EVALUATION OF CREDIT RISK MANAGEMENT PRACTICES: AN EMPIRICAL STUDY OF INDIAN PUBLIC SECTOR COMMERCIAL BANKS

PH.D THESIS

by

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2K11/Ph.D/DSM/01

Delhi School of Management

Submitted in fulfillment of the requirements for the award of the degree of

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to the

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CANDIDATE'S DECLARATION

I, hereby certify that the thesis titled **"EVALUATION OF CREDIT RISK MANAGEMENT PRACTICES: AN EMPIRICAL STUDY OF INDIAN PUBLIC SECTOR COMMERCIAL BANKS"** and submitted in fulfillment of the requirements for the award of the degree of Doctor of Philosophy is an authentic record of my research work carried out under the guidance of Dr. Archana Singh. Any material borrowed or referred to is duly acknowledged.

The matter presented in this thesis has not been submitted elsewhere in part or fully to any other University or Institute for the award of any degree.

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SUPERVISOR'S CERTIFICATE

This is to certify that the thesis titled **"EVALUATION OF CREDIT RISK MANAGEMENT PRACTICES: AN EMPIRICAL STUDY OF INDIAN PUBLIC SECTOR COMMERCIAL BANKS"** submitted to the Delhi Technological University, Delhi-110042, in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Management embodies the original research work carried out by Ms. Renu Arora under my supervision. The matter presented in this thesis has not been submitted elsewhere in part or fully to any other University or Institute for the award of any degree, to the best of our knowledge.

Dr. Archana Singh
Supervisor
Assistant Professor
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ABSTRACT

At present, the biggest problem before Indian public sector banks is to improve their asset quality and control their mounting non- performing loans. RBI reports (2011-15) repeatedly impressed these banks to tighten their credit assessments and monitoring mechanisms especially for loans to business and industry. Thus, this study evaluates the credit risk management practices of Indian public sector banks (PSBs) in the grant of commercial loans to find the grey areas which need review and restructuring to improve banks' asset quality. The research objectives are to identify and examine the characteristics and causes of credit risk, compare credit risk management practices of large and small public sector banks, analyse the extent to which these banks have implemented the Basel norms on credit risk management and evaluate their credit risk rating framework. The study also aims to design a credit risk assessment model for banks based on a comparison of existing and theoretical credit-scoring or rating models. The study is limited to commercial loans to SMEs and mid-corporates.

A conceptual framework of credit risk management (CRM) systems has been developed to delineate the strengths, problems and obstacles in public sector banks' CRM practices through a structured questionnaire. Survey based perception studies have been undertaken on a sample of 337 credit and risk managers working in 12 sample public sector banks. The study also uses secondary data to define the characteristics of credit risk in public sector banks and to design a credit risk assessment model for these banks.

The study concludes that size of the bank is a critical credit risk variable as small public sector banks have higher credit risk in terms of stressed assets ratio (gross non-performing and restructured loans/Total Advances). Credit managers or analysts of large banks are found to be more satisfied with their credit risk management practices. Credit analysts in all public sector banks (PSBs) have found that liquidity and solvency risk factors of the corporate borrower are the most potent causes of default on bank loans followed by his management, business and industry risk factors. Presently the credit and risk managers in these banks are finding the industry risk of their corporate borrowers, the most challenging risk to manage. The study has observed high subjectivity in credit risk assessments in these banks because of a large number of qualitative or experiential risk factors in their credit risk rating framework and because of statistically significant disagreement between different categories of credit and risk managers on these risk factors.

The study also develops a three group multivariate discriminant model (MDA) to predict credit risk in new loan proposals, based on 40 performing and seven non-performing or restructured loans of a sample public sector bank, under High Safety, Moderate Safety, and Inadequate Safety categories. The study found that the combination of quantitative and qualitative risk factors under multi-discriminant analysis improved credit risk assessment.

This research has thus, provided deep insight into the credit risk management practices of the Indian public sector banks. It will serve as a standard research on the subject, and its limitations will provide scope for further research on the subject.

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LIST OF ABBREVIATION

AGM	-	Assistant General Manager
AIRB	-	Advanced Internal Rating Based Approach
Andhra	-	Andhra Bank
BIS	-	Bank for International Settlements
BOB	-	Bank of Baroda
CAR	-	Capital Adequacy Ratio
CARE	-	Credit Analysis & Research Ltd.
CRAR	-	Capital To Risk- Adjusted Assets Ratio
CRISIL	-	Credit Rating & Information Services of India Ltd.
CRM	-	Credit Risk Management
DRTs	-	Debt Recovery Tribunals
EAD	-	Exposure at Default
EBIT	-	Earnings Before Interest and Taxes
EL	-	Expected Loss
FIRB	-	Foundation Internal Rating Based Approach
GDP	-	Gross Domestic Product
GNPAs	-	Gross Non -Performing Assets
IBA	-	Indian Banks' Association
ICRA	-	Investment Information and Credit Rating Agency
IRB	-	Internal Rating Based Approach

KYC	-	Know Your Customer
LGD	-	Loss Given Default
MDA	-	Multivariate Discriminant Analysis
MSMEs	-	Micro, Small, and Medium Enterprises
NIM	-	Net Interest Margin
NNPAs	-	Net Non- Performing Assets
NPAs	-	Non-Performing Assets
OBC	-	Oriental Bank of Commerce
OTS	-	One Time Settlement
P & Sind Bank	-	Punjab & Sind Bank
PBDIT	-	Profit before Depreciation, Interest & Taxes
PD	-	Probability of Default
PNB	-	Punjab National Bank
PSBs	-	Public Sector Banks
RAROC	-	Risk-Adjusted Return on Capital
RBI	-	Reserve Bank of India
ROA	-	Return on Assets
ROCE	-	Return on Capital Employed
ROE	-	Return on Equity
SARFAESI Act	-	Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest Act
SBBJ	-	State Bank of Bikaner & Jaipur

SBI	-	State Bank of India
SLR	-	Statutory Liquidity Ratio
SMEs	-	Small and Medium Enterprises
SMERA	-	SME Rating Agency of India
Synd Bank	-	Syndicate Bank
TOL/TNW	-	Total outside liability/Tangible Net Worth
UL	-	Unexpected Loss
United Bank	-	United Bank of India

CHAPTER 1
INTRODUCTION

1.1 CHALLENGES BEFORE INDIAN BANKING INDUSTRY TO MAINTAIN ASSET QUALITY

As per RBI report on ‘Trends and Progress of Banking in India 2011-12’, the performance of the Indian banking sector during 2011-12 was influenced by the slowdown in the domestic economy. Consequently, balance sheet expansion of banks was lower than the previous year. Major profitability indicators, i.e., return on assets and return on equity dipped marginally. Though Indian banks remained well-capitalized, concerns about the growing non-performing assets (NPAs) loomed large, particularly on the public sector banks. The weakening domestic macroeconomic conditions combined with continuing subdued global growth and its increasing spillover risks posed challenges to the banking sector during 2012-13, and there was a rise in asset impairment coupled with a dip in profitability. The NPA ratio of all major sectors weakened during 2012-13 (RBI Report on Trends and Progress of Banking in India, 2012-13). The growth of the Indian banking sector moderated further during 2013-14. Profitability declined on account of higher provisioning on banks’ delinquent loans and lackluster credit growth. Credit growth on a y-o-y basis continued to decline and recorded low growth at 10.0 percent as of September 2014, with public sector banks (PSBs) underperforming the rest with a growth of 7.9 percent (RBI Financial Stability Report, December 2014). Non-performing assets are bank loans on which interest or repayment of principal amount remains overdue for more than 90 days and are the direct indicator of the credit risk before a bank. NPAs affect liquidity and profitability of banks; threaten their quality of assets and survival. Delayed identification of these stressed loans significantly decreases recovery rates. The incremental NPAs pose a great question mark on the efficiency of credit risk management in India (Siraj, 2012) and it is a great challenge before Indian banks to improve their asset quality.

1.2 PROFILING INDIAN BANKING INDUSTRY

The institutional structure of Indian banking system comprises of the Reserve Bank of India, the central bank, 27 public sector banks, 23 private sector banks, 43 foreign banks, and some regional rural and co-operative banks. The latest addition to public sector banks is the Bharatiya Mahila Bank, which has started operations in November 2013. Public sector banks dominate the commercial banking system in terms of total assets (73%) of the banking industry, followed by 20% share of the private sector banks, and 7% of foreign banks (Figure 1.1).

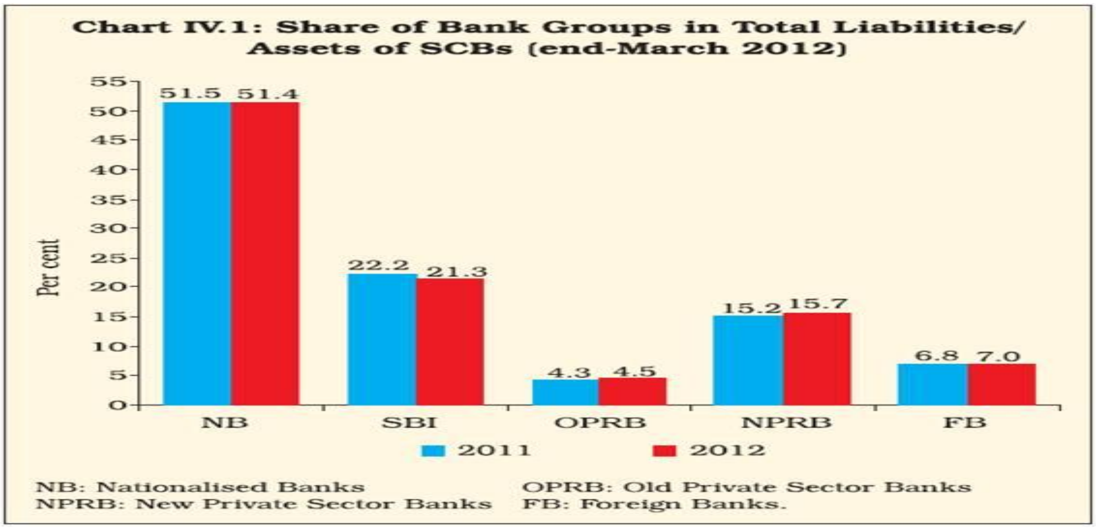

FIGURE 1.1: SHARE OF BANKS IN TOTAL ASSETS (SBI INCLUDES 5 SBI ASSOCIATE BANKS)

(Source: RBI Report on 'Trends and Progress of Banking in India 2011-102')

The predominance of public sector banks was further reinforced in 2013-14, with their share increasing to 74% (Figure 1.2). Indian banking sector is thus, broadly public in nature with public sector banks accounting for more than two-thirds of total assets of all scheduled commercial banks.

A process of liberalization which was initiated in 1992, on the recommendations of the Narasimham Committee (1991) on financial sector reforms has made the Indian banking sector more diversified, global and competitive. RBI guidelines on prudential norms, implementation of Basel Accords, have strengthened the banking industry and increasing number of private and foreign banks has created the desired competitive pressures.

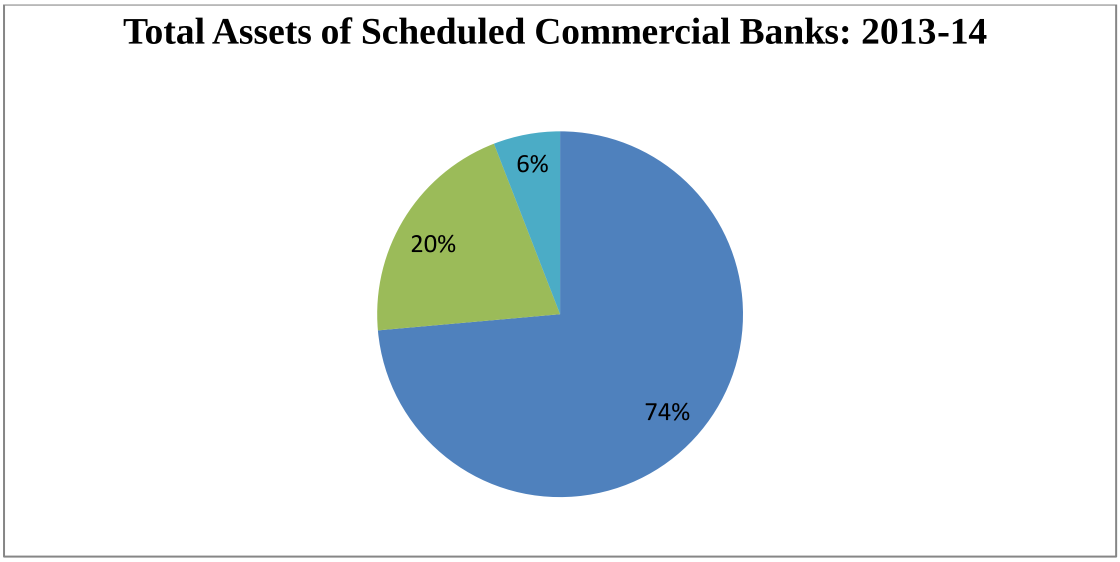

FIGURE 1.2: PREDOMINANCE OF PUBLIC SECTOR BANKS (PSBS 74%, PRIVATE BANKS 20%, FOREIGN BANKS 6%)

(Source: RBI - Statistical Tables Relating to Banks in India, 2013-14)

The Porter's five forces model for the Indian banking industry (Figure 1.3) shows the intensified competition among the Indian banks. All the banks are providing homogeneous or similar kind of services and offering similar terms and conditions for retail and non-retail or commercial loans. All banks are in a race for seemingly profitable loan proposals, with low switching costs for borrowers. The high competitive rivalry among banks to secure business may be a cause of distortion in their credit approval or sanction processes.

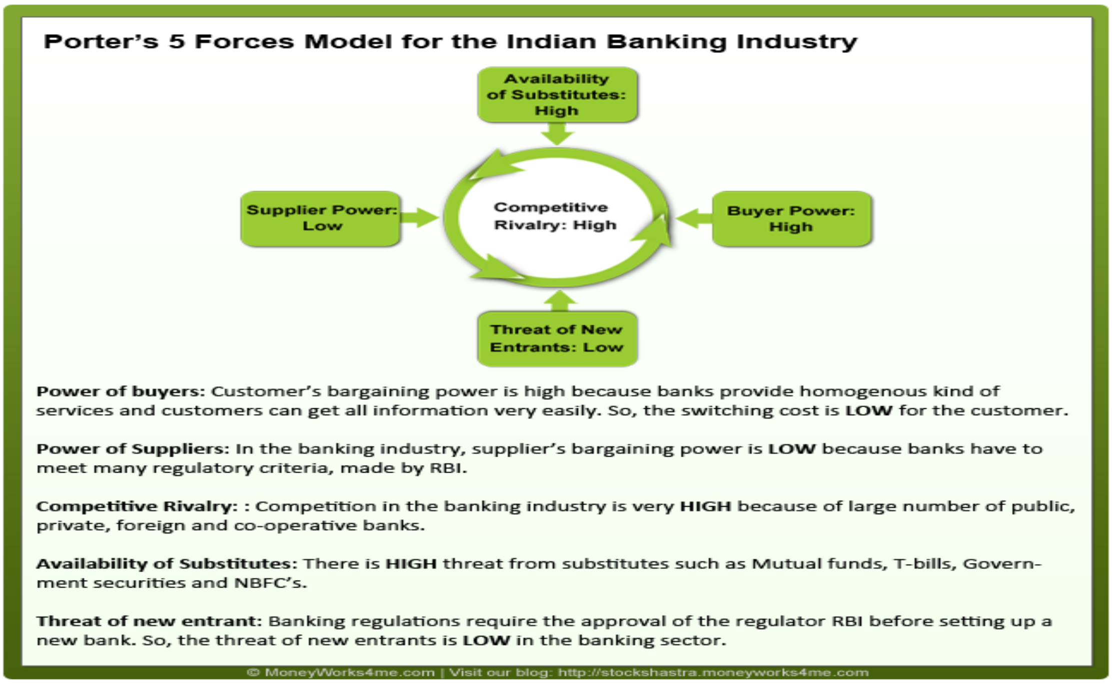

FIGURE 1.3: COMPETITION AMONG INDIAN BANKS
(Source: MoneyWorks4me.com, accessed on 11.03.2013)

1.3 BANKING RISKS

Banks are financial intermediaries between depositors of savings and fund seeking consumers and business entrepreneurs. Commercial banks are in the risk business (Santomero, 1997). In the process of providing financial services, they assume various kinds of financial risks (Santomaro, 1997). They are exposed to higher level of risks due to rising global competition, privatization, increasing deregulations, the introduction of innovative financial products and complexities of the economic and technical environment.

The risk is the possibility of suffering a loss (Raghavan, 2003). The risk is related to the amount of capital that a bank requires to achieve a sufficient level of protection against adverse circumstances (Raghavan, 2003). The risk is used to adjust the returns from business activities to determine whether activities are adding value to the business (Raghavan, 2003). The risk is the probability that both the expected and unexpected events may have an adverse impact on bank's capital, earnings and share prices (Raghavan, 2003). The expected loss is borne by the borrowers and taken care of by banks by adequately pricing the loans through risk premium, creating reserves, and loan loss provision out of earnings (Raghavan, 2003). Unexpected losses on account of individual or portfolio exposures are to be borne by the bank itself and require adequate capital adequacy ratio, risk transfer and mitigation strategies (Raghavan, 2003).

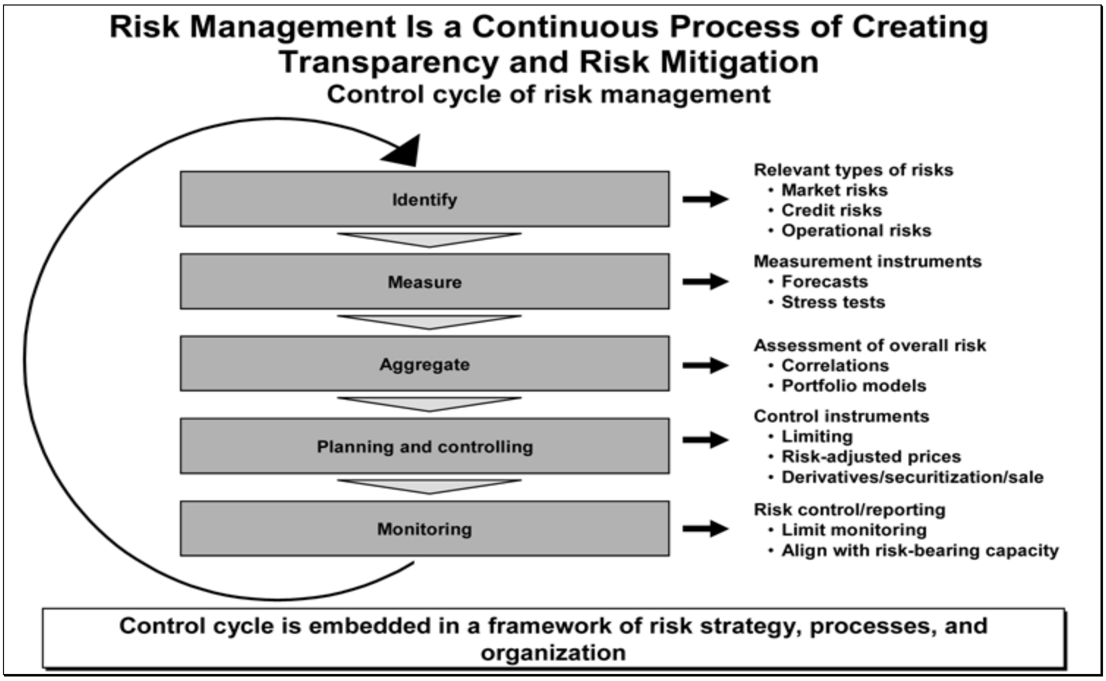

FIGURE 1.4: RISK MANAGEMENT PROCESS

(Source: Oesterreichische National Bank (Austria) Guidelines, 2004)

Risk management is a key to prudent banking practice. The primary risk exposures that a bank faces are the credit risk, market risk, and operational risk (Figures 1.4 & 1.5).

Credit risk is the risk of default by borrowers in debt servicing. Credit risk of a loan or other exposure during a given period includes both probability of default and diminution in the value of loan due to actual or expected default.

Market risk is the expected loss due to adverse movement in market variables like interest rates, exchange rates and other asset prices (Raghavan, 2003). Market risk is the risk to the bank's earnings and capital due to changes in the market level of interest rates, prices of securities, foreign exchange, equities and volatilities in their prices, and is closely related with liquidity and systematic risk (Raghavan, 2003). Liquidity risk arises due to liquidity crunch or that a given security or asset cannot be traded promptly in the market (e.g. to prevent losses) (Beier, 2010). Systematic risk arises due to macroeconomic variables. The global financial crisis mostly happens in the areas of a trading book /off balance sheet derivatives / market risk and inadequate liquidity risk management.

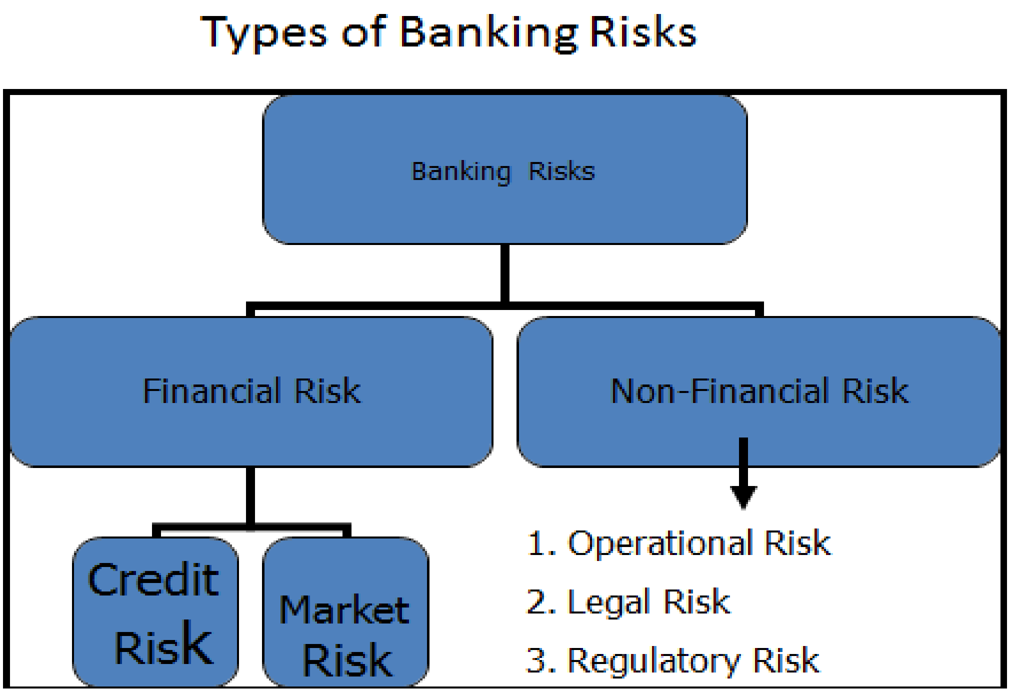

FIGURE 1.5: BANKING RISK

Operational risk arises out of inadequate or failed internal systems and processes, people, and external events. It is unexpected loss resulting from human error, fraud, process failure, technology break down or external factors.

Legal and regulatory risks arising out of unexpected court verdicts or government legislations affecting banks' borrowers are also sources of banking risk.

1.4 CREDIT RISK

In the present day volatile business environment, credit risk is a bank's primary risk area. Credit risk is the risk of default by borrowers or obligors in payment of interest or repayment of loans. The default may be due to inability or unwillingness of a borrower to meet his contractual obligations. Credit risk also arises due to the reduction in credit ratings of a obligor or a counterparty.

Credit risk in a bank's loan portfolio may be counterparty risk, intrinsic risk, and concentration risk. Counterparty risk is a risk of default in individual loan transactions, also called transaction risk, and can be mitigated by loan appraisal and continuous loan review. The intrinsic risk is inherent in individual lines of business or industries like commercial real estate and capital market transactions. Concentration risk is the aggregation of the transaction and intrinsic risks within a loan portfolio and results from the concentration of borrowers from the same industry, regions or same lines of business. Concentration risk within a loan portfolio determines the magnitude of problems a bank will experience under adverse circumstances (simultaneous default) and is measured in terms of assets correlation. Various credit portfolio models differ in the way in which correlation values are derived and applied. Credit portfolio risk can be mitigated by portfolio diversification geographic or business-wise, prudential limits, single/group borrower norms.

Credit risk is inherent in the business of lending funds for business operations. The primary risk faced by banks and financial institutions is credit risk which arises due to default when a firm fails to service its debt obligations (Bandyopadhyay, 2007). Banks need to predict the possibility of default of a potential counterparty before they extend a loan (Atiya, 2001). The default is not an abrupt process to happen overnight (Raghavan, 2003). Borrower's credit worthiness and asset quality decline gradually, known as migration (Raghavan, 2003). Warning signals start appearing in his financial statements, credit ratings, stock prices, etc. The default is the ultimate credit migration (Raghavan, 2003). Thus, the credit assessment in a bank should not be limited to the probability of default estimation at a given horizon but also reflect its variability through time and its sensitivity to the economic fundamentals. The probability of default increases or credit quality deteriorates as borrower's credit rating downgrades.

1.5 CREDIT LOSSES

Credit losses are economic losses from the failure of the counterparty or borrower. Credit losses are both customer and facility specific. Credit losses fluctuate over time and with micro and macroeconomic conditions of the borrower. These can be statistically measured in terms of long run average loss level and standard deviation or volatility of credit losses. Credit losses arising due to deterioration in credit quality of the borrower are of three types-

- Expected Loss (EL)
- Unexpected Loss (UL)
- Exceptional Loss

Expected loss is a function of the probability of default (PD), loss given default (LGD), and exposure at default (EAD) in a given loan transaction.

$$\text{Expected Loss (EL)} = PD * EAD * LGD$$

Two different loans to the same customer can have a very different expected loss (EL) due to differences in PD, LGD, and EAD. EL does not constitute a risk. Expected losses are incorporated in risk-based pricing of loans and loan loss provisioning. EL can be aggregated at various levels (e.g. individual loan or entire credit portfolio), although it is typically calculated at the transaction level. It is normally mentioned either as an absolute amount or as a percentage of transaction size. It is also both customer and facility specific since two different loans to the same customer can have a very different EL due to differences in EAD and LGD. "It is important to note that EL (or, for that matter, credit quality) does not by itself constitute risk; if losses always equaled their expected levels, then there would be no uncertainty. Instead, EL should be viewed as an anticipated "cost of doing business" and should, therefore, be incorporated in loan pricing and ex-ante provisioning" (Stephanou &Mendoza, 2005).

Unexpected loss is the standard deviation (σ) of expected loss. It is the estimated volatility of the potential loss in value of the assets around its EL. Banks are exposed to a portfolio of risky assets that are subject to default rates of varying degrees and severity. It is a measure of uncertainty inherent in loan estimate (difficult to know their timing and severity). It represents volatility/standard deviation of expected loss or simply the volatility in the components of EL.

$$\text{Unexpected Loss (UL)} = \sigma\ (PD*EAD*LGD)$$

PD or probability of default is the likelihood that default will take place over a specified time horizon generally one year.

EAD or exposure at default is the amount owed by the counterparty at the moment of default.

LGD or loss given default is the fraction of the exposure, net of any recoveries, which will be lost following a default event. LGD= (1-Recovery Rate).

Recovery Rates are bank specific and depend on seniority of borrowing, collateral value, industry, economic cycle, and credit rating of the borrower. Banks can calculate recovery rates by their historical experience in recovery in the event of default. During economic downturns, losses on the defaulted loans are likely to be higher than the normal business conditions.

Credit risk, in fact, arises from variations in the actual loss levels, which give rise to the unexpected loss (UL). Statistically speaking, UL is simply the standard deviation of EL (Figure 1.6). Regulatory bank capital or a bank’s capital adequacy ratio cushions a bank against loss volatility (UL) at a certain confidence level.

Exceptional losses are due to exceptional but plausible events and are managed through sensitivity analysis and stress testing of credit risk models by banks. Exceptional losses cause bank failures.

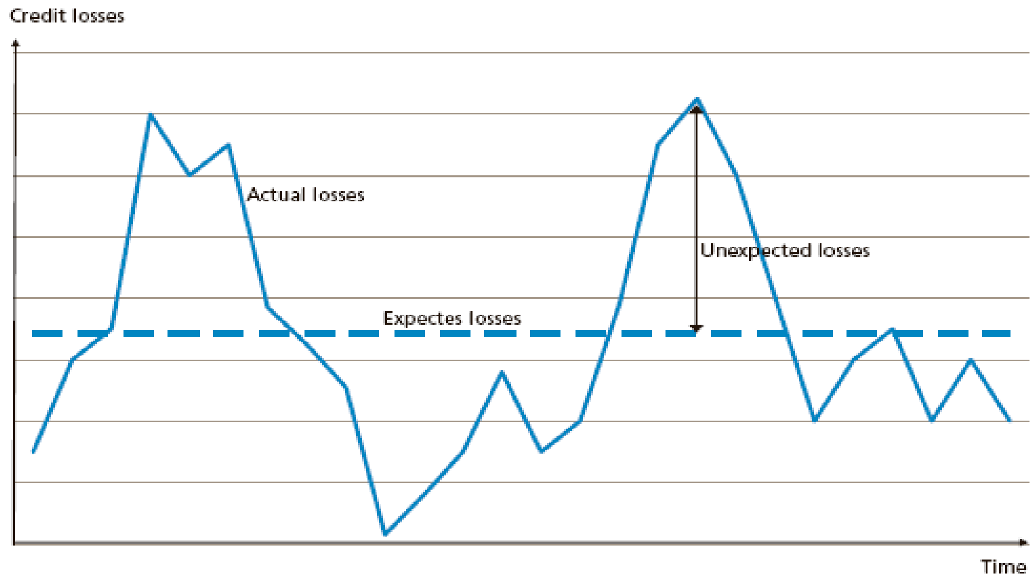

FIGURE 1.6: BANKS CREDIT LOSSES OVER TIME

(Source: NIBM, Pune, www.nibmindia.org.in)

According to Hirtle et al. (2001), in practice, banks concentrate on two such loss figures: expected loss and unexpected loss. Expected loss is the mean of the loss distribution and represents the amount that a bank expects to lose on average on its credit portfolio. Unexpected loss, in contrast, is a measure of the variability in credit losses, or the credit risk inherent in the portfolio. Unexpected loss is computed as the losses associated with some high percentile of the loss distribution (for example, the 99.9th percentile) minus expected loss. A high percentile of the distribution is chosen so that the resulting risk estimates will cover all but the most extreme events (Hirtle et al., 2001).

1.6 CREDIT RISK MANAGEMENT

Credit risk management involves a sound credit policy, credit analysis, risk rating, risk-based loan pricing, collateral management, credit collections, and a creation of loan loss provisions, risk mitigation, risk diversification and regulatory compliance, to manage various types of credit losses.

Credit risk management by banks shall be robust enough that it can select right loan applicants and can give early warning signals of default predictions. Though specific credit risk management practices may differ among banks depending on their size, nature, risk appetite, risk bearing capacity and complexities of their credit activities, a comprehensive credit risk mitigation, and management program shall address these five areas:

(i) Establishing an appropriate credit risk identification system.

(ii) Operating a sound credit - granting process including risk rating/ credit scoring models.

(iii) Appropriate credit administrative, measurement and monitoring processes.

(iv) Loan review mechanism.

(v) Adequate credit risk control and regulatory compliance (RBI's prudential norms).

1.7 RBI FRAMEWORK FOR CREDIT RISK MANAGEMENT

RBI prudential guidelines for effective credit risk management in Indian banks are in the form of:

1. Exposure norms to contain concentration risk.

2. Basel norms for risk-based supervision and maintaining capital adequacy standards.

3. Income recognition, assets classification and provisioning norms for identification and control of non-performing loans.

1.7.1 Exposure Norms

As a prudential measure aimed at better risk management and avoidance of concentration of credit risks, the Reserve Bank of India (2013 & 2015) has advised Indian banks to fix limits on their exposure to specific industry or sectors and has prescribed regulatory limits on banks' exposure to individual and group borrowers. In addition, banks are required to observe certain statutory and regulatory exposure limits in respect of advances against investments in shares, convertible debentures /bonds, units of equity-oriented mutual funds and all exposures to Venture Capital Funds (RBI, 2013&15). As per RBI guidelines on Exposure Norms (RBI, 2013&15), banks should comply with the following guidelines relating to credit exposures to individual/group borrowers:

- The exposure ceiling limits would be 15 percent of capital funds in case of a single borrower and 40 percent of capital funds in the case of a borrower group. The capital funds for the purpose will comprise of Tier I and Tier II capital as defined under capital adequacy standards.

- Credit exposure to a single borrower may exceed the exposure norm of 15 percent of the bank's capital funds by an additional 5 percent (i.e. up to 20 percent) provided the additional credit exposure is on account of the extension of credit to infrastructure projects. Credit exposure to borrowers belonging to a group may exceed the exposure norm of 40 percent of the bank's capital funds by an additional 10 percent (i.e., up to 50 percent), provided the additional credit exposure is on account of the extension of credit to infrastructure projects.

- In addition to the exposure permitted above, banks may, in exceptional circumstances, with the approval of their Boards, consider enhancement of the exposure to a borrower (single as well as group) up to a further five percent of capital funds subject to the borrower consenting to the banks making appropriate disclosures in their Annual Reports.

- The exposure limit in respect of single borrower has been raised to twenty-five percent of the capital funds, only in respect of Oil Companies who have been issued Oil Bonds (which do not have SLR- Statutory Liquidity Ratio- status) by the Government of India.

- The bank should make appropriate disclosures in the 'Notes on account' of the annual financial statements in respect of the exposures where the bank had exceeded the prudential exposure limits during the year.

1.7.2 Basel Norms - Regulatory Wisdom in Credit Risk Management

In its stride for sound global banking practices, Bank for International Settlements (BIS) and the Reserve Bank of India (RBI) have brought about a paradigm shift in Indian banking practices in risk management in the form of Basel Accords.

The Bank for International Settlements (BIS) is an international organization of central banks which exists to foster cooperation among central banks and other agencies in pursuit of monetary and financial stability to regulate capital adequacy and is based in Basel, Switzerland. The BIS sets requirements on two categories of capital, **Tier 1 capital,** and total capital. Tier 1 capital is the book value of its stock plus retained earnings. **Tier 2 capital** is loan loss reserves plus subordinated debt. Total capital is the sum of Tier 1 and Tier 2 capital. Tier 1 capital must be at least 4% of total risk-weighted assets. Total capital must be at least 8% of total risk-weighted assets. When a bank creates a deposit to fund a loan, its assets and liabilities increase equally, with no increase in equity. That causes its capital ratio to drop. Thus, the capital requirement limits the total amount of credit that a bank may issue. It is important to note that the capital requirement applies to assets while the bank reserve requirement applies to liabilities. Tier 1 capital is the core measure of a bank's financial strength from a regulator's point of view.

The Basel Committee on Banking Supervision (BCBS) provides a global forum for regular cooperation on banking supervisory matters. BCBS standards serve as a benchmark for national and regional regulators, which are responsible for implementing the standards within their own jurisdiction. Consistency in the adoption and implementation of Basel standards is critical to improving the resilience of the global banking system, promoting public confidence in prudential ratios and encouraging a predictable and transparent regulatory environment for internationally active banks Therefore, the Basel Committee assesses individual jurisdictions on its regulatory capital regime and the consistency of its capital regime with the international minimum standards established by the Basel Committee (BIS, 2015).

Basel I (1988) introduced a risk - weighted approach to capital adequacy and arrived at a consensus of 8% as the minimum capital adequacy ratio to effectively manage credit risk and market risk confronting banks. Basel II (2004) extended risk management to operational risk and Basel III (2009) to systematic risk and liquidity risk.

It is mainly through **Basel II guidelines** that RBI aims to improve the credit risk management systems and processes of the Indian banks. The structure of Basel II, with regards credit risk management, consists of three mutually reinforcing pillars:

Pillar 1 - Minimum Capital Requirement: A Capital Adequacy Ratio or CRAR of 8% by Basel and 9% by RBI and the prescribed Tier I Capital Adequacy Ratio of six percent.

Pillar 1 offer three distinct options or approaches for computing CRAR (Capital to Risk- Adjusted Assets or Risk- Weighted Assets Ratio) or capital requirement for credit risk, based on risk sensitivity and stage of development of a bank's operations.

(i) Standardized approach – The bank allocates a risk – weight to each asset class like 100% of unrated corporate loans, 20% of inter-bank loans, zero risk weight to sovereign exposures, others based on ratings assigned by external credit rating agencies to arrive at total risk-weighted assets. RBI has accredited six domestic credit rating agencies, viz. CARE, CRISIL, FITCH India, ICRA, Brickworks and SMERA, and three international credit rating agencies, FITCH, Moody's and Standard & Poor's, for the purpose of risk-weighting the bank's claims for capital adequacy. The long-term and short-term ratings issued by these agencies have been mapped to appropriate risk weights applicable as per the standardized approach under Basel II framework. An example of their long-term ratings translated into standardized approach risk weights is shown in Table 1.1.

TABLE 1.1: MAPPING CREDIT RATINGS INTO RISK WEIGHTS

	Standardized Approach risk weights
AAA	20%
AA	30%
A	50%
BBB	100%
BB & below	150%
Unrated	100%

(ii) Foundation Internal Rating Based Approach (FIRB) - Banks themselves rate the borrowers and are expected to provide their own estimates of Probability of Default (PD) and rely on supervisory estimates for other risk components, namely Loss Given Default (LGD), Exposure at Default (EAD) and Maturity(M).

(iii) Advanced Internal Rating Based Approach (AIRB) - The range of risk weights are more diversified. Banks shall provide their own estimates of PD, LGD, EAD, and M.

Pillar 2 - Supervisory Review Process: A bank shall ensure that it has sufficient capital and undertakes credit risk stress test. RBI will also examine that capital held by the bank commensurate with the bank's overall risk profile.

Pillar 3 - Market Discipline: The aim is to develop a set of disclosure requirements regarding capital adequacy of the institution. Market discipline provides for a consistent and comprehensive disclosure framework that enhances comparability. Both qualitative and quantitative disclosures are to be made as at end March each year along with the annual financial statements as "Basel II disclosures".

IRB approaches (ii and iii) above allow banks to use their own internal estimates for some or all of the credit risk components - **Probability of default (PD), Loss Given Default (LGD), Exposure at Default (EAD), and Effective Maturity (M)** in determining the capital requirement for a given credit exposure, and thus risk-weighted assets.

Risk-Weighted Assets = K * 12.5 * EAD

K = Capital requirement which shall be function of LGD, PD, effective Maturity, and

assets correlation and shall be calculated for each asset class.

$$K = \left[LGD * N\left\{\frac{G(PD)}{(1-R)^{0.5}} + \frac{(R)^{0.5}}{(1-R)^{0.5}} * G(0.999)\right\} - LGD * PD\right] * \left[\frac{1+(M-2.5)*b}{1-1.5*b}\right]$$

M = Remaining effective maturity of the exposure.

b = Maturity adjustment coefficient = $\{0.11852-0.05478 \text{ X Ln (PD)}\}^2$.

K = Minimum capital requirement expressed as a percentage of EAD for the exposure.

the exposure.

R = Assets Correlation (between borrower's exposure and systematic risk factor).

Ln = Natural logarithm.

G(3) = Inverse cumulative normal distribution for a standard normal

random variable (i.e. N(x)=Z).

N(x) = Cumulative normal distribution for a standard normal random variable.

$$R = \text{Asset Correlation} = 0.12 \text{ X } \left\{\frac{1-e^{(-50*PD)}}{1-e^{-50}}\right\} + 0.24 \text{ X } \left[1 - \left\{\frac{1-e^{(-50*PD)}}{1-e^{-50}}\right\}\right]$$

Firm – Size Adjustment for Small and Medium – Sized Entities (SMEs)

The firm size of the borrower is assumed to have an impact on correlation, and the same is therefore, adjusted in the corporate risk weight formula. The firm size adjustment is, however, applicable to SME borrowers only. The SME borrower under corporate asset class will be defined as those whom the banking exposure is above Rupees five crore but up to Rupees 25 crore, and who are broadly associated with SME characteristics. The firm size adjustment is based on the assumption that in the event of economic downturn, an exposure to SME borrower may be less correlated to the systematic risk than an exposure to a bigger corporate and hence the reduction in asset correlation.

IRB approach to the capital calculation for credit risk is based upon measures of unexpected losses (UL) and expected losses (EL). The risk components and risk weight functions (equations by which risk components are transferred into capital requirements and risk-weighted assets) would help to calculate capital requirements for unexpected losses. For expected losses, the bank must compare the sufficiency of eligible provisions against expected loss amounts and adjust the regulatory capital accordingly.

The Probability of Default (PD) -The probability of default is the core component of risk weight functions. Probability of default is the probability that the borrower will default within one- year horizon. PD estimation has to be borrower specific, i.e., all exposures to a single borrower will be assigned a single PD. For calculation of long-term average PD, banks may use one or more of the three specific, techniques:

- Internal default experience - The bank may use its own data or pooled data across institutions in its estimate of PD.
- Mapping to external data - Banks may map their internal grades to the scale used by an external credit rating agency and then attribute the default rate observed for the external credit rating agency's grade to the bank's grades.
- Statistical default models - The bank may use a simple average of PD estimates or such estimates as drawn from statistical default prediction models.

PD is a quantitative measure of default risk. Default probability of a borrower can be analyzed and monitored through 'Transition Matrix'. Transition matrix represents moving probabilities from one rating level to all other rating levels within time span of one year, and can map rating migrations in rating grades and across sectors and industries.

Ultimately, the advanced approaches of Basel II will reduce the regulatory capital requirement for banks (Figure 1.7).

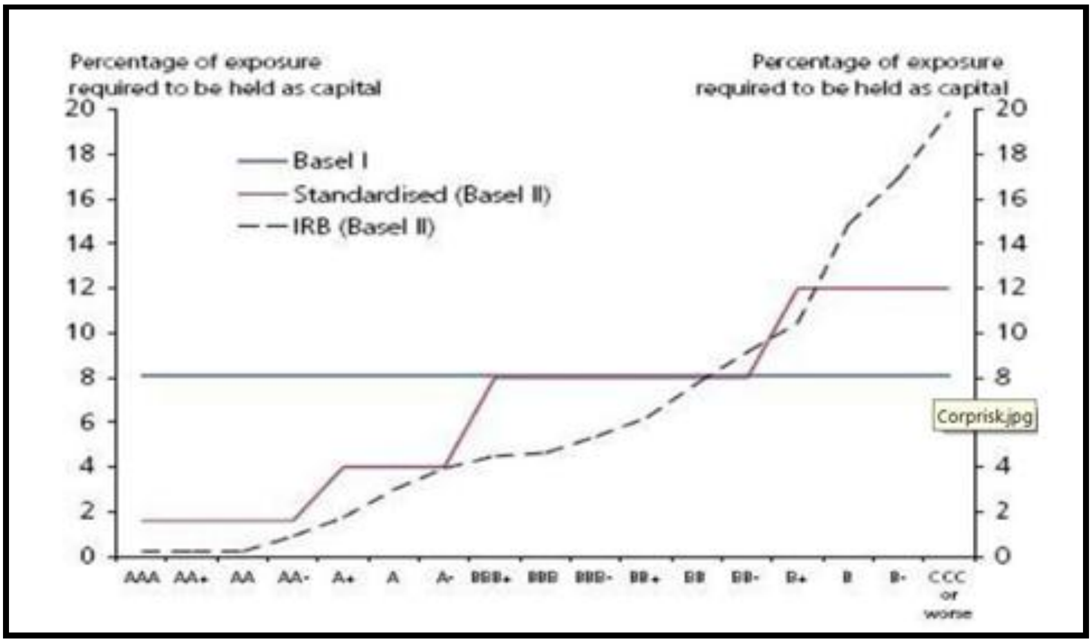

Figure 1.7: REDUCED MINIMUM CAPITAL REQUIREMENT

(Source: NIBM, Pune, www.nibmindia.com)

1.7.3 RBI - Prudential Norms on Income Recognition, Assets' Classification and Provisioning pertaining to Advances

Reserve Bank of India (2013 & 2015) provided the following guidelines on income recognition, classification of non-performing assets into sub-standard, doubtful and loss assets, and provisioning norms pertaining to those advances for greater consistency and transparency in the published accounts and financial statements:

Income Recognition

Banks shall recognize income on accrual basis in respect of standard advances. In the case of non-performing assets, banks shall recognize income only on realization on the cash basis.

Reversal of income - If any advance, including bills purchased and discounted, becomes NPA, the entire interest accrued and credited to income account in the past periods, should be reversed if the same is not realized. This will apply to government-guaranteed accounts also.

Asset Classification

A non-performing asset (NPA) is a loan or an advance where:

1. Interest and/ or installment of principal remain overdue for a period of more than 90 days in respect of a term loan.

2. The account remains ‘out of order’ in respect of an Overdraft/Cash Credit (OD/CC). An account should be treated as 'out of order' if the outstanding balance remains continuously in excess of the sanctioned limit/drawing power.

3. The bill remains overdue for a period of more than 90 days in the case of bills purchased and discounted.

Banks are required to classify non- performing assets further into the following three categories based on the period for which the asset has remained non-performing and the realization of the dues:

i. Sub- standard Assets - A sub-standard asset would be one, which has remained NPA for a period of less than or equal to 12 months. Such an asset will have well

- defined credit weaknesses that jeopardize the liquidation of the debt and are characterized by the distinct possibility that the banks will sustain some loss if deficiencies are not corrected.

ii. Doubtful Assets - an asset would be classified as doubtful if it has remained in the sub-standard category for a period of 12 months. A loan classified as doubtful has all the weaknesses inherent in assets that were classified as sub-standard, with the added characteristics that the weaknesses make collection or liquidation in full, – on the basis of currently known facts, conditions, and values – highly questionable and improbable.

iii. Loss Assets - A loss asset is one where loss has been identified by the bank or internal or external auditors or the RBI inspection, but the amount has not been written off wholly. In other words, such an asset is considered uncollectible and of such little value that its continuance as a bankable asset is not warranted although there may be some salvage or recovery value.

Guidelines for classification of assets:

- If arrears of interest and principal are paid by the borrower in the case of loan accounts classified as NPAs, the account should no longer be treated as non-performing and may be classified as 'standard' account.
- Asset Classification to be borrower -wise and not facility -wise
- The asset classification of borrower accounts where a solitary or a few credits are recorded before the balance sheet date should be handled with care and without scope for subjectivity. Where the account indicates inherent weakness on the basis of the data available, the account should be deemed as an NPA.

Provisioning Norms

In conformity with the prudential norms, provisions should be made on the non-performing assets by classification of assets into prescribed categories.

Loss assets - Loss assets should be written off. If loss assets are permitted to remain in the books for any reason, 100 percent of the outstanding should be provided for.

Doubtful assets - 100 percent of the extent to which the advance is not covered by the realizable value of the security, and with regard to the secured portion, provision may be made on the following basis - at the rates ranging from 25 percent to 100 percent of the secured portion depending upon the period for which the asset has remained doubtful.

Substandard assets - A general provision of 15 percent on total outstanding should be made.

1.8 SECTOR-WISE COMMERCIAL LENDING

Most Indian banks adopt borrower segmentation for credit delivery and control of business lending. Loans to micro enterprises are assessed as retail loans along with housing and personal loans category. Loans to small and medium enterprises (**SMEs**) along with corporate loans are assessed under the non-retail category. Again corporate customers are identified as **Large Corporates** and **Mid-corporates.** Further segmentation is also undertaken under each category for manufacturing, trading, services, new projects, infrastructure lending, real estate developers, capital market brokers, etc., for specialized credit risk management practices.

Indian banks have different definitions for micro, small, and medium enterprises (MSMEs), mid and large corporates. For example, some banks adopt the definitions given by the Micro, Small, and Medium Enterprises Development Act, 2006, and other have their own definitions for these enterprises for risk management purposes. According to the MSME Act, a small- scale industrial (SSI) unit is an industrial undertaking in which investment in plant and machinery, does not exceed Rs.1 crore except in respect of certain specified items under hosiery, hand tools, drugs and pharmaceuticals, stationery items and sports goods where this investment limit has been enhanced to Rs.5 crore. Units with investment in plant and machinery more than the SSI limit and up to Rs.10 crore may be treated as Medium Enterprises (ME). Only SSI financing will be included in priority sector, financing of medium enterprises will be non-priority sector financing. Some banks like Bank of Baroda classify companies having annual sales turnover of over Rs. 500 crore as Large Corporate, those having annual sales turnover between Rs. 100 crore to 500 crore are classified as Mid Corporate, and those having annual sales turnover between one crore to 100 crore as SMEs. The country's largest lender, State Bank of India (SBI), defines a mid-sized company as one with an annual turnover of Rs. 50 crore to Rs. 500 crore (Rs. 500 million to Rs. 5 billion). Thus, there are bank-wise definitions and lending strategies for various business groups.

Each business group has a different and significant role in India’s economic development, and its strengths and weaknesses.

Small and Medium Enterprises (SMEs) play a significant role in the economy in terms of balanced and sustainable growth, employment generation, development of entrepreneurial skills, and contribution to export earnings. The SME sector, contributes around 40 percent of industrial output, 35 percent of total exports and also being the second largest employment provider next to agriculture, and is expected to grow by around 15 percent (www.dcmsme.gov.in, accessed on 18.09.14). Government's policy initiatives, like enactment of the new Micro, Small, and Medium Enterprises Development Act (MSMED Act), 2006, pruning of reserved SSI (Small Scale Industries) list, advising Financial Institutions to increase their flow of credit to the SME sector, promotion of venture capital, receivable financing, leasing finance, soft loans, grants, setting up of finance companies with state participation, microfinance program, etc., have been taken in earnest for boosting entrepreneurship, investment and growth in SMEs. While the government and other development agencies strive to promote SMEs, the percentage of SMEs that are served by the banking industry remains small. There are around 350 clusters of Small and Medium Enterprises with different characteristics like Horizontal Clusters, Vertically Integrated Clusters, Mixed Clusters, etc., and 2000 rural and artisan based clusters in India. Some Indian SSE clusters are so big that they account for 90 percent of India's total production output in selected products (www.dcmsme.gov.in, accessed on 18.09.14). For example, the knitwear clusters of Ludhiana. Almost the entire gems and jewelry exports are from the clusters of Surat and Mumbai. Similarly, the clusters of Chennai, Agra and Kolkata are well known for leather and leather products. The stage of development of cluster determines the kind of products they would require from the banking industry. Banks are facing challenges as they are expected to not only assess the fund requirements but also become a partner in nurturing and shaping the growth of these SME clusters in India. This has created immense pressure on banks used to evaluate proposals primarily based on collateral rather than growth cycle needs. Currently, banks utilize a decision-making process that evaluates many characteristics of the borrower including collateral, inventory, cash flow, history of the company, character of the proprietor, ratings from outside agencies where available, etc. The key issues in SME lending are information asymmetry about the business, moral hazard, lack of risk assessment models leading to under or overpricing and in some cases overdependence on bank credit. The complexities involved in SME financing are, therefore, immense.

Mid-Corporate Group continues to play a major role in India's economic development. Large and successful SMEs have evolved themselves as mid-corporate business groups. Mid-corporates have emerged as a business segment where a sharper focus from the banking system may be required. Appraisal and assessment of credit risk of mid-corporates need monitoring their business environment and identify lending opportunities. The Business Standard, Mumbai (07.09.2007) reported that mid-sized corporate loan defaults were rising. Banks were facing increasing delinquencies by overleveraged mid-sized companies, caught in hardships due to changes in their operating environment. The defaulting mid-sized companies had availed of large amounts of cheaper credit during the lending boom of the last few years, helped by their excellent credit history. These companies were paying a price for over-leveraging themselves, with interest rates having risen sharply in the last few years. Certain export-dependent segments were taking a hit due to the slackening of demand from target markets and a sales slowdown in segments such as automobiles. However, since each bank has a different definition of mid-sized companies, an estimation of defaults for the banking industry in this business group as a whole is not available.

Large corporates are large companies, big business groups, multinationals which have a strong presence in major sectors – power, steel, infrastructure development etc.

IDBI Bank treats companies with annual sales turnover of Rupees 100 crore above as large corporates, SBI and Bank of Baroda define them with annual sales turnover of Rupees 500 crore and above. Other banks define them in other ways. Large companies have high asset correlation or high linkages between transactional or counterparty default risk with systematic or macroeconomic factors. They also create high concentration risk in banks' credit portfolio. Managing portfolio credit risk or joint default and correlated credit migrations are part of managing large corporate loans credit risk.

1.9 CREDIT RISK MODELING

The objective of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposures within acceptable parameters (Raghavan, 2003). Banks need to manage credit risk inherent in the entire portfolio as well as risk in individual credits or transactions. Credit risk models are the tools that assist banks in quantifying, aggregating and managing risk across categories of loans/exposures, sectors, industries and product lines. Banks shall need efficient data acquisition and data management to validate their credit risk and credit-scoring models and document them for regulatory approvals to achieve Basel II IRB compliance. IRB approaches allow banks to use statistical and mechanical models to estimate Probability of Default, provided these models have good predictive powers, free from any material bias and data used is representative of the population of the bank's existing obligors or borrowers.

In very general terms, the purpose of credit risk model is to estimate the probability distribution of future credit losses on a bank's portfolio. (Hirtle, 2001).

1.10 CREDIT RATING OR CREDIT-SCORING MODELS

Credit-scoring models discriminate between good and bad loan applicants and arrive at a cut-off point to accept or reject borrower's claims, based on ratings and risk strategy of the banks. Credit ratings are assigned on the basis of key risk parameters or risk drivers. Credit ratings indicate risk (default risk and recovery risk) associated with a credit exposure, and whether the loans will be in investment or non-investment grade.

Credit rating or scoring models can be classified into six categories: judgment – based methods, decision tree, artificial neural networks, statistical, structural and hybrid models.

A. Expert Judgment Systems.

Traditionally bankers have relied on 5Cs (character, capital, capacity, collateral and cyclical conditions) to assess the credit quality of their borrowers. Expert loan officers use the quantitative information and their tacit knowledge to predict borrower's capacity to repay. Despite the several advantages, it has disadvantage of subjectivity and difficulty in transformation of tacit knowledge into organizational knowledge.

B. Decision Tree or Recursive Partitioning Analysis.

The Decision Tree or Recursive Partitioning Analysis creates a tree-based classification model. It classifies cases into groups or predicts values of a dependent (target) variable based on values of independent (predictor) variables. Decision Tree uses independent variables as step - wise discriminators to divide good and distressed borrowers, based on a cut-point and lowest expected misclassification costs. The method provides validation tools for exploratory and confirmatory classification analysis. The procedure can be used for:

1. Segmentation- Identify persons who are likely to be members of a particular group.

2. Stratification- Assign cases into one of several categories, such as high, medium, and low-risk groups.

3. Prediction- Create rules to predict future events, such as the likelihood that someone will default on a loan or the potential resale value of a vehicle or home.

4. Data reduction and variable screening- Select a useful subset of predictors from a large set of variables for use in building a formal parametric model.

5. Interaction identification- Identify relationships that pertain only to specific subgroups and specify these in a formal parametric model.

C. Artificial Neural Networks (ANN).

Artificial Neural Networks are machine-learning techniques. Multilayer feed - forward neural nets, with input - hidden – output nodes, using back propagation algorithm, have been found to give highest accurate classification of good and bad loans as well as have lowest misclassification costs (Matoussi, 2009), (Angelini,2006). Neural networks can give good results even on a noisy data (Haykins, 2009). This approach is very useful in retail loans and small business lending decisions. However, their basic limitation is being a black –box type of method which produces output without explaining the process involved in hidden layers (Mittal, 2011). Moreover, ANNs require training and validation with real loan data.

D. Statistical Methods.

1. Altman's Z- score model.

This is the most popular method of credit scoring. Altman's Z- score model is based on five ratios : Working Capital/Total Assets Ratio, Retained Earnings/ Total Assets Ratio, Earnings before taxes +Interest/ Total Assets Ratio, Market Value of Equity/ Book Value of Long Term Debt Ratio, Sales/ Total Assets Ratio. A Z- score more than 2.99 indicates a low default risk. A Z-score within 1.8 to 2.7 indicates indeterminate default risk, and Z-score less than 1.81 indicates high default risk. This model can predict borrower's bankruptcy two years in advance if used on lagged data (Chijoriga, 2011). The model is, however, criticized for ignoring macroeconomic factors.

2. Multiple Discriminant Analysis.

Researchers widely use multivariate discriminant analysis (MDA), the Altman's base model, within a credit assessment procedure with several independent creditworthiness criteria to distinguish between solvent and insolvent borrowers as accurately as possible.

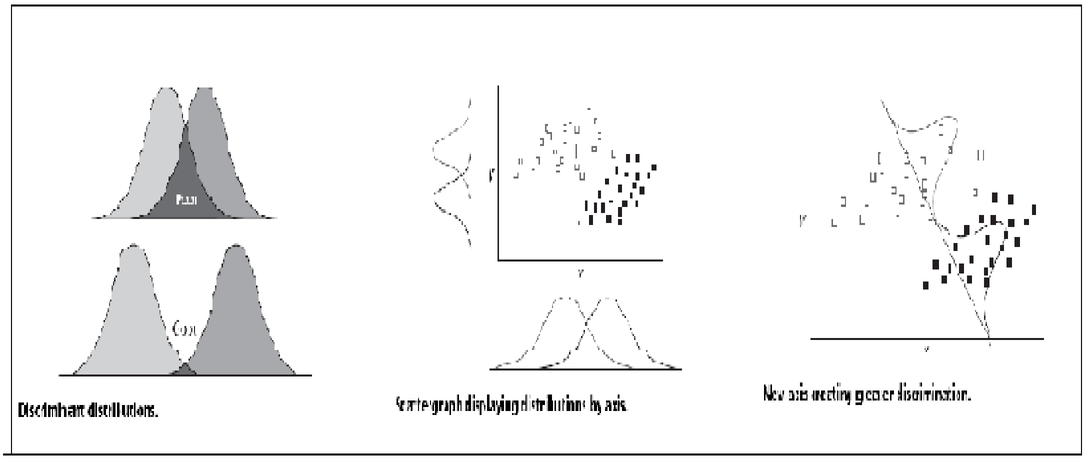

FIGURE 1.8: MDA SCATTER PLOTS

(Source: uk.sagepub.com.discriminant.analysis.pdf)

Discriminant analysis creates an equation which will minimize the possibility of misclassifying cases into respective groups or categories (Figures 1.8 & 1.9).

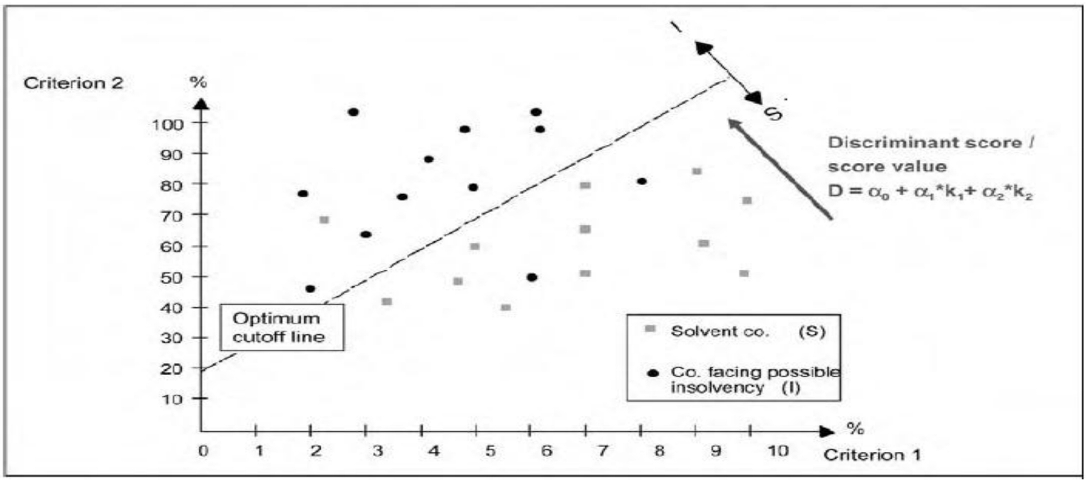

FIGURE 1.9: LINEAR DISCRIMINANT ANALYSIS

(Source: Oesterreichische, 2004)

3. Logistic Regression.

Onesos in 1980 was the first to apply the logistic model to bankruptcy prediction research. Unlike MDA (Multi Discriminant Analysis), the logistic model does not require multivariate normality or the equality of covariance matrices of two populations. Logistic Regression applies Maximum Likelihood Estimation (MLE) procedure for estimation of the parameters. Logit Model can be used by banks directly to estimate the probability of default (PD). It is also a widely used method in credit risk estimation.

E. & F. Structural and Hybrid Models

Structural models use liability structure of the firms along with market prices of its assets to predict default risk whereas hybrid models use statistical models along with market prices of its assets to predict default risk and portfolio risk. Examples are

KMV Expected Default Frequency Model, Black, and Scholes Option Pricing Model (Bandyopadhyay, 2007).

RAROC Model- Another increasingly popular model used by banks is to evaluate the return on a loan to a business borrower is the **Risk-Adjusted Return on Capital (RAROC)** Model. This model, originally pioneered by Bankers Trust (acquired by Deutsche Bank in 1998) is now adopted by virtually all the large banks in Europe and the US. The essential idea behind RAROC is that rather than evaluating the actual promised annual cash flow on a loan as a percentage of the amount lent or ROA or ROE, the lenders balance the loan's expected income against the loan's expected risk.

The RAROC Model is basically represented by:

RAROC = (One year net income on loan)/ (Risk-adjusted assets)

For denominator of RAROC, duration approach can be used to estimate worst case loss in value of the loan. RAROC system provides a uniform measure of performance and bank management can use this measure to evaluate performance of loans for capital budgeting, risk pricing and as an input to the compensation system used for credit managers.

1.11 CRM CHALLENGES

The Indian commercial banks are stressed on account of deteriorating asset quality and rising defaults in loans to business and industry, causing profitability and liquidity pressures. Driven by RBI pressures and profitability thrust, it is imperative for Indian banks especially the public sector banks to focus on their core credit risk management practices and find the problem areas. The adequacy, efficiency and effectiveness of internal credit risk management systems of Indian banks shall be essential in achieving good quality credit assets and minimizing credit losses. A sound credit risk management needs both efficient credit delivery and credit recovery systems. Successful credit risk management (CRM) in Indian public sector banks shall thus, require understanding the issues on credit risk conceptualization, credit risk factors, credit risk analysis and assessment, loan reviews, risk mitigation and control processes.

1.12 THE PRESENT STUDY

This study empirically evaluates the credit risk management practices of Indian public sector banks in the grant of commercial loans in fairly comprehensive manner and aims to find the grey areas which need a review and restructuring to improve banks' asset quality.

RBI observed that gross NPA ratio at system level increased mainly on account of deterioration in asset quality of the public sector banks and the spurt in NPAs could be attributed to the slowdown prevailing in the domestic economy as well as to the inadequate appraisal and monitoring of credit proposals (RBI 2011-14). Thus, this study focuses on public sector banks with research objectives to identify the characteristics and causes of credit risk, compare credit risk management practices of large and small public sector banks, analyze the extent to which these banks have implemented the Basel norms on credit risk management, evaluate the credit risk rating framework followed by them in credit risk assessment. The study also aims to design a credit risk assessment model for banks based on a comparison of existing and theoretical credit-scoring or rating models. The scope of the study has been limited to business loans to SMEs and mid-corporates.

The study uses secondary data such as RBI reports and banks loan statistics from

2008-15, to explore the characteristics of credit risk in Indian PSBs and to design a credit risk assessment model. Research on the other objectives is based on a structured questionnaire based survey on 337 credit and risk managers of 12 sample public sector banks in and around Delhi, during June to December 2013. The empirical analysis of managerial perceptions of three categories of credit managers - in large and small PSBs, in three hierarchical levels - junior, middle and senior level credit managers, and in three experience groups – ‘up to 7 years’, ‘8 to 20 years’ and ‘above 20 years’, has resulted in identification of core characteristics and causes of credit risk in these banks; in understanding the critical CRM problems and obstacles in large and small PSBs; in understanding the progress made by these banks in implementation of advanced Basel II approaches, and in critical evaluation of their internal credit risk assessment models.

1.13 SIGNIFICANT CONTRIBUTIONS OF THE STUDY

The study has identified the main characteristics of credit risk in Indian PSBs and has evaluated the credit risk in these banks in terms of their stressed assets. Stressed assets have included both gross non-performing and restructured loans as many restructured loans were converting into non-performing assets. The study has concluded that the sample PSBs are under high credit risk with their average stressed assets ratio of 8.35% during 2008-15, and 14.19% during 2014-15. The study has also concluded that size of the bank is a significant credit risk variable as small public sector banks have higher credit risk and are less satisfied with their credit risk management practices. The credit and risk managers in all PSBs are finding the liquidity and solvency risk of their commercial borrowers the most potent cause of credit risk and their industry risk the most challenging to manage. The study has observed statistically significant disagreement in various risk managerial levels indicating the need for better risk communication and development of their risk assessment potentials. The study has also designed a three group multivariate discriminant, Z-score model to predict credit risk in banking loans with fair accuracy.

1.14 LAYOUT OF THE STUDY

To present the research work, the full study has been divided into ten chapters. The **first chapter** introduces Indian public sector banks (PSBs), their risk environment, adoption of Basel norms by banks and their deteriorating asset quality and increasing credit risk. The review of literature of the studies conducted in India and other countries are reported in the **second chapter**. The **third chapter** explains the objectives of the study, the scope of the study, and the research methodology used to analyze and interpret the credit risk management practices in the Indian public sector banks. **Chapter four to nine** discuss in detail the data analysis and findings on each of the research objectives. **Chapter four** is regarding the characteristics of credit risk in Indian public sector banks. **Chapter five** analyzes the data to identify the causes of credit risk in these banks. **Chapter six** compares the credit risk management practices of large and small Indian public sector banks. **Chapter seven** evaluates the extent to which the public sector banks have implemented the Basel norms on credit risk. **Chapter eight** evaluates the existing credit risk assessment models of PSBs, and **Chapter nine** designs a credit risk assessment model using multiple discriminant analysis, based on the comparison of existing credit-scoring or rating models of Indian public sector banks. **Chapter ten** reports the conclusion of the study. It highlights the major findings, managerial implications, limitations of the study, reports the suggestions and recommendations for effective credit risk management in

Indian public sector banks, and defines the scope for future research in this field.

The next chapter is thus on the review of literature or previous studies on the subject to develop the theoretical framework of this study.

CHAPTER 2
REVIEW OF LITERATURE

2.1 INTRODUCTION

Banks need to manage their internal credit risk management systems to control transactional credit risk stemming from each loan transaction and to optimize their risk-based profits. Loans to business and industry are their critical risk area, impacting to a large extent the bank's margins, liquidity and asset quality. Studies have been undertaken in India and abroad on sound credit risk management practices, systems and procedures, risk measurement, factors causing credit risk, credit risk regulatory compliance, and non-performing assets in the grant of commercial loans by banks. These studies provide insight into the existing CRM practices in banks. To understand the research issues involved in a better manner, and find the research gap, the review of literature has been grouped under the following heads:

1. Defining credit risk.
2. Credit risk management processes and practices.
3. Credit risk measurement.
4. Risk-based supervision through Basel norms.
5. Determinants of credit risk.
6. Indicators of credit risk.
7. Bank's non-performing assets (NPAs).

8. Trends in NPAs in Indian public sector banks.

9. Credit risk vs. size of the bank.

2.2 DEFINING CREDIT RISK

Risk management is the cornerstone of prudent banking. Banks exist not for eliminating or lowering risk, but managing risk **(Ferguson, 2003).** Commercial banks are mainly faced with credit risk, and loans are the largest and the most obvious source of credit risk **(Al-Tamimi and Al-Mazrooei, 2007).**

Bank for International Settlements (2015) defined credit risk as the risk that a counterparty will fail to perform fully its financial obligations and can arise from multiple activities across sectors. For example, credit risk could arise from the risk of default on a loan or bond obligation, or from the risk of a guarantor, credit enhancement provider or derivative counterparty failing to meet its obligations.

