3 of the chapter spells out the data used, the predictive abilities of the models are discussed in section 4, and section 5 concludes.

4.2 Methodology

The models used in this study for bankruptcy prediction are Multiple Discriminant Analysis (MDA) first pioneered by Altman, Ohlson’s Logit model, and Black-Schole-Merton

(BSM) model. The BSM model was discussed in detail in the previous chapter hence is not reiterated here. However, this section discusses the other two models.

4.2.1 Multivariate Discriminant Analysis

Discriminant Analysis (DA) is a technique used for the classification of data on the basis of certain information. DA is used when the dependent variables are categorical and there are two or more categories of dependent variable. DA is useful in classifying the data into categories. This technique is used in finance to classify firms as either bankrupt or non-bankrupt on the basis of financial ratios. Discriminant Analysis enables: (i) the investigation of differences between groups on the basis of the attributes of the cases, indicating which attributes contribute most to group separation; (ii) the successive identification of the linear combination of attributes (dependent variables) known as canonical discriminant functions which contribute maximally to group separation; (iii) the classification of cases into groups- statistical significance tests based on χ^2 test enable the examination of how well the function separates the groups.

DA involves the determination of a linear equation like regression that will predict which group the case belongs to. The usual form of the discriminant model is:

$$Z = a + v_1 X_1 + v_2 X_2 + v_3 X_3 + ... + v_i X_i \qquad \ldots(4.1)$$

Where, Z = discriminant function

a = constant

v = the discriminate function or the weight for that dependent variable

X = dependent variable

The above discriminant function is similar to the linear regression equation, wherein v is the unstandardized discriminant coefficient similar to the coefficient b in regression equation. These v_i maximize the distance between the means of the criterion (dependent) variable. In other words, this equation minimizes the possibility of misclassifying cases into their respective groups or categories. The number of discriminating functions should be one less the number of groups, which means that if there are two groups (good/bad), then only one discriminant function can be obtained.

A discriminant score can be derived from the above equation by multiplying discriminating variables with their respective weights and adding them up. Hence it is a weighted linear combination of the discriminating variables. A discriminant score is the value resulting from applying a discriminant function formula to the data for a given case. The Z-Score obtained by estimating the above discriminant function is the discriminant score. The discriminant coefficients are used in a formula for making the classifications in discriminant analysis, much as b coefficients are used in regression to make predictions.

4.2.2 Logit Model

The logit model utilizes the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable. In the context of default prediction study, the logit model is used to classify whether a company is healthy or failed by using its financial ratios. The dependent variable in a logit model is binary in nature, *i.e.*, it takes values either 1 or 0. The function used in the logit analysis is known as the logistic function.

If a dependent variable is binary and is a function of a set of independent variables, the Linear Probability Model can be written as (Gujarati, 2004):

$$P_i = E(Y = 1 / X_i) = \beta_1 + \beta_2 X_i \qquad \ldots(4.2)$$

Where, in the present case, P represents probability of failure, X 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 logistic function can be written as:

$$P_i = E(Y = 1 / X_i) = \frac{1}{1 + e^{-(\beta_1 + \beta_2 X_i)}} \qquad \ldots(4.3)$$

For ease of exposition, the equation (4.3) can be written as:

$$P_i = \frac{1}{1 + e^{-Z_i}} = \frac{e^z}{1 + e^z} \qquad \ldots(4.4)$$

Where, $Z_i = \beta_1 + \beta_2 X_i$

One can easily verify that as Z_i ranges from $-\infty$ to $+\infty$, P_i that represents probability of default (PD), ranges between 0 and 1 and that it is nonlinearly related to Z_i (i.e., X_i).

The equation (4.4) represents what is known as (cumulative) logistic distribution function. If Pi is the probability of distress, which is given by (4.4), then $(1 - P_i)$ will be probability of non-distress. Hence,

$$1 - P_i = \frac{1}{1 + e^{Z_i}} \qquad \ldots(4.5)$$

This can be written as

$$\frac{P_i}{1 - P_i} = e^{Z_i} \qquad \ldots(4.6)$$

Where, $\frac{P_i}{1-P_i}$ is known as odds ratio- the ratio of probability of distress to the probability of non-distress. By taking natural log of (4.6)

$$L_i = \ln\left(\frac{P_i}{1 - P_i}\right) = Z_i = \beta_1 + \beta_2 X_i \qquad \ldots(4.7)$$

Here, L, the log of odds ratio is called the Logit and hence the model (4.7) is called as Logit model. To estimate the probability of distress, one has to estimate the equation (4.7).

4.2.3 Black-Schole-Merton Model

Both Altman Z-Score model and Ohlson's logit model are accounting-based bankruptcy prediction model since they use accounting ratios of a firm to predict bankruptcy. On the other hand, BSM model uses market based information such as market value of equity, equity return volatility, market value of assets etc. As noted earlier, the BSM model for bankruptcy prediction is based on the option pricing theory of Black and Schole (1973), subsequently fine tuned by KMV Corporation and various financial institutes to predict corporate bankruptcy. The assumptions and the detailed analyses of the model were discussed in the previous chapter.

4.3 Data Used for the Study

Given that the study examines predictive ability of various credit risk models for Indian companies, financial data of both distressed and non-distressed companies are collected. In India there is no clear and comprehensive corporate bankruptcy law. Unlike USA, India does not have anything like Chapter 11 (where, the USA companies can file for bankruptcy) for bankruptcy filing. Hence, it is not easy to obtain bankruptcy/ default data in India. However, Board for Industrial & Financial Reconstruction (BIFR) looks after the sick companies in India to some extent. Sick companies do register in BIFR when they meet the laid down conditions[12]. The study has identified bankrupt companies from the list of companies registered in BIFR. Due to unavailability of bankruptcy data in India, researchers usually identify distressed companies either from BIFR database of sick companies, or use rating information provided by the rating agencies in India to identify sick companies.

Companies registered in BIFR during 2006 to 2012 are considered for sample selection. More than 500 sick companies are registered in BIFR during this period. Amongst them, the study shortlisted 62 sick companies on the basis of availability of financial data (balance sheet and profit and loss data) and stock data for historical period. Companies, for which at least three years financial data was not available, were not included in the sample. Data for a minimum of three years prior to bankruptcy is required to study the predictive ability of models two years before actual bankruptcy occurs. An equal number of matched non-distressed companies are chosen randomly. The matching is done on the basis of asset size and industry type. The study identifies 62 distressed and 62 non-distressed companies and hence a total of 124 companies are used for examining the accounting based models of Altman and Ohlson. Altman's Z-Score model requires matching sample for distress prediction analysis. The study has used the same

[12] A company which has completed five years in the business, has a factory license, number of workers are 50 or more and the accumulated loss is equal to or greater than its net worth, can file for being classified as 'sick company' under BIFR.

sample for logit and Altman models. For BSM model, the study uses 114 companies comprising of both distressed and non-distressed companies. The number of companies is less in case of BSM model in comparison to other two models since historical stock prices of some of the distressed companies, which is one of the variables used for distressed prediction, are not available for some years. The companies considered in our study are from various industry segments such as cement, automobiles, textiles, chemical, food processing, plastic, electrical, paper, etc. The list of companies used in the study is mentioned in Appendix 5 at the end of the thesis.

Financial information of both distressed and non-distressed companies is collected from their balance sheet and profit and loss statements. We have collected balance sheet and profit and loss statements from Bloomberg, Money Control, Rediff Money and from other online sources. Stock prices are collected from Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) websites and Money Control website. Gross National Product (GNP) data is collected from the Economic Survey 2012-13. GNP index with base year 2004-05 is considered for the analysis. Information related to risk free return is collected from RBI Annual Report. 10 year G-Sec yield is used as the risk free rate. The financial ratios used in the study are calculated from the information content in balance sheet and profit and loss statements of the companies.

Accounting based bankruptcy prediction models use large number of financial ratios which represent liquidity, profitability, leverage, solvency, activity/size and growth of the companies. Some of the significant financial ratios used in the study are: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, sales to total assets, total liabilities to total assets, current liabilities to current assets, net income to total assets, cash flow to total liabilities, market value of equity to total assets. The study has used the financial ratios which were used in the famous Altman's Z-Score model and Ohlson's Logit model. Altman (1968) used market value of equity to total liabilities ratio as one of the five accounting variables in his study. However, in his subsequent studies (Altman, 2000, 2007), he has developed Z-Score model for private companies and SMEs by substituting book value of equity for the market value of equity. This model is very suitable for privately held companies and SMEs, where the market value of equity is not available, since the shares of such companies are not traded in the market. However, the same model can also be used for publicly traded companies. In the present study, for some of the companies, market value of equity is not available; hence, book value of equity is used as the fifth variable instead of market variable of equity in Z-Score model.

4.4 Analysis and Results

This section discusses results obtained from multivariate discriminant analysis, logit model and BSM model using financial data of Indian companies. There are very few studies in India on the predictive ability of various accounting based and market based corporate bankruptcy prediction models. In this context, this study tries to compare the predictive ability of the two accounting based bankruptcy prediction models, which are widely used in the literature of bankruptcy prediction. Also the present study uses one popular market based bankruptcy prediction model to compute probability of default of Indian companies.

Using the financial data of Indian companies, Altman's Z-Score model based on multivariate discriminate analysis technique, Ohlson's model based on logistic regression approach, and the BSM model are estimated. The predictive accuracy of the two accounting-based models is compared. Two Z-Score models and two logit models are estimated. The first model is estimated to predict bankruptcy using financial data of one year prior to bankruptcy, whereas the second model uses financial data of two years prior to bankruptcy[13]. This will enable the comparison of predictive ability of the model that uses data one year prior to bankruptcy with the predictive ability of the model that uses data two years prior to bankruptcy.

4.4.1 Results of Multivariate Discriminant Analysis

Altman's Z-Score model employs multivariable discriminant analysis (MDA) to predict bankruptcy of US firms by using various financial ratios that are statistically associated with future bankruptcy. The five financial ratios used measure liquidity, profitability, leverage and solvency. The present study is based on these five financial ratios to predict distressed and non-distressed firms.

[13] Financial data one year prior to bankruptcy is collected at the end of the fiscal year immediately preceding the year of bankruptcy (bankruptcy data available for calendar year) and data two years prior to bankruptcy is collected at the end of previous fiscal year.

Descriptive Statistics of Z-Score Model

Descriptive statistics of the financial ratios which are used as the explanatory variables in Z-Score model is presented in the Table- 4.1. The mean and the standard deviation of the variables for distressed and non-distressed firms are shown. For distressed firms, mean and standard deviation of the variables using data of one year prior to distress and two years prior to distress are also shown.

It is evident from the Table- 4.1 that the ratio generally deteriorates as the company inches towards distress. The mean of working capital/total assets decreases as the companies move from non-distressed stage (0.276), to two years prior to distress (0.188), and then to one year prior to distress (0.040). Similarly mean values of retained earnings/total assets, earnings before interest and taxes/total assets and sales/total assets decrease as firms move from non-distressed stage to two year prior to distress, and then to one year prior to distress stage. Mean of book value of equity/total liability reduces substantially from non-distressed (0.991) to one year prior to distress (0.740).

The means of retained earnings/total assets are negative for both one year and two years prior to distress, indicating a negative average retained earnings of the firms. The mean of earnings before interest and taxes/total assets and mean of book value of equity/Total liabilities are negative for one year prior to distress, whereas it is positive for non-distressed firms.

Table- 4.1: Descriptive Statistics of the Variables Used in Z-Score Model

	One year prior to distress		Two year prior to distress		Non- distress firms	
variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
X1	0.040	0.627	0.188	0.233	0.276	0.248
X2	-0.195	0.753	-0.135	0.183	0.023	0.056
X3	-0.087	0.236	-0.036	0.150	0.093	0.078
X4	-0.153	0.199	0.081	0.302	1.098	1.505
X5	0.740	0.665	0.822	0.676	0.991	0.555

Note: X1- Working Capital/Total Assets,
X2- Retained Earnings/Total Assets,
X3- Earnings before Interest and Taxes/Total Assets,
X4- Value of Equity/Total Liabilities,
X5- Sales/Total Assets

Estimation of Z-Score Model

The Z-Score model of Altman is estimated using 62 distressed and an equal number of non-distressed firms in India. The statistical software SPSS is used to estimate the discriminant model. The model is estimated using multivariate discriminate analysis technique. The study estimates two Z-Score models- Model 1 uses data one year prior to distress and Model 2 uses data two years prior to distress. Table- 4.2 reports results of the Altman Z-Score model using financial data one year prior to distress. All the coefficients of the discriminant model are seen to be positive except the constant. These coefficients are used to weight the explanatory variables, to arrive at discriminant scores. Our discriminant model based on the data one year prior to distress can be written as:

$$Z = -0.515 + 1.045X_1 + 0.846X_2 + 1.919X_3 + 0.575X_4 + 0.169X_5 \qquad \ldots(4.8)$$

The Z-Scores can be obtained for each of the distressed and non-distressed firms by simply substituting values of X_1 to X_5 in the above equation. Wilkis' Lambda (mentioned against each explanatory variable) has been used to test which variables contribute significantly to the discriminant function. The value of Lambda varies from 0 to 1. The smaller the value of Wilks' Lambda of an independent variable, higher the contribution of that variable to the discriminant function. The F test of Wilks' Lambda can be performed to test the significance of the variables in the discriminant function.

The magnitude of the Wilks' Lambda and F-statistic of the individual variables suggests that the likelihood of the means of the solvent and defaulted groups to be equal is low; *i.e.*, highly unlikely[14]. All the variables are found to contribute significantly to the discriminant function. The null hypothesis that means of the variables in both the groups are equal can be rejected in case of all the independent variables.

[14] 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.

The most important test performed to test significance of the discriminant function as a whole is Wilks' Lambda test for the model. A significant Lambda means one can reject the null hypothesis that the two groups have the same mean discriminant function scores and conclude the model is discriminating. A χ^2 test is performed to test the significance of the discriminant model. The χ^2 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 discriminating function mentioned in the Table- 4.2 is highly significant. Thus, the discriminant function estimated using data one year prior to distress correctly discriminates between distressed and non-distressed firms.

Table- 4.2: Results of Z-score Model 1 (One Year Prior to Distress)

variable		Estimate	Wilks' Lambda for the difference of the mean	F- Statistic for the difference in mean
X1	Working capital/Total assets	1.045	0.941	7.649*
X2	Retained earnings/Total assets	0.846	0.959	5.158**
X3	Earnings before interest and taxes/total assets	1.919	0.79	32.370*
X4	Book value of equity/Total liabilities	0.575	0.743	42.143*
X5	Sales/Total assets	0.169	0.959	5.224**
Constant		-0.515		
Wilks' Lambda for the discriminant function as a whole				0.625
Chi-square (χ^2) test				56.220 (0.000)

Note- * and ** indicate significant at 1% and 5% level of significance.
Value mentioned in the parenthesis against χ^2 test is the significance level at which null hypothesis can be rejected.

The Altman's Z-Score model is also estimated using financial data two years prior to distress. There are 62 distressed and 62 non-distressed firms are considered for the analysis. The estimation method is same as for Model 1 discussed in the previous paragraphs. The discriminant coefficients, Wilks' Lambda and F test are presented in Table- 4.3. The discriminant function based on data two years prior to distress can be written as:

$$Z = -0.458 + 0.339X_1 + 2.456X_2 + 4.815X_3 + 0.101X_4 + 0.304X_5 \qquad \ldots(4.9)$$

The Z score can be obtained by substituting the values of the explanatory variables in the above equation. The magnitude of the Wilks' Lambda and F-statistic of the individual variables suggest that it is highly unlikely that the means of the solvent and defaulted groups are equal. All the variables are significantly contributing to the discriminant function. The null hypothesis that means of the variables in both the groups are equal can be rejected in case of all the independent variables.

The Wilks' Lambda for the model is 0.704 and the χ^2 statistic is 41.875. The χ^2 test shows that the null hypothesis can be rejected at a very low level of significance (less than 1% level of significance). Hence the discriminating function in (4.9) is highly significant, which means the discriminant function correctly discriminates between distressed and non-distressed firms.

The performance of discriminant models 1 and 2 to predict distress is evaluated in the following sections. Though both the Z-Score models are significant, the distress predictive ability of them would be different, which is tested using principles of minimization of total errors.

Table- 4.3: Results of Z-Score Model 2 (Two Years Prior to Distress)

variable		Estimate	Wilks' Lambda for the difference of the mean	F- Statistic for the difference in mean
X1	Working capital/Total assets	0.339	0.962	4.807**
X2	Retained earnings/Total assets	2.456	0.791	32.197*
X3	Earnings before interest and taxes/total assets	4.815	0.767	37.051*
X4	Book value of equity/Total liabilities	0.101	0.948	6.741*
X5	Sales/Total assets	0.304	0.975	3.072**
Constant		-0.458		
Wilks' Lambda for the discriminant function as a whole				0.704
Chi-square (χ^2) test				41.875 (0.000)

Note- * and ** indicate significant at 1% and 5% level of significance.
Value mentioned in the parenthesis against χ^2 test is the significance level at which null hypothesis can be rejected.

Distress Prediction by Z-Score Model

This section considers valuation of model performance and identification of cut-off value. The cut-off value is decided where sum of type I and type II errors is minimum. Type I error occurs when a model incorrectly classifies a distressed company as non-distressed, while type II error occurs when a model incorrectly classifies a non-distressed company as distressed.

The costs associated with type I and type II errors are different. According to some of the authors type I errors are much more costly than type II errors. As mentioned in Bortiz et al. (2007), Altman has discussed the primary costs of type I and type II errors and summarized 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.”

In this study the model is evaluated on the basis of overall prediction accuracy and the cut-off point is identified where sum of type I and type II errors is minimum. The type I and type II errors are estimated at various cut-off points, and the results obtained from some of the cut-off points are shown in the Tables- 4.4 and 4.5. Table- 4.4 shows type I and type II errors at various cut-off points and resultant total errors, percentage of correct prediction and overall correct prediction obtained from Z-Score model 1, which is estimated using data one year prior to distress (as shown in equation (4.8)). The cut-off points which are not shown in the result tables were found to give a higher total error than the values reported in the table and their overall prediction is lower than the reported figures.

It can be seen from the Table- 4.4 that the sum of type I and type II errors at 0.2 cut-off is the lowest (27.42%) among all cut-off points. At this cut-off, 58 distressed firms are predicted correctly out of 62 and 49 non-distressed firms are predicted correctly out of 62. Although type I error in case of 0.5 cut-off is 0, the total error is higher than total error at 0.2 cut-off. Hence cut-off point 0.2 is considered for model evaluation. Companies with Z-scores less than 0.2 are predicted to be distressed and companies with Z-Scores greater than or equal to 0.2 are predicted to be non-distressed.

The overall correct prediction percentage is the ratio between the total number of correct predictions and total number of firms considered for the study. One can see from the table below that the overall correct prediction percentage is higher (86.29%) in case of 0.2 cut-off in comparison to other cut-off points. Overall correct prediction percentage started decreasing as the cut-off point increases from 0.2 to 0.5. At cut-off point 0.2, the sum of type I and type II errors is lowest and the overall prediction percentage is the highest. Hence 0.2 is considered to be cut-off point for Z-Score model 1.

Table- 4.4: Distress Classification Rate of Z-Score Model 1

	Actual	Classified as per Model							
Cut off point		Distressed	Non-distressed	Total	Error	Error	Total Error	Correct Prediction	Overall Correct Prediction
0	Distressed	55	7	62	Type I error	11.29%	29.03%	88.71%	85.48%
	Non-distressed	11	51	62	Type II error	17.74%		82.26%	
0.2	Distressed	58	4	62	Type I error	6.45%	27.42%	93.55%	86.29%
	Non-distressed	13	49	62	Type II error	20.97%		79.03%	
0.3	Distressed	60	2	62	Type I error	3.23%	38.52%	96.77%	82.30%
	Non-distressed	18	33	51	Type II error	35.29%		64.71%	
0.5	Distressed	62	0	62	Type I error	0.00%	45.16%	100.00%	77.42%
	Non-distressed	28	34	62	Type II error	45.16%		54.84%	

In the Table- 4.5, results from the Z-Score model 2 estimated by using data two years prior to distress (as shown in equation (4.9)) are presented. Results at some selected cut-off points are included, whereas the cut-off points which are not mentioned in the result table give a higher total error than the values reported in the table and overall prediction is lower than the reported figures. Table- 4.5 reports type I and type II errors, total errors and overall prediction percentage at selected cut-off points.

It can be seen from the table that the sum of type I and type II errors at 0 cut-off is the lowest (33.87%) among all cut-off points in Z-Score model 2. At this cut-off point, 47 distressed firms are predicted correctly out of 62 and 56 non-distressed firms are predicted correctly out of

62. Although type I error in case of 0.2 and 0.3 cut-off points are lower than the value at 0 cut-off, the total errors at 0.2 and 0.3 are higher than the total error at 0 cut-off. Hence cut-off 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 (83.06%) in case of 0 cut-off in comparison to the overall correct prediction percentage obtained from other cut-off points. Overall correct prediction percentage starts to decrease as we increase our cut-off point from 0 to 0.2 to 0.3 to 0.5. Hence, at cut-off point 0, the sum of type I and type II errors is lowest and the overall prediction percentage is the highest. Hence 0 is considered to be cut-off point for Z-Score model 2.

Table- 4.5: Distress Classification Rate of Z-Score Model 2

	Actual	Classified as per Model							
Cut off Point		Distressed	Non-distressed	Total		Error	Total Error	Correct Prediction	Overall Correct Prediction
0	Distressed	47	15	62	Type I error	24.19%	33.87%	75.81%	83.06%
	Non-distressed	6	56	62	Type II error	9.68%		90.32%	
0.2	Distressed	51	11	62	Type I error	17.74%	37.10%	82.26%	81.45%
	Non-distressed	12	50	62	Type II error	19.35%		80.65%	
0.3	Distressed	51	11	62	Type I error	17.74%	37.10%	82.26%	81.45%
	Non-distressed	12	50	62	Type II error	19.35%		80.65%	
0.5	Distressed	54	8	62	Type I error	12.90%	41.94%	87.10%	79.03%
	Non-distressed	18	44	62	Type II error	29.03%		70.97%	

The cut off points for Z-Score models 1 and 2 are selected at 0.2 and 0 respectively, since the total errors in both the models are minimum at these cut-off points. Total errors and type I errors in case of model 1 (Z-Score model using data one year prior to distress) are 27.42% and 6.45% respectively, whereas total errors and type I errors in case of model 2 (Z-Score model using data two years prior to distress) are 33.87% and 24.19% respectively. The type I errors and total errors come down when the model is applied one year before the event in comparison to two years before the event.

The predictive ability of the model can be evaluated through overall correct prediction. Overall correct prediction is 86.29% in case of model 1, whereas it is 83.06% in case of model 2. The predictive ability of the model increases as we move closer to the distress year. The predictive ability of the model applied on the data one year before the event is higher than the predictive ability of the model applied on data two years prior to the event. Hence, it can be concluded from the above analysis that the overall significance of the model improves as we go near to the event. 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.

4.4.2 Results of Logistic Regression Model

Ohlson's (1980) logistic regression model to predict bankruptcy of US firms is one of the pioneering models in the default prediction literature. Subsequently, there have been a number of works done by researchers on default prediction using logit model. Ohlson applied logit model to financial data of US firms to develop a model to predict firms' failure. The present study uses logit model and the same set of variables that Ohlson used, to study distress prediction for Indian firms.

Descriptive Statistics of the Logit Model

Nine independent variables are used, which are mainly collected from the financial statements of the firms. These explanatory variables are indicators of leverage ratios, profitability ratios, liquidity ratios, size and growth of the firms. The dependent variable in the logit model is binary in nature: 1 if the firm is distressed and 0 if the firm is non-distressed. Descriptive statistics of the explanatory variables are shown in Table- 4.6. As done with the Z-Score model explained in the previous section, there are two logit models estimated: the model 1 is estimated using data one year prior to distress and the model 2 is estimated using data two years prior to bankruptcy. Model 1 predicts bankruptcy within one year and model 2 predicts bankruptcy within two years.

Table- 4.6 shows mean and standard deviation of the nine explanatory variables for non-distressed and distressed firms. Mean and standard deviation of the variables using data of one year prior to distress and two years prior to distress are shown. All the ratios are seen to deteriorate from non-distressed stage, to two years prior to distress, and then to one year prior to distress stage. The mean sizes of the firms shrink as they move from non-distressed to one year prior to distress. As expected the means of TLTA and CLCA increase as firms move from non-distressed category to two years prior to distress to one year prior to distress, whereas the means of WCTA, NITA and FUTL decrease from non-distressed to one year and two years prior to distress. The mean of INTWO is 0.081 for the non-distressed firms and 0.581 and 0.661 at two years prior to distress and one year prior to distress stage respectively, indicating mostly negative incomes for the distressed group. The mean of OENEG increases from non-distressed to two years prior to distress to one year prior to distress, indicating that a firm gets deeper in debt as it moves from non-distressed to two years prior to distress to one year prior to distress. CHIN is used to measure change in the net income. The mean of the CHIN reduces as we move from non-distressed stage to one year prior to distress stage.

Table- 4.6: Descriptive Statistics of the Variables Used in Logit Model

	One year prior to distress		Two year prior to distress		Non- distress firms	
variable	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Size	-0.676	1.537	-0.379	1.488	-0.262	1.033
TLTA	1.314	1.079	0.972	0.316	0.647	0.385
WCTA	0.040	0.627	0.188	0.233	0.276	0.248
CLCA	1.675	5.580	1.000	3.316	0.785	2.138
OENEG	0.871	0.338	0.323	0.471	0.065	0.248
NITA	-0.195	0.753	-0.135	0.183	0.032	0.061
FUTL	-0.107	0.152	-0.073	0.158	0.142	0.214
INTWO	0.661	0.477	0.581	0.497	0.081	0.275
CHIN	-0.145	0.695	-0.184	0.620	0.037	0.477

Note: Size- Ln(Total assets/GNP-price level),
TLTA- Total liabilities/Total assets,
WCTA- Working capital/Total assets,
CLCA- Current liability/Current assets,
OENEG- One if total liabilities exceeds total assets, zero otherwise,
NITA- Net Income/Total assets,
FUTL- Fund provided by operations/Total liabilities,
INTWO- One if net income was negative for the last two years, zero otherwise,
CHIN= (NIt - NIti)/(|NIt| + |NIt-i|), where NIt is net income for the most recent period

Estimation of Logit Model

Table- 4.7 presents results of distress prediction within one year and Table- 4.8 presents results of distress prediction within two years. Based on common sense, theory of finance, and previous studies including Ohlson (1980), it is expected that the sign of the coefficients of the different ratios should be as follows: positive sign for TLTA, CLCA and INTWO; negative sign for Size, WCTA, NITA, FUTL and CHIN; indeterminate sign for OENEG.

The logit model 1 for distress prediction is estimated using 62 distressed and 62 non-distressed Indian firms. Table- 4.7 presents estimated coefficients, Wald statistic and significance level. Wald test helps identify whether the independent variables in a logit model are significant. The sign of the coefficients in our model is as expected, with only two exceptions, CLCA and WCTA. Based on Wald statistic, OENEG and FUTL are found to be significant. However, in logit model, a likelihood ratio (LR) [15] test is more accurate in evaluating the statistical significance of the contribution of independent variables to the explanation of a dependent variable. The log likelihood statistic tests the null hypothesis that the coefficients of independent variables in the model are zero. As mentioned in Abdullah et al. (2008), Wald statistic normally gives an inflated standard error, which could result in a failure to reject the null hypothesis when the null hypothesis is false. Hence likelihood ratio test is used in the study as it is more reliable. LR test is performed to see if all the parameters together are useful to estimate dependent variable. The log likelihood ratio test shows that all the coefficients significantly explain the dependent variable; hence, there exists a strong relationship between the select predictors and the default events.

[15] Log-likelihood test is used to understand if all the parameters together are useful to estimate dependent variable. It is equivalent to the multivariate F-test in the linear regressions.

Table- 4.7: Results of Logit Model 1 (One Year Prior to Distress)

Variable	Estimate	Standard Error	Wald Statistic	Significance Level
Size	-0.204	0.31	0.435	0.509
TLTA	1.703	1.709	0.994	0.319
WCTA	0.176	1.856	0.009	0.924
CLCA	-0.286	0.202	2	0.157
OENEG	2.972	1.13	6.915	0.009
NITA	-0.531	2.009	0.07	0.792
FUTL	-6.996	3.898	3.222	0.073
INTWO	1.542	0.969	2.53	0.112
CHIN	-0.401	0.798	0.253	0.615
Constant	-3.414	1.445	5.586	0.018
Log- likelihood ratio				-26.225
P-Value				0.000

The results mentioned in Table- 4.8 are obtained from the logit model estimated using financial ratios two years prior to distress, using the same 62 distressed and 62 non-distressed firms. The results show that with few exceptions, most variables do have the predicted sign. FUTL and INTWO are found to be significant as per Wald test. However, Likelihood ratio test shows that there exists a strong relationship between explanatory variables and default events.

Both the logit models are found to be significant; however, their predictive abilities would be different. In the following section, we evaluate the predictive ability of the two logit models. This will help us assess whether bankruptcy can be predicted better one year prior to the event or two years prior to the event.

Table- 4.8: Results of Logit Model 2 (Two Years Prior to Distress)

Variable	Estimate	Standard Error	Wald Statistic	Significance Level
Size	-0.109	0.212	0.264	0.607
TLTA	-0.645	1.353	0.227	0.634
WCTA	2.473	1.535	2.595	0.107
CLCA	0.069	0.126	0.303	0.582
OENEG	-0.254	1.21	0.044	0.834
NITA	-6.935	4.933	1.976	0.16
FUTL	-6.357	2.536	6.284	0.012
INTWO	2.473	0.851	8.435	0.004
CHIN	-0.656	0.487	1.811	0.178
Constant	-0.917	1.032	0.79	0.374
Log- likelihood ratio				-50.613
P-Value				0.000

Distress Prediction by Logit Model

This section discusses model performance to predict bankruptcy and identification of cut-off value. As in the Z-Score model discussed earlier, the logit model is evaluated on the basis of overall prediction accuracy and the cut-off point is identified where sum of type of I and type II errors are minimum. Though we have estimated type I and type II errors at various cut-off points, the results at only some selected cut-off points are shown in the following tables. The cut-off points which are not mentioned in the result tables give a higher total error than the values reported in the table; and their overall prediction is lower than the reported figures.

The coefficients estimated from logit model are used to estimate P- value (which is known as probability of default) for both distressed and non-distressed companies, using equation (4.4). Type I and type II errors are observed by applying cut-offs on the estimated P-values of the companies. Table- 4.9 shows type I and type II errors at various cut-off points and resultant total errors, correct prediction percentage and overall correct prediction obtained from logit model 1, which is estimated using data one year prior to distress. It shows that the sum of type I and type II errors at 0.5 cut-off point is lower (11.29%) than the total error obtained from other cut-off points. At this cut-off, 59 distressed firms are predicted correctly out of 62 and 58 non-distressed firms are predicted correctly out of 62. Hence cut-off point 0.5 is considered for model evaluation. Companies with probability value less than 0.5 are predicted to be non-distressed and companies with probability value greater than or equal to 0.5 are predicted to be distressed.

The overall correct prediction percentage is the ratio between the total number of correct predictions and total number of firms considered for the study. It can be seen from the table that the overall correct prediction percentage is higher (94.35%) in case of 0.5 cut-off in comparison to other cut-off points. Overall correct prediction percentage starts decreasing as the cut-off point increases from 0.5 to 0.8. At cut-off point 0.5, the sum of type I and type II errors is lowest and the overall prediction percentage is the highest. Hence 0.5 is considered to be the cut-off point for logit model 1.

Table- 4.9: Distress Classification Rate of Logit Model 1

	Actual	Classified as per Model							
Cut off Point		Distressed	Non-distressed	Total		Error	Total Error	Correct Prediction	Overall Correct Prediction
0.5	Distressed	59	3	62	Type I error	4.84%	11.29%	95.16%	94.35%
	Non-distressed	4	58	62	Type II error	6.45%		93.55%	
0.6	Distressed	58	4	62	Type I error	6.45%	12.90%	93.55%	93.55%
	Non-distressed	4	58	62	Type II error	6.45%		93.55%	
0.7	Distressed	55	7	62	Type I error	11.29%	17.74%	88.71%	91.13%
	Non-distressed	4	58	62	Type II error	6.45%		93.55%	
0.8	Distressed	54	8	62	Type I error	12.90%	17.74%	87.10%	91.13%
	Non-distressed	3	59	62	Type II error	4.84%		95.16%	

Results mentioned in Table- 4.10 are from the logit model 2 estimated by using data two years prior to distress. Results at some selected cut-off points are included; as mentioned in the previously, the cut-off points which are not mentioned in the result table were found to give a higher total errors than the values reported in the table and their overall prediction is lower than the reported figures. Table- 4.10 reports type I and type II errors, total errors and overall prediction percentage at selected cut-off points

Similar to logit model 1, it can be seen from the table that the sum of type I and type II errors at 0.5 cut-off is the lowest (29.03%) among all cut-off points in logit model 2. At this cut-off point, 51 distressed firms are predicted correctly out of 62 and 55 non-distressed firms are predicted correctly out of 62. Hence cut-off point 0.5 is considered for model evaluation. Companies with probability value less than 0.5 are predicted to be non-distressed and companies with probability value greater than or equal to 0.5 are predicted to be distressed. The overall correct prediction percentage is higher (85.48%) in case of 0.5 cut-off in comparison to the overall correct prediction percentage obtained from other cut-off points. Overall correct prediction percentage starts decreasing as we increase our cut-off point from 0.5 to 0.6 to 0.7 to 0.8. Thus, at cut-off point 0.5, the sum of type I and type II errors is lowest and the overall prediction percentage is the highest. Hence 0.5 is considered to be cut-off point for logit model 2.

Table- 4.10: Distress Classification Rate of Logit Model 2

	Actual	Classified as per Model							
Cut off Point		Distressed	Non-distressed	Total		Error	Total Error	Correct Prediction	Overall Correct Prediction
0.5	Distressed	51	11	62	Type I error	17.74%	29.03%	82.26%	85.48%
	Non-distressed	7	55	62	Type II error	11.29%		88.71%	
0.6	Distressed	47	15	62	Type I error	24.19%	33.87%	75.81%	83.06%
	Non-distressed	6	56	62	Type II error	9.68%		90.32%	
0.7	Distressed	42	20	62	Type I errors	32.26%	38.71%	67.74%	80.65%
	Non-distressed	4	58	62	Type II error	6.45%		93.55%	
0.8	Distressed	34	28	62	Type I error	45.16%	51.61%	54.84%	74.19%
	Non-distressed	4	58	62	Type II error	6.45%		93.55%	

The cut off point for both logit models 1 and 2 is selected at 0.5 since the total errors in each of the model is minimum at 0.5. Total error and type I error in case of logit model 1 (using data one year prior to distress) are 11.29% and 4.84% respectively, whereas total errors and type I error in case of logit model 2 (using data two years prior to distress) are 29.03% and 17.74% respectively. The type I error and total errors decrease when the model is applied one year before the event in comparison to two years before the event.

The predictive ability of the logit model is evaluated through overall correct prediction. Overall correct prediction is 94.35% in case of logit model 1, whereas it is 85.48% in case of logit model 2. So, the predictive ability of the model increases as we move closer to the distress year. The predictive ability of the model applied on the data one year before the event is higher than the predictive ability of the model applied on data two years prior to the event. Hence, it can be concluded that the overall performance of the model improves as the default event approaches. Therefore logit model 1, which is based on the data one year prior to distress, has the higher predictive power than the logit model 2, which is based on the data two years prior to distress, for prediction of distress.

Probability of Default from Logit Model

Probability of default (PD) from Logit model is calculated using equation (4.4):

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

Table- 4.11 compares PD estimated for distressed and non-distressed companies. The results show that the differences in mean PD and median PD between distressed and non-distressed firms are as expected. Mean PD of distressed companies (88.85%) is significantly higher than mean PD of non-distressed companies (11.13%). Similarly median PD of distressed firms is also higher than median PD of non-distressed firms. This result suggests that the logit model predicts a higher PD for distressed and lower PD for non-distressed firms, as expected from the model.

Table- 4.11: Comparison of PD from Logit Model

Model	Status	Mean	Standard Deviation	Median
Ohlson's Logit Model	Distressed	88.85%	18.86%	95.97%
	Non-distressed	11.13%	21.72%	4.26%

Comparison between Z-Score and Logit Model

We next compare predictive ability of Z-Score model with Logit model to predict bankruptcy of Indian firms. The results are shown in Table- 4.12. Both Z-Score model and logit model were found to be significant when used to predict bankruptcy one year before the event. A total of 124 firms are used for the study, out of which 62 are distressed and 62 are non-distressed firms. The results show out of 62 distressed firms, 58 firms are predicted correctly by Z-Score model; whereas, logit model predicts 59 firms correctly out of 62 distressed firms. The correct distressed prediction percentage is higher in case of logit model (95.16%) in comparison to Z-Score model (93.55%).

Z-Score model predicts 49 firms correctly out of 62 non-distressed forms, whereas, logit model predicts 58 firms correctly out of 62 non- distressed firms. The correct non-distressed prediction percentage is higher in case of logit model (93.55%) in comparison to Z-Score model (79.03%). Overall correct prediction percentage in case of logit model is 94.35%, which is higher than Z-Score model (86.29%). Out of total 124 firms, logit model predicts 117 firms correctly and Z-Score model predicts 107 firms correctly. Between these two models, logit model clearly performs better than Z-Score model to predict bankruptcy of Indian firms.

Table- 4.12: Comparison between Z-Score Model and Logit Model

		Z-score Model		Logit Model	
	N	Number of Correct	Percent Correct	Number of Correct	Percent Correct
Distressed	62	58	93.55%	59	95.16%
Non-distressed	62	49	79.03%	58	93.55%
Overall	124	107	86.29%	117	94.35%

4.4.3 Results of Black-Schole-Merton Model

The Black-Schole-Merton (BSM) model is also applied to predict bankruptcy of Indian firms, with the use of primary market data. Table- 4.13 to 4.15 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) is calculated as the product of closing price at the end of the fiscal year and the number of shares outstanding (following Bharat & Shumway, 2008; Hillegeist et al., 2004). 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 10-year G-Sec yield is taken as the risk free rate of return (r). The equity return volatility (σ_E) is calculated as the annualized standard deviation of daily returns during the given year.

To estimate probability of default (PD), we need to estimate market value of firm's asset (V), asset volatility (σ_V) and expected return on asset (μ_V), since these values are not directly observable. These are generated by solving equations (3.4) and (3.12) simultaneously, using Excel Solver. We have to first estimate V and σ_V by solving (3.4) and (3.12) simultaneously and then use these values to estimate expected return on asset (μ_V). As per Hillegeist et al. (2004), the starting value of V is defined as face value of debt plus market value of equity (F+E) and starting value of σ_V is defined as: $\sigma_V = \frac{\sigma_E E}{V+F}$. Based on these initial estimates, we perform iterations with the help of Excel Solver routine to generate final values for V and σ_V which serve as inputs for computing risk neutral PD and objective PD. Risk neutral PD is estimated using risk free rate whereas objective PD is estimated using expected return on asset (μ_V). μ_V is estimated using equation (3.13) shown in the previous chapter. PD mentioned in the tables below is objective PD estimated using equation (3.9).

Tables- 4.13 to 4.15 show mean, standard deviation, minimum and maximum values of different variables and ratios used to estimate probability of default using BSM model, for all companies, distressed companies and non-distressed companies respectively. These figures for distressed and non-distressed companies may be compared. The mean of equity return volatility in case of distressed firms is higher than mean of equity return volatility for non-distressed firms. Similarly the mean of face value of debt is higher for distressed companies than for non-distressed companies. The mean of expected return on asset is higher in case of non-distressed companies in comparison to that for distressed companies. PD is mentioned in the last row of the table. It may be seen from the table that mean value of PD for distressed companies (13.63%) is significantly higher than the mean of PD of non-distressed companies (1.08%). The maximum PD for distressed companies is 98.96%, whereas, maximum PD for non-distressed companies is 7.30 %. Hence, as expected, the BSM model predicts a higher PD for distressed companies and lower PD for non-distressed companies.

Results for a few individual companies are shown in Table- 4.16 and Table- 4.17 to compare probability of default of distressed and non-distressed companies. Seven distressed companies' PD, along with the variables used to estimate it, are shown in Table- 4.16 and for non-distressed companies it is shown in Table- 4. 17. Results indicate that the PD estimated using BSM model for seven distressed companies is higher than PD estimated for non-distressed companies. Hence, this result is in tune with the theory and literature, which suggest that the PD for distressed companies should be higher than the PD for non-distressed companies.

Table- 4.13: BSM Model Summary- All Companies

Variable	Mean	Standard Deviation	Minimum	Maximum
Market value of equity (E)	117.370	245.084	1.376	1305.418
Face value of debt (F)	120.591	187.178	2.770	1237.115
Risk free rate (r)	7.66%	0.40%	7.12%	8.40%
Equity return volatility (σ_E)	66.66%	34.92%	28.00%	336.04%
Market value of firm asset (V)	227.071	325.573	6.947	1382.638
Asset volatility(σ_V)	27.22%	29.45%	2.99%	248.01%
Expected return on asset(μ_V)	20.91%	29.36%	7.12%	152.92%
Probability of default (PD)	5.79%	13.80	0.00%	98.96%

Note: Market value of equity (E), face value of debt (F) and market value of firm asset (V) are in Rs. Crore

Table- 4.14: BSM Model Summary- Distressed Companies

Variable	Mean	Standard Deviation	Minimum	Maximum
Market value of equity (E)	18.347	23.380	1.376	100.325
Face value of debt (F)	125.833	175.849	4.390	903.085
Risk free rate (r)	7.64%	0.35%	7.12%	8.40%
Equity return volatility (σ_E)	80.99%	52.75%	50.05%	336.04%
Market value of firm asset (V)	129.442	185.915	6.947	942.752
Asset volatility(σ_V)	21.26%	44.28%	2.99%	248.01%
Expected return on asset(μ_V)	7.64%	0.35%	7.12%	8.40%
Probability of default (PD)	13.63%	20.29%	2.99%	98.96%

Note: Market value of equity (E), face value of debt (F) and market value of firm asset (V) are in Rs. Crore

Table- 4.15: BSM Model Summary- Non-distressed Companies

Variable	Mean	Standard Deviation	Minimum	Maximum
Market value of equity (E)	176.784	294.809	3.736	1305.418
Face value of debt (F)	117.446	195.340	2.770	1237.115
Risk free rate (r)	7.68%	0.43%	7.12%	8.40%
Equity return volatility (σ_E)	58.07%	10.87%	28.00%	79.07%
Market value of firm asset (V)	285.648	375.634	12.516	1382.638
Asset volatility(σ_V)	30.80%	14.24%	3.20%	55.71%
Expected return on asset(μ_V)	28.88%	34.89%	7.12%	152.92%
Probability of default (PD)	1.08%	1.82%	0.00%	7.30%

Note: Market value of equity (E), face value of debt (F) and market value of firm asset (V) are in Rs. Crore

Table- 4.16: BSM Model Summary- Results of Sample Distressed Companies

Variable	Digital Multiforms Ltd.	Midland Plastics Ltd.	Sri Jayalakshmi Spinning Mills Ltd.	Nachmo Knitex Ltd.	Oxford Industries Ltd.	Tuticorin Alkali Chemicals & Fertilisers Ltd.	Ganesh Benzoplast Ltd.
Market value of equity (E)	1.376	1.460	5.856	4.584	3.691	5.918	4.978
Face value of debt (F)	7.915	9.170	36.110	38.880	25.155	59.335	183.990
Risk free rate (r)	7.12%	7.12%	7.78%	7.78%	7.91%	7.60%	7.60%
Equity return volatility (σ_E)	87.69%	171.71%	84.08%	82.37%	88.14%	83.06%	336.04%
Market value of firm asset (V)	8.647	7.439	38.944	40.326	26.653	60.590	11.918
Asset volatility(σ_V)	16.39%	62.83%	14.62%	10.90%	14.53%	9.55%	248.01%
Expected return on asset(μ_V)	7.12%	7.12%	7.78%	7.78%	7.91%	7.60%	7.60%
Probability of default (PD)	18.62%	70.32%	16.45%	15.99%	19.21%	16.68%	98.96%

Note: Market value of equity (E), face value of debt (F) and market value of firm asset (V) are in Rs. Crore

Table- 4.17: BSM Model Summary- Results of Sample Non-distressed Companies

Variable	National Oxygen	Zenith Fibres	Surana Telecom and Power	Shasun Pharmaceuticals	Salona Cotspin	Amarjothi Spinning Mills	ECE Industries
Market value of equity (E)	12.826	9.950	38.071	252.191	14.234	27.675	102.832
Face value of debt (F)	7.080	2.770	30.680	286.520	40.015	65.755	77.475
Risk free rate (r)	7.91%	7.91%	7.60%	7.90%	7.90%	8.40%	8.40%
Equity return volatility (σ_E)	70.96%	56.02%	61.51%	54.94%	60.67%	58.08%	61.02%
Market value of firm asset (V)	19.368	12.516	66.542	517.523	51.229	88.226	174.214
Asset volatility(σ_V)	47.26%	44.54%	35.37%	26.89%	17.29%	18.54%	36.17%
Expected return on asset(μ_V)	7.91%	7.91%	7.60%	7.90%	33.35%	8.40%	38.24%
Probability of default (PD)	1.97%	0.04%	1.20%	0.91%	0.05%	2.52%	0.09%

Note: Market value of equity (E), face value of debt (F) and market value of firm asset (V) are in Rs. Crore

4.5 Conclusion

This chapter empirically examined the predictive ability of three well known and widely used credit risk models. Two are accounting- based bankruptcy prediction models, namely, Altman's discriminant analysis model and Ohlson's logit model. The third model is a market based bankruptcy prediction model, the BSM model. Financial information for a set of distressed and non-distressed Indian firms was obtained from their balance sheet and profit and loss statements to carry out distress prediction using accounting based model. Along with accounting information some of the market based information related to equity and debt are used to estimate PD using BSM model. The study evaluated predictive ability of discriminant analysis and logistic regression model using data one year prior to bankruptcy and two years prior to bankruptcy. It was found from the analysis that the predictive ability of both discriminant model and logit model is higher when data one year prior to bankruptcy is used in comparison to models based on data two years prior to bankruptcy. This finding suggests that the corporate bankruptcy can be predicted more accurately using recent year financial information.

Between these two accounting based models, predictive ability of logit model is found to be higher than the predictive ability of discriminant model, since overall correct prediction percentage is higher in logit model. Also it is found that the mean and median PD computed from logit model for distressed companies is significantly higher than mean and median PD for non-distressed companies. BSM model used for bankruptcy prediction shows that the estimated probability of default for distressed and non-distressed companies is in tune with the theory and literature. The mean PD estimated using BSM model for distressed group is higher than the mean PD estimated from non- distressed group.

CHAPTER 5

OPERATIONAL RISK MANAGEMENT FRAMEWORK

5.1 Introduction

In the late ‘90’s, the global economy witnessed a series of severe stressed uncertainties that originated on account of a number of high profile operational risk events manifesting in the US, UK and European banking sector. The magnitude of the impact was large scale and affected the economies of several countries across continents. The key factors contributing to this global crisis were adoption of sophisticated technology for product design, development, distribution, and sales/ marketing and the day-to-day operations of Banks. This led banks and supervisors to increasingly view operational risk management as an integral part of their risk management framework. The Basel Committee on Banking Supervision of Bank for International Settlement, for the first time, included operational risk management in its Basel II Accord in 2004, as a result of which banks and supervisors are forced to measure and manage operational risk with objectivity, in a more scientific manner.

The Indian economy too could not escape the aftershocks of the crisis and the Reserve Bank of India, in its guidance note on operational risk management highlighted the effects of deregulation/ globalization of financial services; the growing technological sophistication and other factors making the activities of banks complex and consequently making their risk management framework also complex. Evolving banking and risk management practices suggest that apart from the two key risks banks were exposed to, viz. credit and market risks, operational risk was also a significant contributor to the operations of banks.

Some of the sources of these new and growing risks faced by banks include: (1) highly automated technology eventually leading to system failure risk; (2) Emergence of e- Commerce - Growth of e-commerce brings with it potential risks (e.g. internal and external fraud and system security issues); (3) Emergence of banks acting as very large volume service providers creates the need for continual maintenance of high-grade internal controls and back-up systems; (4) Outsourcing- growing use of outsourcing arrangements and the participation in clearing and settlement systems can mitigate some risks but can also present significant other risks to banks; (5) Large-scale acquisitions, mergers, de-mergers and consolidations test the viability of new or newly integrated systems.

This chapter discusses in detail the operational risk management (ORM) framework defined in Basel II Accord for worldwide commercial banks and that defined by RBI for Indian banks specifically. Various approaches used for calculation of operational risk capital charge and the data elements used in advanced measurement approach are also discussed.

5.2 Basel II Accord and Operational Risk Management

The Basel Committee on Banking Supervision (BCBS) introduced Basel I Accord during 1988 and it was adopted by internationally active commercial banks worldwide during early 1990s. There were various amendments made to this Accord by the BCBS to include market risk for bank's capital adequacy ratio and for better risk management by the banks. Operational risk came into the limelight when BCBS came up with the Basel II Accord for risk management. Unlike Basel I Accord, the new Accord included operational risk as an integral part of risk management of the banks, along with credit and market risk.

Operational risk has been defined by the Basel Committee on Banking Supervision as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events". This definition includes legal risk, but excludes strategic and reputational risk. This seeks to identify the causes responsible for happening of an operational risk event, and these are broadly classified into people, processes, systems and external factors. It is very difficult to measure the full range of operational risks that the bank faces and the underlying causes and effects of those risks. Unlike market and credit risks, which are presented in specific areas of business, operational risk is inherent in all areas of business in an organization, like designing of product, selling, marketing, processing, technology used for the business, management of the organization, delivery and many more.

The Basel Committee has classified operational risk events broadly into seven generic categories. Each of these seven primary top-level categories is further classified into a number of sub-categories at second and third levels. The detailed classification of loss event types is given in Appendix 1. The broad level classification includes: (i) Internal Fraud – typically, intentional misreporting of positions, employee theft, and insider trading on an employee's own account; (ii) External Fraud – typically, forgery, cheque kiting, and damage from computer hacking; (iii) Employment Practices and Workplace Safety - instances of employee compensation claims, violation of employee health and safety rules, organized labour activities, discrimination claims, and general liability; (iv) Clients, Products and Business Practices– covering fiduciary breaches, misuse of confidential customer information, improper trading activities on the bank's account, regulatory non-compliance, money laundering, and sale of unauthorized products; (v) Damage to Physical Assets - caused by terrorist acts, vandalism, civil unrest, earthquakes, fires and floods; (vi) Business Disruption and System Failures- hardware and software failures, telecommunication problems, and utility outages; (vii) Execution, Delivery and Process Management – including all types of data entry/ capture errors, collateral management failures, incomplete legal documentation, and unauthorized access given to client accounts, non-client counter party misperformance, and vendor disputes.

5.3 Organizational Setup for ORM

The Basel II Accord has identified certain qualifying criteria for an effective measurement and management of operational risk. It says that the bank's board of directors and senior management must be actively involved in the oversight of operational risk management framework. Reserve Bank of India (RBI) also emphasizes the involvement of board and senior management for operational risk management. The ORM guideline states that "the Board and senior management should create an enabling organizational culture placing high priority on effective operational risk management and adherence to sound operating procedures. Successful implementation of risk management process has to emanate from the top management with the demonstration of strong commitment to integrate the same into the basic operations and strategic decision making processes. Therefore, Board and senior management should promote an organizational culture for management of operational risk (RBI, 2005)".

Coming to the Indian scenario, the guidance note of RBI on operational risk management outlined some of the crucial elements for effective operational risk management, that, apart from clear strategies and oversight by the Board of Directors and senior management, includes a strong operational risk culture, internal control culture (including clear lines of responsibility and segregation of duties), effective internal reporting, and contingency planning. The organizational set-up to drive operational risk management should include: (1) Board of Directors; (2) Risk Management Committee of the Board; (3) Operational Risk Management Committee; (4) Operational Risk Management Department; (5) Operational Risk Managers; (6) Support Group for operational risk management

RBI also directs banks to ensure that each type of key banking risks - credit, market and operational - is managed as an independent function and there should be corresponding risk management committees in the bank to take specific responsibilities. Banks are also allowed to structure their risk management function as appropriate without compromising the above principle. The central bank has also defined the responsibilities for each of the above functions/ committees. The clear flow chart of the organizational set-up as defined by RBI for risk management in general and operational risk in particular, is mentioned in Appendix 3.

5.4 Operational Risk Management Framework

Operational risk management framework should be robust and consist of detailed organizational set-up as discussed in the previous paragraphs, with well defined operational risk measurement, management process, policy & procedures that are applicable firm-wide. The framework should define the roles of both independent operational risk management function and lines of business. It should also address issues and processes pertaining to capturing of data elements needed to measure and verify the organization’s operational risk exposure; as well contain a detailed description of the operational risk analytical framework, reporting systems, and mitigation strategies. Major elements of operational risk should be clearly described. An effective operational risk management framework should cover all aspects of risk management from end-to-end, viz., identification, measurement, monitoring and control or mitigation.

Identification of Risk

The guideline says that “banks should identify and assess operational risk inherent in all material products, activities, processes and systems. Banks should also ensure that before new products, activities, processes and systems are introduced or undertaken, the operational risk inherent in them is identified clearly and subjected to adequate assessment procedures (RBI, 2005)". Risk identification will ultimately help the bank to properly measure, monitor and control all material risks. Effective risk identification process should consider both internal and external factors. Internal factors include bank's structure, the quality of the employees, organizational changes, employee turnover and process controls, checks & balances, etc. External factors include broader and generalized changes in the industry, geographic, political and technological environment.

The first step toward identification of risk events is to list out all the business lines where the bank has its presence. Basel II Accord has made this part easier for banks by listing out 8 generic business lines that are common across all commercial banks. These are: Retail Banking, Commercial Banking, Payment and Settlement, Trading and Sales, Retail Brokerage, Corporate Finance, Agency Services and Asset Management. The detailed classification of the business line is mentioned in Appendix 2.

Within these overall generic Business lines, banks were free to slot their business lines on the basis of their individual needs, country-specific product offerings, etc. For example retail banking could be broken up into retail branch banking, card services and retail asset operations. Again, distinct product offerings within the retail branch banking for instance, may be identified. After listing out all the products/ service offerings in this manner, the bank has to find out operational risk events associated with each of the products/service offering. Drilling down further, distinct risk events can be identified on the basis of expert judgment of the individual unit/product after factoring any loss experience or even plain intuition.

Assessment of Risk

In addition to identifying the risk events, banks should assess their vulnerability to these identified risk events. Effective risk assessment allows a bank to better understand its risk profile and most effectively target risk management resources. Tools such as Risk and Control Self Assessment (RCSA), Key risk Indicators (KRIs) and Risk Mapping can be used for risk assessment. Self risk assessment is a process to assess inherent risk associated with a product or process or system. This assessment is qualitative in nature and is internally driven and incorporates checklists and workshop to identify strength and weaknesses of operational risk environment on an ongoing basis.

Key Risk Indicators (KRIs) are quantitative measurements of risks. These are the indicators which provide insight into the bank's risk position. These indicators help to define alert level for risk and give an indication whether the risk level is rising or falling. In risk mapping process, various business units, organizational functions or process flows are mapped by risk type. This exercise can reveal areas of weakness and help prioritize subsequent management action.

Risk Measurement

A major component of operational risk management is measurement of size and scope of the bank's risk exposure. Banks may have their own measurement methods, which should capture all the material risks across the business group or department. Risk assessment and measurement are complementary to each other. One of the best ways to measure risk is historical loss data. Banks are expected to collect historical loss data for specified periods, typically for 5 years at the minimum under AMA and fit each loss incident into the business line and event type matrix. This data on historical loss experience could provide meaningful information for assessing the bank's exposure to operational risk and developing a policy to mitigate/ control the risk. An effective way to make good use of this information is to define a framework to collect all relevant information related to loss data including frequency and severity of the events. This will help the banks to identify which of the business lines or units are more vulnerable. The details of the loss data collection and mapping are discussed in a later section of this chapter.

Risk Monitoring and Reporting

Risk monitoring is an integral part of risk management. The RBI guideline says "an effective monitoring process is essential for adequately managing operational risk. Regular monitoring activities can offer the advantage of quickly detecting and correcting deficiencies in the policies, processes and procedures for managing operational risk. Promptly detecting and addressing these deficiencies can substantially reduce the potential frequency and/or severity of a loss event (RBI, 2005)". There should be a proper framework defined by the bank for monitoring and reporting of operational risk events.

The risk monitoring function should be able to produce detailed operational risk reports periodically for review by the Bank's board and senior management. These reports should include necessary information regarding the operational risk profile of the organization, including the causal elements for the operational risk events. Risk-owning business lines/ units should get the periodical report on the risk level along with heat maps. The report which is circulated among senior management, board and respective units should highlight problem areas and suggest possible mitigative. Management may also use reports prepared by external sources (auditors, supervisors) to assess the usefulness and reliability of internal reports. Reports should be analyzed with a view to improving existing risk management performance as well as developing new risk management policies, procedures and practices.

Risk Control and Mitigation

Risk management is the process of mitigating the risks faced by the bank. Risk mitigation is perhaps the most important component for effective operational risk management. Banks should define an effective risk control/ mitigation framework. Banks can adopt various methods for mitigating different risks. For example losses that arise on account of natural disasters can be mitigated by insurance. Losses that might arise from business disruption due to telecommunication or electric failure can be mitigated by back-up facilities. Loss due to internal factors, like employee fraud or product flaws, which may be difficult to identify and insure against, can be mitigated through strong internal auditing procedures.

5.5 Computation of Operational Risk Capital Charge

Once the organizational set-up and operational risk management framework are in place, it is important to ensure capital adequacy is worked out and tracked on an ongoing basis. Towards this end, following the Basel Committee on Banking Supervision, operational risk capital calculation can be done using three methods in a continuum of increasing sophistication and risk sensitivity. These are: (1) The Basic Indicator Approach (BIA); (2) The Standardized Approach (TSA); (3) The Advanced Measurement Approach (AMA).

The methods used for calculation of operational risk capital charge are discussed in this section in detail. The first two approaches are comparatively simple and easier to adopt than the third approach. The third approach, called AMA requires a large loss database; in contrast BIA and TSA do not use any operational loss data. However, banks are encouraged to move to the AMA based on their preparedness to meet the regulatory requirement for adoption of more sophisticated approach.

In the Indian context, the RBI guideline states that “though the Reserve Bank proposes to initially allow banks to use the Basic Indicator Approach for computing regulatory capital for operational risk, some banks are expected to move along the range toward more sophisticated approaches as they develop more sophisticated operational risk management systems and practices which meet the prescribed qualifying criteria (RBI, 2005)”.

5.5.1 Basic Indicator Approach (BIA)

The Basic Indicator Approach (BIA) is the simplest among all the approaches, but generally involves a comparatively higher Operational risk capital charge Banks using the Basic Indicator Approach must hold capital for operational risk equal to the average over the previous three years of a fixed percentage (denoted alpha) of positive annual gross income. Figures for any year in which annual gross income is negative or zero should be excluded from both the numerator and denominator when calculating the average[16]. The charge may be expressed as follow:

$$K_{\mathrm{BIA}} = \frac{\sum_{i=1}^{n} \left(GI_i * \alpha \right)}{n} \qquad \text{...(5.1)}$$

Where, K_{BIA} = The capital charged under the Basic Indicator Approach.

GI = Gross income, where positive, over the previous three years.

[16]If negative gross income distorts a bank’s Pillar 1 capital charge, supervisors will consider appropriate supervisory action under Pillar 2.

n = Number of the previous three years for which gross income is positive.

α = 15% (this is set by the committee).

Gross income is defined as net interest income plus net non-interest income as defined by national supervisor and/ or national accounting standards. Basel II Accord (BCBS, 2006) defines that the measure of gross income should (1) be gross of any provisions (e.g. for unpaid interest); (2) be gross of operating expenses, including fees paid to outsourcing service providers (In contrast to fees paid for services that are outsourced, fees received by banks that provide outsourcing services shall be included in the definition of gross income); (3) Exclude realised profits/losses from the sale of securities in the banking book (Realized profits/losses from securities classified as “held to maturity” and “available for sale”, which typically constitute items of the banking book under certain accounting standards, are also excluded from the definition of gross income); (4) Exclude extraordinary or irregular items as well as income derived from insurance.

5.5.2 The Standardized Approach (TSA)

A refined version of the BIA is the “The Standardized Approach” (TSA), where banks’ activities are divided into eight business lines, namely, corporate finance, trading & sales, retail banking, commercial banking, payment & settlement, agency services, asset management, and retail brokerage. Within each business line, gross income is a broad indicator that serves as a proxy for the scale of business operations and thus the likely scale of operational risk exposure within each of these business lines. The capital charge for each business line is calculated by multiplying gross income by a factor (denoted as beta) assigned to that business line. Beta serves as a proxy for the industry-wide relationship between the operational risk loss experience for a given business line and the aggregate level of gross income for that business line. The Beta factors as defined by the Basel Committee are shown in the below table.

Table- 5.1: Business Line-wise Beta Factors

Business Lines	Beta Factors
Corporate finance (β_1)	18%
Trading and sales (β_2)	18%
Retail Banking (β_3)	12%
Commercial Banking (β_4)	15%
Payment and Settlement (β_5)	18%
Agency Services (β_6)	15%
Asset Management (β_7)	12%
Retail Brokerage (β_8)	12%

Unlike the BIA where the capital charge is pegged at a fixed percentage of 15% of gross income of the bank, under TSA capital charge is measured for each business line by using differential percentage of gross income of that business line. For example, in corporate finance, 18% of gross income generated from the corporate finance business line is used to compute capital charge.

The total capital charge is calculated as the three-year average of the simple summation of the regulatory capital charges across each of the business lines in each year. In any given year, negative capital charges (resulting from negative gross income) in any business line may offset positive capital charges in other business lines without limit[17]. However, if the aggregate capital charge across all business lines within a given year is negative, then the input to the numerator for that year will be zero. The capital charge as per TSA is:

$$K_{\mathrm{TSA}} = \frac{\sum_{j}^{3} \max\left[\left(\sum_{i}^{8}\left(GI_i \times \beta_i\right)\right),\ 0\right]}{3} \qquad \ldots(5.2)$$

Where, K_{TSA} = The capital charge under the Standardized Approach.

GI_i = Annual gross income in a given year, as defined above in the Basic Indicator Approach, for each of the eight business lines.

[17]At national discretion, supervisors may however adopt a more conservative treatment of negative gross income.

β_i = A fixed percentage set by the Committee, relating the level of required capital to the level of the gross income for each of the eight business lines.

The Alternative Standardized Approach (ASA)

The ASA is a special variant of TSA. Basel II Accord states that "at national supervisory discretion a supervisor can choose to allow a bank to use the Alternative Standardized Approach (ASA) provided the bank is able to satisfy its supervisor that this alternative approach provides an improved basis by, for example, avoiding double counting of risks (BCBS 2006)". In its February 2010 guidelines, RBI has mentioned ASA and the required qualifying criteria to migrate to ASA.

Under the ASA, the operational risk capital charge/ methodology is the same as for TSA except for two business lines, retail banking and commercial banking. For these business lines, loans and advances multiplied by a fixed factor 'm' replace gross income as the exposure indicator. The betas for retail and commercial banking are unchanged from TSA. The ASA operational risk capital charge for retail banking (with the same basic formula for commercial banking) can be expressed as:

$$K_{RB} = \beta_{RB} \times m \times LA_{RB} \qquad \ldots(5.3)$$

Where, K_{RB} is the capital charge for the retail banking business line,

β_{RB} is the beta for the retail banking business line,

LA_{RB} is total outstanding retail loans and advances (non-risk weighted and gross of provisions), averaged over the past three years

m is the fixed factor 0.035

Overall capital charge under ASA will be calculated as:

$$K_{\text{TSA}} = \frac{\sum_{j}^{3} \max\left[\left(\sum_{i}^{6}\left(GI_i \times \beta_i\right)\right) , \ 0\right]}{3} + \left(\beta_7 \times m \times LA_{RB}\right) + \left(\beta_8 \times m \times LA_{CB}\right) \qquad \ldots(5.4)$$

Where, K_{TSA} is the capital charge under TSA;

LA_{RB} is the total outstanding retail loans and advances (non-risk weighted and gross of provisions), averaged over the past 12 quarters;

LA_{CB} is the total outstanding commercial banking loans and advances (non-risk weighted and gross of provisions), averaged over the past 12 quarters;

The value of the fixed factor m is 0.035 for both retail and commercial banking.

For the purposes of the ASA, total loans and advances in the retail banking business line consists of the total drawn amounts in the credit portfolios consisting of retail, SMEs treated as retail, and purchased retail receivables. For commercial banking, total loans and advances consist of the drawn amounts in the credit portfolios consisting of corporate, sovereign, bank, specialized lending, SMEs treated as corporate and purchased corporate receivables.

For India, the RBI guideline also mentions that if banks wish, under the ASA, they may aggregate retail and commercial banking using a beta of 15%. Similarly, those banks that are unable to disaggregate their gross income into the other six business lines can aggregate the total gross income for these six business lines using a beta of 18%. Like TSA, the total capital charge for the ASA is calculated as the simple summation of the regulatory capital charges across each of the eight business lines.

5.5.3 . The Advanced Measurement Approach (AMA)

By far the most sophisticated and the most superior approach is the Advanced Measurement Approach commonly referred as ‘AMA’. The AMA is designed to be risk sensitive and takes a totally different approach vis-a-vis the former three gross-income based approaches. AMA also requires proper risk management framework in place that should include an independent risk management function; set-up a dependable system for loss data collection and calculation of capital using statistical tools. In terms of costing, the AMA is the most expensive approach in comparison to the other two approaches. However, the quantitative impact study done by the Basel Committee has established that BIA and TSA throw out a higher capital charge vis-à-vis the AMA methodology. Considering all the factors as required under AMA, large banks will have financial power to implement this approach and also get benefit out of this in terms of reduction in capital requirement. Capital computation under advanced measurement approach is based on the actual loss data of the bank along with external data, scenario analysis and business environment and internal control factors. Loss Distribution Approach (LDA) is the most widely used and acceptable method to compute AMA capital for operational risk. It is also the most complicated and sophisticated approach. This approach models historical operational losses of the bank with the help of statistical techniques to compute operational risk capital. The loss data needs to be classified as per the eight business lines and seven loss event types as defined by the Basel Committee.

The historical loss data is used to fit suitable probability distributions for frequency and severity and the best-fit distributions are used in the simulation process to estimate expected and unexpected loss at a certain confidence level over a specific time horizon. The LDA approach involves modeling of loss frequency and loss severity data separately and then combining these distributions via Monte-Carlo simulations to form an aggregated loss distribution for each operational risk category (ORC). The operational value at Risk (OpVaR) is obtained from aggregated loss distribution. The LDA methodology is discussed in detail in the next chapter.

5.5.4 Components of Advanced Measurement Approach

Advanced Measurement Approach (AMA) for calculation of capital charge for operational risk is based on four key components namely, internal loss data, external loss data, scenario analysis and business environment and internal control factor (BEICF). The BCBS document requires a bank to have a credible, transparent, well-documented and verifiable approach for weighing these four fundamental elements in its overall operational risk measurement system. The guidelines require that the final operation risk capital charge for the bank should be derived from the combination of the above four data elements. Assignment of weights is left to the discretion of the banks. Some AMA-migrated banks, in fact assign more weight to scenario analysis than internal loss data; while some banks assign more weights to internal loss data vis-a-vis scenario analysis. Regarding use of BEICF, some of the banks use it as a risk management tool while some banks use it directly or indirectly for capital calculation. The following sub-sections discuss these elements in detail.

5.5.4.1 Internal Loss Data

Under the AMA methodology very high emphasis is laid on to internal loss data as it is directly used for calculation of operational risk capital charge using loss distribution approach. Basel II document insists that banks track internal loss data according to the criteria set out by it.