According to **Ali, (2012)**, credit risk is uncertainty associated with non-payment of a monetary obligation. There are three types of credit risks such as default risk, down-grade risk, and credit spread risk. Default risk is related to actual non-payment of obligation. Down-grade risk is the probability that the credit rating will down-grade the issue or the firm. Credit spread risk is associated with the probability that credit spread of the issue will decrease. To measure credit risk effectively, an active trading market should exist. As no active trading markets are available for commercial loans generally and even so in Pakistan, the default risk becomes the most relevant type of credit risk facing commercial banks in Pakistan **(Ali, 2012).** Same applies to India also.

Beier (2010) stated that credit risk happens when a borrower defaults and is unable to make full payments. Double-default (or wrong-way) risk occurs when collateral is also impaired.

Oesterreichische National Bank, Austria (2004) defined credit or counterparty risk as the chance that a debtor or issuer of a financial instrument—whether an individual, a company or a counterparty will not repay principal and other investment-related cash flows according to the terms specified in a credit agreement.

Greuning and Bratanovic (2009) stated that the credit risk is the chance that the borrower will not repay or that the payment may be delayed or not made at all, which can cause cash flow problems and affect a bank's liquidity. The integrity and credibility of the lending process depend on objective credit decisions that ensure an acceptable risk level in relation to the expected returns. Despite innovation in the financial services sector, more than 70 percent of a bank's balance sheet generally relates to this aspect of risk management and for this reason, credit risk is the principal cause of bank failures.

Raghavan (2003 & 2005) - Credit Risk is measured through Probability of Default (PD) and Loss Given Default (LGD). Bank would estimate the PD associated with borrowers in each of the risk rating grades. However, default probabilities do not capture the risk that a bank might experience as an economic loss through deterioration in the quality of the loan book, rather than outright default.

Brown & Moles (2012) - Another important credit risk is industry risk, which is a form of concentration risk. This applies particularly when the domestic or international economy is in recession and the poor economic condition particularly affects certain industries. The reason industry structure may have credit consequences is the 'supply chain' within which most firms operate. For instance, a steel producer is involved with car manufacturers. This has two important consequences. If car sales decline, this affects manufacturers of motor vehicle components, together with the car manufacturers. Consequently, a producer with all its output destined for one industry finds it impossible to avoid industry risk exposure to that industry.

2.3 CREDIT RISK MANAGEMENT PROCESSES & PRACTICES

Prasad (2016) – Prevention is better than cure. Instead of putting more efforts on side effects of credit risk like providing more provisions, a decrease in net profit and net worth, attracting more Tier-I and Tier-II capital to maintain the required CRAR, etc., the banks should give more focus on "Quality of Lending." This is the only way or remedy or best solution to overcome all problems relating to the Credit Risk in the banks. 'Quality Control' of each and every step of credit delivery process is the need of the hour to mitigate credit risk in banks.

Bank for International Settlements (2015) - Based on the analysis of the responses from the supervisor and banks survey, BIS observed that propelled by the experience of 2008 and by regulators, banks in Europe, North America and Asia had improved their management of credit risk in areas such as governance and risk reporting. Risk aggregation had also become more sophisticated since the financial crisis. Regulatory requirements such as the Basel framework and stress testing had been one driver of the modeling enhancements. Firms highlighted increased reliance upon stress testing using their internal models. Against this background, some supervisors cautioned that there was a risk that some credit risk management or regulatory capital models could mask increased risk-taking.

Arora & Sharma (2014) - The authors studied the risk identification systems in Indian commercial banks. Their results indicated that there was a significant difference between the public and private sector banks in the practice of risk identification. Risk identification was better in new private sector banks. While risk identification in old private sector banks, SBI, and associates and other nationalized banks was found to be less, lesser and least effective respectively. They recommended that to improve risk identification system; risk should be systematically identified and proper risk ranking should be done.

Aneja et al. (2015) – The authors used Z-Index on 73 Indian banks to assess their financial health and probability of being insolvent from 2005-14. Z-Index has been calculated as Return on Assets Ratio (ROA) + Capital to Assets Ratio, divided by σ ROA. The study concluded that the average performance of State Bank group is showing better performance as compared to the other nationalized banks regarding maintaining sound financial health depicted by Z risk index. Except the last year 2013-14 and years of US subprime crisis, overall financial health seems to be strong for Indian banks as measured by Z risk index which is showing overall an upward trend for all the bank groups. The financial health of banks can be improved by reducing the variability of ROA, which represents the risk.

Warsome (2016) - The study reflected that despite the existence of several differences in the adopted strategies, practices and concepts of credit risk management for conventional and Islamic banks in Kenya, both types of banks face similar types of risks with minor variations. However, the study also found that Islamic banks adopt some extra measures to manage their specific risks due to the innovative and unique nature of their Sharia-compliant banking products and services. Similarly, results showed that for both Islamic and conventional banks, the overall objectives of credit risk management policies are communicated at the right organizational levels which indicates the importance of transparency in ensuring the adoption of effective risk management practices for all banks.

Oino (2016) – Their research assessed the impact of credit risk management on 14 Indian public and private banks during 2009-12, using pooled OLS, fixed and random effects. The study concluded that the private banks had better CRM practices, were more capitalized and profitable.

Michelled et al. (2016) – Their study aimed to assess the credit risk management practices of financial institutions in Ghana from 2007-14 and found that overall the CRM practices within the listed banks were in line with sound risk management practices. The only dissimilarity between them was in the role of the Board of Directors in defining acceptable types of loans and maximum maturities for various types of loans.

Maina (2016) – Their study of Kenya savings and credit cooperative societies, found that there was a significant relationship between loan collection period and the loan delinquencies. Loan collection period should be stringently followed to ensure that the credit defaulters are detected early. The study also suggested that the strict measures shall be taken to identify potential defaulters before disbursing loans.

Singh (2016) – The author suggested strong credit appraisal, post-loan monitoring, personal visits to borrowers' factories and sound loan recovery methods to reduce non-performing assets of banks.

Arora and Kumar (2014) – Their study used a CRM Index Score, comprising of quantitative assessment of the current set of CRM practices relating to the organization, policy, strategy, operations and systems at the portfolio level. They found that the strength of the overall CRM framework did not vary significantly between public and private sector banks.

IBM (2004) - Banks in India lack the basic risk management infrastructure that is standard in many developed banking markets. Global banks entering India can wield comparative advantage by leveraging their existing risk management systems and best practices and processes.

RBI (2008) report on Currency and Finance, 2006-08 stated that Indian banks faced several risks for which they needed to take protective measures to ensure that they remained solvent and liquid. Thus, robust risk management and strong capital position were critical in ensuring that individual banking organizations operated in a safe and sound manner, which, in turn, was crucial for maintaining the stability of the financial system and fostering economic growth.

Raghavan (2003) described five tools of credit risk management as exposure ceilings, review/renewal, risk rating model, risk- based scientific pricing, portfolio management, and a loan review mechanism.

Bakiciol et al. (2008) advised to manage the transactional credit risk and risk of adverse selection through efficient risk-based pricing of bank loans (Figure 2.1).

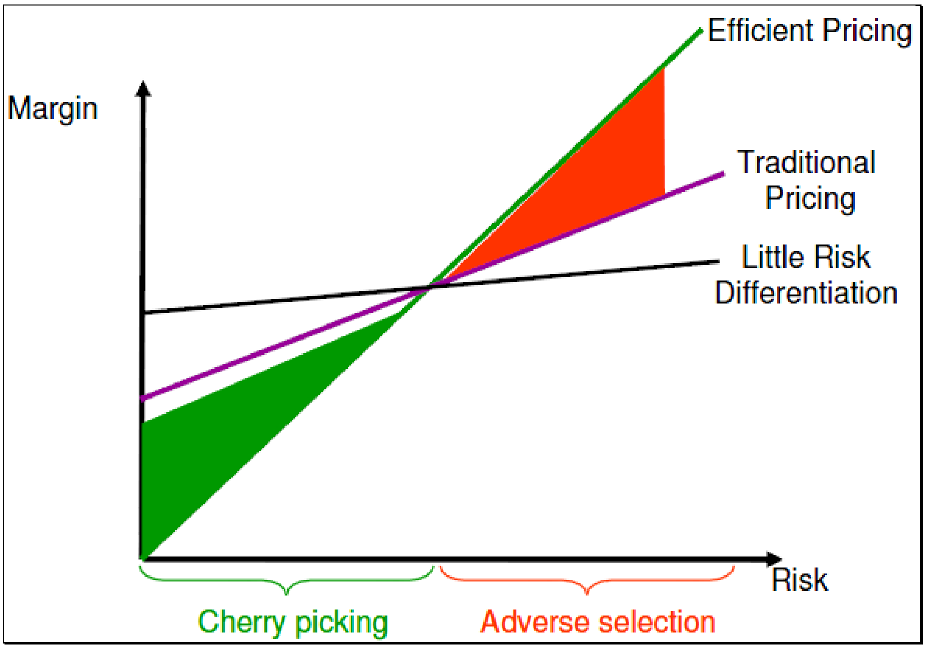

FIGURE 2.1: RISK-BASED PRICING

(Source: Bakiciol et al., 2008)

According to **Oesterreichische National Bank, Austria (2004),** a bank shall have an effective credit approval and monitoring process for efficient credit risk management (Figure 2.2). Within the broad regulatory framework, the credit approval process shall have the following components:

1. Segmentation of the borrowers: There are considerable differences in various categories of borrowers such as individuals, firms, listed companies, banks, governments; and the assets to be financed such as production plants, raw materials, commercial or residential real estate, personal loans, etc. as well as large number of products and their complexities. There cannot be a uniform framework to assess credit risk. For better risk assessment and control, the banks must differentiate between various borrower categories and segment the credit approval process.

2. Credit Rating Process: The rating process shall be based on quantitative (financial) and qualitative (non-financial) factors from borrower's micro and macro environment. The quality of the credit approval process will depend on a transparent and comprehensive presentation of risks and an adequate assessment of these risks. There shall also be standardized models of credit evaluation or rating to deal without bias.

3. Periodical Loan Reviews: Continuous monitoring of credit exposures to detect early warning signals, rating migrations or transitions.

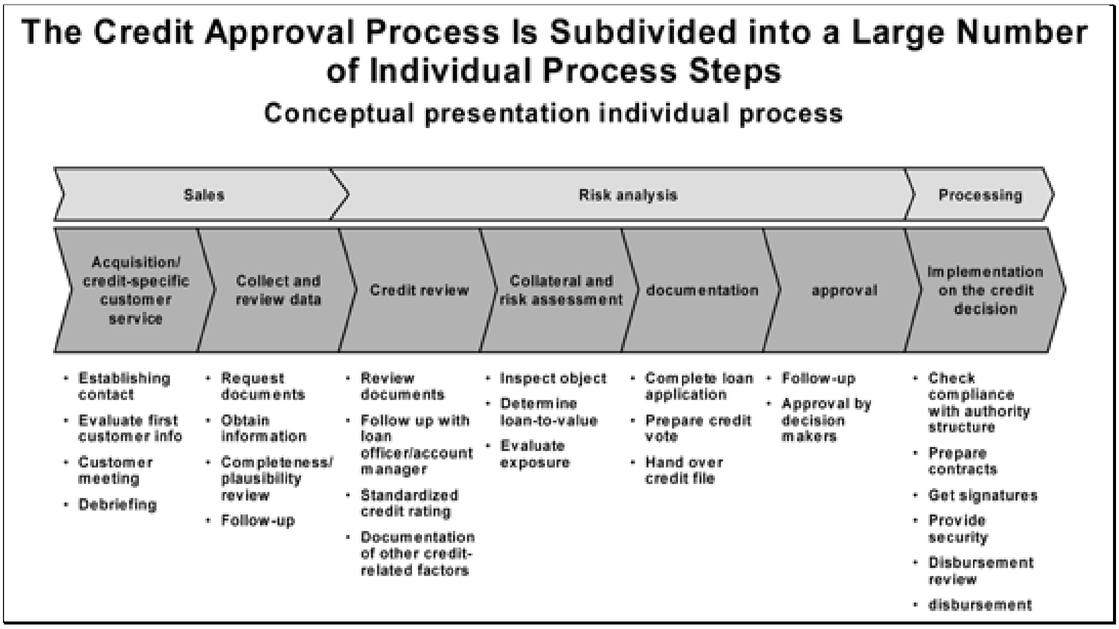

FIGURE 2.2: A BANK'S CREDIT APPROVAL PROCESS

(Source: Oesterreichische National Bank (Austria) Guidelines, 2004)

4. Intensive servicing and handling of problem loans: This may include continuous reminders, restrictive account management, collateral enhancement, restructuring, the sale of collaterals, loan loss provisions, write off, etc. (Oesterreichische, 2004).

Every part and sub-part of the credit approval process must be thoroughly designed for effective credit risk management. Credit departments of the banks need to be highly informed of the business environment, accounting tactics of their customers, and Basel requirements.

Oesterreichische (2004) also provided detailed guidelines on credit approval processes of banks for credit risk management. An optimal design of credit approval process shall minimize substantive and procedural errors and incorporate all possible risk mitigation measures (Figure 2.3).

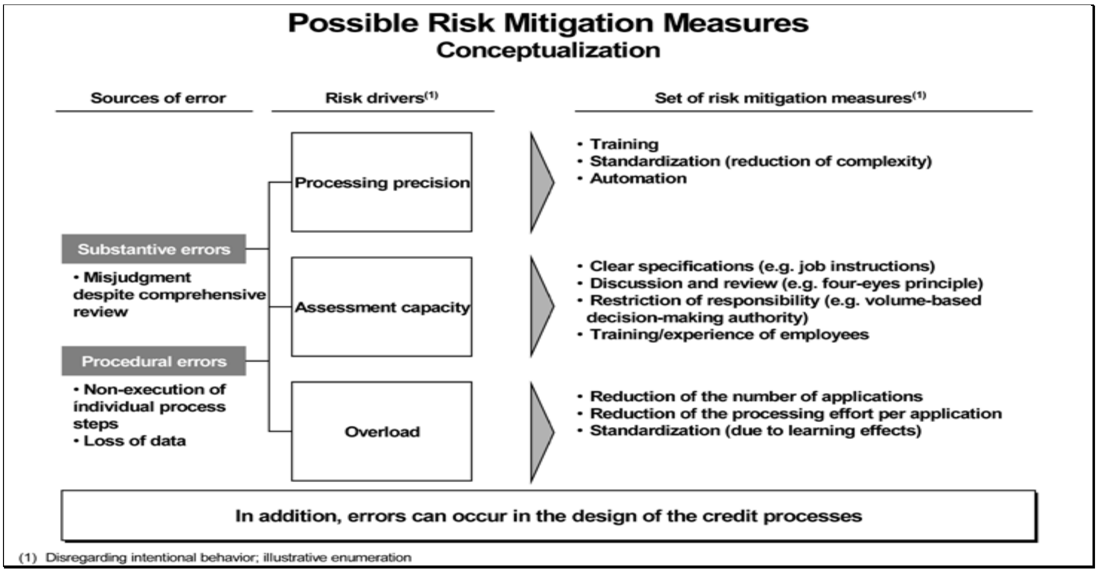

FIGURE 2.3: RISK MITIGATION THROUGH CREDIT APPROVAL PROCESS

(Source: Oesterreichische National Bank (Austria) Guidelines, 2004)

Al-Tamimi and Al-Mazrooei (2007) conducted a comparison study of risk management practices followed by UAE national and foreign banks. Based on a survey of 46 commercial banks in UAE, they found that major types of banking risks were foreign exchange risk, the credit risk, and operating risk. The main techniques used in risk management in these banks were establishing standards, credit-worthiness analyses, credit scoring, risk rating and collateral valuation through inspection by banks' risk managers, audits or physical inspections, financial statement analyses and risk surveys. The study also highlighted the willingness of the UAE commercial banks to use more sophisticated risk management techniques, and that the proper risk monitoring would help the bank management to discover mistakes early.

Fatemi Ali and Iraj Fooladi (2006) studied credit risk management practices of top banking firms headquartered in the US, in their non-traded credit loans and traded bond portfolio. The study researched whether US Financial firms were using vendors-marketed models or their internal credit - risk models. Vendors-marketed models included Algorithmics, Credit Metrics, Credit Risk +, KMV's Portfolio Manager, McKinsey's Credit Portfolio View, etc. It was observed that only a few banks utilized models in credit risk management and those who used models used both vendors-marketed and in - house models. The usage of models was based on correlation modeling via default rate volatility. Observations of the authors were based on a sample of 21 banks and other financial firms in the US.

Qian and Strahan (2007) researched into the legal and institutional environment that shape bank loans. They analyzed a sample of loan environment in 43 countries outside the USA and generated a Credit Risk Index. They demonstrated that strong protection of creditor rights was associated with a greater concentration of loan ownership, increased participation by foreign banks, longer term lending and lower interest rates. With better legal protection, lenders could control borrowers risk because they knew they would be able to take assets, or credibly threaten to take assets in the event of default.

Rottke and Gentgen (2006) - The authors research into the real estate non-performing loans granted by German banks till 2003. German economy had been showing weak performance, thus showing weak demand for commercial and residential demand units and this depressed property debt market resulting into high real estate non-performing loans. The study explored whether German banks should outsource their loan workouts or conduct the same themselves, i.e., a disintegrative or an integrative approach to the non-performing loans. Based on transactions cost economics, the authors concluded:

A) For performing loans, if servicing was not a core competency of the bank, it should be outsourced to a third party.

B) For non-performing loans of high collateral assets, the banks should have own workout management.

C) For non-performing loans of low assets collaterals, outsourcing to external third party should be optimal choice.

According to **Lepus (2004)**, one of the hardest challenges faced by banks in the risk area is active credit risk management. It requires banks to have consistent risk-based credit limits, rational risk-based capital allocations, and consistent credit decisions. As per Lepus, effective credit risk management is a critical component of a bank's overall risk management strategy and is essential to the long- term success of any banking organization. Active credit risk management can also mitigate future crisis events thus bringing considerable financial benefits. Lepus undertook a comprehensive study among senior risk managers in leading global US banks and concluded that the key components of effective credit risk management are - robust technology (38% respondents agreed), defined business processes (25% agreed), detailed policies (25% agreed), exposures management (25% agreed), and sophisticated analytics (15% agreed). According to him, technology plays a significant role in enabling active portfolio management, data transparency, a growth of the organization, elimination of manual processes and efficient management of information. He also states that Basel II is the key driver in shaping the banks' approach to credit risk management. Other drivers include centralization, standardization, consolidation and timeliness of credit risk management along with active portfolio management and efficient tools. Exposures management means the ability to measure monitor and forecast potential credit risk exposures across the entire firm on both counterparty level and portfolio level. Lepus states that the major challenges faced by banks include reporting, analytics and data quality issues. Many banks have yet to integrate the disparate components of their credit risk systems, for a consistent framework. The key solution is to implement a centralized reporting system. Since the commercial bank loans are subject to high degree of irreversibility, banks shall use a variety of methods to design and monitor adherence to credit policy, limit checking, credit inspection, pre -deal checking, global systems, education and training **(Lepus, 2004).**

According to **Nails (2010)**, loan review is the critical element of effective credit risk management, and shall include assessing individual loans, including repayment risks, determining compliance with lending procedures and policies, identifying lapses in documentation, providing credit risk management priority findings, recommending practices and procedures to address findings, and evaluating risk grades and their accuracy.

A study on credit risk management practices of Indian banks including both public and private banks was undertaken by K**umar and Kotreshwar (2005)** at the time when RBI was moving the Indian banks towards risk- based supervision under Basel II. The study was based on both secondary data from RBI reports as well as a survey of credit departments of the banks. The study concluded that the CRM practices of commercial banks in India did not meet the standards set out under the New Basel Capital Accord and that there existed no marked difference between public and private sector banks as regards their credit risk management performance.

Shen's (2012) study proposes an information asymmetry hypothesis to examine why bank credit ratings vary among countries even when bank financial ratios remain constant. Countries are divided among those with low and high information asymmetry. The former include high-income countries, those in North America and West Europe regions, and those with strong institutional environment quality, whereas the latter group possesses the opposite characteristics. This study hypothesizes that the influences of financial ratios on ratings are enhanced in low information asymmetry countries but reduced in countries with high information asymmetry. The sample includes the long-term credit ratings issued by Standard and Poor's from 86 countries during 2002–2008. The estimated results show that the effects of financial ratios on ratings are significantly affected by information asymmetries. Countries wishing to improve the credit ratings of their banks thus should reduce information asymmetry.

Mirchandani, Hegde, and Wendell (2001) studied operations of a consumer loan center in a medium-sized bank in the USA, to improve efficiency and competitiveness of the loan center. Their data collection and model building suggested many ways to improve staff performance and productivity of loan center. The researchers conducted simulation analysis which helped management to modify loan application processing according to an estimated number of applications and target average response time. This helped them to clear backlogs, reassign employees in the morning, filter applications with previous default record, prioritize applications and thus improve efficiency significantly.

Gupta (2003) – The most significant challenge before banks is the maintenance of rigorous credit standards, especially in an environment of increased competition for new and existing clients.

Karunakar and Saravanan (2008) stressed upon the need for organizational restructuring, improvement in the managerial efficiency, and skill up gradation for proper assessment of credit- worthiness of borrowers.

Malyadri and Sirisha (2011) concluded that future of the Indian public sector banks would be based on their capability to continuously build good quality assets and by maintaining capital adequacy and stringent prudential norms.

JIN (2011) emphasized that the **c**redit asset quality problem was one of the obstacles limiting the further development of commercial banks, and the banks shall have a ‘differential treatment, differential control’ loan policy to reduce credit risk.

Thus, an immediate and manageable challenge before Indian public sector banks is to improve their internal CRM systems and procedures in credit risk assessment, mitigation, and control, to track and reduce credit delinquencies, and build quality asset portfolio. Many theoretical and empirical studies have verified that internal organizational, managerial strategies are the determinants of a business’s profitability.

Research by **Lin et al. (2006)** established the internal performance measures to monitor and enhance the operational qualities of the employees in the lending department. Their research utilized the value-added approach analyzing the lending production process and derive the internal performance measures to add value to the lending activities. A comprehensive analytical framework that would improve the accuracy of analyzing a borrower's capacity and condition had also been constructed by them. According to them, by using the internal measures to monitor the output quality of the employees in lending department, there was a likelihood of reduction of employee's moral hazard behavior.

As the entire banking industry is witnessing a paradigm shift in systems, processes, strategies, it would warrant **(Bhatt, 2012)** creation of new competencies and capabilities on an on-going basis for which an environment of continuous learning would have to be created so as to enhance knowledge and skills.

According to **Stulz (2008)**, there is a need to distinguish between flawed assessments by risk managers, and corporate risk taking decisions that, although resulted in losses, were fundamentally reasonable at the time they were made. He also stressed that there are five types of risk management failures:

1) Failure to use appropriate risk metrics.

2) The mismeasurement of known risks.

3) Failure to take known risks into account.

4) Failure in communicating risks to top management.

5) Failure in monitoring and managing risks.

Njanike (2009) highlighted the following obstacles in the successful implementation of effective credit risk management systems by banks – lack of resources, the disintegration of systems across departments, inconsistencies in risk-rating approaches, data management, and stringent regulatory requirements. They concluded that poor CRM contributed to a great extent to the bank failures in Zimbabwe.

Richard et al. (2008) said that the sound CRM systems should be the foundation of credit risk assessment, control, and mitigation processes, and shall be integrated into a bank's decision making, with clear responsibility and accountability for each sub-system. They attempted to understand the credit risk management (CRM) system of commercial banks (CBs) in Tanzania, an economy with the less developed financial sector, after review of existing literature on developed countries. The main findings of their paper were that the components of CRM system differed in commercial banks operating in a less developed economy from those in a developed economy. This implied that the environment within which the bank operated was an important consideration for a CRM system to be successful. They further stated that the Tanzanian banks were not using quantitative credit scoring models. It was observed that poor recordkeeping and lack of effective database systems in various sectors within the country contributed significantly in their not been able to construct and use credit-scoring models.

Raghavan (2005) - SMEs are an important part of economic growth in the country and bank lending is the primary source of external finance to them. SMEs are mostly proprietorship and partnerships, have limited capacity to leverage on the financial structure, facing tough competition, inadequate margins, low collections in account receivables, incapacity to go for technical advancements, and higher turnover. They are often seen as difficult for start-ups to satisfy bank requirements, in terms of demonstrating experience in industry, meeting minimum equity stake and having in place contracts for sale to support the business plans. Personnel with specialized skill sets are sometimes necessary to understand the risks inherent with particular new SME ventures.

International Finance Corporation (2013) - Small and medium enterprises (SMEs) constitute a significant and growing opportunity for commercial banks, but the diversity of their needs and requirements makes them a difficult target. Their needs differ considerably depending on a combination of diverse factors such as their size, sector, financial sophistication, and business maturity. Since size can range from a handful of employees to several hundred, their resultant needs vary dramatically. Industrial cluster- based SME segmentation or dividing according to industry and business linkages, banks can customize SME financing.

Bank for International Settlements (BIS) (2015) – Based on its survey findings, BIS reported that some banks in Europe, North America, and Asia, across sectors, noted some enhancements to credit risk management processes. Changes in reporting of exposures at a counterparty level and by industry were cited across sectors. Also, enhancements to limit frameworks and regular diligence around monitoring limits and escalation of breaches were commonly cited. Regular “watchlists” of counterparties, industries and countries under stress have also been developed. Improvements in systems that enabled more detailed reporting quickly accompanied the improvements in processes.

2.4 CREDIT RISK MEASUREMENT

A key aspect of credit risk management is credit risk pricing based on a risk measurement system. Credit ratings based on estimates of external rating agencies like CRISIL, ICRA are a good indicator of default risk. Simultaneously banks adopt internal rating models as **Richard et al. (2008)** said that given the asymmetric information that exists between lenders and borrowers, banks must have a mechanism to ensure that they not only evaluate default risk that is unknown to them ex- ante in order to avoid adverse selection, but also that can evolve ex- post in order to avoid moral hazards. Credit models are to be based on the uncertainty of default and volatility of loss severity **(Araten and Jacobs, 2001).** The final objective of any credit risk model is to build the probability density function of future losses in a loan portfolio **(Dietsch and Petey, 2002).**

Bank for International Settlements (BIS) (2015) – BIS conducted a survey in 2013 on central banks and few firms across Europe, North America and Asia to gain insight into the current supervisory framework around credit risk and the state of CR management at the firms, as well as implications for the supervisory and regulatory treatments of credit risk. Based on the survey findings, they recommended that supervisors should be cautious against over-reliance on internal models for credit risk management and regulatory capital. Where appropriate, simple measures could be evaluated in conjunction with sophisticated modeling to provide a complete picture.

Few widely used credit-scoring and risk rating models in earlier research and studies are Altman's Z-score model, logistic regression, KMV Expected Default Frequency model, and neural networks.

Pioneer work in the field of predicting borrower or corporate failure has been through discriminant analysis based on a sample of failed and non-failed borrowers, through univariate analysis by **Beaver (1966)** and multivariate analysis (MDA) by **Altman (1968)**. Altman's classic multivariate insolvency prediction MDA or Z-score model was originally for publicly traded manufacturing firms in the USA, for forecasting probability of a firm entering bankruptcy within two years. He used working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, sales/total assets and market value of equity/ book value of total debt ratios. **Altman, Haldemann & Narayanan (1977)** enhanced that model to seven ratios, called Zeta Model, for manufacturers and retailers. **Altman, Hartzell & Peck (1995)** again modified Z-score model for emerging market corporations to suit the private firms who were not publically traded. In this enhanced Emerging Markets Z-score model, they dropped sales/total assets ratio and used book value of equity in place of the market value of equity.

Though many new approaches have been developed for the credit rating of borrowers or prediction of their failure or bankruptcy, Altman models are frequently used by researchers all over the world as base models to compare the effectiveness of their theories and propositions.

Sinky, Joseph and, Dince (1987) tested Zeta-Analysis model by Altman, Haldemann and Narayanan (1977) for identifying failure risk for commercial banks. Zeta Analysis is a bankruptcy model for the non-financial corporation like retailers and manufactures and has been found to be very effective to predict failure and insolvencies. The researchers compared Probit model and Multi Discriminant model with Zeta Analysis and found that Zeta Analysis was more accurate to estimate Type I error of misclassification which was the main source of concern for predicting bank failures. However, they also observed that fraud, insider trading and another form of misapplication of bank funds had been the major cause of bank failures. Since these activities tend to be deliberately masked in bank accounts and audit reports, early warning signals get distorted. Given the current accounting and regulatory systems, most bank failure prediction models would not be good enough to discriminate between failed and non-failed banks with a high degree of accuracy. **Sinkey et al. (1987)** also stated that nevertheless, a subset of variables that was more accurate than **Altman, Haldeman, and Narayanan's (1977)** original set of seven variables was not found.

Altman (2000) also stated that the ZETA model for assessing bankruptcy risk of corporations demonstrated improved accuracy over existing failure classification model (Z-Score) and, perhaps more importantly, was based on data more relevant to current conditions and a larger number of industrial firms. He concluded that the new ZETA model for bankruptcy classification appeared to be quite accurate for up to five years before failure with the successful classification of well over 90% of their sample one year prior and 70% accuracy up to five years. He also observed that the inclusion of retailing firms in the same model as manufacturers did not seem to affect their results negatively. That was probably true due to the adjustments to their data based on recent and anticipated financial reporting changes - primarily the capitalization of leases.

Bandyopadhyay (2006) - Statistical models can help banks to predict default probability to get early warning signals about the default status of its corporate clients. He developed Z-score model for Indian corporates by using working capital/total assets, cash profits/total assets, total non-current and current borrowings/total assets, operating profit/total assets, and sales/total assets ratios, and compared the results with Altman's 4 and 5 ratios models, and found his new Z-score with higher prediction accuracy both for solvent and defaulted firms. Ownership structure, group support, the size of the firm, experience in the industry, industry characteristics and ISO quality certification as predictor variables were found effective in assessing the credit quality of business borrowers. The author also undertook logit (logistic regression) analysis and the empirical results revealed that inclusion of financial and non-financial parameters would be useful in more accurately describing default risk.

Jayadev (2006) evaluated risk rating models of Indian banks, using MDA on current ratio, debt/equity ratio, interest coverage ratio, and operating margin, and found that Altman's models were more effective. He emphasized on Net Worth to Total Debt ratio as an important indicator of credit risk in borrower's financial statements. An important issue in determining the credit risk would be whether the net worth of a firm was sufficient to meet its total debt obligations. Though the market value of equity was a more appropriate variable, due to several asymmetries of the Indian stock market, the book value of debt might be considered. This ratio would be reciprocal of the popularly used debt-equity ratio. Excess of liabilities over assets would be defined as insolvency. This ratio measured the decline in value of assets if a firm's liabilities exceeded its total assets. He explained that if a company's value of equity was Rs.100 and debt was Rs. 50 before insolvency, the likely decline in value of assets would be 50/150, i.e., two-third. If the net worth were only Rs.25, the firm would be insolvent if assets dropped by only one- third in value. The probability of default would increase with a drop in the value of equity.

Chijoriga (2011) evaluated multiple discriminant analysis (MDA) as a credit scoring and risk assessment model in making correct customer classification. The study was conducted on a private commercial bank in Tanzania, using 16 financial ratios and firm size as predictor variables and concluded that leverage and liquidity ratios were more discriminating. The author stressed that MDA had been a traditional technique of credit scoring but can also be used as a risk assessment model. Among commercial banks, the leading causes of risk are credit risk and liquidity risk. The study proved that quantitative credit scoring models improved risk management as compared to subjective risk management methods. The results confirmed that financial ratios were good predictors of firm's performance.

Jain, Gupta & Mittal (2011) developed a credit scoring application framework, for SME borrowers, by classifying them into "good risk', 'foreclosed risk' and 'bad risk' categories, by using multinomial logistic regression technique with both financial and non-financial factors. The study was based on a database covering two years 2007-09 on 2864 SMEs about an emerging cluster.

Abdou A. Hussein (2009) evaluated efficiency and effectiveness of alternative credit - scoring models for bank loans regarding correct classification scoring and misclassification costs. The study had been undertaken on an Egyptian private bank. Credit scoring techniques assess who will get credit, how much credit should they get and what operational strategies will maintain the profitability of the borrowers to the lenders. The author compared the traditional techniques such as Weight of Evidence, Multi Discriminant Analysis, Regression and Probabilistic Neural Networks. The author concluded that BNS 4- MLFN- 5N (Neural Networks) were most reliable regarding classification efficiency rate and the cost effectiveness, associated with misclassification errors.

JIN (2011) - The incidence identification method was established to investigate whether the industry and macroeconomic factor could affect impaired loan ratio of banks using the grey incidence analysis method. From the angle of the industry, their result could determine the risk deviation scope in the grey risk control process which offered new content and ideas within the grey risk control. The results indicated that the impaired loan ratio is different with diverse industry's influence and the macroeconomic also affect it. The authors stressed that under the guidance of the principle of "differential treatment, differential control," their research would help to strengthen the implementation of differentiated credit policy, on guiding and promoting the optimization of credit structure, so as to maintain a reasonable size of credit facilities and build a steady currency credit system.

Fidrmuc et al. (2007) - They used an unbalanced panel of nearly 700 short term loans made to SMEs in Slovakia between January 2000 to January 2005. Of the loans granted, an average 6 per cent of the firms defaulted. Results of Probit model had shown that the liquidity and profitability factors were important determinants of SME defaults while debt factors were less robust. They, however, found that the above average indebtedness significantly increased the probability of default.

Hirtle et al. (2001) stated that in very general terms, the purpose of a credit risk model was to estimate the probability distribution of future credit losses on a bank's portfolio. The first step in constructing a credit risk model was therefore to define the concept of loss that the model was intended to capture, as well as the horizon over which the loss would be measured. According to him regarding the definition of loss, models generally fell into one of two categories: models that measured the losses arising solely from defaults ("default mode" models), and models that incorporated gains and losses arising from less extreme changes in credit quality as well as from defaults ("multistate" or "mark-to-market" models). Assumptions about the distribution of risk factors would be a key element in the design of all credit risk models.

Hirtle et al. (2001) further emphasized the need for validation of internal risk rating models. He stated that validation was the process of ensuring that model was implemented in a rigorous way both in terms of statistical or quantitative and qualitative standards. The qualitative standards address the internal controls and procedures surrounding the design and operation of the models including independence of the risk management function, regular risk reporting to senior management, and periodic independent audit of the models. According to him, a comprehensive credit risk model must be based on a rating process that was sound and rigorous, and that incorporated all relevant information, both public and proprietary. They stressed that in their model validation, banks could include sensitivity analysis – that was the sensitivity of the model results to changes in parameters and key assumptions. Sensitivity analysis would allow management to probe the vulnerabilities in a model that arose from its structure, use of a particular statistical technique or limitations in terms of historical observations. In any case, banks would be expected to maintain adequate documentation to permit a rigorous review of the model development and testing.

Gama & Geraldes (2012) felt that the small, owner-managed enterprises with little capital were strongly likely to receive lower ratings than large enterprises with high levels of equity capital. To address that issue, they diverged from prior research, focused mainly on the bank's behavior, and developed a credit-scoring model that SMEs could use for themselves. Using panel data from a representative sample of Portuguese SMEs operating in food and beverage manufacturing sectors, the study developed a Logit scoring model to estimate a one-year prediction of default. After analyzing a complete set of financial ratios, they applied a stepwise procedure to select the ratios that best explained the probability of default (PD). Because qualitative information was relevant for scoring models, they also integrated selected financial ratios with non-financial indicators. With this model, SMEs could estimate their expected PD, using a combination of financial and non-financial factors. Their model improved SMEs' knowledge about their default risk, which had three key implications. First, the SMEs could monitor their bank's behavior because if they understood how to measure and price their credit risk, they could approximate their risk-adequate cost of debt. Second, they could pursue alternative sources of financing. Third, that knowledge would increase transparency in the credit granting process, which was beneficial in itself.

Berk et al. (2011) -This paper deals with bank credit risk analysis with Bayesian network tools. Using credit scoring system, Bayesian network structure is established. They discussed a method of initializing Bayesian network and calculation of output with observed information. The sample bank credit risk analysis software with Bayesian network has been developed by the authors, and the result of this tool has also been explained. Furthermore, this paper considered the problem of adding and initializing new nodes when no data existed for the given node. Banks could classify customers according to their profile. While classifying, financial background of customers and their subjective factors were evaluated. Objective factors were ranged by very good, good, medium, weak and bad. On the other hand, subjective factors were ranged by high, good, weak and bad.

Makkar & Singh (2012) used Bankometer model developed by IMF in 2000, to evaluate the soundness of Indian banks. Bankometer model is based on Capital Adequacy Ratio, Capital to Assets Ratio, Equity to Total Assets Ratio, NPLs (Non-performing loans) to Total Loans Ratio, Cost to Income Ratio and Total Loans to Total Assets Ratio. Though Bankometer measures the financial soundness , its key parameters are directly related to credit risk management. On the basis of results retrieved by the authors from the Bankometer Model it could be concluded that all the 37 Indian banks were financially sound, as none of the bank had solvency score of Bankometer below 70 percent. The top financially sound banks included Kotak Mahindra, Federal, ICICI, HDFC and Development Credit Bank. On the basis of individual variables, only the UCO Bank had Capital to Asset Ratio slightly lower than that of the 4% as prescribed by IMF. The SBI stood at 25^{th} position in the performance ranking of 37 banks. The banks- Central Bank of India, UCO bank, Syndicate Bank, Bank of Maharashtra and State Bank of Travancore were the worst banks on the basis of their scores in Bankometer Model. The study concluded that private sector banks were in sound position in comparison with public sector banks. The study suggested that the public sector banks required taking some corrective measures to improve their performance to compete with private sector banks.

Bandyopadhyay (2005) used Black, Scholes and Merton (BSM) model which optimally used stock market and balance sheet information of the company to predict its distance to default over a horizon of one year. The author observed that option pricing model could accurately predict the default status even before the ratings were published by CRISIL. Bandyopadhyay observed that there were certain problems with the external ratings as they presumed uniform PD (probability of default) across the same rating class. Moreover these were not responsive to small changes. Option model is based on asset value, asset volatility and balance sheet liquidity, and decides for the corporate to opt for default on corporate bonds or repay. Loan default occurs when the market value of the firm's assets fall below the book value of the debt. The study concluded that BSM model could discriminate between defaulting and solvent firms and by using equity market information, banks could enhance corporate credit appraisal.

Bandyopadhyay & Ganguly (2012) - Estimation of default and asset correlation is crucial for banks to manage and measure portfolio credit risk. The purpose of this paper is to find an empirical relationship between the default and asset correlation with default probability, to understand the effect of systematic risk. The authors empirically found a negative relationship between asset correlation and the probability of default using Moody's global corporate data that support Basel II internal ratings-based (IRB) correlation prescription. However, they did not find any smooth relationship between the probability of default (PD) and asset correlation for Indian corporates. The magnitude of correlation estimates based on a large bank's internal rating-wise default rates were much lower than what was prescribed by the Basel Committee. The authors suggested that the standardized correlation figures as assumed by the Basel Committee on Banking Supervision need to be properly calibrated by the local regulators before prescribing their banks to calculate IRB risk-weighted assets.

He Xubiao & Gong (2008) predicted default probabilities of listed companies by their stock prices alone, to assess their credit quality for lenders and investors. They validated their model using statistical tests and Receiver Operating Characteristics (ROC) Curve method. The purpose of their paper was to simulate internal credit ratings based on stock market data and gain the credit information about listed companies. The internal credit ratings-based default probability could reflect the change of credit quality for listed companies according to market information. According to them for listed companies, especially which possibly suffer from accounting manipulations, the ratings would help investors and supervisors gain their credit information in time.

Glennon and Nigro (2005) examined the risk of small business loans of medium-maturity (i.e. seven years) by using a survival analysis/hazard model to capture default rate on a time dimension. The hazard rate is a measure of the probability that a loan will default in time t, given that it has survived until that time. The timing of default is an important feature of credit risk modeling as banks allocate reserves against expected loan losses. The paper concluded that the likelihood of default increased initially, peaked in the second year after origination, and declined after that. Using survival analysis technique, they have shown that not all business credits are of equal default risk and that a bank's exposure to loss due to default is not constant, but varies significantly over the life of the loan.

Pacelli & Azzollini (2011) - The objective of their research was to analyze the ability of the artificial neural network model developed to forecast the credit risk of a panel of Italian manufacturing companies. The research compared the architecture of the artificial neural network model developed in their study to another one, built for the research conducted in 2004 on a similar panel of companies, showing the differences between the two neural network models. The authors had the opinion that it was not possible to state if traditional methods were better than non-linear one in forecasting credit defaults, but only that the traditional methods and neural networks had different strengths and weaknesses, which must be carefully evaluated by the analysts during the elaboration of the credit risk forecasting model.

Mittal, Gupta & Jain (2011) - The authors had developed neural networks, a non-parametric credit scoring model for micro enterprises that were not maintaining balance sheets, and without having a track record of performance and other credit-worthy parameters. Multilayer perceptron procedure of neural networks was used to evaluate credit reliability in three classes of risk, i.e. bad risk credit, foreclosed risk credit and good risk credit. Their model, instead of categorizing borrowers in terms of their "ability to pay", attempted a solution to the unsolved problem of credit availability to micro enterprises in an Indian context, having no past performance track record.

Priscilla and Ribeiro (2011) emphasized that the use of models for credit risk forecasting would eliminate the subjectivity of the analysis, by creating a standardized decision-making procedure that could be complemented with extra pieces of information that were not contemplated in the mathematical model. Thereby it would be possible to accelerate credit analysis, which might allow an increase in business volume. Their study proposed the use of discriminant analysis, logistic regression, and neural networks. Such methods were chosen because they were among the most widely used for building credit models. Discriminant analysis and logistic regression, the statistical techniques, took different approaches, with the possibility of one of these techniques succeeding when the other failed, especially with regard to complying with certain assumptions. The main assumptions of discriminant analysis needed verification are multivariate normality, homogeneity of variance matrices and the absence of multicollinearity. To assess multivariate normality the Kolmogorov-Smirnov (KS) test was used, to test the homogeneity of variances, Box's M test was employed. Multicollinearity problems would be reduced using the stepwise method, as it identified the best set of independent variables that would comprise the final model. In logistic regression, the only assumption to be checked was that of the absence of multicollinearity. Just as in discriminant analysis, this assumption would be reasonably met by using the stepwise method for selecting independent variables. Neural networks were also part of their proposal because of its ability to deal with nonlinear and discontinuous effects, as they identified ratios that customary statistical methods would not consider.

Balcaen & Hubert (2004) gave an overview of some academically developed corporate failure prediction models and several new alternative approaches like survival analysis, machine learning decision trees, neural networks, rough-set analysis, multi-dimensional scaling, self-organizing maps etc. They compared traditional cross-sectional statistical methods with new alternative methods to study business failure. The study concluded that alternative methods were computationally more complex and more sophisticated. However, whether they performed better or not required further systematic research in corporate prediction failure.

Wei-Dong (2009) used factor analysis and Support Vector Machine (SVM) model for credit risk identification in small and medium enterprises. SVM, like neural networks, is a machine learning method and requires training and validation of model.

Hunjak et al. (2001), Tomic et al. (2006) and Dejan et al. (2011) successfully used Analytic Hierarchy Process (AHP), a multi-criteria operational research technique in ranking of business banks and in credit risk assessment of firms, using financial and non-financial variables. Pair-wise comparisons of risk factors improved risk assessment.

According to **Tomic et al. (2006), c**redit risk assessment is a significant area of financial management which requires credit/financial analysts to investigate a large number of financial indicators of firms and make crucial decisions regarding the financing of firms. The complexity of credit risk assessment process has necessitated the construction of credit risk assessment models based on multi-criteria decision analysis. Their paper deals with the ranking of firms according to the credit risk assessment using the PROMETHEE method and Analytic Hierarchy Process (AHP). The PROMETHEE method was used for final ranking of a great number of Croatian firms and AHP to determine the importance of the eleven criteria from the three main criteria groups: profitability, liquidity, and solvency of the firms.

Leeladhar (2007), the Deputy Governor, RBI emphasized that the banks with better risk management skills would not only have the competitive advantage in the marketplace but would also be better positioned to capitalize on the opportunities for organic and inorganic growth. Since there was a significant correlation between credit ratings and default frequencies, a suitable credit risk rating model would capture probabilities of credit risk with given assumptions. He also impressed upon the need for banks to develop a comprehensive risk scoring system that served as a single point indicator of diverse risk factors of the counterparty.

Greuning & Bratanovic (2009) maintains that credit rating is a tool of loan pricing. Rates on various loan types must be sufficient to cover the costs of funds, loan supervision, administration (including general overhead), and probable losses. At the same time, rates should provide a reasonable margin of profit. Rates should be periodically reviewed and adjusted to reflect changes in costs or competitive factors. Rate differentials may be deliberately maintained either to encourage some types of borrowers to seek credit elsewhere or to attract a specific type of borrower.

Oesterreichische National Bank, Austria (2004) suggested a rating framework to capture both financial and non-financial risk in a borrower category (Figure 2.4).

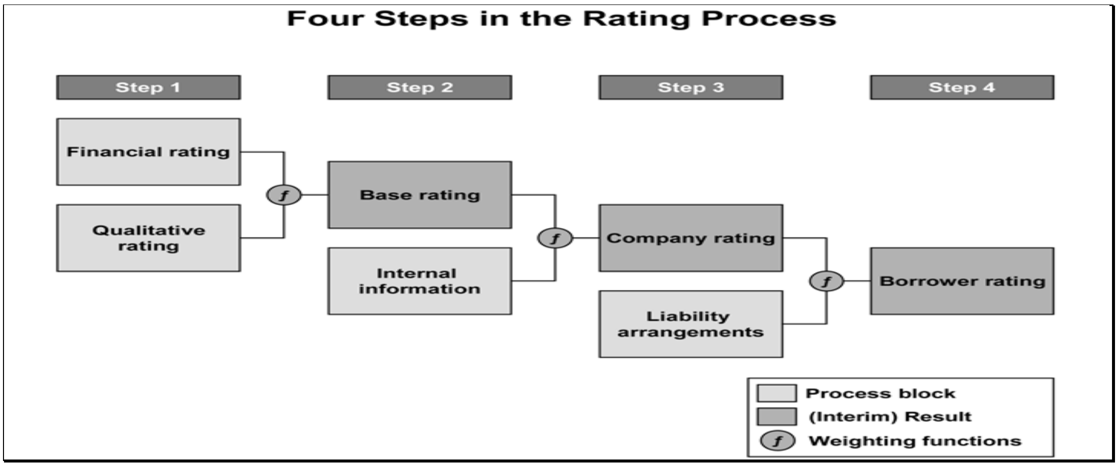

FIGURE 2.4: A RATING PROCESS

(Source: Oesterreichische National Bank, 2004)

Oesterreichische National Bank (2004) also maintained that wherever possible, credit assessment procedures must include all data and information relevant to creditworthiness as credit assessments were meant to help a bank measure whether potential borrowers would be able to meet their loan obligations in accordance with contractual agreements. However, the factors determining creditworthiness would vary according to the type of borrower concerned, which meant that it would not make sense to define a uniform data set for a bank's entire credit portfolio. For example, the credit quality of a government depended largely on macroeconomic indicators while a company would be assessed on the basis of the quality of its management, among other things. Statistical models would provide objectivity to an otherwise subjective task. As for combination of qualitative and quantitative factors, the author stated that in general, the personal traits of the business owner or manager would influence the credit quality of enterprises in smaller-scale rating segments more heavily than in larger companies, or that the influence of qualitative information categories on each overall scoring function increases as the size of the enterprises in the segment decreases (Figure 2.5).

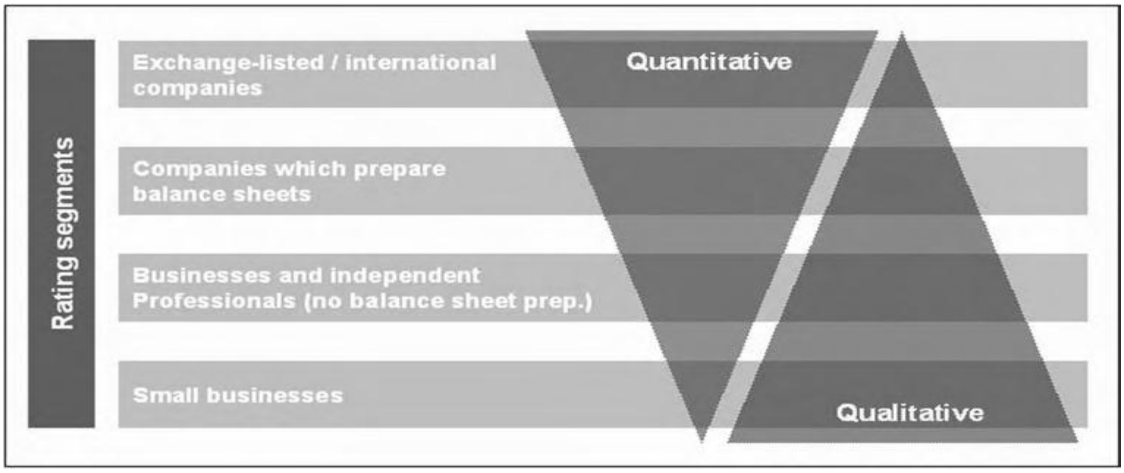

FIGURE 2.5: SIGNIFICANCE OF QUANTITATIVE AND QUALITATIVE DATA IN DIFFERENT RATING SEGMENTS

(Source: Oesterreichische-2004, p.83)

Negret (2006) from the World Bank, stressed that the banks must develop borrower rating tools to overcome the shortcomings of expert or judgmental rating systems, and shall include all types of borrower data – financials, qualitative data, market data and relationship data (Figure 2.6).

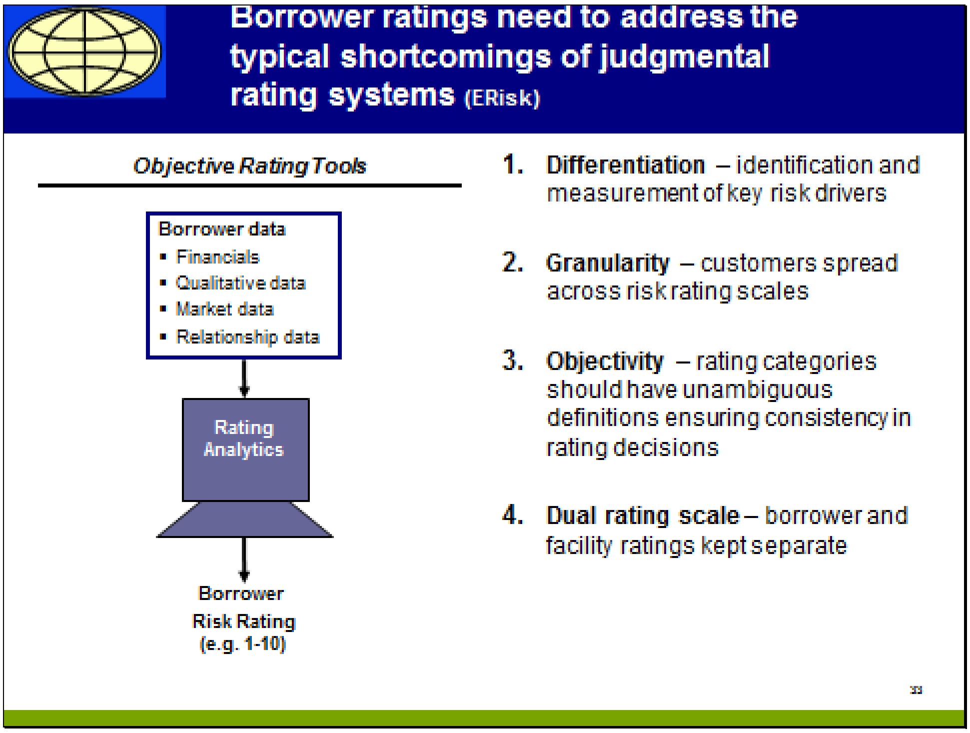

FIGURE 2.6: RISK MANAGEMENT CHALLENGES

(Source: Negret (2006) p.33)

Treacy & Carey (2000) observed that the internal credit risk rating systems were becoming an increasingly important element of large commercial banks' measurement and management of credit risk of both individual exposures and portfolios. They described the internal rating systems in use at the 50 largest US banking organizations. Banks in different lines of business were using internal ratings for different purposes. They designed and operated different systems that met their needs. For example, a bank that used ratings mainly to identify deteriorating or problem loans to ensure proper monitoring might find that a rating scale with relatively few grades was adequate, whereas a bank using ratings in computing the relative profitability of different loans might require a scale with many grades in order to achieve fine distinctions of credit risk.

Krahnen & Weber (2001) defines 12 generally accepted rating principles:

- A rating system is a mapping.
- A bank should rate all current clients and keep on rating its past clients.
- A bank should have as many different rating systems as necessary and as few as possible.
- The reasons for choosing the number of rating systems should be made transparent.
- The probability of default should be well defined.
- The rating system can vary in the degree of fineness. It should always be as fine as necessary.
- The rating system should be reliable.
- The (ex-ante) probability of default should not be significantly different from the (ex-post) realized default frequency.
- Ratings should be informationally efficient, i.e. it should not be possible to predict rating changes based on rating history. All the available information should be modeled correctly in the rating.

- The rating system should cope with biases known from the general literature on rating (splitting bias, range bias, etc.).
- A rating system should be improved over time, and the past and current rating data should be easily available.
- The adherence of a bank's management to its agreed rating standards should be monitored by neutral (uninterested) outside controllers, either on a continuous or on a random basis.

Brown & Moles (2012) - Credit appraisal could involve a number of different techniques which can be used individually but were more often combined as part of the assessment process such as - Judgmental methods to apply the assessor's experience and understanding of the case to the decision to extend or refuse credit;

- Expert systems (e.g. lending committees) using a panel approach to judge the case via lending system and procedures;
- Analytic models using a set of analytic methods, usually on quantitative data, to derive a decision;
- Statistical models (e.g. credit scoring) using statistical inference to derive appropriate relationships for decision making;
- Behavioral models observing behavior over time to derive appropriate relationships for reaching a decision; and
- Market models relying on the informational content of financial market prices as indicators of financial solvency.

Raghavan (2005) - When the risk grading system does not show desired ability to discriminate between good and bad risks—implying a lack of granularity, the outcome may lead to the relationship between risk rate and pricing losing its predictive capability, thereby causing losses to lender larger than the predicted/predictable parameters. This may result in tightening the credit terms or increase in price or both. The situation may lead to overpricing good risk or under-pricing bad risk. This may ultimately end up in the bank building up poorer quality loans on its books as the better quality borrower may seek alternative lending arrangement elsewhere. Such a situation is known as an adverse selection of borrower in banking parlance.

Shen (2012) - External credit ratings could be regarded as comprehensive measures of risk because they incorporate all the risk factors that are perceived to be relevant by rating agencies. They also observed that complete information about non-financial factors like institutional quality, disclosure level, and integrity of management, strategic plans, and immediate past made a difference in assessing the creditworthiness of counterparties.

Lehmann's (2003) empirical study dealt with the question whether soft facts (qualitative information, i.e. subjective judgments of credit analysts) considerably improved the forecast quality of a bank's internal credit ratings that were solely based on hard facts (financial ratios, checking account data). An extensive sample (20,000 observations) of German SME credit data of a commercial bank was used by the researcher to compare two models: one including, the other excluding qualitative information. Logistic regression and ROC (Receiver Operating Characteristic) curve was used to forecast default probabilities of two models. The study concluded that subjective elements in a credit rating system were not necessarily to be seen as negative but rather desirable. They allowed the credit analyst to include information in the analysis that would otherwise be left unused, such as extensive professional experience or additional relevant but non-quantifiable information beyond the one contained in the documents. The study showed through ROC that subjective judgments were indeed capable of yielding valuable information and improved credit rating systems which were based solely on quantitative information by considerable amounts. However, there would be difficulties in objectively comparing and re-examining past credit assessments. Besides, it would be very costly to gather qualitative individual information.

Analyzing credit file data from four major German banks, **Grunert & Weber (2005)** also found evidence that the combined use of financial and non-financial factors would lead to a more accurate explanation of current and future default events than the single use of each of these factors respectively. That was true for default both in the year of the rating assignment and in the subsequent years. They used default definition of the Basel Committee on Banking Supervision, and measured accuracy of default prediction using the Brier Score, the percentage of correctly classified observations and type I and II error rates. They, however, admitted that their results were limited in some ways due to the used data and that since only the benefits of non-financial factors had been analyzed, it was not possible to conclude that their additional use represented a net advantage because they had not examined the costs of acquiring and processing non-financial information. There could be research on how lenders' rating disagreement for common borrowers was related to nonfinancial factors in credit ratings.

NIBM (2013) - Default probabilities of borrowers can be analyzed and monitored through 'Transition Matrix' **(**www.nibmindia.org.in accessed in November 2013**)**. Rating transition matrix shows moving probabilities from one rating level to another rating level within a given span of time. It can monitor credit risk borrower-wise, industry-wise, rating-grade-wise, and also concentration and portfolio risk in business loans.

2.5 RISK-BASED SUPERVISION THROUGH BASEL NORMS

Bank for International Settlements (2015) - Basel II was originally published in mid-2004, but national implementation was delayed significantly. In the EU, Basel II was implemented by the Banking Regulation and Capital Adequacy Regulation (forming together the Capital Requirements Directive, CRD) and transposed into national law by the end of 2006. There were other jurisdictions which delayed implementation further, so that in the financial crisis of 2008, Basel II was not implemented globally. Basel III was agreed upon in early 2011 and has so far not been universally and fully implemented on a global level. As far as the assessment of credit risk is concerned, Basel II Pillar 1 provides two different approaches: the Credit Risk Standardized Approach (CRSA), which relies heavily on external ratings of CRAs, and the Internal Ratings-Based Approach (IRBA).

Commercial banks in India have already adopted Standardized Approach of Basel II where they take credit ratings of their borrowers from external credit rating agencies while assigning risk weights for calculation of regulatory capital. The current challenge before Reserve Bank of India is to prepare banks for Internal Ratings-Based (IRB) approaches of Basel II. These prudential guidelines will help strengthen credit risk management processes in banks in line with their evolving risk appetite and risk perceptions.

The main advantage of IRB approach is that it will promote credit risk sensitivity at all levels in a bank and reduce capital requirement **(RBI's IRB guidelines, 2012)** (Figure 2.7).

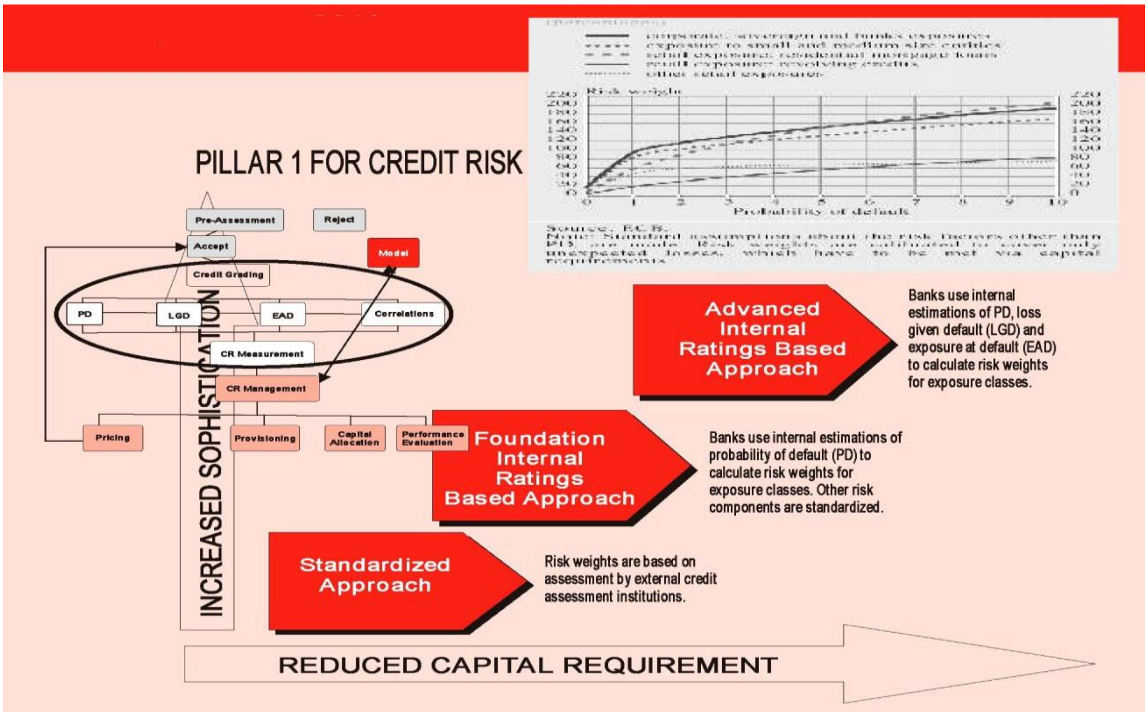

FIGURE 2.7: PILLAR 1 - BASEL II

(Source: National Institute of Bank Management, Pune, www.nibmindia.org.in)

Basel II accord on banking supervision had received many reviews from risk managers, analysts, researchers and policy makers.

Altman & Gabriele (2005), using data from three countries (US, Italy, and Australia) and surveys related studies from several other countries in Europe, investigated the effects of the New Basel Capital Accord on bank capital requirements for small and medium- sized enterprises (SMEs). They found that, for all the countries, banks would have significant benefits, regarding lower capital requirements, when considering small and medium sized firms as retail customers. But they would be obliged to use the Advanced IRB approach and to manage them on a pooled basis. For SMEs as corporates, however, capital requirements would be slightly greater than under the existing Basel I Capital Accord. The authors believed that most eligible banks would use a blended approach (considering some SMEs as retail and some as corporate). Through a breakeven analysis, they found that for all of the countries studied, banking organizations would be obliged to classify as retail at least 20% of their SME portfolio to maintain the current capital requirement (8%).

Fergusan (2003) - Basel II is rooted in modern finance and seeks to develop in the larger banking organizations a comprehensive, systematic approach to assess the various risks to which they are exposed. It inevitably raises both the supervisors' and the market's expectations for banks' risk-management systems. It clearly will increase the resources and management attention devoted to the details of risk management, focusing attention on the kinds of risks being taken and the potential losses that may accompany them. The advanced approaches to credit risk will require large banks to analyze their credit exposures in a formal and systematic way, assigning both default and loss probabilities to such exposures.

Leeladhar, RBI, (2007) gave insights into the requirements of Basel II for credit risk management by the Indian banks. He mentioned that Basel I did not provide for credit- risk transfer products like securitization and credit derivative, which enabled the banks to hide their risk exposures. According to him, the unique aspect of Basel II was the Pillar 2 – the supervisory review process. Pillar 2 required the banks to establish ICAAP, an Internal Capital Adequacy Assessment Process to capture all the material risk and fix a higher Capital Adequacy Ratio as per its risk assessment, though Pillar 1 required only minimum capital ratio. He advised banks to build up comprehensive data base before migration to advanced approaches of risk management provided in Basel II framework. **Leeladhar** also pointed out that the risk sensitive approach of the Basel II framework was likely to give rise to procyclicality in the capital requirements of the banks since in an economic downturn, the capital requirements would rise but would decline during an economic boom. He argued that such an impact could increase the volatility of the banking system. He expected that the bank managers would upgrade the risk governance in their organizations to achieve a sharper risk-reward profile.

Hudson (2003) believed that Basel II was the end of risk management by banks. In the next few years, risk manager would be busy interpreting the regulations, implementing the solutions justifying the output for supervisors and would have little time left for innovation and creative development.

Rowe (2004), however, stated that addressing the data issue properly would allow banks to leverage their Basel II efforts to improve their fundamental risk management process.

The same views were supported by **Trchemernjak (2004)**. According to him, banks realized that Basel II provided them an opportunity to improve their overall risk management strategy, improve business decision making and increase shareholder value.

Basel Committee (2005) maintained that the validation of credit risk models was fundamentally more difficult than the back testing of the market risk models. Market risk models employed a horizon of few days. Credit risk models generally relied on time frame of one year, coupled with higher confidence level (99.9%) and therefore, would present problems to model builders in assessing the accuracy of their models **(Angelini, et al. 2006).**

Sen and Ghosh (2005) reviewed the impact of Basel I norms on Indian banking sector particularly on credit flow to SMEs and the poor in India. The researcher analyzed priority sector lending, micro credit, small scale industry share in banks credit, and found that Basel norms had an adverse impact on social banking.

According to **Basel Committee (2009)**, the stress test is described as the evaluation of the financial position of a bank under a severe but plausible scenario to assist in decision making within the bank. Stress testing is a tool that supplements other risk management approaches and measures. It plays a particularly important role in providing forward-looking assessments of risk; overcoming limitations of models and historical data; supporting internal and external communication; feeding into capital and liquidity planning procedures; informing the setting of a banks' risk tolerance; and facilitating the development of risk mitigation or contingency plans across a range of stressed conditions.

According to **Oesterreichische National Bank, 2004**, the goal is to use the capital required from an economic point of view as the yardstick for the regulatory capital requirement. However, that will only happen if the banks measure the risks by the regulatory criteria.

KPMG (2012) stated that the Indian financial system is expected to grow further not only in size but also in complexity in the years to come. Advanced approaches under

Basel II were expected to help banks improve their risk management by building their own data models and assigning their own ratings to better assess risk while reducing capital requirements.

According to **Greuning & Bratanovic (2009),** a significant aspect of the Basel II Accord was the greater use of the banks' internal systems as an input to the capital assessment and adequacy calculations. It provided incentives for banks to improve their risk management practices, with increasingly sensitive risk weights when banks adopt more sophisticated approaches to risk management. The capital adequacy standard under the Basel Accords is based on the level of a bank's capital related to the bank's specific risk profile.

Basel Committee (2000) on 'Range of Practices in Banks' Internal Rating Systems' noted that banks were using different approaches assigning internal ratings. At one extreme are systems focused on the judgment of expert personnel, and at the other, those based solely on statistical models. Each would probably require a different approach to supervisory review and validation. Data availability remained a challenge to banks' efforts to quantify risk, although some banks were making progress in collecting and analyzing internal data for certain market segments covering the past few years.

RBI Report on Currency & Finance (2008) reported that in line with the international best practices, India had also been strengthening capital adequacy framework and risk management practices of banks. Basel II norms aimed at aligning minimum capital requirements to banks' underlying risk profiles. The framework was also designed to create incentives for better risk measurement and management

Hirtle et al. (2001) - The overall objective of an internal-models regulatory capital charge would be to allow banks and supervisors to take advantage of the benefits of advanced risk-modeling techniques in setting capital standards for credit risk. While stress testing is far from a perfect validation tool, it can provide important information about the impact of unlikely but potentially damaging events that could result in very large losses in a bank's credit portfolio.

Jiminej, Saurina & Lopez (2009) - Corporate credit lines are a key product for banks, and the management of their inherent credit risk requires calibration of their EAD (Exposure at Default) parameters. Using the credit registers maintained by public authorities, they constructed an extensive database of defaulted corporate credit lines over a twenty-year period to calibrate the EAD values at various default horizons. Their results showed that a variety of factors – such as commitment size, collateralization and maturity – influenced the EAD calibrations. Their conclusion is that banks must address these factors in their EAD calibration processes, even if regulatory capital guidelines do not explicitly require it.

Segoviano & Lowe (2002) - They used the ratings assigned by individual Mexican banks to examine how measured credit risk for these banks had changed since the financial crisis in the mid-1990s. They examined the implications of those changes in risk for regulatory capital under the proposed changes to the Basel Capital Accord. They found that measured risk increased after the crisis and then fell as the recovery took hold. In turn, despite the limitations of the data, they also found that the proposed internal ratings-based approach would have generated large swings in regulatory capital requirements over the second half of the 1990s, with required capital increasing significantly in the aftermath of the crisis, and then falling as the economy recovered. Looking forward, if movements in actual bank capital were to show this same cyclical variation, then business cycle fluctuations might be amplified by developments in the banking industry.