Loss data collection combined with classification and mapping is a challenging process requiring a sound data collection process that would include data collection, tallying, verification, reconciliation, mapping of event type and business lines. Data integrity therefore, assumes very high significance in the loss database set-up. Whether the database is based on internal or external data or both these components, it is very important that the process and system assure a good quality, because incorrect and incomplete data will lead to wrong results and wrong capital number, expected and unexpected loss for the banks. Therefore, a clear data collection policy is an essential element for robust collection of loss data. This policy should clearly articulate what data is to be collected, as well as standards, roles and responsibilities for its collection. The detailed information required to be registered while collecting loss data is mentioned below (Table- 5.2).

Table- 5.2: Information to be Collected Related to Loss Data

Serial No.	Data to be collected
1	Event occurrence date
2	Event discovery date
3	Event write-off date
4	Organizational entity in which the loss is booked
5	Regulatory and internal lines of business which bear the loss
6	Event category based on Basel classification
7	Amount of the loss- gross loss
8	Exchange rates if the amount is in foreign currency
9	Types of loss: Actual loss, potential loss or near miss[18,19]
10	Recovery amount and recovery date
11	Type of recovery (e.g. insurance, rectification, reversal, other)
12	Indication as to whether the loss is associated with a credit or market risk Loss
13	Description of the event elaborating the root cause(s) and failed/missing Controls
14	General ledger account number to which the loss was booked

The internal loss data is directly used for operational risk capital calculation. Banks are required to use a minimum of five years of internal loss data for calculating capital under AMA. However RBI prescribes that a three year historical data window is acceptable when banks first move to AMA.

After collection of all relevant information, the next step is the mapping of each operational risk event to relevant level 1 and 2 of risk event type defined by the Basel II Accord (mentioned in the Annexure-1), which can be provided to the supervisor upon request. Each event is to be mapped to relevant business line defined by the Basel II Accord (mentioned in Annexure- 2). The banks are required to document objective criteria for mapping of business line. The mapping of event type can be on the basis of causes of the event, which means if there is a loss event due the fraudulent encashment of cheque by an external person, this has to be mapped to external fraud (level 1) and theft and fraud (level 2). Similarly, if this event has happened at the teller counter in the branch, this will be mapped to retail banking. An appropriate threshold

[18]Near-miss loss events are those cases, which are rectified after occurrence of the events but before loss event takes place. Here, bank does not incur loss as rectification is done well within the time before any loss takes place.
[19]There are certain events where bank does not incur loss at the time of happening of the event, but could lead to loss in future. Such events are known as potential loss events.

can be used by the banks for collection of loss data. They can collect loss data above that threshold. However, particular thresholds should be broadly consistent with those used by peer banks.

Banks usually face problems regarding boundary conditions that overlap credit, market and operational risks. For obvious reasons, there should be no duplication of data, i.e., if one event is considered as part of operational risk capital calculation, the same should get excluded from the capital charge for other risk types. This is based on the principle of avoidance of double counting that may lead to overstatement of the risk. Adopting the Basel II Accord, for the Indian scenario, the RBI guidelines on operational risk states that the banks are required to include in their loss database operational risk cases that are related to credit risk, for internal operational risk management purpose only. However, for Operational risk capital calculation purposes, all such overlapping cases will be considered as part of credit risk event. As far as overlaps in market risk cases are concerned, the guidance note directs banks to consider operational risk cases related to market risk as a part of operational risk capital charge calculation.

Operational risk is inherent in almost all activities carried out by banks. As per definition, operational risk is the risk of loss resulting from inadequate or failed internal processes, people, and systems or from external events. The above four factors may lead to financial loss in credit activities and treasury business of the bank. All such losses are termed as operational risk irrespective of whether it is considered for operational risk capital calculation.

Credit risk normally arises due to counterparty default, i.e., when the credit-worthiness of the counterparty deteriorates and the bank cannot recover principal and interest from the customer. Sometime bank’s people, process and system or external events are responsible for loss during the process of loan documentation, credit assessment or disbursement. For example, if the loan amount is disbursed to a wrong customer or excess amount is credited to the customer’s account, this will lead to a loss to the bank. This loss is due to error made by the bank staff; hence it is an operational risk event due to failure of people. Similarly if the customer submits fake documents for a loan and the bank is not able to detect it and loan is sanctioned, this will lead to financial loss to the bank. Here the loss is due to failure of process or people or external events. Hence it is an operational risk event. As per Basel II Accord, banks are required to identify all such cases and maintain a database for risk management purpose.

In treasury related activities and processes, failure of people, process and system would lead to loss in treasury activities. A small error or mistake by a trader/ dealer may lead to a huge loss to the bank. If the bank fails to arrive at a settlement with the counterparty within the time frame, then it has to make a loss in terms of interest paid or compensation paid to the counterparty. If the trade has incorrect terms, e.g. an incorrect price, valuation of the position could be wrong, as well as the level of market risk calculated using erroneous figure. Operational errors like wrong trade, data integrity and operational failures like timely settlement failure lead to operational risk. If there are errors relating to market position, any measures based on these positions (such as VaR) will consequently be wrong and hence so will be any risk reports containing these figures. Basel II Accord insists that banks identify operational risk events related to market risk and include them in operational risk capital calculation.

5.5.4.2 External Loss Data

External loss events for a bank are those events which are realized by banks in general globally. Basel II Accord insists on using external loss data along with internal loss data for calculation of operational risk capital charge under the AMA method. Banks are required to collect external loss data and use them for their capital calculation after applying an appropriate scaling methodology. Scaling is required because the data is collected from external source; the size and scale of business, business environment and work culture and regulation would be different for different organizations.

Since banks are exposed to infrequent but potentially severe losses, Basel II Accord prescribed that the operational risk measurement system should consider such events even though these events are not realized by it, but are realized by their counterparts or peers. External data should include data on actual loss amounts, information on the scale of business operations where the event occurred, information on the causes and circumstances of the loss events, or other information that would help in assessing the relevance of the loss event for other banks. A bank should have a proper methodology to incorporate such data in its modeling framework. A well defined scaling mechanism can be used to scale external data. A bank can use them directly by incorporating in modeling framework or use them during scenario development process. The guidelines require that the conditions and practices for external data use must be regularly reviewed, documented, and subject to periodic independent review. The usefulness of external loss data can be summarized in the following points:

1. External data can be used to offer a forward-looking perspective, as it contains events that may not have historically been experienced by a bank. It helps banks to consider events which are realised by other banks and could happen in their organization in future if not realised earlier. Hence any possible operational risk events which are faced by the banking industry should be captured for modelling.

2. It helps to populate loss events in those operational risk categories (ORCs) where there is a presence of statistically less number of events or no events. It is possible that banks will have some of the ORCs as blank or with very few data points, which will inhibit performing statistical modelling. Here, the external loss data will help to populate data points in those ORCs.

3. Similar to scenario analysis, external data can be helpful in modelling high severity events particularly in instances where internal loss data is limited.

5.5.4.3 Scenario Analysis

In addition to loss data, under AMA, banks are expected to include scenario analysis for operational risk capital calculation. The Basel II Accord says that a bank must be able to demonstrate that its approach captures potentially severe 'tail' loss events. The severe tail events are unlikely to be available in internal loss data, but can be accessed through scenario analysis. Scenario analysis is thus an integral part of AMA. Scenario analysis is a process of identification of possible unusual but catastrophic events, ascribing probability and consequences of such event in monetary terms e.g. a major fire could be an unusual event with the probability being low but the impact is severe in terms of monetary losses could be in crores of rupees.

A bank uses scenario analysis of expert opinion to evaluate its exposure to high-severity events. This approach draws on the knowledge of experienced business and functional managers and risk management experts to derive reasoned assessments of plausible severe losses. Over time, such assessments can be validated and re-assessed through comparison to actual loss experience to ensure their reasonableness. Scenario analysis is useful for the following reasons.

1. Scenario analysis focuses on catastrophic events which are statistically termed as tail events, where the amount of probable loss due to the event is very high. The historical loss data may not have such events as the bank may not have faced any such catastrophic event in the past, but there is a probability of such happening in near or long term future.

2. As scenario analysis considers cases of high severity (high loss) and low frequency, the operational risk capital charge that is derived from internal loss data together with scenario analysis will better enable banks to weather high loss events.

3. Scenario analysis also helps in the analysis of the ORCs when bank's historical loss data shows presence of few or zero events, thereby enabling banks to compute capital from those ORCs using scenario data.

Given its usefulness, it is important to see how scenario analysis is carried out. Scenario analysis examines the impact of catastrophic events on a bank's financial position. Various probable catastrophic events which bank may face in future should be listed out with detailed description. For example, the events like natural disaster, fire, critical system malfunctioning, major frauds and forgeries, major product flaws are some scenarios which result in a major loss to the bank. Then the financial impacts of these events should be assessed, which are termed as expected losses to the bank. The impact of operational risk scenarios can be evaluated based on a combination of qualitative and quantitative variables. The scenarios are assessed initially qualitatively, to determine the areas of impact, then quantitatively to value these impacts.

Some of the examples of scenarios given in the following table clarify how the scenario assessment is done.

Table- 5.3: Sample Operational Risk Scenarios

Name of the Scenario	Possible Loss Impacts	Frequency	Severity
Loss due to natural disaster like Earthquake / Flood / Cyclone etc.	1. Replacement cost of fixed assets 2. Compensations to employees for accident 3. Loss of tangible assets		
Major loss due to man-made disasters like Terrorist Attack/ Riot / Vandalism etc.	1. Replacement cost of fixed assets 2. Compensations to employees for accident 3. Loss of tangible assets 4. Expenditure on additional security systems		
Very Large loss due to fraud by Internal/External People (including losses by hacking / rogue trading etc.)	1. Customer compensations 2. Legal costs		

In the above examples, the possible high impact scenarios are defined first. The assessment of these scenarios can be made by looking at the probable impact which will finally help us quantify the loss amount. The last two columns show frequency, which is number of times the event could happen in next 1 year or 5 years or 10 years and severity which refers to single event loss amount. The response of frequency and severity obtained from the major units of the bank is then used for modeling capital charge. The potential financial impact of the scenario analysis could be (a) Increased operating costs e.g. external costs made to restore the operations of the bank following an operational risk incident; (b) Increased provisions in future years e.g. expected loss calculations demonstrate higher potential losses; (c) Impact on pillar I capital requirements for operational risk

There are certain advantages and limitations of scenario analysis. The primary advantage of scenario analysis is its incorporation of operational risk events that may not have become apparent yet. The basic constraint in scenario is the description, estimation of severity and frequency can be limited by management’s past experience and imagination. Scenario analysis is by its very nature subjective and highly dependent on management’s subjective assessment of loss severity for each operational risk scenario.

The frequency and severity data collected through scenario assessment are used for scenario modeling to generate operational risk capital charge. Scenario data either can be used along with the internal loss data for modeling; or it can be used separately for modeling. Frequency information collected through scenario assessment may be once in a year, once in five or ten years. For modeling purpose, this needs to be converted into yearly frequency. Various statistical distributions are used to model scenario severity and frequency like internal loss data. Scenario capital can be estimated using simulation approach.

5.5.4.4 Business Environment and Internal Control Factor

Business Environment and Internal Control Factors (BEICFs) are indicators of a bank's operational risk profile that reflect underlying risk factors and an assessment of the effectiveness of the internal control environment. As per the guidelines of BIS and RBI, BEICF is one of the four data elements of AMA framework and should be incorporated, either directly or indirectly, into the operational risk measurement framework. Inclusion of BEICF into AMA framework helps banks to capture and analyze key drivers of operational risk and failure of underlying controls defined for various processes to derive risk profile of the bank. The incorporation of BEICF into AMA framework ensures operational risk capital estimates are sensitive to the change in banks risk profile. Based on the survey done by Basel Committee (BCBS, July 2009), some banks use BEICF directly or indirectly as an input - instead of using the factors to moderate - into modeling to derive operational risk capital requirement. BEICF are also used by some of the banks as an ex-post adjustment to operational risk capital charge and it is often indirectly used as an input into scenario analysis process.

The BCBS document states that "the choice of each factor needs to be justified as a meaningful driver of risk, based on experience and involving the expert judgment of the affected business areas. Also, over time, the process and the outcomes need to be validated through comparison to actual internal loss experience, relevant external data, and appropriate adjustments made (BCBS, 2006)".

Most of the banks do consider BEICF in their operational risk management framework with the help of two components: Risk and Control Self Assessment (RCSA) and Key Risk Indicator (KRI), which are discussed below.

The RCSA process involves bank's assessment of its operations and activities against a menu of potential operational risk vulnerabilities. This process is internally driven and often incorporates check lists and/or workshops to identify the strengths and weaknesses of the operational risk environment. RCSA is used to identify gaps between risks and existing controls, and effectiveness of controls. Here the assessment is made both of the number of times the operational risk event would happen (frequency) and the financial impact due to a single event (severity). These frequency and severity values are used to generate risk profile for the unit. Once the assessment is done, business or functional units have to suggest an action plan or preventive measures to overcome the gaps between risk and controls. This information will be used to derive risk profile of the unit or groups of units or the bank. RCSA helps to obtain information on the level of risk faced by any units and the effectiveness of the existing controls. Accordingly the bank will take control measures to mitigate/ reduce risk. Another use of RCSA is to combine this information with the capital charge obtained from loss data and scenario analysis, as per the regulatory requirement. This can be achieved by defining an appropriate qualitative adjustment framework, which helps to adjust RCSA score with the capital obtained from LDA model.

One obvious limitation of RCSA is that it is subjective in nature. The response related to frequency and severity of an event is completely subjective. The answer is based on the expert judgment of the person who is providing information. This answer may differ from person to person. Hence, expected loss derived by this tool may not reflect the actual picture and may not actually occur in future.

Key Risk Indicators (KRIs) are one of the most common ways of measuring the actual values of risk causes, the risk events and their risk consequences. To give an example, inadequate staffing would be a cause, which leads to the inability of the service help desk to handle the number of calls that it receives per day; the consequences could be multiple, such as, the service level agreement will not be met and customers will have to wait longer for support, customer satisfaction level will reduce and bank will lose new customers in future. A KRI is a variable that provides reliable basis for estimating the loss corresponding to a risk. A KRI can be a specific causal variable or a proxy for the drivers of the loss attributed to risks. It can be used as a predictive indicator of arising risks, risk events, and potential losses and it helps to generate risk profiles of various units and of the bank as a whole. The following example will explain the nature and usage of a KRI.

The KRI considered is the number of untrained staff as a percentage of total staff. The information required is of the number of untrained staff during a month (based on new recruitment), which is known as Risk Driver (RD) and the total number of staff on rolls during that month, which is known as Exposure Indicator (EI). The above KRI is derived through the ratio of RD and EI. This value is then compared with the benchmark for that KRI and categorized as low, medium, high and very high, depending on the value of KRI. Each KRI can be classified into very low to very high based on criticality of the KRI for the unit, which in this example is very high. Depending on the value of KRI and criticality grade, risk profile is generated using mathematical calculation. KRI wise risk profile is further aggregated into risk profile for the unit and finally for the bank.

As noted earlier, the main sources of operational risk are people, process, system and external factors. A sample list of KRI related to the above four sources is mentioned in the Appendix 4. Because financial organizations are faced with these sources of operational risks on a daily basis, organizations should identify KRIs in each of these elements and analyze how they affect business

5.6 Conclusion

The Basel Committee on Banking Supervision included operational risk management in its Basel II Accord. The capital adequacy ratio (CAR) of the bank must include capital requirement for operational risk in addition to credit and market risks as per the new Basel Accord. Operational risk arises due to failure/ error in process execution, inadequate process in place, fraudulent intention of the employee, or due to external party/ events, or due to system failures. Banks frequently face operational risk events in their day to day activities, though the impact of frequently happening events is generally low. However, a single or a few high impact operational risk events may completely wipe out the business; hence the proper measurement and management is inevitable. The organization should have a proper operational risk management framework in place with active participation of senior management and its board for effective management of risk. The Basel Accord has prescribed certain guidelines pertaining to organizational set up, role of senior management and respective units and measurement framework, which includes statistical techniques. Among the three approaches defined in the Basel II Accord for modeling operational risk, the advanced measurement approach (AMA) is the most risk sensitive approach since it uses actual losses of the bank and considers potential high impact scenarios and business environment and internal control factor of the banks, to compute operational risk capital. The other two approaches use gross income as the basis for capital computation. Banks are required to use internal data, external data, scenario data and BEICF for computing final capital requirement for operational risk.

The Reserve Bank of India had also released a circular on timeframe of moving to advanced approaches on Basel II framework in India in July 2009[20]. This circular has mentioned the broad timeframe to move towards more advanced approaches for the regulatory capital requirement. As of now all the banks in India have implemented Basel II framework with standardized approach for credit risk, basic indicator approach for operational risk and standardized duration approach for market risk being used for regulatory capital measurement. Keeping in view the likely lead time that may be needed by the bank to create required technological and risk management infrastructure, including the database, the MIS and skill up-gradation, RBI had proposed a time schedule for implementation of the advanced approaches for the regulatory capital requirement, whereby the earliest date for implementing AMA for operational risk, and IRB Approaches for credit risk (both foundation as well as advanced IRB) was April 1, 2012, with the likely date of approval by the RBI being March 31, 2014. The banks are expected to undertake an internal assessment of their preparedness for migration to advanced approach considering criteria mentioned in the Basel II document. The decision to migrate to any of the advanced approaches should be approved by the Board and banks can approach RBI for necessary approval in due course as per the prescribed schedule. However, banks can chose a later date to migrate to advanced approaches if their internal assessment indicates that they are not prepared for the implementation of this.

[20] "Introduction of Advanced Approaches of Basel II Framework in India – Time Schedule", RBI, July 7, 2009

CHAPTER 6

ADVANCED MEASUREMENT APPROACH

6.1 Introduction

Operational risk modelling is a comparatively new development which has entered the field of risk management only after the Basel II Accord was introduced by the Basel Committee on Banking Supervision (BCBS) of Bank for International Settlement. Some of the European, American and Australian banks have already moved on to the Advanced Measurement Approach (AMA) for estimation of operational risk capital requirement. None of the Indian banks have implemented AMA as on date; but, some of the big Indian banks, both in the public sector and the private sector, are working on the preliminary requirements to initiate the application to the RBI for migration to the AMA. The previous chapter outlined the AMA method of calculating capital charge for operational risk. As noted therein AMA capital is based on four principle data elements, which include both qualitative and quantitative components of AMA.

Worldwide, the majority of the AMA banks estimate their operational risk capital by using Loss Distribution Approach (LDA), under which the capital estimate is obtained by using Monte-Carlo simulation technique. LDA is one of the most preferable approaches used by the banks to compute operational risk capital charge since this approach uses statistical techniques to model losses due to operational risk. This approach helps in estimating operational risk capital charge for the bank at certain confidence level over a specified time horizon. One major objective of this study is to analyse the AMA components and estimate AMA capital for operational risk. Therefore before proceeding to compute capital charge using loss data, the present chapter discusses the components of AMA, modelling techniques, statistical tools used to compute capital charge, etc., in a detailed manner.

The remainder of the chapter is organized as follows. The section 2 is a detailed discussion of LDA, wherein the distribution fitting, identification of best-fit distribution, Monte-Carlo simulation technique are discussed. Section 3 discusses the back testing technique, while section 4 discusses the modelling of tail events. Section 5 and 6 discuss the sensitivity test and correlation and dependency in AMA respectively. Operational risk modeling using external data, scenario data and BEICF are discussed in sections 7, 8 and 9 respectively. Section 10 discusses single loss approximation technique to model operational risk losses. In section 11, some of the literature on AMA and BIS survey results are reviewed. Section 12 concludes.

6.2 Loss Distribution Approach

As the name suggests the loss distribution approach involves modeling loss frequency and loss severity series separately with appropriate statistical distributions and then combining these distributions using simulation technique to form an aggregated loss distribution for each Operational Risk Category (ORC). Monte-Carlo simulation technique is used to arrive at aggregate loss distribution from which the Operational Value at Risk (OpVaR) is computed at a given confidence interval. The process involved in the computation of OpVaR using Monte-Carlo simulation technique is discussed in this section.

Operational Value at Risk (OpVaR)

Operational Value at Risk (OpVaR) is calculated by combining loss frequency and loss severity distribution for each ORC, with the help of Monte-Carlo simulation. The combination of these two distributions is known as aggregated loss distribution for a given time horizon. VaR is defined as the maximum loss that can occur over a time horizon at a given confidence level.

The OpVaR is the maximum possible loss that a bank may incur due to operational failure, at a given confidence level over a given time horizon. The confidence level is set by the Basel Committee at 99.9 percent and the time horizon at one year. Thus, if the OpVaR is, say, X amount at 99.9 percent confidence level, the implication is that the bank will not make loss of more than X amount once in 1000 years. The BCBS committee has not specified any particular statistical technique to be used by the banks to compute OpVaR. It has completely left it to the banks to decide suitable statistical tools and statistical distributions, which will be used to model various data elements. To quote the Basel Committee with reference to statistical assumptions and analytical approaches: "…given the continuing evolution of analytical approaches for operational risk, the Committee is not specifying the approach or distributional assumptions used to generate the operational risk measure for regulatory capital purposes. However, a bank must be able to demonstrate that its approach captures potentially severe ‘tail’ loss events. Whatever approach is used, a bank must demonstrate that its operational risk measure meets a soundness standard comparable to that of the internal ratings-based approach for credit risk, (i.e. comparable to a one year holding period and a 99.9th percentile confidence interval) (BCBS, June 2006)”.

6.2.1 Operational Risk Category

One of the challenges that a bank faces while modeling operational risk is the choice of granularity. The granularity of an AMA reflects the degree to which the quantification approach separately models individual operational risk exposures. As defined in the RBI guideline, “Operational Risk Category (ORC) or unit of measure is the level (for example, organizational unit, operational loss event type, risk category, etc.) at which the bank's quantification model generates a separate distribution for estimating potential operational losses (RBI, April 2011)”. Banks usually calculate operational risk capital charge separately for each ORC and the total operational risk capital for the bank is estimated by combining ORC wise capital estimates using some scientific method.

As per the Basel and RBI requirement, the banks are required to undertake statistical or other analysis to support their choice of granularity and the choice of granularity should not be solely/ exclusively based on data availability. The standard assumption of LDA is that the loss frequency and severity distributions are independent within an ORC. Further, it is assumed that severity values within a cell are independently and identically distributed (IID). A low granularity will lead to a lower capital estimate due to implicit assumptions of zero correlation.

The lowest granular level would be one ORC for the bank as a whole, whereas the highest granularity will be each unit wise capital estimate. Classifying loss data into a large number of units poses various challenges such as, whether categorization is appropriate and factoring correlation while summing up the capital obtained from large units to arrive at bank wide capital. Basel II has mandated that all the loss events should be classified into 8×7 matrix (total 56 cells) of Basel business line and loss event type. But it is not mandatory that banks should follow this principle to form ORCs for modeling operational risk.

There are various ways ORCs may be formed subject to the fulfillment of regulatory requirement. ORCs may be defined considering:

(i) All the loss events across all units in the bank. This will result in a single ORC for the bank.

(ii) Losses in a particular business line level. This will lead to business line wise capital computation.

(iii) Losses in a particular event type level. Here the ORCs will be defined at event type level and capital will be computed event type wise.

(iv) Losses pertaining to a particular Basel business line (BBL) and event type combination. Here, following Basel's BBL and event type combination we will have a total 56 of ORCs.

(v) Combining losses of more than one business line- event type combinations. Here more than one cell will be combined to form an ORC.

6.2.2 Distribution Fitting

Loss distribution approach (LDA) involves modeling of severity (amount of loss) and frequency (number of loss events) distributions separately with different statistical distributions. Each loss event is measured through two parameters: loss amount (loss severity) and number of times the event has happened (loss frequency).

Loss Frequency Distribution

Loss frequency refers to the number of times an event has occurred in a day or month or year. For example, if an event, say fraudulent withdrawal of cheque, has happened 2 times a day, the frequency of the event is two. The horizontal axis of the frequency distribution shows number of loss event per day and the vertical axis shows its probability. The nature of the loss frequency distribution is typically positively skewed, since a large number of events in a day do not happen frequently.

Frequency distribution can be modeled using various discrete statistical distributions like Poisson, Binomial, Negative binomial, etc. In general, most of the frequency data follows either Poisson or Negative binomial distribution. Survey by Bank for International Settlement (BIS)[21] shows that around 93 % of the AMA banks use Poisson distribution for loss frequency series and 19 % of the banks use negative binomial distribution. Also, one needs to check whether a distribution fits the data well. This can be done through graphical method (by Q-Q or P-P plot) and by using goodness-of-fit tests.

Loss Severity distribution

Loss severity means the amount of loss that occurs due to a single event. Like frequency distribution, banks have to generate a loss severity distribution. The horizontal axis of severity distribution shows per event loss and the vertical axis shows its probability. Like frequency distribution, severity distribution is also positively skewed. The reason behind this is the presence of high frequency-low severity and low frequency-high severity in the operational risk database. In general, a bank faces a large number of low impact events and a smaller number of high impact events. Hence the overall severity distribution is combination of low frequency-high severity and high frequency-low severity events.

Dealing with the severity series is a lot more complicated than dealing with the frequency series, due to the unpredictable size of high severity events. While modeling for severity data, one needs to take care of the following type of loss severity: (a) Low severity data, which occurs more frequently; (b) High severity data, which occurs less frequently; (c) Catastrophic event- this event occurs perhaps once in a decade or in five years; this is a very infrequent event, like earthquake, flood, terrorism, etc.

While fitting severity distribution, banks have to take into account the above types of severity data, if present in the database. A suitable statistical distribution needs to be fitted to the severity data. Choice of appropriate severity distribution plays a more crucial role than choice of frequency distribution since the former affects the capital figure significantly. Continuous

21 The detailed survey result can be found in "Observed Range of Practice in Key Elements of Advanced Measurement Approach (AMA)" July 2009, BIS.

distributions like, Lognormal, Weibull, Exponential, Gamma, Pareto, Generalized Extreme Value, Generalized Pareto are used for severity data by the banks. In practice, fat-tailed distributions are appropriate for severity data. Goodness-of-fit tests decide the best-fit distribution. Two different distributions to body and tail part of the severity data may also be fitted. The overriding caveat should always be the selection of a wrong distribution will lead to a wrong OpVaR.

The survey document of BIS (Op.cit) observes that "AMA banks use more than one approach to estimate severity of the body, tail and entire distribution. Only 31% of AMA banks apply a single distribution model to all data, with the Lognormal (33%) and Weibull (17%) most widely used. Nearly 30% of AMA banks use two distributions (for body and tail). In these cases, Lognormal (19%) and Empirical (26%) are the leading approaches for estimating the body, and Lognormal (14%) and Generalized Pareto (31%) are the most frequently used to estimate the tail."

The following are some of the fat-tailed distributions, which can be used for loss severity data.

Table- 6.1: Statistical Distributions

Distribution	Probability Density Function	Parameters
Lognormal	$f(x;\mu,\sigma)=\dfrac{1}{x\sqrt{2\pi\sigma^2}}e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}$	$\mu,\sigma>0$
Generalized Pareto	$f(x;\xi,\mu,\sigma)=\dfrac{1}{\sigma}\left(1+\dfrac{\xi(x-\mu)}{\sigma}\right)^{\left(-\frac{1}{\xi}-1\right)}$	$x>\mu,\xi>0,\mu$
Weibull	$f(x;\eta,\sigma)=\dfrac{\eta}{\sigma}\left(\dfrac{x}{\sigma}\right)^{\eta-1}e^{-\left(\frac{x}{\sigma}\right)^{\eta}}$	$\eta>0,\sigma>0$
Exponential	$f(x;\alpha)=\dfrac{1}{\alpha}e^{-\frac{x}{\alpha}}$	$\alpha>0$
Gamma	$f(x;a,b)=\dfrac{1}{\Gamma(b)}a(ax)^{b-1}e^{-ax}$	$a>0,b>0$

6.2.3 Identification of Best-Fit Distribution

Monte-Carlo simulation method is used to compute OpVaR, which requires selection of at least one frequency and one severity distribution to perform simulation. The best-fit distribution can be selected on the basis of graphical Exploratory Data Analysis (EDA) and quantitative techniques used for goodness-of-fit test.

Graphical EDA includes Histograms, Quantile-Quantile (Q-Q), Probability-Probability (P-P) plots and Empirical Cumulative Distribution Functions (ECDF). The graphical EDA is an easy way to identify the pattern of the distribution just by looking at the graphs. Among these histogram, Q-Q and P-P plot are useful to identify the pattern of distribution that loss data follows. The Q-Q plot depicts the mismatch between the observed values in the data and the estimated value given by the hypothesized fitted distribution. If the data is generated from the hypothesized distribution, then the points of the graph will lie on the 45 degree line. Similarly in case of P-P plot, if the data is generated from the hypothesized distribution, then the points of the graph will lie on the 45 degree line. Hence the distribution, for which most of the data points are closer to the 45 degree line, will be treated as the best-fit distribution.

Quantitative goodness-of-fit tests are more scientific method of identifying a good-fit distribution among a set of statistical distributions. This includes Chi-square, Kolmogorov-Smirnov (K-S), Anderson-Darling (A-D) and Cramer-Von Mises tests. Chi-square test is used to check goodness-of-fit of statistical distributions used for frequency series, whereas K-S, A-D and Cramer-Von Mises tests can be used to check goodness-of-fit of severity distributions.

6.2.4 Parameter Estimation

LDA uses various statistical distributions for frequency and severity data, and performs goodness-of-fit tests to identify best-fit distribution. Therefore it requires estimation of various parameters of different statistical distributions used for modelling. There are a number of methods used for the estimation of the parameters. Maximum Likelihood Estimation (MLE), Method of Moment (MOM), Quantile Distance Estimation method, etc. are some of the parameter estimation methods used by statisticians.

Among all the methods available for parameter estimation, MLE is the most acceptable and widely used method. This estimation technique is used in most of the statistical software. ML estimators are consistent and asymptotically normally distributed. The statistical software used in this study uses MLE method for the estimation of the parameters of various statistical distributions.

6.2.5 Monte-Carlo Simulation Technique

Monte-Carlo simulation approach was initially used to obtain Value at Risk for market risk instruments and credit Value at Risk. This technique is now being similarly used for calculation of operational Value at Risk. Monte-Carlo Simulation methodology relies on the principle of generating a huge set of random numbers which follow some set pattern or model. This set of random numbers is then used for obtaining the VaR as the percentile at the required confidence level. A very high number of simulations are required to obtain consistent result. One of the limitations of this method is that it depends heavily on the model's assumptions: the parameters of the good-fit models and shape of the distribution. The VaR value will change if the distributions are changed.

If the frequency series follows Poisson distribution, the only parameter Lambda (λ) is to be used for generating random numbers. Similarly if severity series follows Lognormal distribution, two parameters (μ and σ) are to be used for random number generation. A large number of random numbers should be generated in order to obtain a more consistent result. The following steps are to be followed to compute OpVaR using Monte-Carlo simulation technique:

(i) Fit a discrete distribution to the frequency data (say, Poisson) and a continuous distribution to the severity data (say, Lognormal). Estimate parameters from the Poisson distribution and Lognormal distribution.

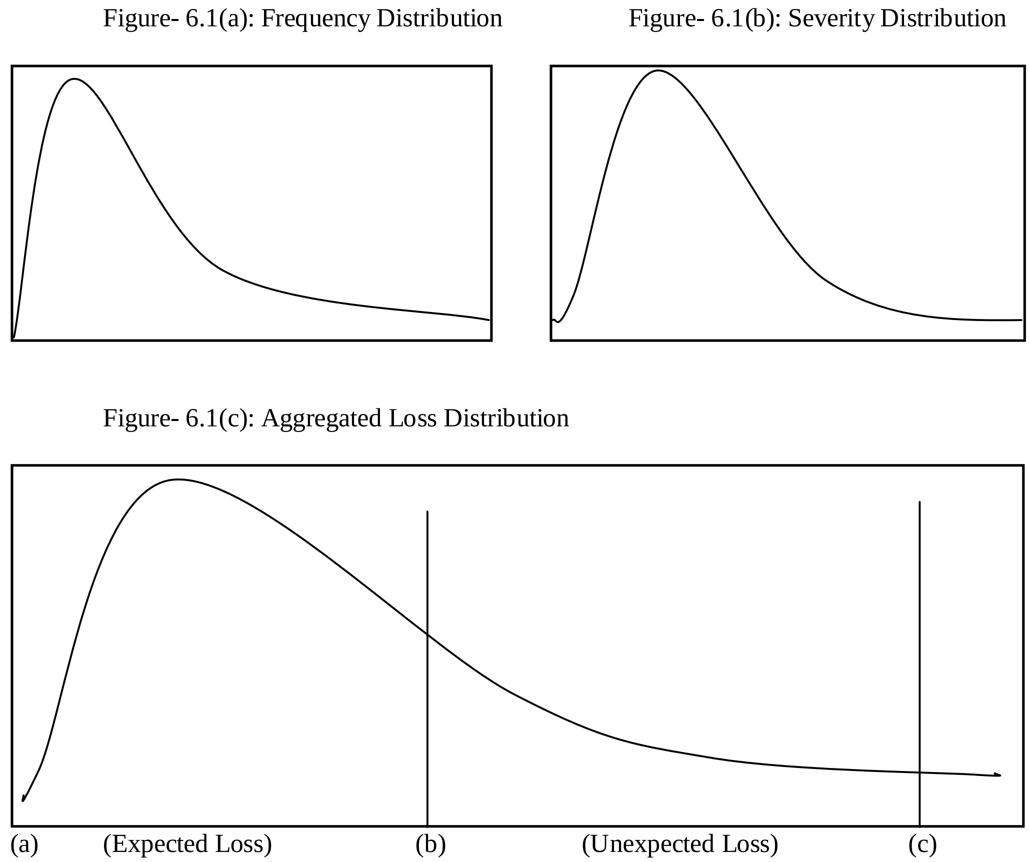
(ii) The next step is to generate a large number of random numbers (for example, 1 lakh or 10 lakh) using Poisson parameter (λ). The number of random numbers needs to be large to provide a consistent capital estimate.

(iii) Against each frequency number generated in the previous step, a set of equal number of severity random numbers will be generated using lognormal distribution. The sum of these severity random numbers will represent aggregated loss for the said frequency.

(iv) The step (iii) will be repeated for 1 lakh times if random number generated for frequency distribution is one lakh. The resultant loss series is known as aggregated loss distribution, which shows one lakh possible yearly losses.

(v) The value at the required percentile will be the OpVaR figure. In case of operational risk, the 99.9th percentile value of the aggregated loss distribution is the yearly OpVaR. (This is the required confidence level as mentioned in the RBI and Basel II guidelines.)

Figure- 6.1: OpVaR Based on Loss Distribution Approach (LDA)



Note: Figure 6.1 (a): horizontal-axis represents no. of loss events and vertical-axis represents probaility; Figure 6.1 (b) and 6.1 (c): horizontal-axis represents loss amount and vertical-axis represents probaility

The Figure- 6.1 shows graphically how the aggregated loss distribution is arrived at by combining frequency and severity distributions through a convolution process. The Figure- 6.1(a) shows frequency distribution of loss data. Horizontal-axis represents number of loss event per day and Vertical-axis represents probability. Figure- 6.1(b) represents loss severity distribution, where horizontal-axis represents single event loss amount and vertical-axis represents probability. Figure- 6.1(c) represents aggregated loss distribution obtained from severity and frequency distribution using Monte-Carlo simulation. The aggregated loss distribution is usually right skewed as shown in the graph. Point 'c' represents OpVaR at 99.9th percentile confidence level. 'b' represents expected loss and c-b is the unexpected loss amount.

There are certain performance measures that one should take care of while selecting severity distribution and modelling methods. As mentioned in Dutta and Perry (2007), one should look into the following measures:

(i) Good Fit - Statistically, how well does the method fit the data?

(ii) Realistic - If a method fits well in a statistical sense, does it generate a loss distribution with a realistic capital estimate?

(iii) Well-Specified - Are the characteristics of the fitted data similar to the loss data and logically consistent?

(iv) Flexible - How well is the method able to reasonably accommodate a wide variety of empirical loss data?

(v) Simple - Is the method easy to apply in practice, and is it easy to generate random numbers for the purposes of loss simulation?

6.3 Back-Testing of Operational Risk Models

The OpVaR model is further validated with the help of back testing. Back testing serves as a reliable validation process that helps one to ascertain the robustness and efficacy of the model and whether the model's working provides correct results. As per the definition of value at risk, if the VaR at 99% confidence level is Rs. X, then the losses on not more than 1% of the days should exceed Rs. X.

The predicted OpVaR amount is checked with the aggregate yearly losses for each year obtained from the actual internal data. The number of years when losses exceed OpVaR (say, V) and the total number of years (say, T) are noted. The ratio V/T is compared with the confidence level used for OpVaR computation. Kupiec test, which is based on hypothesis testing approach, is performed to compare V/T with confidence level used. A good operational risk model should provide the OpVaR, which satisfies back-testing.

Kupiec's Test:

The accuracy of an OpVaR model (back test) can be assessed statistically by applying Kupiec's test. The idea behind this test is that the ratio of number of violations to total number of observations (proportion of cases of actual loss exceeding OpVaR estimate) should be statistically equal to the probability level for which OpVaR is estimated. Kupiec proposed a likelihood ratio statistic for testing the said hypothesis.

If x denotes the number of times the loss is worse than the true OpVaR in the sample (of size T) then x follows a binomial distribution with parameters (T, p), where p is the probability level of OpVaR (level of significance, say 5%). Here x is actually summation of I_t at T time points.

Where, I_t = 1 if operational loss exceeds OpVaR at time t

0, otherwise

The closer x/T is to p, the more accurate estimated OpVaR is.

Hence, the null hypothesis H_0: x/T = p can be tested against the alternative hypothesis $H_1 \neq$ p using the likelihood ratio (LR) test.

$$LR = 2\left[\log_e\left(\left(\frac{x}{T}\right)^x\left(1-\frac{x}{T}\right)^{T-x}\right) - \log_e\left(p^x(1-p)^{T-x}\right)\right] \qquad \ldots(6.1)$$

Under the null hypothesis, LR-statistic follows a χ^2 distribution with 1 degrees of freedom. If critical value is greater than calculated value, null hypothesis will be rejected. Hence, back testing will not be satisfied.

In addition to the above test, the RBI guideline (2011) has mentioned a set of potential back testing alternative for operational risk models that a bank should perform. The operational risk capital is to be compared with:

(i) The largest loss in the data base
(ii) Aggregate loss amount over the period
(iii) Losses in external data
(iv) Peer operational risk capital estimate

6.4 Modelling Tail Events Using Extreme Value Theory

A typical operational loss database follows a distribution that is not Gaussian. In general, an operational risk database is composed of a few large events and several smaller ones. The risk managers are more interested to know the behavior of tail events (or high impact losses) and the capital allocation should be done for these rare events. The HFLS (high frequency low severity) and LFHS (low frequency high severity) events cannot be treated equally in risk management framework. In practice large and small/ medium sized losses are treated separately. Operational risk data consists of two types of event: the first one, driven by high-frequency low impact events, constitutes the body of the distribution and refers to expected losses; the second one, driven by low-frequency high-impact events, constitutes the tail of the distribution and refers to unexpected losses.

In practice, the body and tail of the loss data set do not belong to the same distribution or even to distributions belonging to the same family. As far as body of the distribution is concerned, one can use fat tail statistical distributions like Lognormal, Weibull, Gamma, Exponential, etc. But, for tail area, extreme distribution streaming from the 'Extreme Value Theory (EVT)' is to be utilized. The reason lies in the fact that EVT has solid foundations in the mathematical theory of the behavior of extremes and, moreover, many applications have indicated that EVT appears to be a satisfactory scientific approach in treating rare, large losses. It has been widely applied in structural engineering, oceanography, hydrology, reliability, total quality control, pollution studies, meteorology, material strength, highway traffic and, in the financial and insurance fields.

There are certain advantages of using EVT:

(1) The traditional OpVaR modelling is based on entire loss distributions, which are dominated by small and medium-sized losses. In contrast, EVT works only with extreme losses.

(2) EVT does not require any knowledge of underlying distributions for all the observations. Irrespective of the distributions that the entire data series follows, EVT focuses only on the tail part of the distribution.

(3) While traditional theorems tell us how the average of variables from an unknown distribution behaves, EVT tells us how extreme observations behave.

Extreme Value Theory can be applied to the data in two different ways: (i) The Block Maxima Approach (BM), and (ii) The Peak over Threshold Approach (POT). The present study will use the second approach, since the POT approach is the most recent development to model tail part of a loss distribution.

The BM approach deals with maximum losses in successive periods, e.g. months or years. First of all the data sample is to be divided into a number of non-overlapping subsamples for fixed lengths of time. The maximum losses obtained from each subsample are then used to estimate the parameters of a suitable probability distribution, regardless of the original distribution (pattern) followed by the losses. These largest observations are referred to as block maxima. The GEV distribution has three parameters: μ is measure of its central tendency, σ is measure of its dispersion and ξ is a measure of the shape (or heaviness) of its tail. The higher is ξ, the fatter is the tail. This method is not discussed in details as it is not used in the present study.

The Peak over Threshold (POT) approach deals with the behavior of losses above a threshold level. Generalized Pareto Distribution (GPD) is fitted for extreme events (losses above the threshold) only. Applying the POT method requires choosing a sufficiently high threshold to divide the distribution into a body and tail and fitting GPD to the losses above the threshold value in the tail region. OpVaR will be derived using GPD at a specified level of confidence (99.9th percentile as per RBI guideline). The GPD is a two parameter distribution with distribution function:

$$G_{\xi,\beta} = \begin{cases} 1-\left(1+\dfrac{\xi x}{\beta}\right)^{\frac{-1}{\xi}} & \xi \neq 0 \\ 1-\exp\left(-\dfrac{-x}{\beta}\right)^{\frac{-1}{\xi}} & \xi \neq 0 \end{cases} \qquad \ldots(6.2)$$

Where, $\beta > 0$ and where, $x \geq 0$ when $\xi \geq 0$ and $0 \leq x \leq -\beta/\xi$ when $\xi < 0$

ξ is the shape parameter of the distribution, and

β is the scale parameter.

As discussed above, the GPD fitting under POT method depends on the following elements:

(i) A higher threshold, which should be defined scientifically
(ii) The tail events, which is defined as the losses in excess of the selected threshold
(iii) The GPD parameters namely shape (ξ) and scale (β)

6.4.1 Selection of EVT Threshold

Since fitting of Generalized Pareto Distribution (GPD) highly depends on a very high threshold value, identifying an appropriate threshold level is one of the most important activities that has to be performed at the outset. Threshold (u) is the point where the tail starts. The choice of threshold should be large enough to satisfy the limit law condition (theoretical condition: u should tend to the right-end point), while at the same time leaving sufficient observations for the estimation (practical condition). As mentioned in Dutta and Perry (2007), the methods, which can be considered for threshold selection include: (1) Mean Excess Plot (MEP) method; (2) Goodness-of-fit test; and (3) Ad hoc method.

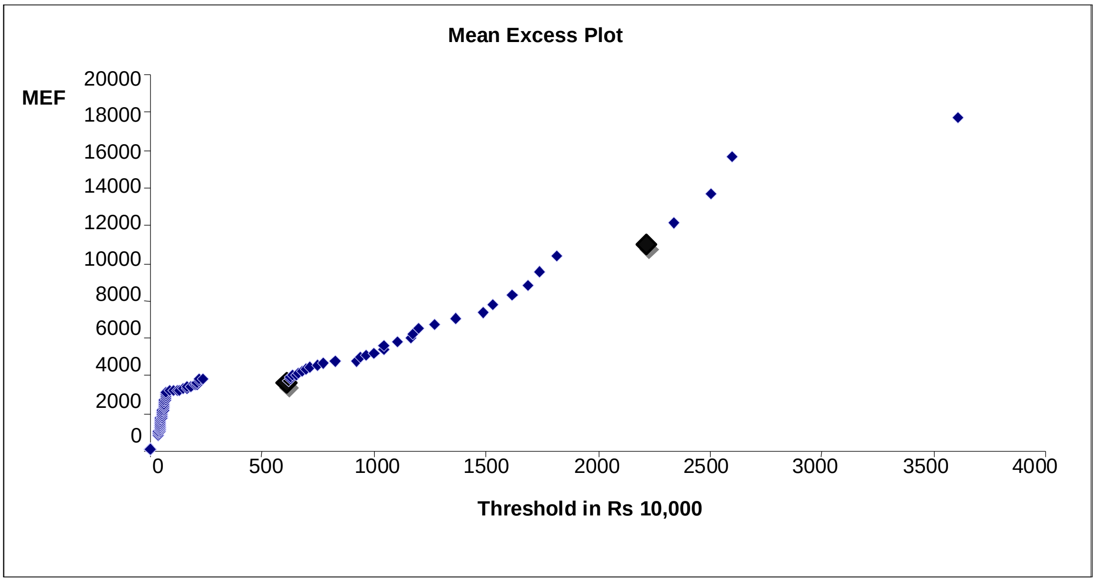
One of the widely used techniques for threshold selection is Mean Excess Plot (MEP). MEP is a graphical tool based on the sample mean excess function (SMEF) defined as:

$$SMEF(u) = \frac{\sum_{i=1}^{n}(x_i - u)}{n} \qquad \ldots(6.3)$$

Where, u is the threshold, n is the number of events exceeding the threshold and x_i is the events above the threshold u. The SMEF is defined as the sum of the excesses over the threshold u divided by the number of data points that exceed the threshold itself.

One can obtain MEP by plotting mean excess function against various threshold values (u) as shown in the following figure (Figure- 6.3). If MEP shows upward trend (+ve slope), then data follows a heavy tail distribution; if plot shows –ve slope, then this is a sign of thin tail distribution. If the plot is a positively sloped straight line above a certain threshold u, it is an indication that the data follows a GPD in the tail area above u.

Figure- 6.2: Mean Excess Plot



The Figure- 6.2 is a mean excess plot, where horizontal-axis represents various threshold level and respective mean excess functions are plotted on the vertical axis. The graph shows that MEP takes a positive slope at two points (highlighted in bold), indicating that the distribution includes some tail events. Since the first point is within the body part of the distribution and occurs at a low threshold level, this can safely be ruled out as the GPD threshold and the second point should be considered as the GPD threshold. One problem with using this method is that the choice of threshold is still somewhat arbitrary. However, one can perform goodness-of-fit tests to identify a proper threshold in case there is no clear-cut indication from the MEP.

Goodness-of-fit test method entails choosing the threshold such that the GPD fits the data in the tail better than any other threshold. Along with MEP analysis, one has to perform goodness-of-fit tests to identify a GPD threshold. Both graphical methods like Q-Q, P-P plots and quantitative goodness-of-fit tests like K-S, A-D and Cramer-Von-Misses tests can be used. There may be more than one threshold for which the GPD fit is good. Hence, this method also suffers from the problem of a multiplicity of possible thresholds.

The last method refers to the use of an ad hoc objective criterion for choosing the threshold. One such criterion would be to choose the threshold such that 40 observations are in the tail of the distribution. Another possibility would be to choose the threshold such that 15% of the observations in the data set are in the tail. To identify a correct threshold, ideally one should check all these three methods and finalize the threshold level which will be somewhat better than the alternative threshold values

6.4.2 Computation of OpVaR Using GPD

GPD parameters ξ and β can be estimated using maximum Likelihood Estimation (MLE) technique. OpVaR from tail events can be computed using GPD by two ways: (i) Simulating body and tail together and (ii) Computing separate OpVaR from tail.

Simulating Body and Tail

Under this approach, the tail events of an ORC will be modeled using simulation techniques. Separate statistical distributions are used for body and tail to compute a single aggregated loss distribution. The detailed approach is mentioned in Dutta and Perry (2007). Below are the steps to compute capital from the tail events and to obtain combined capital from body and tail:

(i) Identify a threshold *u* above which events will be treated as tail events. Events below the threshold will form body of the distribution and events above the threshold will form tail part of the distribution.

(ii) Fit a heavy tail distribution say Lognormal (LN) to the severity data of the body and Generalized Pareto Distribution for the tail events.

(iii) Generate frequency random number using Poisson distribution, say, N, which shows number of events in a year.

(iv) Multiply N by the fraction of the data in the body to get N_L and the fraction of the data in the tail to get N_H.

(v) Generate N_L loss severity randomly using log normal distribution for the body and N_H loss severity randomly using GPD for the tail.

(vi) Sum all N_L and N_H losses together to get the total annual losses.

(vii) Repeat these steps for 1 lakh times or more to obtain aggregated loss distribution. This will contain 1 lakh possible loss scenarios.

(viii) The OpVaR will be computed by considering values at 99.9th percentile from the aggregated loss distribution. The OpVaR obtained here is the operational risk capital charge for the ORC.

Computing Separate OpVaR from Tail

Under this approach, OpVaR from tail will be computed separately using GPD and combined with OpVaR computed from body. Using shape, scale and location parameters, the OpVaR from the tail events using GPD can be computed as (Cruz, M. G. (2002), Alexander McNeil J. (1999) and Moscadelli M. (2004)):

$$\widehat{VaR}_q = u + \frac{\hat{\beta}}{\hat{\xi}}\left(\left(\frac{n}{N_u}(1-q)\right)^{-\xi} - 1\right) \qquad \ldots(6.4)$$

Where, ξ is the shape parameter,

β is the scale parameter,

u is the threshold value,

n is the total data points considered for analysis,

N_u is the number of data points exceed the threshold limit,

q is the confidence interval used for VaR calculation.

Since, GPD only deals with severity distribution of the losses and does not address frequency of the distribution, the OpVaR calculated above may not reflect OpVaR for a time period of one year. However, the first approach, which is based on simulation, will take care of this limitation.

6.5 Sensitivity Test

As per the regulatory requirement, banks are required to perform sensitivity analysis to check sensitivity of the operational risk capital to changes in various data elements, modeling framework and the assumptions. A bank must have in place a comprehensive and rigorous process for performing sensitivity analysis of its operational risk measurement model. The RBI guidelines on AMA says “sensitivity analysis must include consideration of the sensitivity of the Banks’ ORRC to change in modeling choice, assumptions and data inputs (including internal data, external data, scenarios and business environment and internal control factors) (RBI, 2011).”

6.6 Correlation and Dependency in AMA Model

The regulatory minimum capital requirement for operational risk for a bank should be calculated by combining the individual operational risk capital charge calculated from each ORC. A simple addition of ORC-wise capital to arrive at bank-wide capital assumes 100% correlation among ORCs. A correlation coefficient of less than 1 among any of the ORCs will reduce overall capital requirement for the bank.

Banks are required to factor correlation and dependency presence among various ORCs while computing operational risk capital charge for the whole bank in order to get diversification benefit of operational risk exposure across various ORCs. In operational risk, correlation among ORCs arises because of the presence of common factors each with different features/ characteristics, for instance, common people, processes and systems or due to environmental elements that affect several geographical, business or legal units. The AMA guideline of RBI says, “a bank may use internally determined correlations/dependence in operational risk losses across individual operational risk estimates, provided it can demonstrate to the satisfaction of RBI that its systems for determining correlations are sound, implemented with integrity, and take into account the uncertainty surrounding any such correlation estimates (particularly in periods of stress) (RBI, 2011)”. The guideline also prescribes that if the banks are not able to identify correlation among various ORCs, they can compute capital for the bank as a whole by simply adding capital obtained from various ORCs.

As mentioned in the RBI guideline (RBI, 2011), dependence structures could occur as a result of business cycles (e.g., persisting economic downturn that induces an increase in rogue trading and fraud), bank-specific factors (e.g., a new senior manager changes the control environment across a number of business lines) or cross-dependence of large events (e.g., flooding/riots results in widespread looting and increases the number of fraudulent transactions) or a change in the legal risk associated with certain business practices.

Since low frequency and high severity loss events, which form tail part of the distribution, are the main drivers of operational risk estimates under AMA, the banks are required to study their dependency and correlation structure carefully. The correlation and dependency assumptions used by the bank should be validated using appropriate quantitative and qualitative method. Also, it should be substantiated by empirical analysis of data. One of the suitable approaches to factor diversification effect in operation risk is Copula technique. Copula methodology is not discussed since it is not within the scope of this study.

6.7 External Data and Operational Risk Model

External loss data can be treated in the modeling similar to internal data. Banks can directly incorporate external losses in the loss database after scaling the same using an appropriate scaling mechanism. Alternatively, External loss can use them indirectly by considering them during scenario generation process. Similar to internal data classification, external loss also needs to be classified under different business line and loss event type. The guidelines also provide enough flexibility in the methodology inasmuch as for a particular business line and event type combination, both, internal as well as external data can be considered together for modeling. The combined data set will be used for fitting of statistical distribution and parameter estimation. The frequency and severity series will have both external and internal data points. The best-fit distribution will be obtained on the basis of goodness-of-fit result. The parameters of the best-fit distributions will be used for OpVaR calculation based on simulation approach.

6.8 Scenario Modeling

There is very little literature available on how scenario analysis is carried out by the banks, as some of the banks have only recently started scenario analysis while banks that are AMA-compliant would be doing scenario analysis; however, the scenario modeling methodology is not in the public domain for reasons of confidentiality. As a practice scenario data can be used in two different ways. The first approach is modeling scenario data on standalone basis and the second approach is modeling scenario along with the internal loss data. In the first approach scenario data is modeled separately to avoid complications of combining internal and scenario data. Here, scenario modeling should be performed independently for each ORC. The modeling techniques used for internal loss data can be used to model scenario data. Capital from internal data and scenario data will be combined using weighted aggregate method.

One of the biggest challenges is the selection of weights to aggregate OpVaR from internal data and scenario data. A statistically sound technique should be used to combine scenario capital with capital from internal data. Since the scenario analysis is generally performed to capture the impact of catastrophic events which results in a very high loss impact, this plays a very crucial role in quantifying operational risk capital for the bank. A few new scenarios of very high loss impact can distort the quantum of capital required by the bank for operational risk. Hence, identifying the whole list of scenarios and combining its impact with bank's capital requirement obtained from internal data is big challenge. One has to be extra careful in assigning weights to capital obtained from scenario data, since scenario capital are much higher than the capital obtained from internal loss data.

The second approach is to model both scenario and internal data together. Here, like external data, frequency and severity values obtained from scenario assessment will be used for fitting statistical distribution, along with internal data. Subsequently, the parameters of the combined distribution will be used to obtain aggregated loss distribution with the help of simulation technique. One significant disadvantages of this approach is since the nature of scenario losses is different from internal data, it may be inappropriate to fit a single distribution to model both the data together. Scenario losses usually form tail part of the distribution whereas internal data form body of the distributions. Banks need to carefully choose an appropriate methodology to combine these two distributions if they go for this approach.

6.9 BEICF and Operational Risk Capital Charge

In the previous sections, we discussed the AMA framework considering various data elements like internal loss data, external data and scenario data. Apart from these three data elements, banks are required to factor another element in their operational risk modeling framework, which is Business Environment and Internal Control Factors (BEICFs). BEICFs are forward looking indicators of bank’s operational risk profile that reflect underlying business risk factors juxtaposed against assessment of the effectiveness of the internal control environment. By incorporating these into the measurement framework, it is ensured that the measurement framework is sensitive to the continually changing operational risk profile and effectiveness of control environment. BEICFs can be used for risk measurement by the bank in a variety of ways:

(1) As input into the capital calculation directly through score card approach to obtain initial operational risk capital charge

(2) BEICF can be used for ex-post adjustment to total capital for the bank as a whole or business line-wise capital. Here, previous year’s BEICF score can be compared with the current score to obtain the risk profile and trend. The AMA capital obtained from other data elements can be adjusted downward or upward on the basis of risk and trend. If it shows there is an enhancement of risk as a result of change in business

environment and decrease in control factor, the capital may be adjusted upward and vice-versa.

(3) BEICFs can also be indirectly used as an input into the scenario analysis process to facilitate scenario identification and quantify frequency and severity values for scenarios.

6.10 Single Loss Approximation Method

Normally operational risk severity distributions are heavy-tailed (there is the presence of extreme events). A single extreme loss event can cause major changes in the estimate of the parameters of the distribution. As a result of which the simulation based OpVaR may not provide a correct estimate of operational risk capital. In such cases where loss severity follows a heavy-tailed distribution, modeling the whole distribution for capital computation will be superfluous. Modeling tail events using a closed form solution like single loss approximation method will provide a better result. Bocker and Kluppelberg (2005) developed this method of approximating the risk amount at a particular point on the loss distribution (the value of one loss event).

If the severity function is heavy-tailed (sub-exponential), the risk amount OpVaR at a confidence level of 99.9th percentile given the average annual number of event as λ and using the appropriate severity distribution function, can be defined as follows:

$$OPVaR(\alpha) = F^{-1}(1 - \frac{1-\alpha}{\lambda}) \qquad \text{…(6.5)}$$

Where, F is the sub-exponential severity distribution function,

α is the confidence level,

λ is the average total annual number of events.

Setting $N = \frac{1}{1-\alpha}$, the above equation can be rewritten as:

$$OPVaR(\alpha) = F^{-1}(1 - \frac{1}{N\lambda}) \qquad \text{…(6.6)}$$

Unlike loss distribution approach, single loss approximation method does not require modeling the whole data for computation of OpVaR; the tail part of the loss data will be sufficient to compute capital at a very high confidence level.

6.11 Operational Risk Management Practice: A Review of the Literature

The Basel II Accord, which is more advanced and risk sensitive in comparison to Basel I, arose after a number of high profile operational risk events occurred during late 1990s making the regulators to rethink about risk management practices of the banks. The new approach addresses the issues related to operational risk and capital requirement for it. As per the RBI guidelines, all the Indian banks which have overseas presence were to move to Basel II Accord by March 2008 and other Indian banks were to be Basel II compliant by March 2009. It also requires banks to start with BIA for operational risk capital calculation and gradually move to the Advanced Measurement Approach (AMA).

At present all the scheduled commercial banks in India have already moved to Basel II Accord and are maintaining capital for operational risk. Some of the Indian banks who have overseas presence had implemented Basel II Accord and started maintaining operational risk capital as per basic indicator approach since the financial year 2008-09. The capital adequacy ratio of the bank at present constitutes risk weighted assets for market risk and capital requirements for market and operational risks.

Some of the leading nationalized and private sector banks in India have a separate operational risk management function/ department in place, to drive, oversee and manage all operational risk related matters including collection of loss data due to operational failure, analysis of bank-wide risk indicators and assessment of risks involved in various products, activities and processes the bank is engaged in and the effectiveness of existing controls. These banks have already started preparation for moving to advanced measurement approach (AMA). AMA is the most risk sensitive approach among the available three approaches and it would provide relief to the banks in terms of reduction in capital requirement for operational risk. As discussed in the previous chapter, the operational risk management framework constitutes four elements namely, internal loss data, external loss data, scenario analysis and BEICF. Some of the Indian banks are targeting one or some of these elements and planning to cover all the four elements gradually. Banks like, HDFC Bank, ICICI Bank, Axis Bank and Punjab National Bank are maintaining loss database which constitutes last three to five or more years of operational loss events incurred in their own bank. A few Indian banks are also maintaining external data collected from sources like published report, internet, newspaper, etc or through subscription to the external database provided by third party vendor.

Along with the collection of loss data banks also have identified various internal control factors, like Key Risk Indicators (KRIs) and Risk and Control Self Assessment (RCSA) and started collecting and analyzing data related to these internal control factors. Few banks have also started collecting scenario data. Banks have also in the process of putting together robust system for recording the various operational risk and data elements; measurement, modeling, and to serve as a repository for historical loss data points; doing KRI, RCSA and scenario analysis and for performing other ORM related computation including issue and action management and report generation. Some of the vendors, like CRISIL, SAS, Algorithmics and Oracle have developed software for operational risk management and some of the Indian banks have started using off-the-shelf or customized vendor-based systems.

Many of the banks in European and in Australian jurisdictions have already implemented the advanced measurement approach. As far as Indian banks are concerned, the time line mentioned by the Reserve Bank of India for applying for AMA is after April 2012. Some of the banks have completed ground work and intend to apply while couple of big banks have already submitted letter of intent to RBI. The rest of this section reviews some of the literature on operational risk management, using the advanced measurement approach, and in particular the Loss Distribution Approach.

Duetsche Bank's (DB) approach for quantifying operational risk, based on loss distribution approach, was discussed by Aue and Kalkbrener (2007). DB uses all the AMA data elements like internal data, external data scenario data and BEICFs. DB started collection of loss data in 1999 for all business lines. Their loss database also includes external loss data collected from ORX and OpVantage. They form ORCs on the basis of data availability, relative importance of the cell, comparable loss profile, whether same insurance type taken and same management responsibilities prevail. On the basis of above criteria DB has formed 23 ORCs.

The DB's modeling of operational risk is based on loss distribution approach, where internal loss data is the important data source in the model. Internal loss data is used to arrive at frequency distribution and severity distribution. Severity distributions are constructed by using internal, external and scenario data. Scenario and external loss data are used as the additional data source to model the tail of the severity distribution. The main application of scenario data in DB is to supplement loss data. Separate models for body and tail are taken. Operational risk capital is estimated using Monte-Carlo simulation technique. Tail events are modeled using Generalized Pareto Distribution (GPD) in DB. It also factors correlation among frequency of the loss data to arrive at total capital for the organization. The economic capital calculated using various data elements for a business line is further adjusted on the basis of business environment and internal control factors. Qualitative adjustment utilizes data from key risk indicators and risk self assessment.

Frachot et al (2003) is one of the initial studies on Loss Distribution Approach (LDA) to compute operational risk capital requirement. Their study focused on describing, step by step, how a full Loss Distribution Approach can be implemented in practice and how both quantitative and qualitative points of view can be reconciled. The study also presented some numerical calculations of the capital charge estimates. It addressed detailed steps to identify and fit severity and frequency distributions, identification of best-fit distributions on the basis of goodness-of-fit tests, scaling of data elements, scenario analysis, computation of operational risk capital charge and aggregation of capital estimates obtained from different business line and event type combination. The study also suggested a few methods to check parameter accuracy namely, bootstrap method and Gaussian approximation approach.

Fontnouvelle et al (2003) conducted a study on quantification of operational risk capital charge for large internationally active banks using loss data collected from public information sources. Since the internal losses of the banks are not publicly available, the study used external loss data obtained from several vendors, despite the fact that the external data poses unique modeling challenges since the base usually contains large number of high impact events and less number of smaller losses. The study computed operational risk capital charge using loss distribution approach. Extreme value theory approach was used to model tail events since the data base was constituted with some tail events. Their study found that the operational losses are an important source of risk for banks and the capital charge for operational risk would often exceed the capital charge for market risk. Another important finding of the study was that the distribution of observed losses varied significantly by business line. The authors suggested that supplementing internal data with external data on extremely large rare events may significantly improve banks' operational risk models.

Dutta and Perry (2007) carried out a detailed study on modeling operational risk using loss distribution approach. They analyzed and compared various approaches that could be used to measure operational risk using financial institutions' internal loss data collected under the 2004 Loss Data Collection Exercise (LDCE). In order to ensure a meaningful analysis, they used data from seven institutions that reported a sufficient number of losses (at least one thousand total loss events) and whose data was also consistent and coherent relative to the other institutions. These seven institutions adequately covered various business types and asset sizes for financial institutions. The study performed a comprehensive evaluation of commonly used methods for modeling operational risk and introduced new techniques to measure this risk with respect to various criteria. It discussed the techniques to be used to identify best-fit distributions using various exploratory data analysis techniques and goodness-of-fit tests. Various heavy-tailed distributions were used to model severity distributions. The study used a set of statistical distributions which include Weibull, Lognormal, Generalized Pareto and g-and-h distribution. It discussed the steps to compute capital from internal loss data and aggregation mechanism to compute aggregated capital for the bank. One of the significant aspects of the study was that it did a detailed analysis of modeling of tail events including threshold selection for extreme value theory approach. They used Peak over Threshold (POT) technique to model tail part of the distribution. A very scientific and logical approach to model body and tail of the distributions together was discussed in the study.

Moscadelli (2004) conducted a study on modeling of operational risk using loss data collected by the Basel Committee. The study computed capital using loss distribution approach and compared the sensitivity of the results with the result obtained from extreme value theory. The exercise showed that the extreme value model, in its Peaks over Threshold (POT) representation, explains the behavior of the operational risk data in the tail area well. The study outlined various elements of operational risk modeling such as distribution fitting for frequency and severity, identification of best-fit distributions using graphical data analysis tools and goodness of fit tests, modeling tail events using Generalized Pareto Distribution (GPD), identification of EVT threshold using mean excess plot (MEP). For each Business Line and in the eight Business Lines as a whole, the contributions of the expected losses to the capital figures were evaluated and the relationships between the capital charges and the corresponding average level of Gross Incomes were determined in the study.

Jobst (2007) analyzed economic and regulatory implications of modeling operational risk in compliance with the regulatory capital standard defined by the new Basel Accord. The study used Generalized Pareto Distribution, Generalized Extreme Value Distribution, g-and-h distribution to model operational risk. The results suggested that the AMA- compliant risk estimates of operational risk under both EVT and g-and-h distribution generated reliable and realistic estimates of unexpected loss.

Peter et al (2006) studied operational risk modeling using Bayesian approach. The Loss Distribution Approach was enhanced by the use of Bayesian technique in their study. Bayesian approach is useful when subjective assessments are used to model along with internal loss data in a loss distribution setting. The authors strongly advocate that Bayesian approach to operational risk modeling can be considered as a serious alternative for banks and financial institutions, as they provide a mathematically rigorous paradigm in which to combine observed data and expert opinion.

Another study was done by Shevchenko et al (2006) on modeling operational risk by combining internal and scenario data through Bayesian approach. Bayesian inference method was used for the quantification of the frequency and severity distributions for operational risk. The method was based on specifying the prior distributions for the parameters of the frequency and severity distributions using expert opinions or industry data. Since scenario data is based on expert opinion and is subjective in nature, Bayesian approach was found to be suitable to combine expert opinion and historical losses to compute operational risk capital charge. The study conducted an analysis with the help of an example, to quantify operational risk capital charge using Bayesian inference method.

Ergashev (2008) compared the performance of four parameter estimation techniques used in the literature of operational risk modeling, since the parameter estimation techniques play a vital role in the computation of operational risk capital requirement. The estimation methods used in his study were Maximum Likelihood Estimation (MLE), Cramer–von Mises (CVM), the Anderson– Darling (AD) and quantile distance (QD) estimation methods. MLE is based on the maximization of the likelihood function, whereas, CVM and AD are based on minimizing different types of statistics that measure the distance between empirical and fitting loss distributions, and QD is based on distance between the quantiles of empirical and fitting distributions. This simulation based study shows that the QD estimation method is possibly superior to the other three estimation methods, including the MLE, in the sense that it leads to more accurate capital numbers, especially when loss data sets are relatively small and/or the fitting model is possibly mis-specified.

Ergashev (2011) introduced a theoretically justified framework that incorporates scenario analysis into operational risk modeling. Since scenario data is one of the important elements that significantly affect operational risk capital charge of the bank, the obvious question is how it should be incorporated in to the modeling framework. This study has suggested a very logical framework to address this issue. The basis of this framework is the idea that one needs to focus on worst-case scenarios, because only those scenarios contain valuable information about the tail behavior of operational losses. Since all the scenarios including low impact scenarios are not relevant for operational risk modeling, he proposed a simple rule for identifying the worst-case scenarios from the pool of all scenarios. He suggested that the information contained in the worst-case scenarios enters the quantification process in the form of lower bound constraints on the specific quantile levels of the severity distribution. The study also presented five alternative approaches to incorporating scenarios in to the operational risk modeling. These include the stochastic dominance approach, the constraint estimation approach, the constraint MCMC (Markov Chain Monte Carlo) approach, the curve fitting approach and the minimum distance approach.

A detailed analysis of operational risk management framework is done by Cruz (2002). In his book, he has discussed most of the elements of operational risk management and measurement including theory and quantitative techniques to model, measure and hedge operational risk. He has discussed the input required for measurement and modeling methodology used for operational risk capital requirement. A set of commonly used statistical distributions to model frequency and severity data are also discussed. He has discussed how frequency and severity distribution should be fitted to the data and aggregated loss distribution be arrived at through simulation process. Modeling tail events using extreme value theory and back testing of operational risk models are also discussed.. The author also discussed in detail stress testing and scenario analysis and hedging of operational risk using instruments like insurance and operational risk derivatives.