According to **Stephanou & Mendoza (2005)**, Basel II (particularly in its IRB form) implied fundamental changes to the way that many developing country banks were actually managed. The Accord effectively forced those banks (and their regulators) to play "catch up" with credit risk concepts and measurement tools that had long been used in more developed banking systems. In particular, the use of concepts such as economic capital and RAROC allowed senior bank management to measure performance under a common metric and meaningfully compare different businesses in a better way than the traditional measures (such as ROE) that failed to explicitly take risk into consideration. At a business unit level, these tools simplified the process of credit analysis, lowered the subjectivity in the loan approval process and provided guidance for risk-adjusted pricing. Given their inherent complexity and required change in incentives, it would take a time to embed these concepts in banks that had historically been managed on different metrics. Even though the revised credit capital rules represented a dramatic change compared to Basel I, it was shown that Basel II merely sought to codify (albeit incompletely) existing good practices in bank risk measurement. However, its effective implementation in many developing countries would be hindered by fundamental weaknesses in financial infrastructure such as cost of implementation, inadequate supervisory capacity, impact on domestic banking system not fully understood, and unavailability of required risk data in easily accessible or comprehensive format, potentially excessive capital requirement due to inappropriate calibration, training and development of new supervisory culture.

RBI (2011) - All scheduled commercial banks in India had become Basel II compliant as per the standardized approach with effect from April 1, 2009. For migrating to advanced approaches of Basel II, the Reserve Bank of India issued a separate set of guidelines and the applications received from banks for migration to advanced approaches of Basel II are at various stages of examination with the Reserve Bank. Parallel to this process, the Reserve Bank came out with the final guidelines for implementation of Basel III in May 2012. The guidelines issued by the Reserve Bank would be effective from January 1, 2013. Against this backdrop, it is important to examine the existing capital position and other soundness indicators of Indian banks in order to assess banks' preparedness to migrate to the more advanced regulatory approaches (RBI Trends, 2011-12, Para 4.24).

Bank for International Settlements (2015) however, stated that the supervisors should be cautious against over-reliance on internal models for credit risk management and regulatory capital. Where appropriate, simple measures could be evaluated in conjunction with sophisticated modeling to provide complete picture. Regulatory requirements such as the Basel framework and stress testing have been one driver of the modeling enhancements. Firms highlighted increased reliance upon stress testing using their internal models. Against this background, some supervisors cautioned that there was a risk that some credit risk management or regulatory capital models could mask increased risk-taking.

Thus, there is a need to study the Indian public banks preparedness for Basel II and implementation challenges being faced by them in the light of Basel's international best practices.

2.6 DETERMINANTS OF CREDIT RISK

Being state-owned banks, Indian public sector commercial banks have always been under tremendous pressure to boost priority sector financing along with acting as engines of growth for reviving investment in manufacturing, services and infrastructure sectors of the Indian economy. They are striving to achieve profitability targets, direct credit flow to all the productive business lines, manage asset quality of their loans, and keep a supportive interest rate environment to raise demand for investible resources in an atmosphere of recessionary trends and inflationary pressures.

It is necessary to understand factors or causes of credit risk in commercial banks and especially in Indian public or state-owned banks. There are several studies on what causes credit risk in banks. Effectiveness in measurement and control of credit risk will depend on the identification of key risk factors or risk drivers.

Das and Ghosh (2007) examined credit risk determinants in Indian state- owned banks during the period 1994-2005. Their findings revealed that at the macro level, GDP growth and, at the bank level , real loan growth, operating expenses and bank size played an important role in influencing problem loans. According to them, to compensate for declining profitability, bank managers might sacrifice objectivity in credit evaluation standards and increase loan growth indiscriminately at the expense of quality of their loan portfolio. Such loans turned out to be non- performing only with a lag, and that encouraged future loan growth. Collaterals also played a role in influencing bad loans. Rapid increase in land prices increased the cushion, propelling banks to increase lending, discarding the credit standards.

A study by **Misra and Dhal (2010)** analyzed pro-cyclicality of bank indicators with a focus on the non-performing loans of Indian public sector banks. They demonstrated that banks' NPAs were influenced by three major set of factors, i.e., terms of credit such as interest rates, maturity, and collaterals; bank specific indicators relating to asset size, credit orientation, financial innovations, regulatory capital requirement; and the business cycle shocks. They also specifically highlighted that bank size variable had a positive impact on gross NPA ratios. This could imply that large banks were more likely to have relatively more NPAs. Due to balance sheet constraints, small banks could show greater managerial efficiency than the large banks in terms of loan screening and post loan monitoring, leading to lower defaults.

Thiagarajan et al. (2011) conducted an empirical study on 22 public sector banks and 15 private sector banks in India, by using panel logistic regression on historical data about non- performing assets and GDP. Their results showed that the lagged non-performing assets had a strong and statistically significant positive influence on the current non-performing assets. Their study concluded that both macroeconomic and bank specific factors played a crucial role in determining the credit risk of commercial banking sector. Large NPAs were generated due to high risk appetite of banks in boom period. The bank-specific variables were the size of the bank, branch growth, inefficiency, loan growth rate, and macroeconomic variables were GDP and inflation.

Sah Bittu & Dwivedi (2012) empirically analyzed the fundamental factors affecting periodic addition (slippage rate) to non-performing assets (NPAs or fresh slippage), taken as a proxy for measuring credit risk, by performing panel regression for five-year period, 2005-2009, on all 70 Indian banks. They investigated variations on ownership dimension, aggressiveness, risk taking behavior and performance of banks. The study indicated variations in fresh slippage was inversely related to the efficiency of bank performance and directly related to capital-adequacy ratio. Standard Granger causality test based on quarterly fresh slippage data of a large public sector bank revealed that macroeconomic factor(s) – gross domestic product (GDP) had a significant implication on credit risk management of banks – direction of causality established from GDP to NPA while no 'reverse causation' was observed.

KPMG (2012) on FY12 (the financial year 2012) results stated that the economic slowdown and stress in some sectors, such as aviation, power, and commercial real estate, led to a deterioration in banks' asset quality which increased in fresh slippages and higher provisioning expenses for banks, thereby impacting their profitability. The banking sector's credit demand from the corporate sector was primarily driven by working capital requirements rather than the incremental capital expenditure and infrastructural investment. Several projects had become unviable due to increasing interest rates and commodity prices which reduced the demand for incremental loans. India's corporates were awaiting better investment environment characterized by low interest rate, low commodity prices, removal of supply-side bottlenecks and government action on some of the pending reforms.

Aver (2008) during an empirical analysis of credit risk factors of the Slovenian banking system emphasized on both industry and company factors causing credit risk. According to him, industry factors included the structure and economic successfulness of the industry, maturity of the industry and its stability while company factors include factors such as general characteristics of the company, management, financial position, sources of funds and financial reporting. For macroeconomic factors, the credit risk of the loan portfolio depends on the employment or unemployment rate in Slovenia, on short and long-term interest rates of Slovenian banks and the Bank of Slovenia, and on the value of the Slovenian stock exchange index.

Greuning & Bratanovic (2009) stresses that ineffective supervision invariably results in a lack of knowledge about the borrower's affairs over the lifetime of the loan, and consequently, initially sound loans may develop problems and losses because of lack of effective supervision. Incomplete credit information which indicated that loans had been extended without a proper appraisal of borrower's creditworthiness and complacency are the frequent causes of bad loan decisions. According to him, the signs of the distorted credit culture are - self-dealing, compromise of credit principles, anxiety over income, incomplete credit information, complacency, lack of supervision, technical incompetence, and poor selection of risk.

Altman (2005) observed that the collateral values and recovery rates on corporate default could be volatile, and moreover, those would go down just when the number of defaults goes up in economic downturns.

This was also supported by **Acharya et al. (2007).** While researching on defaulted firms in the United States over the period from 1982 to 1999, they showed that creditors of defaulted firms recovered significantly lower amounts in present-value terms when the industry of defaulted firms was in distress. They investigated whether that was purely an economic-downturn effect or also a fire-sales effect along the lines of Shleifer and Vishny (1992). They found that the fire-sales effect to be also at work.

Creditors recovered less if the industry was in distress and non-defaulted firms in the industry were illiquid, particularly if the industry was characterized by assets that were specific, not easily re-deployable by other industries, and if the debt was collateralized by such specific assets. They also documented that defaulted firms in distressed industries were more likely to emerge as restructured firms than to be acquired or liquidated, and would spend longer in bankruptcy. Their evidence suggested that recoveries fall during industry distress not only due to a downward revision in the economic worth of firm's assets but also because of the financial constraints that industry peers of the defaulted firm faced.

Glennon & Nigro (2005) stressed that causes of credit risk might emanate from loan specific characteristics, lender characteristics, and borrower characteristics of a business loan.

Wahlen (1994) analyzed the association between loan loss information, future cash flows and stock returns of a bank based on annual returns and accounting data. Bank's financial statements provided three separate disclosures of changing default risks- (a) non–performing loan, (b) loan loss provisions and (c) loan charge- offs. Banks managers had limited discretionary ability to change the level of non-performing loans and loan charge - offs (bad debts) but they could exercise discretion over the timings of provision for certain loan losses. The study concluded that non-performing loans and unexpected loans charge- offs were negatively related to future changes in cash flows and stock prices. However, these enabled investors to observe when managers were exercising discretion with respect to loan loss provisions. Investors interpreted increased unexpected loan loss provisions as "good news" and it had a positive impact on future cash flows and bank stock prices.

An internal study conducted by **RBI (Muniappan, 2002)** pointed out at many internal and external variables posing credit risk and causing NPAs in banks. These were borrower's willful default, siphoning of funds, industrial disputes, poor debt management, not compliance with sanctioned terms and conditions, excess capacities, time/cost overruns in new project implementation, business failure, product obsolescence along with deficiencies on the part of banks in credit appraisal, monitoring and follow - up. The external factors were the recession, non-payment in other countries, input/power shortage, price escalation, accidents, natural calamities, changes in government policies, etc. Muniappan (2002) also dealt with the impact of NPAs in a comprehensive manner. According to him, the consequences of the high level of NPAs would be the higher carrying costs on non-income yielding assets, reduction in interest income, the higher level of provisioning, stress on profitability, increased pressure on net interest margin, erosion of capital resources, reducing competitiveness and general risk aversion.

Siraj (2012), based on historical data from 2001-11 about Indian banks, concluded that recessionary pressure faced by the banking sector was an important reason for the growth of NPA indicators viz. gross NPAs, net NPAs, and provisions towards NPAs.

Mckinsey (2011-12) had projected that the Indian mid-corporate sector would grow to become a Rs. 44000 crore opportunity by 2015 across various products. However, mid-corporates would be riskier than the large obligors, as their financial data was less reliable, had a short life cycle, were less liquid, and more sensitive to the economic cycle. These businesses were mostly owned or run by families. According to them, mid-corporates to succeed shall develop three competencies- building distinctive front-to-back risk capabilities, boosting product design and delivery capabilities, and maximizing franchise value through coverage and cross-sell.

The Indian Express (24.05.2013), Mumbai reported that the SBI was more cautious in corporate lending. The bank plans to tighten entry norms for mid-corporates by making the credit selection process stricter. SBI Chairman, Mr. Pratip Chaudhuri, said, "The mid-corporate segment is still reeling under pressure due to difficult economic conditions. Lower profitability is rendering it difficult for the companies in the segment to service their interest liability."

The Indian Express, Mumbai (22.08.2013) further reported that worried at the growing delinquencies in the mid-corporate advances portfolio, the country's largest lender, State Bank India (SBI), was going slow on lending to that segment. Mr.SB Nayar, DMD, and group executive of corporate banking at SBI, conceded the bank was being cautious in expanding mid-corporate loan book. Mid-corporates account for about 20% of SBI's loan book. The corporate sector, led by mid-corporate borrowers, contributed around a-third of these fresh slippages in the April-June 2012 quarter. Gross NPLs for the mid-corporate segment was 9.3%. Nayar said various constraints including the stalled reform process, weak investment climate, and supply side bottlenecks were affecting the health of mid-corporates. This was reflected in the loan growth numbers for the April-June 2012 quarter. While the public sector bank saw an overall advances book growth of 19% year-on-year (y-o-y), the mid-corporate segment grew a much slower at 6.3% y-o-y. The overall gross NPA level for SBI at the end of the quarter stood at 5% of the advances book, compared with a gross NPA level of 3.52% of the advances book, in the April-June 2011 quarter.

Mukherjee, Nath and Pal (2003) attempted to integrate operational research methods and marketing methods to find linkages between tangible resources, service quality and performance in Indian public sectors banks. The authors concluded that the almost 70% of Indian public sector banks were inefficient in utilizing their infrastructure, human resource and other capabilities for optimal service delivery. Though the authors basically studied service quality in public sector banks, their conclusions may be extended to inefficiencies in the management of credit risk as well.

Njanike(2009) conducted research on credit risk management systems in Zimbabwe's banks. The author concluded that bank failures were mainly caused by poor corporate governance, inadequate risk management systems, chronic liquidity challenges, ill planned expansion drives and speculative banking activities. The study recommended implementation of prudential guidelines and credit assessment methodologies. A number of financial institutions had collapsed or had experienced financial problems due to inefficient credit risk management systems. The study sought to evaluate the extent to which failure to effectively manage credit risk led to Zimbabwe's banks' demise in 2003-2004 bank crises. It also sought to establish other factors that led to the banking crisis and to outline the components of an effective credit risk management system. The study found that the failure to effectively manage credit risk contributed to a greater extent to the banking crisis. The research also identified poor corporate governance, inadequate risk management systems, ill-planned expansion drives, chronic liquidity challenges, foreign currency shortages and diversion from core business to speculative non-banking activities as other factors that caused the crisis. The study stressed that there was a need for banks to develop and implement credit scoring and assessment methodologies, review and update the insider lending policies and adopt prudential corporate governance practices.

Dahiya, Saunders, and Srinivasan (2003) analyzed the wealth effects for lead banks' shareholders when banks' borrowers faced financial distress. When banks were ranked according to their exposure to distressed firms, the share price decline for low exposure banks was insignificant, while that for high exposure banks, share price decline was large and significant. They found a significant negative return for the lead lending bank when a major corporate borrower announced default or bankruptcy.

Llewellyn (1998) advised that prompt action should be taken to prevent problems which might arise from extending credit to high-risk borrowers or from capitalization of unpaid interest on delinquent loans into new credit. It was essential to reduce the moral hazard risk in bank restructuring loans that arose when institutions with low and declining net worth continued to operate under the protection of public policies designed to maintain the integrity of the banking system.

Ghosh (2011) developed a Banking Stability Index (BSI) of 28 Indian public sector banks on the basis of annual data from 1997 – 2007. He utilized three indicators of banking operations-Loans-loss Provisions to Total Asset Ratio, Total Capital to Total Risk-Weighted Asset Ratio and Profitability Return on Asset Ratio. The author classified banks as of high stability, moderate stability, and low stability. He classified ten public sector banks with BSI of low stability. The paper concluded that existing private and foreign banks have improved competition and promoted stability. Regulatory mechanism to provide international best practices has also been advantageous for banking sector.

Basel committee (2005) stated that asset correlation would increase with firm size. Larger a firm, the higher would be its dependency upon the overall state of the economy and vice-versa. Smaller firms were more likely to default for borrower specific factors. However, they also stated that the asset correlations decreased with increasing PDs (probability of default). The higher the PD, the higher would be the impact of idiosyncratic (individual) risk components of a borrower. The default risk would then depend less on the overall state of the economy and more on individual risk drivers.

Thus, based on evidence from literature, important factors or determinants of credit risk in banks are summarized as:

- Borrower-specific factors such as his financial ratios, business risk, management capabilities, industrial problems, loan maturity, value of collaterals, willful defaults, funds diversion to associate concerns etc., (Muniappan, 2002).
- Bank-specific factors such as size of bank, loan growth rate, branch growth rate, interest rates, credit approval and monitoring process, operating efficiency, capital to risk-adjusted assets ratio (financial leverage), (Misra, 2010); insider loans, poor corporate governance, creative accounting, rapid expansion drives, disintegration of systems, inconsistencies in risk appraisal, (Njanike, 2009) disaster myopia, herd behavior, short-term concerns (Das & Ghosh, 2007).
- Macroeconomic variables such as GDP growth rate, recession, unemployment, inflation, interest rates, exchange rates, etc. (Das & Ghosh, 2007, Aver, 2008, KPMG, 2012).

2.7 INDICATORS OF CREDIT RISK

The measure of the effectiveness of credit risk management practices needs identification of the indicators of credit risk. Based on review of literature, the following indicators of credit risk in banks have been deduced:

- Gross NPAs and Net NPAs (Net NPAs are Gross NPAs –Provisions).
- Gross NPA Ratio and Net NPA Ratio (Gross NPAs as a percentage of Gross Advances, and Net NPAs as a percentage of Net advances).
- Provisioning Coverage Ratio (Ratio of Outstanding Provisions to Gross NPAs).
- Slippage Ratio (Fresh accretion of NPAs during the year as a percentage of standard assets during the year).
- Recovery Ratio (NPAs recovered during the year as a percentage of gross NPAs outstanding at the beginning of the year).
- Written off Ratio (NPAs written off as a percentage of gross NPAs outstanding at the beginning of the year).
- Capital to Risk-adjusted Assets Ratio (financial leverage) or Capital Adequacy Ratio.
- Return on Risk-adjusted Capital Ratio (RORAC).
- Net NPAs to Capital Ratio.
- Gross NPA to ROA Ratio, Net NPA to ROA Ratio.
- Restructured loans and advances.

2.8 BANK'S NON-PERFORMING ASSETS

The main indicator of the credit risk in banks is their non-performing assets (NPAs). A non-performing asset (NPA) is a loan or an advance where interest and/ or installment of principal remain overdue for a period of more than 90 days in respect of a term loan (RBI, 2013). Non-performing assets, also known as problem loans negatively impact a bank's profitability, liquidity, and growth prospects.

RBI Trends (2015) - The performance of the Indian banking sector during the year, however, remained subdued. First, the banking sector experienced a slowdown in balance sheet growth in 2014-15, a trend that had set in since 2011-12. The slowdown was most notable in the case of bank credit, which dipped to a single-digit figure during the year.

Das (2002) studied risk and productivity change of public sector banks in India during 1995- 2000, to find the impact of financial liberalization on the productivity of banks. The interrelationship among risk, capital and productivity of public sector banks was researched using Leightner and Lovell approach which they had undertaken on Thai banks. The study examined two types of banking risks – Credit Risk as the ratio of Net Non- Performing Loans to Net Advances (NNPA) and financial leverage as the ratio of Capital to Risk Weighted Assets (CRAR). The study concluded that productivity, capital, and risk were jointly determined, reinforced and compensated each other. NNPA ratio had the positive effect whereas the CRAR had the negative effect on credit risk. The study observed the increase in productivity especially in small-sized public sector banks as against the popular belief.

Rajput (2012) researched correlation of gross and net NPAs with Return on Assets (ROA), for the public sector banks from 1996 to 2010 on the basis of data from the annual reports of the Indian banks. The author concluded that there was a high degree of negative correlation between NPA ratios and ROA and that in a banking system, NPA was inevitable and could not be totally eliminated. Most important was to arrest fresh accretion and contain it to the barest minimum by preventing slippage through effective proactive steps at the right time.

Siraj (2012) studied the performance of non-performing assets of public, private and foreign banks for the period from 2001-11, based on RBI reports, using statistical tools like regression analysis. They concluded that NPAs remained a major threat and incremental component explained through additions to NPA was a great question mark on efficiency of credit risk management of banks in India.

Malaydri & Sirisha (2011) studied the non-performing assets of the Indian banking industry and concluded that the future of PSB's would be based on their capability to continuously build good quality assets in an increasingly competitive environment and maintaining capital adequacy and stringent prudential norms. Consolidation and competition may be the key factors impacting the nationalized banks in future. Due to reforms, it has been felt that there is a need not only to increase profits but also reduce nonperforming assets (NPA's) of banks.

Gurumoorthy & Sudha (2012) argued that complete elimination of NPAs in public sector banks was not possible because government business and development schemes were mostly routed through the PSBs, but banks could always aim to keep the losses at low level. Banking system played a very important role in the economic life of the nation. The health of the economy was closely related to the soundness of its banking system. Complete elimination of NPA in PSBs was not possible because government business and development schemes were mostly routed through the PSBs, but banks could always aim to keep the losses at a low level. Non-performing assets might not turn banks into non-performing banks; instead, steps should be taken to convert Non-Performing Assets into Now-Performing Assets. As far as old NPAs were concerned, a bank could remove it on its own or sell the assets to Asset Management Companies (AMCs) to clean up its balance sheet. For preventing fresh NPAs, the bank itself should adopt the proper policies. It was better to avoid NPAs at the budding stage of credit consideration by putting in place of rigorous and appropriate credit appraisal mechanisms. PSBs should be well versed in proper selection of borrower or project and in analyzing the financial statement.

Shukla (2010) also stressed that the management and not the elimination of the NPAs was prudent. A developing country like India could never aim at zero NPAs. However, containing NPAs which optimized risk with return while maintaining competitive efficiency was needed.

Tracey and Leon (2011) maintained that overindulgence with NPAs led managers preoccupied with recovery procedures rather than concentrating on expanding the business. A higher NPA level forced banks to invest in risk - free investments, thus directly affecting the flow of funds for productive purpose. The paper assessed the impact of Non-performing loans (NPLs) on loan growth. In making lending decisions, banks were assumed to react differently to NPL ratios above or below a threshold, with NPLs above the threshold having an adverse effect on lending. This was also contingent on the level of CAR (Capital Adequacy Ratio) banks hold for regulatory standards or own internal capital ratio requirements. They estimated the Loan-NPL relationship using a threshold model for a sample of Caribbean countries. The results suggested threshold range for the ratio of NPL/Total Loans as determining differential loan behavior of banks. One implication was that bank lending behavior could restrain economic activity, especially in periods of stress when NPLs were high.

Dong He, IMF (2002) analyzed NPAs of the Indian banking system. According to him, NPAs of large size were industrial loans collateralized by the fixed assets of the borrowers; that typically did not have much value if the viability of the borrowers was in doubt. Credit quality was low in the public sector banks (PSBs) and Development Finance Institutions (DFIs), the dominant sub-sectors of the Indian banking system. The high incidence of non-performing assets (NPAs) was the result of many factors, including poor credit analysis skills and lending decisions, external shocks (e.g., unexpected slowdown in economic activities), and shortcomings in the legal and judicial system that prevented the timely exercise of creditor rights.

Chakrabarty, RBI (2012) brings out debt restructuring as a powerful tool for credit risk management. Projects which are otherwise viable but facing problems in loan servicing, due to the general economic downturn, or delay in government approval or project implementations, may be restructured for mutual advantage to the borrower or lender. However, he argues that the PSBs (public sector banks) are not making judicious use of restructuring as a credit risk management tool. The need for restructuring should arise only due to circumstances beyond the control of the borrowers and not generally for errors / mismanagement by them. In any case, the restructuring proposals should be considered from a purely commercial angle albeit with a bias towards giving a benefit of doubt to the customer. Also, a uniform approach needs to be adopted for both Standard and NPA accounts while examining the restructuring proposals. Further, the viability of the project should be established and only after that should any restructuring proposal be considered.

Chaudhary & Sharma (2011)- An efficient management information system should be developed. The bank staff involved in sanctioning the advances should be trained about the proper documentation and charge of securities and motivated to take measures in preventing advances turning into NPA. Public banks must pay attention on their functioning to compete with private banks.

Samantraya (2007) - Their study attempted to empirically examine the pro-cyclicality behavior of bank credit in India, particularly exploring various contributory factors for drawing important implications for monetary policy. The most important finding of the study is that despite taking into account the influence of other key factors influencing bank credit, NPA and capital requirements are found to have statistically significant influence on bank credit. One per cent increase in NPA leads to 0.01 percent fall in bank credit. Similarly, 10 percent increase in CRAR above the prescribed minimum results in 0.04 percent increase in credit growth. This implies that raising minimum capital requirement, which is concomitant with reducing the buffer above the prescribed minimum, will constrain credit growth.

2.9 TRENDS IN NON-PERFORMING ASSETS (NPAS) IN INDIAN PUBLIC SECTOR BANKS

During 2011-12, the trends in non-performing assets as per **RBI report 'Trends and Progress of Banking in India 2011-12'** show that there is a problem of asset quality maintenance and credit risk management before banks and that the deteriorating asset quality of the banking sector emerged as a major concern with gross NPAs of banks registering a sharp increase (Figure 2.8). Reserve Bank of India (RBI) in its report on 'Trends and Progress of Banking in India, 2011-12' dated 08 November 2012 (Para 4.29) has specifically maintained, " Gross NPA ratio at system level increased mainly on account of deterioration in asset quality of public sector banks… The spurt in NPAs could be attributed to the slowdown prevailing in the domestic economy as well as to inadequate appraisal and monitoring of credit proposals". The deterioration in asset quality was more pronounced in the case of public sector banks. During this period, the gross NPAs of public sector banks increased at a higher rate as compared with the growth rate of NPAs at a system level. In sync with the acceleration in the growth of gross NPAs as well as a lower provisioning coverage, Net NPAs registered higher growth. The Net NPAs ratio was also on a higher side for public sector banks as compared with the private sector and foreign banks.

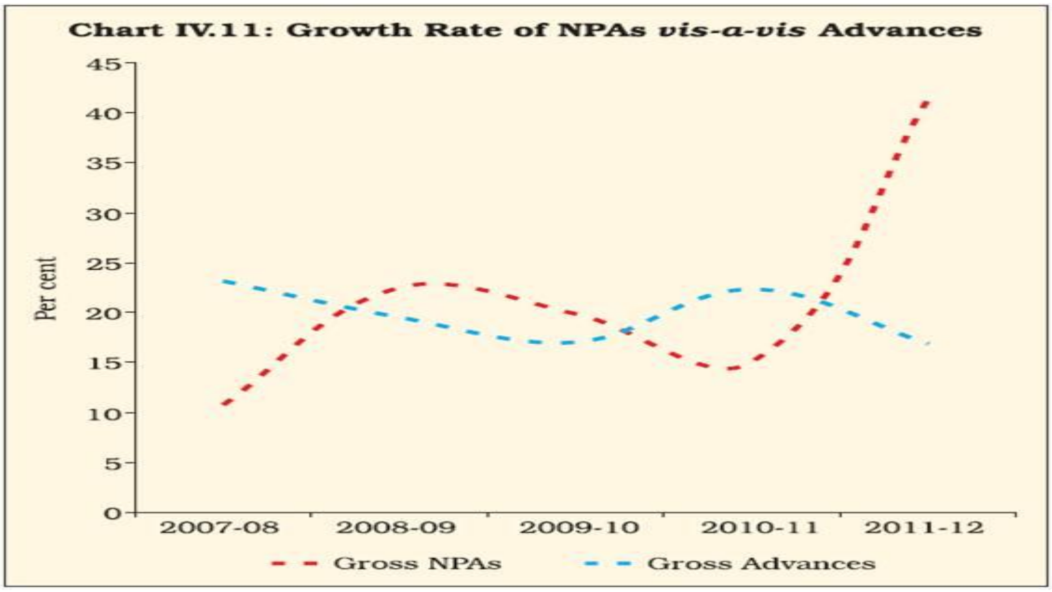

FIGURE 2.8: GROWTH RATE OF NPAS VIS-À-VIS ADVANCES

(Source: RBI Trends, 2011-12)

Sectoral deployment of gross bank credit data in RBI report indicated that gross bank credit to industry and services together constituted two-third of total bank credit. Against the popular contention of linking NPAs with priority sector, more than half of the NPAs emerged from the non-priority sectors (Figure 2.9). Non-priority sectors consist of retail or consumer loans market, medium and large enterprises, corporates, infrastructure sectors like power, road, bridges; services, non-banking financial companies, etc. Deterioration in asset quality of public sector banks was found spread across both priority and non-priority sectors. Public sector banks had increased NPAs in both the sectors.

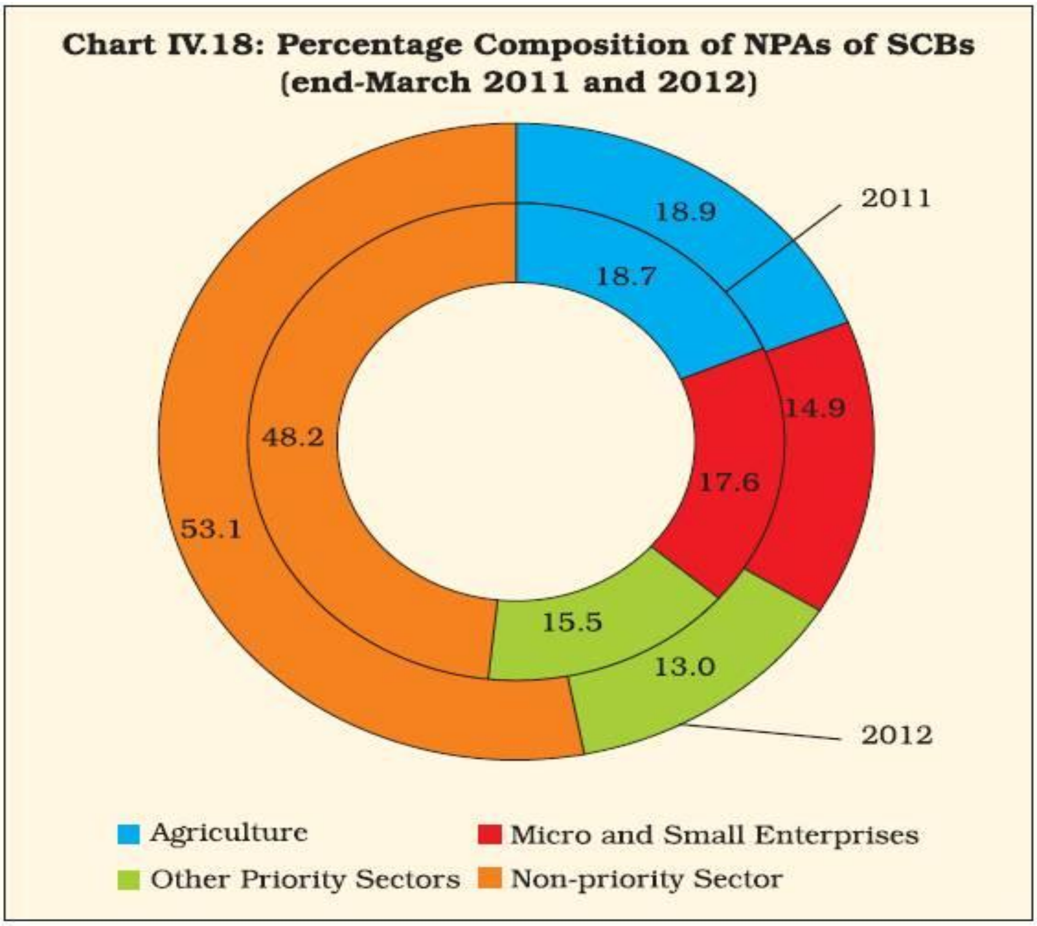

FIGURE 2.9: SECTOR-WISE NPAS OF ALL BANKS

(Source: RBI Trends, 2011-12)

RBI observed that NPAs became stickier with the proportion of substandard as well as doubtful assets in gross advances registered an increase. Thus, there is a great challenge before banks particularly public sector banks to tighten their credit risk management practices.

RBI (2013) reported that against the backdrop of a slowdown in the domestic economy and tepid global recovery, the growth of the Indian banking sector slowed down for the second consecutive year in 2012-13, and the asset quality also deteriorated, more perceptibly for public sector banks. Industry, which accounts for a little less than half the total credit of domestic banks, has shown a steady deterioration in asset quality in the recent years, particularly in 2012-13. The current statistics of non-performing assets (NPAs) of Indian banks show that the public sector banks have the largest share of sticky loans. State Bank of India, the largest Indian bank, tops in bad loans, followed by the Punjab National Bank, another large bank, and the Central Bank of India (RBI, 2013).

The RBI's Financial Stability Report, December 2013, also states that the risks to the banking sector have further increased, and all major risk dimensions captured in the Banking Stability Indicator show increase in vulnerabilities in the banking sector, whereas the corporate performance continued to be weighed downed by boom period expansions and excess capacities. RBI further observed that economic slowdown is not the sole reason for deteriorating asset quality but also the inadequate appraisal and monitoring of credit proposals by banks.

According to **KPMG (2012)** survey, while there was no major increase in new restructured loans for private sector banks, it has continued to remain high for PSBs due to the latter's exposure to State Electricity Boards (SEBs) and sectors such as aviation, textile, and steel. Though all the sectors in the economy contributed to the decline in credit growth, the deceleration was more visible in agriculture, real estate, hotels and restaurants, professional services, telecommunication, power, cement, textiles, iron and steel and personal vehicle loans (KPMG, 2012). During FY12, both the global and Indian economies were under stress resulting in an increase in the GNPAs, net non-performing assets (NNPAs) and restructured assets (KPMG, 2012).

The Live Mint (20.01.2013) highlighted a **Goldman Sachs Group Inc.** report that while the banking system is largely healthy, the key concern is asset quality. Their chart (Figure 2.10) shows that net non-performing assets (NPAs), together with restructured loans, add up to half of Indian banks' net worth. **Goldman Sachs** report says, "Using the Reserve Bank of India's assessment of increase in NPLs (non-performing loans) in this scenario, we estimate that NPLs + restructured loans could rise to above 8% of system credit".

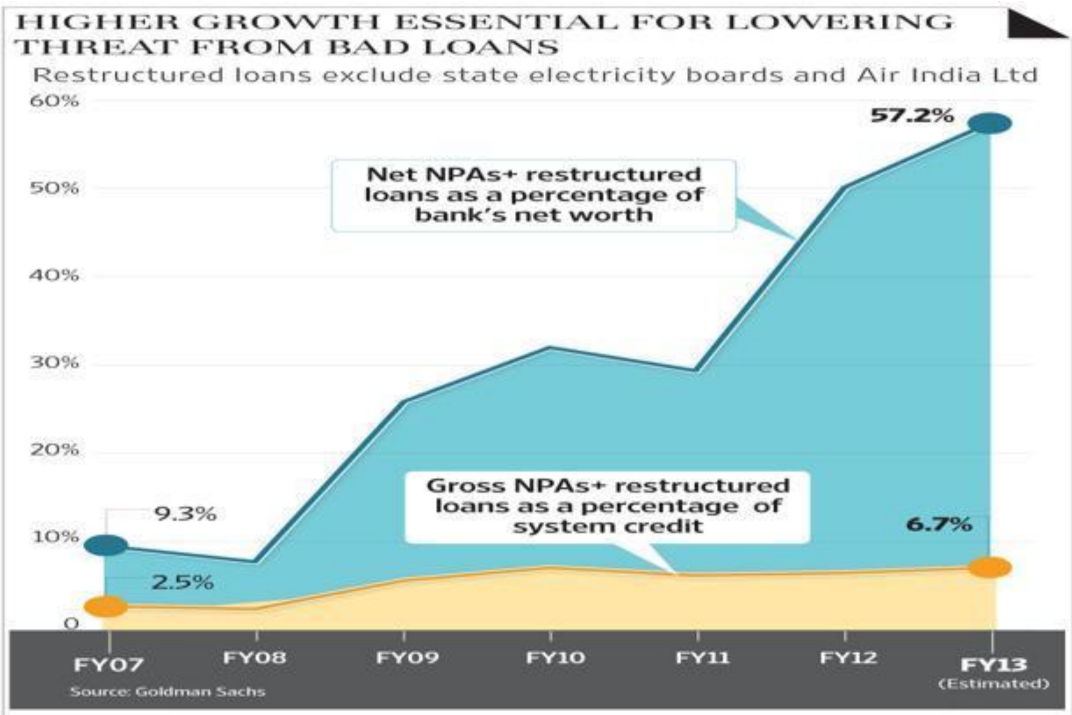

FIGURE: 2.10 STRESSED ASSETS

(Source: The Live Mint 20.01.2013, The Hindustan Times)

The RBI's Financial Stability Report, December 2014 (Para 2.9) supported it. They reported that gross non-performing advances (GNPAs) of SCBs as a percentage of the total gross advances increased to 4.5 percent in September 2014 from 4.1 percent in March 2014. The net non-performing advances (NNPAs) as a percentage of total net advances also increased to 2.5 percent in September 2014 from 2.2 percent in March 2014. Stressed advances increased to 10.7 percent of the total advances from 10.0 percent between March and September 2014. PSBs continued to record the highest level of stressed advances at 12.9 percent of their total advances in September 2014 followed by private sector banks at 4.4 percent.

RBI Trends (2015) - The return on assets (ROA), a common indicator of financial viability, did not show any improvement in 2014-15. In particular the profitability of public sector banks (PSBs) diminished with their ROA declining significantly in recent years. The deterioration in the asset quality of banks in general, and PSBs in particular, continued during the year with a rise in volume and proportion of stressed assets (Para 1.2).

2.10 CREDIT RISK VS. SIZE OF THE BANK

The review of literature shows that credit policy of banks, their CRM systems and procedures play a significant role in ensuring credit health of banks. Previous research on different aspects of the Indian banking systems has reported the size of the bank as one of the critical variables. **Malhotra & Singh (2010)** observed that large banks were sometimes thought to be more capable. They may have higher quality or more technically able people on their staff, they may be freer from financial constraints, they may have market power or be more inclined to strategically pre-empt smaller rivals, and they may have economies of scale, more scope in R&D activities and the application of their results and being able to take greater risks.

Ghosh (2011) stated that to the extent bank size acted as a proxy for diversification, it seemed likely that bigger banks could exhibit higher stability. However, his statistical results indicated a negative impact of bank-size on banking stability index. In other words, larger banks had higher credit risk.

Das and Ghosh (2007) studied the problem loans of the Indian state-owned banks for the period from 1994-2005 and concluded that large banks appear to have higher problem loans than the smaller ones. Although bigger banks allow for greater diversification opportunities, it could be outweighed by higher problem loans on an overall quantum of credit extended. They suggested that the potential risk-reducing benefit of diversification might have been traded-off against the paucity of adequate skills in credit evaluation in big banks.

In contrast, **Thiagarajan et al. (2011)** found a negative correlation between bank size and the non-performing assets. According to them, reason could be that the banks with more assets had more resources for developing protocols and training of credit officers than banks with fewer assets.

2.11 RESEARCH GAP

The review of literature shows that though there are many studies on the performance of Indian banks, trends in their non-performing assets, and risk orientation, however, there are only few studies towards critical evaluation of the internal credit risk management practices of these banks especially their credit approval processes.

Moreover, these studies have narrow conceptual focus. Many Indian banks are developing comprehensive credit risk rating frameworks for risk - based loan pricing, and for computation of Probability of Default (PD), Loss Given Default (LGD), with a larger purpose to migrate to advanced IRB approaches of Basel II for calculation of capital adequacy ratios. There is a research gap on the credit risk rating methodology of Indian banks by which they capture and manage credit risk.

Again there are previous studies on credit risk factors in Indian banks especially public sector banks, but this research is based mainly on historical data, and not on a survey of managerial perception of causes of credit risk in these banks. Since the banks credit managers are directly associated with policy and operations of credit risk management, understanding how they perceive about causes of credit risk and about effectiveness of their CRM practices, will immensely contribute to the management of non-performing loans.

Studies like Thiagarajan (2011), Misra (2010), and Das (2009), based on panel regression analysis of historical data, have categorically concluded that among other things, size of the bank is an important determinant of credit risk and there is a positive relation between size of the bank in terms of assets, and its NPAs. There is a need to study through a managerial survey whether our small sized banks have better credit risk management practices than the large banks or vice-versa.

Further, RBI reports specifically implicate public sector banks for higher NPAs in the Indian banking industry due to their inefficient credit approval and monitoring processes (RBI Trends & Progress, 2011-14). About half of the defaulting loans have been reported in non-priority sector loans to industries and services. For all the above reasons, there is a need for systematic evaluation of credit appraisal, and monitoring mechanism of Indian public sector banks in grant and recovery of business loans, for efficient credit risk management. Since public sector banks dominate the Indian banking industry in terms of total assets(73%), deposits, branches, and lending to different sectors of the economy, any research undertaken on credit risk management framework for public sector banks will be representative of the Indian banking industry to a great extent.

The next chapter discusses the research objectives and the research design of the study.

CHAPTER 3
RESEARCH DESIGN AND METHODOLOGY

3.1 INTRODUCTION

Credit risk is inherent in the business of lending funds for business operations. However, credit risk management by banks shall be robust enough that it can select creditworthy borrowers and give timely default predictions. To contain future uncertain NPA growth, banks' credit risk management (CRM) systems and procedures shall carefully monitor their borrowers and track their performance on an ongoing basis.

Most of the discussed studies in review of literature are based on historical data about the Indian public sector banks. There are not many studies based on primary data or surveys to probe the characteristics and causes of credit risk in these banks, to understand their internal credit risk management systems, association of credit risk with bank size, and significance of various risk factors. There is thus, a need to study the strengths and weaknesses of CRM systems of Indian public sector banks, homogeneity or heterogeneity in their CRM practices, their credit risk assessment framework, the CRM problems or obstacles especially for loans to business and industry in comprehensive manner. There is also need to study whether theoretical credit-scoring or rating models will perform better than the existing rating models in these banks.

3.2 OBJECTIVES OF THE STUDY

As such the study sets the following research objectives:

1. To identify and examine the characteristics and causes of credit risk in Indian public sector commercial banks.

2. To compare the credit risk management practices of large and small public sector banks.

3. To analyze the extent to which the public sector banks have implemented the Basel norms on credit risk management.

4. To evaluate the credit risk rating framework followed by the public sector banks in credit risk assessment.

5. To design a credit risk assessment model for banks based on comparison of existing and theoretical credit-scoring or rating models.

3.3 SCOPE OF THE STUDY

The present study examines the credit risk management of commercial bank loans to Indian business and industries by the Indian public sector banks (PSBs). Owing to time and resource constraints, the study is confined to commercial loans to SMEs and mid-corporates. SMEs and mid-corporates are as defined by PSBs in sample. Sample banks in this study include six large and six small public sector banks.

3.4 PERIOD OF THE STUDY

The period of this study is from 2008 to 2015.

3.5 RESEARCH DESIGN

Research is the process of systematically obtaining accurate answers to significant and pertinent questions by the use of the scientific methods of gathering and interpreting information.

The present research on the credit risk management practices of Indian public sector commercial banks is analytical and quantitative in nature, to achieve the research objectives.

3.5.1 Data Collection

Data for this research has been collected through both primary and secondary sources.

3.5.1.1 *Primary Sources*

Primary sources of data are observations, personal interactions, unstructured interviews and survey through a structured questionnaire. The questionnaire has been used to survey the characteristics and causes of credit risk before banks, their credit approval, and monitoring processes, Basel compliance, NPA management, etc. to find out the strengths and weaknesses of credit risk management practices of sample banks. Various risk factors taken from the literature review and banks credit risk rating models have also been surveyed through the questionnaire.

3.5.1.2 *Secondary Sources*

Data has been collected from various secondary sources. These are the annual reports of the public sector banks, RBI Statistical Tables Relating to Banks in India, from 2008-2015, RBI Reports on Trends and Progress of Banking in India, 2008-2015, RBI Financial Stability Reports up to December, 2015, and RBI's prudential guidelines issued during this period. The study has also sourced information from the publications of the Indian Banks' Association (IBA), and reports of the Ministry of Finance. Published material in newspapers and journals as well as online data sources such as E-journals, websites of public sector banks, RBI and IBA, etc. have also been thoroughly studied for an intensive review of the literature.

Further for design and development of credit risk assessment model, the study has used loan records of five years from 2008-2013 of few branches (Level VI/IV, DGM/AGM managed) of a sample Indian public sector bank located in Delhi.

Data sources used for each of the research objectives are summarized in Table 3.1.

TABLE 3.1: RESEARCH OBJECTIVE–WISE DATA SOURCES.

Research Objectives	**Primary Sources (Questionnaire)**	**Secondary Sources**
1a. Characteristics of credit risk.	Q.11, 25 & 26.	Annual reports (2008-15) of 12 sample banks.
1b. Causes of credit risk.	Q.14, 22, 24 & Part III.	-
2. Comparison of CRM practices.	Q. 1 to 3, 5 to 10, 20, 24 & 27	-
3. Basel norms.	Q. 16 to 19.	-
4. Credit rating models.	Q. 3, 4, 12, 13, 15, 21 & 23	-
5. Designing a Model.	-	Bank loans data for 47 SMEs & Mid-corporates.

3.5.2 Sampling Design

3.5.2.1 *Universe of the Study*

The universe of the study is 26 public sector commercial bank in India including the State Bank of India, and its five associate banks which were operational as on 31st March 2012. Though one more public sector bank, the Bharatiya Mahila Bank has also started operations, it has not been made part of the study as it started functioning after 31.03.2012 (on 19 November 2013).

3.5.2.2 *Selection of Sample*

The sample for the study is 12 public sector commercial banks, covering six large and six small banks. Banks in large and small categories have been divided by share of a bank in total banking assets of public sector banks. Banks with less than 2.5% share of assets have been treated as small banks (cut-off 2.5% decided by the researcher). Based on banks' 2011-12 annual reports, 14 public sector banks are classified as large banks and 12 public sector banks as small banks. Public sector banks ranked in large and small categories and their share in total banking assets have been defined in Table 3.2.

TABLE 3.2: LARGE AND SMALL PUBLIC SECTOR BANKS (AS ON 31 MARCH 2012).

Large Public Sector Banks			**Small Public Sector Banks**		
S.No.	**Bank**	**Percentage of PSBs Assets**	**S.No.**	**Bank**	**Percentage of PSBs Assets**
1.	State Bank of India	22.10	1.	Indian Bank	2.34
2.	Punjab National Bank	7.59	2.	Andhra Bank	2.07
3.	Bank of Baroda	7.41	3.	State Bank of Hyderabad	1.97
4.	Bank of India	6.37	4.	United Bank of India	1.69
5.	Canara Bank	6.20	5.	State Bank of Patiala	1.63
6.	IDBI Bank	4.82	6.	Vijaya Bank	1.59
7.	Union Bank of India	4.34	7.	Bank of Maharashtra	1.48
8.	Central Bank of India	3.81	8.	Dena Bank	1.45
9.	Indian Overseas Bank	3.64	9.	State Bank of Travancore	1.42
10.	Allahabad Bank	3.03	10.	Punjab and Sind Bank	1.21
11.	Syndicate Bank	3.02	11.	State Bank of Bikaner& Jaipur	1.20
12.	UCO Bank	2.99	12.	State Bank of Mysore	1.00
13.	Oriental Bank of Commerce	2.95			
14.	Corporation Bank	2.71			

(Source: Indian Banks' Association – www.iba.org.in)

The selected sample of six large banks has State Bank of India (SBI), Punjab National Bank (PNB), Bank of Baroda (BOB), IDBI Bank, Syndicate Bank and Oriental Bank of Commerce (OBC). Six small banks in the sample are Andhra Bank, United Bank of India, Vijaya Bank, Dena Bank, Punjab & Sind Bank, and State Bank of Bikaner & Jaipur (Appendix 1: List of Sample Banks).

Sample banks in each category have been selected on judgment or convenience basis.

Since credit risk management is a specialized activity, the study has been carried through the risk management departments and loan branches of sample banks who are processing commercial loans. The study has been conducted through the sampling units located in and around Delhi.

3.5.2.3 *Respondents' Profile*

Respondents for the survey are the risk officers, risk rating officers, validators and other bank officials engaged in credit risk management, loan sanctioning process, loan audit and loan recovery in different categories of commercial loans. Total 337 complete responses have been collected from 12 sample banks. Attempts have been made to cover all the commercial loan branches of selected banks in and around Delhi. However, respondents have been selected on judgment or convenience basis. The respondents' profile has been depicted in Figure 3.1.

Out of total 337 respondents, 172 are from large PSBs and 165 from small PSBs. Large banks' respondents are from the State Bank of India (30), Punjab National Bank (28), Bank of Baroda (30), Oriental Bank of Commerce (26), IDBI Bank (28), the Syndicate Bank (30), and the small banks' respondents are from the Vijaya Bank (28), Dena Bank (26), United Bank of India (26), Punjab and Sind Bank (29), Andhra

Bank (26), and the State Bank of Bikaner and Jaipur (30). The 39 percent of 337 respondents have up to 7 years of banking experience (133), 25 percent from 8 to 20 years (82), whereas 36 percent have more than 20 years' experience (122).

The 14.8 percent respondents are junior managers (50), 53.4 percent middle- level managers (180), and 31.8 percent senior level managers (107). Junior managers are of the rank of officers and assistant managers, middle-level managers include managers and senior managers, and senior level managers consist of chief managers, assistant general managers, and deputy general managers in these banks.

The 61 percent of respondents are graduates, and 39 percent are post graduates (as marked by them in the questionnaire responses). The respondents also have adequate professional qualifications. The 42.1 percent of respondents are MBA/CA, 34.7 percent CAIIB qualified (a bank professional examination), 8.6 percent with other degrees like LLB.

The respondents also have real work experience, with 48.7 percent dealing with loan approvals, 7.7 percent with loan recoveries, and 43.6 percent dealing with both.

Thus, our survey respondents are working as credit analysts, risk-raters, validators, relationship managers, risk managers, recovery officers, at different credit policy formulation and operational levels, have adequate educational, professional and first-hand banking experience in business loans. The interbank differences in respondents have been found to be not very marked. The respondents' profile is also similar to large and small public sector banks. As such, the respondents in all groups have adequate loan exposure to respond to the questionnaire in a meaningful way. The respondents are fairly distributed across sample banks, thereby providing greater generalization to the results.

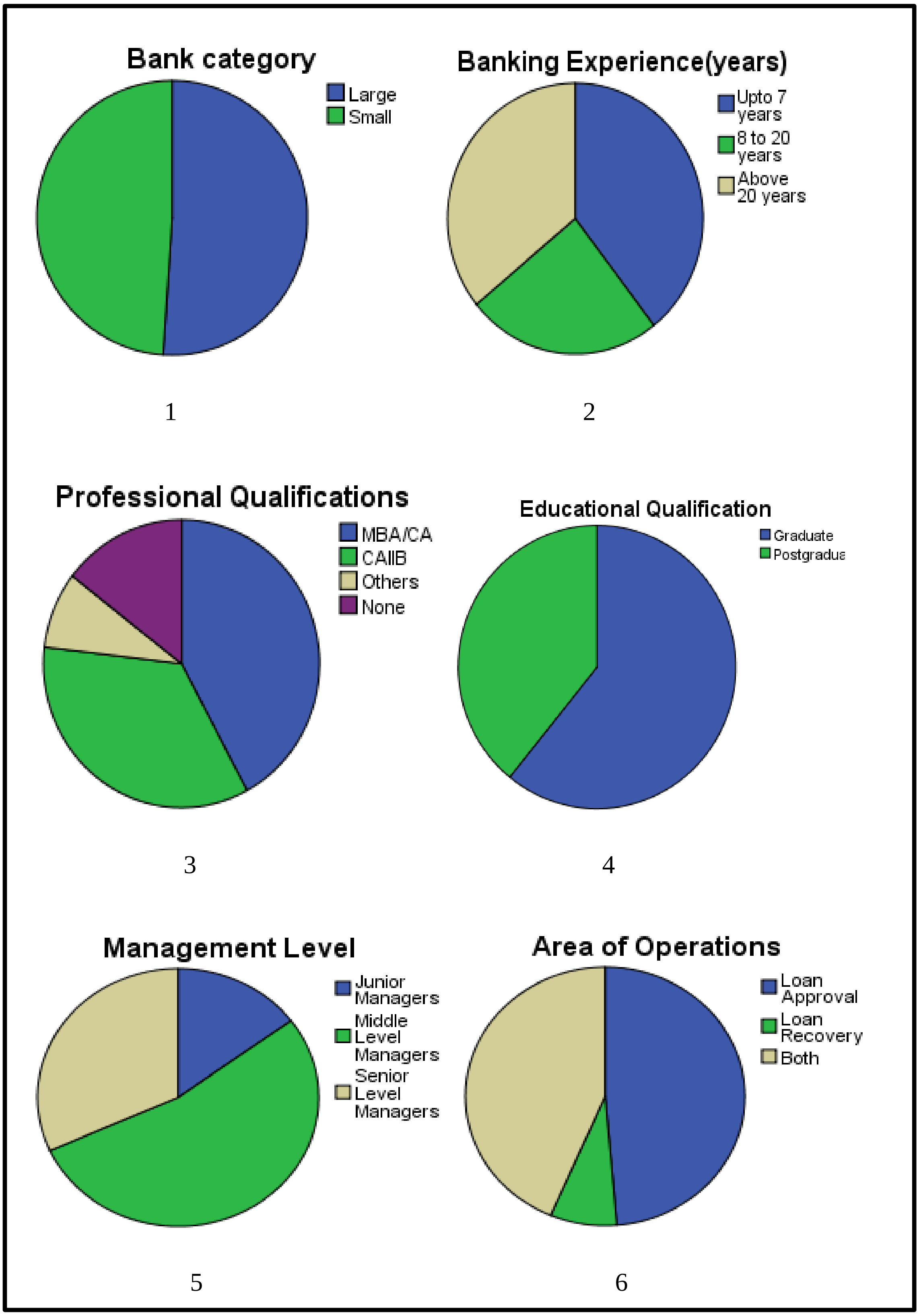

FIGURE 3.1: RESPONDENTS' PROFILE (1 TO 6)

3.5.3 The Structured Questionnaire

The questionnaire (Appendix 2) has been designed through an exhaustive review of literature and discussions with credit experts in sample public sector banks. The questionnaire or the research instrument has three parts:

Part 1: Part 1 has general details of the respondents regarding their educational and professional qualifications, work experience, the level of management, and their area of operations. These features have been used to categorize respondent credit and risk managers in three categories for perception studies. The three managerial categories are - managers in large or small banks, managers in three experience groups- ‘up to 7 years’, ‘8 to 20 years’ ‘above 20 years’, and managers at three management levels- junior, middle and senior levels.

Part II: Part II has 27 close-ended questions to probe various credit risk management practices of the Indian public sector banks, on 3 to 5- point scales.

Part III: Part III has a score sheet of 30 borrower-specific credit risk factors on 5-point ordinal scale and respondents have scored responses out of five, in order of a variable’s importance in causing credit risk. (1 for least important…5 for most important). The primary data source for causes or factors of credit risk in this part of the questionnaire is the internal credit rating models of the PSBs, which have been substantiated with research studies on causes of credit risk in India and abroad. All the 12 sample banks together have more than 85 risk factors to assess the creditworthiness and repayment capacity of the loan applicants. Fourteen senior credit managers in these banks were interviewed for critical credit risk factors and after several rounds of discussions, 30 key credit risk factors were identified and were made part of the survey in part III of the questionnaire (DELPHI method).

3.5.4 Reliability Tests

The reliability means the consistency or repeatability of the measures or the consistency in responses pattern. Cronbach alpha is a measure of scale reliability. It is a function of the number of items in a test, the average covariance between item-pairs, and the variance of the total score. Cronbach alpha coefficient is an indicator of internal consistency and is calculated based on the average items correlation or the extent to which the items in the questionnaire are related to each other. The generally agreed upon lower limit is 0.70, although it may decrease to 0.60 in exploratory research.

The questionnaire was pre-tested by gathering data from 38 credit managers in sample PSBs. The responses were put to the reliability tests through SPSS, which yielded a Cronbach alpha coefficient of 0.898 (Part II of the questionnaire) and 0.753 (Part III of the questionnaire) (Tables 3.3A & 3.3B) which are satisfactory according to the accepted guidelines.

TABLE 3.3A: RELIABILITY STATISTICS-PART II OF THE QUESTIONNAIRE (PRE-TEST SAMPLE)

Cronbach's Alpha	N of Items tested
.898	83

TABLE 3.3B: RELIABILITY STATISTICS-PART III OF THE QUESTIONNAIRE (PRE-TEST SAMPLE)

Cronbach's Alpha	N of Items tested
.753	30

Finally, the questionnaire with minor modifications was placed on 337 respondents, including the 38 who were part of pre-testing. The responses were again put to a reliability test.

TABLE 3.4A: RELIABILITY STATISTICS- PART II OF QUESTIONNAIRE (FULL SAMPLE)

Cronbach's Alpha	N of Items tested
.832	83

TABLE 3.4B: RELIABILITY STATISTICS - PART III OF THE QUESTIONNAIRE (FULL SAMPLE)

Cronbach's Alpha	N of Items tested
.904	30

The Cronbach alpha coefficient for Part II of the questionnaire was then calculated as 0.832, and for Part III as 0.904 (Tables 3.4A & 3.4B), which are also satisfactory as per the existing norms of being above 0.70.

The outcome of the survey development process has thus, been a more reliable and valid questionnaire, and the selected survey questionnaire is reliable for further research.

3.5.5 Setting Hypotheses

Data analysis to explore the causes of credit risk (Research Objective 1- Chapter 5) and to compare the credit risk management practices of large and small public sector banks (Research Objective 2- Chapter 6), has been based on setting and testing of null hypotheses.

In statistical analysis of responses to explore the causes of credit risk (Chapter 5), by three categories of credit and risk managers, the study has set the following 3 null hypotheses:

Hypothesis 1

H_0: There is no significant difference in risk perception of credit managers towards various causes of credit risk, in large and small banks.

Hypothesis 2

H_0: There is no significant difference in risk perception of credit managers with different levels of banking experience, towards various causes of credit risk.

Hypothesis 3

H_0: There is no significant difference in risk perception of different management levels towards various causes of credit risk.

Further, to compare the credit risk management practices of large and small public sector banks, and research the relative obstacles in implementation of sound credit risk management systems in large and small banks (Chapter 6), the study has set another 2 null hypotheses:

Hypothesis 4

H_0: There is no significant difference in practices of credit risk management in large and small public sector banks.

Hypothesis 5

H_0: There is no significant difference in obstacles in the implementation of sound credit risk management systems in large and small public sector banks.

The null hypotheses have been tested at 5 % level of significance, with F statistic (one-way ANOVA). The null hypothesis (H_0) is that the population means of the dependent variable for the level of the independent variable are equal ($\mu_1=\mu_2$). If H_0 is true, then the ratio of the between, to the within estimates of variance (σ^2) should be equal to 1. If H_0 is false, and the population means are not equal ($\mu_1 \neq \mu_2$), the F ratio will be significantly greater than unity (1). In statistical hypothesis testing, p-value (probability value) is used to decide whether there is enough evidence to reject the null hypothesis and say that the research hypothesis is supported by the data. When p-value is less than or equal to 0.05 ($p \leq 0.05$), it is concluded that the null hypothesis can be rejected, and the results are statistically significant.

3.5.6 Statistical Tools

The present study aims to evaluate the credit risk management practices of Indian public sector banks in the grant of business loans and advances to firms and mid-corporates. The data collected through primary and secondary sources has been analyzed by using various statistical tools to get analytical results on the data. The following methods have been used to analyze the data through SPSS (SPSS version 21) and EXCEL (version 2010):

1. Mean Scores
2. Standard Deviation
3. Ratio Analysis
4. Growth Rates
5. Coefficient of Variation
6. Linear Regression Analysis
7. Factor Analysis
8. One-way Analysis of Variance (ANOVA)
9. Tukey's HSD Post Hoc Tests
10. Multiple Discriminant Analysis

Mean Scores

The study has used mean scores or arithmetic mean for measuring credit risk in sample Indian PSBs based on their seven years annual reports, and to understand the perceptions of respondent credit and risk managers in three managerial groups while evaluating various credit risk management practices.

The mean scores $(\bar{X})$ are obtained by adding together all the observations and dividing the total by the number of observations. It is the most commonly used measure of central tendency. If there are no outliers (extremely large values), the mean is a robust measure and does not change markedly as data values are added or deleted (Malhotra & Dash, 2011).

$$\bar{X} = \frac{\Sigma X}{n}$$

Where n= number of observations, and $\sum X$ = sum of values of observations.

In this study, mean scores have been calculated from eight credit risk ratios to define the characteristics of credit risk in sample banks. A further average of seven- year ratios has been used as benchmark to interpret the degree of credit risk faced by these banks. Mean scores have also been calculated for various credit risk factors and CRM practices to find core causes of credit risk, to compare CRM practices of large and small banks, to study the Basel II compliance in banks' credit risk rating framework and to evaluate the credit risk assessment models of the Indian public sector banks.

Standard Deviation

The study uses standard deviation in comparing mean scores.
Standard deviation is the square root of the mean of the squared deviations from the arithmetic mean. Standard deviation is the square root of the variance. The greater the

amount of dispersion or variability, the greater will be the magnitude of the deviations of the values from their means or the standard deviation. The standard deviation of a sample is:

$$\text{Standard Deviation} = \frac{\sqrt{\sum(X - \bar{X})^2}}{\text{n-1}}$$

Where X is the value of observations, n is a number of observations, and $\overline{X}$ is the arithmetic mean.

The study has calculated standard deviation values along with mean scores to measure the variability or dispersion in the observations while measuring credit risk and while evaluating various credit risk management practices. A small standard deviation means a high degree of uniformity of the observations as well as homogeneity of a series, and a large standard deviation means high variability in the observations.

Ratio Analysis

Effectiveness of measurement and control of credit risk will depend on the identification of main characteristics of credit risk in Indian PSBs. The review of literature (Das & Ghosh, 2007; Misra & Dhal, 2010; Thiagarajan, 2011) has shown that the main indicators of banking credit risk are banks' gross and net NPA ratios, capital adequacy ratios, exposure to sensitive sectors, restructured loans, and their operational efficiency parameters such as ROA and Net Interest Margin. The study has thus, used following eight ratios to define the characteristics of credit risk in Indian public sector banks (Research Objective 1- Chapter 4):

1. Capital Adequacy Ratio or CRAR. It is Capital to Risk-weighted Assets Ratio.

2. GNPA Ratio. It is Gross Non-performing Assets to Gross Advances Ratio.

3. NNPA Ratio. It is Net Non-performing Assets to Net Advances Ratio.

4. Exposures to Sensitive Sectors to Total Advances Ratio.

5. Restructured Standard Advances to Total Advances Ratio.

6. Restructured Standard Advances and Gross Non-performing Assets to Total Advances Ratio.

7. Return on Assets (ROA).

8. Net Interest Margin or NIM. It is Net Interest Income to Total Assets Ratio.

Ratio analysis is the process of determining and presenting in arithmetical terms, the relationships between figures or group of figures, for a meaningful assessment of related aspects.

The study computes and compares these ratios for 12 sample public sector banks for seven years, based on their annual reports from 2008-15, to analyze the changes in the characteristics of credit risk for commercial loans in these banks. The data sources are the annual 'Statistical Tables Relating to Banks in India' published by RBI.

Further, based on literature review (Altman, 1968; Altman et al., 1995; Bandyopadhyay, 2005; Chijoriga, 2011), the study has identified the following thirteen financial ratios for developing a credit risk assessment model for Indian PSBs, for predicting transactional credit risk using multiple discriminant analysis (Research Objective 5):

1. Net Sales/Total Assets Ratio.

2. Retained Earnings/Total Assets Ratio.

3. Net Working Capital/Total Assets Ratio.

4. Earnings before Interest and Taxes (EBIT)/Total Assets.

5. Total Outside Liabilities/Tangible Net Worth (TOL/TNW). TOL means total liabilities, short-term and long-term. TNW means share capital + reserves – intangible assets.

6. Debt/Equity Ratio. Debt means long-term debt. Equity means equity share capital+ reserves.

7. Current Ratio (Current Assets/Current Liabilities).

8. Profit before Taxes /Net Sales Ratio.

9. Profit after Taxes / Net Sales Ratio.

10. Book Value of Equity/Long term Debt Ratio.

11. Securities Coverage Ratio (Value of securities/Loan amount).

12. Net working Capital to Total Current Assets Ratio.

13. Return on Capital Employed (ROCE).

For model development, the study uses a sample of 47 bank loans to SMEs and mid-corporates, by an Indian public sector bank, to design a three group discriminant model, based on 13 financial ratios and four non-financial factors for predicting credit risk. The sample of 47 firms has 40 performing and seven restructured/non-performing bank loans during 2008-13 and has been collected from loan documents of few Delhi branches of a sample public sector bank.

Growth Rates

Annual growth rates have been calculated for all the eight ratios indicating the characteristics of credit risk in 12 sample public sector banks based on their annual reports from 2008-2015 (Research Objective 1). Growth rates have shown the increasing or decreasing trend in these risk variables to find the stress areas in credit risk management.

Growth rates (g) have been computed using:

$$g = \left(\frac{Y_t - Y_{t-1}}{Y_{t-1}}\right) * 100$$

Where Y is the value of a particular year t or t-1. In the study, annual growth rates have been calculated on eight credit risk characteristics ratios from 2008-09 to 2014-15 (seven years).

Coefficient of Variation

The coefficient of variation (C.V.) is the relative measure of dispersion. It is the percentage variation in mean whereas standard deviation is considered as the absolute or total variation in the mean.

$$C.V. = 100 * \sigma / \overline{X}$$

σ denotes standard deviation and $\overline{X}$ is the mean score.

The coefficient of variation is used to measure the relative variation. The series is said to be more variable or conversely less consistent, less uniform, less stable, and less homogeneous when the coefficient of variation is greater.

The study uses the coefficient of variation to measure the variability of mean ratios to understand the characteristics of credit risk in Indian PSBs, for achieving research objective 1.

Linear Regression Analysis

The study uses simple or linear regression analysis to find the degree and direction of relationship between the following ratios to understand the relational characteristics of credit risk in the Indian public sector banks (Research Objective 1):

1. NNPA ratio and Capital Adequacy ratio,

2. GNPA ratio and Restructured Standard Advances ratio, and

3. Return on Assets ratio and GNPA ratio.

Linear or bivariate regression is a statistical tool to model the dependence of a variable on an explanatory variable. The functional relationship between the two may be formally stated as an equation with associated statistical values that describe how well the equation fits the data. The value of the coefficient of determination (R^2), which range between 0 to 1, is an indication of how much of the variance in the dependent variable about its mean is explained by the regression equation. A higher value of R^2 shows better fit.

Regression analysis may thus, determine whether a significant relationship exists between dependent and independent variables, the strength of the relationship, and a mathematical equation to predict the values of the dependent variable. Though regression analysis is concerned only with the nature and degree of association between variables and does not assume causation.

The basic regression equation is:

$Y_i = \breve{\alpha} + ßXi + e_i$

Where Y is dependent or criterion variable, X is independent or predictor variable, $\breve{\alpha}$ is the intercept or constant of the regression line, ß is the slope, and e_i is the error term associated with the ith observation.

The linear regression models in our study for the three credit risk characteristics ratios are represented as:

NNPA Ratio= 9.695 – 0.628*CRAR.

GNPA Ratio= 1.327+ 0.323*Restructured Standard Advances Ratio.

Return on Asset= 1.149-0.105*GNPA Ratio.

The regression results are establishing the significant negative relationship between NNPA Ratio and CRAR (Capital to Risk Adjusted Assets Ratio) or Capital Adequacy Ratio; a significant positive relationship between GNPA Ratio and increasing debt restructuring; and the increasing GNPA Ratio or credit risk showing a significant negative impact on the profitability of the Indian public sector banks.

The three linear regression equations have been developed from seven yearly ratios of sample public sector banks from 2008-15. The data sources are the annual RBI ‘Statistical Tables Relating to Banks in India’.

Factor Analysis

This study uses factor analysis to reduce the 30 credit risk variables into seven underlying factors, to select the surrogate variables and to calculate the factor scores for each of the 337 respondent on the derived factors. The derived factor scores have been used in one-way analysis of variance (ANOVA) to test the hypotheses about the significant differences in risk perception of three groups of credit managers towards various causes of credit risk (Research Objective 1 -Chapter 5).

Factor analysis is a multivariate statistical technique that is used primarily in data reduction or to summarize the information contained in a large number of variables into a smaller number of subsets or factors. The purpose of factor analysis is to simplify the data. With factor analysis there is no distinction between dependent and independent variables; rather, all variables under investigation are analyzed together to identify underlying factors. Factor analysis thus, attempts to identify underlying factors that explain the pattern of correlations within a set of observed variables. These factors explain most of the variance observed in a much larger number of variables. Factor analysis can be used to generate hypotheses regarding the causal relationship or to screen variables for subsequent multivariate analysis like performing a regression analysis or ANOVA.