BIS Survey on ORM Practices by Banks Worldwide

Basel Committee on Banking Supervision (BCBS) had conducted a survey on Loss Data Collection Exercise (LDCE) in 2008, which includes collection of information on all four data elements that are used in the Advanced Measurement Approach of the Basel II Framework. This exercise involves collection of the information from various banks across regions and practices followed by them for operational risk management.

A total of 121 banks from 17 countries participated in the 2008 LDCE survey. The regions covered were grouped into Australia, Europe, Japan, North America and Brazil/India. Among the participants, there are 42 banks who have implemented AMA framework for operational risk management. This section will discuss some of the findings related to these four components of operational risk management and capital calculation processes followed by the banks, as mentioned in the BIS's two survey documents published in July 2009: "Results from the 2008 Loss Data Collection Exercise for Operational Risk" and "Observed Ranges of Practice in Key Elements of Advanced Measurement Approaches (AMA)."

a. Internal Loss Data

Loss data collected from the participating banks constitute a minimum period of three years. Most institutions provided data up to 31 December 2007 or 31 March 2008. Some of the major findings are mentioned as follows.

- Business line with the highest loss frequency and total loss amount was Retail Banking. The second highest loss frequency was reported in Retail Brokerage, which was somewhat surprising given that participants reported a small proportion of income from this business.

- Basel event types with the highest frequency of losses were Execution, Delivery, and Process Management (EDPM), followed by External Fraud. The event type with the highest annual loss amount was Clients, Products, and Business Practices (CPBP). A few losses were reported for Business Disruption and System Failures and Damage to Physical Assets.

- Insurance recoveries were reported for a small proportion of losses with the typical bank reporting insurance recoveries of 2.1% of losses.

- Frequency of internal losses of €20,000 or more varies significantly across regions when the data are scaled by various exposure indicators

b. Scenario Data

Participating banks were asked to provide their scenario data. The collection of scenario data enables national supervisors to compare scenarios across jurisdictions as well as to assess how scenarios relate to internal loss data. Some of the findings on scenario data are:

- 65 of the 121 participants submitted a total of 9,687 scenarios. The median number of scenarios used in participating banks' operational risk frameworks was 115 scenarios. There was significant variation across banks and regions in both the number and size of scenarios used.

- The typical bank had the largest proportion of scenarios in the unallocated business line (36%), which includes group-wide scenarios, and in Retail Banking (28%). By event type, the typical bank had the highest proportion of scenarios related to EDPM (29%) and CPBP (20%).

- Most banks' scenario data extends the tail of the loss distribution beyond the point at which they have experienced internal losses.

- The expected annual frequency of losses exceeding €88 million for the typical bank was 1-in-100 years and the expected annual frequency of losses exceeding €194 million was 1-in-1000 years.

c. External Loss Data

External loss data for a Bank comprises operational risk losses experienced by other banks. Banks can use information contained in external loss data to assess the relevance of a particular loss to their circumstances. Almost all the AMA banks make use of external loss data for operational risk capital calculation. Some of the findings of the survey are:

- 71% of AMA banks collect external loss data from vendors and 48% from participation in industry consortia. Also, 33% of the AMA banks collect databases of public sources, including newspapers, magazines and various journals and from public domain.

- External loss data are primarily used as input to scenario analysis by 86% of AMA banks; as an aid for risk management purposes by 71%, and to a lesser extent as a direct input into the AMA model by 29% of AMA banks. 26% of the banks use it as an input into BEICFs tools. However, none of the AMA-compliant banks solely relied on external data for AMA calculation.

- Around 45% of AMA banks use external loss data mainly to estimate severity of tail events (low frequency/ high severity). External data is used less widely by 22% of AMA banks to estimate parameters of the frequency distribution.

- One of the major issues that the banks face is scaling of external loss data. The current range of practice indicates that only a few AMA-compliant banks (around 21%) are able to scale external data, with the remaining banks using unscaled external loss data in their AMA models. Banks use revenue or assets as the scaling factors.

d. Business Environment and Internal Control Factor (BEICF)

Common tools that the banks follow worldwide for BEICFs are Risk and Control Self Assessment (RCSA), Key Risk Indicators (KRI), Key Performance Indicators (KPI), or Key Control Indicators. Some of the findings of the BIS survey related to BEICF are as follows:

- All AMA banks generally as a process use some type of BEICF tools for risk management and/or risk quantification. The most commonly used BEICFs tools for risk management are RCSAs (by 95%) followed by audit results (by 88%) and KRIs/KPIs (around 81%).

- One of the important challenges for AMA banks is quantification of the impact of BEICF on capital calculation. Most AMA banks use BEICFs as an indirect input to risk quantification (69% of AMA banks). Only 14% of the banks use BEICFs in a way that directly affects the total amount of AMA Capital (7% use it as direct input into the model and remaining 7% use it as an ex-post adjustment to AMA capital).

- RCSAs are updated generally on an annual basis by 43% of AMA banks, quarterly to semi-annual basis by 26%, and semi-annually to annually by 24% of AMA banks. KRIs/KPIs are updated more frequently, typically monthly to quarterly by 52% of AMA banks. Audit scores or findings are most often reviewed when triggered.

e. Capital Calculation

Some of the findings related to operational risk capital calculation are:

- The operational risk capital estimates of AMA banks are lower than those of non-AMA banks, while AMA banks have a higher frequency and severity of large losses than non-AMA banks, even after the data are scaled by exposure indicators.

- The typical AMA bank has a ratio of operational risk capital relative to gross income that is lower than the 15% alpha for the BIA and the range of betas (12%-18%) used in TSA.

- Expected losses (EL) account for about 11% of operational risk capital at the typical participating bank. The use of EL offsets is limited, with half of participants taking no capital offset, and three quarters of participants taking an offset of less than 1% of operational risk capital.

6.12 Conclusion

This chapter discussed the Advanced Measurement Approach (AMA) for operational risk management. It included a detailed analysis of the framework for computation of operational risk capital charge using loss distribution approach (LDA). In general, various exploratory data analysis techniques and goodness of fit tests are performed to identify best-fit statistical distributions to model frequency and severity data; and aggregated loss distribution is arrived at through Monte-Carlo simulation technique, all of which were discussed. The chapter also discussed various alternative modeling techniques such as EVT and single loss approximation method. EVT is used to model extreme events, wherein a single distribution cannot be used to model loss data due to the presence of tail events in the database. In such cases, EVT approach can be used to model losses above a defined threshold. The EVT threshold can be defined through graphical technique like MEP or using various goodness-of-fit tests. Single loss approximation method is suitable wherein a single event in the database will lead a significant change in shape and scale parameters of the distributions.

The chapter also outlined framework for scenario modelling, modelling of external data and business environment and internal control factor (BEICF). Scenario modelling is a challenging task since it involves losses due to catastrophic events, which are subjectively assessed by the seniors in the bank. Back-testing technique used to validate operational model was also discussed. Some of the literature on advanced measurement approach including practice followed by various banks was reviewed as part of this chapter. A brief review of survey conducted by BCBS on loss data collection exercise and range of practice on AMA was also included in the chapter.

CHAPTER 7

COMPUTATION OF OPERATIONAL RISK CAPITAL CHARGE UNDER AMA

7.1 Introduction

The last two chapters were concerned with a discussion of capital for operational risk. As noted there capital requirement for operational risk of a bank can be estimated either through BIA or through TSA or through AMA. Among these three approaches, AMA is the most risk sensitive approach since it uses actual losses faced by the bank, high impact scenario losses, external losses and BEICF to estimate operational risk capital requirement, whereas the other two approaches use gross income to compute capital requirement. Unlike models for credit risk and market risk capital charge, which have been there in the banking system for a long time and are relatively well established in terms of availability of modeling techniques and modeling assumptions to be used, operational risk model to estimate capital requirement for operational risk is in a preliminary stage. Neither is there any clear regulatory direction regarding modeling techniques and statistical assumptions to be used to measure operational risk, nor is there any comprehensive work addressing various modeling issues, available for the banks. The situation is even worse in case of India, where no research work is found on the modeling aspects of operational risk.

Most banks in other countries that have implemented AMA are estimating operational risk capital using the Loss Distribution Approach (LDA). The details of this have been discussed in chapter 6. This chapter carries out a detailed study on actual computation of capital charge for operational risk, using AMA. This is based on various modelling techniques and statistical tools. The details of these techniques are discussed through actual application to data. This chapter considers various modelling approaches to compute capital charge using historical loss data under different circumstances related to type of data set present in the operational risk category (ORC), the distribution it follows, etc. Modelling techniques depend on the pattern/ distribution of losses, so a single modelling technique cannot be used to model operational losses of different ORCs. Hence, the study tries to identify suitable modelling techniques for various ORCs using different types of data set. The objective of this chapter is to compute operational risk capital charge under AMA using internal loss data. The modelling approaches for other components of AMA are not discussed here. However a similar methodology can be used for modelling external and scenario data; a brief outline of modelling external and scenario data was presented in the previous chapter. However one disclaimer needs to be made here. One of the most important components used for the computation of operational risk capital charge is the actual loss of a bank. Under AMA, banks are required to maintain historical loss database in a systematic manner to enable them analyse and use for the computation of operational risk capital charge. In India, as per the RBI guidelines, banks are required to use a minimum of five years loss data for operational risk capital charge computation. However, this data is not available for reasons to be discussed. Hence, in place of actual loss data, this study uses constructed data for the computation, which will enable a demonstration of modelling techniques to be used under different operational risk categories. The details of the data construction are discussed below.

Accordingly, the chapter is organised as follows: the construction of the data used in the study is discussed in the immediately following section; Section 3 of the chapter discusses the various statistical techniques used; Section 4 discusses the results obtained and the capital requirement so computed; Section 5 concludes.

7.2 Data Used for the Study

Computation of operational risk capital charge requires historical loss data. However, the operational risk related losses are very sensitive and are confidential information of the bank, which are not publicly available. Such information, if available in the public domain will tarnish the image of the bank in the eyes of the customers and share holders. This may result in loss of customer base, business volume, deposit volume of the bank; which will subsequently affect the financial health of the bank in terms of reduction in the gross income and profit margin. This poses serious challenges for the researchers to work on operational risk modelling using historical losses of the banks. One possibility is to use external loss data provided by the data consortium to study operational risk modelling. However, in India there is no publicly available external database[22], which can be used by the researchers. Also, the external databases available internationally, are very expensive for a researcher to subscribe to. Since the operational risk modelling is comparatively a new regulatory direction in comparison to credit and market risk modelling, it will take some time for the banking sector in India to systematise their loss database and to form an external database for Indian banks. Some of the Indian banks have just begun their loss data collection exercise while a few banks had started collecting a few years ago.

Due to the above mentioned difficulties in obtaining actual operational risk loss data for empirical analysis, the present study uses constructed data for the computation of AMA capital. The data construction is done on the basis of available literature and industry experience of the researcher. A typical operational loss database constitutes large number of high frequency and low severity events and less number of low frequency and high severity events. Some data sets may include one or a few very extreme loss events, which would be incurred due to severe natural disaster or a high profile syndicate fraud or due to some other such events. Typically, the occurrence of less severe operational risk events are more frequent than the occurrence of high impact events in a bank, due to the strong control mechanism available for high valued transactions. Taking into consideration all these factors, one can say that the operational risk losses are skewed and follow a medium tailed to heavy-tailed distribution. The earlier studies done by Kalkbrener (2007), Fontnouvelle et al (2003), Dutta and Perry (2007) and Moscadelli (2004) using either external loss data or data collected by BCBS from the member countries, suggest that the operational losses follow some kind of heavy-tailed distributions. Heavy-tailed distributions like Lognormal, Exponential, Weibull, Generalized Pareto Distribution (GPD), etc. were found to be best-fit distributions for losses, in these studies. Also, the loss data collection exercise of BCBS (BCBS, 2009) suggests that the operational risk losses are skewed and follow heavy-tailed distributions.

This study constructs operational risk data set considering all the above mentioned facts and findings. Since theory and literature suggest that the operational risk losses are skewed with a heavy-tailed distribution, we have constructed our database by generating random losses,

[22]Indian Banker's Association (IBA) is in the process of creating an external loss database for the Indian banks, which will help banks and researchers to get access to the external loss database for their analysis.

which will be skewed and follow a heavy-tailed distribution. Since the study tries to compute operational risk capital charge using statistical techniques under various scenarios, we have created different types of loss database, by incorporating single or more extreme events into the database. This will help in analysing and identifying appropriate modelling techniques that should be used to model a particular loss data set. The constructed data ranges from 1-Apr-2008 to 31-Mar-2011. There are four operational risk categories (ORCs) formed using the database. These four ORCs are representative of the nature and behaviour of the loss data that a bank experiences. Out of these four ORCs, two ORCs include extreme events, which will be modeled through a different statistical technique.

7.3 Statistical Techniques to Compute OpVaR

The broad methodology for operational risk capital estimation under AMA was discussed in chapter 6. This was based on LDA which uses various statistical techniques for distribution fitting, goodness of fit tests, etc. The best-fit statistical distributions are used to compute Operational Value at Risk (OpVaR) using Monte-Carlo simulation technique. These techniques are discussed in this section.

7.3.1 Statistical Distributions Used to Model Losses

Discrete statistical distributions like Poisson, Negative Binomial are commonly used for modelling frequency data. Similarly a set of continuous statistical distributions like Lognormal, Weibull, Exponential, Gamma, Generalized Pareto distribution are commonly used for modelling severity data (operational losses). In operational risk modeling, the choice of severity distribution plays a crucial role in comparison to choice of frequency distribution, since selection of severity distribution affects capital estimates significantly. This study uses the Poisson distribution for frequency data, and above mentioned continuous distributions for modelling loss severity. These distributions are briefly outlined below.

Poisson distribution

Poisson distribution is a discrete statistical distribution. It is named after the French mathematician Simeon Denis Poisson (1781–1840) who was the first to present this distribution in 1837. This distribution is most widely used for modelling frequency data of operational risk losses. Poisson distribution is a single parameter distribution where λ is the only parameter. λ represent both mean and standard deviation of the distribution. The probability density function of Poisson distribution is:

$$f(r,\lambda) = \frac{\lambda^r e^{-\lambda}}{r!} \qquad ...(7.1)$$

Where the variable r is an integer and r≥0 and λ is the Poisson parameter. λ is a positive real number which is equal to the expected number of occurrences during the given interval. When frequency is modeled with Poisson distribution, it is assumed that probability of occurrence of one event is independent of the other.

Since mean and variance of Poisson distribution are equal, a simple way to check whether a loss frequency distribution follows a Poisson distribution is to compare the mean and the variance of the numbers of events and see if they are fairly equal. The only parameter λ can be estimated by using simple average formula.

Lognormal Distribution

Lognormal distribution is a continuous probability distribution of a random variable whose logarithmic transformation is normally distributed. X is said to follow Lognormal distribution if log(x) is normally distributed. Lognormal distribution is a skewed distribution with two parameters, mean and standard deviation. Since operational losses follow a heavy tail distribution due to the presence of a large number of high frequency and low severity events and less number of low frequency and high severity events, a Lognormal distribution is found to be the best-fit distribution for modelling severity distribution by many banks. The probability density function of Lognormal distribution is:

$$f(x;\mu,\sigma) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}} \qquad \ldots(7.2)$$

Where, x is a positive random number (x > 0), μ and σ are two positive parameters representing mean and standard deviation ($\mu, \sigma > 0$).

Exponential Distribution

Exponential distribution is a single parameter continuous distribution. This distribution is used for modelling of operational risk severity distribution and this is suitable when loss severity does not have heavy tail losses. The probability density function of Exponential distribution is:

$$f(x;\alpha) = \frac{1}{\alpha} e^{-\frac{x}{\alpha}} \qquad \text{...(7/3)}$$

Where, x is a positive random number (x > 0) and α is the only parameter (α > 0)

Weibull Distribution

Weibull distribution is a two parameter generalization of the Exponential distribution. The two parameters reflect scale and shape of the distribution. Like Lognormal distribution, Weibull distribution is suitable for modeling operational risk losses when the data set contains many small losses and few large losses. The probability density function of Weibull distribution is:

$$f(x;\eta,\sigma) = \frac{\eta}{\sigma}\left(\frac{x}{\sigma}\right)^{\eta-1} e^{-\left(\frac{x}{\sigma}\right)^{\eta}} \qquad \text{...(7.4)}$$

Where, x is a positive random number (x > 0); η and σ are shape and scale parameters respectively ($\eta > 0, \sigma > 0$).

Gamma Distribution

Gamma distribution is a two parameter continuous distribution. This is a right skewed distribution, which fits data with a heavy tail distribution. This distribution is used for modeling operational risk losses since operational risk losses are generally skewed in nature. The probability density function of Gamma distribution is given by:

$$f(x;a,b) = \frac{1}{\Gamma(b)} a(ax)^{b-1} e^{-ax} \qquad \text{...(7.5)}$$

Where, x is a positive random number (x > 0); a and b are the parameters ($a > 0, b > 0$) of Gamma distribution.

These are some of the distributions that can be (and usually are) fitted to the severity data. However, to choose between them in particular applications, the goodness of fit needs to be tested.

7.3.2 Goodness-of-Fit Tests

Goodness-of-fit tests are performed to identify the best-fit distributions for frequency and severity data. Both graphical and quantitative goodness-of-fit tests are used in the study. Graphical tests include Quantile-Quantile (Q-Q) plot and Probability-Probability (P-P) plot. The quantitative techniques include Kolmogorov-Smirnov (K-S) test.

Graphical Tests

Q-Q Plot and P-P Plot are two graphical techniques that are used to check if two data sets are from the same population with a common distribution. A Q-Q plot is obtained by plotting quantile of one distribution set against quantile of another distribution. By a quantile, we mean the point below which a given fraction (or percent) of points lies. That is, the 0.3 (or 30%) quantile is the point at which 30% percent of the data fall below and 70% fall above the value.

In the Q-Q plot empirical quantiles are plotted against the quantiles of hypothesized distribution fitted to the data. In applications to operational risk, Q-Q plot is used to identify the distribution the actual loss data follows. If the actual loss data is compared with a hypothesized distribution and the resultant Q-Q plot coincides with 45 degree line, then we can infer that the actual data follows the hypothesized distribution. Hence, the Q-Q plot of the best-fit distribution will be the one that is closest to the 45 degree line.

Similar to the Q-Q plot, a P-P plot is another graphical technique used to check if two data sets follow the same distribution. It is used to determine how well a specific distribution fits the observed data. A P-P plot is obtained by plotting empirical cumulative distribution function (CDF) against the theoretical or hypothesised cumulative distribution function. If P-P plot for a particular data set follows a 45 degree line, then it can be said that the theoretical distribution is the correct model, which means the data set follows the theoretical distribution.

In operational risk modelling, P-P plot is used to identify the kind of distribution that a loss data set follows. Various statistical distributions are fitted to operational risk losses and that particular distribution is selected for which P-P plot is closest to the 45 degree line.

Quantitative Tests: Kolmogorov-Smirnov (K-S) Test

The Kolmogorov-Smirnov (K-S) test is a quantitative test used to decide if a sample, i.e., a given data set comes from a population with a specified distribution. The K-S test is based on empirical cumulative distribution function (ECDF). It is based on the maximum distance between empirical CDF and CDF of the theoretical distribution. The K-S test statistic is defined as:

$$D = \max_{1 \le i \le N} \left(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i) \right) \qquad \ldots(7.6)$$

Where, F is the theoretical cumulative distribution function, which must be a continuous distribution and N is the number of data points. Here the null hypothesis and alternative hypothesis are as follows:

H_0: The data follows a specific distribution

H_1: The does not follow the specific distribution

The calculated K-S value is compared with the critical value. If it is found that the calculated value is greater than critical value, then the data set does not follow the specified distribution. One of the advantages of the K-S test is that the distribution of the K-S test statistic itself does not depend on the underlying cumulative distribution function being tested. This study uses the K-S test to identify a best-fit statistical distribution to model operational risk losses.

7.4 Analysis and Results

The operational risk capital charge is estimated for each of the four ORCs separately and then combined to arrive at total capital for the bank as a whole. The study will demonstrate various techniques that can be used to compute operational risk capital depending on the type of distribution loss data follows in a particular ORC. Monte-Carlo simulation technique is used to compute capital for ORC1 and ORC2. Extreme Value Theory (EVT) is used for ORC3 and Single Loss Approximation technique is used for ORC4. The results are estimated using statistical software like SPSS, R and MATLAB. This section includes results obtained from exploratory data analysis with the help of graphical method, goodness-of-fit tests to identify a best-fit distribution for severity series and Monte-Carlo simulation. Results obtained from EVT and single loss approximation techniques are also reported.

Descriptive Statistics

So far no research has demonstrated that operational loss severity data follows a particular distribution. Both Basel Committee on Banking Supervision (BCBS) and RBI, for this reason, have not directed banks to use any particular distribution for severity and frequency series. The regulators have given a free hand to the banks to identify suitable statistical distributions for their database. Before choosing a suitable statistical distribution to model the severity of los data, it is essential to study the structure and characteristics of the loss data with the help of descriptive statistics.

Table- 7.1 reports descriptive statistics of loss data in all four ORCs in the data that was constructed. Number of events, total loss, average loss, standard deviation, skewness and kurtosis for each of the ORCs are mentioned. The total loss in ORC4 is 32.618 crore and number of events is 58. This ORC includes an extreme event of 30 crore. Skewness values in all the ORCs are high, which shows that the severity distributions are skewed towards the right. The kurtosis values show that the distributions are leptokurtic. It is well known, and has been found in various studies conducted by the BCBS that the operational loss severity distribution is heavy-tailed and skewed. From the descriptive statistics mentioned in the following table, it is evident that the loss severity distributions in all the ORCs follow heavy-tailed distributions. However, it is very difficult to identify the type of distribution that the loss severity follows merely from the descriptive statistics. Hence various goodness-of-fit tests are carried out to identify the best-fit distribution for severity data.

Table- 7.1: Descriptive Statistics of Loss Data

ORC	No of Events	Total Loss (Rs)	Mean(Rs)	Standard deviation	Kurtosis	Skewness
ORC1	95	180937717	1904608	7163251.90	67.41	7.78
ORC2	88	120820736	1372963	4276574.27	59.24	7.22
ORC3	57	25368484	445061	1499428.64	31.56	5.39
ORC4	58	326185484	5623888	39360177.67	57.82	7.60

7.4.1 Exploratory Data Analysis

In LDA a separate statistical distribution is fitted to the frequency and severity data. Frequency distribution is arrived at by plotting number of events in a day/ month/ year on the horizontal axis and its probability on the vertical axis whereas, severity distribution is arrived by plotting loss per event on horizontal axis and its probability on vertical axis. Exploratory data analysis (EDA) coupled with descriptive statistics helps identify the kind of distributions a loss severity series follows. The graphical EDA includes Quantile-Quantile (Q-Q) and Probability-Probability (P-P) plots. Q-Q and P-P plots of various continuous distributions, used to model severity data are analysed in this section.

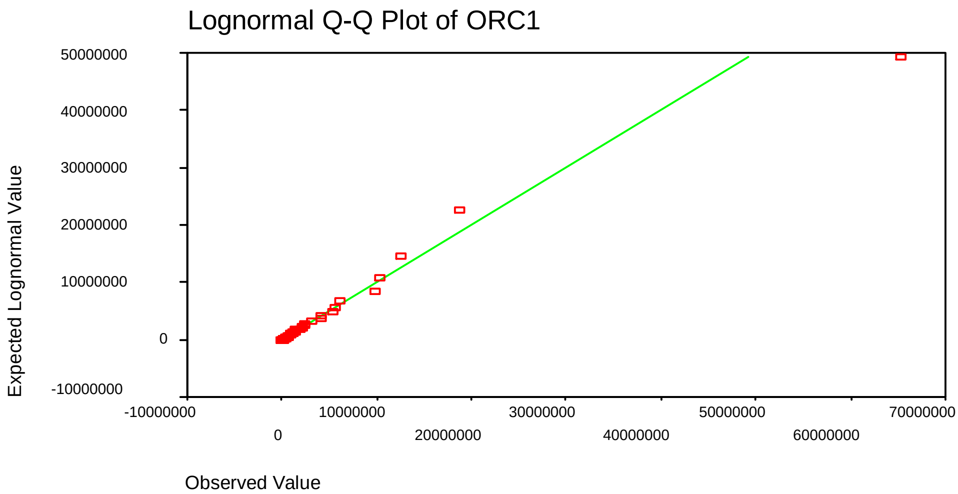
The study uses various continuous heavy-tailed distributions namely, Lognormal, Weibull, Exponential, Gamma and Generalized Pareto to model severity data. The study identifies the best-fit continuous distribution using graphical exploratory data analysis and goodness-of-fit tests. When it comes to selection of frequency distribution, there are two important discrete distributions namely, Poisson and Negative Binomial distributions, which are used by the banks for modelling frequency distribution.

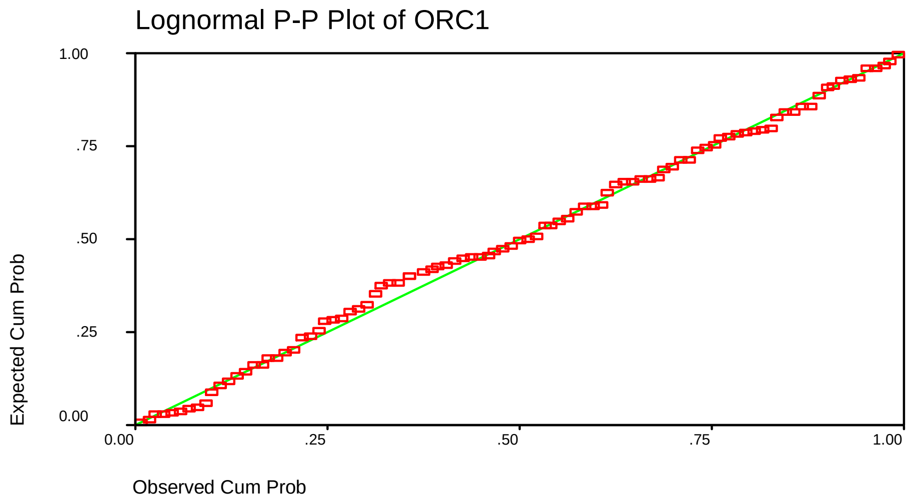
From the BIS study on observed range of practices in key elements of AMA (BCBS, July 2009), it is found that the most commonly used distribution for frequency is the Poisson distribution. Overall the Poisson distribution was found to be used by 93% of participating AMA banks followed by Negative Binomial distribution by 19%. RBI also has mentioned in the AMA guidelines that a thumb rule will help to identify a suitable frequency distribution. When mean is equal to variance one can use Poisson distribution to model frequency distribution. The mean and the variance of the frequency distribution for all the four ORCs used in the present study are found to be equal. Hence based on the BIS findings and using thumb rule, the Poisson distribution is found to be the best-fit for modelling our frequency data.

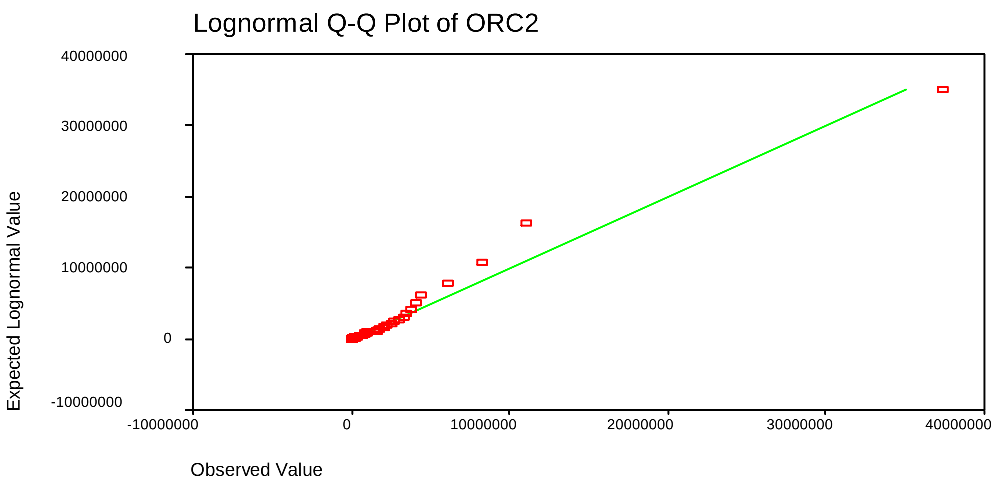
The best-fit severity distributions are selected on the basis of Q-Q and P-P plots and Kolmogorov-Smirnov (K-S) goodness-of-fit test. Q-Q and P-P plots of Lognormal, Exponential, Gamma and Weibull distributions are reported below (Figure- 7.1). Both for ORC1 and ORC2, Q-Q and P-P plots show that Lognormal distribution fits better than other continuous distributions. Results of ORC3 and ORC4 are shown in the subsequent sections.

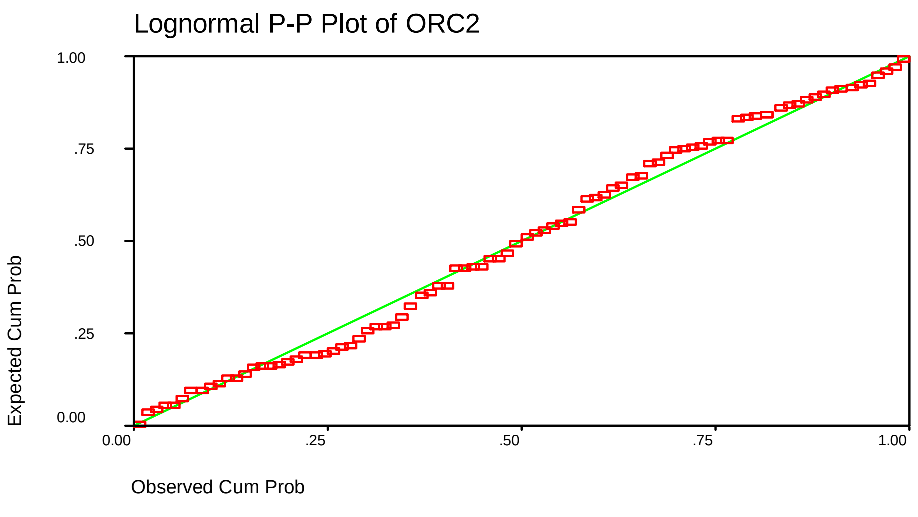
In case of Lognormal distribution, Q-Q and P-P plots follow a 45 degree line indicating that the data set follows Lognormal distribution. However, these two plots are far away from the 45 degree line in case of Exponential and Gamma distributions, indicating that these are not best-fit distributions. In case of Weibull distribution, P-P plots are very close to the 45 degree line, indicating that the data in ORC1 and ORC2 can be approximated by Weibull distribution. One can conclude from the exploratory data analysis that the data in ORC1 and ORC2 can be fitted to Lognormal or Weibull distributions. This result can be further verified and substantiated by using K-S goodness-of-fit test.

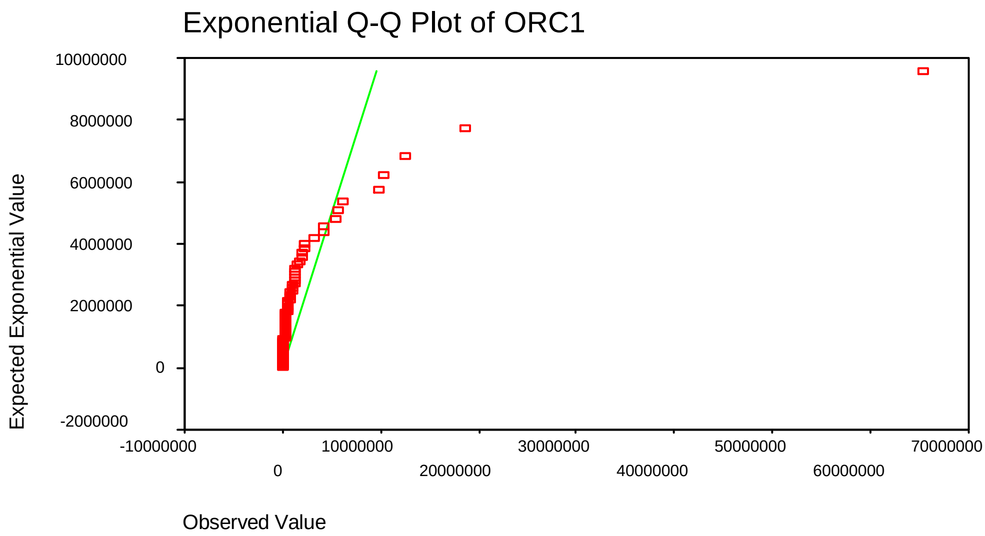
Figure- 7.1: Q-Q and P-P Plots for ORC1 and ORC2

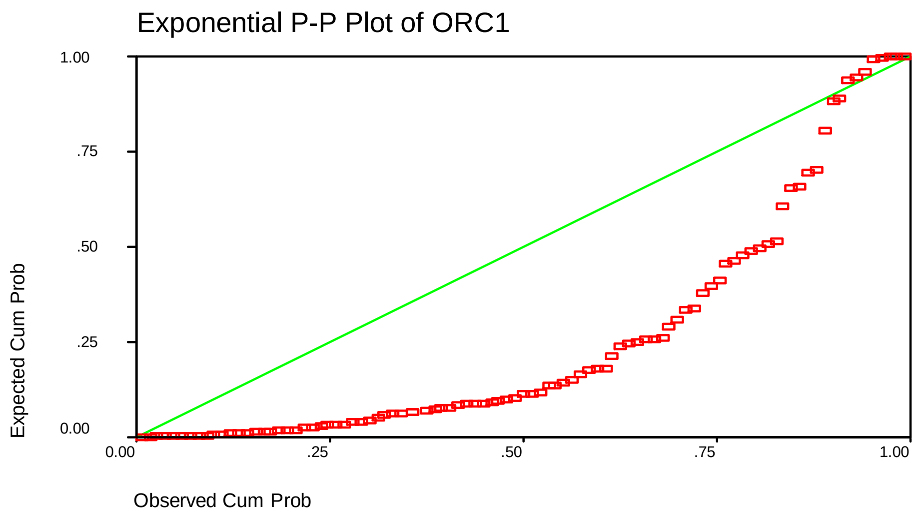


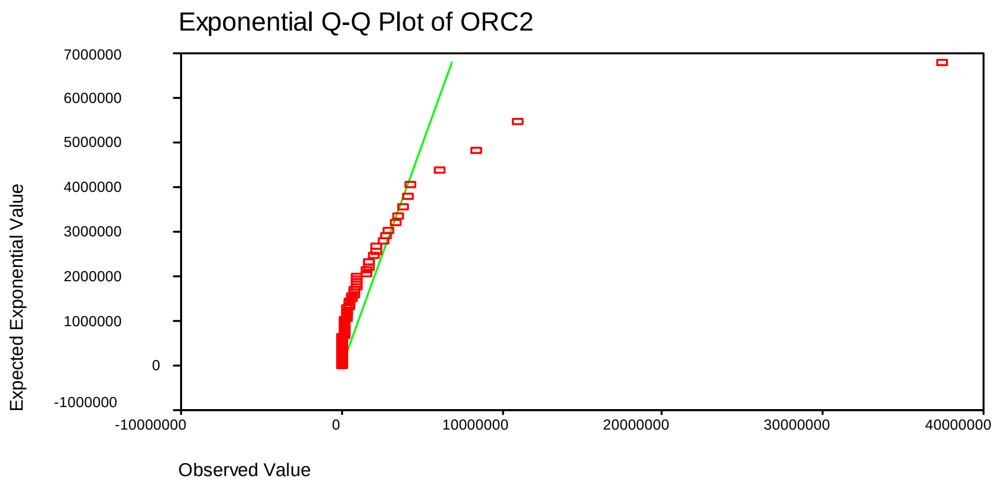

Lognormal P-P Plot of ORC1
1.00
.75
.50
.25
0.00
Expected Cum Prob
0.00
.25
.50
.75
1.00
Observed Cum Prob

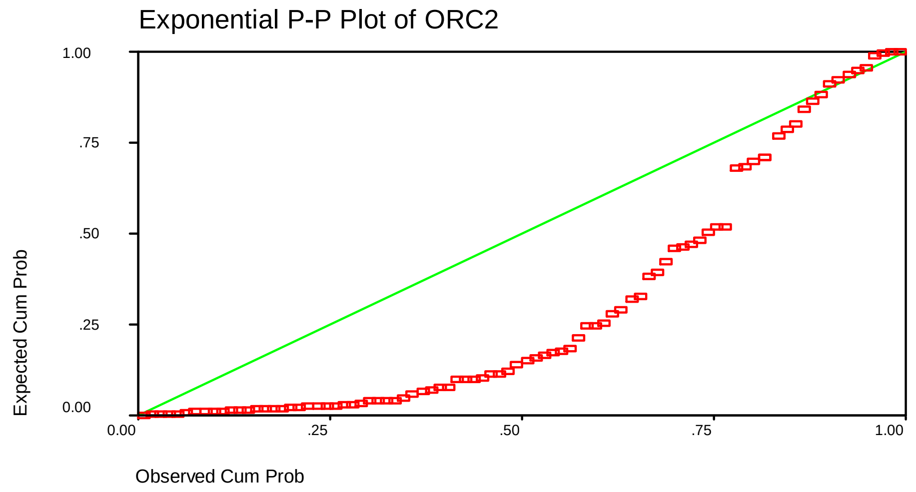

Lognormal Q-Q Plot of ORC2
40000000
30000000
20000000
10000000
0
-10000000
Expected Lognormal Value
-10000000
0
10000000
20000000
30000000
40000000
Observed Value

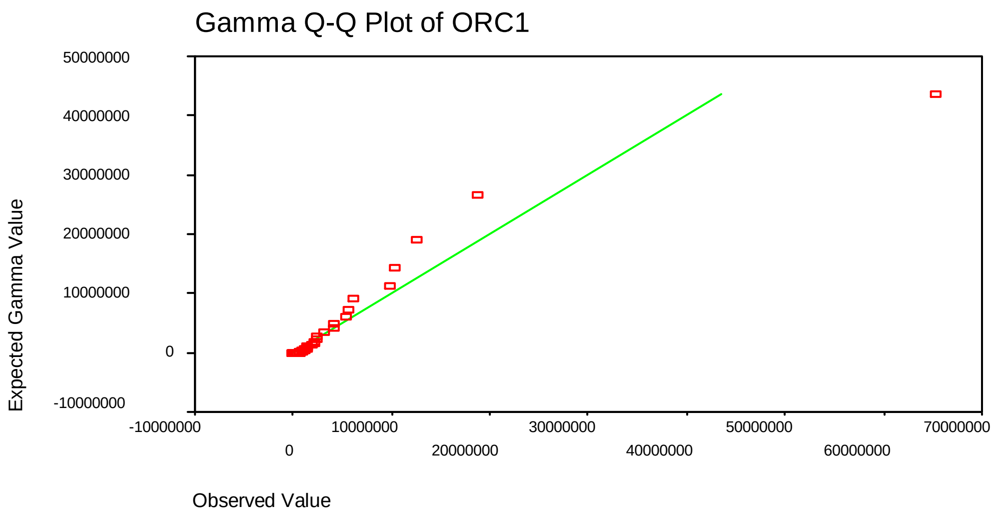

Lognormal P-P Plot of ORC2
1.00
.75
.50
.25
0.00
Expected Cum Prob
0.00
.25
.50
.75
1.00
Observed Cum Prob

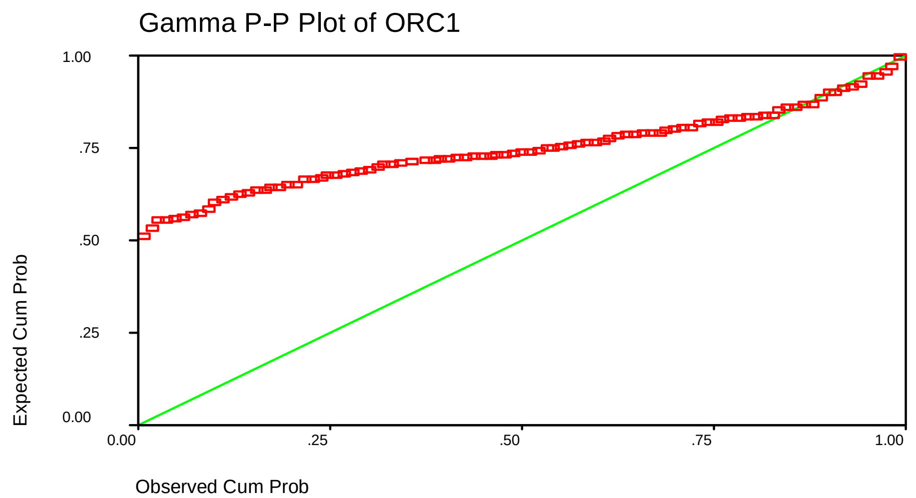

Exponential Q-Q Plot of ORC1
Expected Exponential Value
10000000
8000000
6000000
4000000
2000000
0
-2000000
-10000000
0
10000000
20000000
30000000
40000000
50000000
60000000
70000000
Observed Value

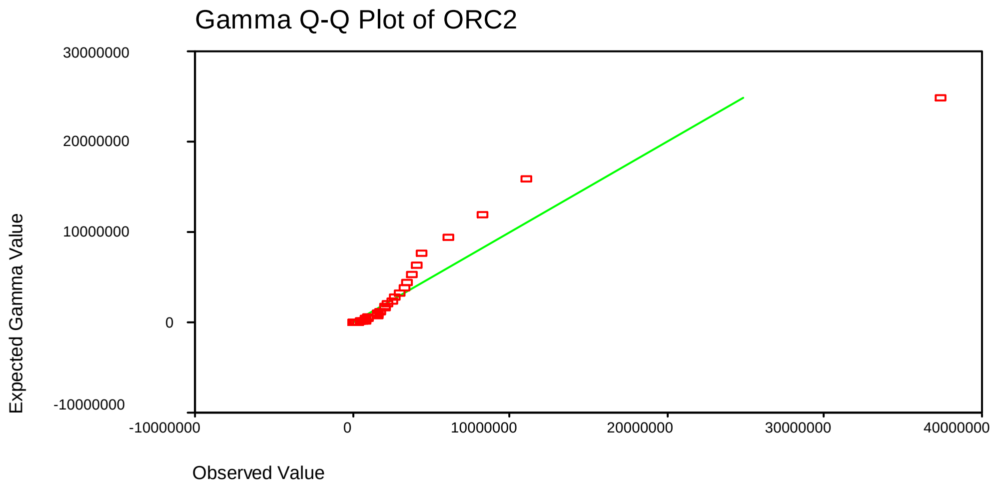

Exponential P-P Plot of ORC1
Expected Cum Prob
1.00
.75
.50
.25
0.00
0.00
.25
.50
.75
1.00
Observed Cum Prob

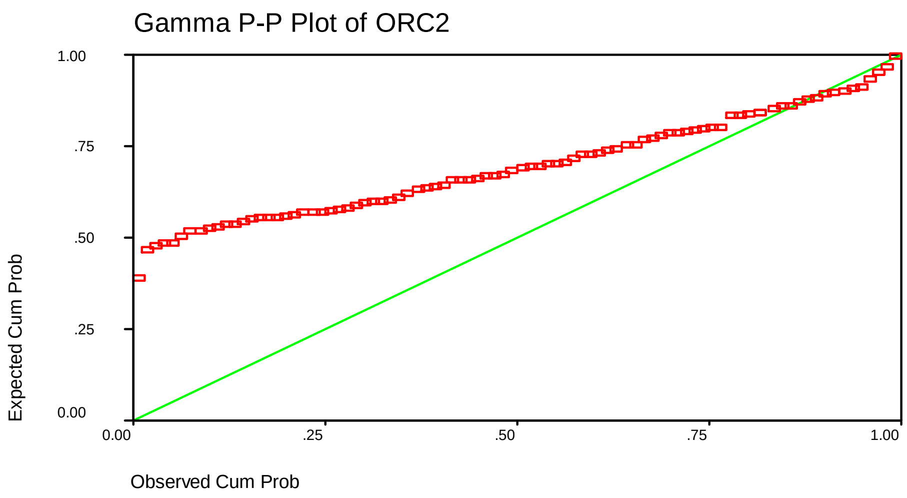

Exponential Q-Q Plot of ORC2
Expected Exponential Value
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
-1000000
-10000000
0
10000000
20000000
30000000
40000000
Observed Value

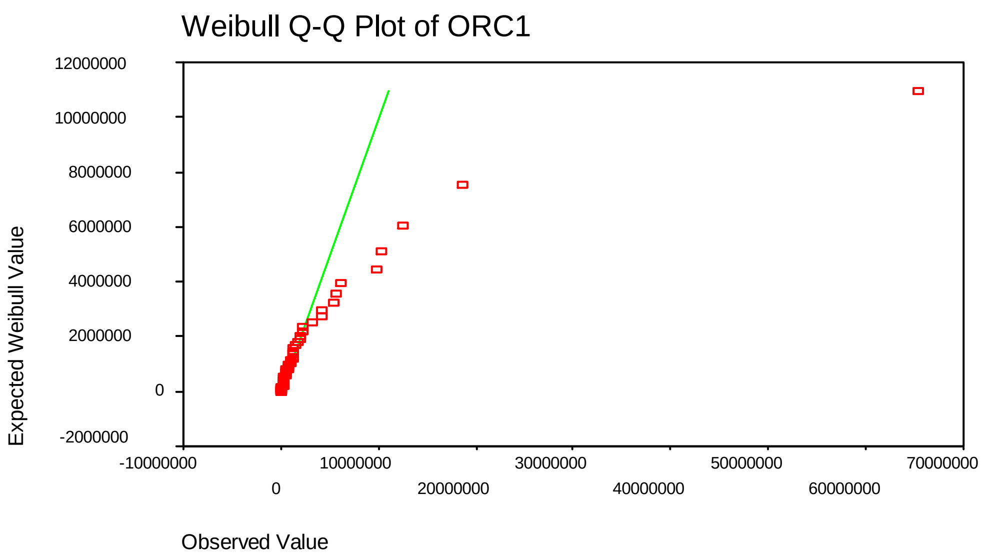

Exponential P-P Plot of ORC2
Expected Cum Prob
1.00
.75
.50
.25
0.00
0.00
.25
.50
.75
1.00
Observed Cum Prob

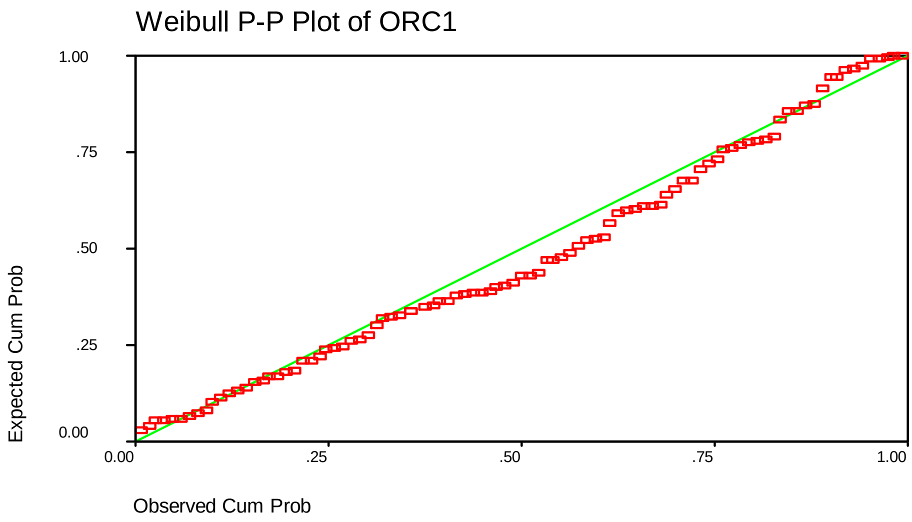

Gamma Q-Q Plot of ORC1
Expected Gamma Value
50000000
40000000
30000000
20000000
10000000
0
-10000000
-10000000
10000000
30000000
50000000
70000000
0
20000000
40000000
60000000
Observed Value

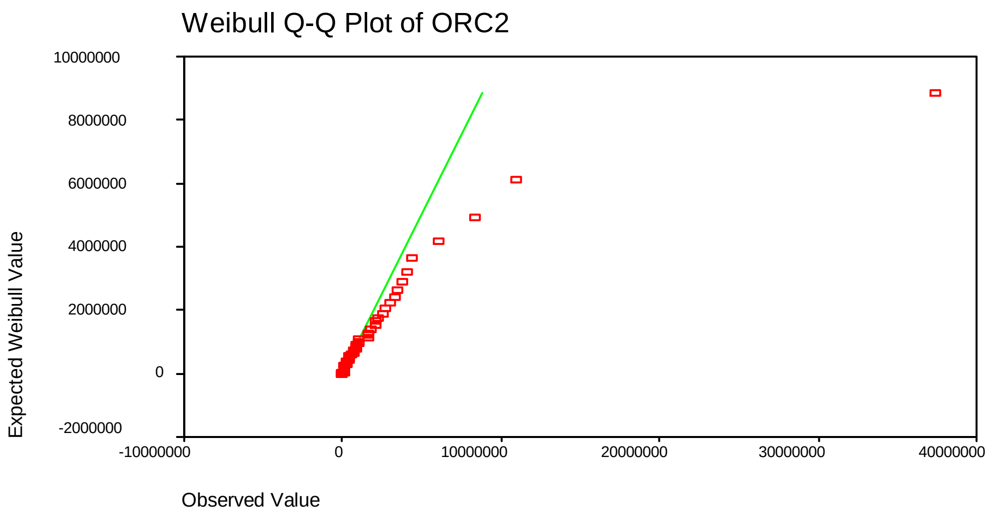

Gamma P-P Plot of ORC1
Expected Cum Prob
1.00
.75
.50
.25
0.00
0.00
.25
.50
.75
1.00
Observed Cum Prob

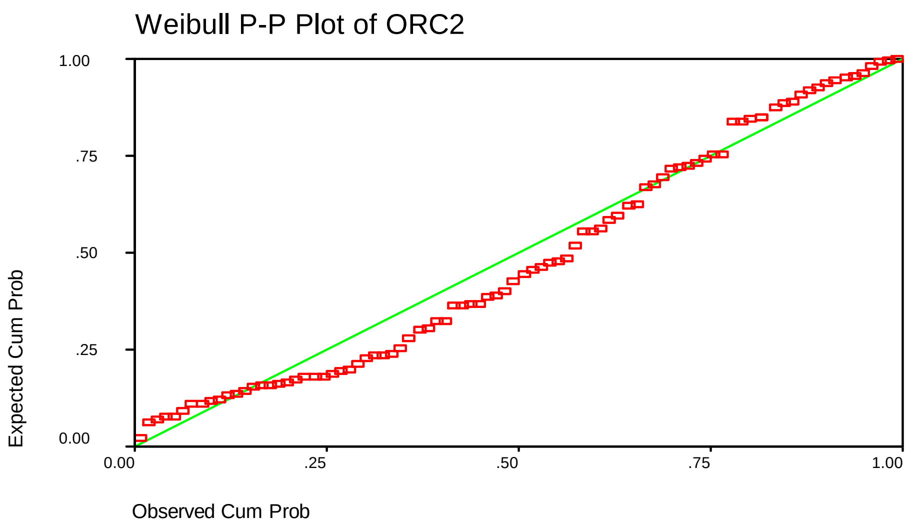

Gamma Q-Q Plot of ORC2
30000000
20000000
10000000
0
-10000000
Expected Gamma Value
-10000000
0
10000000
20000000
30000000
40000000
Observed Value


Gamma P-P Plot of ORC2
1.00
.75
.50
.25
0.00
Expected Cum Prob
0.00
.25
.50
.75
1.00
Observed Cum Prob


Weibull Q-Q Plot of ORC1
12000000
10000000
8000000
6000000
4000000
2000000
0
-2000000
Expected Weibull Value
-10000000
10000000
30000000
50000000
70000000
0
20000000
40000000
60000000
Observed Value


Weibull P-P Plot of ORC1
Expected Cum Prob
1.00
.75
.50
.25
0.00
0.00
.25
.50
.75
1.00
Observed Cum Prob


Weibull Q-Q Plot of ORC2
Expected Weibull Value
10000000
8000000
6000000
4000000
2000000
0
-2000000
-10000000
0
10000000
20000000
30000000
40000000
Observed Value


Weibull P-P Plot of ORC2
Expected Cum Prob
1.00
.75
.50
.25
0.00
0.00
.25
.50
.75
1.00
Observed Cum Prob

7.4.2 Goodness-of-Fit Test Result

K-S goodness-of-fit (GOF) test results for ORC1 to ORC4 are reported in Table- 7.2a to 7.2d. K-S test statistic, critical values, P values are mentioned in these tables. In case of ORC1, the test statistic is less than the critical value and P value is 0.8735 for Lognormal distribution indicating that it satisfies GOF test since, the null hypothesis of data follows Lognormal distribution cannot be rejected at 5% level of significance. The same is the case with Weibull distribution, where test statistic is less than the critical value and P value is greater than 0.05, indicating GOF test is satisfied. However, in case of Exponential and Gamma, test statistic are greater than the critical value and P values are less than 0.05; hence null hypothesis can be rejected at 5% level of significance. This shows that both Gamma and Exponential distributions failed GOF test. Between Lognormal and Weibull distributions, the former is selected to model severity distribution since P value of Lognormal distribution is higher (0.8735) than P value of Weibull distribution (0.6088).

The K-S test for ORC2 shows that the test statistic of Lognormal and Weibull distributions are less than the critical values and P value in both the cases are greater than 0.05. Hence both Lognormal and Weibull distributions satisfy goodness-of-fit test. The P value in case of Exponential distribution is 0 indicating a bad fit distribution, since null hypothesis can be rejected at less than 5% level of significance. The test statistic of Gamma distribution is greater than the critical value and the P value is slightly greater than 0.05 (0.0649), which indicates that the Gamma distribution satisfies GOF test. Among Lognormal, Weibull and Gamma distributions, Lognormal is found to be the best-fit distribution and considered for modeling loss severity in ORC2, since the P value for Lognormal distribution is highest among these three distributions.

The goodness-of-fit test results for ORC3 and ORC4 (Table- 7.2c and 7.2d) show that none of the distributions satisfies GOF test since, the test statistic value is greater than the critical value and P value is less than 0.05 in case of all the four distributions, which shows that the null hypothesis that data follows a particular distribution can be rejected in all cases at even less than 5% level of significance. In both the ORCs, P value of Lognormal distribution is highest among the four distributions, but it is still less than 0.05; hence GOF test is not satisfied. This inference can also be drawn from Q-Q and P-P plots mentioned below for ORC3 and ORC4 (Figure- 7.2). Both Q-Q and P-P plots for Lognormal distribution indicate that the data in ORC3 and ORC4 do not follow Lognormal distribution.

The scenario like ORC3 and ORC4 are sometimes found in the operational risk loss database of a bank, wherein heavy-tailed distributions like Lognormal, Weibull and Gamma are not found to be good-fit. This kind of scenario arises either due to the presence of some extreme events or due to presence of even one highly extreme event. Here, ORC4 includes one event of 30 crore, as a result of which none of the heavy-tailed distributions are found to be good-fit. ORC3 includes some extreme events, as a result of which a single distribution for the whole data set is not found to be good-fit.

In case of ORC3, the body and tail should be modeled separately by bifurcating the whole data set into two parts, body and tail. Body should be modeled using any heavy-tailed distribution and tail part should be modeled using Extreme Value Theory (EVT). In case of ORC4, one can use single loss approximation method to model such data set, wherein the presence of a single event significantly affects mean and standard deviation of the whole data set. The results for ORC3 and ORC4 are presented in later sections.

Table- 7.2a: Goodness-of-fit Test Result for ORC1

ORC1				
Distribution	K-S Statistic	Critical Value	P Value	GOF Test Result
Lognormal	0.0600	0.1375	0.8735	Good fit
Exponential	0.4292	0.1375	0.0000	Bad fit
Gamma	0.1694	0.1375	0.0074	Bad fit
Weibull	0.0770	0.1375	0.6088	Good fit

Table- 7.2b: Goodness-of-fit Test Result for ORC2

ORC2				
Distribution	K-S Statistic	Critical Value	P Value	GOF Test Result
Lognormal	0.0697	0.1427	0.7712	Good fit
Exponential	0.3858	0.1427	0.0000	Bad fit
Gamma	0.1376	0.1427	0.0649	Good fit
Weibull	0.0759	0.1427	0.6739	Good fit

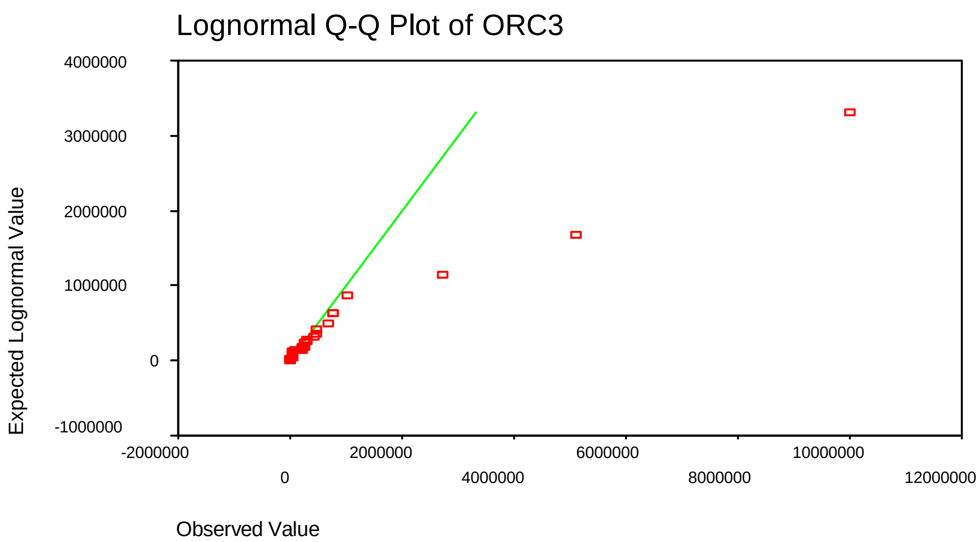
Table- 7.2c: Goodness-of-fit Test Result for ORC3

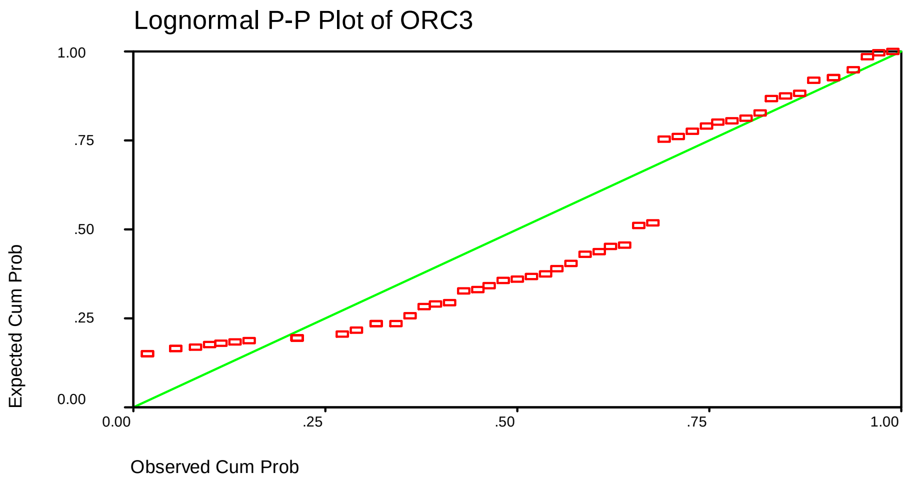
ORC3				
Distribution	K-S Statistic	Critical Value	P Value	GOF Test Result
Lognormal	0.1921	0.1767	0.0256	Bad fit
Exponential	0.5465	0.1767	0.0000	Bad fit
Gamma	0.2824	0.1767	0.0002	Bad fit
Weibull	0.2276	0.1767	0.0044	Bad fit

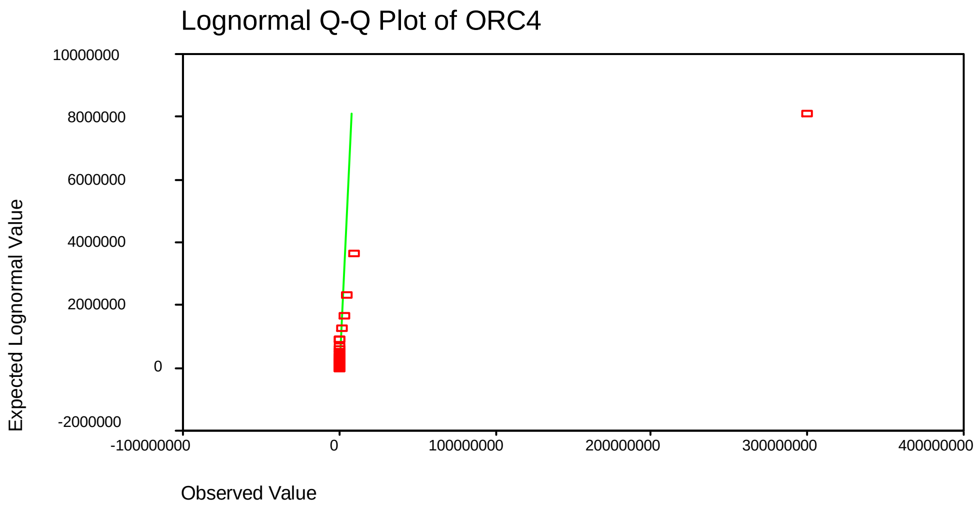
Table- 7.2d: Goodness-of-fit Test Result for ORC4

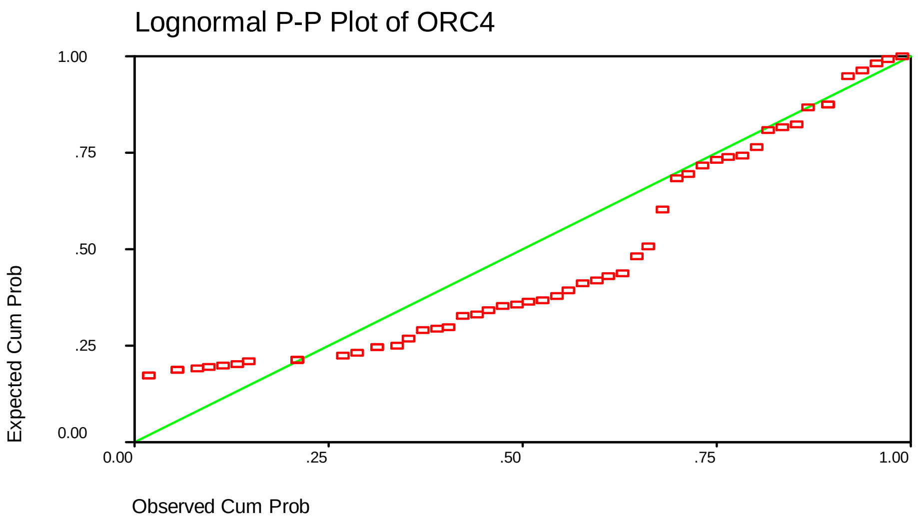
ORC4				
Distribution	K-S Statistic	Critical Value	P Value	GOF Test Result
Lognormal	0.2016	0.1752	0.0151	Bad fit
Exponential	0.7889	0.1752	0.0000	Bad fit
Gamma	0.3510	0.1752	0.0000	Bad fit
Weibull	0.2838	0.1752	0.0001	Bad fit

Figure- 7.2: Q-Q and P-P Plots for ORC3 and ORC4




Lognormal P-P Plot of ORC3
1.00
.75
.50
.25
0.00
Expected Cum Prob
0.00
.25
.50
.75
1.00
Observed Cum Prob


Lognormal Q-Q Plot of ORC4
10000000
8000000
6000000
4000000
2000000
0
-2000000
Expected Lognormal Value
-100000000
0
100000000
200000000
300000000
400000000
Observed Value


Lognormal P-P Plot of ORC4
1.00
.75
.50
.25
0.00
Expected Cum Prob
0.00
.25
.50
.75
1.00
Observed Cum Prob

7.4.3 OpVaR for ORC1 and ORC2

The previous section discussed the identification of suitable distributions for frequency and severity series using goodness-of-fit tests. The next step in computing operational risk capital charge is to simulate loss data to arrive at OpVaR. OpVaR is the maximum operational loss that a bank will incur at 99.9th percentile confidence level with holding period of one year. The present study uses Monte-Carlo simulation technique to estimate AMA capital for ORC1 and ORC2. The modeling approach for ORC3 and ORC4 is discussed in the subsequent sections.

The detailed process to compute OpVaR using Monte-Carlo simulation technique was discussed in the previous chapter. Lognormal and Poisson distributions are used to model severity and frequency data respectively. The parameters of Lognormal distribution (μ and σ) are estimated using Maximum Likelihood Estimation (MLE) technique. The Poisson parameter 'λ' shows average number of events in a year. Table- 7.3 reports results of parameters estimated, OpVaR, expected loss, unexpected loss and back testing results. The study performs one lakh simulations to compute OpVaR. One lakh random frequencies using Poisson distribution are generated. An equal amount of severity random numbers is generated using Lognormal distribution for each of the frequency values and summed up to arrive at aggregated loss. This process is continued 1 lakh times for each of the one lakh frequencies to obtain 1 lakh such aggregated loss scenarios. This will form an aggregated loss distribution of one lakh. The value at 99.9th percentile of aggregated loss distribution represents OpVaR.

OpVaR in ORC1 is 142.60 crore, whereas expected and unexpected losses are 7.58 crore and 135.02 crore respectively. Expected loss is calculated by taking simple average of the aggregated loss distribution and unexpected loss is the difference between OpVaR and expected loss. As per the regulatory guideline, banks are required to maintain capital for both expected and unexpected losses. However, if banks predict expected loss correctly and maintain provision for expected loss then the operational risk capital can be based on only unexpected loss. In case of ORC2, the OpVaR is 95.06 crore while expected and unexpected losses are 5.45 crore and 89.60 crore respectively. The unexpected losses are much higher than expected losses, since unexpected losses are computed at a very high confidence level, namely, 99.9th percentile.

The last column of Table- 7.3 reports back testing results obtained using Kupiec's test. Back testing is performed to validate operational risk measurement model. It compares the actual yearly losses with the OpVaR figure obtained for one year holding period. The detailed process of back testing methodology was mentioned in the previous chapter. The result shows that the back testing is satisfied in both ORC1 and ORC2. It is found that the yearly losses are much less than the OpVaR figure and also the OpVaR is greater than total loss.