In our study, the factor analysis has merged the 30 possible causes of credit risk into seven categories of risk factors. These are Business & Industry Risk, Management Risk, Financial Performance Risk, Loan Characteristics, Enterprise Value, Liquidity & Solvency Risk, Labour & Environmental Risk. The analysis has also identified seven surrogate risk variables in each risk category.

The derived factor scores have been used to test hypotheses through one- way analysis of variance (ANOVA).

One- Way Analysis of Variance (ANOVA)

This study uses one-way ANOVA or F statistic to test the null hypotheses on various credit risk variables with responses of three categories of credit managers in Indian public sector banks as independent variables.

Analysis of variance (ANOVA) is used as a test of means for two or more populations. One-way ANOVA examines the differences in the mean values of the dependent variable associated with the effect of one independent categorical variable, also called factor, by decomposition of total variance observed in the dependent variable (Y). This variation is measured by the sums of squares corrected for the mean (SS). The total variation in Y, denoted by SS_y is decomposed into two components:

$$SS_y = SS_{between} + SS_{within}$$

Where $SS_{between}$ is the variation in Y (dependent variable) related to the variation in the means of the categories of X (independent variable). This represents the variation between the categories of X or the portion of the sum of squares in Y related to X.

SS_{within} also called SS_{error} is the variation in Y due to the variation within each of the categories of X. This variation is not accounted for by X.

F statistic is the ratio of mean square related to X and mean square related to the error. F statistic is used to test the null hypothesis that the category means are equal in the population or there is no significant difference in means ($H_0: \mu_1 = \mu_2 = \mu_3$). The one-way ANOVA is an extension of the independent two-sample t-test. In case of two groups, these tests produce the same results. However, when there are three or more groups, one-way ANOVA has to be used to test the equality of means.

In the present study, one- way analysis of variance (ANOVA) has been conducted to examine the statistical significance of the difference in mean values of various CRM systems and procedures in large and small banks, to find out the strengths and weaknesses of their CRM practices, risk mitigation measures, and the obstacles or constraints in their CRM systems (Research Objective 2 - Chapter 6). ANOVA has also been conducted to test the significant differences in managerial perceptions about the characteristics and causes of credit risk (Research Objective 1- Chapters 4 & 5), about implementation of Basel norms (Research Objective 3- Chapter 7) and while evaluating the internal credit risk assessment framework of Indian PSBs (Research Objective- Chapter 8), for three categories of credit managers viz. managers in large and small PSBs, managers in three experience groups – 'Up to 7 years', 8 to 20 years' and 'Above 20 years', and managers at three hierarchical levels – junior, middle and senior managers.

Tukey's HSD Post Hoc Tests

Tukey's HSD test is a post hoc test, meaning that it is performed after an analysis of variance (ANOVA) test. Post hoc tests are used for further data analysis to compare means of groups that have been determined to have some overall statistically significant differences. While ANOVA tells whether there is a significant difference in group means, Tukey's HSD clarifies which groups in the sample have significant differences. Post hoc tests require minimum three groups to compare, and the original overall analysis must have been significant.

Tukey's HSD multiple comparison tests work through defining a value known as the Honest Significant Difference (HSD). This value is a number that acts as a distance between groups. It is calculated by the following procedure. Divide the mean square within from the ANOVA analysis by the total number of data points for a given group. Take the square root of the resulting value. Finally, multiply this result by the studentized range statistic (statistical tables). This result is the Honest Significant Difference. It represents the minimum distance between the two group means that must exist before the difference between the two groups is to be considered statistically significant.

The formula for Tukey's is:

$$\frac{M_1 - M_2}{\sqrt{MS_w\left(\frac{1}{n}\right)}}$$

Where M is group mean, n is number per group; MS_w is mean square within.

The study has used the post hoc tests to understand the managerial perceptions of subgroups in three categories of credit and risk managers on whom ANOVA tests have been found significant. The perceptional differences between sub-groups in three experience groups and three managerial levels, helped to mark the managerial groups and sub-groups, and CRM systems and procedures which required more potential or skill development, information sharing, risk- based training, management of subjectivity, etc. to improve effectiveness of credit risk management in Indian public sector banks.

Multiple Discriminant Analysis

Discriminant analysis helps in finding out the discriminant functions or linear combinations of predictor or independent variables which will best discriminate between the categories of dependent variables and whether significant differences exist among the groups. Discriminant analysis helps in finding the most discriminating predictor variables, and judging the accuracy of classification.

Discriminant coefficients make the groups differ as much as possible. The differences in the groups are the highest only when the ratio of between-group sum of squares to the within-group sum of squares for the discriminant scores is at a maximum.

The linear discriminant analysis model involves combination of the following form:

Z=a+b1*x1+b2*x2+b3*x3+..…..bk*xk

Where

Z= discriminant score.

a= a constant.

b= discriminant co-efficient or weight of variable.

x= predictor or independent variable.

The assumptions in the discriminant analysis are that each of the group is a sample from a multivariate normal population, and all the populations have the same covariance matrix. Box's M statistic evaluates conformity to the assumption of homogeneity of group variances. When the Box's M test shows p (probability/significance) is greater than 0.01, the co-variances are not statistically different, and the assumption of homoscedasticity is upheld. Wilks' Lambda (λ) tests discriminant functions for statistical significance. The functions' probability (significance) shall be less than or equal to the level of significance.

The present study uses a three - group multivariate discriminant analysis to model transactional credit risk in Indian public sector banks. The purpose is to develop a credit risk assessment model for predicting default risk in business loans by Indian

PSBs and compare it with their existing credit rating models. The study has developed two significant discriminant functions using thirteen financial variables and four non-financial factors of 40 bank loans, to classify borrowers in three credit risk categories, High Safety, Moderate Safety, and Inadequate Safety. The model has 97% correct classification rate in the validation sample and has also been tested on a holdout sample of seven banking loans.

3.6 CONCLUSIONS

The risk- rating methodology, robust credit risk management systems and procedures are the foundations of effective credit risk management. The capital adequacy norms of Basel accords have increased risk sensitivity in Indian banks. The banks especially the public sector banks need to upgrade their risk governance to achieve a sharper risk-reward profile. For that, there is a need to research their present CRM practices and systems. This study has a quantitative research design to evaluate empirically the CRM practices of the Indian public sector banks by which they manage credit risk. The empirical analysis has been performed to find the strengths and weaknesses in their CRM systems and suggest improvements.

The following chapter is empirically evaluating the first research objective of identifying the characteristics of credit risk for commercial loans in the Indian public sector commercial banks.

CHAPTER 4

IDENTIFYING AND EXAMINING THE CHARACTERISTICS OF CREDIT RISK

4.1 INTRODUCTION

The first objective of the present study to identify and examine the characteristics and causes of credit risk in Indian public sector commercial banks has been studied in two parts. In first part (Chapter 4) the study examines the characteristics of credit risk, and in second part (Chapter 5), it examines the causes of credit risk in Indian PSBs. Thus this chapter empirically evaluates the data sources to identify and examine the characteristics or features of credit risk in these banks.

In respect of the characteristics of credit risk, the study identifies these through the survey of literature as indicators of credit risk. It then examines the changes in these characteristics over the study period (2008-15) in sample banks, employing secondary as well as primary data. The characteristics of credit risk are identified as differential credit risk, capital adequacy ratios, asset quality in terms of Gross NPAs, Net NPAs, incremental NPAs, loans to sensitive sectors, debt restructuring, relative efficiency of NPA recovery channels, willful defaults, and relationship between credit risk parameters and operational efficiency parameters. To examine the changes in these characteristics, secondary data were obtained on GNPAs, NNPAs, Sensitive Sectors Advances Ratios, Restructured Advances Ratios, Capital Adequacy Ratios, Return on Assets Ratios and Net Interest Margin. These data have been obtained from the RBI reports and the annual reports of the sample banks for seven years from 2008-2015. Primary data were obtained using structured questionnaire (Questions 11, 25 and 26) regarding the nature of risk prone sectors, efficiency of NPA recovery channels and controlling willful defaults.

Secondary data have been analyzed using ratios, descriptive statistics, benchmark values, growth rates and linear regression analysis. Primary data have been analyzed employing descriptive statistics, ANOVA and Tukey's HSD post hoc tests.

4.2 CREDIT RISK CHARACTERISTICS

Banking loans to business and industry account for more than two-third of total advances by the Indian banking sector. Since public sector banks (PSBs) dominate commercial banking in India, the business or commercial loans are their main channel for credit and default risk. Annual growth rate of commercial loans by PSBs indicate their risk appetite or risk aversion. The study has observed that the stressful macroeconomic factors like slow GDP growth, high inflation, as well as growing non-performing assets, increased the risk aversion, and the PSBs have reduced their annual credit growth to commercial sectors (Figures 4.1& 4.2).

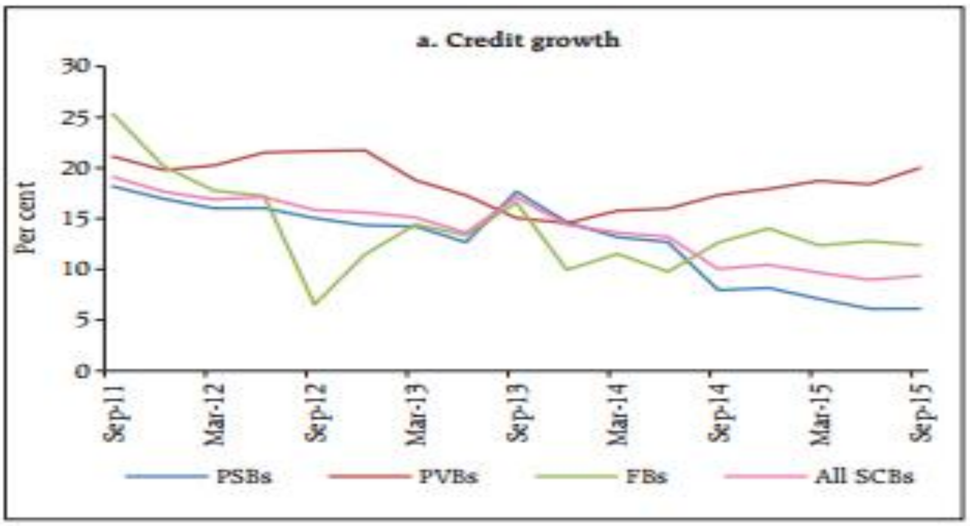

FIGURE 4.1: CREDIT GROWTH RATE FOR ALL SECTORS

(Source: The RBI Financial Stability Report, December 2015)

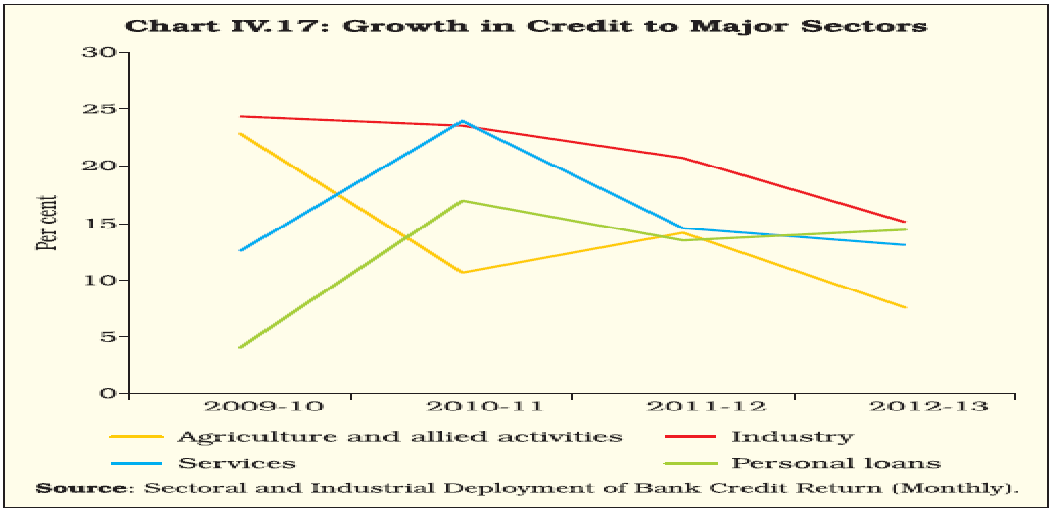

FIGURE 4.2: CREDIT GROWTH TO MAJOR SECTORS

(Source: The RBI Report on Trends and Progress of Banking in India, 2012-13)

Based on RBI's annual reports, annual accounts of the sample public sector banks, and survey on 337 credit managers of these banks, the study identifies and evaluates the following major indicators of credit risk to conclude on present characteristics of credit risk in these banks:

1. Differential credit risk.
2. Capital adequacy ratios.
3. Asset quality (Gross and Net NPAs, and Incremental NPAs).
4. Loans to sensitive sectors.
5. Debt Restructuring.
6. Relative efficiency of NPA recovery channels.
7. The willful defaults.
8. Relation between credit risk and the operational efficiency parameters.

4.2.1 Differential Credit Risk

An important indicator of credit risk faced by Indian PSBs is that not all commercial sectors or industries are equally risky or equally contributing towards the non-performing assets of banks. Both macro and microeconomic factors are changing the credit risk spectrum of different business groups and various industries, in a different manner. Presently medium and large industries, and within various industry groups, the aviation, iron and steel, infrastructure, textile, mining, power generation, telecommunication, and coal sectors have highest stressful banking loans in the form of both restructured and non-performing loans (Figures 4.3 to 4.5). Thus, it is imperative for banks to undertake technical studies for assessing industry risk, to mitigate both transactional and portfolio credit risk.

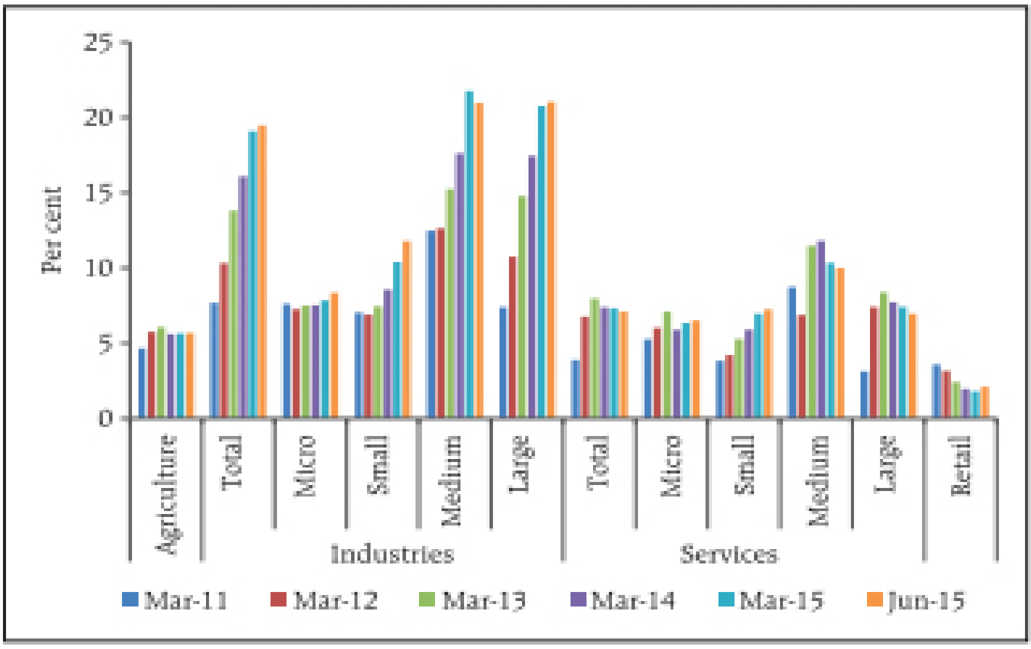

FIGURE 4.3: STRESSED ADVANCES IN BROAD SECTORS

(Source: The RBI Financial Stability Report, December 2015)

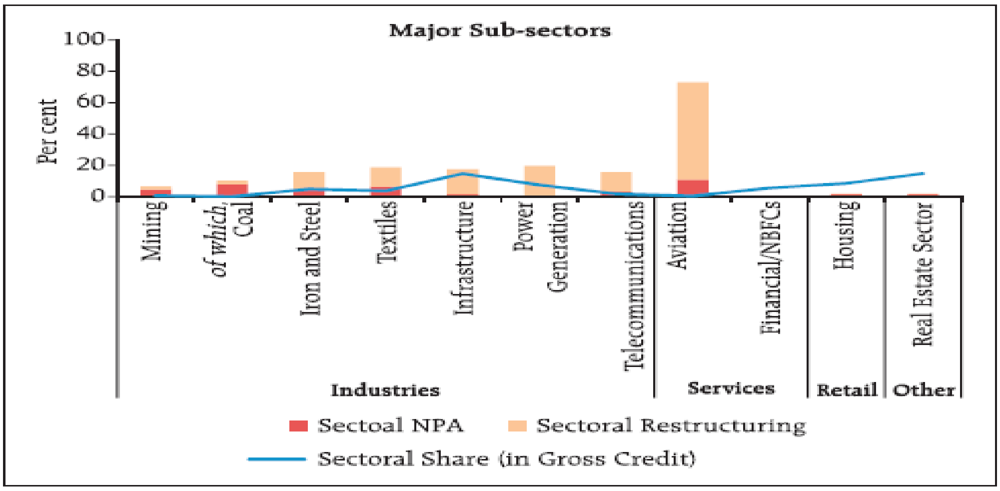

FIGURE 4.4: STRESSFUL INDUSTRIES IN 2012-13

(Source: The RBI Financial Stability Report, June 2013)

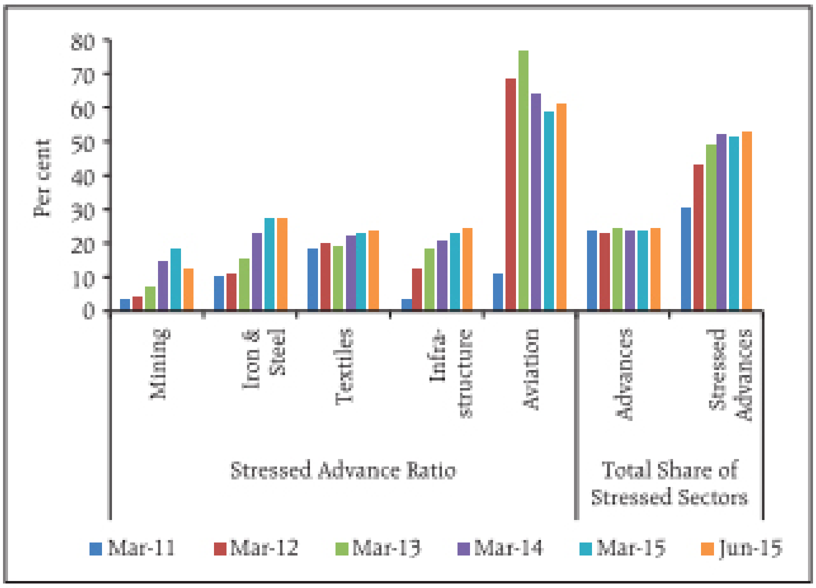

FIGURE 4.5: STRESSFUL INDUSTRIES 2011-15

(Source: The RBI Financial Stability Report, December 2015)

A survey was conducted on 337 credit managers about which sector in any industry is more risk prone (Question 11), manufacturing, services or trading. The results revealed that 43 % agreed that trading activities in any industry/sector are most risky, 35% found manufacturing risky and only 22% held services sectors more hazardous (Table 4.1) (Figure 4.6).

TABLE 4.1: RESPONSES TO Q. 11- WHICH IS MORE RISK PRONE SECTOR?

Business Sectors	Frequency	Percent	Valid Percent	Cumulative Percent
Manufacturing	118	35.0	35.0	35.0
Services	74	22.0	22.0	57.0
Trading	145	43.0	43.0	100.0
Total	337	100.0	100.0	

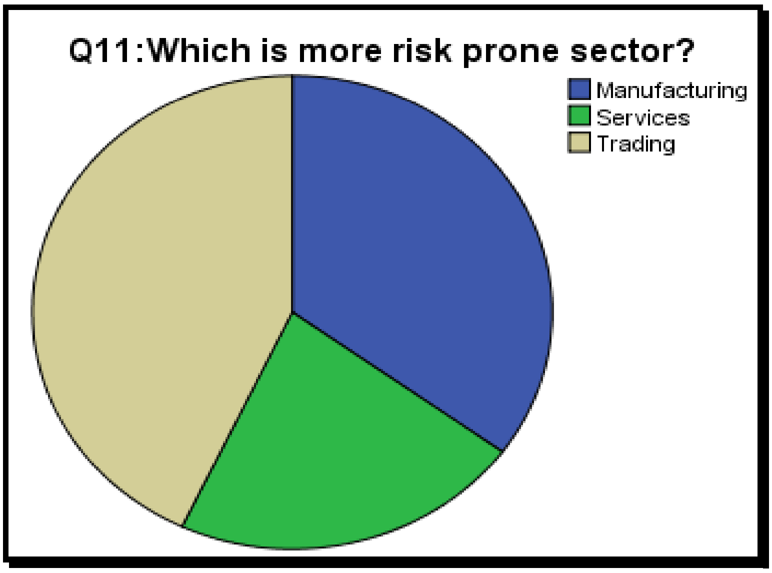

FIGURE 4.6: DIFFERENTIAL CREDIT RISK IN ANY INDUSTRY

One-way analysis of variance (ANOVA) was conducted to find the statistical significance of mean difference between and within three management groups. The groups are managers of large and small banks; managers at junior, middle and senior levels; and managers with three levels of experience, up to 7 years, 8 to 20 years, and above 20 years (Tables 4.2 to 4.4). The F statistics shows that only responses from large and small bank managers are statistically significant. Mean values indicate that the managers in large PSBs find trading activities riskier, whereas managers in small banks find manufacturing activities riskier (Table 4.14). In other words, differential credit risk in various industries as well as in different activities in the same industry shall require thorough credit analysis by banks to manage credit risk.

TABLE 4.2: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.11: Which is more risk prone sector?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.124	1	3.124	4.061	.045
Within Groups	257.713	335	.769		
Total	260.837	336			

TABLE 4.3: ANOVA BY LEVEL OF MANAGEMENT

Q.11: Which is more risk prone sector?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.851	2	1.425	1.845	.160
Within Groups	257.986	334	.772		
Total	260.837	336			

TABLE 4.4: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.11: Which is more risk prone sector?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.937	2	.468	.602	.548
Within Groups	259.900	334	.778		
Total	260.837	336			

4.2.2 Capital Adequacy Ratios or CRAR

Capital to Risk-weighted Assets Ratio (CRAR) is the indicator of banking soundness. Risk-weighted assets of a bank are valued on different risk weights for different category of business loans/exposures, based on loans' credit ratings. As per RBI's prudential guidelines, the banks shall have minimum 9 percent CRAR or regulatory capital under Basel II framework. All the public sector banks have been consistently above the mark (Figure 4.7), showing these banks are well capitalized or with a sound capital position. Though the CRAR of public sector banks is also consistently lower than the industry average (SCBs – all scheduled commercial banks), and the average of foreign banks (FBs), and the average of old and new private banks (OPBs and NPBs) (Figure 4.7). Thus, the public sector banks are the least capitalized in the Indian banking industry, and with the highest risk- bearing assets.

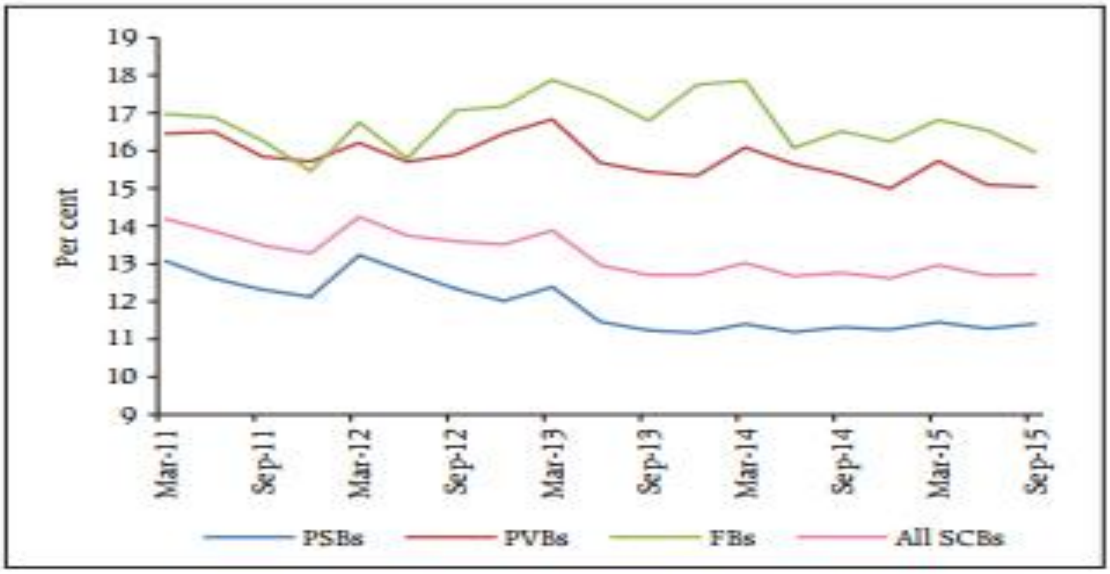

FIGURE 4.7: CAPITAL ADEQUACY RATIOS OF INDIAN BANKS

(Source: The RBI Financial Stability Report, December 2015)

A study of CRAR of 12 sample public sector banks for the period 2008-15 (Table 4.5) shows that the mean values of capital adequacy ratios of banks are ranging from 11.98% to 13.87%. The mean value is highest in BOB (13.87), followed by SBI (13.16), the largest PSB (Figure 4.8). Dena Bank has the lowest mean CRAR (11.98). For 2014-15, the seven banks, Andhra Bank, Syndicate Bank, SBBJ, Dena Bank, United Bank of India, Vijaya and Punjab & Sind Bank; had their capital adequacy ratios less than the benchmark ratio (11.96). Benchmark ratio is the computed average for all sample banks. The most important point is that during 2014-15, seven banks have reduced CRAR, with the highest reduction by the Syndicate Bank (-9.08%).

While studying the dispersion of capital adequacy ratios, it has been observed that the standard deviation and coefficient of variation in case of Andhra Bank remained the highest (SD 1.272, CV 1.618), which was much above the benchmark values of SD 0.578 and CV 0.335. It indicates the greatest fluctuations in this ratio in Andhra Bank.

TABLE 4.5: CRAR OR CAPITAL ADEQUACY RATIOS (%)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	14.25		14.03		14.05		12.98		11.57		12.68	
2009-10	13.39	-6.04	14.16	0.927	14.36	2.206	12.54	-3.39	11.31	-2.25	12.7	0.158
2010-11	11.98	-10.5	12.42	-12.3	14.52	1.114	14.23	13.48	13.64	20.6	13.04	2.677
2011-12	13.86	15.69	12.63	1.691	14.67	1.033	12.69	-10.8	14.58	6.891	12.24	-6.13
2012-13	12.92	-6.78	12.72	0.713	13.3	-9.34	12.04	-5.12	13.13	-9.95	12.59	2.859
2013-14	12.96	0.31	11.52	-9.43	12.87	-3.23	11.85	-1.58	13.13	0	12.01	-4.61
2014-15	12.79	-1.31	12.21	5.99	13.34	3.652	12.28	3.629	13.2	0.533	10.92	-9.08
Mean	13.16		12.81		13.87		12.66		12.94		12.31	
S.D.	0.693		0.889		0.648		0.734		1.059		0.647	
C.V.	0.48		0.79		0.42		0.538		1.122		0.418	

P & Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench Mark	
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
14.35		12.07		13.15		13.28		13.22		14.52		13.35	
13.1	-8.71	12.77	5.8	12.5	-4.94	12.8	-3.61	13.93	5.371	13.3	-8.4	13.07	-2.05
12.94	-1.22	13.41	5.012	13.88	11.04	13.05	1.953	14.38	3.23	11.68	-12.2	13.26	1.473
13.26	2.473	11.51	-14.2	13.06	-5.91	12.69	-2.76	13.18	-8.34	13.76	17.81	13.18	-0.65
12.91	-2.64	11.03	-4.17	11.32	-13.3	11.66	-8.12	11.76	-10.8	12.16	-11.6	12.3	-6.7
12.1	-6.27	11.87	7.616	10.97	-3.09	11.46	-1.72	11.18	-4.93	11.71	-3.7	11.97	-2.65
11.88	-1.82	11.21	-5.56	11.7	6.655	11.42	-0.35	10.88	-2.68	11.69	-0.17	11.96	-0.08
12.93		11.98		12.37		12.34		12.65		12.69		12.73	
0.751		0.793		0.992		0.737		1.272		1.078		0.578	
0.564		0.629		0.985		0.544		1.618		1.161		0.335	

Note 1: CRAR is Capital to Risk Adjusted Assets Ratio.

Note 2: GR is Growth Rate percent per annum.

Note 3: Benchmark values are computed averages per year.

Note 4: CV is Coefficient of Variation.

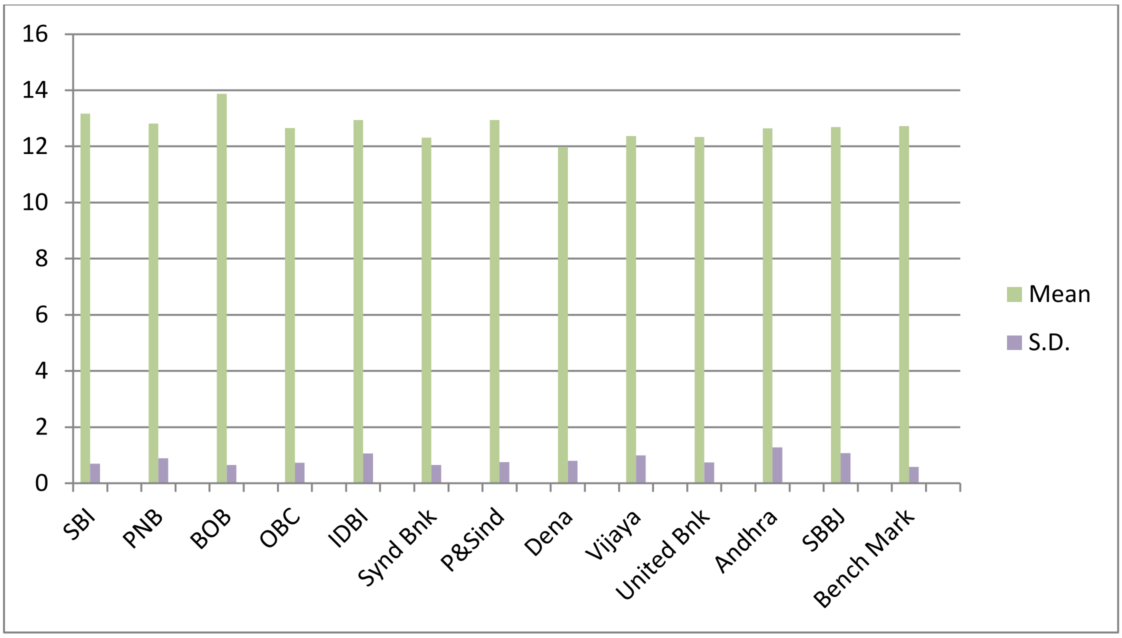

FIGURE 4.8: CRAR (%): 2008-2015

The Result of Linear Regression Analysis (NNPA Ratio on CRAR): Capital adequacy ratio is the indicator of financial leverage risk before a bank. Higher is the CRAR; lower is the financial leverage. Since financial leverage risk and credit risk reinforce each other, higher is the CRAR lower shall be the credit risk (Das, 2002). Credit risk is measured by gross or net non-performing assets (GNPA or NNPA). A linear regression analysis has been conducted, at 5% level of significance, to find the impact of CRAR on NNPA/ Net Advances ratios in 12 sample banks from 2008-15 (Tables 4.6.I to III).

TABLE 4.6.I: REGRESSION ANOVA OF NNPA RATIO ON CRAR

Model		Sum of Squares	df	Mean Square	F	Sig.
	Regression	32.902	1	32.902	30.321	.000
1	Residual	88.980	82	1.085		
	Total	121.881	83			

Note 1. Dependent Variable: NNPA Ratio

Note 2. Predictors: (Constant), CRAR

TABLE 4.6.II: REGRESSION COEFFICIENTS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9.695	1.456		6.658	.000
	CRAR	-.628	.114	-.520	-5.506	.000

Note. Dependent Variable: NNPA Ratio

TABLE 4.6.III: REGRESSION MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.520	.270	.261	1.04169	1.226

Note 1. Predictors: (Constant), CRAR

Note 2.Dependent Variable: NNPA Ratio

Linear regression analysis shows statistically significant inverse linear relationship between CRAR and NNPA ratio. F statistic is 30.321 (df 1,82), at p=0.000. The t-statistic is also significant for intercept and CRAR, with unstandardized coefficients equal to 9.695 and -0.628. R Square is 0.270, and Durbin-Watson statistic is 1.226.

The regression equation is:

NNPA Ratio= 9.695 – 0.628*CRAR

Thus, during the period the banks have reduced CRAR, they have increased the credit risk. During 2012-13, there was a major decrease in average CRAR of sample banks by 6.70% (Table 4.5) with a corresponding increase in NNPA ratio by 33% (Table 4.8) showing increased credit risk. During 2014-15, the sample PSBs had recorded 0.08% reduction in CRAR and 9.003% increase in NNPA ratio, showing the inverse relation between these two ratios.

4.2.3 Asset Quality

The asset quality of the Indian public sector banks has been continuously deteriorating. The main indicators of asset quality of a bank are its gross non-performing (GNPAs) and net non-performing (NNPAs) assets.

Net NPAs are Gross NPAs – (Balance in Interest Suspense account + credit insurance claims received and held pending adjustment + Part payment received and kept in suspense account + Total provisions held).

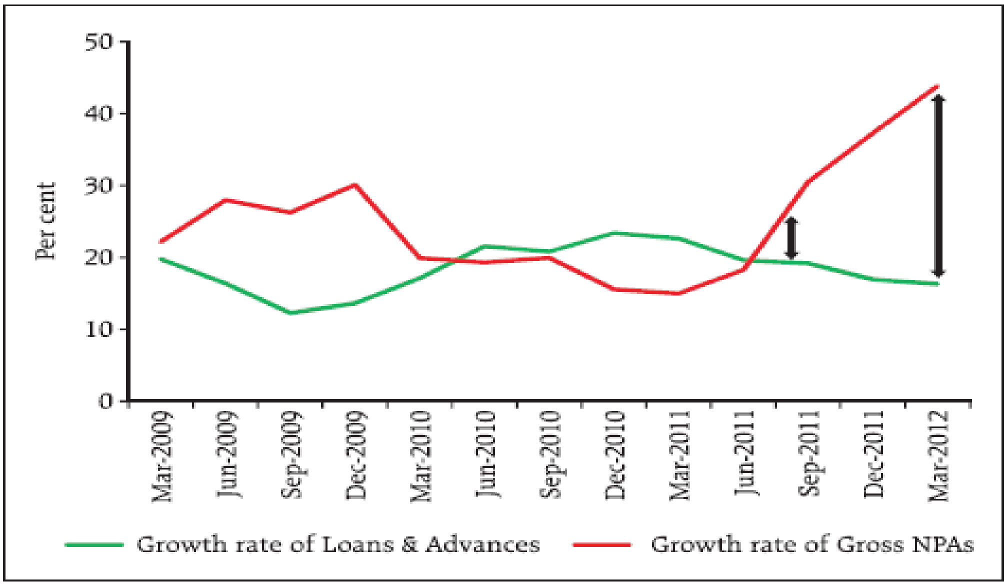

FIGURE 4.9: INCREASING GNPAS

(Source: The RBI Financial Stability Report, June 2012)

Gross NPA ratio (Gross NPA to Gross Advances) and Net NPA ratio (Net NPA to Net Advances) are indexed to measure the quality of banking assets or level of credit risk faced by any bank. Since March 2011, the gap between the growth rate of loans and advances, and growth rate of Gross NPAs has been widening (Figure 4.9). The GNPA ratio, Restructured Standard Advances ratio, and NNPA ratio have been increasing at a higher rate for public sector banks (Figures 4.10 & 4.11).

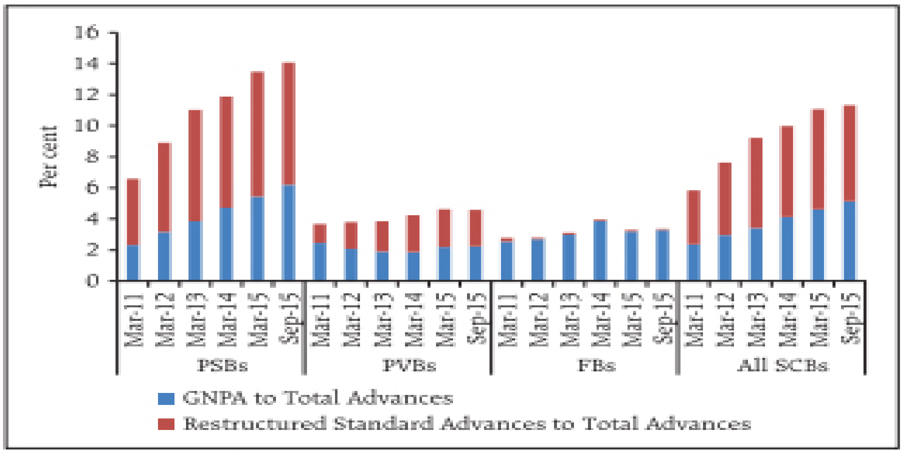

FIGURE 4.10: WORSENING ASSET QUALITY OF INDIAN PSBS

(Source: The RBI Financial Stability Report, December 2015)

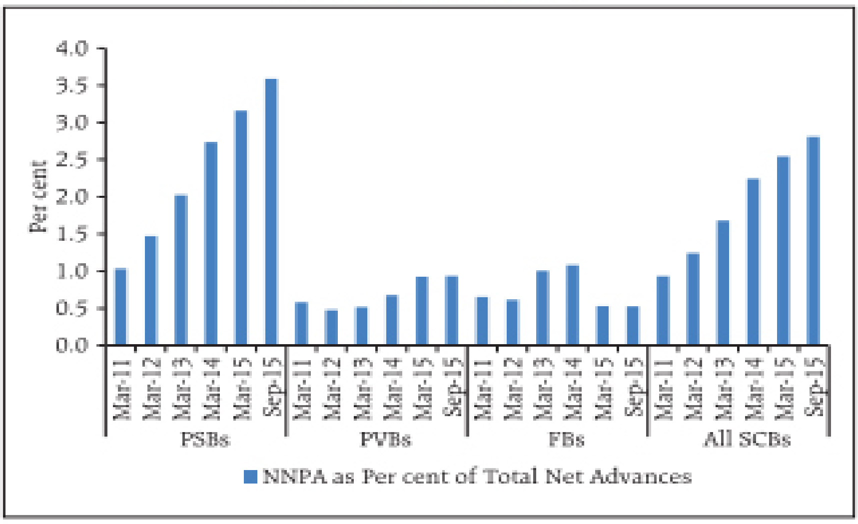

FIGURE 4.11: INCREASING NNPA RATIO OF INDIAN PSBS

(Source: The RBI Financial Stability Report, December 2015)

An analytical study has been undertaken of GNPA and NNPA ratios of 12 sample public sector banks from 2008-2015 (Tables 4.7 & 4.8). GNPA and NNPA ratios are important elements of risk- based supervision by banks.

Asset quality measurement by GNPA/ Gross Advances ratio: The mean values of GNPA ratio range from 5.17% to 2.21% during 2008-15. United Bank of India has shown the highest value (5.17), whereas the Bank of Baroda has the lowest value of

2.21 (Table 4.7) (Figure 4.12). The proportion of gross NPAs are at an alarming rate in United Bank of India (5.17), and SBI (4.09), and thus, these banks have the highest credit risk among the sample PSBs. Another bank which has higher than the bench mark GNPA ratio (3.05) is PNB (3.5). During 2014-15 also, the United Bank of India has recorded the highest GNPA ratio at 9.49%. Other five banks which have GNPA ratio more than 5% during this year are PNB (6.55%), IDBI Bank (5.88%), Dena Bank (5.45%), Andhra Bank (5.31%) and OBC (5.18%).

TABLE 4.7: GNPA/GROSS ADVANCES RATIOS (%)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	2.98		1.77		1.27		1.53		1.38		1.93	
2009-10	3.28	10.07	1.71	-3.39	1.64	29.13	1.74	13.73	1.54	11.59	2.43	25.91
2010-11	3.5	6.707	1.79	4.678	1.62	-1.22	1.98	13.79	1.79	16.23	2.65	9.053
2011-12	4.9	40	3.15	75.98	1.89	16.67	3.17	60.1	2.57	43.58	2.75	3.774
2012-13	4.75	-3.06	4.27	35.56	2.4	26.98	3.21	1.262	3.22	25.29	1.99	-27.6
2013-14	4.95	4.211	5.25	22.95	2.94	22.5	3.99	24.3	4.9	52.17	2.62	31.66
2014-15	4.25	-14.1	6.55	24.76	3.72	26.53	5.18	29.82	5.88	20	3.13	19.47
Mean	4.087		3.499		2.211		2.971		3.04		2.5	
S.D.	0.765		1.781		0.803		1.23		1.619		0.394	
C.V.	0.585		3.172		0.644		1.513		2.621		0.155	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench Mark	
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
0.65		2.13		1.95		2.85		0.83		1.63		1.742	
0.63	-3.08	1.8	-15.5	2.37	21.54	3.21	12.63	0.86	3.614	1.72	5.521	1.911	9.713
0.99	57.14	1.86	3.333	2.56	8.017	2.51	-21.8	1.38	60.47	2	16.28	2.053	7.414
1.65	66.67	1.67	-10.2	2.93	14.45	3.41	35.86	2.12	53.62	3.3	65	2.793	36.05
2.96	79.39	2.19	31.14	2.17	-25.9	4.25	24.63	3.71	75	3.62	9.697	3.228	15.61
4.41	48.99	3.33	52.05	2.41	11.06	10.47	146.4	5.29	42.59	4.18	15.47	4.562	41.3
4.76	7.937	5.45	63.66	2.79	15.77	9.49	-9.36	5.31	0.378	4.14	-0.96	5.054	10.8
2.293		2.633		2.454		5.17		2.786		2.941		3.049	
1.63		1.259		0.315		3.094		1.83		1.046		1.219	
2.656		1.584		0.099		9.571		3.35		1.094		1.486	

Note: GR is Growth Rate percent per annum.

The study of dispersion (standard deviation) of asset quality, based on this ratio, shows that the United Bank of India has the highest variation (SD 3.09), followed by Andhra Bank (SD 1.83). Vijaya Bank has the highest stability (0.32). The five banks, Vijaya Bank, Syndicate Bank, SBI, BOB and State Bank of Bikaner & Jaipur have lower dispersion values (SD) than the benchmark value of 1.22 during 2008-15 (Table 4.7) (Figure 4.12).

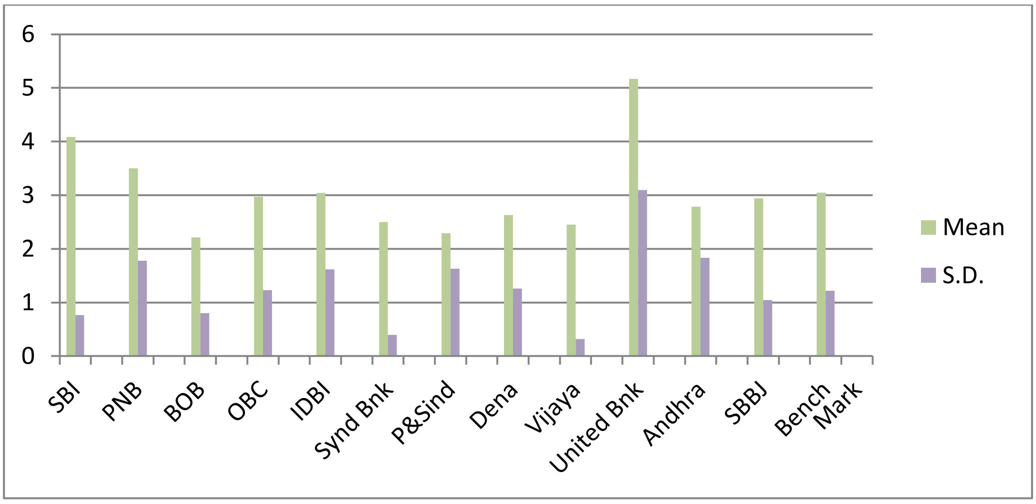

FIGURE 4.12: GNPA RATIO (%): 2008-2015

Asset quality measurement by NNPA/ Net Advances ratio: The mean values of NNPA ratio in sample banks are ranging from 0.89% (BOB) to 3.25% (United Bank of India) (Table 4.8) (Figure 4.13). The United Bank of India, which had the highest average GNPA ratio, also has the highest NNPA ratio at 3.25%. Other banks which have poor asset quality or high credit risk in term of this ratio are SBI (1.96), OBC (1.88), PNB (1.76), and Dena Bank (1.73). These five banks, United Bank of India, SBI, OBC, PNB and Dena Bank are also having the proportion of NPAs higher than the benchmark value of 1.70. The dispersion study (SD) of Net NPA ratio of sample banks indicates that the United Bank of India has the highest variation at 2.243, whereas the SBI has the highest stability at 0.301. The comparison of S.D. value with benchmark S.D. (0.879) reveals that seven banks, namely United Bank of India, PNB, Punjab & Sind Bank, Andhra Bank, OBC, SBBJ, and Dena Bank had the highest fluctuation in their NNPA ratios during the sample period 2008-15 (Table 4.8).

Thus, taking both GNPA and NNPA ratios, United Bank of India, SBI and PNB have the highest credit risk among the sample banks.

TABLE 4.8: NNPA/NET ADVANCES RATIOS (%)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	1.79		0.17		0.31		0.65		0.92		0.77	
2009-10	1.72	-3.91	0.53	211.8	0.34	9.677	0.87	33.85	1.02	10.87	1.07	38.96
2010-11	1.63	-5.23	0.85	60.38	0.35	2.941	0.98	12.64	1.06	3.922	0.97	-9.35
2011-12	1.82	11.66	1.52	78.82	0.54	54.29	2.21	125.5	1.61	51.89	0.96	-1.03
2012-13	2.1	15.38	2.35	54.61	1.28	137	2.27	2.715	1.58	-1.86	0.76	-20.8
2013-14	2.57	22.38	2.85	21.28	1.52	18.75	2.82	24.23	2.48	56.96	1.56	105.3
2014-15	2.12	-17.5	4.06	42.46	1.89	24.34	3.34	18.44	2.88	16.13	1.9	21.79
Mean	1.964		1.761		0.89		1.877		1.65		1.141	
S.D.	0.301		1.296		0.61		0.972		0.706		0.397	
C.V.	0.09		1.679		0.372		0.946		0.498		0.157	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench Mark	
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
0.32		1.09		0.82		1.48		0.18		0.38		0.74	
0.36	12.5	1.21	11.01	1.4	70.73	1.84	24.32	0.17	-5.56	0.55	44.74	0.923	24.77
0.56	55.56	1.22	0.826	1.52	8.571	1.42	-22.8	0.38	123.5	0.83	50.91	0.981	6.227
1.19	112.5	1.01	-17.2	1.72	13.16	1.72	21.13	0.91	139.5	1.92	131.3	1.428	45.54
2.16	81.51	1.39	37.62	1.3	-24.4	2.87	66.86	2.45	169.2	2.27	18.23	1.898	32.98
3.35	55.09	2.35	69.06	1.55	19.23	7.18	150.2	3.11	26.94	2.76	21.59	2.842	49.69
3.55	5.97	3.82	62.55	1.92	23.87	6.22	-13.4	2.93	-5.79	2.54	-7.97	3.098	9.003
1.641		1.727		1.461		3.247		1.447		1.607		1.701	
1.287		0.951		0.323		2.243		1.233		0.923		0.879	
1.656		0.904		0.104		5.032		1.519		0.852		0.773	

Note: GR is Growth Rate per cent per annum.

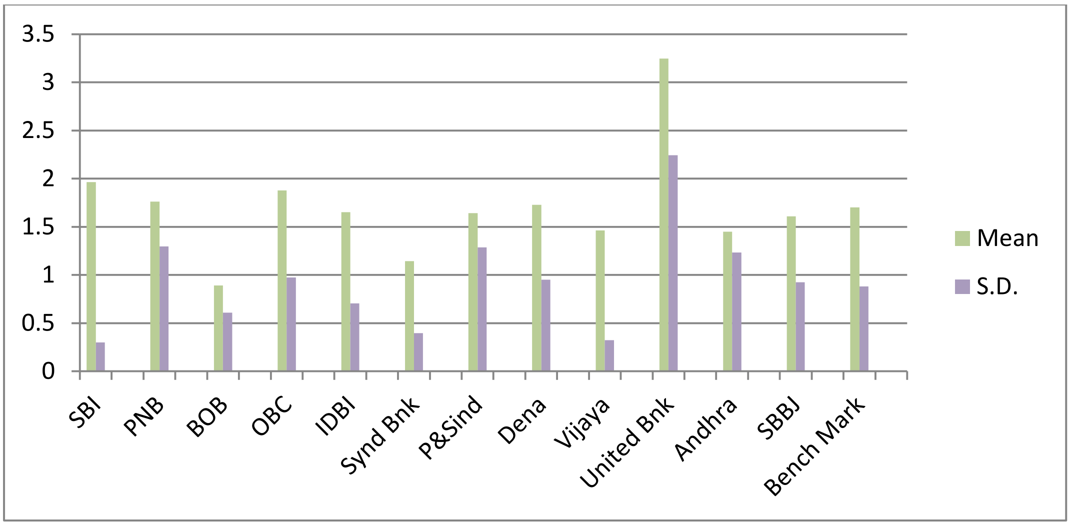

FIGURE 4.13: NNPA RATIO (%): 2008-2015

4.2.4 Loans to Sensitive Sectors

Sensitive business sectors are those who are prone to business cycle volatility or are speculative in nature, and thus, have high credit risk. RBI prudential norms categorize capital market exposures such as loans to stockbrokers, market makers, loans against security of shares and debentures; real estate sector, both residential and commercial; and commodity market exposures as sensitive sectors. Prudent credit risk management practices and cautious approach are needed to regulate the flow of credit to these segments. RBI report on trends and progress of banking in India, 2012-13 said that credit to sensitive sectors picked up even in a period of slowdown in overall credit growth, growth almost doubled for real estate sector, may be due to a steep rise in real estate prices, and high- profit margins.

For our sample PSBs during 2008-15, the mean value of Exposure to Sensitive Sectors/ Total Advances ratio ranged from 11.81% (BOB) to 22.8% (IDBI Bank) (Table 4.9) (Figure 4.14). Against the benchmark value of 15.86, IDBI Bank (22.8), Vijaya Bank (21.99), PNB (18.99), SBI (16.79), OBC (16.76), and Punjab & Sind

Bank (16.23) had the high proportion of loan and advances to sensitive sectors, and thus, more credit risk.

TABLE 4.9: EXPOSURE TO SENSITIVE SECTORS/TOTAL ADVANCES RATIOS (%)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	13.1		21.46		11.98		20.7		23.92		13.96	
2009-10	15.04	14.81	18.38	-14.4	14.35	19.78	19.34	-6.57	24.69	3.219	17.49	25.29
2010-11	19.16	27.39	19.2	4.461	11.57	-19.4	17.12	-11.5	22.8	-7.65	14.6	-16.5
2011-12	17.09	-10.8	17.88	-6.88	10.47	-9.51	14.15	-17.3	22.52	-1.23	14.69	0.616
2012-13	18.25	6.788	18.18	1.678	10.59	1.146	14.68	3.746	21.41	-4.93	15.44	5.106
2013-14	19.59	7.342	19.25	5.886	12.77	20.59	17.09	16.42	22.01	2.802	13.24	-14.2
2014-15	15.32	-21.8	18.58	-3.48	10.92	-14.5	14.25	-16.6	22.24	1.045	13.2	-0.3
Mean	16.79		18.99		11.81		16.76		22.8		14.66	
S.D.	2.221		1.111		1.284		2.386		1.054		1.376	
C.V.	4.931		1.234		1.648		5.694		1.111		1.894	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench	Mark
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
17.02		15.14		25.95		6.56		13.97		14.97		16.56	
17.75	4.289	13.95	-7.86	25.07	-3.39	5.69	-13.3	9.93	-28.9	12.38	-17.3	16.17	-2.35
15.49	-12.7	12.09	-13.3	21.77	-13.2	17.59	209.1	14.09	41.89	12.36	-0.16	16.49	1.948
15.92	2.776	11.14	-7.86	20.3	-6.75	12.79	-27.3	12.15	-13.8	12.08	-2.27	15.1	-8.42
15.36	-3.52	11	-1.26	17.25	-15	12.47	-2.5	13.54	11.44	12.69	5.05	15.07	-0.18
19.18	24.87	11.91	8.273	21.48	24.52	14.03	12.51	16.72	23.49	10.95	-13.7	16.52	9.599
12.91	-32.7	11.22	-5.79	22.13	3.026	15.47	10.26	10.92	-34.7	14.26	30.23	15.12	-8.48
16.23		12.35		21.99		12.09		13.05		12.81		15.86	
1.854		1.472		2.694		4.099		2.095		1.263		0.673	
3.437		2.167		7.26		16.8		4.388		1.595		0.452	

Note 1: GR means Growth Rate percent per annum.

Note 2: Sensitive Sector means capital market and real estate exposures.

Note 3: Exposure to capital market is inclusive of both investments and advances.

Note 4: Exposure to real estate is inclusive of both direct and indirect lending.

During 2012-13, seven out of 12 sample PSBs increased their exposures to these high-risk sectors, and during 2013-14, ten banks increased. However, in 2014-15, eight banks decreased their exposure to the sensitive sectors, average decrease of 8.48%. Nonetheless, IDBI Bank and Vijaya Bank have the highest exposure to these sectors consistently.

Comparing the dispersion values (SD), it is observed that the United Bank of India (4.099) has the greatest variation, and IDBI Bank (1.054) has the lowest variation in exposures to sensitive segments.

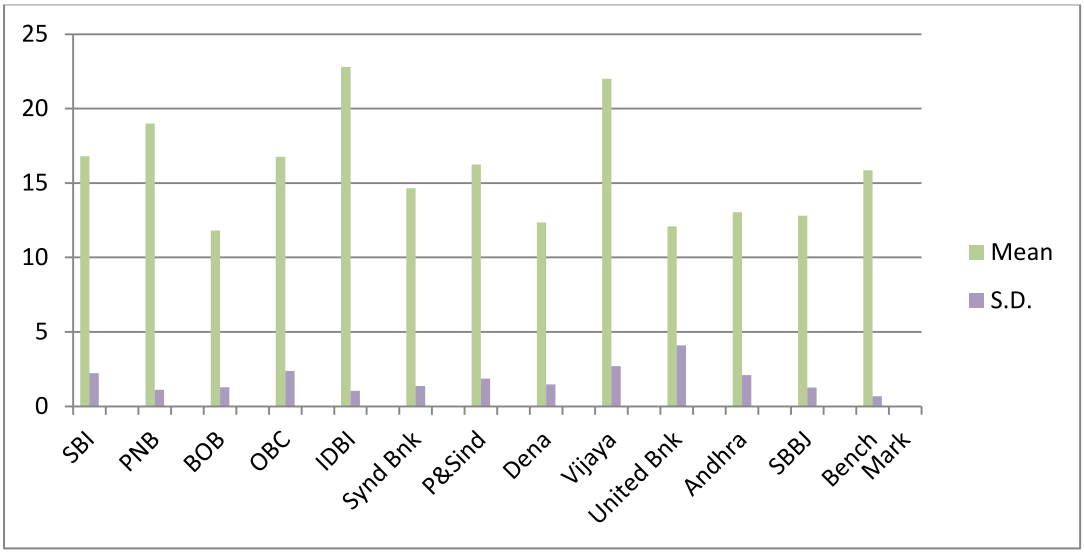

FIGURE 4.14: SENSITIVE ASSETS RATIO (%): 2008-2015

4.2.5 Debt Restructuring

Restructuring and rescheduling of standard or performing loans under RBI’s schemes has helped banks to contain the problem loans from becoming a non-performing asset. Public sector banks have the highest proportion of restructured standard loans, even above the industry average. (Figure 4.10). Again, the largest restructuring has been undertaken of loans to industry and services. (Figure 4.15).

Restructuring loans to facilitate payments by borrowers, however, also indicate that the loans may be under pressure anytime. Hence, higher is the proportion of restructured loans to total advances; higher is the credit risk. Further, in case both restructured standard loans and gross NPAs are weighed against total advances, it will indicate the real or actual degree of credit risk the bank is facing. It will also show the strain on a bank's capacity to issue new credit.

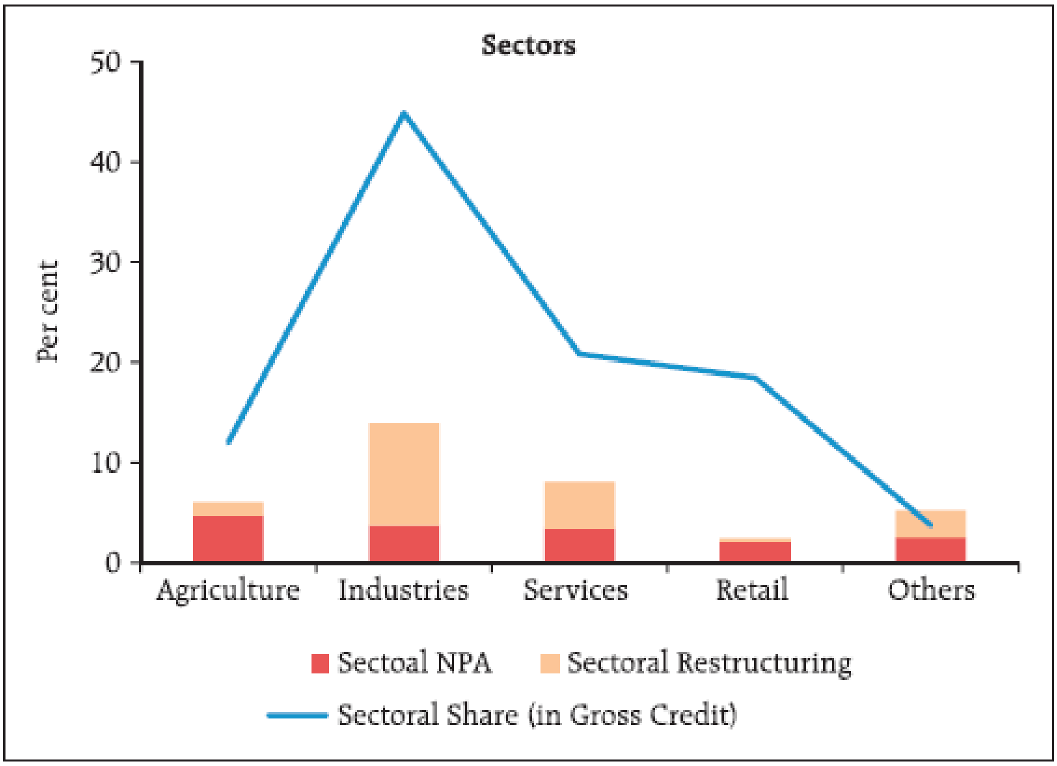

FIGURE 4.15: HIGHEST LOAN RESTRUCTURING FOR INDUSTRIES AND SERVICES

(Source: The RBI Financial Stability Report, June 2013)

For our 12 sample banks, the ratios of Restructured Standard Loans/ Total Advances (Table 4.10), and Restructured Standard Loans and GNPAs/ Total Advances (Table 4.12) have been calculated to find the PSBs, which have the highest credit risk.

Restructured Standard Loans/ Total Advances Ratio: During the period 2008-15, the mean value of this ratio ranged from 2.51 (SBI) to 6.99 (OBC) (Table 4.10) (Figure 4.16).

TABLE 4.10: RESTRUCTURED STANDARD ADVANCES/TOTAL ADVANCES RATIOS (%)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	2.39		2.32		1.71		3.74		2.54		4.03	
2009-10	2.67	11.72	4.28	84.48	1.38	-19.3	4.16	11.23	6.73	165	4.75	17.87
2010-11	0.62	-76.8	1.32	-69.2	1.24	-10.1	0.88	-78.8	6.26	-6.98	3.75	-21.1
2011-12	0.97	56.45	5.04	281.8	3.08	148.4	5.87	567	4.51	-28	2.55	-32
2012-13	3.08	217.5	9.89	96.23	5.87	90.58	9.54	62.52	5.89	30.6	5.55	117.6
2013-14	3.56	15.58	10.17	2.831	5.66	-3.58	10.91	14.36	6.3	6.961	5.82	4.865
2014-15	4.3	20.79	10.07	-0.98	6.03	6.537	13.83	26.76	8.03	27.46	4.49	-22.9
Mean	2.513		6.156		3.567		6.99		5.751		4.42	
S.D.	1.231		3.55		2.058		4.239		1.629		1.032	
C.V.	1.516		12.61		4.233		17.97		2.655		1.064	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench	Mark
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2.13		3.84		2.58		1.7		3.6		2.22		2.733	
1.94	-8.92	3.62	-5.73	3.48	34.88	1.84	8.235	2.5	-30.6	4.74	113.5	3.508	28.32
2.9	49.48	2.59	-28.5	1.83	-47.4	3.48	89.13	2.99	19.6	5.13	8.228	2.749	-21.6
4.8	65.52	5.88	127	4.51	146.4	3.69	6.034	6.72	124.7	5.65	10.14	4.439	61.47
11.58	141.3	7.22	22.79	5.75	27.49	5.68	53.93	9.84	46.43	6.55	15.93	7.203	62.27
11.22	-3.11	8.54	18.28	4.83	-16	7.38	29.93	9.87	0.305	7.2	9.924	7.622	5.807
13.12	16.93	10.12	18.5	4.71	-2.48	12.7	72.09	11.1	12.46	9.65	34.03	9.013	18.25
6.813		5.973		3.956		5.21		6.66		5.877		5.324	
4.582		2.588		1.282		3.586		3.386		2.129		2.386	
20.99		6.697		1.643		12.86		11.47		4.531		5.691	

Note: GR means Growth Rate percent per annum.

Against the benchmark value of 5.32%, seven banks have a higher proportion of restructured loans. These are OBC (6.99), Punjab & Sind Bank (6.81), Andhra Bank (6.66), PNB (6.16), Dena Bank (5.97), SBBJ (5.88) and IDBI Bank (5.75). During 2014-15, the United Bank of India had the biggest increase of 72.09%, and Syndicate

Bank had the largest decrease of 22.9% in restructured advances, as against the average increase of 18.25% by 12 sample PSBs, showing the still persistent high stress on their asset quality.

The average dispersion (S.D.) during the study period of 2008-15, has been the biggest in Punjab & Sind Bank (4.58) and lowest in Syndicate Bank (1.032) (Table 4.10).

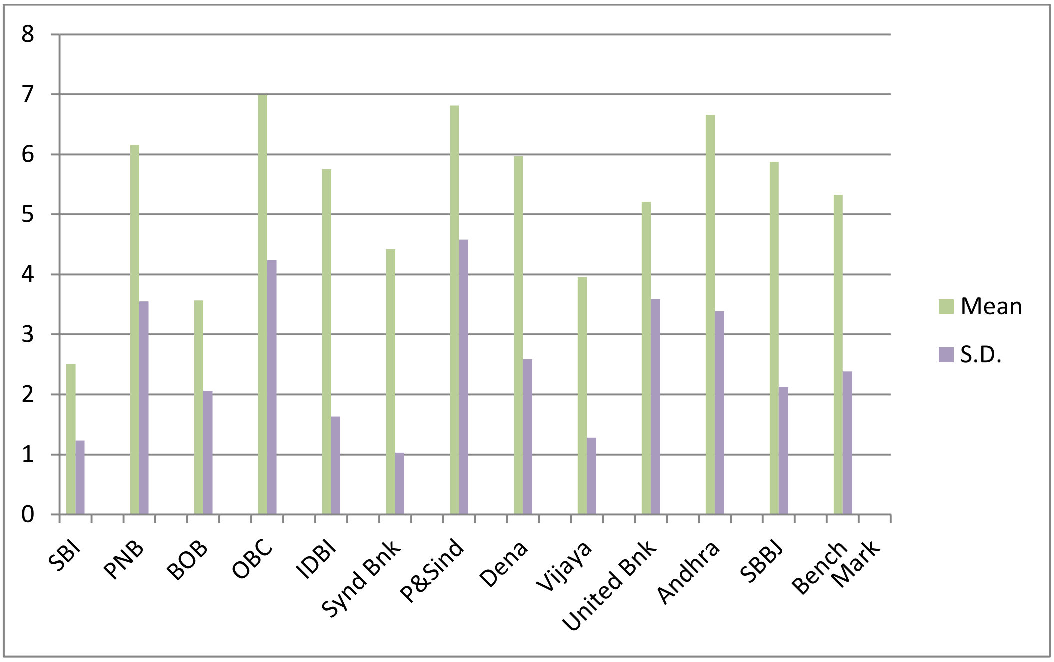

FIGURE 4.16: RESTRUCTURED STANDARD ADVANCES RATIO (%): 2008-2015

The Result of Linear Regression Analysis (GNPA Ratio on Restructured Advances): Restructured loans have increased chances of default or becoming a non-performing asset. Thus, loan restructuring is expected to have a positive relation with GNPA ratio, the credit risk measure. The impact of this variable on GNPA ratios of sample banks for the period 2008-15 has been studied to find the degree and direction of relationships between them. The findings of linear regression analysis (Tables 4.11.I to III), at 95% confidence level, show a direct and positive relationship between Restructured Standard Loans/ Total Advances Ratio with GNPA/Gross Advances Ratio.

TABLE 4.11.I: REGRESSION ANOVA OF GNPA RATIO ON RESTRUCTURED ADVANCES RATIO

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	88.105	1	88.105	46.027	.000
	Residual	156.964	82	1.914		
	Total	245.070	83			

Note 1. Dependent Variable: GNPA Ratio.

Note 2. Predictors: (Constant), Restructured Standard Advances/ Total Advances Ratio.

TABLE 4.11.II: REGRESSION COEFFICIENTS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.327	.295		4.493	.000
	Rest. Standard Advances/ Tot. Advances Ratio	.323	.048	.600	6.784	.000

Note: Dependent Variable: GNPA Ratio

TABLE 4.11.III: REGRESSION MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.600	.360	.352	1.38355	.805

Note 1. Predictors: (Constant), Restructured Standard Advances/ Total Advances Ratio.

Note 2. Dependent Variable: GNPA Ratio.

Linear regression analysis shows statistically significant positive relationship between restructured standard advances ratio and GNPA ratio (Tables 4.11.I to III). F statistic is 46.027 (df 1, 82), at p=0.000. The t-statistic is also significant for intercept and Restructured Standard Advances ratio indicating a significant linear relationship between the two. The unstandardized coefficients are equal to 1.327 and +0.323. R Square is 0.360, and Durbin-Watson statistic is 0.805.

The regression equation is:

GNPA Ratio= 1.327+ 0.323*Restructured Standard Advances Ratio

The regression results are establishing that increasing loan restructuring have a direct and positive relationship with credit risk in public sector banks, and can be used to predict future GNPAs.

Restructured Standard Loans and GNPAs/ Total Advances Ratio (Stressed Assets Ratio): This ratio represents the stressed loans/assets of a bank as restructured loans have high chances of turning non-performing. The mean value of this ratio ranged between 5.67 % (BOB) and 10.03 % (United Bank of India) during 2008-15 (Figure 4.17).