Table- 7.3: Operational Value at Risk (OpVaR) for ORC1 and ORC2

ORC	Mu	Sigma	Poisson Lambda	OpVaR (Rs)	Expected Loss (Rs)	Unexpected Loss (Rs)	Back Testing Result
ORC1	12.3432	2.1652	31.67	1426059089	75800869	1350258220	Satisfied
ORC2	12.2555	2.0862	29.33	950608493	54592771	896015722	Satisfied

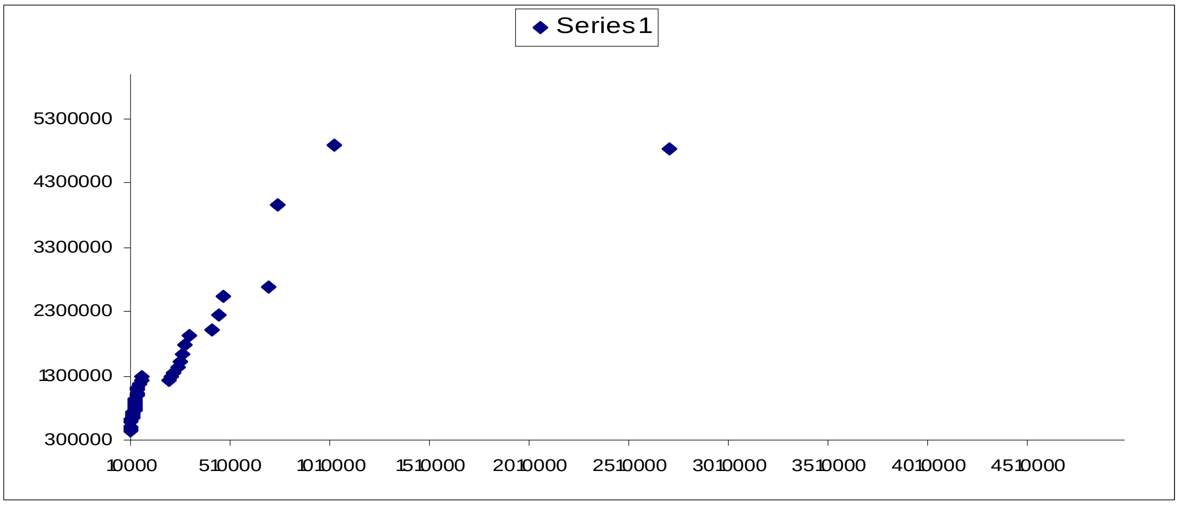
7.4.4 OpVaR for ORC3 - Extreme Value Theory (EVT)

Extreme value theory is used to model tail events of operational losses. As shown earlier, none of the distributions are found to be a good-fit for ORC3 due to the presence of extreme events. Operational risk capital charge from such ORCs can be computed by modeling body and tail separately. A separate distribution for body and tail losses should be fitted to compute capital. Hence, one needs to identify a threshold above which the events will form a tail distribution and events below the threshold will form body of the distribution. One of the methods to identify EVT threshold is mean excess plot (MEP) method. One can also identify EVT threshold using ad hoc method or goodness-of-fit test. However, MEP method is widely used and the most accepted method, which is used in most of the literature on operational risk.

MEP method plots mean excess function against various threshold values. Figure- 7.3 shows mean excess plot for ORC3, where x-axis shows threshold values and y-axis shows mean excess function. The detailed discussion on MEP was carried out in the previous chapter. If MEP shows upward trend (+ve slope), then data follows a heavy tail distribution; if plot shows –ve slope, then this is a sign of thin tail distribution. Figure- 7.3 shows that the MEP shows an upward trend, indicating that the losses in ORC follow a heavy-tailed distribution. The threshold for EVT can be chosen by identifying the point where MEP takes a positive slope. If the plot is a positively sloped straight line above a certain threshold u, then the losses above the threshold u follow GPD.

The mean excess plot for ORC3 shows a continuous upward trend except at the highest loss value, which does not distinctly identify the EVT threshold where loss values start taking a positive slope. However, at threshold 2 lakh, there is a break and mean excess plot takes an upward positive slope at this value. Hence, 2 lakh can be considered as the EVT threshold for our analysis[23]. We have also used an ad hoc method where we stipulate the minimum number of extreme events to be around 15% of total events, along with the MEP technique. Each bank may have its own ad hoc method based on expert judgment. In addition to MEP, one can also perform goodness-of-fit test to identify EVT threshold. If MEP shows multiple threshold values that can be considered for modeling, in such a scenario, GOF test will help in identifying a particular threshold.

Figure- 7.3: Mean Excess Plot for ORC3



The tail part of the distribution, which includes losses above 2 lakh will be modeled with Generalised Pareto Distribution, whereas, the body of the distribution will be fitted to any of the

[23]The main purpose of the study is to analyze how extreme operational risk losses in a bank can be modeled and EVT threshold can be selected using MEP. The actual MEP may be different for different data sets when it will be used by different banks and it may show a distinct loss threshold, unlike the current MEP drawn from our constructed data.

heavy-tailed disributions. The results of GOF test for the body are reported in Table- 7.4. Lognormal, Gamma and Weibull distributions are found to be good fit since K-S test statistic is less than the critical value and P value is greater than 0.05 in all the three cases. However, P value of the Lognormal distribution is highest among these three distributions; hence, Lognormal distribution will be used to model body losses. Exponential distribution does not satisfy GOF test since, P value is closer to 0 and test statistic is greater than the critical value.

Table- 7.4: Goodness-of-fit Test Result for Body for ORC3

Distribution	K-S Statistic	Critical Value	P Value	GOF Test Result
Lognormal	0.171	0.2127	0.1845	Good fit
Exponential	0.3319	0.2127	0.0003	Bad fit
Gamma	0.1823	0.2127	0.1332	Good fit
Weibull	0.1772	0.2127	0.1546	Good fit

The study uses simulation technique to model extreme events using Generalized Pareto distribution. The modeling process employed here is similar to one mentioned in Dutta and Perry (2007). Lognormal distribution and GPD are used for the body and tail part respectively. GPD parameters (scale and shape) are estimated using maximum likelihood estimation technique. The detailed computational process of EVT was discussed in the previous chapter. Table- 7.5 reports GPD parameters, OpVaR, expected loss, unexpected loss and back testing results computed from ORC3.

The Poisson parameter (lambda) obtained from the data is 19, which shows yearly average number of events. N_L and N_H losses are generated for body and tail using Lognormal distribution and GPD respectively and combined to arrive at total annual loss. N_L is the number of random numbers generated from Lognormal distribution while N_H represents number of random numbers generated from GPD.The above process is repeated one lakh times to obtain aggregated loss distribution. The loss amount at 99.9th percentile of aggregated loss distribution is OpVaR for ORC3.

As shown in the following table (Table- 7.5), the OpVaR using EVT is estimated as 13.44 crore while expected and unexpected losses are 97.86 lakh and 12.46 crore respectively. Expected loss is calculated by taking simple average of aggregated loss distribution and unexpected loss is the difference between OpVaR and expected loss. The capital requirement for

ORC3 is thus 13.44 crore. Back testing is perfomed in the same manner as it is done for ORC1 and ORC2. Both yearly losses and total losses in ORC3 are less than OpVaR; hence the EVT model used here satisfies back testing as shown in the following table.

Table- 7.5: OpVaR for ORC3 using Extreme Value Theory

	Distribution	Parameter	OpVaR (Rs)	Expected Loss (Rs)	Unexpected Loss (Rs)	Back Testing Result
Body	Mu	9.9568	134402750	9786345	124616405	Satisfied
	Sigma	0.5622				
Tail	GPD Threshold	200000				
	Scale	1156000				
	Shape	0.4949				
	Poisson Lambda	19				

7.4.5 OpVaR for ORC4 - Single Loss Approximation

The study has used single loss approximation method for ORC4, since the presence of one event of 30 crore affects the whole distribution, as a result of which statistical distributions did not satisfy goodness-of-fit as shown in the foregoing section. In such a case simulation based OpVaR will provide an incorrect estimate of operational loss and a closed form solution like single loss approximation technique will provide a better result. Unlike LDA, single loss approximation method does not require whole data to be modeled for computation of OpVaR; the tail part of the loss data will be sufficient to compute capital at a very high confidence level. The study has considered losses above the threshold of one lakh, which is identified using threshold selection criteria.

Goodness-of-fit test is performed to identify a good-fit distribution for the losses above one lakh. The GOF test results are reported in Table- 7.6. It is evident from the results that the Lognormal and Weibull distributions are found to be good-fit; since P value is greater than 0.05, null hypothesis cannot be rejected. However, Exponential and Gamma distributions are found to be bad-fits since null hypothesis can be rejected at less than 5% level of significance. Between Lognormal and Weibull distributions, the present study has considered Lognormal distribution since Lognormal distribution has a higher P value than Weibull distribution.

Table- 7.6: Goodness-of-fit Test Result for ORC4 (Losses above the Threshold)

ORC4- Losses above 1 lakh				
Distribution	K-S Statistic	Critical Value	P Value	GOF Result
Lognormal	0.2523	0.3014	0.1509	Good fit
Exponential	0.6955	0.3014	0.0000	Bad fit
Gamma	0.3623	0.3014	0.0097	Bad fit
Weibull	0.2658	0.3014	0.1138	Good fit

Since the Lognormal distribution is found to be a good fit, this distribution is used to compute OpVaR using single loss approximation technique for ORC4. Table- 7.7 reports OpVaR results obtained by using single loss approximation technique. Parameters of Lognormal distribution and Poisson parameters are mentioned in the second column. The OpVaR is estimated as 65.28 crore, and expected and unexpected losses are 2.87 crore and 62.41 crore respectively. The back testing result shows that the model satisfies back testing, since OpVaR is greater than the actual yearly losses and also total loss is less than the OpVaR

Table- 7.7: OpVaR based on Single Loss Approximation Technique

ORC4					
	Parameter	OpVaR (Rs)	Expected Loss (Rs)	Unexpected Loss (Rs)	Back Testing Result
Threshold	100000	652888850	28752312	624136538.1	Satisfied
Mu	13.6001				
Sigma	1.8592				
Lambda	6.33				

7.4.6 ORC wise Operational Risk Capital Requirement

Table- 7.8 reports a summary of capital requirement for four ORCs used in the present study. The study has used four ORCs for the analysis of operational risk measurement, wherein each ORC represents a typical type of loss data set that every bank faces in real life. Three different types of data sets are used to compute capital charge using three different techniques. ORC1 and ORC2 are modeled using Monte-Carlo simulation technique, whereas, ORC3 is modeled using EVT technique. ORC4 is modeled using single loss approximation method.

The total capital for a bank as a whole is obtained by combining ORC wise capital. In this case, the total capital obtained from the internal loss data for the bank is 316.39 crore assuming that the bank forms only four ORCs for operational risk management. The modeling techniques and computation carried out in the foregoing sections used hypothetical/constructed internal loss data of the bank. A similar approach can be used for external data and scenario data. The total operational risk capital will be a combination of these three elements and BEICF adjustment factor.

Table- 7.8: ORC wise OpVaR Summary

	Severity Distribution	Frequency Distribution	OpVaR (Rs)	Expected Loss (Rs)	Unexpected Loss (Rs)	Back Testing Result
ORC1	Lognormal	Poisson	1426059089	75800869	1350258220	Satisfied
ORC2	Lognormal	Poisson	950608493	54592771	896015722	Satisfied
ORC3	Lognormal & GPD	Poisson	134402750	9786345	124616405	Satisfied
ORC4	Lognormal	Poisson	652888850	28752312	624136538	Satisfied
Total			3163959182	168932297	2995026885	

7.5 Conclusion

This chapter studied the computation of operational risk capital as per Advanced Measurement Approach (AMA), using loss data which was constructed for the purpose. Methodology of the study was discussed in detail along with the results obtained from each step. Exploratory data analysis (EDA) such as Q-Q and P-P plots are checked for distribution fitting and K-S test conducted for goodness-of-fit test. Constructed operation risk data was used to check modeling aspects since actual operational risk loss data faced by the banks are not publicly available, nor is any consortium of external data available in India. OpVaR is estimated from four ORCs using Monte-Carlo simulation technique, EVT and single loss approximation method as applicable. It is found that the operational risk losses follow a heavy-tailed distribution due to the presence of low frequency and high severity events. Lognormal distribution is found to be suitable for such data set. However, when data set contained a few extreme events, GPD was found to be suitable for modeling such data set. Single loss approximation method was used for ORC4, wherein a single high impact event significantly affects shape of the distribution. Thus this chapter constitutes a comprehensive study on modeling aspects using internal loss data.

CHAPTER 8

SUMMARY, LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

In a globalised economy, the competition between financial institutions in general and in the banking sector in particular is extremely significant, and is reflected in terms of attempts to increase the customer base, provide innovative delivery channels, adopt e-commerce and e-banking, expand business to accumulate more profit, etc. These factors are some of the significant contributors to the exposure to financial and non-financial risks. Risk, by definition is exposure to an adverse situation, which may lead to monetary loss or reputational loss. Banks deal with the hard earned money of individuals. Hence it is the responsibility of every bank to safeguard depositors' money. Since the primary activity of banks is to accept deposit from the customer and lend money to the borrower, they are exposed to risks that emanate from credit activity, as well as from the process execution, people involved in executing the process, external factors and systems used to carry out various banking activities. While the risk that arises due to non-repayment of credit sanctioned to the customer is treated as credit risk or default risk, the risk that arises due to failure in process, people, system and external factors is termed as operational risk.

The measurement and management of these two types of risks along with market risk are critical for the bank. The Capital Adequacy Ratio (CAR) of the bank, which shows how solvent a bank is in case unforeseen adverse circumstances arise, is based on these risks. The present study discusses empirically, in great detail, the measurement of credit and operational risks from Basel II perspective, through various statistical and mathematical techniques. The objective was to evaluate performance of accounting based and market based credit risk models in predicting probability of default and to analyze and compute capital for operational risk under Advanced Measurement Approach (AMA) as per the Basel II norms.

Credit risk modeling is performed using two market based models namely, Altman's Z-Score model and Ohlson's logit model. Accounting data of both distressed and non-distressed companies one year prior to bankruptcy and two years prior to bankruptcy are used to estimate two separate distress prediction models. The results obtained from the Z-Score model suggest that the distress predictive ability of the model based on data one year prior to bankruptcy is higher than the predictive ability of the model based on data two years prior to bankruptcy. Similar results are found using logit model. This shows that the distress predictive ability of the model increases as we move closer towards the default date.

The predictive ability of these two models are compared by analyzing overall correct prediction accuracy percentage. It is found that the predictive ability of the logit model is higher than the predictive ability of the Z-Score model, since the overall correct prediction percentage is higher in logit model. Also, the correct prediction percentages of distressed and non-distressed firms are higher in case of logit model in comparison to Z-Score model. The probability of default (PD) computed from logit model suggests that there is significant difference between PD computed from distressed firms and non-distressed firms. The mean and the median PD of distressed firms are significantly higher than the mean and the median PD of non-distressed firms.

In addition to predicting corporate bankruptcy using two well-known accounting based models, the present study has also estimated probability of default using the famous Black-Schole-Merton (BSM) model. The BSM model is termed as a market based model since it estimates probability of default using market determined variables. Market variables such as market value of equity, equity return volatility, market value of firm assets, asset volatility etc. are used in BSM model. The mean PD estimated using this model for distressed companies is found to be significantly higher than the mean PD estimated for non-distressed companies. Therefore, the BSM model can be used in predicting probability of default of Indian companies using financial information and market determined variables.

Thus, corporate bankruptcy can be predicted well before the default time, using financial information of the companies and market variables, with the help of these statistical models. The 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 these models, 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 is 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 PD of their own companies as an early warning measure.

Since operational risk management (ORM) is a relatively new area of research and is a much talked about topic in the banking and financial institutes after the circulation of Basel II guidelines, this study conducts a theoretical analysis of operational risk management framework and Advanced Measurement Approach (AMA). It has also empirically computed operational risk capital requirement under AMA using statistical techniques. Since the gamut of operational risk is very large and it is not so easy to be measured, unlike credit or market risks, the Basel Committee on Banking Supervision (BCBS) of Bank for International Settlement (BIS), and the central banks of the member countries, are giving a great deal of importance to operational risk management through issuing various guidelines on operational risk time to time. As part of operational risk management framework, banks are required to effectively identify, assess, measure, monitor and mitigate operational risk. This requires capturing both qualitative and quantitative information related to operational risk, in order to effectively measure and manage such risks.

The AMA is considered the most risk sensitive approach in ORM framework since it considers historical losses of the bank, along with external data, catastrophic events assessed through scenario analysis and business environment and internal control factors, to compute operational risk capital charge for the bank. The capital computation process under AMA is based on statistical techniques, wherein the loss distribution approach (LDA) is widely used by the banks. The present study computes operational risk capital requirement for a bank using LDA and discusses the computation technique in a detailed manner. Frequency and severity of loss events are modeled by fitting statistical distributions and aggregated loss distribution is arrived at through Monte-Carlo simulation process. A single severity distribution is found to be suitable to model severity data when database does not include extreme events. But, in case the database includes some extreme events, the study shows a single distribution cannot be fitted to the entire data set. However, Extreme Value Theory (EVT) can be used to model tail events by fitting two separate distributions for body and tail. A sub-exponential distribution for body and the Generalized Pareto Distribution for tail are used to model such losses. The single loss approximation technique is found to be suitable to model operational risk when the parameters of the distributions are significantly affected by the presence of a single loss event with extreme impact. Banks are also required to consider external data and scenario data to compute operational risk capital requirement. Scenario analysis is one of the critical elements in AMA framework in terms of scenario assessment and scenario modeling, since this is a purely subjective element, wherein the assessment is done on the basis of expert judgment. Capital requirement computed from internal loss data, external data and scenario data can be adjusted ex-post to the business environment and internal control factors.

One of the very important implications of modeling operational risk is that a systematic and scientific way of measurement of operational risk will help financial institutes quantify unexpected losses due to operational risk and ultimately help in taking mitigating measures. A comprehensive operational risk management framework, which captures both qualitative and quantitative elements for the measurement of risk, will help manage and mitigate such risk. Since Loss Distribution Approach is based on statistical techniques and is widely used in the literature of operational risk modeling, the banks and financial institutes can use this approach to compute both economic and regulatory capital for operational risk. As shown in the study, various alternative statistical techniques can be used, depending on the pattern of distribution that loss data follows, to compute operational risk capital charge. Since the Basic Indicator Approach (BIA) and the Standardized Approach (TSA) are based on the gross income of the bank, the Advanced Measurement Approach (AMA) is always preferable, although it requires certain expertise and proper system in place to understand and execute the modeling processes.

Limitations and Scope for Further Research

The corporate bankruptcy prediction is studied using data on Indian companies. A comparative analysis of model performance to predict corporate bankruptcy is carried out, which is a rare study in the context of the Indian economy. 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, which helps researchers to obtain information on default data, India does not have such a provision for filing bankruptcy. However, the sick companies in India can register in 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 data. This study is limited to the distressed companies registered in BIFR.

Although the study compares distress predictive ability of Z-Score model and logit model and estimates PD using BSM model, further research can be done to evaluate performance of other bankruptcy prediction models such as artificial neural network model and hazard model. Since macroeconomic factors have certain influence on the performance and financial situation of the firms, corporate bankruptcy can be profitably studied by using such variables, which 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 variables.

The present study discusses operational risk and empirically computes operational risk capital charge under Advanced Measurement Approach. This is necessarily based on loss data. However, the loss data of any bank is very sensitive information, which is not publicly available, since no bank will wish to reveal the kind of operational risks they are facing, and the resultant losses, to their customers or public, since it will damage the reputation of the bank. Under such circumstances, research is restricted to using either external loss data obtained from the data consortium or to go for data construction. In India the problem is more acute since we do not have any external data consortium, although Indian Banks' Association is in the process of creating an external database for the Indian banks. Due to the data limitation, this study has used constructed data to perform empirical analysis. Care has been taken to see that the constructed data is similar to the industry standard data. Nonetheless, the use of actual losses incurred by the bank may throw up more and better insights.

Since, operational risk capital charge under advanced measurement approach is based on various quantitative and qualitative elements and the modeling framework is as yet in a preliminary stage, it poses several challenges for the banks. The biggest challenge in operational risk modeling is related to historical loss data and ongoing collection of internal losses. Since in the Loss Distribution Approach, loss frequency and severity are modeled using statistical distributions, a significantly large number of events will always help in fitting distributions and provide statistically correct results. However, it is not so easy for the banks to collate historical losses, which were incurred in the long past. Also, ongoing loss data collection process poses challenges in terms of timely reporting, and reporting of required fields like amount, date of event, cause of the event, control failure, etc. Mapping of such events to the relevant business line and event type is another challenge that banks face, since it requires a laid down process of an objective way of mapping, to avoid any subjective thinking of the individual.

Banks usually face challenges in collecting information related to scenario and risk and control self assessment, which are highly subjective in nature. Since scenario database involves catastrophic events, it will significantly affect capital requirement of the banks for operational risks. Hence, the banks should try to remove biases in scenario assessment and have strong justification for the final values considered for scenario modeling. Risk and control self assessment exercise is usually conducted to assess frequency and severity of various risk events and the control effectiveness of the available controls. Since these values are obtained from various departments of the bank, a lot of subjectivity is involved in that. The challenge before the banks is to address this subjectivity.

Capital computation process under AMA is highly technical. Losses are modeled using various statistical techniques. The challenge for the bank is to justify the statistical assumptions related to distribution fitting, parameter estimation and goodness-of-fit tests, used in modeling operational risk. A small change in statistical assumptions may result in volatility in the capital estimates. For example, instead of using medium tail distribution to model severity data, if a heavy-tailed distribution is used, it will lead to significant increment in capital estimates. Various studies suggest modeling tail events separately when the operational risk database contains extreme events. But, the challenge here is related to the identification of the appropriate modeling threshold for tail of the distributions, when multiple thresholds are found to satisfy threshold selection criteria. Modeling scenario data is another challenge that the banks face. Though there are studies already done on modeling operational risks, a detailed and comprehensive study is required to be done, which would address various modeling issues and challenges.

The modeling approaches to be used to model scenario data, the type of distributions to be used are some of the challenges in scenario analysis. Incorporating business environment and internal control factors into the modeling framework is a gray area in operational risk modeling. Since these factors are qualitative in nature, it is a challenge to quantify and use them in the modeling framework. Further study is required to address such issues, related to modeling scenario data and qualitative information. Factoring correlation among operational risk categories while aggregating capital estimates is another challenge in operational risk modeling. Stress testing and sensitivity tests of operational risk models are some of the areas which require further study to identify methodology to carry out such exercises. Since the operational risk capital is computed considering four elements, namely internal losses, external losses, scenario data and business environment and internal control factors, the challenge faced by the banks is on how to combine these four elements to arrive at a single figure. A detailed study is required on this aspect.

BIBLIOGRAPHY

Abdullah, N. A., A. Halim, H. Ahmad, and R. M. Rus, (2008), "Predicting corporate failure of Malaysia's listed companies: comparing multiple Discriminant analysis, logistic regression and hazard model", *International research journal of finance and economics*, 15, 201-217.

Acharya, V. V., S. T. Bharat, and A. Srinivasan, (2004), "Understanding the recovery rates on defaulted securities", *Centre for Economic Policy research (CEPR) Discussion Paper*, London, URL: http://www.cepr.org/pubs/dps/DP4098.asp.

Agarwal, D., I. Korablev, D. W. Dwyer, (2008) "Valuation of corporate loans: A credit migration approach", *Moody's KMV,* Jan 25, 2008, URL: http://www.moodysanalytics.com/~/media/Insight/Quantitative-Research/Credit-Valuation/08-01-01-Valuation-of-Corporate-Loans-a-Credit-Migration-Approach

Agarwal, V. and R. J. Taffler, (2007), "Twenty-five years of the Taffler z-score model: does it really have predictive ability?", *Accounting and Business Research*, 37 (4), 285-300.

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

Akkizidis, I. S. and V. Bouchereau, (2006), "*Guide to optimal operational risk and Basel II*", Auerbach publications, Taylor & Francis group.

Alexander, C. (2000), "Bayesian methods for measuring operational risk", *Discussion Paper in Finance- ISMA Centre, the Business school of Financial Markets.*

Alexander, C. (ed.) (2003), "*Operational Risk: Regulation, analysis and management*", Pearson Education Ltd.

Altman, E. I. (2011), "Default recovery rates and LGD in credit risk modeling and practice", *NYU Salomon Center Working Paper,* Stern School of Business, URL: http://people.stern.nyu.edu/ealtman/UpdatedReviewofLiterature.pdf

Altman, E. I., Brooks Brady, Andrea Resti and Andrea Sironi, (2003**)**, "The link between default and recovery rates: Theory, empirical evidence and implications", *NYU Salomon Center Working Paper Series,* Stern School of Business. URL: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1296371.

Altman, E. I., R. G. Haldeman, and P. Narayanan, (1977), "Zeta analysis: A new model to identify bankruptcy risk of corporations", *Journal of Banking and Finance*, 1, 29-54.

Altman, E. I. (1968), "Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy", *The Journal of Finance*, 23 (4), 589-609.

Altman, E. I. (1989), "Measuring corporate bond mortality and Performance", *The Journal of Finance*, 44 (4), 909-922.

Altman, E. I. (2000), "predicting financial distress of companies: revisiting the Z –score and Zeta models", *Working Paper*, Stern School of Business, New York University.

Altman, E. I. (2002), "Revisiting credit scoring models in a Basel 2 environment", *Working Paper*, Stern School of Business, New York University.

Altman, E. I. (2005), "An emerging market credit scoring system for corporate bonds", *emerging market review*, 6, 311-323.

Altman, E. I. and G. Sabato (2007), "Modelling Credit Risk for SMEs: Evidence from the U.S. Market", *ABACUS*, 43 (3), 332-357.

Anderson, D. R., D. J. Sweeney, and T. A. Williams, (2011), "*Statistics for business and economics*", Eleventh Edition, South-Western- Cengage Learning Pub.

Appiah, K. O. and J. Abor, (2009), "Predicting corporate failure: some empirical evidence from the UK", *Benchmarking: An International Journal*, 16 (3), 432-444.

Arora, N., J. R. Bohn, and F. Zhu, (2005), "Reduced form vs. Structural models of credit risk: A case study of three models", *Moody's KMV*, Feb 17, 2005, URL: http://www.moodysanalytics.com/~/media/Insight/Quantitative-Research/Credit-Valuation/05-17-02-Arora-Bohn-Zhu-reduced-structural.

Aziz, M. A. and H. A. Dar, (2006), "Predicting corporate bankruptcy: where we stand", *CORPORATE GOVERNANCE*, 6 (1), 18-33.

Bandyopadhyay, A. (2006), "Predicting probability of default of Indian corporate bonds: logistic and Z-score model approaches", *The Journal of Risk Finance*, 7 (3), 255-272.

Bandyopadhyay, A. (2007), "Credit risk models for managing bank's agricultural loan portfolio", *Working Paper, NIBM*, URL: http://mpra.ub.uni-muenchen.de/5358/.

Bandyopadhyay, A. (2007), "Mapping corporate drift towards default", *The Journal of Risk Finance*, 8(1), 46-55.

Bandyopadhyay, A., T. Chherawala, and A. Saha, (2007), "Calibrating asset correlation for Indian corporate exposures: Implications for regulatory capital", *The Journal of Risk Finance*, 8(4), 330-348.

Basel Committee on Banking Supervision, (1988), "International convergence of capital measurement and capital standards", *Bank for International Settlement,* July.

Basel Committee on Banking Supervision, (2004), "International convergence of capital measurement and capital standards- A revised framework", *Bank for International Settlement,* June.

Basel Committee on Banking Supervision, (2006), "International convergence of capital measurement and capital standards- A revised framework- Comprehensive Version", *Bank for International Settlement,* June.

Basel Committee on Banking Supervision, (2006), "Observed range of practice in key elements of Advanced Measurement Approaches (AMA)", *Bank for International Settlement,* October.

Basel Committee on Banking Supervision, (2009), "Observed range of practice in key elements of Advanced Measurement Approaches (AMA)", *Bank for International Settlement,* July.

Basel Committee on Banking Supervision, (2009), "Principles for sound stress testing practices and supervision", *Bank for International Settlement,* May.

Basel Committee on Banking Supervision, (2009), "Results from the 2008 loss data collection exercise for operational risk", *Bank for International Settlement,* July.

Basel Committee on Banking Supervision, (2010), "Results of the comprehensive quantitative impact study", *Bank for International Settlement,* December.

Basel Committee on Banking Supervision, (2010), "An assessment of the long-term economic impact of stronger capital and liquidity requirements", *Bank for International Settlement,* August.

Basel Committee on Banking Supervision, (2010), "Basel III: A global regulatory framework for more resilient banks and banking systems", *Bank for International Settlement,* December.

Basel Committee on Banking Supervision, (2011), "Basel III definition of capital frequently asked questions", *Bank for International Settlement,* July.

Basel Committee on Banking Supervision, (2011), "Basel III: A global regulatory framework for more resilient banks and banking systems", *Bank for International Settlement,* June.

Basel Committee on Banking Supervision, (2011), "Operational risk – Supervisory guidelines for the Advanced Measurement Approaches", *Bank for International Settlement,* June.

Basel Committee on Banking Supervision, (2011), "Principles for the sound management of operational risk", *Bank for International Settlement*, June.

Beaver, W. H. (1967), "Financial ratios as predictors of failures", *Journal of Accounting Research*, Empirical Research in Accounting: Selected Studies, 4, 71-111.

Beaver, W. H., McNichols, M.F. and J. Rhie, (2004), "Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy", *Working Paper, Stanford University - Graduate School of Business*, URL: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=634921

Benos, A. and George Papanastasopoulos, (2007), "Extending the Merton Model: A hybrid approach to assessing credit quality", *Mathematical and Computer Modelling*, 46, 47–68.

Bernhardsen, E. (2001), "A model of bankruptcy prediction", *Working Paper*, *Norges Bank,* Dec 5, 2001.

Bharath, S.T. and T. Shumway, (2008), "Forecasting default with the Merton distance to default model", *The Review of Financial Studies*, 21, 1339-1369.

Black, F. and J. C. Cox, (1976), "Valuing corporate securities: Some effects of bond indenture provisions", *The Journal of Finance*, 31 (2), 351-367.

Black, F. and M. Scholes, (1973), "The pricing of options and corporate liabilities", *Journal of Political Economy*, 81, 637-654.

Bluhm, C., L. Overbeck, and C. Wagner, (2003), "*An introduction to credit risk modeling*", Chapman & Hall/CRC Financial mathematics Series.

Bocker, K. and C. Kluppelberg, (2005). "Operational VAR: a closed-form solution", *RISK Magazine*, December, 90–93, URL: http://www.risk.net/data/risk/pdf/technical/risk_1205_3.pdf

Boritz, J. E., D. B. Kennedy, and J. Y. Sun, (2007), "Predicting business failures in Canada", *Accounting Perspectives*, 6 (2), 141-65.

Caouette, J. B., E. I. Altman, and Paul Narayanan, (1998), "*Managing credit risk: the next great financial challenges*", John Wiley & Sons Inc.

Capuano, C. J. Chan-Lau, G. Gasha, C. Medeiros, A. Santos, and M. Souto, (2009), "Recent advances in credit risk modelling", *IMF Working Paper*, August, 2009.

Carey, M. (1998), "Credit risk in private debt portfolios", *The Journal of Finance*, 53 (4), 1363-1386.

Carling, K., Jacobson, I., J. Linde, and Roszbach. (2007), "Corporate credit risk modeling and the macroeconomy", *Journal of Banking & Finance*, 32 (3), 845-868.

Cebrian, A. C., M. Denuit, and P. Lambert, (2003), "Generalized Pareto fit to the society of actuaries' large claims database", *North American Actuarial Journal*, 7 (3), 18-36.

Charitou, A., E. Neophytou, and C. Charalambous, (2004), "Predicting corporate failure: Empirical evidence for the UK", *European Accounting Review*, 13 (3), 465–497.

Cole, R. A. and J. W. Gunther, (1998), "Predicting bank failures: A comparison of on- and off-site monitoring systems", *Journal of Financial Services Research*, 13 (2), 103-117.

Cole, R. A. and W. Qiongbing, (2010), "Is Hazard or Probit more accurate in predicting financial distress? Evidence from U.S. bank failures", *Working Paper, DePaul University*, Chicago, URL: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1460526.

Cope, E. W., (2012), "Combining scenario analysis with loss data in operational risk quantification", *The Journal of Operational Risk*", 7 (1), Spring, 39-56.

Crapp, H. (2008), "AMA four data elements: The Australian experience", *Presented at Brazilian Federation of Banks Operational Risk Seminar by Australian Prudential regulatory Authority (APRA)*, August.

Credit Suisse, (1997), "CreditRisk+- A credit risk management framework", *Credit Suisse First Boston International*.

Crosbie, Peter and Jeff Bohn, (2003), "Modeling default risk", *Moody's KMV*, December 18, 2013, URL: http://www.moodysanalytics.com/~/media/Insight/Quantitative-Research/Default-and-Recovery/03-18-12-Modeling-Default-Risk.ashx.

Crouhy, M., D. Galai, and R. Mark, (2000), "A comparative analysis of current credit risk models", *Journal of Banking and Finance*, 24, 59-117.

Crusz, M. G. (2002), "*Modelling, Measuring and Hedging Operational Risk*", Wiley.

Currie, C. (2004), "Basel II and operational risk- Overview of key concerns", *Working Paper No. 134- University of Technology Sydney*, March.

Dahen, H. and G. Dionne, (2010), "Scaling models for the severity and frequency of external operational loss data", *Journal of Banking and Finance*, 34 (7), 1784-1496.

Das, S. R., D. Duffie, N. Kapadia, and L. Saita, (2007), “Common failings: How corporate defaults are correlated”, *The Journal of Finance*, 62 (1), 93-117.

Davis, E. (ed), (2005), “*Operational risk: Practical approaches to implementation*”, Risk Books.

Deakin, E.B. (1972), “A discriminant analysis of predictors of business failure”, *Journal of Accounting Research*, 10(1), 167-179.

Degan, M. (2010), “The calculation of minimum regulatory capital using Single Loss Approximations”, *Working Paper, School of Operations Research and Information Engineering*, Cornell University, September 29.

Delianedis, G. and R. Geske, (1998), “Credit risk and risk neutral default probabilities: Information about migrations and defaults”, *Working paper of Anderson Graduate School of Management*, University of California.

Dionne, G., S. Laajimi, S. Mejri, and M. Petrescu, (2006), "Estimation of the default risk of publicly traded Canadian companies," *Working Papers*, Bank of Canada.

Du, Y. and W. Suo, (2007), “Assessing credit quality from the equity market: can a structural approach forecast credit ratings?”, *Canadian Journal of Administrative Sciences*, 24 (3), 212- 228.

Duffee, G. R. (1999), “Estimating the price of default risk”, *The Review of Financial Studies*, Spring, 12 (1), 197-226.

Duffie, D. and K. Singleton, (1999), “Modeling term structure of defaultable bonds”, *Review of Financial Studies*, 12, 687-720.

Dutta, K. and David, F. Babbel, (2012), “Scenario analysis in the measurement of operational risk capital: A change of measure approach”, *Working paper*, University of Pennsylvania, URL: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1565805.

Dutta, K. and J. Perry, (2007), “A tale of tails: An empirical analysis of loss distribution models for estimating operational risk capital”, *Working Paper- Federal Reserve Bank of Boston*, January, 2007.

Elizalde, A. (2005), “Credit risk models II: Structural models”, November, 2005, URL: http://www.abelelizalde.com/pdf/survey2%20-%20structural.pdf.

Elizalde, A. and R. Repullo, (2007), “Economic and Regulatory Capital in Banking: What Is the Difference?”, *International Journal of Central Banking*, 3 (3), 87-117.

Embrechts, P., H. Furrer, and R. Kaufmann, "Quantifying regulatory capital for operational risk", *Working Paper*, URL: http://www.math.ethz.ch/~embrecht/ftp/OPRiskWeb.pdf.

Eom, Y. H., J. Helwege, and J. Huang, (2004), "Structural models of corporate bonds pricing: An empirical analysis", *The Review of Financial Studies*, 17 (2), 499-544.

Ergashev, B., (2008), "Should risk managers rely on the maximum likelihood estimation method while quantifying operational risk?", *Journal of Operational Risk*, 3 (2), Summer, 63-86.

Ergashev, B., (2011), "A theoretical framework for incorporating scenarios into operational risk modeling", *Working Paper - The Federal Reserve Bank of Richmond*, URL: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1635279.

Farmen, Tom, Sjur Westgaard, Stein-Erik Fleten, and Nico Van Der Wijst, (2007) "Default risk and its Greeks under an objective probability measure", URL: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=975294, http://www.defaultrisk.com/pp_score_38.htm.

Financial Stability Institute (FSI), (2010), "2010 FSI survey on the implementation of the new capital adequacy framework", Occasional Paper No 9, *Bank for International Settlement*, August.

Fontnouvelle, P, J. Jordan, and E. Rosengren (2005), "Implication of alternative operational risk modelling techniques", *National Bureau of Economic Research (NBER) Working Paper 11103*", February.

Frachot, A, O. Moudoulaud, and T. Roncalli, (2003), "Loss Distribution Approach in practice", Working *Paper- Groupe de Recherche Op´erationnelle, Cr´edit Lyonnais, France*" May 7, 2003.

Gallati, R. R. (2003), "*Risk management and capital adequacy*", McGraw-Hill.

Giesecke, K. (2004), "Credit risk modelling and valuation: An introduction", *Working Paper- Cornell University*, Available online at: http://www.stanford.edu/dept/MSandE/cgi-bin/people/faculty/giesecke/pdfs/introduction.pdf.

Gourier, E., W. Farkas, and D. Abbate, (2009), "Operational risk quantification using extreme value theory and copulas: from theory to practice", *The Journal of Operational Risk*", 4 (3), Fall, 3-26.

Guegan, D. B. K. Hassani, and C. Naud, (2012), "An efficient threshold choice for the computation of operational risk capital", *The Journal of Operational Risk*", 6 (4), Winter, 3-19.

Gujarati, D. N., (2004), "*Basic econometrics*", Fourth edition, Tata McGraw-Hill.

Guptan, G. M., C. C. Finger, and M. Bhatia, (1997), "Credit metrics- technical document", *J. P. Morgan*.

Hao Hui (2006), "Measuring firms' credit risk within structural models", *Working Paper, Queen's School of Business,* Queen's University, June.

Hillegeist, Stephen A., E. K. Keating, D.P. Cram, and K. G. Lunstedt, (2004), "Assessing the probability of bankruptcy", *Review of Accounting Studies*, 9, 5–34

Hol, S., S. Westgaard, and N. V. Wijst, (2002), "Capital Structure and the Prediction of Bankruptcy", *Working Paper*, *Norwegian University of Science and Technology*, July.

Holthausen, R. W. and W. Leftwich, (1986), "The effect of bond rating changes on common stock price", *Journal of Financial Economics*, 17, 57-89.

Hull, J. C., (2006), "*Options, futures and other derivatives*", Sixth edition, Pearson education.

Hull, John, and Alan White, (2008), "Dynamic models of portfolio credit risk: A simplified approach", *Working Paper of Rotman School of Management*, Uiversity of Toronto, Publishes in *Journal of derivatives*, 15 (4), 9-28, URL: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.139.7145&rep=rep1&type=pdf

J. P. Morgan and Reuters, (1996), "Riskmetrics- Technical Document", *Morgan Guaranty Trust Company of New York*, Fourth Edition.

Jarrow, R. A., and P. Potter, (2004), "Structural versus reduced form models: A new information based perspective", *Journal of Investment Management*", 2 (2), 1-10.

Jayadev, M. (2006), "Internal credit rating practices of Indian banks", *Economic and Political Weekly*, March 18, 2006, 1069-1078.

Jobst, A. A. (2007), "Operational risk—the sting is still in the tail but the poison depends on the dose", *The Journal of Operational Risk*" 2 (2), 3-59.

Jobst, A. A. (2007), "Consistent quantitative operational risk measurement and regulation: Challenges of model specification, data collection, and loss reporting", *International Monetary Fund (IMF) Working Paper,* November, 2007.

Jorion, P. (2003), "*Financial Risk Manager- Handbook*", JohnWiley & Sons, Inc., Hoboken, New Jersey.

Jorion, P. (2007), "*Value at Risk: the benchmark for managing financial risk*", Third edition, McGraw-Hill.

Kalkbrener, M. and F. Aue, (2007), LDA at work: Deutsche Bank's approach to quantifying operational risk", *Journal of Operational Risk*, 1 (4), 49–93.

Kern, M. and B. Rudolph, (2001), "Comparative analysis of alternative credit risk models – An application on German middle market loan portfolios" *Working Paper- Center for Financial Studies (CFS), Goethe University Frankfurt, No- 2001/03*, URL: http://econstor.eu/bitstream/10419/78084/1/755300432.pdf.

Kulkarni, A., A. K. Mishra, and J. Thakker, (2005), How Good is Merton Model at Assessing Credit Risk? Evidence from India", URL: http://www.defaultrisk.com/pp_model122.htm

Lambrigger, D. D., P. V. Shevchenko, and M. V. Wuthrich, (2007) "The quantification of operational risk using internal data, relevant external data and expert opinion", The *Journal of Operational Risk*, 2 (3), fall, 3-27.

Longstaff, F. A., and E. S. Schwartz, (1995), "A simple approach to valuing risky fixed and floating rate debt", *Journal of Finance*, 50 (3), 789-819.

Maddala, G. S. (1983), "*Limited-dependent and qualitative variable sin econometrics*", Cambridge University press.

Manganelli, S. and Robert F. Engle, (2001), "Value at Risk models in finance", *Working Paper- European Central Bank*, 75, August.

McNeil, A. J. (1999), "Extreme Value Theory for risk managers", *Working Paper- ETH Zentrum, Zurich*, 17th may, 1999, URL: http://www.macs.hw.ac.uk/~mcneil/ftp/cad.pdf.

Merton R. C. (1974), "On the pricing of corporate debt: The risk structure of interest rates", *Journal of Finance*, 29, 449-470.

Michael, T., Gapen, D. F., Gray, Cheng Hoon Lim and Yingbin Xiao, (2004), "The contingent claims approach to corporate vulnerability analysis: Estimating default risk and economy-wide risk transfer", *IMF Working paper*, 04/121.

Miyake, M. and H. Inoue, (2009), "A default probability estimation model: an application to Japanese companies", *Journal of Uncertain System*, 3 (3), 210-220.

Moscadelli, M. (2004), "The modeling of operational risk: experience with the analysis of the data collected by the Basel Committee", *Working Paper- Bank of Italy*, July, 2004.

Neftci, S. N., (2000), "*An introduction to the mathematics of financial derivatives*", Second edition, Academic Press.

O'Leary, D. E. (1998), "Using neural networks to predict corporate failure", *International Journal of Intelligent Systems in Accounting, Finance & Management*, 7, 187-197.

Ohlson, J. A. (1980), "Financial ratios and the probabilistic prediction of bankruptcy", *Journal of Accounting Research*, 18 (1), 109-131.

Ong Michael, K. (ed.), (2004), "*The Basel handbook: a guide for financial practitioners*", Risk Books.

Ong Michael, K., (1999), "*Internal credit risk models: capital allocation and performance measurement*", Risk Books.

Patrick de Fontnouvelle, P., V. DeJesus-Rueff, J. Jordan, and E. Rosengren, (2003), "Using loss data to quantify operational risk", *Working Paper- Federal Reserve Bank of Boston*, April, 2003,

Peter, G. W. and S. A. Sisson, (2006), "Bayesian inference, Monte Carlo sampling and operational risk", *Journal of Operational Risk*, 1 (3), Fall, 27-50.

Piacenza, F., D. Ruspantini, and A. Soprano, (2006), "Operational risk class homogeneity", *The Journal of Operational Risk*", 1 (3), Fall, 51-59.

Pongsatat, S., J. Ramage, and H. Lawrence, (2004), "Bankruptcy prediction for large and small firms in Asia: A comparison of Ohlson and Altman", *Journal of Accounting and Croporate Governance*, 1 (2), 1-13.

Premachandra, I. M., G. S. Bhabra, T. Sueyoshi, (2009), "DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique", *European Journal of Operational Research*, 193, 412–424

Rajan, R. G. and D. W. Diamond, (1999), "A theory of bank capital", *Working Paper- University of Chicago"*.

Ramakrishnan, P. R. (2005), "Financial Distress Prediction Models: A Case of Potential Sick Companies in India", *The ICFAI Journal of applied Finance*, October 2005, 68-77.

Rencher, A. C. (2002), "*Methods of multivariate analysis*", Second Edition, JohnWiley & Sons, Inc.

Reserve Bank of India, (2005), "*Guidance note on management of operational risk*", October 2005., URL: http://www.rbi.org.in.

Reserve Bank of India, (2005), "*Prudential guidelines on capital adequacy – Implementation of the new capital adequacy framework*", Feb 15, 2005, URL: http://www.rbi.org.in.

Reserve Bank of India, (2007), "*Prudential guidelines on capital adequacy and market discipline – Implementation of the new capital adequacy framework*", March 20, 2007, URL: http://www.rbi.org.in.

Reserve Bank of India, (2009), "*Introduction to the advanced approaches of Basel II framework in India- Time schedule*", July 7, 2009, URL: http://www.rbi.org.in.

Reserve Bank of India, (2010), "*Guidelines on The Standardized Approach (TSA) for calculation of capital charge for operational risk*", March 31, 2010, URL: http://www.rbi.org.in.

Reserve Bank of India, (2011), "*Capital Adequacy - The Internal Ratings Based (IRB) Approach to calculate capital requirement for credit risk*", December 22, 2011, URL: http://www.rbi.org.in

Reserve Bank of India, (2011), "*Guidelines on Advanced Measurement Approach (AMA) for calculation of capital charge for operational risk*", April 27, 2011, URL: http://www.rbi.org.in.

Reserve Bank of India, (2012), "*Guidelines on implementation of Basel III capital regulation in India*", May 2, 2012, URL: http://www.rbi.org.in.

Reserve Bank of India, (2013), "*Master Circular on Basel III Capital Regulations*", July 1, 2013, URL: http://www.rbi.org.in.

Rippel, M., and P. Teply, (2008), "Operational risk- Scenario Analysis", *Working paper- Institute of Economic Studies (IES),* Charles University, No- 15/2008.

Rocco, M. (2011), "Extreme value theory for finance: a survey", *Occasional Paper, Bank of Italy*, No. 99, July, 2011, URL: http://ssrn.com/abstract=1998740.

Saunders, A., (1999), "*Credit risk measurement: New approaches to value at risk other paradigms*", John Wiley & Sons, Inc.

Scott, A, F. Larry, and R. Dan, (2000), "Building a Credit Risk Valuation Framework for Loan Instruments" *Algo Research Quarterly*, 3 (3), December 2000.

Shevchenko, P. V. and M. Wuthrich (2006), "The structural modeling of operational risk via Bayesian inference: Combining loss data with expert opinions", *Journal of Operational Risk*, 1 (3), Fall, 3-26.

Shevchenko, P. V., (2009), “Implementing loss distribution approach for operational risk”, *Applied Stochastic Models in Business and Industry,* 26 (3), 205-330.

Shumway, T. (2001), “Forecasting bankruptcy more accurately: A simple hazard model”, *The Journal of Business,* 74 (1), 101-124.

Sobehart, J., Keenan, S. and R. Stein, (2001), “Benchmarking quantitative default risk models: A validation methodology”, *Algo Research Quarterly*, Mar/June 2001, 57-72.

Subbarao, D. (2009), “Risk management in the midst of the global financial crisis”, Speech by Governor of the RBI at the Financial Management Summit 2009 organized by the Economic Times, Mumbai, 22 May 2009, *BIS Review 63/2009*.

Subbarao, D. (2010), “Challenges for central banks in the context of the crisis”, Inaugural address Governor of the RBI at the International Research Conference on “Challenges for Central Banks in the Context of the Crisis”, Mumbai, 12 February 2010, *BIS Review 16/2010*.

Sundaram, R. K. (2001), “The Merton/ KMV approach to pricing credit risk”, *Working Paper, Stern School of Business,* New York University, January, 2001.

Taffler, R. J. (1982), “Forecasting company failure in the UK using Discriminant Analysis and financial ratio data”, *Journal of the Royal Statistical Society*. Series A, 145 (3), 342-358.

Takami, M. Y. and B. M. Tabak, (2007), “Evaluation of the default risk for the Brazilian banking sector”, *Working Paper Series of Central bank of Brazil,* May, 2007.

Tapiero, C. (2004), “*Risk and financial management-Mathematical and computational methods*”, JohnWiley & Sons, Ltd.

Varma, J. R. and V. Raghunathan, (2000), “Modeling credit risk in Indian bond markets”, *The ICFAI Journal of Applied Finance*, 6 (3), 53-67.

Wang, Y. and M. Campbell, (2010), “Financial ratios and the prediction of bankruptcy: The Ohlson model applied to Chinese publicly traded companies”, *Journal of Organizational Leadership & Business,* Summer.

Watchorn E. and Andre Levy, (2008), “Developing Business Environment and Internal Control Factors for Operational Risk Measurement and Management”, *Information Paper-Australian Prudential regulatory Authority (APRA)*, April, 2008.

Wu, Y., C. Gaunt, and S. Gray, (2010), “A comparison of alternative bankruptcy prediction models”, *Journal of Contemporary Accounting and Economics*, 6, 35-45.

Yazdipour, R. and R. L. Constand, (2010), "Predicting Firm Failure: A Behavioral Finance Perspective", *The Journal of Entrepreneurial Finance*, 14 (3), 90-104.

Young, B, and R. Coleman, (2009), "*Operational risk assessment: The commercial imperative of a more forensic and transparent approach*", Wiley.

Zhang, J., F. Zhu, and J. Lee, (2008), "Asset correlation, realized default correlation, and portfolio credit risk", *Moody's KMV,* Mar 3, 2008, URL: http://www.moodysanalytics.com/~/media/Insight/Quantitative-Research/Portfolio-Modeling/08-03-03-Asset-Correlation-and-Portfolio-Risk.ashx.

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

APPENDIX 1

Basel Loss Event Type Classification

Event-Type Category (Level 1)	**Definition**	**Categories (Level 2)**	**Activity Examples (Level 3)**
Internal fraud	Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations, the law or company policy, excluding diversity/ discrimination events, which involves at least one internal party	Unauthorised Activity	Transactions not reported (intentional)
			Transaction type unauthorised (with monetary loss)
			Mismarking of position (intentional)
		Theft and Fraud	Fraud / credit fraud / worthless deposits
			Theft / extortion / embezzlement / robbery
			Misappropriation of assets
			Malicious destruction of assets
			Forgery
			Kite flying
			Smuggling
			Account take-over
			Tax non-compliance / evasion
			Bribes / kickbacks
			Insider trading (not on firm's account)
External fraud	Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party	Theft and Fraud	Theft/Robbery
			Forgery
			Kite flying
		Systems Security	Hacking damage
			Theft of information (with monetary loss)
Employment Practices and Workplace Safety	Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events	Employee Relations	Compensation, benefit, termination issues
			Organised labour activity
		Safe Environment	General liability (slips and falls, etc.)
			Employee health & safety rules
			Workers compensation

		Diversity & Discrimination	All discrimination types
Clients, Products & Business Practices	Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product.	Suitability, Disclosure & Fiduciary	Fiduciary breaches / guideline violations
			Suitability / disclosure issues (KYC, etc.)
			Retail customer disclosure violations
			Breach of privacy
			Aggressive sales
			Account churning
			Misuse of confidential
			Lender liability
		Improper Business or Market Practices	Antitrust
			Improper trade / market practices
			Market manipulation
			Insider trading (on firm's account)
			Unlicensed activity
			Money laundering
		Product Flaws	Product defects (unauthorised, etc.)
			Model errors
		Selection, Sponsorship & Exposure	Failure to investigate client per guidelines
			Exceeding client exposure limits
		Advisory Activities	Disputes over performance of advisory activities
Damage to Physical Assets	Losses arising from loss or damage to physical assets from natural disaster or other events.	Disasters and other events	Natural disaster losses
			Human losses from external sources (terrorism, vandalism)
Business disruption and system failures	Losses arising from disruption of business or system failures	Systems	Hardware
			Software
			Telecommunications
			Utility outage / disruptions
Execution, Delivery & Process Management	Losses from failed transaction processing or process management, from relations with trade counterparties and vendors	Transaction Capture, Execution & Maintenance	Miscommunication
			Data entry, maintenance or loading error
			Missed deadline or responsibility
			Model / system mis-operation

			Accounting error / entity attribution error
			Other task mis-performance
			Delivery failure
			Collateral management failure
			Reference Data Maintenance
		Monitoring and Reporting	Failed mandatory reporting obligation
			Inaccurate external report (loss incurred)
		Customer Intake and Documentation	Client permissions / disclaimers missing
			Legal documents missing / incomplete
		Customer / Client Account Management	Unapproved access given to accounts
			Incorrect client records (loss incurred)
			Negligent loss or damage of client assets
		Trade Counterparties	Non-client counterparty misperformance
			Misc. non-client counterparty disputes
		Vendors & Suppliers	Outsourcing
			Vendor disputes

(Source: "Guidelines on Advanced Measurement Approach (AMA) for Calculating Operational Risk Capital Charge", Reserve Bank of India, April, 2011)

APPENDIX 2

Basel Business Line Classification

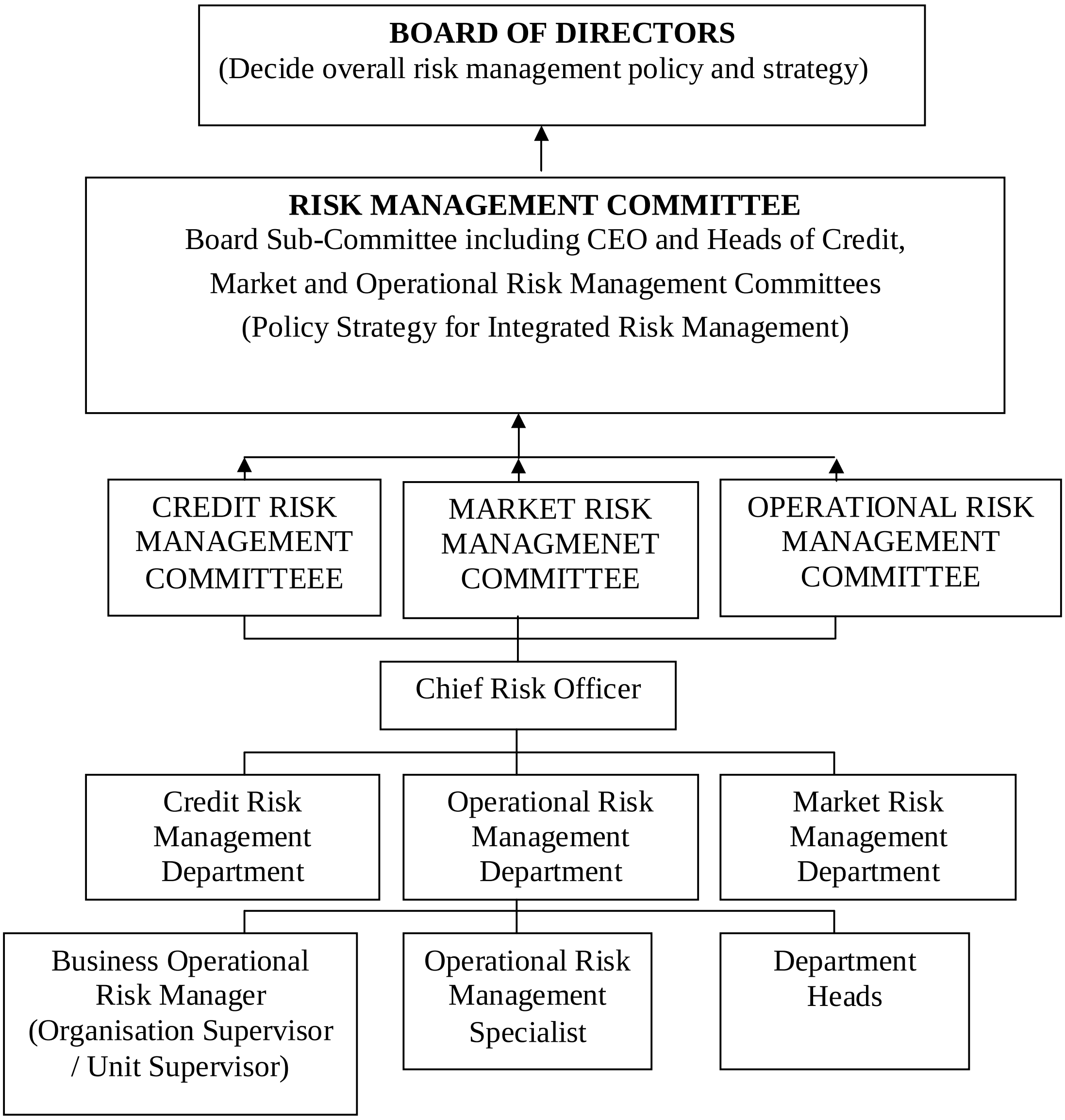
Level 1	**Level 2**	**Activity Groups**
Corporate Finance	Corporate Finance	Mergers and acquisitions, underwriting, privatisations, securitisation, research, debt (government, high yield), equity, syndications, IPO, secondary private placements
	Government Finance	
	Merchant Banking	
	Advisory Services	
Trading & Sales	Sales	Fixed income, equity, foreign exchanges, credit products, funding, own position securities, lending and repos, brokerage, debt, prime brokerage and sale of Government bonds to retail investors.
	Market Making	
	Proprietary Positions	
	Treasury	
Payment and Settlement	External Clients	Payments and collections, inter-bank funds transfer (RTGS, NEFT, EFT, ECS etc.), clearing and settlement
Agency Services	Custody	Escrow, securities lending (customers) corporate actions, depository services
	Corporate Agency	Issuer and paying agents
	Corporate Trust	Debenture trustee
Asset Management	Discretionary Fund Management	Pooled, segregated, retail, institutional, closed, open, private equity
	Non-Discretionary Fund Management	Pooled, segregated, retail, institutional, closed, open
Retail Brokerage	Retail Brokerage	Execution and full service
Retail Banking	Retail Banking	Retail lending including trade finance, cash credit etc. as defined under Basel II and also covering non fund based and bill of exchange facilities to retail customers, housing loans, loans against shares, banking services, trust and estates, retail deposits, intra bank fund transfer on behalf of retail customers.
	Private Banking	Private lending (personal loans) and

		private/bulk deposits, banking services, trust and estates, investment advice
	Card Services	Merchant/commercial/corporate cards, private labels and retail
Commercial Banking	Commercial Banking	Project finance, corporate loans, cash credit loans, real estate, export and import finance, trade finance, factoring, leasing, lending, guarantees including deferred payment and performance guarantees, LCs, bills of exchange, take-out finance, interbank lending other than in call money and notice money market.

(Source: "Guidelines on Advanced Measurement Approach (AMA) for Calculating Operational Risk Capital Charge", Reserve Bank of India, April, 2011)

APPENDIX 3

Organizational Structure for Operational Risk Management



(Source: "Guidance note on management of operational risk", Reserve Bank of India, October, 2005)

APPENDIX 4

Sample List of KRIs

Sources of operational risk	Types of Risks	Some Key Risk Indicators (KRIs)
People	Internal control and corporate governance breakdown leading to financial losses, incompetence, internal/external fraud, theft: Employee theft and smuggling, insider and outsider trading, bribes, robbery, forgery, damage from computer hacking, etc.	• Staff turnover rates • Number of documentation error • Staff training & experience level • Transaction and trade volumes
Process	Process execution: Management failure, product service complexity, delivery and process management, employment practices and workplace safety, delivery failure and vendor disputes, security failure, violation of employee health and safety rules, etc.	• No. of fraudulent accounts rejected after Verification of documents as a percentage of total accounts sourced • No. of KYC discrepant cases as a percentage of total number of cases verified • No. of customer complaints received on account of misselling/aggressive selling as a percentage of total applications received
Technological systems	System failures caused by internal and external events: Programming error, loss of information data, failure of system to meet business requirement, internal telecommunication failure, IT crash caused by new application, etc.	• preventive maintenance by number of hardware units • System downtime rate • Number of instances of network systems downtime • Backup failure rate • System failure retrieval time
External events	Political uncertainties: Damage to physical assets, fires, virus/mass diseases, terrorism, vandalism, riots, earthquakes, floods, bankruptcy of supplier, transportation failures, etc.	• No of external attempted frauds • Number of hacking cases

(Source: "Guide to Optimal Operational Risk and Basel II", Akkizidis, I.S and V. Bouchereau (2006), Auerbach Publications)

APPENDIX 5

List of Companies

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	Unimin India Ltd.	Plastic
5	2006	Distressed	Shree Rama Multi-Tech Ltd.	Packing
6	2006	Distressed	Duncans Industries Ltd.	Tea And Coffee
7	2006	Distressed	Digital Multiforms Ltd.	Printing And Stationary
8	2006	Distressed	Lml Ltd.	Automobiles
9	2006	Distressed	Midland Plastics Ltd.	Plastic
10	2006	Distressed	Shamken Cotsyn Ltd.	Textile-Processing
11	2006	Distressed	Shamken Spinners Ltd.	Textile-Spinning
12	2006	Distressed	Shamken Multifab Ltd.	Textile-Weaving
13	2007	Distressed	Sri Jayalakshmi Spinning Mills Ltd.	Textiles-Spinning
14	2007	Distressed	Hotline Glass Ltd.	Glass And Glass Product
15	2007	Distressed	Bpl Engineering Ltd.	Electricals
16	2007	Distressed	Polar Industries Ltd.	Domestic Appliances
17	2007	Distressed	Rathi Ispat Ltd.	Casting And Forgings
18	2007	Distressed	Nachmo Knitex Ltd.	Textiles-General
19	2008	Distressed	Gwalior Polypipes Limited	Chemicals
20	2008	Distressed	Indo Gulf Industries Ltd.	Chemicals
21	2008	Distressed	Lime Chemicals Ltd	Chemicals
22	2008	Distressed	Oxford Industries Ltd.	Weaving
23	2008	Distressed	Sarda Papers Ltd	Paper
24	2008	Distressed	Micro Forge (India) Ltd.	Casting And Forgings
25	2008	Distressed	Hanjer Fibres Ltd.	Textile-Spinning
26	2008	Distressed	Quantum Digital Vision (India) Ltd.	Packaging
27	2008	Distressed	Bharat Fertiliser Industries Ltd.	Fertiliser
28	2008	Distressed	Arora Fibres Ltd.	Textile-Manmade
29	2008	Distressed	Nrc Ltd.	Textile-Manmade
30	2009	Distressed	Scanpoint Geomatics Ltd.	Consumer Goods-Electronics
31	2009	Distressed	Prudential Sugar Corporation Ltd.	Sugar
32	2009	Distressed	Tuticorin Alkali Chemicals & Fertilisers Ltd.	Chemicals
33	2009	Distressed	Alumeco India Extrusion Ltd.	Aluminum
34	2009	Distressed	Polylink Polymers (India) Ltd.	Petrochemicals
35	2009	Distressed	Mp Telelinks Ltd.	Cables-Telephone
36	2009	Distressed	Rainbow Denim Ltd.	Readymade Apparels
37	2009	Distressed	Indo Biotech Foods Ltd.	Food Processing
38	2009	Distressed	Nova Petrochemicals Ltd.	Textile-Manmade
39	2009	Distressed	Ganesh Benzoplast Ltd.	Chemicals
40	2009	Distressed	Polar Pharma India Ltd.	Miscellaneous

41	2010	Distressed	Scooters India Ltd.	Auto - 2 & 3 Wheelers
42	2010	Distressed	Shah Alloys Ltd.	Steel
43	2010	Distressed	Uniflex Cables Ltd.	Power
44	2010	Distressed	Alps Industries Ltd.	Textile
45	2010	Distressed	Noble Explochem Ltd.	Chemicals
46	2010	Distressed	Celebrity Fashions Ltd.	Textile
47	2011	Distressed	Modern Dairies Ltd.	Food Processing
48	2011	Distressed	Kdl Biotech Ltd.	Pharmaceuticals
49	2011	Distressed	Blue Bird (India) Ltd.	Printing & Stationary
50	2011	Distressed	Yashraj Containeurs Ltd.	Packaging
51	2011	Distressed	Agro Dutch Industries Ltd.	Food Processing
52	2011	Distressed	Vanasthali Textile Industries Ltd.	Textiles-Terry Towels
53	2011	Distressed	Marksans Pharma Ltd.	Pharmaceuticals
54	2011	Distressed	Amit Spinning Industries Ltd.	Textiles
55	2012	Distressed	Kanco Enterprises Ltd.	Textiles
56	2012	Distressed	Abhishek Corporation Ltd.	Textile
57	2012	Distressed	Faze Three Ltd.	Textile-Spinning
58	2012	Distressed	Radha Madhav Corporation Ltd.	Packaging
59	2012	Distressed	Samtel Color Ltd.	Electricals
60	2012	Distressed	Vikash Metal & Power Ltd.	Sponge Iron
61	2012	Distressed	Ramsarup Industries Ltd.	Steel
62	2012	Distressed	Saffron Industries Ltd.	Paper
63	2006	Non-distressed	Chettinad Cement	Cement
64	2006	Non-distressed	Indag Rubber	Miscellaneous
65	2006	Non-distressed	Remsons Industries Ltd.	Auto Ancillaries
66	2006	Non-distressed	Peacock Industries Ltd.	Plastic
67	2006	Non-distressed	Balmer Lawrie And Company	Packing
68	2006	Non-distressed	Assam Company (Ndia)	Tea And Coffee
69	2006	Non-distressed	Orient Press	Printing And Stationary
70	2006	Non-distressed	Scooters India Ltd.	Automobiles
71	2006	Non-distressed	Tokyo Plast International	Plastic
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	2007	Non-distressed	Amit Spinning Industries	Textiles-Spinning
76	2007	Non-distressed	Empire Industries	Glass And Glass Product
77	2007	Non-distressed	Ece Industries	Electrical
78	2007	Non-distressed	Panasonic Home Appliances India Company Ltd.	Domestic Appliances
79	2007	Non-distressed	Hinduja Foundries	Casting And Forgings
80	2007	Non-distressed	Aunde India	Textiles-General
81	2008	Non-distressed	Jyoti Resins And Adhesives	Chemicals
82	2008	Non-distressed	Tanfac Industries Ltd.	Chemicals
83	2008	Non-distressed	National Oxygen	Chemicals
84	2008	Non-distressed	Orbit Exports	Weaving
85	2008	Non-distressed	Kay Power And Paper	Paper

86	2008	Non-distressed	Hilton Metal Forging	Casting And Forgings
87	2008	Non-distressed	Salona Cotspin Ltd.	Textile-Spinning
88	2008	Non-distressed	Paramount Printpacking Ltd.	Packaging
89	2008	Non-distressed	Shiva Global Agro Industries	Fertilizer
90	2008	Non-distressed	Zenith Fibres	Textile-Manmade
91	2008	Non-distressed	Nirlon Ltd.	Textile-Manmade
92	2009	Non-distressed	Photoquip (India) Ltd.	Consumer Goods-Electronics
93	2009	Non-distressed	Jk Sugar Ltd.	Sugar
94	2009	Non-distressed	Chemfab Alkalies	Chemicals
95	2009	Non-distressed	Sacheta Metal Ltd.	Aluminum
96	2009	Non-distressed	Diamines And Chemicals	Petrochemicals
97	2009	Non-distressed	Surana Telecom And Power	Cables-Telephone
98	2009	Non-distressed	Zodiac Clothing Company Ltd.	Readymade Apparels
99	2009	Non-distressed	Rt Exports	Food Processing
100	2009	Non-distressed	Sumeet Industries	Textile-Manmade
101	2009	Non-distressed	Alkyl Amines Chemicals Ltd.	Chemicals
102	2009	Non-distressed	Sun Pharma Advanced Research Company Ltd.	Miscellaneous
103	2010	Non-distressed	Atul Auto	Auto - 2 & 3 Wheelers
104	2010	Non-distressed	Mahindra Ugine Steel Company	Steel
105	2010	Non-distressed	Cords Cable Industries	Power
106	2010	Non-distressed	Sutlej Textiles And Industries	Textile
107	2010	Non-distressed	Alkali Metals	Chemicals
108	2010	Non-distressed	Maxwell Industries	Textile
109	2011	Non-distressed	Adf Foods Industries	Food Processing
110	2011	Non-distressed	Celestial Labs	Pharmaceuticals
111	2011	Non-distressed	Navneet Publications	Printing & Stationary
112	2011	Non-distressed	Xpro India	Packaging
113	2011	Non-distressed	Usher Agro	Food Processing
114	2011	Non-distressed	Store One Retail India	Textiles-Terry Towels
115	2011	Non-distressed	Shasun Pharmaceuticals	Pharmaceuticals
116	2011	Non-distressed	Salona Cotspin	Textiles
117	2012	Non-distressed	Eurotex Industries And Exports	Textiles
118	2012	Non-distressed	Amarjothi Spinning Mills	Textile
119	2012	Non-distressed	Kandagiri Spinning Mills	Textile-Spinning
120	2012	Non-distressed	Manjushree Technopack	Packaging
121	2012	Non-distressed	Ece Industries	Electricals
122	2012	Non-distressed	Tata Sponge Iron	Sponge Iron
123	2012	Non-distressed	Varun Industries	Steel
124	2012	Non-distressed	Shreyans Industries	Paper