Against the benchmark value of 8.35 % (2008-15), eight banks have a higher mean ratio. The banks are United Bank of India (10.03), OBC (9.996), PNB (9.697), Andhra Bank (9.51), Punjab & Sind Bank (9.13), IDBI Bank (8.89), SBBJ (8.87) and Dena Bank (8.64). These are the public sector banks which have the highest credit risk in our sample. SBI, the largest PSB has a mean ratio of 6.51% (SD 1.746) of stressed assets during 2008-15 (Table 4.12). During 2008-15, large banks' mean ratio of stressed assets is 7.94% whereas small banks' mean ratio is 8.77%. Thus, small public sector banks had higher credit risk during this period.

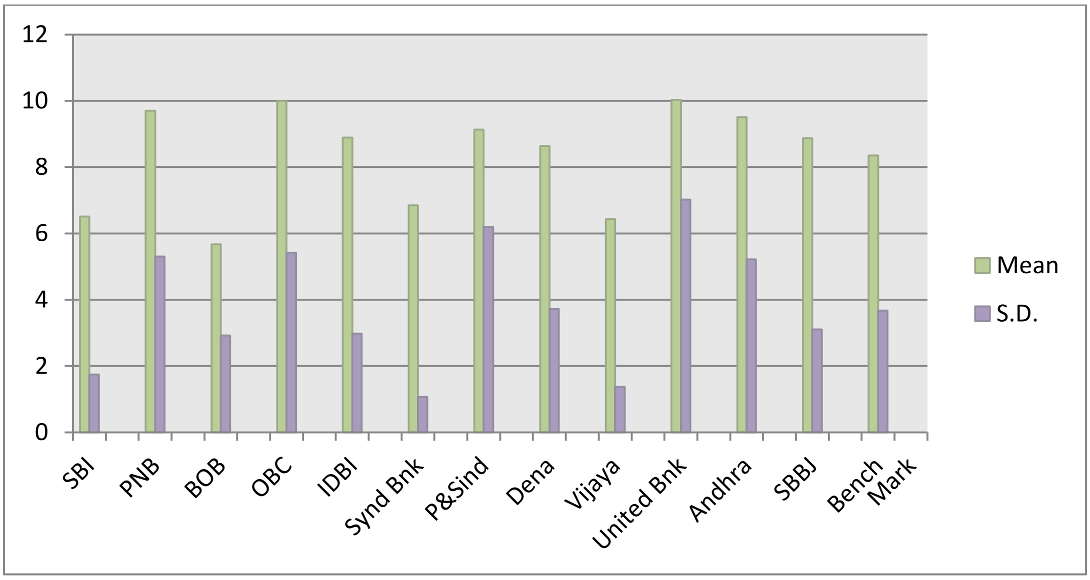

FIGURE 4.17: STRESSED ASSETS RATIO (%): 2008-2015

TABLE 4.12: RESTRUCTURED STANDARD ADVANCES AND GNPA/ TOTAL ADVANCES (STRESSED ASSETS) RATIOS (%)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	5.25		4.11		3		5.28		3.93		5.98	
2009-10	5.49	4.571	6	45.99	2.64	-12	5.92	12.12	8.27	110.4	6.96	16.39
2010-11	3.98	-27.5	3.13	-47.8	2.62	-0.76	2.88	-51.4	8.34	0.846	6.18	-11.2
2011-12	5.54	39.2	8	155.6	4.63	76.72	9.06	214.6	7.03	-15.7	5.12	-17.2
2012-13	7.98	44.04	14.25	78.13	8.3	79.27	12.78	41.06	9.18	30.58	7.57	47.85
2013-14	8.65	8.396	15.57	9.263	8.65	4.217	14.95	16.98	11.34	23.53	8.47	11.89
2014-15	8.66	0.116	16.82	8.028	9.83	13.64	19.1	27.76	14.11	24.43	7.67	-9.45
Mean	6.507		9.697		5.667		9.996		8.886		6.85	
S.D.	1.746		5.303		2.923		5.419		2.978		1.071	
C.V.	3.048		28.12		8.542		29.36		8.869		1.147	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench	Mark
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2.78		5.99		4.55		2.76		4.44		3.86		4.328	
2.57	-7.55	5.43	-9.35	5.83	28.13	2.99	8.333	3.37	-24.1	6.48	67.88	5.163	19.3
3.9	51.75	4.47	-17.7	4.41	-24.4	6.61	121.1	4.39	30.27	7.16	10.49	4.839	-6.26
6.45	65.38	7.56	69.13	7.47	69.39	7.15	8.169	8.88	102.3	9	25.7	7.158	47.91
14.57	125.9	9.43	24.74	7.95	6.426	9.99	39.72	13.62	53.38	10.23	13.67	10.49	46.52
15.68	7.618	11.91	26.3	7.27	-8.55	18.21	82.28	15.31	12.41	11.46	12.02	12.29	17.18
17.95	14.48	15.68	31.65	7.52	3.439	22.51	23.61	16.56	8.165	13.88	21.12	14.19	15.47
9.129		8.639		6.429		10.03		9.51		8.867		8.351	
6.19		3.718		1.376		7.021		5.213		3.103		3.67	
38.31		13.82		1.894		49.3		27.18		9.63		13.47	

Note: GR means Growth Rate percent per annum.

The ratio has increased consistently from 4.33% in 2008-09 to 14.19% in 2014-15 registering growth of 228% in seven years (Figure 4.18). Bank and year-wise, these assets have piled up with United Bank of India, OBC, Punjab & Sind Bank, PNB, Dena Bank and Andhra Bank (Figure 4.19).

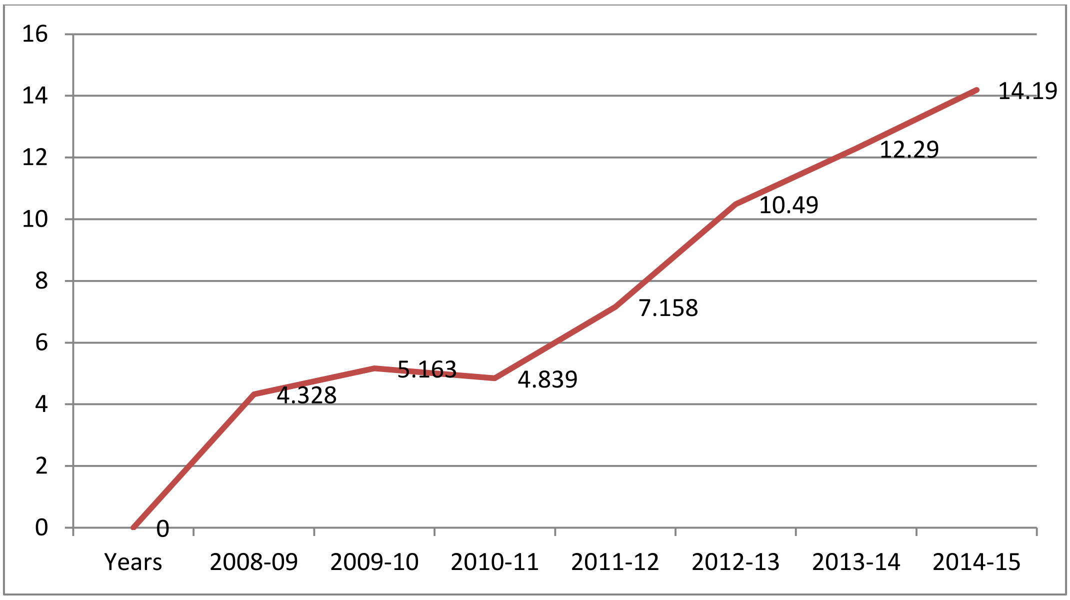

FIGURE 4.18: GROWING STRESSED ASSETS RATIO OF SAMPLE PSBS

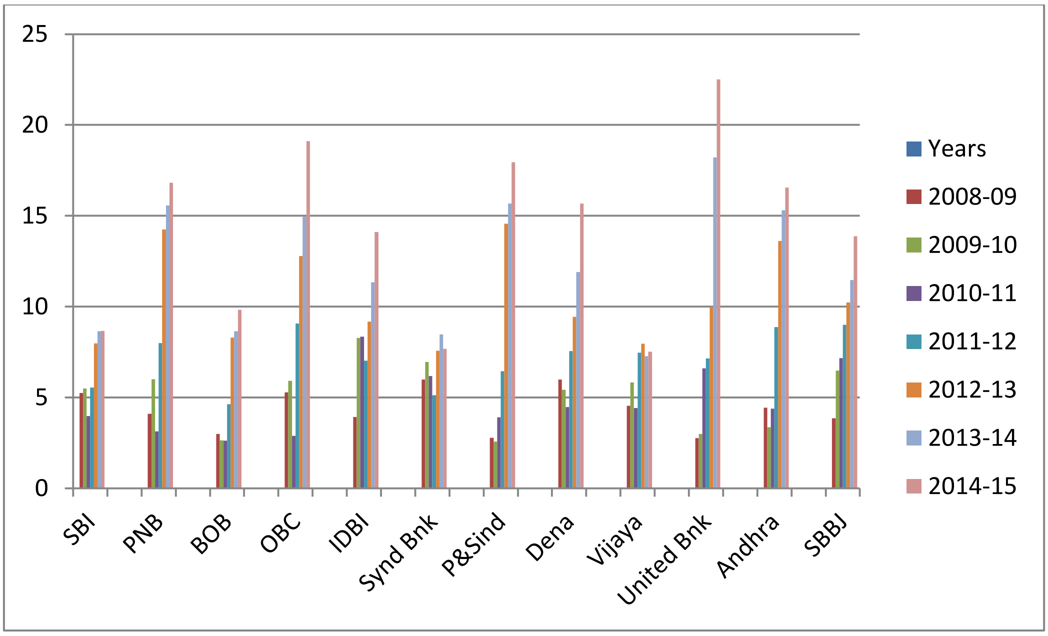

FIG 4.19: BANK/YEAR-WISE STRESSED ASSETS RATIO 2008-15

The highest stressed assets during 2014-15, were with United Bank of India (22.51%), followed by the OBC (19.1%) as shown in Figure 4.20. Dena Bank has recorded the highest growth in this ratio during the year at 31.65%, against the benchmark growth rate of 15.47% (Table 4.12).

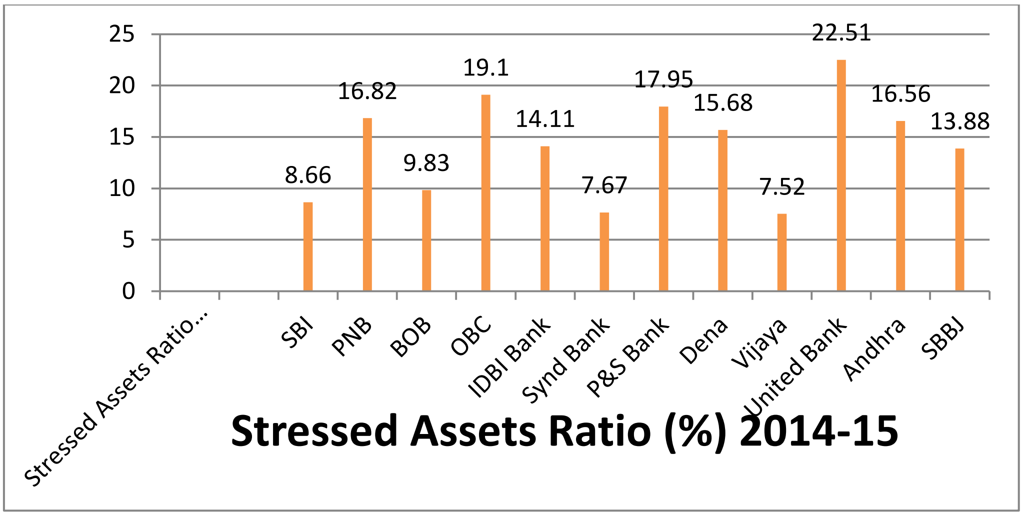

FIGURE 4.20: STRESSED ASSETS RATIO (%): 2014-2015

Regarding stressed assets ratio, the ranking of sample banks regarding credit risk during 2014-15 (high to low) is:

1. United Bank of India	7. IDBI Bank
2. Oriental Bank of Commerce	8. State Bank of Bikaner & Jaipur
3. Punjab & Sind Bank	9. Bank of Baroda
4. Punjab National Bank	10. State Bank of India
5. Andhra Bank	11. Syndicate Bank
6. Dena Bank	12. Vijaya Bank.

The ranking for 2014-15 also shows that the smaller PSBs have higher credit risk, with their mean stressed assets ratio of 15.68%, against 12.70% for large PSBs.

4.2.6 Relative Efficiency of NPA Recovery Channels

A sound credit risk management system requires efficient credit delivery and credit recovery systems. Recovery should be fast and efficient, preserving the value of viable assets, and putting unviable assets to new uses. The quarterly recovery ratio shows that the public sector banks are not faring well in the recovery of their non-performing loans, with an average recovery rate of around 7% only (Figure 4.21).

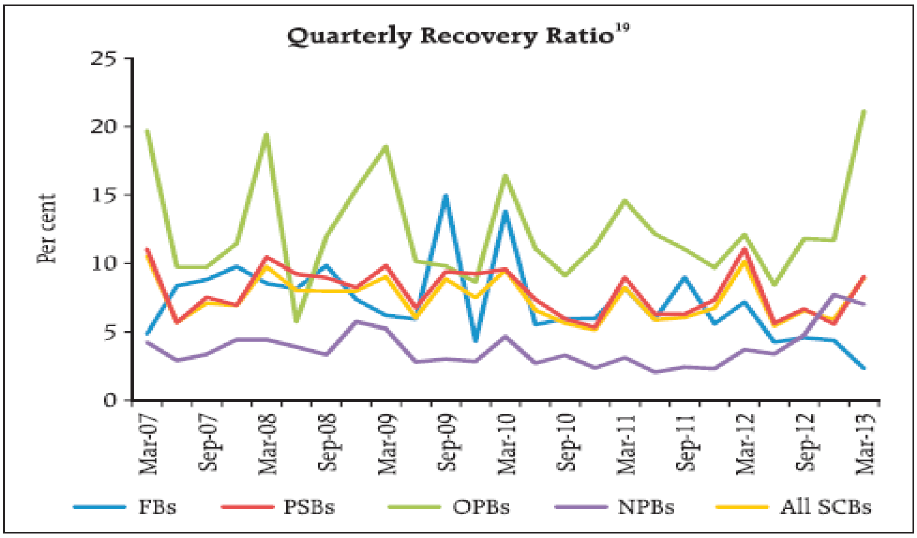

FIGURE 4.21: SLOW LOAN RECOVERIES

(Source: The RBI Financial Stability Report, June 2013)

In 2012-13, among the three channels of NPA recovery, *viz*., the Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest Act, 2002 (The SARFAESI Act), Debt Recovery Tribunals (DRT) and Lok Adalats, the largest amount was recovered through the SARFAESI Act (Table 4.13).

TABLE 4.13: NPA RECOVERY CHANNELS

Recovery channel	2011-12				2012-13			
	No. of cases referred	Amount involved	Amount recovered*	Col. (4) as % of Col. (3)	No. of cases referred	Amount involved	Amount recovered*	Col.(8) as % of Col.(7)
1	2	3	4	5	6	7	8	9
i) Lok Adalats	4,76,073	17	2	11.8	8,40,691	66	4	6.1
ii) DRTs	13,365	241	41	17.0	13,408	310	44	14.0
iii) SARFAESI Act	1,40,991	353	101	28.6	1,90,537	681	185	27.1
Total	**6,30,429**	**611**	**144**	**23.6**	**10,44,636**	**1,058**	**232**	**21.9**

(Source: RBI Report on Trends & Progress of Banking in India, 2012-13)

This secondary data on NPA recovery channels has also been made the basis of a survey among 337 credit managers of sample banks (Question no.25) to understand the perceptions of managers about the effectiveness of various methods to recover or resolve non-performing assets. The mean and standard deviation values (Tables 4.14 to 4.16) for different methods of NPA recoveries are shown in Figure 4.22.

TABLE 4.14: MEAN AND STANDARD DEVIATION BY BANK-SIZE

Q.11:Which is more risk prone sector? Q.25a:More effective methods to recover/resolve NPAs: One time compromise settlement scheme Q.25b:Debt recovery tribunals Q.25c:Recovery agents Q.25d:Lok adalats Q.25e:SARFAESI Act Q.25f:Writing off (partial) Q.25g:Debt restructuring Q.26a:How to control willful defaulters: Ban on financing new ventures Q.26b:Making their name public Q.26c:Filing criminal charges against them * Bank category

Bank category		Q.11:	Q.25a	Q.25b	Q.25c	Q.25d	Q.25e	Q.25f	Q.25g	Q.26a	Q.26b	Q.26c
Large	Mean	2.17	3.87	3.90	3.27	3.19	4.47	2.34	3.73	4.16	4.52	4.26
	N	172	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	.874	.979	.879	1.200	1.120	.653	1.157	1.009	1.091	.679	.863
Small	Mean	2.02	3.76	3.58	3.13	3.33	4.58	2.27	3.46	4.25	4.51	4.21
	N	165	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.917	1.081	1.127	1.122	1.060	.636	1.235	1.021	1.069	.746	.923
Total	Mean	2.10	3.82	3.74	3.20	3.26	4.52	2.31	3.60	4.21	4.51	4.24
	N	337	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.897	1.030	1.018	1.163	1.092	.646	1.195	1.022	1.079	.712	.891

Table 4.15: Mean and Standard Deviation by Management Level.

Q.11:Which is more risk prone sector? Q.25a:More effective methods to recover/resolve NPAs: One time compromise settlement scheme Q.25b:Debt recovery tribunals Q.25c:Recovery agents Q.25d:Lok adalats Q.25e:SARFAESI Act Q.25f:Writing off (partial) Q.25g:Debt restructuring Q.26a:How to control willful defaulters: Ban on financing new ventures Q.26b:Making their name public Q.26c:Filing criminal charges against them * Management Level

Management Level		Q.11	Q.25a	Q.25b	Q.25c	Q.25d	Q.25e	Q.25f	Q.25g	Q.26a	Q.26b	Q.26c
Junior Managers	Mean	2.02	3.44	3.64	2.88	3.32	4.34	2.48	3.62	4.08	4.24	3.92
	N	50	50	50	50	50	50	50	50	50	50	50
	Std. Deviation	.892	1.110	1.064	1.272	1.077	.658	1.199	.945	1.175	1.080	1.226
Middle Level Managers	Mean	2.04	3.89	3.81	3.19	3.33	4.50	2.37	3.61	4.09	4.53	4.24
	N	180	180	180	180	180	180	180	180	180	180	180

	Std. Deviation	.899	.991	1.013	1.147	1.057	.713	1.219	1.049	1.145	.672	.841
Senior Level Managers	Mean	2.24	3.87	3.67	3.37	3.10	4.64	2.11	3.57	4.47	4.62	4.38
	N	107	107	107	107	107	107	107	107	107	107	107
	Std. Deviation	.889	1.029	1.007	1.112	1.149	.481	1.135	1.020	.861	.507	.748
Total	Mean	2.10	3.82	3.74	3.20	3.26	4.52	2.31	3.60	4.21	4.51	4.24
	N	337	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.897	1.030	1.018	1.163	1.092	.646	1.195	1.022	1.079	.712	.891

TABLE 4.16: MEAN AND STANDARD DEVIATION BY BANKING EXPERIENCE.

Q.11:Which is more risk prone sector? Q.25a:More effective methods to recover/resolve NPAs: One time compromise settlement scheme Q.25b:Debt recovery tribunals Q.25c:Recovery agents Q.25d:Lok adalats Q.25e:SARFAESI Act Q.25f:Writing off (partial) Q.25g:Debt restructuring Q.26a:How to control willful defaulters: Ban on financing new ventures Q.26b:Making their name public Q.26c:Filing criminal charges against them * Banking Experience(years)

Banking Experience (years)		Q.11	Q.25a	Q.25b	Q.25c	Q.25d	Q.25e	Q.25f	Q.25g	Q.26a	Q.26b	Q.26c
Up to 7 years	Mean	2.17	3.72	3.67	2.95	3.34	4.40	2.35	3.54	3.92	4.35	4.08
	N	133	133	133	133	133	133	133	133	133	133	133
	Std. Deviation	.906	1.040	1.050	1.183	1.014	.738	1.220	1.070	1.187	.863	.974
8 to 20 years	Mean	2.04	3.87	3.88	3.38	3.34	4.61	2.15	3.88	4.46	4.66	4.38
	N	82	82	82	82	82	82	82	82	82	82	82
	Std. Deviation	.895	1.028	.999	1.214	1.102	.515	1.145	.921	.819	.526	.826
20 years and above	Mean	2.07	3.89	3.73	3.36	3.11	4.60	2.36	3.47	4.35	4.59	4.32
	N	122	122	122	122	122	122	122	122	122	122	122
	Std. Deviation	.892	1.022	.996	1.061	1.158	.598	1.200	1.006	1.044	.600	.816
Total	Mean	2.10	3.82	3.74	3.20	3.26	4.52	2.31	3.60	4.21	4.51	4.24
	N	337	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.897	1.030	1.018	1.163	1.092	.646	1.195	1.022	1.079	.712	.891

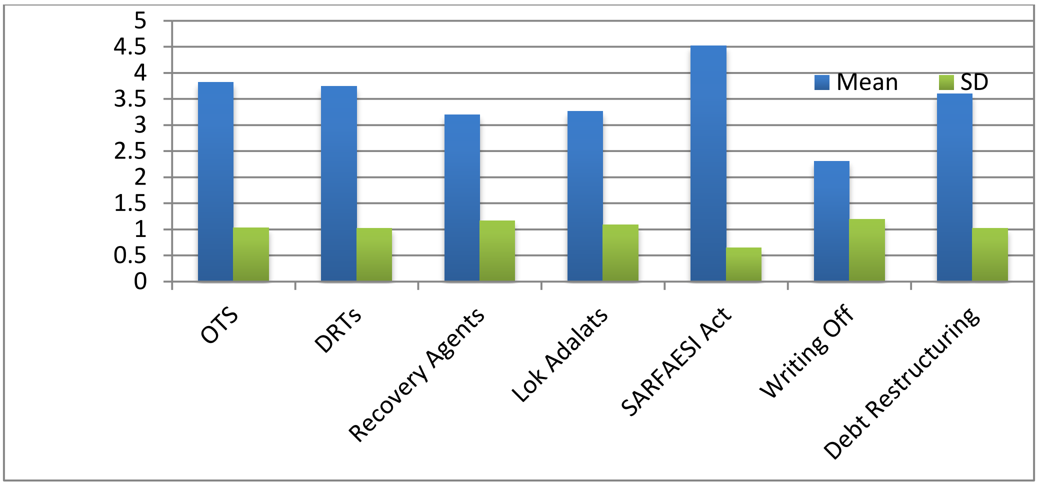

FIGURE 4.22: NPA RECOVERY CHANNELS- MEAN & S.D

Thus, in line with RBI report, the survey respondents find the SARFAESI Act, 2002, the most efficient method to recover defaulted loans, followed by OTS (one- time settlement schemes), and DRTs. The least favored method is writing off debt (Figure 4.22).

One-way analysis of variance (ANOVA) was conducted to find the statistical significance of mean differences between and within three management groups, managers of large and small banks; managers at junior, middle and senior levels; and managers with three levels of experience, up to 7 years, 8 to 20 years, and above 20 years (Tables 4.17, 4.18 and 4.20). Tukey's post hoc tests were also conducted to find the sub-management groups where significant differences existed (Tables 4.19 and 4.21).

The F statistics shows that responses of large and small bank managers are significantly different for debt recovery tribunals and debt restructuring (Table 4.17).

The responses of credit managers at different management levels are significantly different for one- time compromise settlement scheme, recovery agents, and effectiveness of SARFAESI Act, 2002 (Table 4.18). Differences are mainly between junior and senior level managers (Post hoc tests - Table 4.19).

TABLE 4.17: ANOVA BY BANK SIZE (Q. 25)

		Sum of Squares	df	Mean Square	F	Sig.
Q.25a:More effective methods to recover/resolve NPAs: One- time compromise settlement scheme	Between Groups	.887	1	.887	.836	.361
	Within Groups	355.706	335	1.062		
	Total	356.593	336			
Q.25b:Debt recovery tribunals	Between Groups	8.278	1	8.278	8.150	.005
	Within Groups	340.262	335	1.016		
	Total	348.540	336			
Q.25c:Recovery agents	Between Groups	1.795	1	1.795	1.329	.250
	Within Groups	452.484	335	1.351		
	Total	454.279	336			
Q.25d:Lok adalats	Between Groups	1.544	1	1.544	1.297	.256
	Within Groups	398.996	335	1.191		
	Total	400.540	336			
Q.25e:SARFAESI Act	Between Groups	.925	1	.925	2.228	.136
	Within Groups	139.158	335	.415		
	Total	140.083	336			
Q.25f:Writing off (partial)	Between Groups	.491	1	.491	.343	.558
	Within Groups	479.028	335	1.430		
	Total	479.519	336			
Q.25g:Debt restructuring	Between Groups	5.965	1	5.965	5.789	.017
	Within Groups	345.151	335	1.030		
	Total	351.116	336			

The responses of credit managers with different experience are significantly different for recovery agents, SARFAESI Act, and debt restructuring (Table 4.20). Differences are mainly among managers with up to 7 years' experience and with experience of 20 years' and above (Post hoc tests – Table 4.21).

TABLE 4.18: ANOVA BY LEVEL OF MANAGEMENT (Q. 25)

		Sum of Squares	df	Mean Square	F	Sig.
Q.25a:More effective methods to recover/resolve NPAs: One- time compromise settlement scheme	Between Groups	8.327	2	4.164	3.993	.019
	Within Groups	348.266	334	1.043		
	Total	356.593	336			
Q.25b:Debt recovery tribunals	Between Groups	1.891	2	.945	.911	.403
	Within Groups	346.649	334	1.038		
	Total	348.540	336			

Q.25c:Recovery agents	Between Groups	8.374	2	4.187	3.136	.045
	Within Groups	445.905	334	1.335		
	Total	454.279	336			
Q.25d:Lok Adalats	Between Groups	3.791	2	1.895	1.596	.204
	Within Groups	396.749	334	1.188		
	Total	400.540	336			
Q.25e:SARFAESI Act	Between Groups	3.358	2	1.679	4.102	.017
	Within Groups	136.725	334	.409		
	Total	140.083	336			
Q.25f:Writing off (partial)	Between Groups	6.324	2	3.162	2.232	.109
	Within Groups	473.195	334	1.417		
	Total	479.519	336			
Q.25g:Debt restructuring	Between Groups	.117	2	.058	.056	.946
	Within Groups	350.999	334	1.051		
	Total	351.116	336			

Thus, among three groups of managers, the managerial perception is highly different regarding the effectiveness of debt restructuring, SARFAESI Act, and recovery agents for recovery or resolution of NPAs. As such managers at senior levels and with high experience are more for the use of SARFAESI Act and recovery agents to recover non-performing assets. Managers in small banks and at ‘up to 7 years’ experience groups are feeling more favorably for debt restructuring in case of problem loans.

TABLE 4.19: MULTIPLE COMPARISONS: LEVELS OF MANAGEMENT (Q. 25)

Tukey HSD Post hoc tests

Dependent Variable	**(I) Management Level**	**(J) Management Level**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
						Lower Bound	Upper Bound
Q.25a:More effective methods to recover/resolve NPAs: One- time compromise settlement scheme	Junior Managers	Middle Level Managers	-.449*	.163	.017	-.83	-.06
		Senior Level Managers	-.429*	.175	.039	-.84	-.02
	Middle Level Managers	Junior Managers	.449*	.163	.017	.06	.83
		Senior Level Managers	.020	.125	.986	-.27	.31
	Senior Level Managers	Junior Managers	.429*	.175	.039	.02	.84
		Middle Level Managers	-.020	.125	.986	-.31	.27

Q.25c:Recovery agents	Junior Managers	Middle Level Managers	-.309	.185	.217	-.74	.13
		Senior Level Managers	-.494*	.198	.035	-.96	-.03
	Middle Level Managers	Junior Managers	.309	.185	.217	-.13	.74
		Senior Level Managers	-.185	.141	.390	-.52	.15
	Senior Level Managers	Junior Managers	.494*	.198	.035	.03	.96
		Middle Level Managers	.185	.141	.390	-.15	.52
Q.25e:SARFAESI Act	Junior Managers	Middle Level Managers	-.160	.102	.263	-.40	.08
		Senior Level Managers	-.305*	.110	.016	-.56	-.05
	Middle Level Managers	Junior Managers	.160	.102	.263	-.08	.40
		Senior Level Managers	-.145	.078	.154	-.33	.04
	Senior Level Managers	Junior Managers	.305*	.110	.016	.05	.56
		Middle Level Managers	.145	.078	.154	-.04	.33

*. The mean difference is significant at the 0.05 level.

TABLE 4.20: ANOVA BY BANKING EXPERIENCE (Q. 25)

		Sum of Squares	df	Mean Square	F	Sig.
Q.25a:More effective methods to recover/resolve NPAs: One -time compromise settlement scheme	Between Groups	1.969	2	.984	.927	.397
	Within Groups	354.625	334	1.062		
	Total	356.593	336			
Q.25b:Debt recovery tribunals	Between Groups	2.242	2	1.121	1.081	.340
	Within Groups	346.298	334	1.037		
	Total	348.540	336			
Q.25c:Recovery agents	Between Groups	14.236	2	7.118	5.403	.005
	Within Groups	440.043	334	1.317		
	Total	454.279	336			
Q.25d:Lok adalats	Between Groups	3.933	2	1.967	1.656	.192
	Within Groups	396.607	334	1.187		
	Total	400.540	336			
Q.25e:SARFAESI Act	Between Groups	3.372	2	1.686	4.118	.017
	Within Groups	136.712	334	.409		
	Total	140.083	336			

Q.25f:Writing off (partial)	Between Groups	2.753	2	1.377	.964	.382
	Within Groups	476.766	334	1.427		
	Total	479.519	336			
Q.25g:Debt restructuring	Between Groups	8.944	2	4.472	4.365	.013
	Within Groups	342.172	334	1.024		
	Total	351.116	336			

TABLE 4.21: MULTIPLE COMPARISONS BY LEVEL OF MANAGERIAL EXPERIENCE (Q. 25)

Tukey HSD Post hoc tests

Dependent Variable	(I) Banking Experience(years)	(J) Banking Experience(years)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Q.25c:Recovery agents	Up to 7 years	8 to 20 years	-.431*	.161	.021	-.81	-.05
		20 years and above	-.413*	.144	.012	-.75	-.07
	8 to 20 years	Up to 7 years	.431*	.161	.021	.05	.81
		20 years and above	.017	.164	.994	-.37	.40
	20 years and above	Up to 7 years	.413*	.144	.012	.07	.75
		8 to 20 years	-.017	.164	.994	-.40	.37
Q.25e:SARFAESI Act	Up to 7 years	8 to 20 years	-.211	.090	.050	-.42	.00
		20 years and above	-.200*	.080	.035	-.39	-.01
	8 to 20 years	Up to 7 years	.211	.090	.050	.00	.42
		20 years and above	.011	.091	.991	-.20	.23
	20 years and above	Up to 7 years	.200*	.080	.035	.01	.39
		8 to 20 years	-.011	.091	.991	-.23	.20
Q.25g:Debt restructuring	Up to 7 years	8 to 20 years	-.337*	.142	.048	-.67	.00
		20 years and above	.074	.127	.829	-.22	.37
	8 to 20 years	Up to 7 years	.337*	.142	.048	.00	.67
		20 years and above	.411*	.145	.013	.07	.75
	20 years and above	Up to 7 years	-.074	.127	.829	-.37	.22
		8 to 20 years	-.411*	.145	.013	-.75	-.07

*. The mean difference is significant at the 0.05 level.

4.2.7 The Willful Defaults

Willful defaulters are banks' borrowers who default in debt servicing though they have the capacity to pay, or who divert funds for unauthorized purposes, or when funds from bank loans are not available with them in the form of assets or when funds are siphoned off. RBI provides for some punitive measures like no additional loans, criminal proceedings, a track of their promoters/directors, and circulation of caution lists. RBI also stipulates that banks shall not misuse these penalties, and have a transparent policy. However, the banks are not able to control the problem. First, in many cases, they find it difficult to differentiate between a genuine or willful defaulter because of accounting dressings. In many cases, banks are not strict in handling identified willful defaulters. A survey has been undertaken on 337 credit managers (Question no. 26) to understand their perception about controlling willful defaulters through a ban on financing their new ventures, making their names public, or filing criminal charges against them. The mean and standard deviation values of their responses are shown in Figure 4.23.

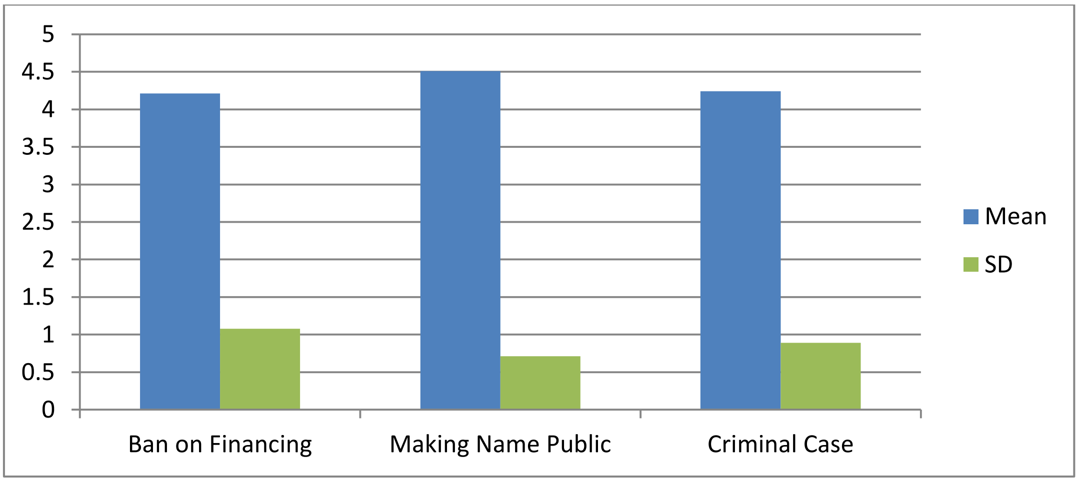

FIGURE 4.23: CONTROLLING WILLFUL DEFAULTERS

TABLE 4.22: CONTROLLING WILLFUL DEFAULTS -DESCRIPTIVE STATISTICS

	N	Mean	Std. Deviation
Q.26a:How to control willful defaulters: Ban on financing new ventures	337	4.21	1.079
Q.26b:Making their name public	337	4.51	.712
Q.26c:Filing criminal charges against them	337	4.24	.891

Though, there are high mean values for all three methods to control willful defaults, the highest agreement is on making their names public (Figure 4.23) (Table 4.22).

4.2.8 Relationship between Credit Risk and Operational Efficiency Parameters - Return on Assets (ROA) and Net Interest Margin (NIM)

The Return on Assets and Net Interest Margin are the primary indicators of the impact of credit risk on the profitability of banks.

Return on Assets: Return on Assets (ROA) measures the total profitability of banks. The mean value of ROA for sample banks during 2008-15 (Table 4.23) ranges between 0.25% (United Bank of India) and 1.076% (PNB). The SBBJ has the highest stability in profits (0.937) with a standard deviation of 0.062 and coefficient of variation of 0.004 (Figure 4.24). Against the benchmark mean value of 0.765% (2008-15), the seven well- performing banks are PNB (1.076), BOB (1.001), Andhra Bank (0.956), SBBJ (0.937), SBI (0.821), Dena Bank (0.814) and Syndicate Bank (0.776). During 2012-13, the most performing banks were Syndicate Bank (1.07) and PNB (1.0). During 2014-15, the most performing banks were PNB (1.076) and BOB (1.001). Though there has been a consistent decline in profitability of sample banks since 2011-12, the highest decline was in 2013-14 (-45.8%).

Comparing the ROA and the stressed assets (restructured standard assets + GNPA ratios), during 2012-13, Syndicate Bank had the lowest credit risk and the highest ROA, during this year (Tables 4.12 & 4.23). Comparing the ROA, GNPA Ratio, NNPA Ratio, and the Stressed Assets Ratio for 2014-15, United Bank of India has been found with the highest GNPA Ratio (9.49%), the highest NNPA Ratio (6.22%), the highest Stressed Assets Ratio (22.51%), and the second lowest ROA (0.21%). (Tables 4.7, 4.8, 4.12 and 4.23) (Figure 4.24)

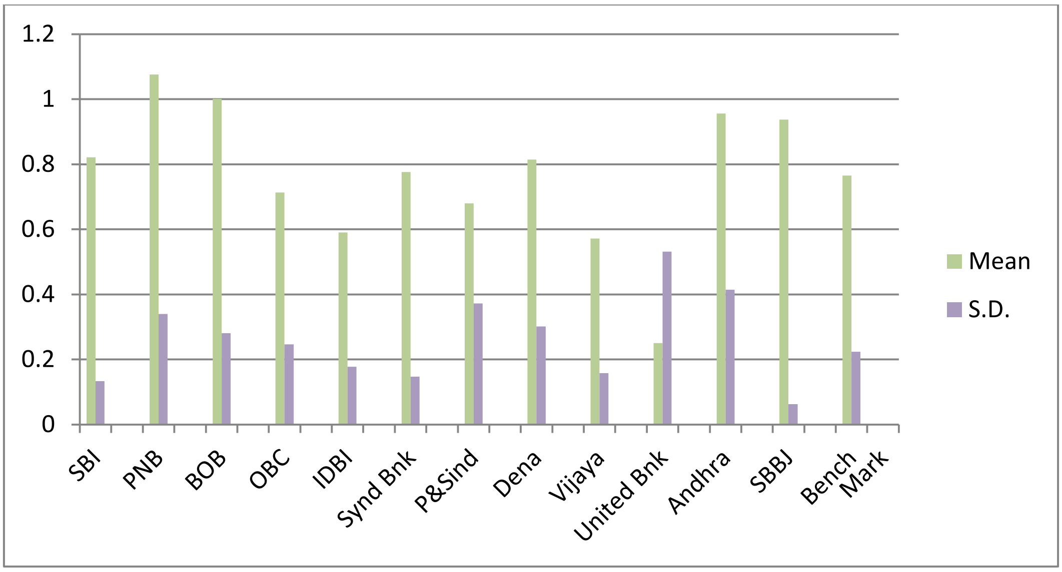

FIGURE 4.24: RETURN ON ASSETS (%): 2008-2015

TABLE 4.23: RETURN ON ASSETS (%) (ROA)

	SBI		PNB		BOB		OBC		IDBI		Synd Bnk	
Years	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
2008-09	1.04		1.39		1.09		0.88		0.62		0.81	
2009-10	0.88	-15.4	1.44	3.597	1.21	11.01	0.91	3.409	0.53	-14.5	0.62	-23.5
2010-11	0.71	-19.3	1.34	-6.94	1.33	9.917	1.03	13.19	0.73	37.74	0.76	22.58
2011-12	0.88	23.94	1.19	-11.2	1.24	-6.77	0.67	-35	0.83	13.7	0.81	6.579
2012-13	0.91	3.409	1	-16	0.9	-27.4	0.71	5.97	0.72	-13.3	1.07	32.1
2013-14	0.65	-28.6	0.64	-36	0.75	-16.7	0.56	-21.1	0.41	-43.1	0.78	-27.1
2014-15	0.68	4.615	0.53	-17.2	0.49	-34.7	0.23	-58.9	0.29	-29.3	0.58	-25.6
Mean	0.821		1.076		1.001		0.713		0.59		0.776	
S.D.	0.133		0.34		0.281		0.247		0.178		0.147	
C.V.	0.018		0.115		0.079		0.061		0.032		0.022	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench	Mark
Value	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**	**Value**	**GR**
1.24		1.02		0.59		0.34		1.09		0.91		0.918	
1.05	-15.3	1.01	-0.98	0.76	28.81	0.45	32.35	1.39	27.52	1.03	13.19	0.94	2.359
0.9	-14.3	1	-0.99	0.72	-5.26	0.66	46.67	1.36	-2.16	0.96	-6.8	0.958	1.95
0.65	-27.8	1.08	8	0.66	-8.33	0.7	6.061	1.19	-12.5	0.99	3.125	0.908	-5.3
0.44	-32.3	0.86	-20.4	0.59	-10.6	0.38	-45.7	0.99	-16.8	0.96	-3.03	0.794	-12.5
0.35	-20.5	0.51	-40.7	0.35	-40.7	-0.99	-361	0.29	-70.7	0.87	-9.38	0.431	-45.8
0.13	-62.9	0.22	-56.9	0.33	-5.71	0.21	-121	0.38	31.03	0.84	-3.45	0.409	-5.03
0.68		0.814		0.571		0.25		0.956		0.937		0.765	
0.372		0.301		0.157		0.531		0.414		0.062		0.224	
0.138		0.091		0.025		0.282		0.172		0.004		0.05	

Note: GR means Growth Rate percent per annum.

The Result of Linear Regression Analysis (ROA on GNPA): Linear regression analysis has been undertaken to study the impact of GNPAs or credit risk on Return on Assets (ROA) of sample banks for 2008-15, as high credit risk is expected to reduce profitability and vice-versa. The results show a statistically significant, inverse relationship between GNPA/Gross Advances ratio (independent variable), and ROA (dependent variable) (Tables 4.24.I to 4.24.III).

TABLE 4.24.I: REGRESSION ANOVA (ROA ON GNPA)

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.698	1	2.698	12.290	.001
1 Residual	17.999	82	.219		
Total	20.696	83			

Note 1. Dependent Variable: ROA

Note 2. Predictors: (Constant), GNPA Ratio

TABLE 4.24.II: REGRESSION COEFFICIENTS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.149	.105		10.989	.000	.941	1.357
	GNPA Ratio	-.105	.030	-.361	-3.506	.001	-.164	-.045

Note. Dependent Variable: ROA

TABLE 4.24.III: REGRESSION MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.361	.130	.120	.46850	.540

Note 1. Predictors: (Constant), GNPA Ratio.

Note 2. Dependent Variable: ROA.

The F-statistic is 12.290 (df 1, 82), at p=0.001, significant at 5% level of significance.

The t-statistic is also significant for intercept and GNPA ratio indicating a significant linear relationship. The unstandardized coefficients are equal to 1.149 and -0.105. R Square is 0.130, and Durbin-Watson statistic is 0.540. The regression equation is:

Return on Assets = 1.149 - 0.105*GNPA Ratio

The regression results are establishing that increasing GNPA ratio or credit risk had significant negative relation with the profitability of Indian public sector banks during 2008-15.

Net Interest Margin (NIM): Net Interest Margin or ratio of Net Interest Income to Total Assets indexes an important component of profit for banks. It measures the operational efficiency in the financial intermediation of collecting savings and providing loans, the main banking function. Figure 4.25 shows the lowest net interest margin of public sector banks consistently since 2008-09.

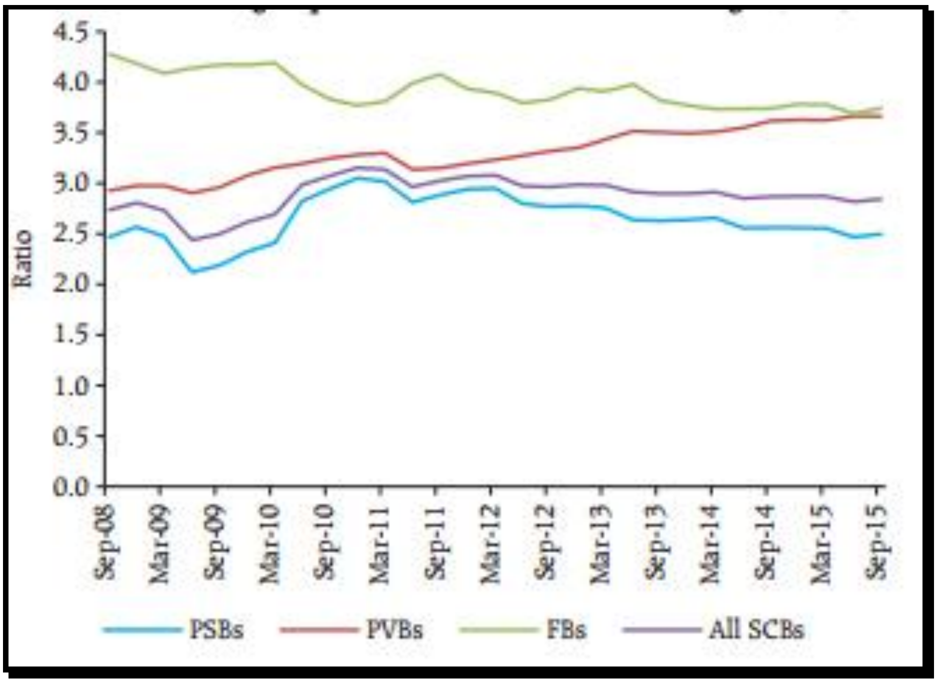

FIGURE 4.25: BANK-GROUP WISE TRENDS IN NET INTEREST MARGIN (NIM)
(Source: RBI Financial Stability Report, December 2015)

TABLE4.25: NET INTEREST INCOME/TOTAL ASSETS RATIOS (%) (NET INTEREST MARGIN- NIM)

	SBI		PNB		BOB		OBC		IDBI		Synd Bank	
Years	Value	GR	Value	GR	Value	GR	Value	GR	Value	GR	Value	GR
2008-09	2.48		3.06		2.52		1.96		0.82		2.15	
2009-10	2.35	-5.24	3.14	2.614	2.35	-6.75	2.33	18.88	1.12	36.59	2.03	-5.58
2010-11	2.86	21.7	3.5	11.46	2.76	17.45	2.8	20.17	1.75	56.25	2.97	46.31
2011-12	3.38	18.18	3.21	-8.29	2.56	-7.25	2.49	-11.1	1.67	-4.57	3	1.01
2012-13	3.06	-9.47	3.17	-1.25	2.28	-10.9	2.49	0	1.75	4.79	2.74	-8.67
2013-14	2.93	-4.25	3.4	7.256	1.98	-13.2	2.44	-2.01	1.85	5.714	2.37	-13.5
2014-15	2.86	-2.39	2.87	-15.6	1.92	-3.03	2.26	-7.38	1.68	-9.19	1.99	-16
Mean	2.846		3.193		2.339		2.396		1.52		2.464	
S.D.	0.32		0.194		0.285		0.238		0.361		0.404	
C.V.	0.103		0.038		0.081		0.057		0.13		0.163	

P&Sind		Dena		Vijaya		United Bank		Andhra		SBBJ		Bench	Mark
Value	GR	Value	GR	Value	GR	Value	GR	Value	GR	Value	GR	Value	GR
2.8		2.44		1.9		2		2.6		2.12		2.238	
2.42	-13.6	2.07	-15.2	2.19	15.26	2	0	2.76	6.154	2.25	6.132	2.251	0.596
2.49	2.893	2.75	32.85	2.56	16.89	2.6	30	3.23	17.03	3.02	34.22	2.774	23.25
2.12	-14.9	2.86	4	2.14	-16.4	2.58	-0.77	3.22	-0.31	3.28	8.609	2.709	-2.34
2.14	0.943	2.37	-17.1	1.82	-15	2.3	-10.9	2.77	-14	3.24	-1.22	2.511	-7.32
1.85	-13.6	2.1	-11.4	1.68	-7.69	2.4	4.348	2.38	-14.1	3.19	-1.54	2.381	-5.18
1.75	-5.41	1.92	-8.57	1.64	-2.38	2.01	-16.3	2.57	7.983	3.05	-4.39	2.21	-7.18
2.224		2.359		1.99		2.27		2.79		2.879		2.439	
0.343		0.328		0.303		0.25		0.301		0.449		0.215	
0.118		0.108		0.092		0.062		0.09		0.201		0.046	

Note: GR means Growth Rate percent per annum.

The analytical study of 12 sample banks for the period from 2008-15 shows that the mean values of NIM range between 1.52% (IDBI Bank) to 3.193% (PNB) (Table 4.25). PNB has the highest average interest income, with lowest dispersion (SD=0.194, CV=0.038) in the group, showing both efficiency and stability in interest margin. Against the benchmark value of 2.439 (2008-15), the five banks performing well in terms of NIM are PNB (3.193), SBBJ (2.879), SBI (2.846), Andhra Bank (2.7), and Syndicate Bank (2.464). In 2012-13, the most performing banks were SBBJ, PNB, and SBI, they were also the most performing in 2014-15.

However, all the sample banks except Andhra Bank, have recorded decline in NIM during 2014-15, the highest decline by the United Bank of India (-16.3%) against the average decline by 7.18%.

4.3 RESULTS AND DISCUSSION

The data analysis on identified characteristics of credit risk in Indian public sector banks shows:

1. For the last five years (2010-15), the Indian public sector banks (PSBs) have been under high stress on account of growing non-performing assets, mainly for business and industry. There is also a consistent decline in their profitability (ROA) since 2011-12. The decline in ROA of sample banks was highest in 2013-14 (-45.8%).

2. The PSBs are well capitalized, with their capital adequacy ratios more than the Basel II norm of RBI (9%). However, the fact remains that their capital adequacy ratios are less than the private sector banks, foreign banks and the average of all scheduled commercial banks. Since capital adequacy ratios are inversely related to credit risk, the Indian public sector banks are under higher credit risk than the other banks in the industry. Capital adequacy ratio of banks has also been declining because risk-weighted assets have increased more than the increase in capital.

3. Stressed Assets Ratio of the public sector banks is continuously growing from

4.33% in 2008-09 to 14.19% in 2014-15. Bank-wise, United Bank of India, OBC, PNB, Punjab & Sind Bank and Dena Bank have been the worst performers in managing their stressed assets during 2008-15. Whereas BOB, Vijaya Bank, and the Syndicate Banks have managed to keep their stressed assets consistently at a low level during this period.

4. Regarding stressed assets on an average, small PSBs ranked higher in credit risk than the large PSBs (in the sample).

5. During 2014-15, the various indicators of credit risk are showing high pressure on public sector banks (sample banks), such as:

   (a) 10.8% increase in GNPA/Gross Advances ratio.

   (b) 9% increase in NNPA/Net Advances ratio.

   (c) 18.25% increase in Restructured Standard Advances/Total Advances ratio.

   (d) 15.47% increase in Stressed Assets ratio. (Restructured assets + GNPAs/Total Advances).

   (e) 7.18% decrease in NIM.

   (f) 5.03% decrease in ROA.

6. During 2014-15, the United Bank of India had the highest credit risk among the sample banks with highest GNPA Ratio (9.49%), highest NNPA Ratio (6.22%), highest Stressed Assets Ratio (22.51%), and the second lowest ROA (0.21%). Other banks under high stress on their asset quality during this period were OBC (19.1%), Punjab & Sind Bank (17.95%), PNB (16.82%), Andhra Bank (16.56%) and Dena Bank (15.68%).

7. Since micro and macroeconomic factors impact the various industries or sectors within any industry, in a different manner, this necessitates clear identification of credit risk factors and adoption of differential credit risk assessment practices to measure and control credit risk for different industries or business groups.

8. The efficiency of NPA recovery systems is crucial to manage defaulted loans and minimize credit losses. The empirical analysis shows a significantly different perception of credit managers in large and small banks, as well as among junior and senior managers. There is a need to understand the perceptions of bank managers for different recovery channels to optimize recoveries and minimize credit losses.

9. Banks must tighten their control on willful defaulters through a ban on new financing, initiating criminal proceedings, attaching their personal property and making their names public. Banks also need a transparent staff accountability framework to ensure compliance with credit policy and procedures. The possibility of connivance of bank staff with willful defaulters must also be investigated.

4.4 CONCLUSIONS

This chapter has thus, ascertained the main characteristics of credit risk in Indian public sector banks during the period 2008-2015. The public sector banks are least capitalized in terms of capital adequacy ratios and have highest non-performing and restructured assets in the Indian banking industry. Some public sector banks such as United Bank of India, Oriental Bank of Commerce, Punjab National Bank, and the Andhra Bank have about 10 percent of their advances in the form of GNPAs and restructured and rescheduled advances. There has also been a consistent decline in profitability of sample public sector banks since 2011-12, the highest decline in 2013-14 (-45.8%). Further, on an average, the small public sector banks have higher stressed assets ratio than the large public sector banks.

The next chapter empirically evaluates the second part of first research objective, i.e., to identify and examine the causes of credit risk in these banks.

CHAPTER 5
ANALYZING MANAGERIAL PERCEPTION TOWARDS CAUSES OF CREDIT RISK

5.1 INTRODUCTION

The purpose of this section is to investigate the causes of credit risk faced by the Indian public sector banks through the perception of their credit managers. Since the human resource is central for any organization to improve its performance and efficiency, and to achieve a sustainable competitive advantage, it would be worthwhile to assess the managerial perception of causes of credit risk in Indian PSBs, before taking significant efforts to control and mitigate credit risk. Appraisal and assessment of credit risk in commercial lending shall require monitoring the business environment of borrowers and identifying their key risk factors.

5.2 CAUSES OF CREDIT RISK

The study analyzes three categories of credit risk causes or factors in Indian PSBs:

1. Borrower-specific credit risk factors which include 30 risk variables given in Part III of the questionnaire, and a comparative study of predictability of these risk factors (Question no. 14).

2. Bank-specific credit risk factors, which include two risk factors, viz. banks' credit appraisal systems (Question no. 24), and bank size in terms of large and small banks.

3. Macroeconomic credit risk factor with regard to economic slowdown (Question no. 22).

The following 3 null hypotheses have been tested:

Hypothesis 1

H_0: There is no significant difference in risk perception of credit managers towards various causes of credit risk, in large and small banks.

Hypothesis 2

H_0: There is no significant difference in risk perception of credit managers with different levels of banking experience, towards various causes of credit risk.

Hypothesis 3

H_0: There is no significant difference in risk perception of different management levels towards various causes of credit risk.

Data collected for the study has been analyzed by descriptive statistics, factor analysis, one-way ANOVA, and Tukey's HSD post hoc tests, using SPSS (SPSS version 21). The null hypotheses have been tested at 5% level of significance.

5.3 BORROWER-SPECIFIC RISK FACTORS

5.3.1 Mean and Standard Deviation

The mean values of credit risk variables (Part III of the questionnaire) show that five variables have the highest risk component in terms of borrower's creditworthiness (Figure 5.1 & Table 5.1). These variables are TOL/TNW (Total Outside Liabilities/Tangible Net Worth), payment record, the integrity of management, current ratio, and the managerial competence.

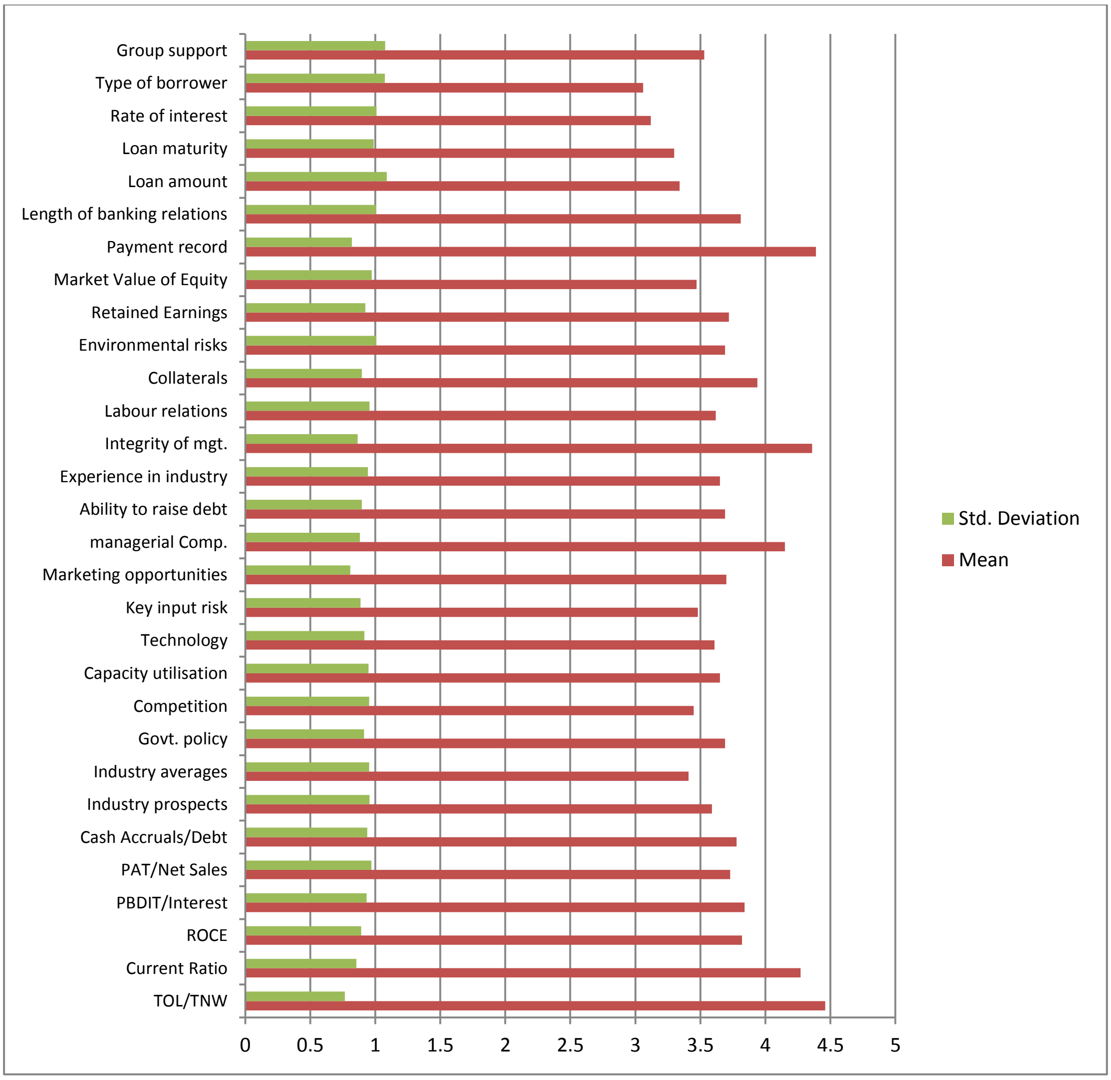

FIGURE 5.1: MEAN AND STANDARD DEVIATION VALUES OF BORROWER RISK VARIABLES

TABLE 5.1: DESCRIPTIVE STATISTICS- BORROWER RISK VARIABLES

	N	Mean	Std. Deviation
TOL/TNW	337	4.46	.767
Current Ratio	337	4.27	.856
ROCE	337	3.82	.893
PBDIT/Interest	337	3.84	.934
PAT/Net Sales	337	3.73	.971
Cash Accruals/Debt	337	3.78	.940
Industry prospects	337	3.59	.957

Industry averages	337	3.41	.954
Govt. policy	337	3.69	.913
Competition	337	3.45	.953
Capacity utilization	337	3.65	.949
Technology	337	3.61	.916
Key input risk	337	3.48	.887
Marketing opportunities	337	3.70	.808
Managerial Competence	337	4.15	.881
Ability to raise debt	337	3.69	.896
Experience in industry	337	3.65	.943
Integrity of management	337	4.36	.866
Labour relations	337	3.62	.956
Collaterals	337	3.94	.898
Environmental risks	337	3.69	1.007
Retained Earnings	337	3.72	.925
Market Value of Equity	337	3.47	.973
Payment record	337	4.39	.821
Length of banking relations	337	3.81	1.006
Loan amount	337	3.34	1.090
Loan maturity	337	3.30	.989
Rate of interest	337	3.12	1.011
Type of borrower	337	3.06	1.073
Group support	337	3.53	1.077

5.3.2 Factor Analysis

Factor analysis with principal component extraction, at 5% level of significance, was applied on 30 credit risk variables, with varimax rotation to understand the factor loadings across the derived components.

TABLE 5.2: KMO AND BARTLETT'S TEST

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.870
Bartlett's Test of Sphericity	Approx. Chi-Square	4066.136
	df	435
	Sig.	.000

Kaiser-Meyer-Olkin (KMO) for the sampling adequacy and Bartlett's test of sphericity were conducted to examine the correlation matrix based on chi-square transformation.

The Kaiser-Meyer-Olkin measure of sampling adequacy came out to be 0.870 which is above 0.65 (the acceptable level). This measure shows the appropriateness of factor analysis.

The chi- square value of Bartlett's test of sphericity was found to be significant, with chi- square (df 435) = 4066.136 at p= 0.000, indicating that the factor analysis is acceptable (Table 5.2).

The varimax rotation clubbed the 30 variables on seven principal components or factors, and using the Rotated Matrix Component Table; the Factor Loadings were derived (Table 5.3).

Total variance explained in the seven factors is 60.508% (cumulative) (Table 5.4). Varimax rotation maximizes the variance of each of the factors so that the total amount of variance accounted for is redistributed over the extracted factors. Regarding mean scores, the most important factor is Liquidity and Solvency Risk factor (mean score 4.36), followed by Management Risk factor (mean score 3.76) (Table 5.4).

TABLE 5.3: ROTATED COMPONENT MATRIX: FACTOR LOADINGS

	Components						
	1.Business & Industry Risk	**2.Management Risk**	**3.Financial Performance Risk**	**4.Loan Characteristics**	**5.Enterprise Value**	**6.Liquidity & Solvency Risk**	**7.Labour & Environmental Risk**
Capacity utilization	.784						
Technology	.717						
Competition	.698						
Key input risk	.686						
Marketing opportunities	.637						
Govt. policy	.566						
Payment record		.728					
Integrity of management		.706					
Managerial Competence		.668					
Collaterals		.571					
Experience in industry		.551					
Length of banking relations		.468					
Ability to raise debt		.429					
ROCE			.710				
Industry averages			.683				
PBDIT/Interest			.645				
Industry prospects			.614				
PAT/Net Sales			.564				
Cash Accruals/Debt			.486				
Loan maturity				.854			
Loan amount				.780			
Rate of interest				.777			
Type of borrower				.694			
Group support				.499			
Market Value of Equity					.756		
Retained Earnings					.663		
Current Ratio						.789	
TOL/TNW						.768	
Labour relations							.473
Environmental risks							.448

Note: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

TABLE 5.4: MEAN SCORES &TOTAL VARIANCE EXPLAINED

Component and Mean Scores	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1 - 3.72	4.075	13.584	13.584
2 - 3.76	3.272	10.906	24.489
3 - 3.70	3.089	10.298	34.787
4 - 3.31*	3.023	10.076	44.864
5 - 3.54	1.810	6.034	50.898
6 - 4.36**	1.789	5.964	56.862
7 - 3.65	1.094	3.646	60.508

Extraction Method: Principal Component Analysis.
** Most important factor *Least important factor

The scree plot graphs the eigenvalues against the factor numbers (Figure 5.2).

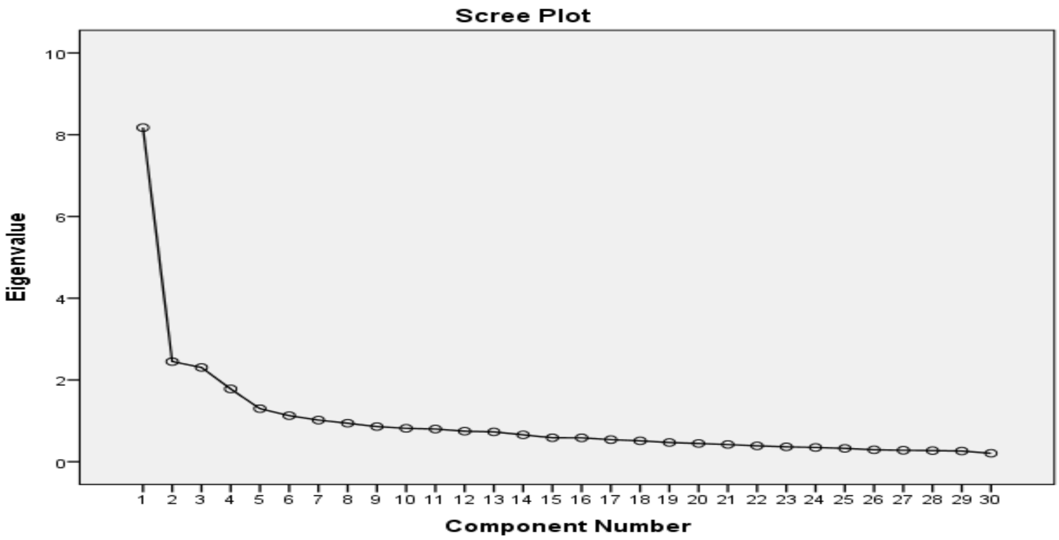

FIGURE 5.2: PLOTTING EIGENVALUES

From the 30 variables, the following seven dimensions of borrower-specific credit risk factors or causes have been derived:

1. Business and Industry risk factors. (Total variance accounted: 13.584 percent)

2. Management risk factors. (Total variance accounted: 10.906 percent)
3. Financial performance risk factors. (Total variance accounted: 10.298 percent)
4. Loan characteristics. (Total variance accounted: 10.076 percent)
5. Enterprise value. (Total variance accounted: 6.034 percent)
6. Liquidity and solvency risk factors. (Total variance accounted: 5.964 percent)
7. Labor and environmental risk factors. (Total variance accounted: 3.646 percent)

Thereby all the borrower-specific credit risk factors (30) are grouped into seven risk categories for further analysis. To analyze the risk perception of bank managers across these seven categories and to test hypotheses, two approaches have been adopted.

The first approach called **surrogate variable approach**, is to select the surrogate variable (dependent variable) in each risk category and conduct ANOVA or F test on three independent variables(three groups of credit managers):

- Bank managers in large or small banks.
- Bank managers in three experience groups.
- Bank managers at three levels of management.

A second approach called **factors scores approach**, has been to calculate factor scores (dependent variable) for each respondent for seven credit risk factors, and conduct ANOVA on derived factor scores, on the above three categories of bank managers as independent variables.

One- way analysis of variance or ANOVA compares the between estimates of mean variance with the within estimates.

Tukey's HSD post hoc tests have been conducted in those cases where significant differences are observed in risk perceptions to find which sub-groups of the sample groups, in specific have the statistically significant difference.

5.3.3 Surrogate Variables Approach

Surrogate or substitute variable is the variable with highest factor loading in each factor category. Conducting statistical analysis on surrogate variables facilitates interpretation of results regarding original variables rather than the factor scores. The seven surrogate risk variables for each of seven factors are capacity utilization, payment record, return on capital employed, loan maturity, the market value of equity, current ratio, and labour relations (Table 5.5). In terms of mean scores, greater risk variable is the track record of payments of interest and repayment of loan installment by the borrower (mean score 4.39), followed by his current ratio or liquidity position (mean score 4.27).

TABLE 5.5: SURROGATE RISK VARIABLES

Sl. No.	Factor	Surrogate Variable	Factor Loading	Mean Score
1	Business and Industry risk factors	Capacity utilization	.784	3.65
2	Management risk factors	Payment record	.728	4.39**
3	Financial performance risk factors	ROCE	.710	3.82
4	Loan characteristics	Loan maturity	.854	3.30*
5	Enterprise value	Market value of equity	.756	3.47
6	Liquidity and solvency risk factors.	Current ratio	.789	4.27
7	Labour and environmental risk factors	Labour relations	.473	3.62

** Most important risk variable * Least important risk variable

Loan maturity has highest factor loadings (0.854), followed by current ratio (0.789) and capacity utilization (0.784) (Figure 5.3).

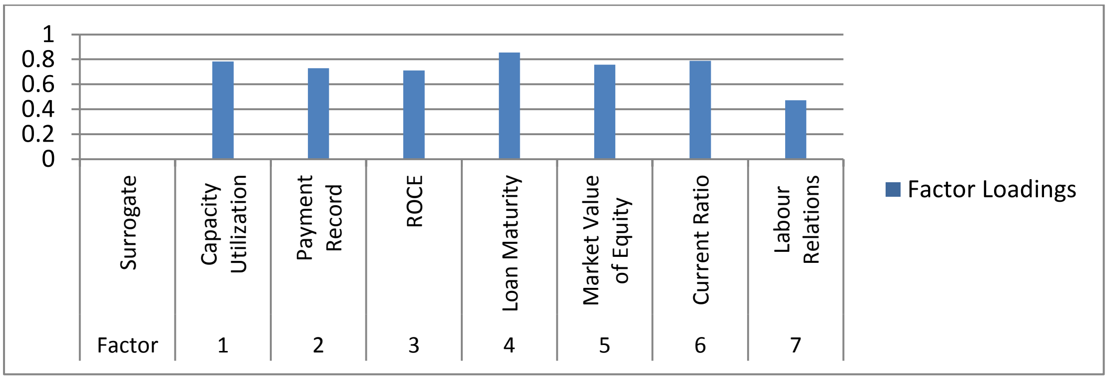

FIGURE 5.3: FACTOR LOADINGS OF SURROGATE RISK VARIABLES

TABLE 5.6: ANOVA OF SURROGATE VARIABLES BY BANK SIZE(LARGE BANKS VS. SMALL BANKS)

		Sum of Squares	df	Mean Square	F	Sig.
Current Ratio	Between Groups	.352	1	.352	.479	.489
	Within Groups	246.075	335	.735		
	Total	246.427	336			
ROCE	Between Groups	1.402	1	1.402	1.762	.185
	Within Groups	266.556	335	.796		
	Total	267.958	336			
Capacity utilization	Between Groups	.535	1	.535	.594	.441
	Within Groups	301.844	335	.901		
	Total	302.380	336			
Labour relations	Between Groups	.173	1	.173	.189	.664
	Within Groups	306.966	335	.916		
	Total	307.139	336			
Payment record	Between Groups	.179	1	.179	.265	.607
	Within Groups	226.332	335	.676		
	Total	226.510	336			
Market Value of Equity	Between Groups	.735	1	.735	.777	.379
	Within Groups	317.122	335	.947		
	Total	317.858	336			
Loan maturity	Between Groups	.000	1	.000	.000	.997
	Within Groups	328.326	335	.980		
	Total	328.326	336			

One-way analysis of variance (ANOVA) was conducted on seven surrogate risk variables to identify the significant differences in risk perceptions of credit managers in large and small public sector banks, of credit managers with different length of banking experience, and of credit managers at the various levels of management (ANOVA Tables 5.6 to 5.8).

The results show no statistically significant differences in perception of bank managers in large and small banks, or of bank managers with different banking experience, towards any of surrogate variables. Any difference in these groups' mean scores may be random or by chance, or in other words, the groups are similar in their choice.

TABLE 5.7: ANOVA OF SURROGATE VARIABLES BY EXPERIENCE OF BANK MANAGERS

		Sum of Squares	df	Mean Square	F	Sig.
Current Ratio	Between Groups	.034	2	.017	.023	.977
	Within Groups	246.394	334	.738		
	Total	246.427	336			
ROCE	Between Groups	1.625	2	.813	1.019	.362
	Within Groups	266.333	334	.797		
	Total	267.958	336			
Capacity utilization	Between Groups	2.576	2	1.288	1.435	.240
	Within Groups	299.804	334	.898		
	Total	302.380	336			
Labour relations	Between Groups	3.860	2	1.930	2.126	.121
	Within Groups	303.279	334	.908		
	Total	307.139	336			
Payment record	Between Groups	.158	2	.079	.117	.890
	Within Groups	226.352	334	.678		
	Total	226.510	336			
Market Value of Equity	Between Groups	.029	2	.014	.015	.985
	Within Groups	317.829	334	.952		
	Total	317.858	336			
Loan maturity	Between Groups	1.757	2	.878	.898	.408
	Within Groups	326.570	334	.978		
	Total	328.326	336			

However, there is a significant difference in mean scores for ROCE (Return on Capital Employed), with F (2, 334) = 3.544, at p= 0.030, of bank managers at different levels of management (Table 5.8). Tukey’s post hoc test was applied at 95% confidence level to find exactly at what level, the differences were significant. Post hoc tests revealed a significant difference in risk perceptions for ROCE between junior credit managers and middle - level credit managers, but not between them with senior credit managers (Table 5.9).

TABLE 5.8: ANOVA OF SURROGATE VARIABLES BY LEVEL OF MANAGEMENT

		Sum of Squares	df	Mean Square	F	Sig.
	Between Groups	.840	2	.420	.571	.565
Current Ratio	Within Groups	245.587	334	.735		
	Total	246.427	336			
	Between Groups	5.568	2	2.784	3.544	.030
ROCE	Within Groups	262.390	334	.786		
	Total	267.958	336			
	Between Groups	2.405	2	1.203	1.339	.264
Capacity utilization	Within Groups	299.975	334	.898		
	Total	302.380	336			
	Between Groups	3.233	2	1.616	1.776	.171
Labour relations	Within Groups	303.907	334	.910		
	Total	307.139	336			
	Between Groups	2.111	2	1.056	1.571	.209
Payment record	Within Groups	224.399	334	.672		
	Total	226.510	336			
	Between Groups	2.660	2	1.330	1.409	.246
Market value of equity	Within Groups	315.197	334	.944		
	Total	317.858	336			
	Between Groups	1.188	2	.594	.606	.546
Loan maturity	Within Groups	327.139	334	.979		
	Total	328.326	336			

TABLE 5.9: POST HOC TESTS - MULTIPLE COMPARISONS- SURROGATE VARIABLES

Dependent Variable: ROCE

Tukey's HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle-Level Managers	-.362*	.142	.030	-.70	-.03
	Senior Level Managers	-.206	.152	.364	-.56	.15
Middle Level Managers	Junior Managers	.362*	.142	.030	.03	.70
	Senior Level Managers	.156	.108	.321	-.10	.41
Senior Level Managers	Junior Managers	.206	.152	.364	-.15	.56
	Middle-Level Managers	-.156	.108	.321	-.41	.10

*. The mean difference is significant at the 0.05 level.

TABLE 5.10.I: ROCE –MEAN/SD BY BANK SIZE

ROCE

Bank category	Mean	N	Std. Deviation
Large	3.76	172	.930
Small	3.88	165	.851
Total	3.82	337	.893

TABLE 5.10.II: ROCE –MEAN/SD BY BANKING EXPERIENCE (YEARS)

ROCE

Banking Experience(years)	Mean	N	Std. Deviation
Up to 7 years	3.89	132	.835
8 to 20 years	3.84	83	.876
20 years and above	3.73	122	.962
Total	3.82	337	.893

TABLE 5.10.III: ROCE-MEAN/SD BY MANAGEMENT LEVEL

ROCE

Management Level	Mean	N	Std. Deviation
Junior Managers	3.56	50	.812
Middle-Level Managers	3.92	180	.875
Senior Level Managers	3.77	107	.937
Total	3.82	337	.893

The mean scores for ROCE by junior, middle and senior credit managers are 3.56, 3.92 and 3.77 respectively, and thus, the highest score is given by middle- level managers (Table 5.10.III).

These results clearly point to the possibility of greater subjectivity in the rating of ROCE as a credit risk variable among different ranks of managers than the other surrogate risk variables. Higher subjectivity in credit risk rating is one of the serious obstacles in effective credit risk management.

5.3.4 Factor Scores Approach

Factor scores are composite scores estimated for each respondent on each of the derived factors. Since the purpose of factor analysis in our case is to reduce the original set of variables to a smaller set of composite variables (factors) for further statistical analysis, factor scores have been computed for seven derived factors through SPSS, under principal component analysis.

TABLE 5.11: ANOVA OF CREDIT RISK FACTORS BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

		Sum of Squares	df	Mean Square	F	Sig.
Business & Industry Risk	Between Groups	4.674	1	4.674	4.726	.030
	Within Groups	331.326	335	.989		
	Total	336.000	336			
Management Risk	Between Groups	3.834	1	3.834	3.867	.050
	Within Groups	332.166	335	.992		
	Total	336.000	336			
Financial Performance Risk	Between Groups	5.999	1	5.999	6.090	.014
	Within Groups	330.001	335	.985		
	Total	336.000	336			
Loan Characteristics	Between Groups	.287	1	.287	.287	.593
	Within Groups	335.713	335	1.002		
	Total	336.000	336			

Enterprise Value	Between Groups	.102	1	.102	.102	.749
	Within Groups	335.898	335	1.003		
	Total	336.000	336			
Liquidity & Solvency Risk	Between Groups	.254	1	.254	.254	.615
	Within Groups	335.746	335	1.002		
	Total	336.000	336			
Labour & Environmental Risk	Between Groups	.000	1	.000	.000	.982
	Within Groups	336.000	335	1.003		
	Total	336.000	336			

One-way analysis of variance (ANOVA) was conducted on factor scores to study the differences in management's risk perception towards the seven categories of causes or factors of credit risk amongst the three groups (Tables 5.11, 5.13 & 5.16). Post-hoc tests were carried out on factor groups found to be significant, to identify the sub-groups in which significant differences would exist (Tables 5.14, 5.17 & 5.18). Mean and standard deviation analysis is tabulated in Tables 5.12, 5.15 and 5.19.

Table 5.11 shows the results of the **ANOVA with bank size category**, and it indicates that the first three factors are statistically significant. In other words, there is a significant difference in perception of the bank management in large and small public sector banks towards the importance of Business and Industry Risk (mean scores higher in large banks); Management Risk and Financial Performance Risk (mean scores higher in small banks) while rating the expected credit risk in a business loan transaction. Since these three factors cover 57.49% of the total 60.51% variance explained by all the seven factors, there will be significant differences in credit risk assessment of the same borrower in large and small banks.

The mean scores (Tables 5.12) show higher scores by large bank managers on all variables in Business and Industry Risk; Loan characteristics; Labor and Environmental Risk; and on the market value of equity in Enterprise Value category and TOL/TNW in Liquidity and Solvency Risk category. It means credit managers in large banks perceive them to be more important causes of credit risk.

TABLE 5.12.I: MEAN & STANDARD DEVIATION BY BANK SIZE

Bank category		TOL/ TNW	Current Ratio	ROCE	PBDIT/ Interest	PAT/ Net Sales	Cash Accruals/ Debt	Industry prospects	Industry averages	Govt. policy	Competition
Large	Mean	4.47	4.24	3.76	3.69	3.60	3.76	3.52	3.32	3.75	3.47
	N	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	.729	.928	.930	1.022	1.012	.928	1.029	1.041	.950	1.000
Small	Mean	4.45	4.30	3.88	3.99	3.85	3.81	3.66	3.50	3.62	3.43
	N	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.807	.776	.851	.808	.912	.956	.873	.846	.872	.905
Total	Mean	4.46	4.27	3.82	3.84	3.73	3.78	3.59	3.41	3.69	3.45
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.767	.856	.893	.934	.971	.940	.957	.954	.913	.953

TABLE 5.12.II: MEAN & STANDARD DEVIATION BY BANK SIZE

Bank category		Capacity utilization	Technology	Key input risk	Marketing oppo	Managerial Comp.	Ability to raise debt	Experience in industry	Integrity of mgt.	Labour relations	Collaterals
Large	Mean	3.69	3.65	3.58	3.74	4.13	3.68	3.58	4.28	3.65	3.81
	N	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	.999	.934	.911	.768	.902	.935	.973	.957	.947	.955
Small	Mean	3.61	3.57	3.38	3.65	4.17	3.70	3.73	4.45	3.60	4.07
	N	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.894	.899	.852	.847	.860	.857	.906	.753	.968	.816
Total	Mean	3.65	3.61	3.48	3.70	4.15	3.69	3.65	4.36	3.62	3.94
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.949	.916	.887	.808	.881	.896	.943	.866	.956	.898

TABLE 5.12.III: MEAN & STANDARD DEVIATION BY BANK SIZE

Bank category		Environmental risks	Retained Earnings	Market Value of Equity	Payment record	Length of banking relations	Loan amount	Loan maturity	Rate of interest	Type Of borrower	Group support
Large	Mean	3.69	3.69	3.51	4.37	3.70	3.34	3.30	3.14	3.09	3.55
	N	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	1.018	.958	1.012	.918	1.054	1.100	1.037	1.050	1.115	1.156
Small	Mean	3.68	3.76	3.42	4.42	3.92	3.33	3.30	3.10	3.02	3.52
	N	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.999	.891	.931	.708	.943	1.084	.939	.970	1.030	.991
Total	Mean	3.69	3.72	3.47	4.39	3.81	3.34	3.30	3.12	3.06	3.53
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	1.007	.925	.973	.821	1.006	1.090	.989	1.011	1.073	1.077

There are higher scores by small banks on all variables in Management Risk, Financial Performance Risk, the retained earnings variable under Enterprise Value, and the current ratio under Liquidity and Solvency Risk categories, and thus, their credit managers perceive them as riskier causes of credit risk. In other words, there are significant differences in risk perceptions of managers of large and small public sector banks. It also means that size of the bank changes the credit risk perceptions of managers.

TABLE 5.13: ANOVA OF CREDIT RISK FACTORS BY EXPERIENCE OF CREDIT MANAGERS

		Sum of Squares	df	Mean Square	F	Sig.
Business & Industry Risk	Between Groups	6.668	2	3.334	3.381	.035
	Within Groups	329.332	334	.986		
	Total	336.000	336			
Management Risk	Between Groups	3.258	2	1.629	1.635	.197
	Within Groups	332.742	334	.996		
	Total	336.000	336			
Financial Performance Risk	Between Groups	2.818	2	1.409	1.412	.245
	Within Groups	333.182	334	.998		
	Total	336.000	336			
Loan Characteristics	Between Groups	.797	2	.398	.397	.673
	Within Groups	335.203	334	1.004		
	Total	336.000	336			

Enterprise Value	Between Groups	4.204	2	2.102	2.116	.122
	Within Groups	331.796	334	.993		
	Total	336.000	336			
Liquidity & Solvency Risk	Between Groups	.545	2	.272	.271	.763
	Within Groups	335.455	334	1.004		
	Total	336.000	336			
Labour & Environmental Risk	Between Groups	.173	2	.087	.086	.917
	Within Groups	335.827	334	1.005		
	Total	336.000	336			

Table 5.13 shows the results of **ANOVA with level of experience of credit managers.** The results indicate that except for one factor, Business and Industry Risk, none of the other factors were found to be statistically significant. ANOVA results indicate that credit managers with 'Up to 7 Years', ' 8 to 20 Years' and '20 Years and above' experience have significantly different opinion about Business and Industry Risk factor, as a cause of credit risk, with F value = 3.381(df 2,334) at p=0.035 (95% confidence level).

Post hoc tests, however, reveal that the significant difference exists only between ''Up to 7 Years', and '20 years and above' experience groups (Table 5.14).

TABLE 5.14: POST HOC TEST -MULTIPLE COMPARISONS

Dependent Variable: Business & Industry Risk

Tukey's HSD

(I) Banking Experience (years)	(J) Banking Experience (years)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Up to 7 years	8 to 20 years	-.23233655	.13910314	.218	-.5598145	.0951414
	20 years and above	-.31403436*	.12470782	.033	-.6076228	-.0204460
8 to 20 years	Up to 7 years	.23233655	.13910314	.218	-.0951414	.5598145
	20 years and above	-.08169782	.14128683	.832	-.4143167	.2509210
20 years and above	Up to 7 years	.31403436*	.12470782	.033	.0204460	.6076228
	8 to 20 years	.08169782	.14128683	.832	-.2509210	.4143167

*. The mean difference is significant at the 0.05 level.

Further, it is observed that on most of the variables under Business and Industry Risk category, highest mean scores (Table 5.15.I) have been given by credit managers with 20 years and above banking experience. In other words, more experienced credit managers find Business and Industry Risk category, to be the highest risk category/group or causing more credit risk.

TABLE 5.15.I: MEAN & STANDARD DEVIATION BY BANKING EXPERIENCE

Banking Experience (years)		TOL/ TNW	Current Ratio	ROCE	PBDIT/ Interest	PAT/ Net Sales	Cash Accruals/ Debt	Industry prospects	Industry averages	Govt. policy	Competition
Up to 7 years	Mean	4.50	4.26	3.89	4.02	3.83	3.77	3.60	3.43	3.55	3.32
	N	132	132	132	132	132	132	132	132	132	132
	Std. Deviation	.796	.888	.835	.961	1.013	.987	1.010	.959	.911	.991
8 to 20 years	Mean	4.41	4.28	3.84	3.75	3.71	3.87	3.54	3.30	3.89	3.52
	N	83	83	83	83	83	83	83	83	83	83
	Std. Deviation	.781	.846	.876	.867	.877	.894	.928	1.021	.870	.915
20 years and above	Mean	4.45	4.28	3.73	3.70	3.62	3.75	3.61	3.46	3.70	3.55
	N	122	122	122	122	122	122	122	122	122	122
	Std. Deviation	.728	.836	.962	.924	.982	.923	.923	.901	.926	.928
Total	Mean	4.46	4.27	3.82	3.84	3.73	3.78	3.59	3.41	3.69	3.45
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.767	.856	.893	.934	.971	.940	.957	.954	.913	.953

TABLE 5.15.II: MEAN & STANDARD DEVIATION BY BANKING EXPERIENCE

Banking Experience (years)		Capacity utilization	Technology	Key Input risk	Marketing oppo.	managerial Comp.	Ability to raise debt	Experience in industry	Integrity of mgt.	Labour relations	Collaterals
Up to 7 years	Mean	3.55	3.53	3.44	3.59	4.02	3.77	3.68	4.14	3.52	4.00
	N	132	132	132	132	132	132	132	132	132	132
	Std. Deviation	.952	.895	.803	.856	.895	.946	1.014	.958	1.037	.957
8 to 20 years	Mean	3.70	3.61	3.51	3.69	4.06	3.52	3.61	4.42	3.58	3.88
	N	83	83	83	83	83	83	83	83	83	83
	Std. Deviation	.959	.922	.967	.748	.874	.802	.867	.871	.977	.875
20 years and above	Mean	3.74	3.70	3.51	3.82	4.34	3.72	3.64	4.57	3.76	3.92
	N	122	122	122	122	122	122	122	122	122	122
	Std. Deviation	.934	.935	.920	.782	.841	.893	.919	.692	.834	.849
Total	Mean	3.65	3.61	3.48	3.70	4.15	3.69	3.65	4.36	3.62	3.94
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.949	.916	.887	.808	.881	.896	.943	.866	.956	.898

TABLE 5.15.III: MEAN & STANDARD DEVIATION BY BANKING EXPERIENCE

Banking Experience (years)		**Environmental risks**	**Retained Earnings**	**Market Value of Equity**	**Payment record**	**Length of banking relations**	**Loan amount**	**Loan maturity**	**Rate Of interest**	**Type of borrower**	**Group support**
Upto 7 years	Mean	3.70	3.73	3.46	4.39	3.70	3.29	3.30	3.15	3.17	3.56
	N	132	132	132	132	132	132	132	132	132	132
	Std. Deviation	1.011	.925	1.080	.836	1.112	1.102	.996	1.030	1.064	1.086
8 to 20 years	Mean	3.83	3.72	3.48	4.36	3.88	3.41	3.18	3.10	2.81	3.49
	N	83	83	83	83	83	83	83	83	83	83
	Std. Deviation	.867	.954	.915	.820	.955	1.159	1.061	1.066	1.163	1.108
20 years and above	Mean	3.57	3.71	3.46	4.42	3.89	3.34	3.37	3.10	3.11	3.53
	N	122	122	122	122	122	122	122	122	122	122
	Std. Deviation	1.083	.913	.892	.811	.911	1.035	.929	.957	.997	1.054
Total	Mean	3.69	3.72	3.47	4.39	3.81	3.34	3.30	3.12	3.06	3.53
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	1.007	.925	.973	.821	1.006	1.090	.989	1.011	1.073	1.077

Table 5.16 shows the results of the **ANOVA with the level of management**, and it indicates that except for two factors, Management Risk, and Financial Performance Risk, none of the other factors were found to be statistically significant. There is a significant difference in the perception of management towards the severity of credit risk caused by the Management Risk Factor (F = 4.783, df 2,334, with p=0.009), and the Financial Performance Risk factor (F = 3.219, df 2,334, with p=0.041) of a business borrower. These two factors had shown significant differences between management of large and small banks as well and thus, can be treated as critical risk factors.

TABLE 5.16: ANOVA OF CREDIT RISK FACTORS BY LEVEL OF MANAGEMENT

		Sum of Squares	df	Mean Square	F	Sig.
Business & Industry Risk	Between Groups	5.206	2	2.603	2.628	.074
	Within Groups	330.794	334	.990		
	Total	336.000	336			
Management Risk	Between Groups	9.375	2	4.687	4.793	.009
	Within Groups	326.625	334	.978		
	Total	336.000	336			
Financial Performance Risk	Between Groups	6.355	2	3.177	3.219	.041
	Within Groups	329.645	334	.987		
	Total	336.000	336			
Loan Characteristics	Between Groups	2.625	2	1.313	1.315	.270
	Within Groups	333.375	334	.998		
	Total	336.000	336			
Enterprise Value	Between Groups	5.659	2	2.829	2.861	.059
	Within Groups	330.341	334	.989		
	Total	336.000	336			
Liquidity & Solvency Risk	Between Groups	.018	2	.009	.009	.991
	Within Groups	335.982	334	1.006		
	Total	336.000	336			
Labour & Environmental Risk	Between Groups	1.400	2	.700	.699	.498
	Within Groups	334.600	334	1.002		
	Total	336.000	336			

Tukey's post hoc tests on Management Risk factors are showing significant differences in risk perceptions of middle - level managers and senior level managers, but not between them and junior level managers (Table 5.17).

TABLE 5.17: POST HOC TESTS - MULTIPLE COMPARISONS

Dependent Variable: Management Risk

Tukey HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle Level Managers	-.01344327	.15808634	.996	-.3856117	.3587252
	Senior Level Managers	-.36867841	.16940437	.077	-.7674919	.0301351

Middle Level Managers	Junior Managers	.01344327	.15808634	.996	-.3587252	.3856117
	Senior Level Managers	-.35523514*	.12071590	.010	-.6394257	-.0710446
Senior Level Managers	Junior Managers	.36867841	.16940437	.077	-.0301351	.7674919
	Middle Level Managers	.35523514*	.12071590	.010	.0710446	.6394257

*. The mean difference is significant at the 0.05 level.

As for Financial Performance Risk factors, though ANOVA is showing significant F value (p=0.041), post hoc tests on multi-comparison are not showing significant differences (p= 0.071) across three management levels (Table 5.18).

TABLE 5.18: POST HOC TESTS - MULTIPLE COMPARISONS

Dependent Variable: Financial Performance Risk

Tukey HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle Level Managers	-.35124657	.15881551	.071	-.7251316	.0226385
	Senior Level Managers	-.13028657	.17018574	.724	-.5309395	.2703664
Middle Level Managers	Junior Managers	.35124657	.15881551	.071	-.0226385	.7251316
	Senior Level Managers	.22096000	.12127270	.164	-.0645414	.5064614
Senior Level Managers	Junior Managers	.13028657	.17018574	.724	-.2703664	.5309395
	Middle Level Managers	-.22096000	.12127270	.164	-.5064614	.0645414

Under Management Risk category of credit risk factors, senior level credit managers are giving the highest mean scores to Integrity of Management (4.62), Payment Record (4.49), Managerial Competence (4.32), and Length of Banking Relations (3.97), whereas junior credit managers are giving highest mean scores to Collaterals (4.10), Experience in the Industry (3.80) and Ability to Raise Debt (3.86) (Table 5.19.I to III).

TABLE 5.19.I: MEAN AND STANDARD DEVIATION BY LEVEL OF MANAGEMENT

Management Level		TOL/TNW	Current Ratio	ROCE	PBDIT/Interest	PAT/Net Sales	Cash Accruals/Debt	Industry prospects	Industry averages	Govt. policy	Competition
Junior Managers	Mean	4.48	4.16	3.56	3.90	3.60	3.68	3.38	3.28	3.56	3.36
	N	50	50	50	50	50	50	50	50	50	50
	Std. Deviation	.886	.955	.812	1.035	1.107	1.096	.967	1.011	.972	1.005
Middle Level Managers	Mean	4.44	4.31	3.92	3.85	3.79	3.76	3.63	3.42	3.72	3.40
	N	180	180	180	180	180	180	180	180	180	180
	Std. Deviation	.764	.826	.875	.954	.955	.924	1.009	1.019	.903	.966
Senior Level Managers	Mean	4.48	4.26	3.77	3.79	3.67	3.87	3.62	3.46	3.69	3.58
	N	107	107	107	107	107	107	107	107	107	107
	Std. Deviation	.718	.862	.937	.855	.929	.891	.854	.804	.905	.901
Total	Mean	4.46	4.27	3.82	3.84	3.73	3.78	3.59	3.41	3.69	3.45
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.767	.856	.893	.934	.971	.940	.957	.954	.913	.953

TABLE 5.19.II: MEAN AND STANDARD DEVIATION BY LEVEL OF MANAGEMENT

Management Level		Capacity utilization	Technology	Key input risk	Marketing oppo.	managerial Comp.	Ability to raise debt	Experience in industry	Integrity of mgt.	Labour relations	Collaterals
Junior Managers	Mean	3.62	3.66	3.36	3.60	4.02	3.86	3.80	4.02	3.54	4.10
	N	50	50	50	50	50	50	50	50	50	50
	Std. Deviation	1.008	.895	.921	.881	1.000	.969	.990	1.000	1.182	.953
Middle Level Managers	Mean	3.59	3.48	3.46	3.63	4.08	3.66	3.53	4.31	3.56	3.81
	N	180	180	180	180	180	180	180	180	180	180
	Std. Deviation	.950	.918	.899	.852	.890	.910	.965	.917	.929	.926
Senior Level Managers	Mean	3.78	3.80	3.57	3.86	4.32	3.66	3.79	4.62	3.77	4.08
	N	107	107	107	107	107	107	107	107	107	107
	Std. Deviation	.914	.895	.848	.665	.784	.835	.858	.609	.875	.791
Total	Mean	3.65	3.61	3.48	3.70	4.15	3.69	3.65	4.36	3.62	3.94
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.949	.916	.887	.808	.881	.896	.943	.866	.956	.898

TABLE 5.19.III: MEAN AND STANDARD DEVIATION BY LEVEL OF MANAGEMENT

Management Level		Environmental Risks	Retained Earnings	Market Value of Equity	Payment Record	Length of Banking Relations	Loan Amount	Loan Maturity	Rate of Interest	Type of Borrower	Group Support
Junior Managers	Mean	3.66	3.74	3.58	4.24	3.56	3.42	3.42	3.22	3.26	3.32
	N	50	50	50	50	50	50	50	50	50	50
	Std. Deviation	1.099	1.006	1.108	.981	1.110	1.126	.971	1.016	1.157	1.220
Middle Level Managers	Mean	3.62	3.66	3.38	4.38	3.78	3.37	3.30	3.13	3.08	3.54
	N	180	180	180	180	180	180	180	180	180	180
	Std. Deviation	1.010	.947	.993	.841	1.043	1.118	1.008	1.003	1.056	1.010
Senior Level Managers	Mean	3.81	3.82	3.55	4.49	3.97	3.25	3.23	3.06	2.93	3.62
	N	107	107	107	107	107	107	107	107	107	107
	Std. Deviation	.953	.845	.860	.692	.863	1.029	.967	1.026	1.052	1.113
Total	Mean	3.69	3.72	3.47	4.39	3.81	3.34	3.30	3.12	3.06	3.53
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	1.007	.925	.973	.821	1.006	1.090	.989	1.011	1.073	1.077

Significant differences in managerial perception for Management Risk factor for commercial borrower shows the scope for higher subjectivity in this area of credit risk assessment.

5.3.5 Predictability of Credit Risk Factors

Question 14 tests the predictability of or difficulty in managing financial, business, industry and management risk of business borrowers.

TABLE 5.20: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

		Sum of Squares	df	Mean Square	F	Sig.
Q.14a:Financial risk is easy to predict	Between Groups	2.029	1	2.029	2.060	.152
	Within Groups	329.995	335	.985		
	Total	332.024	336			
Q.14b:Industry risk is unpredictable and more challenging to manage	Between Groups	.576	1	.576	.647	.422
	Within Groups	298.415	335	.891		
	Total	298.991	336			
Q.14c:Business risk can be predicted to good accuracy	Between Groups	.472	1	.472	.486	.486
	Within Groups	325.285	335	.971		
	Total	325.757	336			
Q.14d:Management risk is difficult to predict	Between Groups	.027	1	.027	.020	.888
	Within Groups	456.192	335	1.362		
	Total	456.220	336			
Q.22:Economic slowdown is the main cause of credit losses in banks	Between Groups	.046	1	.046	.048	.827
	Within Groups	319.960	335	.955		
	Total	320.006	336			
Q.24:Inadequate appraisal of borrower's credit-worthiness is causing higher NPAs	Between Groups	.011	1	.011	.011	.918
	Within Groups	353.769	335	1.056		
	Total	353.780	336			

TABLE 5.21: ANOVA BY EXPERIENCE OF MANAGERS

		Sum of Squares	df	Mean Square	F	Sig.
Q.14a:Financial risk is easy to predict	Between Groups	6.833	2	3.416	3.509	.031
	Within Groups	325.191	334	.974		
	Total	332.024	336			
Q.14b:Industry risk is unpredictable and more challenging to manage	Between Groups	1.576	2	.788	.885	.414
	Within Groups	297.415	334	.890		
	Total	298.991	336			

Q.14c:Business risk can be predicted to good accuracy	Between Groups	1.614	2	.807	.832	.436
	Within Groups	324.143	334	.970		
	Total	325.757	336			
Q.14d:Management risk is difficult to predict	Between Groups	5.050	2	2.525	1.869	.156
	Within Groups	451.170	334	1.351		
	Total	456.220	336			
Q.22:Economic slowdown is the main cause of credit losses in banks	Between Groups	3.967	2	1.983	2.096	.125
	Within Groups	316.039	334	.946		
	Total	320.006	336			
Q.24:Inadequate appraisal of borrower's credit-worthiness is causing higher NPAs	Between Groups	1.792	2	.896	.850	.428
	Within Groups	351.988	334	1.054		
	Total	353.780	336			

TABLE 5.22: ANOVA BY LEVEL OF MANAGEMENT

		Sum of Squares	df	Mean Square	F	Sig.
Q.14a:Financial risk is easy to predict	Between Groups	3.280	2	1.640	1.666	.191
	Within Groups	328.744	334	.984		
	Total	332.024	336			
Q.14b:Industry risk is unpredictable and more challenging to manage	Between Groups	.441	2	.220	.246	.782
	Within Groups	298.551	334	.894		
	Total	298.991	336			
Q.14c:Business risk can be predicted to good accuracy	Between Groups	.524	2	.262	.269	.764
	Within Groups	325.233	334	.974		
	Total	325.757	336			
Q.14d:Management risk is difficult to predict	Between Groups	3.581	2	1.790	1.321	.268
	Within Groups	452.639	334	1.355		
	Total	456.220	336			
Q.22:Economic slowdown is the main cause of credit losses in banks	Between Groups	.872	2	.436	.456	.634
	Within Groups	319.134	334	.955		
	Total	320.006	336			
Q.24:Inadequate appraisal of borrower's credit-worthiness is causing higher NPAs	Between Groups	.244	2	.122	.115	.891
	Within Groups	353.537	334	1.058		
	Total	353.780	336			

Tables 5.20 to 5.22 evaluate ANOVA results on this question among three groups of credit managers. The results indicate statistically no significant differences in perception of management of large or small banks, and also no significant difference as per level of management, on any variable. However, results of ANOVA with the level/degree of experience of managers indicate there is one significant difference in managerial perception for Q.14a - 'Financial Risk is Easy to Predict' with F=3.509 (df 2,334), p=0.031.

TABLE 5.23: POST HOC TEST - MULTIPLE COMPARISONS

Dependent Variable: Q.14a:Financial risk is easy to predict

Tukey's HSD

(I) Banking Experience(years)	(J) Banking Experience(years)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Up to 7 years	8 to 20 years	-.042	.139	.951	-.37	.28
	20 years and above	-.310*	.124	.034	-.60	-.02
8 to 20 years	Up to 7 years	.042	.139	.951	-.28	.37
	20 years and above	-.268	.141	.139	-.60	.06
20 years and above	Up to 7 years	.310*	.124	.034	.02	.60
	8 to 20 years	.268	.141	.139	-.06	.60

*. The mean difference is significant at the 0.05 level.

Post hoc tests (Table 5.23) point at this significant difference between managers with 'Up to 7 years' (mean 3.71/SD 1.049) and '20 years and above' (mean 4.02/SD .961), and not with '8 to

20 years' (mean 3.76/SD .919) (Tables 5.24). Mean values indicate that managers with lesser experience are not finding borrower's financial risk easy to predict, and shall need proper training for that.

TABLE 5.24: DESCRIPTIVE STATISTICS

Banking Experience(years)		Q.14a:Financial risk is easy to predict	Q.14b:Industry risk is unpredictable and more challenging to manage	Q.14c:Business risk can be predicted to good accuracy	Q.14d:Management risk is difficult to predict
Up to 7 years	Mean	3.71	3.78	3.26	3.17
	Std. Deviation	1.049	.948	.959	1.104
8 to 20 years	Mean	3.76	3.92	3.40	3.20
	Std. Deviation	.919	.940	.910	1.295
Above 20 years	Mean	4.02	3.93	3.40	3.45
	Std. Deviation	.961	.941	1.060	1.125
Total	Mean	3.84	3.87	3.34	3.28
	Std. Deviation	.994	.943	.985	1.165

Analysis of mean scores (Table 5.25.I to IV) on predictability of credit risk factors, by 337 respondents, irrespective of the bank size, the level of management or the level of experience, indicates:

- Highest mean scores (3.87) for Q.14b - 'Industry risk is unpredictable and more challenging to manage' with the least standard deviation (0.943), and 75.6% agree/strongly agree with it (Tables 5.24 & 5.25.II).

- 77.1% agree/ strongly agree that financial risk is easy to predict (Table 5.25.I).

However, for other variables, respondents' opinion is fragmented across various choices, and only

- 57.2% agree/strongly agree that business risk can be predicted with a good accuracy (Table 5.25.III).

- 53.7% agree/strongly agree that management risk is hard to predict (Table 5.25.IV).

TABLE 5.25.I: Q.14A-FINANCIAL RISK IS EASY TO PREDICT

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	7	2.1	2.1	2.1
Disagree	43	12.8	12.8	14.8
Cannot say	27	8.0	8.0	22.8
Agree	181	53.7	53.7	76.6
Strongly agree	79	23.4	23.4	100.0
Total	337	100.0	100.0	

TABLE 5.25.II: Q.14B-INDUSTRY RISK IS UNPREDICTABLE AND MORE CHALLENGING TO MANAGE

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	5	1.5	1.5	1.5
Disagree	34	10.1	10.1	11.6
Cannot say	43	12.8	12.8	24.3
Agree	174	51.6	51.6	76.0
Strongly agree	81	24.0	24.0	100.0
Total	337	100.0	100.0	

TABLE 5.25.III: Q.14C-BUSINESS RISK CAN BE PREDICTED TO GOOD ACCURACY

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	11	3.3	3.3	3.3
Disagree	74	22.0	22.0	25.2
Cannot say	59	17.5	17.5	42.7
Agree	175	51.9	51.9	94.7
Strongly agree	18	5.3	5.3	100.0
Total	337	100.0	100.0	

TABLE 5.25.IV: Q.14D-MANAGEMENT RISK IS DIFFICULT TO PREDICT

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	16	4.7	4.7	4.7
Disagree	100	29.7	29.7	34.4
Cannot say	40	11.9	11.9	46.3
Agree	135	40.1	40.1	86.4
Strongly agree	46	13.6	13.6	100.0
Total	337	100.0	100.0	

5.4 BANK-SPECIFIC RISK FACTORS

The study of responses of the different category of bank managers regarding Question no. 24, “Inadequate appraisal of borrower’s creditworthiness is causing higher NPAs” through ANOVA reveals that there is statistically no significant difference in responses among managers of large and small banks, managers at different experience and hierarchy levels (Tables 5.20 to 5.22).

TABLE 5.26: Q.24 - INADEQUATE APPRAISAL OF BORROWER'S CREDITWORTHINESS IS CAUSING HIGHER NPAS

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	9	2.7	2.7	2.7
Disagree	45	13.4	13.4	16.0
Cannot say	48	14.2	14.2	30.3
Agree	164	48.7	48.7	78.9
Strongly agree	71	21.1	21.1	100.0
Total	337	100.0	100.0	

However, there is a consensus (agree and strongly agree) among 77.1% of 337 respondents that inadequate credit appraisal systems in banks are causing higher non-performing loans or loan defaults (Table 5.26).

5.5 MACROECONOMIC RISK FACTOR

The study of responses of the different category of bank managers regarding Question no. 22, “Economic slowdown is the main cause of credit losses in banks” through ANOVA reveals that for this risk factor also, there is statistically no significant difference in responses among managers of large and small banks, managers at different experience and hierarchy levels (Tables 5.20 to 5.22). However, there is a consensus (agree and strongly agree) among 68.3% of 337 respondents that this macroeconomic risk factor is causing credit losses in banks through non-performing loans or loan defaults (Table 5.27).

TABLE 5.27: Q.22-ECONOMIC SLOWDOWN IS THE MAIN CAUSE OF CREDIT LOSSES IN BANKS

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	2	.6	.6	.6
Disagree	64	19.0	19.0	19.6
Cannot say	56	16.6	16.6	36.2
Agree	166	49.3	49.3	85.5
Strongly agree	49	14.5	14.5	100.0
Total	337	100.0	100.0	

5.6 TESTING HYPOTHESES

Hypothesis 1(H_0) stands rejected. Null hypothesis 1 that there is no significant difference in risk perception of credit managers towards various causes of credit risk, in large and small banks, is rejected. ANOVA shows that there is a significant difference in perception of the bank management in large and small public sector banks towards the Business and Industry Risk, Management Risk and Financial Performance Risk, as the expected causes of credit risk in a business loan transaction.

Hypothesis 2(H_0) stands rejected. Null hypothesis 2 that there is no significant difference in risk perception of credit managers with different levels of banking experience, towards various causes of credit risk, stands rejected only for Business and Industry Risk as the expected cause of credit risk from a business borrower.

Hypothesis 3(H_0) stands rejected. Hypothesis 3 that there is no significant difference in risk perception of different management levels towards various causes of credit risk stands rejected for Management Risk and Financial Performance Risk factors of a business loan proposal.

5.7 RESULTS AND DISCUSSION

The chapter has empirically investigated borrower-specific, bank-specific, and economic slowdown factors as possible causes of credit risk in Indian public sector banks and it has been found that:

1. A business borrower has highest chances of default in terms of ability and willingness to service his debt if he has low Total Outside Liabilities/ Tangible Net Worth ratio (TOL/TNW), weak record of past payments or banking discipline, little managerial integrity, small current ratio, and incompetent management (based on mean values of risk variables). In terms of factor loadings, other critical risk variables are capacity utilization, ROCE, loan maturity, the market value of equity, and labour relations.

2. The most important risk factor is Liquidity and Solvency Risk factor, with the highest mean score of 4.36, including the most potent causes of credit risk – TOL/TNW and Current Ratio.

3. Other important risk factors are Management Risk factor (mean score 3.76), Business and Industry Risk factor (mean score 3.72) and Financial Performance Risk factor (3.70).

4. More experienced credit managers (experience 20 years and above) find business and industry Risk category/group, to be the highest risk category or causing more credit risk.

5. There are significant differences in managerial perception, among different levels of managers for ROCE (Return on Capital Employed) as risk variable showing the scope for higher subjectivity in this area of credit risk assessment.

6. The most challenging risk for the Indian public sector banks or the risk hard to predict is the industry risk of their borrowers. For management of industry risk, banks shall undertake regular industry studies and gather market intelligence.

7. Bank size was found to be a critical risk variable affecting Indian banking sector in terms of credit risk factors. For large banks, business and industry risk factors of the borrower are posing serious credit risk, whereas for small banks, management and financial risk factors of the borrower are the primary causes of credit risk.

8. Indian public sector banks' credit managers agree with RBI observation that inadequate appraisal of business borrowers, is creating high non-performing loans (77.1% in the sample).

9. They also believe that the economic slowdown is stressing firms and industries, and causing weak loan recoveries and bad loans (63.8% in the sample).

10. Further three risk factors - Business and Industry Risk, Management Risk, and Financial Performance Risk have statistically significant different opinions in two out of three managerial groups tested. These factors assessment for credit risk would be subject to more subjectivity and therefore, shall require more interactive discussions between risk managers to discuss their impact on borrowers' credit risk assessments.

11. The study has also looked into the statistically significant disagreement between middle and senior level credit managers, and between 'up to 7 years' and '20 years and above' category of managers. Other than the financial risk factors, credit risk

assessment of remaining factors is highly subjective. Thus, there is an emergent need for regular discussions, sharing of risk information, job- related training, and continuous watch on compliance with credit risk policy and procedures at all levels in banks' credit departments. This will reduce subjectivity and inconsistencies in credit risk assessment, and thereby control and mitigate credit risk.

5.8 CONCLUSIONS

The empirical study on causes of credit risk in loans to business and industry through the managerial perspective or tacit knowledge of the risk managers in Indian PSBs, finds that a commercial borrower with low Total Outside Liabilities/ Tangible Net Worth Ratio, small Current Ratio, poor payment record, weak managerial integrity, and incompetent management has the highest risk of default. Further, his business, industry, management and financial risk factors in this order, are the most potent causes of credit risk. Bank size has also been found to be a significant risk variable affecting managerial risk perceptions.

The next chapter will empirically evaluate and compare the credit risk management practices of large and small public sector banks to find the grey areas, for effective credit risk management.

CHAPTER 6
COMPARISON OF CREDIT RISK MANAGEMENT PRACTICES OF LARGE AND SMALL PUBLIC SECTOR BANKS

6.1 INTRODUCTION

This chapter empirically evaluates the credit risk management (CRM) practices of Indian public sector banks in the grant of commercial loans to find the areas which need review and restructuring to improve banks' asset quality. Based on literature review and unstructured personal interviews with banks' credit managers, a conceptual model of credit risk management systems for commercial loans of these banks has been developed. This model has been used to underline the problems areas and obstacles in credit risk management through comparison of large and small banks. The empirical comparison of CRM practices of Indian public sector banks has resulted into the emergence of various grey areas which need immediate attention to reduce these banks' non-performing assets.

6.2 MODELING CRM PRACTICES OF INDIAN PUBLIC SECTOR BANKS

The Indian public sector commercial banks have an elaborate credit/loan policy which is revised annually to keep up with the changing business environment and regulatory guidelines. CRM goals are shaped by their corporate philosophy and risk appetite. Banks employ a pro-active credit risk strategy which gets translated into various CRM systems and procedures in identification, assessment, monitoring, control and mitigation of credit risk (Figure 6.1). RBI through its prudential guidelines has maintained the pace of convergence of international standards and risk practices (Basel guidelines and capital adequacy norms).

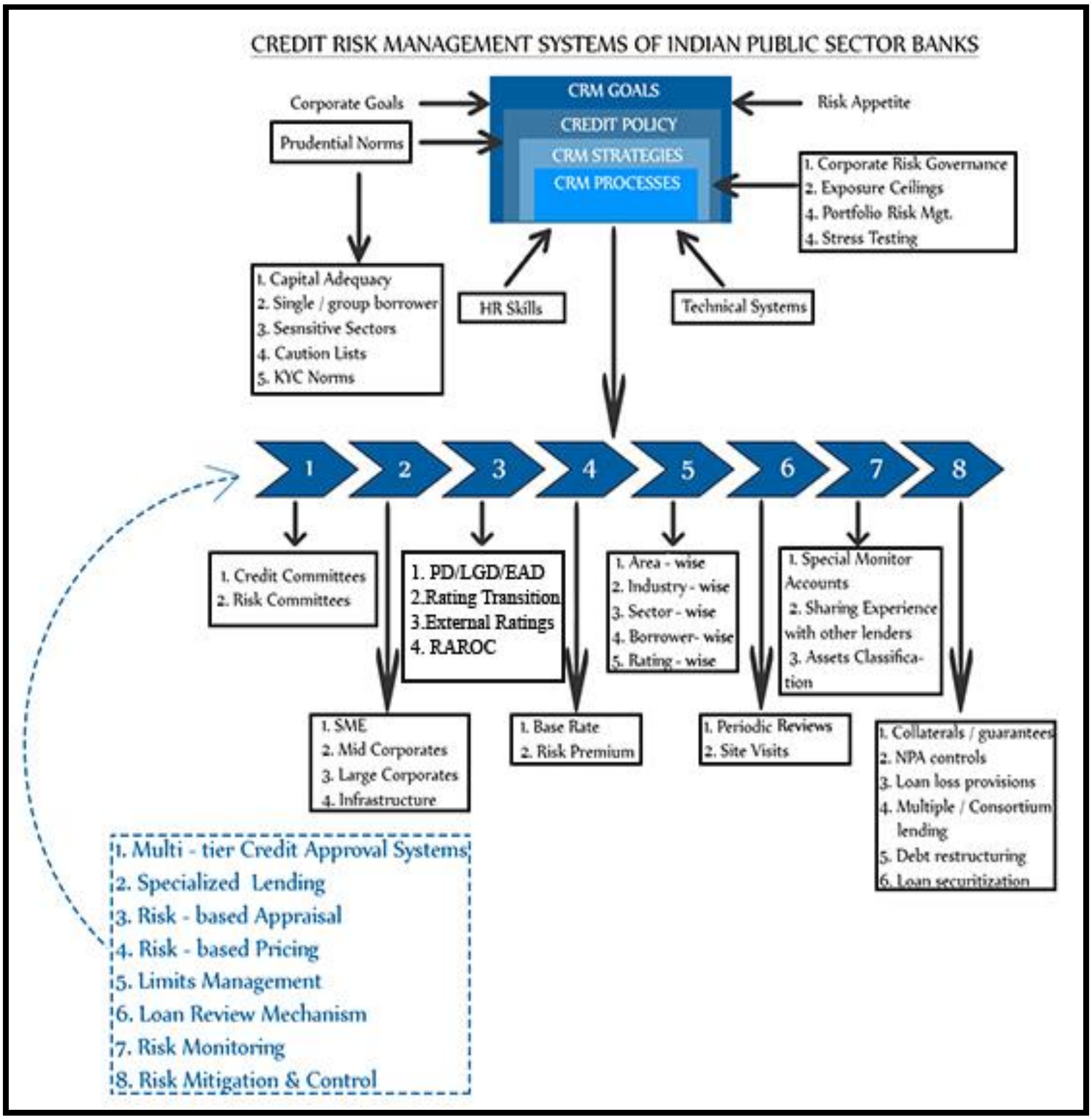

FIGURE 6.1: MODELING CRM SYSTEMS OF INDIAN PSBS

(Source: Self Study)

The banks' credit and risk committees, at various levels, manage and control credit risk within overall prudential limits, set by the RBI and bank's management. Portfolio credit risk is managed with exposure norms for single/group borrowers, sensitive sectors like stock brokers, real estate lending, and with industry studies, sector/industry-wise limits. KYC norms, caution lists like defaulters lists, watch on special monitoring accounts, assets classification, loan loss provisions, help in mitigation and control of credit risk.

KYC (Know Your Customer) norms enable banks to understand their customers and prudently manage various risks associated with bank lending, like proper identification of management, businesses, and projects, backward and forward linkages. Any slackness in compliance of KYC norms may result in heavy credit losses to banks.

Most of the banks have well-defined credit appraisal systems for different borrower segments and loan review mechanism. For transactional credit risk assessment and control, banks segment borrowers through specialized lending units for small businesses, mid-corporates, large corporates, power, road, bridges and other infrastructure projects, etc. Banks have the software driven credit risk assessments and calculate PD/LGD/EAD. Some PSBs also calculate RAROC (risk-adjusted return on capital) for each credit transaction.

Despite these comprehensive credit risk management systems, problems and errors erupt in CRM processes of these banks. The CRM model defined in Figure 6.1 has been the basis to probe into various structural and procedural problems or issues before the Indian PSBs in their credit risk management efforts. There is a need to compare the efficiency of internal credit risk management systems of large and small Indian public sector banks, their loan appraisal/review mechanisms, staff efficiency/accountability. Thus, the researcher could assess the banks' efficiency in capturing commercial loan proposals in highly competitive environment and evaluate the effectiveness of their procedures to deal with problem loans and willful defaults.

6.3 STATISTICAL TOOLS USED AND HYPOTHESES SET

The empirical investigation into the CRM practices of large and small PSBs and obstacles faced by them in the implementation of CRM systems, has been undertaken through data analysis of responses of 337 sample credit managers. Their responses have been evaluated on 12 questions, numbered 1, 2, 3, 5, 6, 7, 8, 9, 10, 20, 24, and 27 in the questionnaire.

11 questions (36 variables) have measured the effectiveness of their CRM practices regarding CRM policies & procedures (9 variables), CRM instruments (15 variables) and risk mitigation measures (12 variables). One question (Question. no. 9 with 11 variables) has measured the strength of various obstacles faced by large and small PSBs in implementation of CRM systems.

Data collected for the study has been analyzed through descriptive statistics like frequencies, percentages, mean score, standard deviation and one-way ANOVA, using SPSS (SPSS version 21).

One-way analysis of variance (ANOVA) has been conducted to examine the significance of differences in perception of credit managers between both the groups (Large vs. Small Banks) for each survey item. F and p values have been calculated, at 95% level of confidence. The findings have indicated statistically significant differences in many cases. These have been analyzed through category mean scores and standard deviation values, for hypotheses testing.

The following 2 null hypotheses have been tested:

Hypothesis 4

H_0: There is no significant difference in practices of credit risk management in large and small public sector banks.

Hypothesis 5

H_0: There is no significant difference in obstacles in the implementation of sound credit risk management systems in large and small public sector banks.

The null hypotheses have been tested at 5% level of significance. Responses from question no. 9 are the basis of testing Hypothesis 5 (H_0), and others for testing Hypothesis 4 (H_0).

6.4 ANALYSIS OF CREDIT RISK MANAGEMENT PRACTICES

Comparison of credit risk management (CRM) practices of large and small public sector banks has been undertaken through their CRM policies and procedures, the effectiveness of their CRM instruments and risk mitigation measures.

6.4.1 Analysis by Mean and Standard Deviation Values

For understanding the managerial perception about various CRM practices, mean and standard deviation values, have been compared to these two categories of banks, in three parts. Part1 (Table 6.1 and Figure 6.2) evaluates descriptive statistics about nine CRM policies and procedures in large and small banks. Part II evaluates descriptive statistics about 15 instruments of credit risk management (Table 6.2 and Figure 6.3). Part III evaluates descriptive statistics about the effectiveness of 12 risk mitigation measures (Table 6.3 and Figure 6.4).

TABLE 6.1: MEAN AND STANDARD DEVIATION OF CRM POLICIES & PROCEDURES

Bank category		Q.1	Q.2	Q.3	Q.5	Q.6	Q.7	Q.20	Q.24	Q.27
	Mean	4.60	4.34	4.34	4.34	3.73	4.06	4.05	3.73	3.83
Large	N	172	172	172	172	172	172	172	172	172
	Std. Deviation	.568	.752	.576	.625	.956	.863	.975	1.055	.926
	Mean	4.47	4.25	4.30	4.28	3.75	4.08	3.67	3.72	3.87
Small	N	165	165	165	165	165	165	165	165	165
	Std. Deviation	.579	.702	.700	.714	.979	.855	1.191	.999	.985
	Mean	4.54	4.30	4.32	4.31	3.74	4.07	3.86	3.72	3.85
Total	N	337	337	337	337	337	337	337	337	337
	Std. Deviation	.577	.729	.639	.670	.966	.858	1.102	1.026	.954

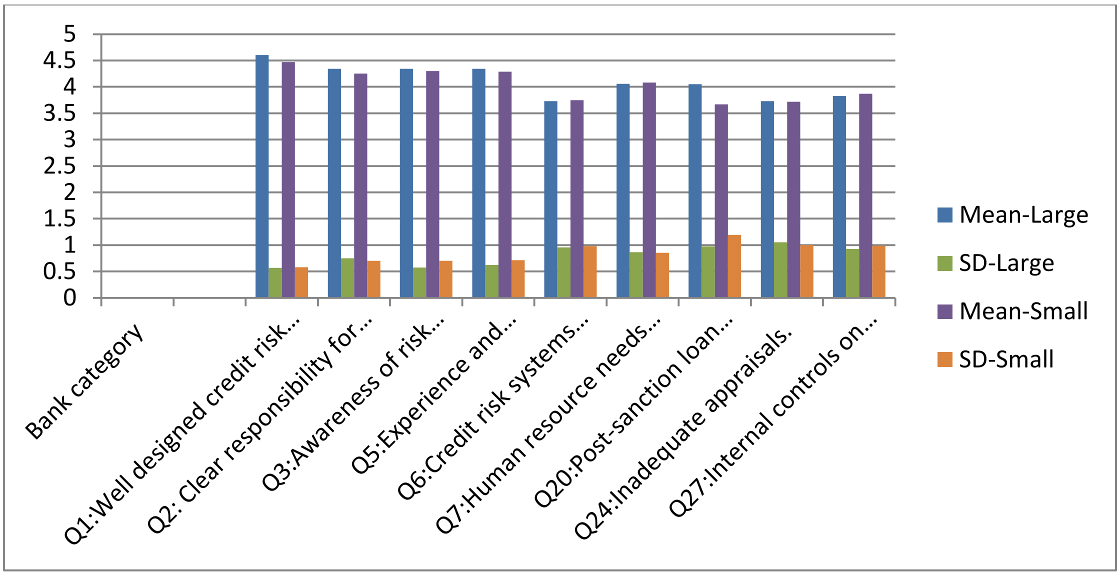

FIGURE 6.2: MEAN AND SD OF CRM POLICIES & PROCEDURES

Analysis of mean scores (Table 6.1) on CRM policies and procedures shows that except for questions 6, 7, and 27, the average scores are higher for large banks. Thus, managers of small banks do not perceive that their credit risk policies are as well designed as in large banks, or there are clearly set out responsibilities for CRM. They also do not perceive that there is as much awareness of strengths and weaknesses of risk management systems of their banks vis-à-vis other competing banks, or that their post-sanction loan monitoring is as strong as of large banks. However, they do not agree as much as with the large banks that inadequate appraisals of borrower's creditworthiness is causing higher NPAs or that they have lesser internal controls on the identification of non-performing assets, a primary source of credit losses. Though, small banks' credit managers are of the opinion that they require more changes in their credit risk systems and procedures, and more skill, training and motivation for credit departments' human resource.

Analysis of mean scores and standard deviation values (Table 6.2 and Figure 6.3)) given by large and small bank managers for effectiveness of fifteen instruments of credit risk management systems in their banks show that large bank managers perceive that they are better in following seven CRM instruments:

1. Risk-rating or credit-scoring.
2. Risk-based pricing.
3. Portfolio management.
4. Industry studies.
5. Periodic plant visits.
6. Securitization of loans.
7. The issue of credit derivatives.

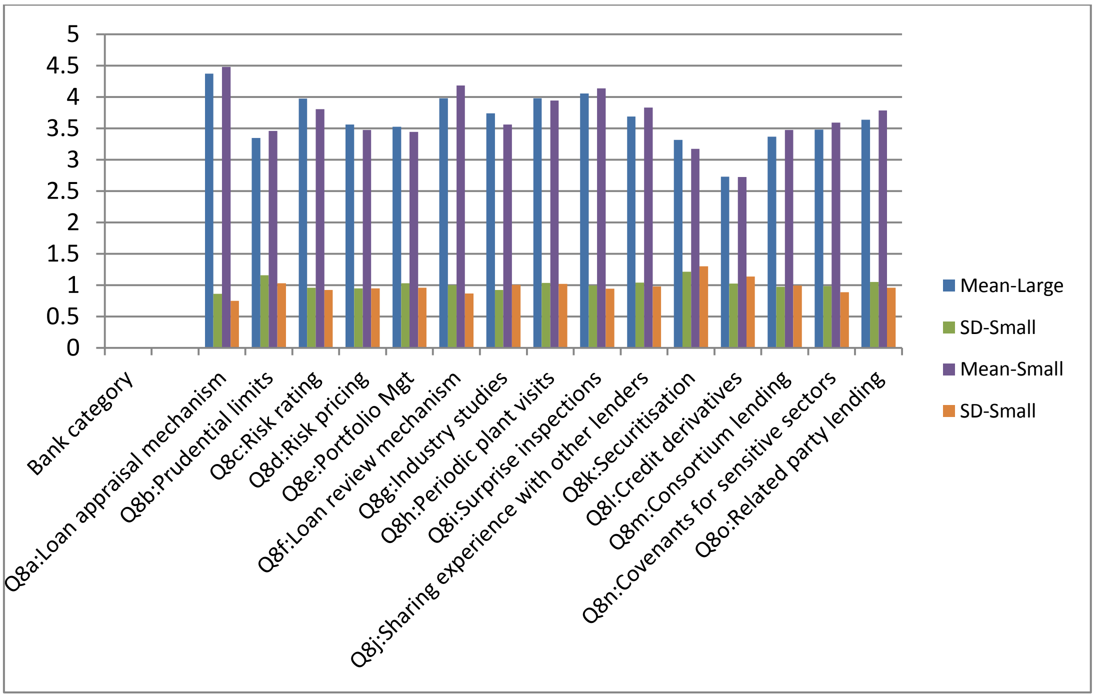

FIGURE 6.3: MEAN AND STANDARD DEVIATION OF INSTRUMENTS OF CRM

TABLE 6.2: MEAN AND STANDARD DEVIATION OF CRM INSTRUMENTS

Bank category		Q.8a: Loan appraisal	Q.8b :Prudential limits	Q.8c:Risk rating	Q.8d:Risk pricing	Q.8e:Portfolio Mgt	Q.8f: Loan review	Q.8g: Industry studies	Q.8h:Periodic plant visits	Q.8i:Surprise inspections	Q.8j: Sharing experience	Q.8k: Securitisation	Q.8l: Credit derivative	Q.8m: Consortium lending	Q.8n: sensitive sectors	Q.8o: /related party lending
Large	Mean	4.37	3.34	3.97	3.56	3.52	3.98	3.74	3.98	4.05	3.69	3.31	2.73	3.37	3.48	3.63
	N	172	172	172	172	172	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	.859	1.157	.958	.944	1.029	.997	.922	1.031	.993	1.040	1.212	1.021	.973	.982	1.048
Small	Mean	4.48	3.45	3.81	3.47	3.44	4.18	3.56	3.94	4.13	3.83	3.17	2.72	3.47	3.59	3.78
	N	165	165	165	165	165	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.746	1.027	.923	.947	.959	.864	1.002	1.016	.941	.979	1.300	1.135	.991	.883	.957
Total	Mean	4.42	3.40	3.89	3.52	3.48	4.08	3.65	3.96	4.09	3.76	3.24	2.72	3.42	3.53	3.71
	N	337	337	337	337	337	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.806	1.095	.943	.945	.994	.939	.965	1.023	.967	1.012	1.256	1.076	.982	.935	1.006

However, small bank managers perceive themselves better (higher mean scores) in following eight CRM instruments:

1. Loan appraisal mechanism.
2. Implementation of prudential limits.
3. Loan reviews mechanism.
4. Surprise inspections.
5. Sharing experience with other lenders.
6. Multiple banks' lending/ consortium lending.
7. Covenants for sensitive sectors.
8. Controls on related party lending/insider loans.

Analysis of descriptive statistics for effectiveness of 12 risk mitigation measures (Table 6.3 and Figure 6.4) in large and small public sector banks, reveal that except in three measures, credit managers of large banks feel better (higher mean scores) about the following 9 risk mitigation steps in their banks:

1. Restriction on responsibility for volume-based credit approvals and reviews.
2. Independence of credit risk assessment from credit sanctioning process.
3. Reduction of processing effort per loan application.
4. Regular rating reviews.
5. Reduction of subjectivity in credit rating.
6. Internal audits.
7. Risk-based appraisals and sanctions.
8. Independence of loan reviews mechanism.
9. Focused attention on problem/weak credit exposures.

TABLE 6.3: MEAN AND STANDARD DEVIATION OF RISK MITIGATION MEASURES

Bank category		Q.10a: Regular discussions	Q.10b: Restriction on responsibility	Q.10c: Independent assessment	Q.10d: Reduction in processing	Q.10e: Regular rating reviews	Q.10f: Reduction of subjectivity	Q.10g: Internal audits	Q.10h: Risk-based appraisal	Q.10i: Independent loan review	Q.10j: Implementation of KYC	Q.10k:Multi-tier approvals	Q.10l: attention on problem
Large	Mean	3.90	3.81	3.91	3.66	4.12	3.66	4.08	4.11	4.09	4.28	4.03	3.94
	N	172	172	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	.845	.845	.969	.833	.694	.874	.679	.729	.771	.769	.841	.877
Small	Mean	4.01	3.70	3.72	3.42	3.86	3.47	3.92	4.00	3.80	4.33	4.12	3.79
	N	165	165	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.785	.783	.928	.938	.910	.873	.773	.773	.905	.835	.927	.861
Total	Mean	3.95	3.76	3.82	3.54	3.99	3.56	4.00	4.06	3.95	4.31	4.07	3.87
	N	337	337	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.817	.816	.952	.893	.816	.878	.730	.752	.850	.801	.884	.871

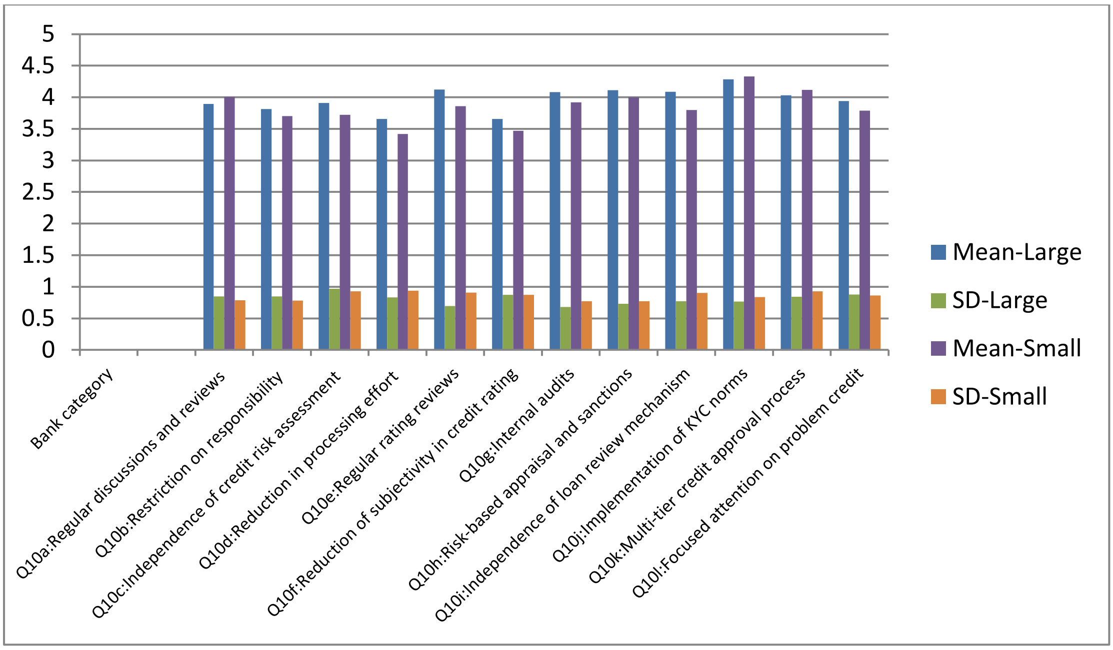

FIGURE 6.4: MEAN AND STANDARD DEVIATION VALUES OF RISK MITIGATION MEASURES

Small banks' credit managers find (higher mean scores) their banks have following three better risk mitigation measures:

1. Regular discussions, reviews and feedback reports.

2. Implementation of KYC norms.

3. Multitier credit approval process.

6.4.2 Analysis of Variance (ANOVA)

One-way analysis of variance (ANOVA) has been conducted to examine the statistical significance of the differences in the mean values of various credit risk management practices (the dependent variable) for two categories of PSBs, large and small (the independent variable). ANOVA compares the between estimates of mean-variance with the within estimates, and results are interpreted in terms of F-statistic and p values. ANOVA analysis has also been undertaken in three parts. Table 6.4

displays ANOVA results regarding nine CRM policies and procedures. Table 6.5 shows ANOVA results regarding 15 CRM instruments. Table 6.6 shows ANOVA results on 12 risk mitigation measures, totalling 36 variables.

TABLE 6.4: ANOVA OF CRM POLICIES & PROCEDURES BY SIZE OF BANK

		Sum of Squares	df	Mean Square	F	Sig.
Q.1: The bank has a well-designed credit risk policy and strategy.	Between Groups	1.603	1	1.603	4.875	.028
	Within Groups	110.183	335	.329		
	Total	111.786	336			
Q.2: Responsibility for Credit Risk Management is clearly set out and understood throughout the bank.	Between Groups	.753	1	.753	1.420	.234
	Within Groups	177.574	335	.530		
	Total	178.326	336			
Q.3: Bank is aware of strength and weaknesses of its risk management system vis-a-vis, other banks.	Between Groups	.179	1	.179	.436	.509
	Within Groups	137.210	335	.410		
	Total	137.389	336			
Q.5: Experience and judgment of risk managers are more important than to apply the sophisticated techniques of credit risk management.	Between Groups	.285	1	.285	.635	.426
	Within Groups	150.374	335	.449		
	Total	150.659	336			
Q.6: Credit risk systems and procedures of the bank need review and change to increase effectiveness of credit risk management.	Between Groups	.029	1	.029	.032	.859
	Within Groups	313.466	335	.936		
	Total	313.496	336			
Q.7: For effective credit risk systems and procedures, the human resource needs better skill, training, and motivation.	Between Groups	.036	1	.036	.049	.826
	Within Groups	247.394	335	.738		
	Total	247.430	336			
Q.20: The post-sanction loan monitoring in the bank as strong as the loan approval process.	Between Groups	12.525	1	12.525	10.617	.001
	Within Groups	395.196	335	1.180		
	Total	407.721	336			

Q.24: Inadequate appraisal of borrower's credit-worthiness is causing higher NPAs	Between Groups	.011	1	.011	.011	.918
	Within Groups	353.769	335	1.056		
	Total	353.780	336			
Q.27: There are sufficient internal controls to eliminate the tendency to postpone identification of NPAs.	Between Groups	.142	1	.142	.156	.693
	Within Groups	305.834	335	.913		
	Total	305.976	336			

TABLE 6.5 : ANOVA OF CRM INSTRUMENTS BY SIZE OF BANK

		Sum of Squares	df	Mean Square	F	Sig.
Q.8a: Loan appraisal mechanism.	Between Groups	.959	1	.959	1.478	.225
	Within Groups	217.362	335	.649		
	Total	218.320	336			
Q.8b: Prudential limits.	Between Groups	1.047	1	1.047	.874	.351
	Within Groups	401.671	335	1.199		
	Total	402.718	336			
Q.8c: Risk rating.	Between Groups	2.289	1	2.289	2.585	.109
	Within Groups	296.649	335	.886		
	Total	298.938	336			
Q.8d: Risk pricing.	Between Groups	.614	1	.614	.687	.408
	Within Groups	299.546	335	.894		
	Total	300.160	336			
Q.8e: Portfolio management.	Between Groups	.550	1	.550	.556	.456
	Within Groups	331.610	335	.990		
	Total	332.160	336			
Q.8f: Loan reviews mechanism.	Between Groups	3.542	1	3.542	4.057	.045
	Within Groups	292.452	335	.873		
	Total	295.994	336			
Q.8g: Industry studies.	Between Groups	2.753	1	2.753	2.975	.085
	Within Groups	309.930	335	.925		
	Total	312.682	336			
Q.8h: Periodic plant visits.	Between Groups	.117	1	.117	.112	.738
	Within Groups	351.301	335	1.049		
	Total	351.418	336			
Q.8i: Surprise inspections.	Between Groups	.553	1	.553	.590	.443
	Within Groups	313.596	335	.936		
	Total	314.148	336			

Q.8j: Sharing experience with other lenders.	Between Groups	1.752	1	1.752	1.715	.191
	Within Groups	342.295	335	1.022		
	Total	344.047	336			
Q.8k: Securitization.	Between Groups	1.752	1	1.752	1.111	.293
	Within Groups	528.295	335	1.577		
	Total	530.047	336			
Q.8l: Credit derivatives.	Between Groups	.003	1	.003	.002	.962
	Within Groups	389.333	335	1.162		
	Total	389.335	336			
Q.8m: Consortium lending.	Between Groups	.954	1	.954	.990	.321
	Within Groups	323.052	335	.964		
	Total	324.006	336			
Q.8n: Covenants for sensitive sectors.	Between Groups	1.040	1	1.040	1.190	.276
	Within Groups	292.883	335	.874		
	Total	293.923	336			
Q.8o: Insider loans/related party lending.	Between Groups	1.847	1	1.847	1.830	.177
	Within Groups	338.070	335	1.009		
	Total	339.917	336			

TABLE 6.6: ANOVA OF RISK MITIGATION MEASURES BY SIZE OF BANK

		Sum of Squares	df	Mean Square	F	Sig.
Q.10a: Regular discussions, reviews and feedback.	Between Groups	1.032	1	1.032	1.550	.214
	Within Groups	223.110	335	.666		
	Total	224.142	336			
Q.10b: Restriction on responsibility for volume-based credit approvals and reviews.	Between Groups	1.036	1	1.036	1.560	.213
	Within Groups	222.495	335	.664		
	Total	223.531	336			
Q.10c: Independence of credit risk assessments from credit sanctioning process.	Between Groups	2.906	1	2.906	3.227	.073
	Within Groups	301.687	335	.901		
	Total	304.593	336			
Q.10d: Reduction in processing effort per loan application.	Between Groups	4.802	1	4.802	6.119	.014
	Within Groups	262.907	335	.785		
	Total	267.709	336			
Q.10e: Regular rating reviews.	Between Groups	5.758	1	5.758	8.839	.003
	Within Groups	218.230	335	.651		
	Total	223.988	336			

Q.10f: Reduction of subjectivity in credit ratings.	Between Groups	3.050	1	3.050	3.994	.046
	Within Groups	255.828	335	.764		
	Total	258.878	336			
Q.10g: Internal audits.	Between Groups	2.161	1	2.161	4.093	.044
	Within Groups	176.836	335	.528		
	Total	178.997	336			
Q.10h: Risk-based appraisal and sanctions.	Between Groups	1.028	1	1.028	1.822	.178
	Within Groups	188.901	335	.564		
	Total	189.929	336			
Q.10i: Independence of loan review mechanism.	Between Groups	6.947	1	6.947	9.857	.002
	Within Groups	236.092	335	.705		
	Total	243.039	336			
Q.10j: Implementation of KYC norms.	Between Groups	.151	1	.151	.235	.628
	Within Groups	215.368	335	.643		
	Total	215.519	336			
Q.10k: Multi-tier credit approval process.	Between Groups	.624	1	.624	.799	.372
	Within Groups	261.667	335	.781		
	Total	262.291	336			
Q.10l: Focused attention on problem/weak credit exposures.	Between Groups	1.997	1	1.997	2.644	.105
	Within Groups	252.994	335	.755		
	Total	254.991	336			

The comparative analysis of mean and standard deviation scores with ANOVA, the F and p values, is shown in Tables 6.7, 6.8 and 6.9.

TABLE 6.7: STATISTICAL ANALYSIS OF CRM POLICIES & PROCEDURES

CRM Policies & Procedures		**ANOVA**	**Mean**		**S.D.**	
		F stat.(sig)	**Large**	**Small**	**Large**	**Small**
Q.1	**The Bank has a well-designed credit risk policy and strategy.**	**4.875(.028)**	**4.60**	**4.47**	**.568**	**.579**
Q.2	Responsibility for CRM is clearly set out through-out the bank	1.420(.234)	4.34	4.25	.752	.702
Q.3	Bank is aware of strength and weaknesses of other banks' CRM systems	.436(.509)	4.34	4.30	.576	.700
Q.5	Experience & judgment of risk manager is more important than to apply the sophisticated CRM techniques.	0.635(.426)	4.34	4.28	.625	.714
Q.6	CRM system of the bank need review and change to increase effectiveness.	0.032(.859)	3.73	3.75	.956	.979
Q.7	The human resource needs better skill, training and motivation.	0.049(.826)	4.06	4.08	.863	.855
Q.20	**The post-sanction loan monitoring is as strong as loan approval process.**	**10.617(.001)**	**4.05**	**3.67**	**.975**	**1.191**
Q.24	Inadequate appraisal of borrower's credit-worthiness is causing higher NPAs.	0.011(.918)	3.73	3.72	1.055	.999
Q.27	There are internal controls to avoid postponement of identification of NPAs.	0.156(.693)	3.83	3.87	.926	.985

(Scale: Strongly Agree 5, Agree 4, Cannot Say 3, Disagree 2, Strongly Disagree 1)

TABLE 6.8 : STATISTICAL ANALYSIS OF CRM INSTRUMENTS (Q. 8)

Effectiveness of CRM Instruments		**ANOVA**	**Mean**		**S.D.**	
		F stat.(sig)	**Large**	**Small**	**Large**	**Small**
1.	Loan appraisal mechanism.	1.478(.225)	4.37	4.48	.859	.746
2.	Prudential limits.	.874(.351)	3.34	3.45	1.157	1.027
3.	Risk-rating or credit scoring.	2.585(.109)	3.97	3.81	.958	.923
4.	Risk-based pricing.	.687(.408)	3.56	3.47	.944	.947
5.	Portfolio management.	.556(.456)	3.52	3.44	1.029	.959
6.	**Loan reviews mechanism.**	**4.057(.045)**	**3.98**	**4.18**	**.997**	**.864**
7.	Industry studies.	2.975(.085)	3.74	3.56	.922	1.002
8.	Periodic plant visits.	.112(.738)	3.98	3.94	1.031	1.016
9.	Surprise inspections.	.590(.443)	4.05	4.13	.993	.941
10.	Sharing experience with other lenders.	1.715(.191)	3.69	3.83	1.040	.979
11.	Securitisation of loans.	1.111(.293)	3.31	3.17	1.212	1.30
12.	Issue of credit derivatives.	.002(.962)	2.73	2.72	1.021	1.135
13.	Consortium lending.	.990(.321)	3.37	3.47	.973	.991
14.	Covenants for sensitive sectors.	1.190(.276)	3.48	3.59	.982	.883
15.	Controls on related party lending.	1.830(.177)	3.63	3.78	1.048	.957

(Scale: 1 for Least Effective and 5 for Most Effective)

TABLE 6.9 : STATISTICAL ANALYSIS OF RISK MITIGATION MEASURES (Q.10)

Effectiveness of risk mitigation		**ANOVA**	**Mean**		**S.D.**	
		F stat.(sig)	**Large**	**Small**	**Large**	**Small**
1.	Regular discussion & feedback.	1.550(.214)	3.90	4.01	.845	.785
2.	Restriction on responsiiluty for credit approval and reviews.	1.560(.213)	3.81	3.70	.845	.783
3.	Independence of risk assessment from loan sanction.	3.227(.073)	3.91	3.72	.969	.928
4.	**Reduction in loan processing effort.**	**6.119(.014)**	**3.66**	**3.42**	**.833**	**.938**
5.	**Regular rating reviews.**	**8.839(.003)**	**4.12**	**3.86**	**.694**	**.910**
6.	**Reduction of subjectivity in credit ratings.**	**3.994(.046)**	**3.66**	**3.47**	**.874**	**.873**
7.	**Internal audits.**	**4.093(.044)**	**4.08**	**3.92**	**.679**	**.773**
8.	Risk-based appraisal and sanctions.	1822(.178)	4.11	4.00	.729	.773
9.	**Independent loan reviews.**	**9.857(.002)**	**4.09**	**3.80**	**.771**	**.905**
10.	Implementation of KYC norms.	0.235(.628)	4.28	4.33	.769	.835
11.	Multi-tier credit approval processes.	0.799(.372)	4.3	4.12	.841	.927
12.	Focus on weak/problem loans.	2.644(.105)	3.94	3.97	.877	.861

(Scale: Very Good- 5, Good-4, Average- 3, Below Average-2, Bad-1)

The above analysis shows that on eight variables out of 36 tested, the differences between the means of large and small banks are statistically significant (significance is less than or equal to 0.05), or the responses of credit managers are statistically different. As such there is a significant difference in perception of credit managers towards CRM practices of large and small public sector banks in the following eight areas:

1. **The bank has a well-designed credit risk policy and strategy.** The mean score for large banks is 4.60(S.D 0.568), and for small banks 4.47(S.D 0.579), with F value 4.875 (df 1, 335) at p= 0.028 (Table 6.4 - ANOVA). As such, credit managers in small banks do not perceive credit policy of their banks as well-designed as in large banks.

2. **The post-sanction loan monitoring in the bank is as strong as the loan approval process.** The mean score for large banks, 4.05 (S.D 0.975) is higher than for small banks (3.67 with S.D 1.191) with F value 10.617 (df 1, 335) at p=0.001 (Table 6.4 - ANOVA). Large banks' risk managers are more satisfied with their banks' two fundamental CRM processes, loan approval and loan monitoring.

3. **Loan reviews mechanism as a tool of CRM.** The mean score for large banks is 3.98 (S.D 0.997), and for small banks 4.18 (S.D 0.864), with F value 4.075 (df 1, 335) at p=0.045 (Table 6.5 - ANOVA). Small public sector banks' credit risk managers perceive their loan reviews as a more potent tool to manage credit risk.

4. to 8. There is a significant difference in mean scores given by risk managers to the following **risk mitigation measures** (Table 6.6 - ANOVA) in large and small banks:

- **Reduction in processing effort per loan application.** F value 6.119 (1, 335) at p=0.014.

- **Regular rating reviews.** F value 8.836 (1, 335) at p=0.003.

- **Reduction in subjectivity in credit ratings.** F value 3.994 (1, 335) at p=0.046.

- **Internal audits.** F value 4.093 (1, 335) at p=0.044.

- **Independence of loan review mechanism.** F value 9.857 (1, 335) at p=0.002.

In all the above five areas, mean scores for small PSBs are less than the large banks. In other words, the small banks' risk managers are feeling the need for improvement in these areas, which are the source of various substantive and procedural errors in design and execution of CRM systems and procedures.

The results, however, show no significant statistical difference in managerial perception in large and small banks towards other 28 variables of CRM practices. Any difference in groups' mean scores on these variables may be random or by chance. In other words, the groups are similar in their opinion on these variables.

6.5 Analysis of Obstacles in Credit Risk Management

6.5.1 Mean and Standard Deviation

Obstacles in credit risk management are the problems or constraints in design and implementation of effective credit risk management systems, processes, and procedures. Data analysis has been undertaken on the intensity of eleven obstacles (Figure 6.5) as perceived by the credit managers in large and small public sector banks.

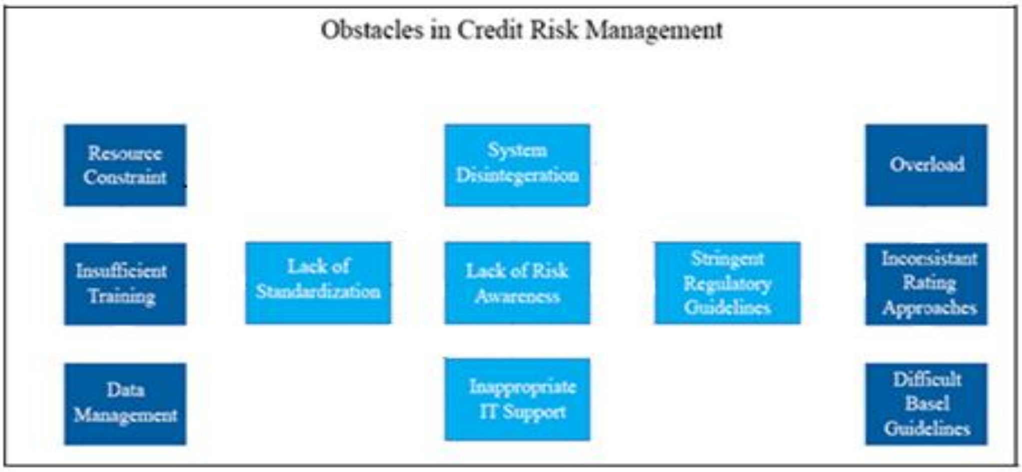

FIGURE 6.5: SURVEY OF 11 CRM OBSTACLES

Analysis of mean scores and standard deviation values (Figure 6.6 and Table 6.10) shows that the managers of small banks perceive higher obstacles (higher mean scores) in all the eleven obstacle variables.

The gap in mean scores between large and small banks' managers is highest for the following obstacles:

1. Lack of resources.

2. Lack of risk awareness.

3. The disintegration of systems across departments.

4. Inconsistencies in risk-rating approaches.

5. Inappropriate IT supports.

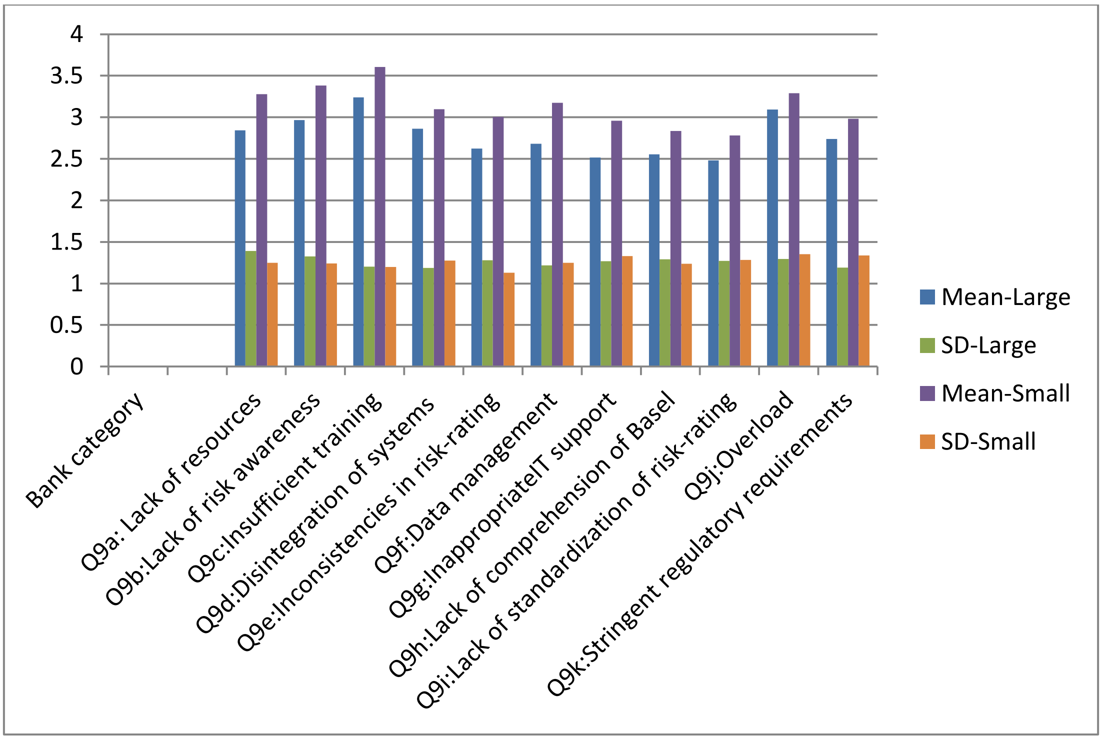

FIGURE 6.6: MEAN AND STANDARD DEVIATION OF OBSTACLES IN CRM

TABLE 6.10: MEAN & STANDARD DEVIATION OF OBSTACLES IN CRM.

Bank category		Q.9a: Lack of resources	O.9b: Lack of risk awareness	Q.9c: Insufficient training	Q.9d: Disintegration of systems across departments	Q.9e: Inconsistencies in risk-rating approaches	Q.9f: Data management	Q.9g: InappropriateIT support	Q.9h: Lack of comprehension of Basel guidelines	Q.9i: Lack of standardization of risk-rating and review processes	Q.9j: Overload	Q.9k: Stringent regulatory requirements
Large	Mean	2.84	2.97	3.24	2.86	2.62	2.68	2.52	2.55	2.48	3.09	2.74
	N	172	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	1.391	1.324	1.202	1.186	1.281	1.217	1.268	1.290	1.273	1.294	1.193
Small	Mean	3.28	3.38	3.61	3.10	3.01	3.18	2.96	2.84	2.78	3.29	2.98
	N	165	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	1.247	1.242	1.198	1.275	1.129	1.249	1.331	1.236	1.283	1.353	1.337
Total	Mean	3.06	3.17	3.42	2.98	2.81	2.92	2.73	2.69	2.63	3.19	2.86
	N	337	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	1.338	1.299	1.213	1.234	1.222	1.256	1.316	1.270	1.285	1.325	1.269

6.5.2 Analysis of Variance (ANOVA)

The eleven obstacles (Figure 6.5) have been tested through ANOVA /F statistic to find the significant differences in mean scores of credit managers in large and small PSBs (Table 6.11).

TABLE 6.11: ANOVA OF OBSTACLES (Q. 9) BY SIZE OF BANK (LARGE BANKS VS. SMALL BANKS)

		Sum of Squares	df	Mean Square	F	Sig.
Q.9a: Lack of resources.	Between Groups	15.991	1	15.991	9.143	.003
	Within Groups	585.937	335	1.749		
	Total	601.929	336			
Q.9b: Lack of risk awareness.	Between Groups	14.623	1	14.623	8.863	.003
	Within Groups	552.736	335	1.650		
	Total	567.359	336			
Q.9c: Insufficient training.	Between Groups	11.385	1	11.385	7.903	.005
	Within Groups	482.621	335	1.441		
	Total	494.006	336			
Q.9d: Disintegration of systems across departments.	Between Groups	4.710	1	4.710	3.112	.079
	Within Groups	507.100	335	1.514		
	Total	511.810	336			
Q.9e: Inconsistencies in risk-rating approaches.	Between Groups	12.416	1	12.416	8.498	.004
	Within Groups	489.430	335	1.461		
	Total	501.846	336			
Q.9f: Data management.	Between Groups	20.678	1	20.678	13.601	.000
	Within Groups	509.316	335	1.520		
	Total	529.994	336			
Q.9g: Inappropriate IT support.	Between Groups	16.314	1	16.314	9.662	.002
	Within Groups	565.651	335	1.689		
	Total	581.964	336			
Q.9h: Lack of comprehension of Basel guidelines.	Between Groups	6.794	1	6.794	4.253	.040
	Within Groups	535.111	335	1.597		
	Total	541.905	336			
Q.9i: Lack of standardization of risk-rating and review processes.	Between Groups	7.542	1	7.542	4.618	.032
	Within Groups	547.093	335	1.633		
	Total	554.635	336			

Q.9j: Overload.	Between Groups	3.298	1	3.298	1.883	.171
	Within Groups	586.548	335	1.751		
	Total	589.846	336			
Q.9k: Stringent regulatory requirements.	Between Groups	4.991	1	4.991	3.118	.078
	Within Groups	536.172	335	1.601		
	Total	541.163	336			

TABLE 6.12: STATISTICAL ANALYSIS OF RESPONSES: OBSTACLES IN CREDIT RISK MANAGEMENT

Obstacles in CRM		ANOVA	Mean		S.D.		
		F-stat (sig)	**Large**	**Small**	**Large**	**Small**	
(a)	**Lack of resources.**	**9.143(.003)**	**2.84**	**3.28**	**1.391**	**1.247**	
(b)	**Lack of risk awareness.**	**8.863(.003)**	**2.97**	**3.38**	**1.324**	**1.247**	
(c)	**Insufficient training.**	**7.903(.005)**	**3.24**	**3.61**	**1.202**	**1.198**	
(d)	Disintegration of systems across departments.	3.112(.079)	2.86	3.1	1.186	1.275	
(e)	**Inconsistencies in risk-rating approaches.**	**8.498(.004)**	**2.62**	**3.01**	**1.281**	**1.129**	
(f)	**Data management**	**13.601(.000)**	**2.68**	**3.18**	**1.217**	**1.249**	
(g)	**Inappropriate IT support.**	**9.662(.002)**	**2.52**	**2.96**	**1.268**	**1.331**	
(h)	**Lack of comprehension of Basel guidelines.**	**4.253(.040)**	**2.55**	**2.84**	**1.290**	**1.236**	
(i)	**Lack of standardization of risk-rating processes**	**4.618(.032)**	**2.48**	**2.78**	**1.273**	**1.283**	**and review**
(j)	Overload	1.883(.171)	3.09	3.29	1.294	1.353	
(k)	Stringent regulatory requirements.	3.118(.078)	2.74	2.98	1.193	1.337	

(Scale: Very Much-5, Somewhat- 4, Cannot Say- 3, A Little Bit- 2, Not At All- 1)

The results (Table 6.12) show that F statistic is significant for the following eight obstacles:

1. Lack of resources.

2. Lack of risk awareness.

3. Insufficient training.

4. Inconsistencies in risk-rating approaches.

5. Data management.

6. Inappropriate IT supports.

7. Lack of comprehension of Basel guidelines.

8. Lack of standardization of risk-rating and review processes.

Through analysis of category means and standard deviation (Table 6.12), it can be conclusively mentioned that credit officers in small public sector banks perceive more obstacles in the implementation of credit risk management systems in their banks. They have scored higher for all the obstacles evaluated, and their mean score differences with large banks are statistically significant in 73 percent obstacles (8 out of 11 tested).

6.6 TESTING HYPOTHESES

The null hypotheses have been tested by F-statistic. The independent variable is the banks' size or large /small bank category, and the dependent variables are the 47 variables. Through ANOVA, the null hypotheses are that bank category means are equal in the population. In other words,

$$\mathbf{H_0: \mu_1=\mu_2}$$

The null hypothesis is rejected when the associated probability is less than or equal to 0.05, the level of significance and it concludes that population means for two categories of banks are indeed different. In other words, there will be a significant difference in CRM practices of large and small public sector banks or obstacles in the implementation of CRM systems.

Hypothesis 4 (H_0)

Null hypothesis 4 (H_0) that there is no significant difference in practices of credit risk management in large and small public sector banks has been tested, using ANOVA

(Tables 6.4 to 6.6). Data analysis shows that in eight major areas of CRM practices, systems and procedures, there are significant differences in large and small PSBs. Thus, the null hypothesis 4 (H_0) is rejected to that extent. It may be concluded that there are many critical credit risk management areas where there are significant differences in large and small Indian public sector banks which require the attention of banks' top management, especially of small banks, to reduce credit risk.

Hypothesis 5 (H_o)

Null Hypothesis 5 (H_0) is that there is no significant difference in obstacles in the implementation of sound credit risk management systems in large and small public sector banks.

Null hypothesis stands rejected in 8 (shown in bold) out of 11 variables (Table 6.11) tested. The study thus, rejects the null hypothesis 5 (H_0) that there is no significant difference in obstacles in the implementation of sound credit risk management systems in large and small public sector banks, and concludes that the small public sector banks are facing more problems than the large public sector banks in managing credit risk. The statistically significant obstacles felt by them are a lack of resources, insufficient training, and a lack of risk awareness, inconsistencies in their risk-rating approaches and inappropriate IT support.

6.7 RESULTS AND DISCUSSION

1. There is a significant difference in managerial perceptions in large and small public sector banks about the effectiveness of their credit risk management systems, policies, and procedures, to reduce credit losses and non-performing assets.

2. The study has provided empirical evidence that the small Indian public sector banks do not perceive their CRM systems as well designed as that of large banks and they are facing many problems and obstacles in managing credit risk and require better risk inputs and restructuring of their various credit appraisal and loan review processes.

3. The managers of small PSBs do not find their credit risk policy and strategy as well designed as of large banks, their post-sanction loan monitoring process and awareness of strengths and weaknesses of other banks' risk management systems as reliable as of large PSBs. They are also finding more than the large banks for review and change in their credit systems and procedures and the need for more HR skills, training, and motivation. They also do not perceive that responsibility for credit risk management is clearly set out and understood throughout their banks.

4. In the comparative study of the effectiveness of their various CRM instruments, small banks' managers are feeling better than the large bank' managers on more than 50 per cent of such instruments such as their loan appraisal mechanism, surprise inspections, implementation of prudential limits, covenants for sensitive sectors, insider or related party lending. However, for twelve risk mitigation measures evaluated, they are optimistic only for 25 per cent of such measures such as regular discussions, reviews and feedback, multi-tier credit approvals and implementation of KYC norms.

5. The small banks' credit and risk managers have scored higher for all the obstacles or constraints surveyed, in design and implementation of CRM systems

and procedures. The more severely felt barriers by them are a lack of specialized training for credit and risk managers, creating poor risk awareness, lack of resources for proper risk management, poorly designed credit risk assessment framework causing inconsistencies in risk-rating approaches.

6. For other variables, though the differences in responses in large and small PSBs are not statistically significant, respondent credit officers in both these bank categories strongly agree/ agree that:

   - Experience and judgment of risk managers are more important than to apply the sophisticated techniques of credit risk management. (93% strongly agree/agree).

   - Credit risk systems and procedures of the bank need review and change to increase the effectiveness of credit risk management. (71%). The mean score for large banks is 3.73 (S.D .956) and for small banks is 3.75 (S.D .956). This means credit managers in small PSBs are more for review and changes in current systems and procedures.

   - For effective credit risk systems and procedures, the human resource needs better skill, training, and motivation. (82.79%). Again the mean score is higher for small banks, and they require more skill up gradation and training for their risk managers.

   - More effective instruments of CRM are loan appraisal mechanism (86%), loan reviews mechanism (75%), the surprise inspections (75%), and risk-rating or credit-scoring (68%).

- Effective risk mitigation measures in a bank are KYC norms (89%), risk-based appraisal and sanctions (84%), internal audits (82%), and multi-tier credit approval processes (80%).

- Major obstacles in the implementation of credit risk management systems in banks are insufficient training (61.4%), and lack of risk awareness (54.8%), lack of resources (50%), and overload (50%).

- Inadequate appraisal of borrower's credit-worthiness is causing higher NPAs. (70%). The mean score for large banks is 3.73 (S.D 1.055), and for small banks is 3.72 (S.D .999). Credit officers of large PSBs feel more strongly that weak loan appraisals are the cause of non-performing commercial loans.

- Another important observation from mean scores given by respondents to various instruments of credit risk management in large and small banks, is that the small banks give more importance to loan appraisal, prudential limits, loan reviews, the surprise inspections, sharing experience with other lenders, consortium lending, covenants for sensitive sectors and controls on related party lending. Whereas the large banks are giving more importance to risk-rating, risk pricing, portfolio management, industry studies, plant visits, credit derivatives, and securitization of loan.

6.8 CONCLUSIONS

The study has observed that the CRM problems are more severe for small public sector banks. They require better IT support, data management, standardization of risk-rating approaches to reduce inconsistencies, higher risk awareness and specialized risk management training. However, it is worthwhile to stress the need for continuous restructuring of credit policy, systems and procedures for large banks also as they also have an alarming size of non-performing and restructured assets. Since there are significant competitive pressures among all banks to secure lucrative loan offers, the challenge before all PSBs shall be to follow client focused competitive CRM practices, without compromising on credit evaluation and asset quality, and to implement the advanced approaches of Basel II in credit risk.

The next chapter will empirically evaluate the implementation of Basel norms in Indian public sector banks on credit risk management (Research Objective 3).

CHAPTER 7
IMPLEMENTATION OF BASEL NORMS IN CREDIT RISK MANAGEMENT

7.1 INTRODUCTION

All scheduled commercial banks in India have become Basel II compliant as per the Standardized Approach with effect from April 1, 2009 (RBI Trends, 2011-12). Presently the banks are migrating to advanced approaches of Basel II i.e., the Internal Rating Based (IRB) Approach and are at various stages of development of Basel II compliant Internal Credit Risk Rating Models for calculation of capital charge for credit risk (Capital Adequacy Ratio). The research objective is to analyze the extent to which the Indian PSBs have implemented the Basel norms on credit risk management.

7.2 STATISTICAL TOOLS USED

The purpose of this chapter is to empirically evaluate the managerial perceptions regarding capability of bank's credit rating model to deliver output required by the Basel norms and thereby the preparedness of Indian public sector banks for migrating to the advanced approaches of Basel II. Also the study captures managerial perceptions regarding complexity and usefulness of Basel norms in credit risk mitigation. Data for this have been obtained from the structured questionnaire (Question 16 to 19).

Data has been analyzed by frequencies, mean and standard deviation values, one-way analysis of variance (ANOVA) for three categories of independent variables and Tukey's HSD post hoc tests for multiple comparisons. The three independent variables are managers in large and small banks, managers at three levels of banking experience, and managers at three levels of management.

7.3 BASEL II COMPLIANCE IN CREDIT RATINGS (Q.16)

Question 16 examines the Indian public sector banks' preparedness to migrate to the Internal Rating Based Approach by probing whether banks' credit risk assessment models are capable of calculating Probability of Default (PD), Loss Given Default (LGD), Exposure at Default (EAD), Capital Adequacy requirements, Portfolio Credit Risk, Rating Transition Matrix and RAROC (Risk-adjusted Return on Capital).

7.3.1 Probability of Default (PD)

The probability of default is the possibility of default by the borrower in a loan transaction. In a rating model, lower is the credit score; higher is the probability of default. Higher is PD, higher will be risk weight of a loan transaction, and higher will be the capital adequacy ratio. Estimates of PD shall be based on quantitative and qualitative risk characteristics of the counterparty and historical experience.

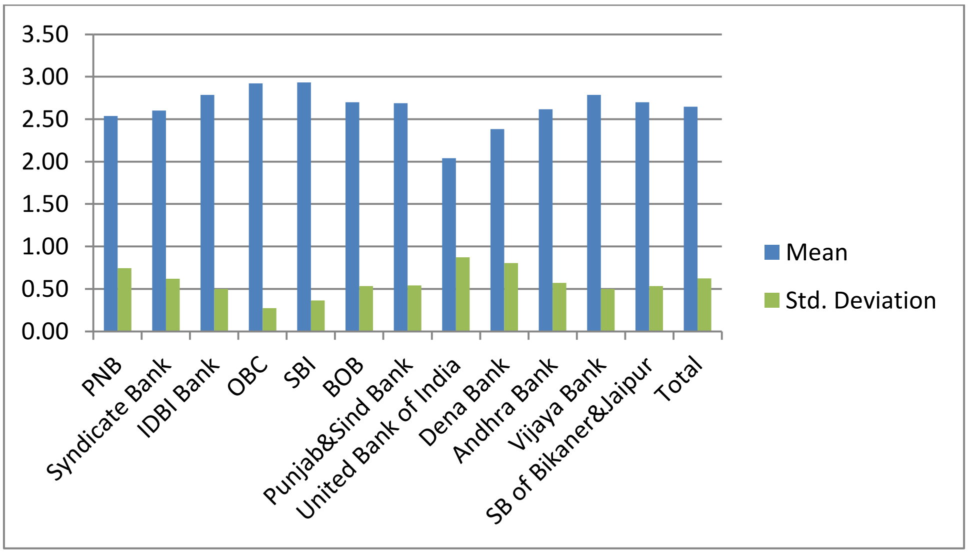

FIGURE 7.1: BANK-WISE MEAN & STANDARD DEVIATION OF PD

TABLE 7.1: BANK-WISE DESCRIPTIVE STATISTICS- Q.16

BANK NAME		Q.16a: PD	Q.16b: LGD	Q.16c: EAD	Q.16d: Capital Adequacy	Q.16e: Portfolio credit risk	Q.16f: Rating Transition	Q.16g: RAROC
PNB	Mean	2.54	2.36	2.39	2.36	2.50	2.50	1.36
	N	28	28	28	28	28	28	28
	Std. Deviation	.744	.826	.832	.911	.745	.745	.488
Syndicate Bank	Mean	2.60	2.63	2.73	2.77	2.93	2.87	2.97
	N	30	30	30	30	30	30	30
	Std. Deviation	.621	.556	.521	.568	.254	.346	.490
IDBI Bank	Mean	2.79	2.68	2.64	2.89	2.57	2.96	2.57
	N	28	28	28	28	28	28	28
	Std. Deviation	.499	.670	.678	.315	.634	.189	.634
OBC	Mean	2.92	2.92	2.88	2.96	2.85	2.65	2.81
	N	26	26	26	26	26	26	26
	Std. Deviation	.272	.272	.326	.196	.464	.629	.491
SBI	Mean	2.93	2.90	2.83	2.97	2.83	2.90	2.57
	N	30	30	30	30	30	30	30
	Std. Deviation	.365	.403	.531	.183	.531	.305	.728
BOB	Mean	2.70	2.57	2.67	2.83	2.83	2.80	2.93
	N	30	30	30	30	30	30	30
	Std. Deviation	.535	.626	.547	.379	.379	.484	.254
Punjab&Sind Bank	Mean	2.69	2.31	2.24	2.76	2.10	2.34	1.66
	N	29	29	29	29	29	29	29
	Std. Deviation	.541	.712	.689	.511	.724	.614	.484
United Bank of India	Mean	2.04	2.12	2.00	2.69	2.62	2.54	2.31
	N	26	26	26	26	26	26	26
	Std. Deviation	.871	.864	.849	.618	.637	.647	.736
Dena Bank	Mean	2.38	2.35	2.31	2.65	2.77	2.54	1.54
	N	26	26	26	26	26	26	26
	Std. Deviation	.804	.797	.788	.629	.514	.647	.647
Andhra Bank	Mean	2.62	2.31	2.27	2.88	2.69	2.85	2.27
	N	26	26	26	26	26	26	26
	Std. Deviation	.571	.679	.724	.326	.618	.368	.604

Vijaya Bank	Mean	2.79	2.57	2.64	2.71	2.75	2.86	2.71
	N	28	28	28	28	28	28	28
	Std. Deviation	.499	.634	.621	.460	.518	.356	.600
SB of Bikaner&Jaipur	Mean	2.70	2.77	2.73	2.93	2.83	2.80	2.83
	N	30	30	30	30	30	30	30
	Std. Deviation	.535	.504	.583	.365	.531	.551	.531
Total	Mean	2.65	2.55	2.54	2.79	2.69	2.72	2.39
	N	337	337	337	337	337	337	337
	Std. Deviation	.624	.680	.694	.514	.592	.539	.779

PD estimation through credit rating models has the highest response or mean score from credit managers of SBI, OBC, IDBI Bank and the Vijaya Bank (Figure 7.1 & Table 7.1).

In all, 72.7 % agree that the credit risk models of the bank calculate the probability of default (Table 7.2).

TABLE 7.2: Q.16A- ARE BANK'S CREDIT RISK ASSESSMENT MODELS CAPABLE OF CALCULATING PROBABILITY OF DEFAULT

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	27	8.0	8.0	8.0
Not sure	65	19.3	19.3	27.3
Yes	245	72.7	72.7	100.0
Total	337	100.0	100.0	

One-way analysis of variance (ANOVA) has been conducted for three independent variables, i.e., groups of managers in large or small banks; managers at three levels of experience; and managers at three levels of management (Tables 7.3 to 7.5).

TABLE 7.3: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16a: Are bank's credit risk assessment models capable of calculating: Probability of Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.326	1	3.326	8.728	.003
Within Groups	127.653	335	.381		
Total	130.979	336			

TABLE 7.4: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16a: Are bank's credit risk assessment models capable of calculating: Probability of Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.984	2	.992	2.569	.078
Within Groups	128.995	334	.386		
Total	130.979	336			

TABLE 7.5: ANOVA BY LEVEL OF MANAGEMENT

Q.16a: Are bank's credit risk assessment models capable of calculating: Probability of Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.001	2	1.001	2.591	.076
Within Groups	128.978	334	.386		
Total	130.979	336			

The ANOVA results show statistically significant mean differences in the opinion of large and small banks managers, with F-statistic 8.728 (df 1,335), at p= 0.003 (Table 7.3). Mean differences are not statistically different among other categories of bank managers. Thus, **large** public sector banks' (PSBs) credit rating models can capture PD for each borrower more precisely than of **small** PSBs.

7.3.2 Loss Given Default (LGD)

Loss Given Default means expected loss to the bank in case of default by a borrower and depends on facility ratings or security coverage ratio. The loss will depend on loan recoveries and value of collaterals. Bank-wise descriptive statistics on LGD calculations by banks' internal credit risk assessment models are shown in Figure 7.2 and Table 7.1.

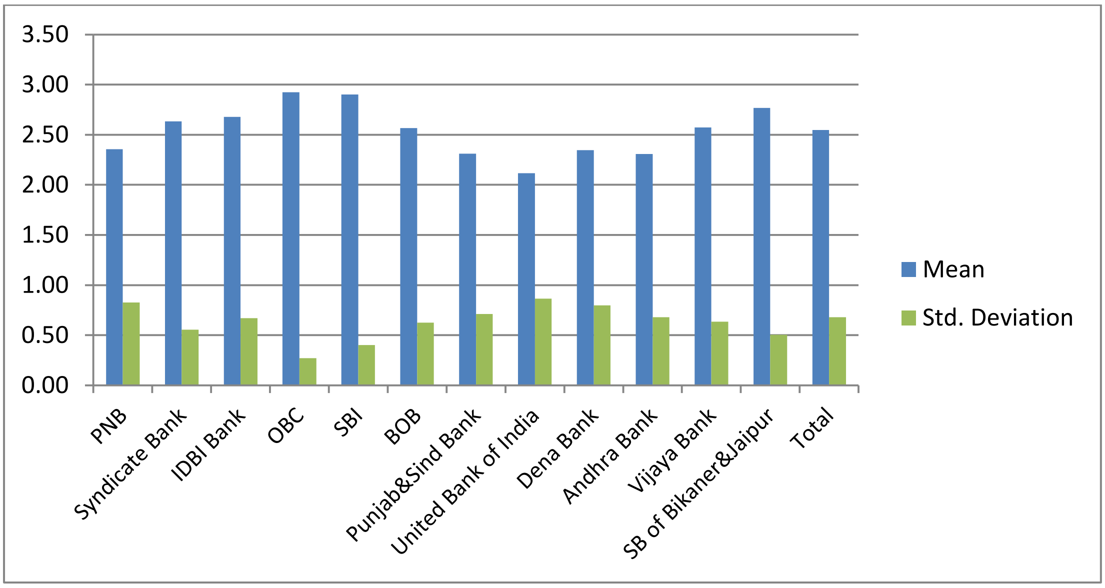

FIGURE 7.2: BANK-WISE DESCRIPTIVE STATISTICS- LGD

In all, 65.3% of respondents agree about the calculation of Loss Given Default of loan counterparties through internal credit rating models of banks (Table 7.6). Again the highest mean score is from large banks (2.69). The mean score of small banks is 2.41 (Table 7.7).

TABLE 7.6: Q.16B-LOSS GIVEN DEFAULT

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	36	10.7	10.7	10.7
Not sure	81	24.0	24.0	34.7
Yes	220	65.3	65.3	100.0
Total	337	100.0	100.0	

TABLE 7.7: DESCRIPTIVE STATISTICS (LARGE BANKS VS. SMALL BANKS)

Bank category		Q.16a: PD	Q.16b: LGD	Q.16c: EAD	Q.16d: Capital Adequacy	Q.16e: Portfolio credit risk	Q.16f: Rating Transition	Q.16g: RAROC	Q.17: Basel II is a business enhancement skill	Q.18: Basel II is complex	Q.19: Basel II as risk mitigation tool
Large	Mean	2.74	2.67	2.69	2.80	2.76	2.78	2.53	3.97	3.28	3.90
	N	172	172	172	172	172	172	172	172	172	172
	Std. Deviation	.545	.611	.605	.529	.539	.502	.737	.948	1.068	.807
Small	Mean	2.55	2.41	2.38	2.78	2.62	2.65	2.23	3.75	3.19	3.77
	N	165	165	165	165	165	165	165	165	165	165
	Std. Deviation	.685	.724	.744	.498	.638	.570	.770	1.062	1.115	.992
Total	Mean	2.65	2.55	2.54	2.79	2.69	2.72	2.38	3.86	3.24	3.84
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.624	.680	.694	.514	.592	.539	.767	1.010	1.090	.903

TABLE 7.8: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16b:Loss Given Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.794	1	5.794	12.962	.000
Within Groups	149.743	335	.447		
Total	155.537	336			

TABLE 7.9: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16b:Loss Given Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.205	2	.603	1.304	.273
Within Groups	154.332	334	.462		
Total	155.537	336			

TABLE 7.10: ANOVA BY LEVEL OF MANAGEMENT

Q.16b:Loss Given Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.785	2	1.392	3.044	.049
Within Groups	152.752	334	.457		
Total	155.537	336			

TABLE 7.11: POST HOC TESTS-MULTIPLE COMPARISONS

Dependent Variable: Q.16b:Loss Given Default

Tukey HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle Level Managers	.179	.108	.224	-.08	.43
	Senior Level Managers	-.005	.116	.999	-.28	.27
Middle Level Managers	Junior Managers	-.179	.108	.224	-.43	.08
	Senior Level Managers	-.184	.083	.068	-.38	.01
Senior Level Managers	Junior Managers	.005	.116	.999	-.27	.28
	Middle Level Managers	.184	.083	.068	-.01	.38

ANOVA results have been found to be statistically significant for large and small banks managers (F-statistic =12.962, df 1,335, at p=0.000). For managers at three hierarchy levels, junior, middle and senior levels also, ANOVA results are statistically significant (F-statistic=3.044, df 2,334, at p= 0.049). There is, however, no significant difference in responses of managers in different experience groups (Tables 7.8 to 7.10).

Post hoc tests for multiple comparisons, however, do not find significant differences between junior, middle and senior level credit managers (Table 7.11), though ANOVA on managerial levels depicted significant differences in this group. Only managers in large and small banks have significantly different opinions.

7.3.3 Exposure at Default (EAD)

Exposure at Default means the amount of loan at risk of loss, in the case of default. Estimation of EAD will require exposure analysis of defaulted credit.

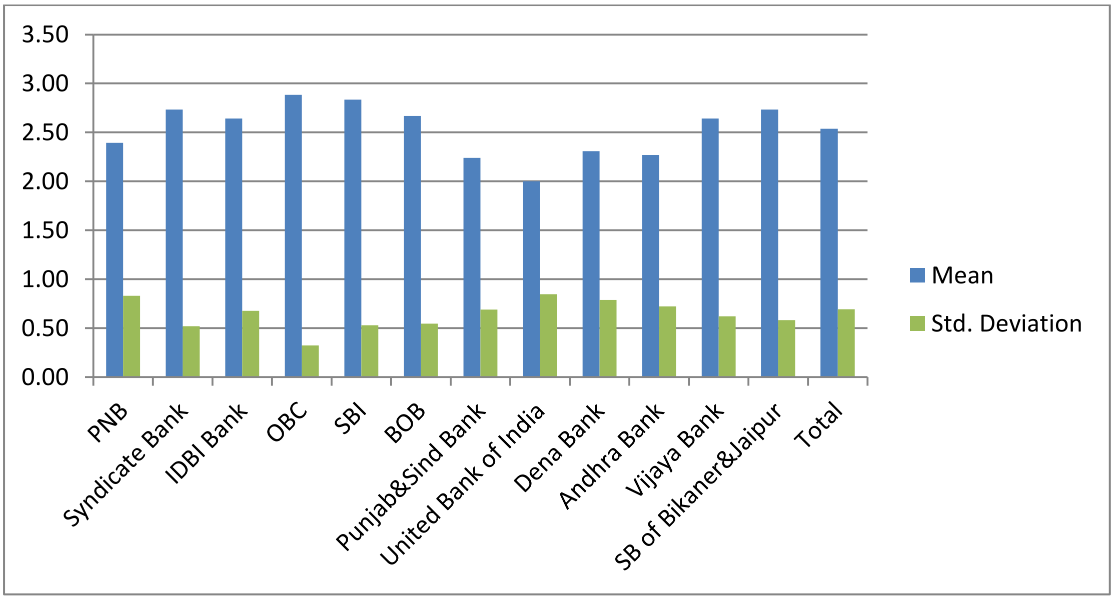

FIGURE 7.3: EXPOSURE AT DEFAULT- MEAN AND STANDARD DEVIATION VALUES

Out of 337 respondents, 65.3 % agree that banks' credit rating models can calculate Exposure at Default (Table 7.12). The trend in mean and standard deviation scores is very similar with that for Loss Given Default (Figure 7.3 & Table 7.1).

TABLE 7.12: Q.16C-EXPOSURE AT DEFAULT

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	39	11.6	11.6	11.6
Not sure	78	23.1	23.1	34.7
Yes	220	65.3	65.3	100.0
Total	337	100.0	100.0	

ANOVA results are also similarly significant for large and small banks managers (F statistic=18.380, df 1,335, at p=0.000); and for different levels of management (F statistic=4.946, df 2,334, at p=0.008) (Tables 7.13 to 7.15).

TABLE 7.13: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16c:Exposure at Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.415	1	8.415	18.380	.000
Within Groups	153.372	335	.458		
Total	161.786	336			

TABLE 7.14: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16c:Exposure at Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.532	2	.766	1.596	.204
Within Groups	160.254	334	.480		
Total	161.786	336			

TABLE 7.15: ANOVA BY LEVEL OF MANAGEMENT

Q.16c:Exposure at Default

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.654	2	2.327	4.946	.008
Within Groups	157.133	334	.470		
Total	161.786	336			

TABLE 7.16: POST HOC TESTS - MULTIPLE COMPARISONS

Dependent Variable: Q.16c: Exposure at Default
Tukey HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle Level Managers	.212	.110	.130	-.05	.47
	Senior Level Managers	-.033	.117	.958	-.31	.24
Middle Level Managers	Junior Managers	-.212	.110	.130	-.47	.05
	Senior Level Managers	-.245*	.084	.010	-.44	-.05
Senior Level Managers	Junior Managers	.033	.117	.958	-.24	.31
	Middle Level Managers	.245*	.084	.010	.05	.44

*. The mean difference is significant at the 0.05 level.

Again, post hoc tests are not showing any significant difference between any of sub-management groups except for large and small bank managers (Table 7.16).

7.3.4 Capital Adequacy Requirement

Capital adequacy means estimation of regulatory capital based on risk-weighted assets of the bank. Risk weights of asset classes under Basel II advanced approaches are based on internal estimates of PD, LGD, EAD, etc.

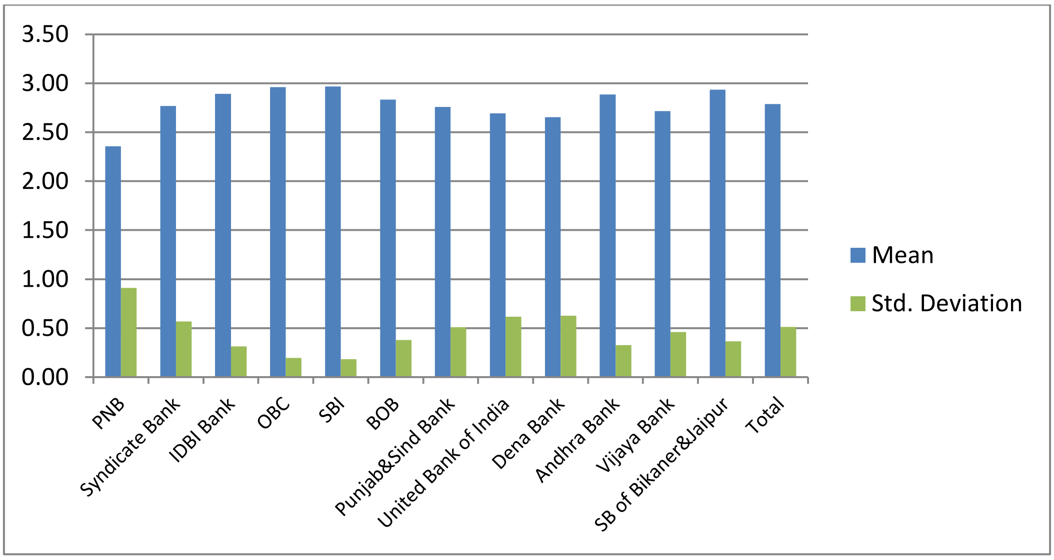

FIGURE 7.4: CAPITAL ADEQUACY RATIO- DESCRIPTIVE STATISTICS

83.4 percent of respondents agree that calculation of capital adequacy ratios of banks are based on credit risk models (Table 7.17). The mean score of all responses is 2.79 (S.D. 0.514) (Table 7.1). The mean score for large PSBs is 2.80, and for small banks 2.78 (Table 7.7). The highest mean score is for State Bank of Bikaner & Jaipur (2.93), and lowest for PNB (2.36) (Table 7.1).

TABLE 7.17: Q.16D-CAPITAL ADEQUACY REQUIREMENT

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	16	4.7	4.7	4.7
Not sure	40	11.9	11.9	16.6
Yes	281	83.4	83.4	100.0
Total	337	100.0	100.0	

ANOVA results indicate statistically significant mean differences only between and within managers of different experience groups (F= 5.798, df 2,334, at p=0.003)

(Tables 7.18 to 7.20). Tukey's post hoc tests for multiple comparisons show statistically significant difference in opinions between 'up to 7 years' and '8 to 20 years' only and not between them with 'above 20 years' group (Table 7.21).

TABLE 7.18: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16d:Capital Adequacy Requirement

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	.036	1	.036	.137	.711
Within Groups	88.581	335	.264		
Total	88.617	336			

TABLE 7.19: ANOVA BY LEVEL OF MANAGEMENT

Q.16d:Capital Adequacy Requirement

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	.048	2	.024	.090	.914
Within Groups	88.570	334	.265		
Total	88.617	336			

TABLE 7.20: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16d:Capital Adequacy Requirement

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.973	2	1.487	5.798	.003
Within Groups	85.644	334	.256		
Total	88.617	336			

TABLE 7.21: POST HOC TEST- MULTIPLE COMPARISONS

Dependent Variable: Q.16d:Capital Adequacy Requirement

Tukey HSD

(I) Banking Experience(years)	**(J) Banking Experience(years)**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
					Lower Bound	**Upper Bound**
Up to 7 years	**8 to 20 years**	**-.241***	**.071**	**.002**	**-.41**	**-.07**
	Above 20 years	-.078	.064	.442	-.23	.07
8 to 20 years	**Up to 7 years**	**.241***	**.071**	**.002**	**.07**	**.41**
	Above 20 years	.163	.072	.063	-.01	.33
Above 20 years	Up to 7 years	.078	.064	.442	-.07	.23
	8 to 20 years	-.163	.072	.063	-.33	.01

*. The mean difference is significant at the 0.05 level.

7.3.5 Portfolio Credit Risk

Portfolio credit risk is measured in terms of assets correlation and concentration risk.

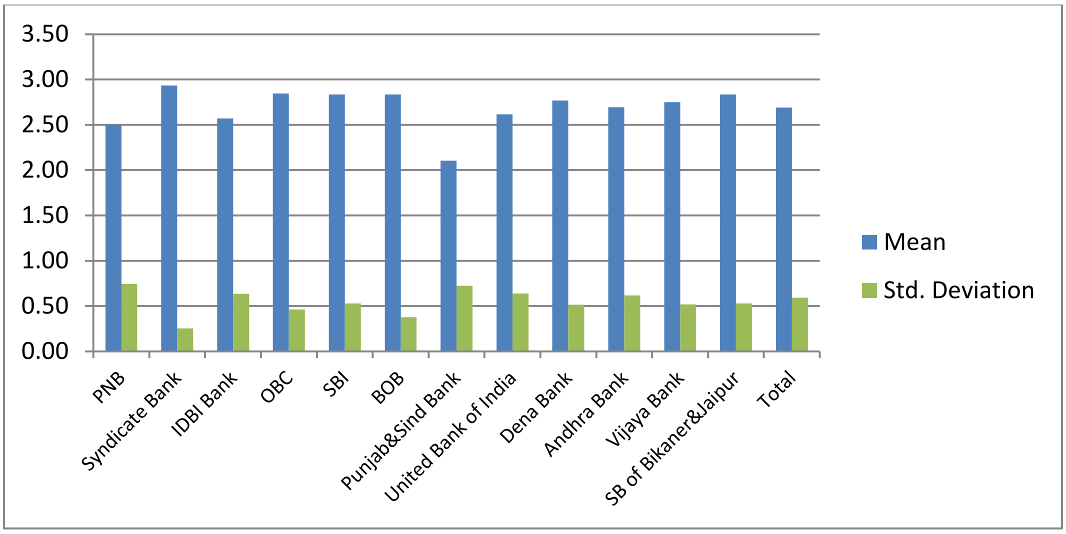

FIGURE 7.5: MEASUREMENT OF PORTFOLIO CREDIT RISK

Banks credit rating models can measure borrower's credit risk, and through networking can measure group-wise, sector-wise, industry-wise, and thereby portfolio credit risk.

76 % respondents agree (Table 7.22). Bank-wise, Syndicate Bank has the highest mean score (2.93) with S.D. 0.254. Punjab & Sind Bank has the lowest mean score (2.10) with S.D. of 0.724, against all banks mean score response of 2.69 (S.D. 0.592) (Table 7.1).

Group-wise, large banks have higher mean score (2.76) than the small banks (2.62) (Table 7.7). Managers in '8 to 20 years' experience group have higher score (2.88) than the other groups (Table 7.23). Senior managerial levels have a higher score (2.75) than the other hierarchy levels (Tables 7.24).

TABLE 7.22: Q.16E-PORTFOLIO CREDIT RISK

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	23	6.8	6.8	6.8
Not sure	58	17.2	17.2	24.0
Yes	256	76.0	76.0	100.0
Total	337	100.0	100.0	

TABLE 7.23: DESCRIPTIVE STATISTICS (MANAGEMENT EXPERIENCE-WISE)

Banking Experience(years)		Q.16a: PD	Q.16b: LGD	Q.16c: EAD	Q.16d: Capital Adequacy	Q.16e: Portfolio credit risk	Q.16f: Rating Transition	Q.16g: RAROC	Q.17: Basel II a business skill	Q.18: Basel II is complex	Q.19: Basel II as risk mitigation tool
	Mean	2.56	2.51	2.47	2.70	2.60	2.67	2.40	3.74	3.02	3.85
Up to 7 years	N	133	133	133	133	133	133	133	133	133	133
	Std. Deviation	.667	.692	.724	.564	.627	.574	.738	.984	1.066	.793
	Mean	2.76	2.65	2.63	2.94	2.88	2.87	2.46	3.90	3.30	3.80
8 to 20 years	N	82	82	82	82	82	82	82	82	82	82
	Std. Deviation	.534	.636	.639	.287	.397	.377	.789	1.084	1.119	.999
	Mean	2.66	2.52	2.55	2.78	2.66	2.68	2.31	3.97	3.44	3.84
20 years and above	N	122	122	122	122	122	122	122	122	122	122
	Std. Deviation	.625	.695	.694	.553	.638	.579	.783	.979	1.061	.954
	Mean	2.65	2.55	2.54	2.79	2.69	2.72	2.38	3.86	3.24	3.84
Total	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.624	.680	.694	.514	.592	.539	.767	1.010	1.090	.903

TABLE 7.24: DESCRIPTIVE STATISTICS (MANAGEMENT LEVEL-WISE)

Management Level		Q.16a:PD	Q.16b:LGD	Q.16c:EAD	Q.16d:Capital Adequacy	Q.16e:Portfolio credit risk	Q.16f:Rating Transition	Q.16g:RAROC	Q.17:Basel II business skill	Q.18: Basel II is complex	Q.19:Basel II as risk mitigation tool
Junior Managers	Mean	2.68	2.64	2.64	2.78	2.64	2.76	2.52	3.74	3.08	3.66
	N	50	50	50	50	50	50	50	50	50	50
	Std. Deviation	.513	.563	.598	.418	.563	.476	.677	.986	.986	.872
Middle Level Managers	Mean	2.58	2.46	2.43	2.78	2.67	2.71	2.33	3.90	3.21	3.91
	N	180	180	180	180	180	180	180	180	180	180
	Std. Deviation	.668	.727	.748	.534	.606	.546	.784	.992	1.122	.861
Senior Level Managers	Mean	2.75	2.64	2.67	2.80	2.75	2.73	2.40	3.85	3.37	3.79
	N	107	107	107	107	107	107	107	107	107	107
	Std. Deviation	.584	.633	.611	.522	.584	.559	.775	1.053	1.077	.978
Total	Mean	2.65	2.55	2.54	2.79	2.69	2.72	2.38	3.86	3.24	3.84
	N	337	337	337	337	337	337	337	337	337	337
	Std. Deviation	.624	.680	.694	.514	.592	.539	.767	1.010	1.090	.903

ANOVA results show significant results for bank size category, large and small (F statistic =4.194, df 1,335, p=0.041), and for managers of different experience groups (F statistic=6.051, df 2, 334, at p=0.003) only (Tables 7.25 to 7.27). Post hoc tests reveal that this significant difference is only between experience groups of 'up to 7 years' and '8 to 20 years', and not between them with 'above 20 years' group (Table 7.28).

TABLE 7.25: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16e:Portfolio credit risk

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	1.458	1	1.458	4.194	.041
Within Groups	116.447	335	.348		
Total	117.905	336			

TABLE 7.26: ANOVA BY LEVEL OF MANAGEMENT

Q.16e:Portfolio credit risk

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.537	2	.269	.764	.467
Within Groups	117.368	334	.351		
Total	117.905	336			

TABLE 7.27: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16e:Portfolio credit risk

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.123	2	2.061	6.051	.003
Within Groups	113.782	334	.341		
Total	117.905	336			

TABLE 7.28: POST HOC TEST - MULTIPLE COMPARISONS

Dependent Variable: Q.16e:Portfolio credit risk

Tukey HSD

(I) Banking Experience(years)	**(J) Banking Experience(years)**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
					Lower Bound	**Upper Bound**
Up to 7 years	**8 to 20 years**	**-.278***	**.082**	**.002**	-.47	-.09
	Above 20 years	-.060	.073	.695	-.23	.11
8 to 20 years	**Up to 7 years**	**.278***	**.082**	**.002**	.09	.47
	Above 20 years	.218*	.083	.025	.02	.41
Above 20 years	Up to 7 years	.060	.073	.695	-.11	.23
	8 to 20 years	-.218*	.083	.025	-.41	-.02

*. The mean difference is significant at the 0.05 level.

7.3.6 Rating Transition Matrix

Rating Transition Matrix maps rating migration or change from one risk category to another. It can track the upward or downward movements in credit risk in loan transactions, and in asset classes, and in the case of a downward swing, give early warning signals of default.

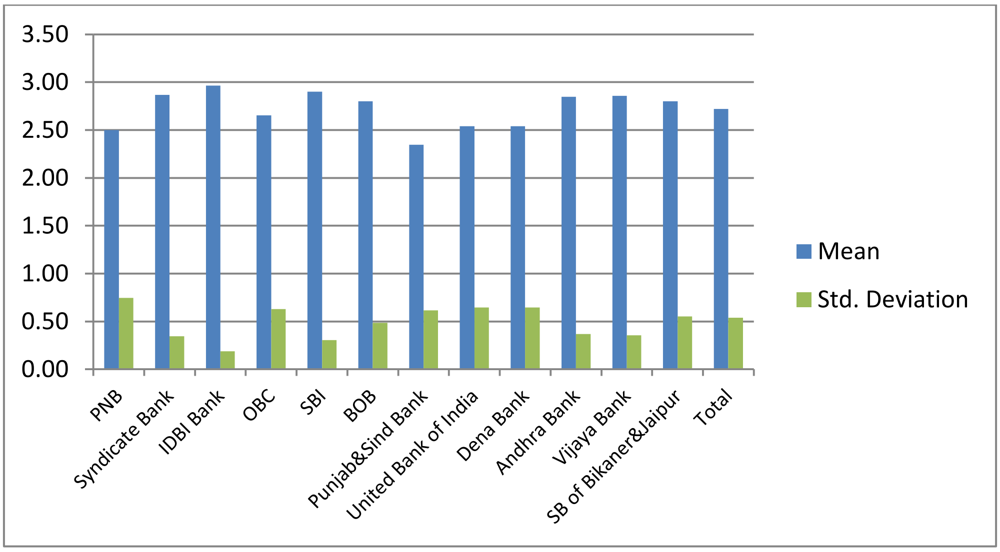

FIGURE 7.6: MAPPING RATING TRANSITIONS

IDBI Bank has the highest mean score (2.96), followed by SBI (2.90) in the mapping of rating transitions of borrowers during the tenure of the loan to measure the distance to default or credit health of the loan. Punjab & Sind Bank has the least mean score (2.34) (Table 7.1). Large banks mean score (2.78) is higher than for small banks (2.65) (Table 7.7). Managers at junior levels are giving the highest scores, with the mean score of 2.76, for mapping rating migration (Table 7.24). In all 76.6% respondents agree that they measure rating migrations or movements in credit risk assessments (Table 7.29).

TABLE 7.29: Q.16F-RATING TRANSITION

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	15	4.5	4.5	4.5
Not sure	64	19.0	19.0	23.4
Yes	258	76.6	76.6	100.0
Total	337	100.0	100.0	

ANOVA results are significant for managers in large and small banks, and also for managers in three experience groups, but not for managers in three hierarchical levels (Tables 7.30 to 7.32). For three managerial levels, the mean differences are only chance differences. Post hoc test reveals significant differences in all the three experience groups (Table 7.33).

TABLE 7.30: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16f:Rating Transition

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.431	1	1.431	4.974	.026
Within Groups	96.350	335	.288		
Total	97.780	336			

TABLE 7.31: ANOVA BY LEVEL OF MANAGEMENT

Q.16f:Rating Transition

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.126	2	.063	.215	.807
Within Groups	97.655	334	.292		
Total	97.780	336			

TABLE 7.32: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16f:Rating Transition

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.365	2	1.182	4.139	.017
Within Groups	95.416	334	.286		
Total	97.780	336			

TABLE 7.33: POST HOC TESTS - MULTIPLE COMPARISONS

Dependent Variable: Q.16f:Rating Transition

Tukey HSD

(I) Banking Experience(years)	(J) Banking Experience(years)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Upto 7 years	**8 to 20 years**	**-.198***	**.075**	**.023**	-.37	-.02
	Above 20 years	-.009	.067	.991	-.17	.15
8 to 20 years	**Up to 7 years**	**.198***	**.075**	**.023**	.02	.37
	Above 20 years	**.190***	**.076**	**.035**	.01	.37
Above 20 years	Up to 7 years	.009	.067	.991	-.15	.17
	8 to 20 years	-.190*	.076	.035	-.37	-.01

*. The mean difference is significant at the 0.05 level.

7.3.7 Risk-Adjusted Return on Capital (RAROC)

It is a risk-based performance measurement. Measuring RAROC on each loan transaction, in each asset class helps banks in risk-based pricing of loans, measuring loan performance, comparing loan performances across businesses, industries, and sectors, in better risk management. RAROC is calculated based on risk-adjusted net income, the cost of funds and economic capital.

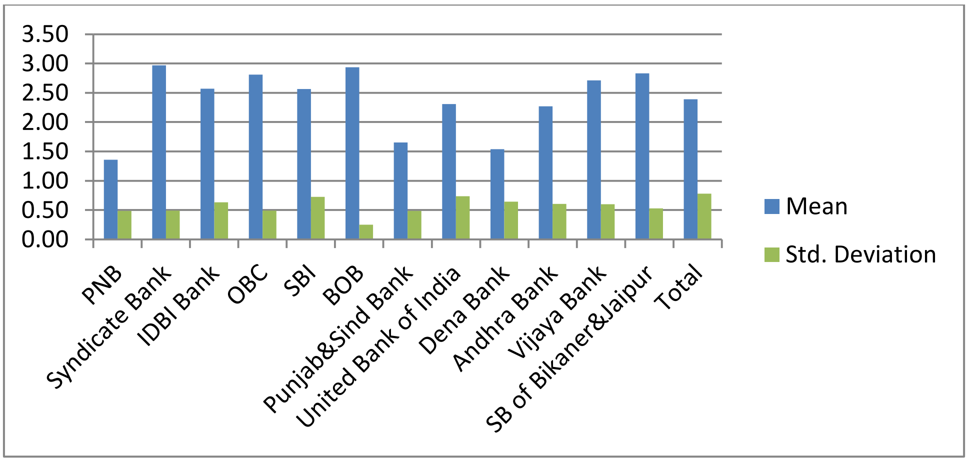

FIGURE 7.7: MEASURING RAROC- DESCRIPTIVE STATISTICS

Only 55.8% respondent credit managers agree that their banks are measuring loan performance through RAROC (Table 7.34). Responses for not measurement of RAROC are from PNB and Punjab & Sind Bank. Very less response is from Dena Bank, United Bank of India, and Andhra Bank. Thus out of five such banks, four are small banks (Table 7.35). The mean score for large banks is 2.53 (S.D. 0.737), and for small banks is 2.23 (S.D. 0.770) (Table 7.7).

TABLE 7.34: Q.16G-RAROC

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	59	17.5	17.5	17.5
Not sure	90	26.7	26.7	44.2
Yes	188	55.8	55.8	100.0
Total	337	100.0	100.0	

TABLE 7.35: BANK WISE Q.16G: RAROC

		Q.16g:RAROC			Total
		No	Not sure	Yes	
BANK NAME	PNB	18	10	0	28
	Syndicate Bank	0	3	27	30
	IDBI Bank	2	8	18	28
	OBC	1	3	22	26
	SBI	4	5	21	30
	BOB	0	2	28	30
	Punjab & Sind Bank	10	19	0	29
	United Bank of India	4	10	12	26
	Dena Bank	14	10	2	26
	Andhra Bank	2	15	9	26
	Vijaya Bank	2	4	22	28
	SB of Bikaner & Jaipur	2	1	27	30
Total		59	90	188	337

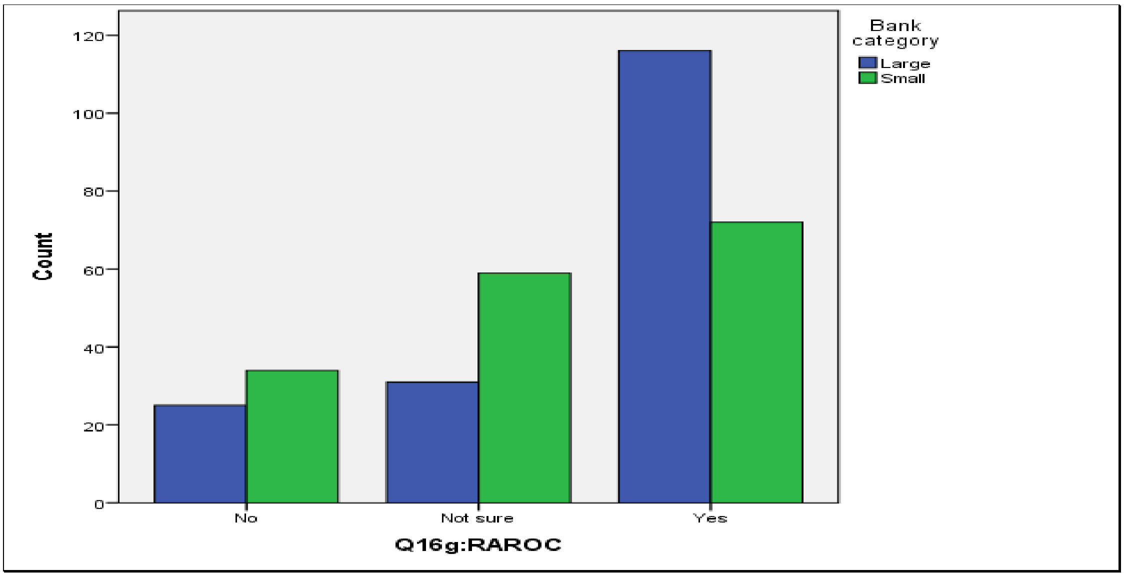

FIGURE 7.8: RESPONSES - LARGE BANKS VS. SMALL BANKS

ANOVA results also show significant mean differences between and within large and small group credit managers, with F-statistics = 13.870 (df 1,335) at p=0.000 (Table 7.36). Other managerial groups have only chance differences (Tables 7.37 and 7.38). Thus RAROC, the powerful tool of credit risk management is more significantly used in large banks and less in small banks.

TABLE 7.36: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.16g:RAROC

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	7.517	1	7.517	13.247	.000
Within Groups	190.103	335	.567		
Total	197.620	336			

TABLE 7.37: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.16g:RAROC

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.380	2	.690	1.174	.310
Within Groups	196.240	334	.588		
Total	197.620	336			

TABLE 7.38: ANOVA BY LEVEL OF MANAGEMENT

Q.16g:RAROC

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.421	2	.710	1.209	.300
Within Groups	196.200	334	.587		
Total	197.620	336			

7.4 MANAGERIAL PERCEPTION TOWARDS BASEL II (Q.17 TO 19)

Questions 17 to 19 probe the managerial perception of credit managers of Indian public sector banks towards Basel II in effective credit risk management. Basel norms are based on international best practices for integrated risk management in banks. However, their guidelines have complex quantitative requirements, and especially the emerging economies and developing nations find it difficult to implement them. By understanding the managerial perception, banks may find better ways to implement the Basel guidelines.

Question 17: Against the question that the Basel II is a business enhancement skill in risk management, and not merely a compliance issue, 76.5% agreed/strongly agreed (Table 7.39). The mean score of responses is 3.86 (S.D 1.010). Highest mean/average score is by SBI (4.10) with S.D. 0.995, followed by the Syndicate Bank (4.07) with S.D. 0.980 (Figure 7.9) (Table 7.40). Large banks mean score is 3.97, and small banks 3.75 (Table 7.7). ANOVA results are not significant for any of the three groups of managers, the independent variables (Tables 7.41 to 7.43).

TABLE 7.39: Q.17-BASEL II IS A BUSINESS ENHANCEMENT SKILL IN RISK MGT. AND NOT MERELY A COMPLIANCE ISSUE

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	5	1.5	1.5	1.5
Disagree	47	13.9	13.9	15.4
Cannot say	27	8.0	8.0	23.4
Agree	169	50.1	50.1	73.6
Strongly agree	89	26.4	26.4	100.0
Total	337	100.0	100.0	

TABLE 7.40: BANK-WISE DESCRIPTIVE STATISTICS- Q. 17 TO 19

BANK NAME		Q.17:Basel II is a business enhancement skill in risk mgt. and not merely a compliance issue	Q.18:The quantitative framework of Basel II is complex and difficult to train the staff	Q.19:Basel II has helped in credit risk mitigation in bank
	Mean	3.75	3.64	3.79
PNB	N	28	28	28
	Std. Deviation	.887	.826	.630
	Mean	4.07	3.03	4.03
Syndicate Bank	N	30	30	30
	Std. Deviation	.980	1.066	.765
	Mean	3.82	2.96	3.79
IDBI Bank	N	28	28	28
	Std. Deviation	1.056	1.071	.738
	Mean	4.04	3.27	4.08
OBC	N	26	26	26
	Std. Deviation	.916	1.002	1.055
	Mean	4.10	3.43	3.80
SBI	N	30	30	30
	Std. Deviation	.995	1.165	.761

BOB	Mean	4.00	3.37	3.93
	N	30	30	30
	Std. Deviation	.871	1.159	.868
Punjab&Sind Bank	Mean	4.03	3.17	4.00
	N	29	29	29
	Std. Deviation	.823	1.136	.926
United Bank of India	Mean	3.73	3.04	3.35
	N	26	26	26
	Std. Deviation	1.041	1.248	1.129
Dena Bank	Mean	3.81	3.58	3.65
	N	26	26	26
	Std. Deviation	1.132	.902	1.093
Andhra Bank	Mean	3.65	3.27	3.92
	N	26	26	26
	Std. Deviation	.977	1.185	.845
Vijaya Bank	Mean	3.89	3.07	3.93
	N	28	28	28
	Std. Deviation	1.133	1.184	.940
SB of Bikaner&Jaipur	Mean	3.40	3.07	3.73
	N	30	30	30
	Std. Deviation	1.192	1.015	.944
Total	Mean	3.86	3.24	3.84
	N	337	337	337
	Std. Deviation	1.010	1.090	.903

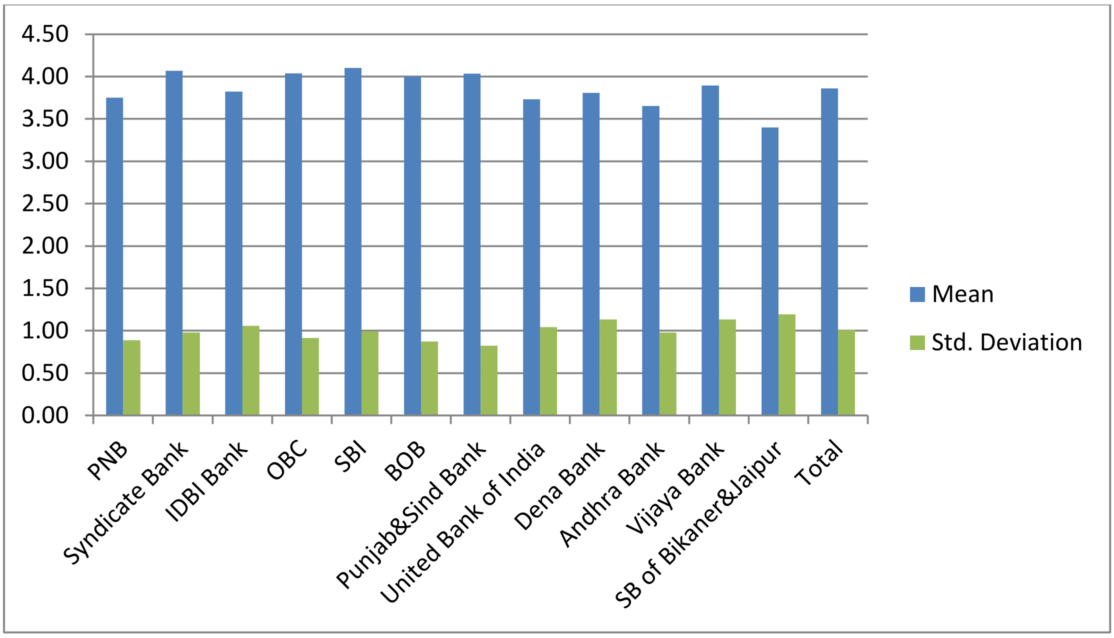

FIGURE7.9: BASEL II AS A RISK MANAGEMENT TOOL

TABLE 7.41: ANOVA (Q. 17 TO 19) BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

		Sum of Squares	df	Mean Square	F	Sig.
Q.17:Basel II is a business enhancement skill in risk mgt. and not merely a compliance issue	Between Groups	3.842	1	3.842	3.801	.052
	Within Groups	338.603	335	1.011		
	Total	342.445	336			
Q.18:The quantitative framework of Basel II is complex and difficult to train the staff	Between Groups	.697	1	.697	.585	.445
	Within Groups	398.835	335	1.191		
	Total	399.531	336			
Q.19:Basel II has helped in credit risk mitigation in bank	Between Groups	1.455	1	1.455	1.789	.182
	Within Groups	272.568	335	.814		
	Total	274.024	336			

TABLE 7.42: ANOVA (Q. 17 TO 19) BY LEVEL OF MANAGEMENT

		Sum of Squares	df	Mean Square	F	Sig.
Q.17:Basel II is a business enhancement skill in risk mgt. and not merely a compliance issue	Between Groups	1.018	2	.509	.498	.608
	Within Groups	341.427	334	1.022		
	Total	342.445	336			
Q.18:The quantitative framework of Basel II is complex and difficult to train the staff	Between Groups	3.410	2	1.705	1.438	.239
	Within Groups	396.121	334	1.186		
	Total	399.531	336			
Q.19:Basel II has helped in credit risk mitigation in bank	Between Groups	2.749	2	1.375	1.693	.186
	Within Groups	271.274	334	.812		
	Total	274.024	336			

TABLE 7.43:ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

		Sum of Squares	df	Mean Square	F	Sig.
Q.17:Basel II is a business enhancement skill in risk mgt. and not merely a compliance issue	Between Groups	3.559	2	1.779	1.754	.175
	Within Groups	338.886	334	1.015		
	Total	342.445	336			
Q.18:The quantitative framework of Basel II is complex and difficult to train the staff	Between Groups	11.921	2	5.960	5.136	.006
	Within Groups	387.610	334	1.161		
	Total	399.531	336			
Q.19:Basel II has helped in credit risk mitigation in bank	Between Groups	.099	2	.050	.060	.941
	Within Groups	273.925	334	.820		
	Total	274.024	336			

Question 18: Against the question that the quantitative framework of Basel II regulatory guidelines is complex and difficult to train the staff, only 51% agree, 32% disagree/ strongly disagree, and 17% are indecisive (response-cannot say) (Table 7.44). Highest agreement is from PNB, Dena Bank and SBI where respondent credit managers agree with the complicated and challenging form of Basel guidelines (Table 7.1). In total, largest agreement is coming from large PSBs, middle-level managers, and managers with more than 20 years' experience (Tables 7.7, 7.23 & 7.24) (Figures 7.11 to 13). Mean responses (Figure 7.10) show highest complexity being felt by the credit managers at the PNB and Dena Bank.

TABLE 7.44: Q.18-THE QUANTITATIVE FRAMEWORK OF BASEL II IS COMPLEX AND DIFFICULT TO TRAIN THE STAFF

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	14	4.2	4.2	4.2
Disagree	95	28.2	28.2	32.3
Cannot say	56	16.6	16.6	49.0
Agree	140	41.5	41.5	90.5
Strongly agree	32	9.5	9.5	100.0
Total	337	100.0	100.0	

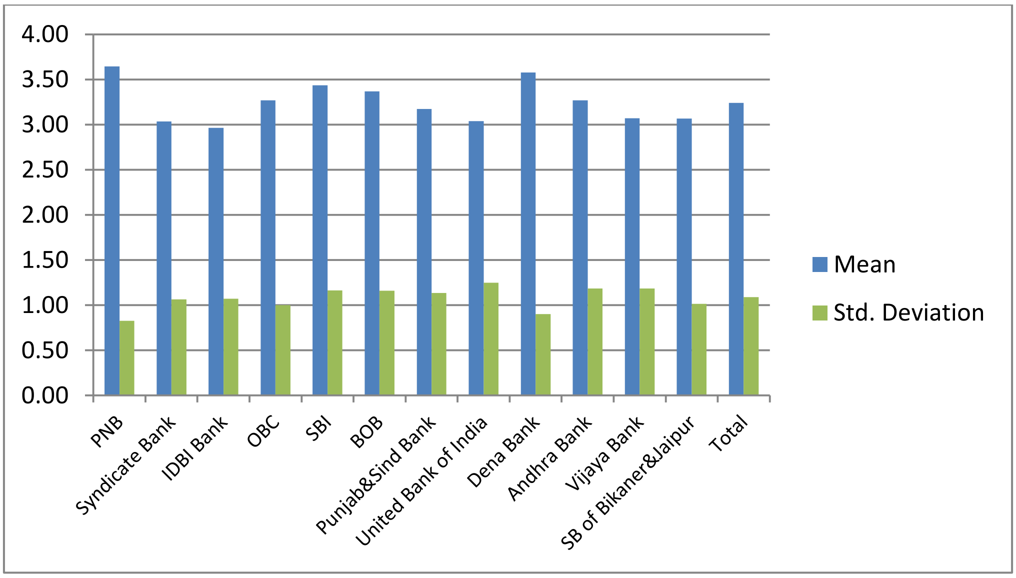

FIGURE 7.10: BASEL II IS A COMPLEX FRAMEWORK

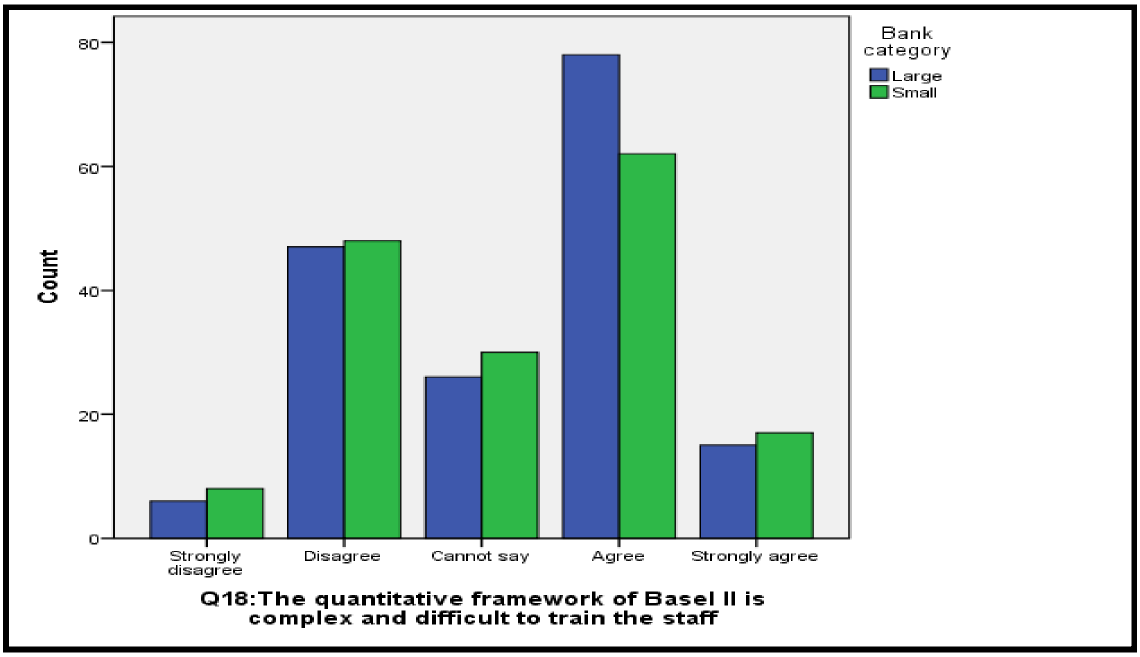

FIGURE 7.11: COMPARISON OF RESPONSES (LARGE BANKS VS. SMALL BANKS)

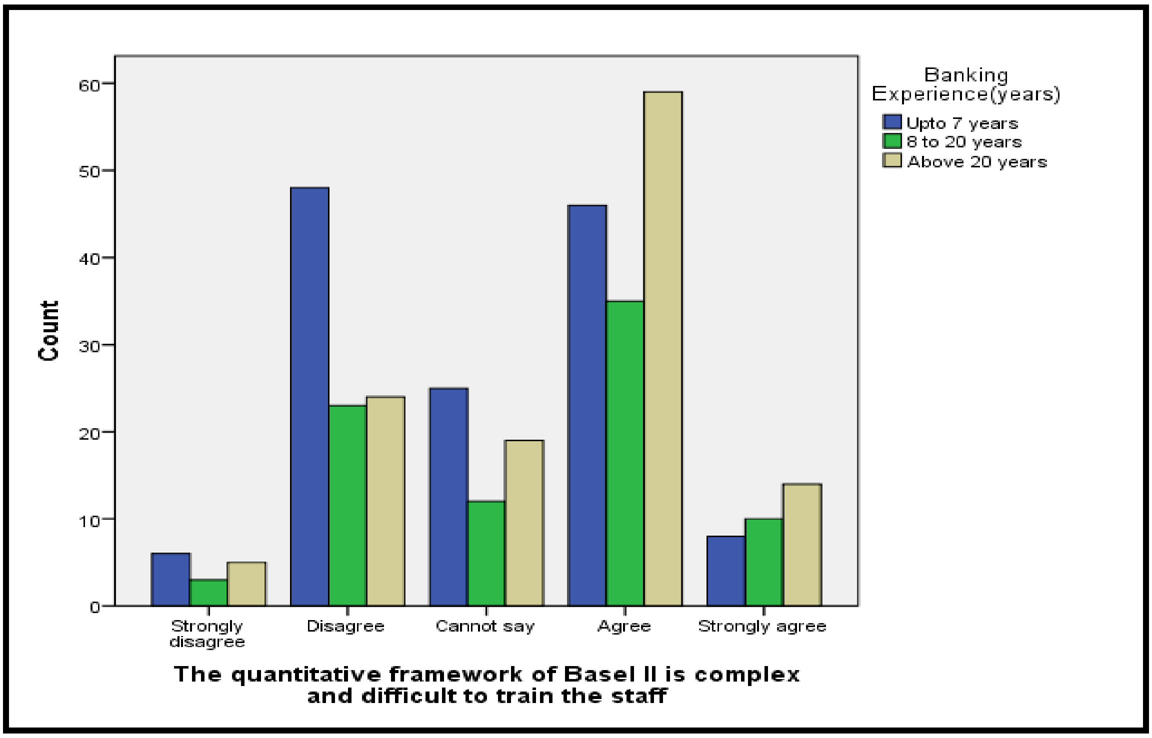

FIGURE 7.12: COMPARISON OF RESPONSES- MANAGEMENT EXPERIENCE-WISE

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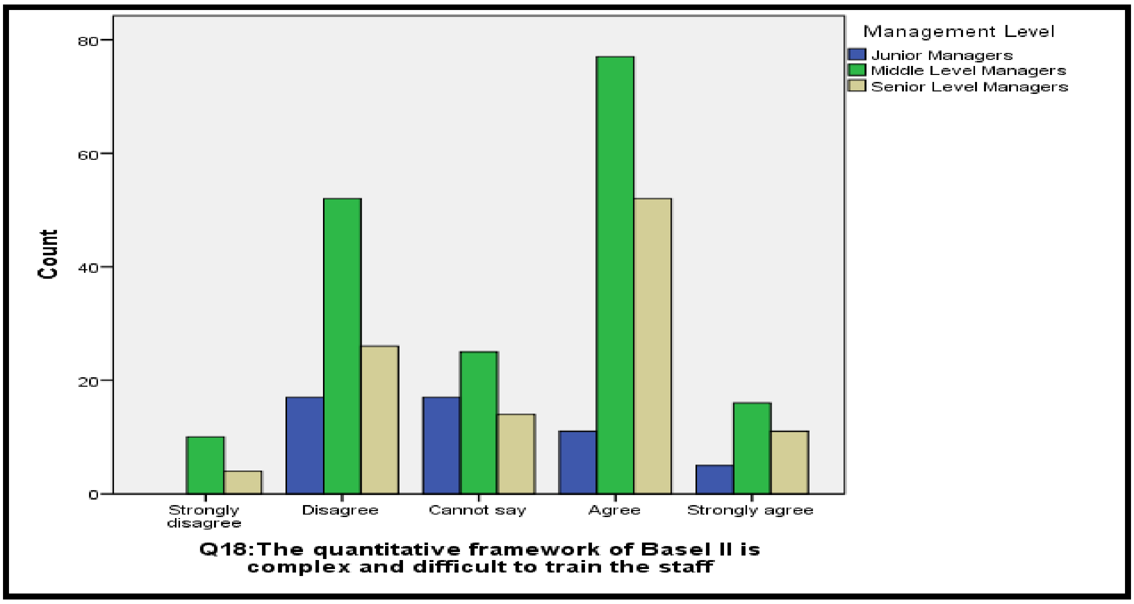

FIGURE 7.13: COMPARISON OF RESPONSES- MANAGEMENT LEVEL-WISE

ANOVA results are, however, significant only for groups of managers in different experience groups (Tables 7.41 to 7.43). Post hoc tests show the statistical difference only in 'up to 7 years' and 'above 20 years' experience groups of managers (Table 7.45).

TABLE 7.45: POST HOC TEST - MULTIPLE COMPARISONS

Dependent Variable: Q.18:The quantitative framework of Basel II is complex and difficult to train the staff

Tukey HSD

(I) Banking Experience(years)	(J) Banking Experience(years)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Up to 7 years	8 to 20 years	-.298	.151	.119	-.65	.06
	Above 20 years	-.423*	.135	.005	-.74	-.10
8 to 20 years	Upto 7 years	.298	.151	.119	-.06	.65
	Above 20 years	-.125	.154	.695	-.49	.24
Above 20 years	Upto 7 years	.423*	.135	.005	.10	.74
	8 to 20 years	.125	.154	.695	-.24	.49

*. The mean difference is significant at the 0.05 level.

Question 19: Against the question that the Basel II has helped in credit risk mitigation in banks, 78.8% agreed/strongly agreed (Table 7.46).

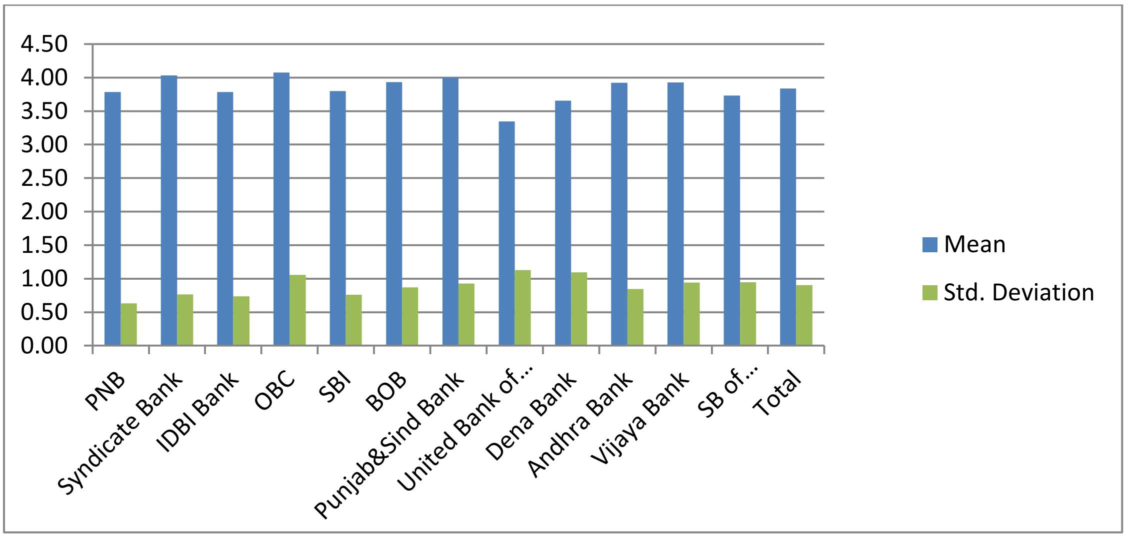

FIGURE 7.14: RISK MITIGATION THROUGH BASEL II-DESCRIPTIVE STATISTICS

Large banks' mean score (3.90) was higher than that of small banks' (3.77). The mean scores were higher for managers in 'up to 7 years' experience group (3.85), and for middle-level managers (3.91) (Tables 7.7, 7.23 and 7.24) (Figure 7.14). However, ANOVA results show no statistically significant difference in any of the groups (Tables 7.41 to 7.43).

TABLE 7.46: Q.19-BASEL II HAS HELPED IN CREDIT RISK MITIGATION IN BANK

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	4	1.2	1.2	1.2
Disagree	37	11.0	11.0	12.2
Cannot say	34	10.1	10.1	22.3
Agree	197	58.5	58.5	80.7
Strongly agree	65	19.3	19.3	100.0
Total	337	100.0	100.0	

7.5 RESULTS AND DISCUSSION

1. Large public sector banks have better compliance with Basel II IRB guidelines than the small public sector banks in developing internal credit risk rating models. Thus, as per credit managers' perception, the size of the bank has been a key discriminatory variable in the implementation of Basel norms in credit risk modeling.

2. Among small banks, Punjab & Sind Bank and the United Bank of India have been found to be under performers on many Basel II implementation variables.

3. Among seven variables tested, RAROC has been found to be the most differentiating factor among sample public sector banks. Punjab National Bank and Punjab & Sind Bank have yet to develop this framework. The mean scores for Dena Bank, United Bank of India, and the Andhra Bank are very less. Whereas Syndicate Bank, Bank of Baroda, Oriental Bank of Commerce, Vijaya Bank, IDBI Bank, SBI, and State Bank of Bikaner & Jaipur are measuring credit risk on each loan transaction through risk-adjusted return on capital (RAROC).

4. The managerial perceptions in credit and risk departments of the Indian public sector banks, about the utility of Basel II IRB guidelines as a business enhancement skill in risk management and credit risk mitigation, are quite encouraging. Though many of them also find the quantitative framework of these guidelines complex. The positive feedback for these prudential guidelines would have facilitated their implementation in these banks.

7.6 CONCLUSIONS

In this chapter, the Indian public sector banks preparedness to migrate to the Internal Rating Based Approach of Basel II has been studied through the perception of banks' credit managers. The study finds that the large public sector banks have a better compliance with these guidelines in their internal credit risk rating models than the small banks.

The next chapter shall be empirically evaluating the credit risk rating framework of the public sector banks in credit risk assessment.

CHAPTER 8
EVALUATION OF CREDIT RISK ASSESSMENT MODELS

8.1 INTRODUCTION

A key aspect of credit risk management is credit risk pricing based on a risk measurement system. Credit ratings based on estimates of external rating agencies like CRISIL, ICRA are a good indicator of default risk. Simultaneously, banks develop their internal rating models to sharpen their credit risk management efforts. Internal credit risk rating or credit-scoring is an important part of banks' credit risk management. The credit risk assessment score awarded by a bank to a business unit is a single point risk indicator of an individual credit exposure, which can measure and monitor credit risk. It becomes a tool in credit selection, risk-based pricing; and in terms of corporate, group or industry exposures, in tracking the quality of a bank's credit portfolio. The purpose of this chapter is to study the main features of public sector banks' internal credit risk assessment models for business loans to SMEs and mid-corporates, and statistically evaluate them based on primary data collected through a survey (Questions no. 3, 4, 12, 13, 15, 21 & 23). The data has been analyzed through frequencies, percentages, descriptive statistics, one- way analysis of variance (ANOVA) and Tukey's HSD post hoc tests.

8.2 FEATURES Of BANK'S CREDIT RATING MODELS.

Based on unstructured personal interviews with credit managers, and the analytical study of responses from a structured questionnaire, the study finds the following **main features** of the internal credit risk assessment models of the Indian public sector banks:

1. Basel II Compliant Internal Credit Rating Models

2. Outsourcing of Credit Rating Framework
3. Segmentation of Borrowers
4. Entry Barriers
5. Rating Grades
6. Risk Factors
7. Subjectivity in Assessment
8. Use of Statistical Models
9. Awareness of Other Banks' Risk Assessment Models
10. Public Disclosures of Rating Models
11. Stress Testing of Credit Risk
12. Sensitivity Analysis of Credit Risk
13. Importance of External Ratings
14. Evaluation of Credit Risk Assessment Framework

8.2.1 Basel II Compliant Internal Credit Rating Models

In compliance with the Central Bank's (RBI) Basel II guidelines, most of the Indian public sector banks have started developing internal credit risk rating models for risk differentiation by calculation of PD, LGD, EAD; risk-based pricing, and for calculation of capital adequacy ratios under the Foundation and Advanced approaches i.e., Internal Rating Based Approach of Basel II.

8.2.2 Outsourcing of Credit Rating Framework

Some banks like SBI and its associate banks, and Andhra Bank, United Bank of India have in-house credit rating framework but larger number of other public sector banks (PSBs) have vendor-developed, software-driven credit risk assessment models, especially from CRISIL and ICRA, the external rating agencies.

8.2.3 Segmentation of Borrowers

For risk specialization, banks segment their borrowers in many categories namely, Large Corporates, Mid-corporates, SMEs, Large Traders, Real Estate Developers, Large Brokers, Infrastructure Sector, Greenfield Projects, etc. This segmentation has helped them in assessing the unique risk characteristics of the counterparties.

8.2.4 Entry Barriers

Many public sector banks have created entry barriers for loan applicants. For example, borrowers whose management has doubtful integrity or who lack environmental clearances or who appear negative in RBI's Defaulters lists, etc. are not assessed.

8.2.5 Rating Grades

The banks' internal credit rating models (Figure 8.1) generate two-dimensional ratings i.e., **borrower's rating** indicating his risk category or Probability of Default; and transaction-specific or **facility rating** reflecting Loss Given Default. The composite rating showes **Expected Loss** on a loan transaction on the scale of 0-10 or 0-100, from highest safety to highest risk/caution/default levels. Facility rating includes both fund based and non-fund based facility (bank loans) ratings. Fund based means term loans and working capital loans. Non-fund based means bank guarantees and letters of credit. Based on composite ratings or scores, borrowers are divided into 8 to 16 risk categories indicating his investment grading, sub-investment or non-investment grading, for loan approvals and loan pricing (Table 8.1). Big banks like SBI and its associates have 16 risk categories, Punjab National Bank has 15, and other banks have eight to10 categories.

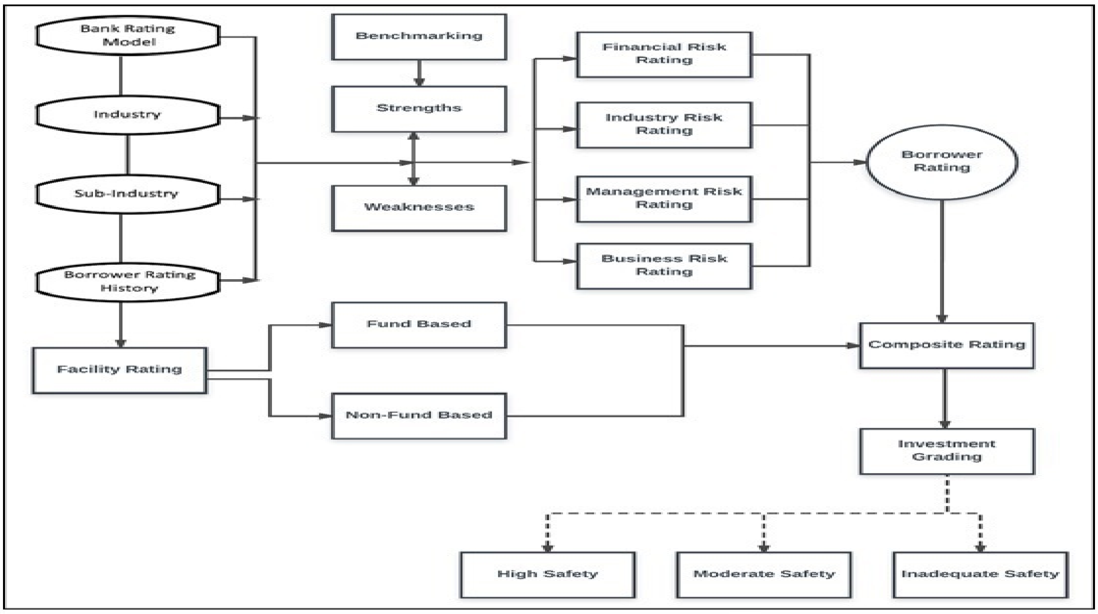

FIGURE 8.1: INTERNAL CREDIT RATING PROCESS IN INDIAN PSBs

(Source: Personal Interviews with Credit Managers)

TABLE 8.1: CREDIT RISK CATEGORIES IN INDIAN PSBs

S.No.	Borrower Rating	Range of Scores	Risk Level
1.	CR-1	94-100	Absolute Safety
2.	CR-2	90-93	High Safety
3.	CR-3	86-89	High Safety
4.	CR-4	81-85	High Safety
5.	CR-5	76-80	Adequate Safety
6.	CR-6	70-75	Moderate Safety
7.	CR-7	64-69	Safety
8.	CR-8	57-63	Safety
9.	CR-9	50-56	Safety
10.	CR-10	45-49	Safety
11.	**CR-11**	**40-44**	**Inadequate Safety**
12.	**CR-12**	**35-39**	**Low Safety**
13.	**CR-13**	**30-34**	**Low Safety**
14.	**CR-14**	**25-29**	**Low Safety**
15.	**CR-15**	**24**	**Caution/Default Grade**
16.	**CR-16**	**Less than 24**	**Default Grade**

(Source: Personal interviews with credit managers)

8.2.6 Risk Factors

These rating models capture borrower's risk under four parameters, financial risk, industry risk, business risk and management risk, covering 30 to 80 risk factors by different banks (Table 8.2). The weighting scheme for various risk parameters and for each risk factor differ considerably across banks. Though most banks assign 40% to 60% to financial risk parameters, and remaining points to qualitative risk parameters, like business, industry and management risk.

8.2.7 Subjectivity in Assessment

Financial risk assessment is based on annual financial statements and has objective evaluation. Whereas assessment of other risk factors relies on subjective rationalization of risk-raters, risk-validators and credit analysts of these banks.

8.2.8 Use of Statistical Models

Since the credit rating models in Indian public sector banks are software-driven, the use of statistical tools in risk rating could not be established. The survey (Question no. 15), on kind of statistical tools used in their internal credit risk rating models (Table 8.3.I to V), revealed that:

- 94% had no knowledge of use of Altman's Z-score Model.
- 98% of KMV Credit Monitor Model.
- 72% of use of Credit Risk + Model.
- 92% of Mckinsey's Credit Portfolio View.
- 95.5% of Black and Scholes' Option Pricing Model.

Table 8.2: LIST OF FACTORS IN CREDIT RISK RATINGS MODELS OF INDIAN PUBLIC SECTOR BANKS (I-IV)

I. FINANCIAL RISK FACTORS		II. MANAGEMENT RISK FACTORS	
1	Total Outside Liabilities/Tangible Net Worth (TOL/TNW). TNW is share capital + reserves – intangible assets.	1	Integrity
2	Current Ratio (Current Assets/Current Liabilities)	2	Track record/ conduct of account
3	Return on Capital Employed	3	Managerial Competence/Commitment/Expertise
4	Retained Profits/Total Assets	4	Payment record/ Banking relationships
5	PBDIT (Profit before Depreciation, Interest & Taxes)/Interest	5	Structure and systems
6	Debt Service Coverage Ratio (PAT + Interest/Installments + Interest)	6	Experience in the industry
7	PAT (Profit after Taxes) /Net Sales or Net Profit Margin	7	Strategic initiative
8	Net Cash Accruals (Net Profit + Depreciation+ Misc. Expenses Written off – Dividend)/Total Debt	8	Length of relationship with banks
9	Receivable Turnover (Net Credit Sales/Average Receivables)	9	Credibility or ability to achieve sales/profit projection
10	Inventory Turnover (Cost of Goods Sold/Average Inventory)	10	Past success in introducing new products
11	Average annual increase in sales	11	Ability to manage change
12	Financial Flexibility	12	Risk appetite level
13	Group Risk	13	Succession plan/key persons
14	Foreign Exchange Risk	14	Adherence to covenants of sanction
15	Contingent Liabilities	15	Business and financial policy
16	Accounting Quality	16	Quality of information submitted by the company
17	Ability To Raise Debt	17	Working capital management
18	Ability To Raise Equity	18	Labour relations/Management-employee relations
19	Contingent Liabilities as percent of TNW	19	Litigation against the entity
20	Internal Rate of Return	20	Credentials and background of the promoters
21	Peak Debt/Equity ratio	21	Constitution/management/ownership pattern
22	Peak level working capital	22	Corporate governance
23	Repayment period in years	23	Risk-bearing capacity
24	Sensitivity analysis	24	Capital market perception of the group

III. INDUSTRY AND BUSINESS RISK FACTORS			
1	Industry Outlook/Prospects	21	Research development and innovation
2	Industry Cyclicality	22	Level of integration
3	Industry Financials (ROCE %, Operating Margin, Growth in Operating Margin)	23	Debtor's velocity
4	Industry Characteristics	24	Patent and proprietary technology
5	Compliance with Environmental Regulations	25	Dependence on imports
6	Regulatory risk	26	Regional rating in States
7	Business environment	27	Distribution network
8	Vulnerability to macroeconomic factors	28	User/product profile/product range
9	Infrastructure risk	29	Threat of substitutes
10	Restructuring	30	Diversified markets
11	Competition	31	Financial position to withstand price competition
12	Energy cost saving	32	Customization of product
13	Multi-locational advantage	33	Brand equity
14	Availability of skilled labour	34	Long-term contracts/assured off-take
15	Capacity utilization	35	Proximity to markets
16	Access to cost-effective technology	36	Nature of economy of export country
17	Key Input risk/access to resources	37	Assessment of the immediate buyers
18	Raw material usage	38	Demand for the product
19	Hygienic processing facilities	39	Selling cost
20	Consistency in quality		
IV. FACILITY RISK FACTORS			
Type and Value of collaterals			

(Source: Personal interviews with credit managers)

TABLE 8.3.I: Q.15A-ALTMAN MODEL

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	155	46.0	46.0	46.0
Not sure	162	48.1	48.1	94.1
Yes	20	5.9	5.9	100.0
Total	337	100.0	100.0	

TABLE 8.3.II: Q.15B-KMV MODEL

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	161	47.8	47.8	47.8
Not sure	169	50.1	50.1	97.9
Yes	7	2.1	2.1	100.0
Total	337	100.0	100.0	

TABLE 8.3.III: Q.15C-CREDIT RISK +

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	110	32.6	32.6	32.6
Not sure	133	39.5	39.5	72.1
Yes	94	27.9	27.9	100.0
Total	337	100.0	100.0	

TABLE 8.3.IV: Q.15D-CREDIT PORTFOLIO VIEW

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	144	42.7	42.7	42.7
Not sure	166	49.3	49.3	92.0
Yes	27	8.0	8.0	100.0
Total	337	100.0	100.0	

TABLE 8.3.V: Q.15E-OPTION PRICING MODEL

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	153	45.4	45.4	45.4
Not sure	169	50.1	50.1	95.5
Yes	15	4.5	4.5	100.0
Total	337	100.0	100.0	

In other words, these theoretical models are not part of credit risk rating by the Indian public sector banks, and if they are, it has not been disclosed by their software developing vendors.

8.2.9 Awareness of Other Banks' Risk Assessment Models

The internal rating models are closely held by the public sector banks, but during consortium/multiple loans inter-bank meetings, and discussions with borrowers, their rating frameworks get widely known to all the stakeholders. During the survey (Question no. 3), against the question "Is the bank aware of strength and weaknesses of its risk management system vis-à-vis, other banks", 92.28% of the respondents agreed/strongly agreed (Figure 8.2).

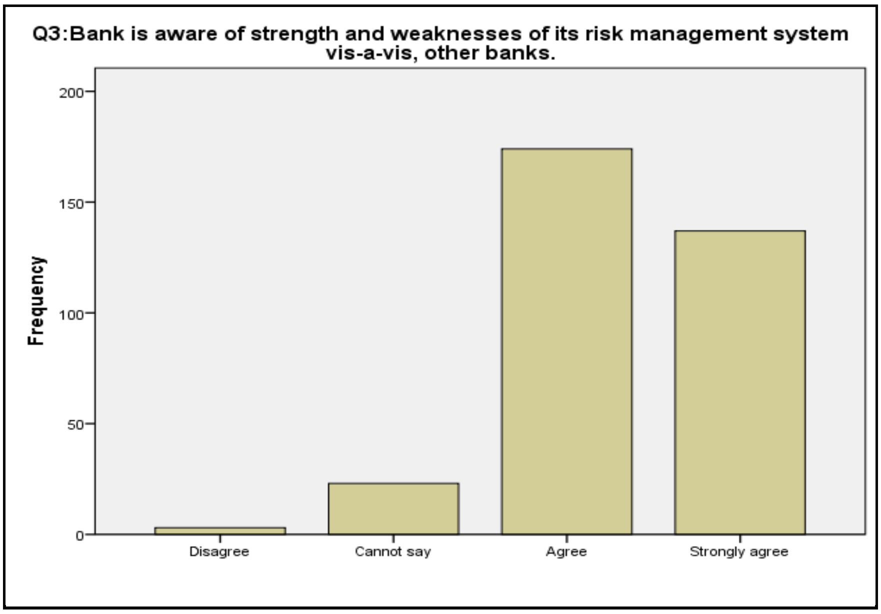

FIGURE 8.2: AWARENESS OF OTHER BANKS' RISK MANAGEMENT SYSTEMS

TABLE 8.4: AWARENESS ABOUT RISK MANAGEMENT SYSTEMS OF OTHER BANKS

		Q.: Bank is aware of strength and weaknesses of its risk management system vis-a-vis, other banks.				Total
		Disagree	Cannot say	Agree	Strongly agree	
Management Level	Junior Managers	0	5	29	16	50
	Middle Level Managers	2	17	90	71	180
	Senior Level Managers	1	1	55	50	107
Total		3	23	174	137	337

Moreover, this awareness is at all levels of management, indicating high sharing of information among them (Table 8.4). Since there has been strong competition among these banks to procure profitable loan proposals, knowledge of other banks' risk management systems would have improved banks' competitive strength.

8.2.10 Public Disclosures of Rating Models

Against the question (Question no. 4) whether public disclosures of credit risk rating models shall be undertaken to match risk perceptions of lenders and borrowers, only 62.91% agreed/strongly agreed (Table 8.5) (Figure 8.3).

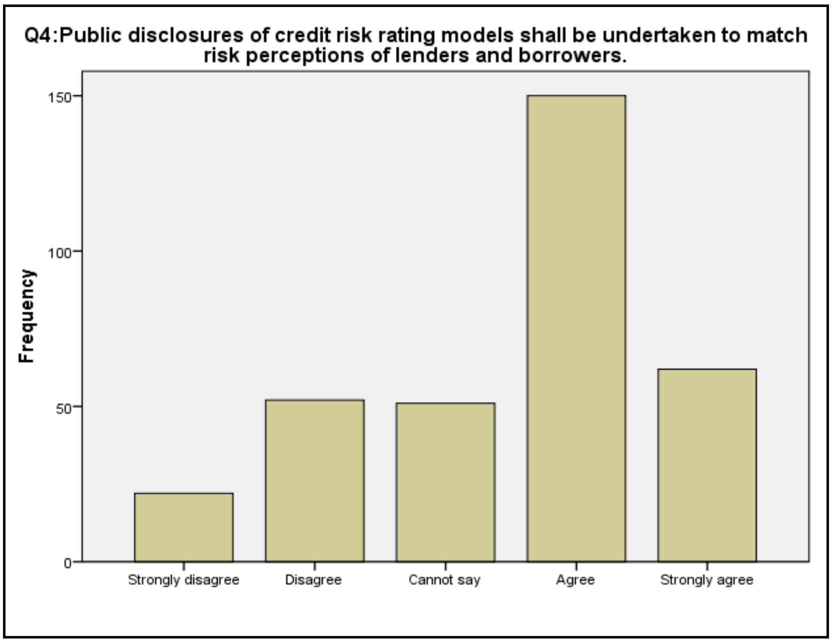

FIGURE 8.3: RESPONSES ON PUBLIC DISCLOSURES OF CREDIT RATING MODELS

TABLE 8.5: PUBLIC DISCLOSURE OF CREDIT RATING MODELS

		Q.: Public disclosures of credit risk rating models shall be undertaken to match risk perceptions of lenders and borrowers.					**Total**
		Strongly disagree	**Disagree**	**Cannot say**	**Agree**	**Strongly agree**	
Management Level	Junior Managers	3	9	11	21	6	50
	Middle Level Managers	12	22	30	82	34	180
	Senior Level Managers	7	21	10	47	22	107
Total		22	52	51	150	62	337

Those who agreed were mostly the middle-level managers. Those who were against it may be to avoid window dressing of credit requests by the borrowers.

8.2.11 Stress Testing of Credit Risk

Stress testing helps banks to estimate the likely credit losses under exceptional but plausible scenarios. It is an important tool of corporate risk governance, to measure and control credit portfolio of a bank to a given risk factor(s), mainly macroeconomic variables, and identifies credit risk concentration and its impact on the main financial ratios of banks.

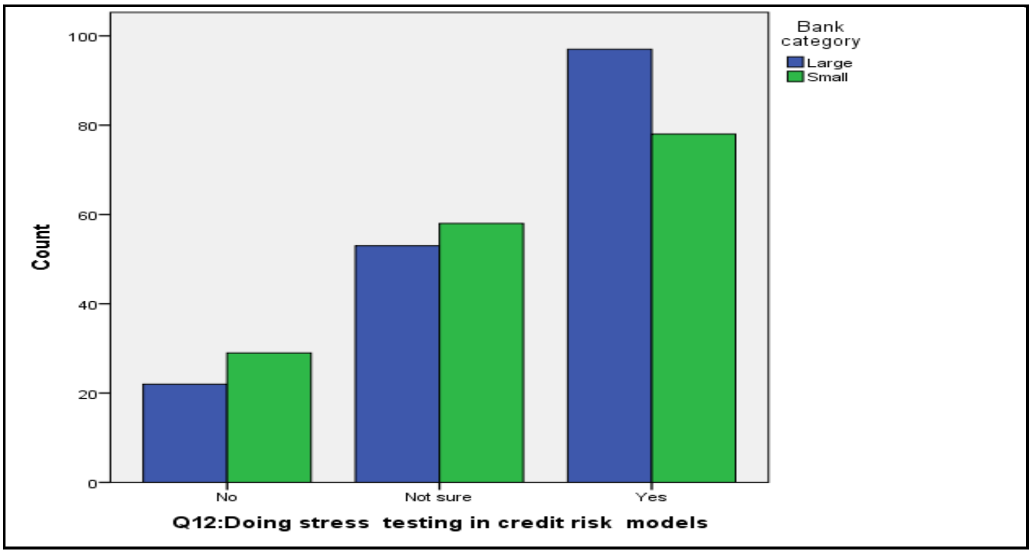

FIGURE 8.4: STRESS TESTING BY PUBLIC SECTOR BANKS

Only 51.93 % respondents agreed that the banks were doing stress testing on credit risk models (Table 8.6). Those who agreed belonged more to the large banks than to the small banks (Figure 8.4).

TABLE 8.6: Q.12: DOING STRESS TESTING IN CREDIT RISK MODELS

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	51	15.1	15.1	15.1
Not sure	111	32.9	32.9	48.1
Yes	175	51.9	51.9	100.0
Total	337	100.0	100.0	

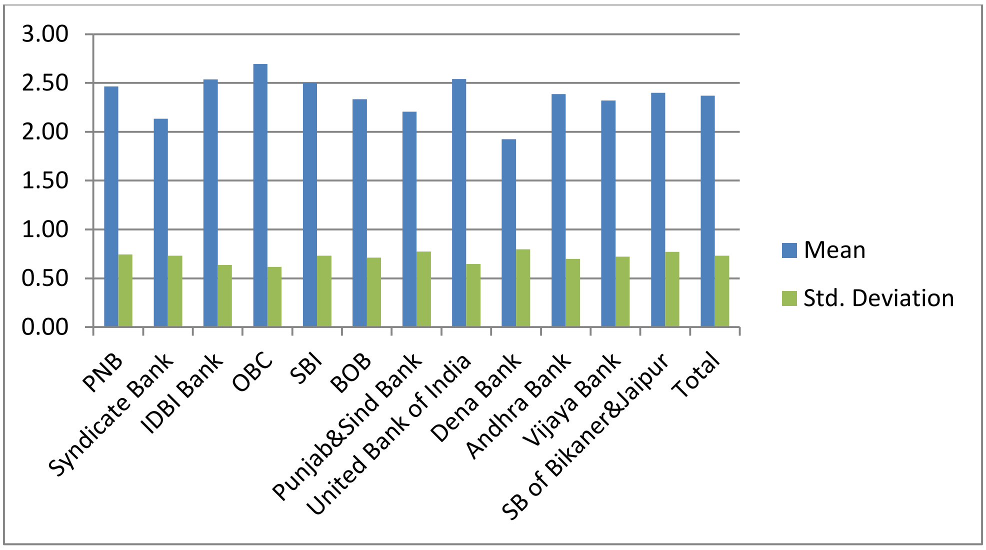

FIGURE 8.5: STRESS TESTING- MEAN & STANDARD DEVIATION

A further study was undertaken on mean scores (Table 8.7 & Figure 8.5) to find which group of managers had more favorable replies, through one-way variance analysis (ANOVA), on three independent variables viz. managers in large or small public sector banks, managers with different length of experience or managers at junior, middle or senior levels (Tables 8.8, 8.9, to 8.11). Tukey's post hoc tests were also undertaken to find which sub-management group was causing significant mean score differences (Tables 8.10 & 8.12).

ANOVA and Post hoc tests' findings indicate:

a. There is no significant mean score difference between managers of large and small public sector banks (Tables 8.8 & 8.13).

b. There is a significant difference in mean scores of managers of banking experience groups, i.e., 'up to 7 years', '8 to 20 years' and 'above 20 years'. The F statistic is 4.240 (df 2, 334), at p= 0.015 (Table 8.8). Post hoc tests of multiple comparisons, find significant differences between managers of 'up to 7 years and 8 to

20 years' and 'up to 7 years and above 20 years' experience groups. (Table 8.10). Mean scores for three experience groups are 2.23, 2.46 and 2.46 (Table 8.14). Mean scores for medium and high experience groups are equal.

TABLE 8.7: MEAN AND STANDARD DEVIATION VALUES- BANK WISE

BANK NAME		Q.12: Doing stress testing.	Q.13: Doing sensitivity analysis.	Q.21: Rely on the external credit ratings?	Q.23: Effectiveness of Credit rating models.
	Mean	2.46	2.89	3.46	3.71
PNB	N	28	28	28	28
	Std. Deviation	.744	.416	1.261	.763
	Mean	2.13	2.80	3.80	3.67
Syndicate Bank	N	30	30	30	30
	Std. Deviation	.730	.551	.805	.758
	Mean	2.54	2.68	3.36	3.71
IDBI Bank	N	28	28	28	28
	Std. Deviation	.637	.612	.989	.763
	Mean	2.69	2.96	4.62	3.50
OBC	N	26	26	26	26
	Std. Deviation	.618	.196	.496	.812
	Mean	2.50	2.73	3.83	3.87
SBI	N	30	30	30	30
	Std. Deviation	.731	.640	.986	.629
	Mean	2.33	2.63	4.03	3.83
BOB	N	30	30	30	30
	Std. Deviation	.711	.718	1.033	.791
	Mean	2.21	2.83	3.86	3.28
Punjab &Sind Bank	N	29	29	29	29
	Std. Deviation	.774	.384	1.156	1.222
	Mean	2.54	2.77	3.54	2.85
United Bank of India	N	26	26	26	26
	Std. Deviation	.647	.514	.989	1.084
	Mean	1.92	2.88	4.15	3.00
Dena Bank	N	26	26	26	26
	Std. Deviation	.796	.588	.368	.849
	Mean	2.38	2.92	3.62	2.77
Andhra Bank	N	26	26	26	26
	Std. Deviation	.697	.392	.941	.815
	Mean	2.32	2.75	4.25	3.00
Vijaya Bank	N	28	28	28	28
	Std. Deviation	.723	.701	.887	.943

	Mean	2.40	2.67	3.90	3.57
SB of Bikaner &Jaipur	N	30	30	30	30
	Std. Deviation	.770	.661	1.094	.817
	Mean	2.37	2.79	3.87	3.41
Total	N	337	337	337	337
	Std. Deviation	.733	.556	.998	.932

TABLE 8.8: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.12:Doing stress testing in credit risk models

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	1.629	1	1.629	3.053	.082
Within Groups	178.745	335	.534		
Total	180.374	336			

TABLE 8.9: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.12:Doing stress testing in credit risk models

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	4.466	2	2.233	4.240	.015
Within Groups	175.908	334	.527		
Total	180.374	336			

TABLE 8.10: POST HOC TEST - MULTIPLE COMPARISONS

Dependent Variable: Q.12:Doing stress testing in credit risk models

Tukey HSD

(I) Banking Experience(years)	**(J) Banking Experience(years)**	**Mean Difference (I-J)**	**Std. Error**	**Sig.**	**95% Confidence Interval**	
					Lower Bound	**Upper Bound**
Up to 7 years	**8 to 20 years**	**-.244***	**.102**	**.044**	-.48	-.01
	Above 20 years	**-.229***	**.091**	**.033**	-.44	-.01
8 to 20 years	Up to 7 years	.244*	.102	.044	.01	.48
	Above 20 years	.015	.103	.988	-.23	.26
Above 20 years	Up to 7 years	.229*	.091	.033	.01	.44
	8 to 20 years	-.015	.103	.988	-.26	.23

*. The mean difference is significant at the 0.05 level.

TABLE 8.11: ANOVA BY LEVEL OF MANAGEMENT

Q.12:Doing stress testing in credit risk models

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.754	2	1.877	3.549	.030
Within Groups	176.620	334	.529		
Total	180.374	336			

TABLE 8.12: POST HOC TEST - MULTIPLE COMPARISONS

Dependent Variable: Q.12:Doing stress testing in credit risk models

Tukey HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle Level Managers	-.102	.116	.654	-.38	.17
	Senior Level Managers	-.294*	.125	.049	-.59	.00
Middle Level Managers	Junior Managers	.102	.116	.654	-.17	.38
	Senior Level Managers	-.192	.089	.080	-.40	.02
Senior Level Managers	**Junior Managers**	**.294***	**.125**	**.049**	.00	.59
	Middle Level Managers	.192	.089	.080	-.02	.40

*. The mean difference is significant at the 0.05 level.

c. Significant differences in mean scores of managers of three levels of management- junior, middle and senior levels have also been found. The F statistic is 3.549 (df 2, 334) at p= 0.030 (Table 8.11). Post hoc tests find significant difference in perception of junior and senior managers only, and not between them with middle-level managers (Table 8.12). Mean scores by junior managers are 2.22, middle-level managers 2.32 and of senior level managers 2.51 (Table 8.15).

d. Thus, managers in higher experience groups and at senior managerial levels are actively engaged in stress testing.

TABLE 8.13: DESCRIPTIVE STATISTICS (LARGE BANKS VS. SMALL BANKS)

Bank category		Q.12:Doing stress testing in credit risk models	Q.13:Doing sensitivity analysis in credit risk rating models	Q.21: Should the bank rely on the external credit ratings?	Q.23: Credit rating models of the bank are effective in capturing the credit risk.
Large	Mean	2.44	2.78	3.84	3.72
	N	172	172	172	172
	Std. Deviation	.710	.560	1.028	.752
Small	Mean	2.30	2.76	3.89	3.09
	N	165	165	165	165
	Std. Deviation	.751	.554	.969	.993
Total	Mean	2.37	2.77	3.87	3.41
	N	337	337	337	337
	Std. Deviation	.733	.556	.998	.932

TABLE 8.14: DESCRIPTIVE STATISTICS (MANAGERIAL EXPERIENCE LEVELS)

Banking Experience(years)		Q.12:Doing stress testing in credit risk models	Q.13:Doing sensitivity analysis in credit risk rating models	Q.21: Should the bank rely on the external credit ratings?	Q.23: Credit rating models of the bank are effective in capturing the credit risk.
Up to 7 years	Mean	2.23	2.68	3.82	3.36
	N	133	133	133	133
	Std. Deviation	.724	.691	.960	.956
8 to 20 years	Mean	2.46	2.80	3.95	3.56
	N	82	82	82	82
	Std. Deviation	.773	.483	.942	.904
20 years and above	Mean	2.46	2.90	3.86	3.37
	N	122	122	122	122
	Std. Deviation	.694	.394	1.078	.920
Total	Mean	2.37	2.79	3.87	3.41
	N	337	337	337	337
	Std. Deviation	.733	.556	.998	.932

TABLE 8.15: DESCRIPTIVE STATISTICS (MANAGEMENT LEVELS)

Management Level		Q.12:Doing stress testing in credit risk models	Q.13:Doing sensitivity analysis in credit risk rating models	Q.21: Should the bank rely on the external credit ratings?	Q.23: Credit rating models of the bank are effective in capturing the credit risk.
Junior Managers	Mean	2.22	2.60	3.86	3.58
	N	50	50	50	50
	Std. Deviation	.764	.700	1.069	.883

Middle Level Managers	Mean	2.32	2.81	3.84	3.41
	N	180	180	180	180
	Std. Deviation	.722	.550	.979	.955
Senior Level Managers	Mean	2.51	2.85	3.91	3.35
	N	107	107	107	107
	Std. Deviation	.719	.472	1.005	.912
Total	Mean	2.37	2.79	3.87	3.41
	N	337	337	337	337
	Std. Deviation	.733	.556	.998	.932

8.2.12 Sensitivity Analysis of Credit Risk

Sensitivity analysis or what-if analysis is used in credit risk assessment to determine how projected performance of a borrower will respond to changed assumptions, for the tenure of the loan. It measures risk profile of the borrower, and its sensitivity to economic, industrial, and market developments, such as expected profit, sales, cash generation, stock position, working capital gap, net worth, etc. Sensitivity analysis is undertaken by banks mostly at different levels of activity or production and sales, to understand borrowers' projected key financials.

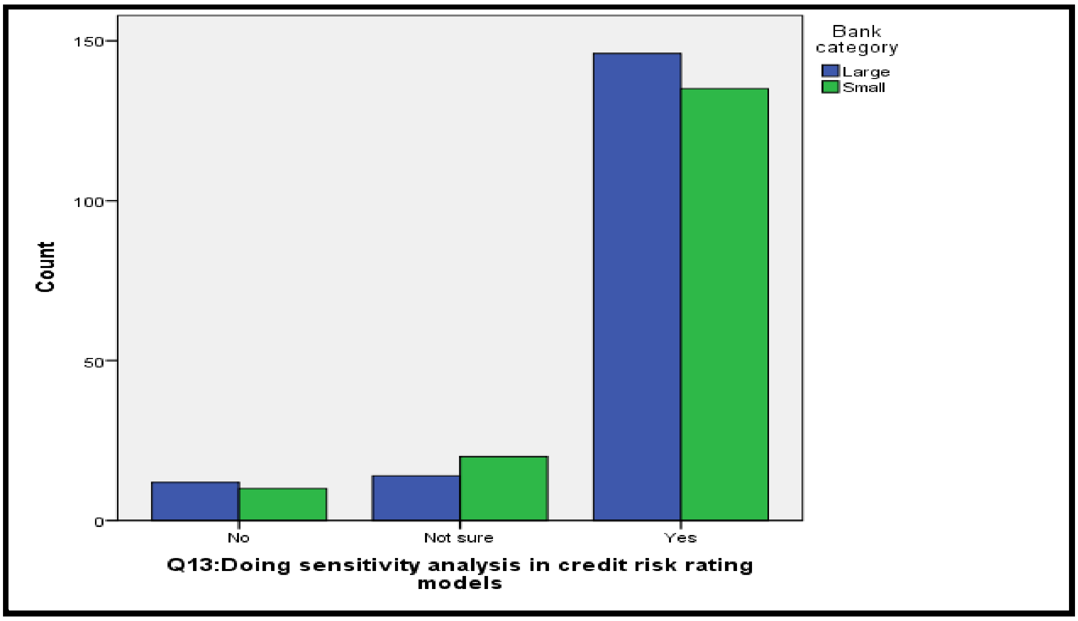

FIGURE 8.6: SENSITIVITY ANALYSIS BY PUBLIC SECTOR BANKS

The survey on sample credit managers on whether the banks are doing sensitivity analysis in credit risk rating models for business loans, found 83.4 % agreed/ strongly agreed (Table 8.16), with about equal proportion in large and small banks (Figure 8.6). Thus sensitivity analysis, a powerful tool for credit risk management is being given due importance by the Indian public sector banks.

TABLE 8.16: Q.13-DOING SENSITIVITY ANALYSIS IN CREDIT RISK RATING MODELS

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
No	22	6.5	6.5	6.5
Not sure	34	10.1	10.1	16.6
Yes	281	83.4	83.4	100.0
Total	337	100.0	100.0	

Further study was undertaken on mean scores (Table 8.7 & Figure 8.7) to find which group of managers had more favorable replies. Study was conducted through one-way variance analysis (ANOVA), on three independent variables viz. managers in large or small public sector banks, managers with different length of experience or managers at junior, middle or senior levels (Tables 8.17, 8.18 and 8.20). Tukey's post hoc tests were also undertaken to find which sub-group was causing significant mean score differences (Tables 8.19 & 8.21).

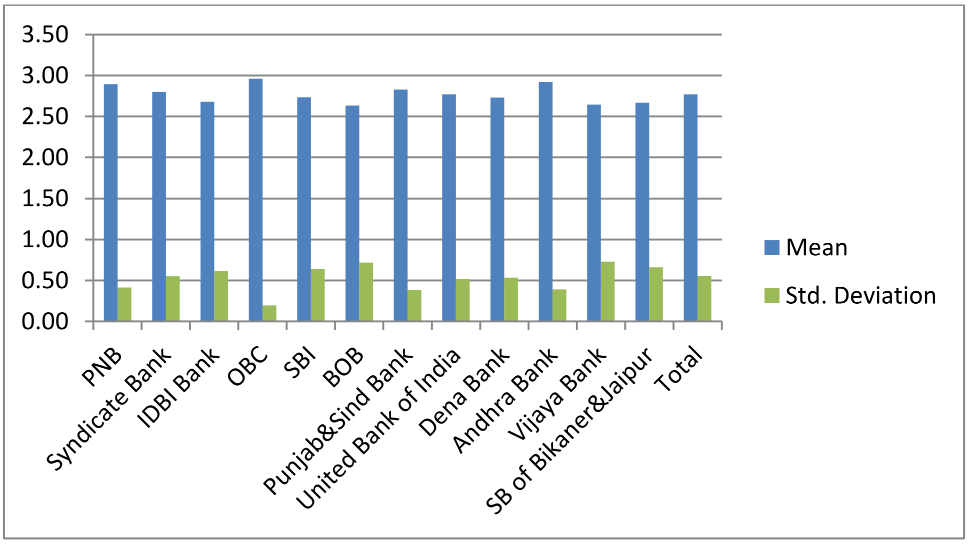

FIGURE 8.7: SENSITIVITY ANALYSIS – MEAN & STANDARD DEVIATION

ANOVA findings indicate:

a. No significant mean score difference between managers of large and small banks (Table 8.17).

b. Significant difference in mean scores of managers of three levels of banking experience i.e., ‘up to 7 years’, ‘8 to 20 years’ and ‘above 20 years’. The F statistic is 8.471 (df 2, 334), at p= 0.000 (Table 8.17). Post hoc tests for multiple comparisons find significant differences between perceptions of managers of ‘up to 7 years and above 20 years’ and between managers of ‘up to 7 years and 8 to 20 years’ experience groups. (Table 8.19). Mean scores of three groups are 2.68, 2.80 and 2.90 (Table 8.14) indicating more awareness at senior positioned credit managers levels than at lower and middle levels.

c. Significant differences in mean scores of managers of three levels of management- junior, middle and senior levels. The F statistic is 3.509 (df 2, 334), at p= 0.031 (Table 8.20). Post hoc tests find significant difference in perception of junior and senior managers only, and not between them with middle level managers (Table 8.21). Mean scores of three managerial levels are 2.60, 2.81 and 2.85. (Table 8.15), again indicating significantly more awareness at higher managerial levels.

TABLE 8.17: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.13: Doing sensitivity analysis in credit risk rating models

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.039	1	.039	.125	.723
Within Groups	103.908	335	.310		
Total	103.947	336			

TABLE 8.18: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.13: Doing sensitivity analysis in credit risk rating models

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.018	2	2.509	8.471	.000
Within Groups	98.929	334	.296		
Total	103.947	336			

TABLE 8.19: POST-HOC TESTS - MULTIPLE COMPARISONS

Dependent Variable: Q.13: Doing sensitivity analysis in credit risk rating models

Tukey HSD

(I) Banking Experience(years)	(J) Banking Experience(years)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Up to 7 years	8 to 20 years	-.183*	.076	.044	-.36	.00
	Above 20 years	-.277*	.068	.000	-.44	-.12
8 to 20 years	Up to 7 years	.183*	.076	.044	.00	.36
	Above 20 years	-.094	.078	.450	-.28	.09
Above 20 years	Up to 7 years	.277*	.068	.000	.12	.44
	8 to 20 years	.094	.078	.450	-.09	.28

*. The mean difference is significant at the 0.05 level.

TABLE 8.20: ANOVA BY LEVEL OF MANAGEMENT

Q.13: Doing sensitivity analysis in credit risk rating models

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.139	2	1.070	3.509	.031
Within Groups	101.807	334	.305		
Total	103.947	336			

TABLE 8.21: POST-HOC TESTS - MULTIPLE COMPARISONS

Dependent Variable: Q.13: Doing sensitivity analysis in credit risk rating models

Tukey HSD

(I) Management Level	(J) Management Level	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Junior Managers	Middle Level Managers	-.167	.088	.144	-.37	.04
	Senior Level Managers	-.250*	.095	.023	-.47	-.03
Middle Level Managers	Junior Managers	.167	.088	.144	-.04	.37
	Senior Level Managers	-.084	.067	.428	-.24	.07
Senior Level Managers	Junior Managers	.250*	.095	.023	.03	.47
	Middle Level Managers	.084	.067	.428	-.07	.24

*. The mean difference is significant at the 0.05 level.

8.2.13 Importance of External Ratings

Bank Loan Ratings (BLRs) by the external rating agencies accredited by the Reserve Bank of India, such as CRISIL, ICRA, SMERA, etc. are considered by the Indian banks in deciding creditworthiness of their borrowers. In fact, the Standardized Approach of Basel II norms for calculation of risk weights of regulatory capital or capital adequacy ratios for banks is based on external ratings of banks' credit exposures. The internal credit rating models of the banks give weight to external ratings of the borrowers through mapping or conversion of external ratings into credit scores, though there are wide or extensive practices followed by the Indian PSBs in this regard. Some banks like SBI do not add credit score for external ratings but consider them in final credit approvals. Few banks like PNB prepare variance reports against external and internal ratings, and give reasons for difference in ratings.

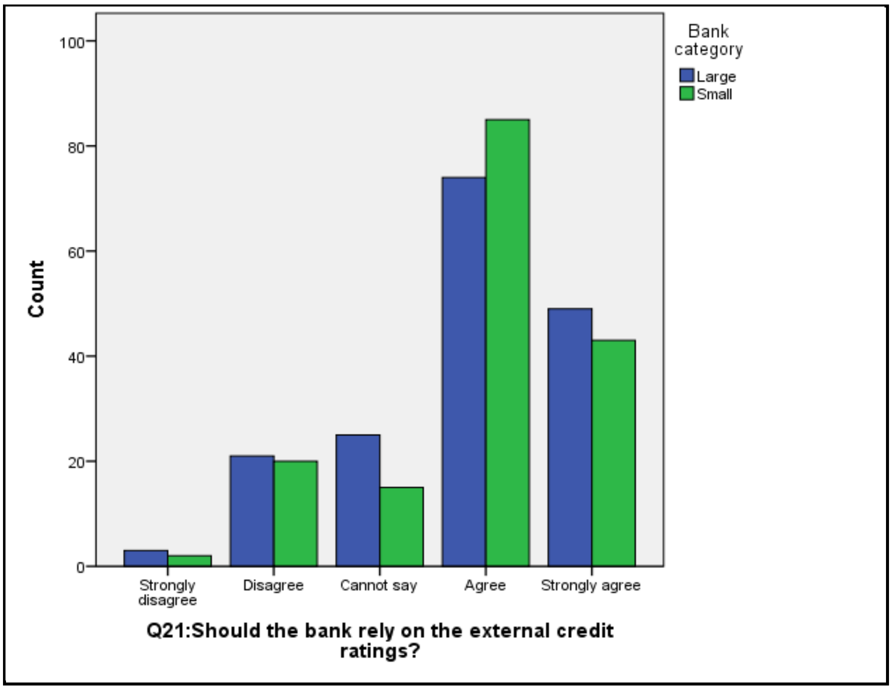

FIGURE 8.8: IMPORTANCE OF EXTERNAL RATINGS

The survey among credit managers on (Question no. 21), “Should the bank rely on external credit ratings?” revealed that 74.48 % agreed/ strongly agreed that the banks should depend on them (Table 8.22). Regarding large and small banks, their percentage ranged between 71.51 % and 77.58 % (Figure 8.8).

TABLE 8.22: Q.21- SHOULD THE BANK RELY ON THE EXTERNAL CREDIT RATINGS?

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	5	1.5	1.5	1.5
Disagree	41	12.2	12.2	13.6
Cannot say	40	11.9	11.9	25.5
Agree	159	47.2	47.2	72.7
Strongly agree	92	27.3	27.3	100.0
Total	337	100.0	100.0	

One-way analysis of variance (ANOVA) was undertaken to understand the statistical significance of mean score (Table 8.7 & Figure 8.9) differences between and within three management categories (independent variables) viz. of managers of large and small banks; of managers of different experience groups; and managers at three levels of hierarchy. The ANOVA results indicate no statistically significant differences in mean scores of any of three categories of managers (Tables 8.23 to 8.25).

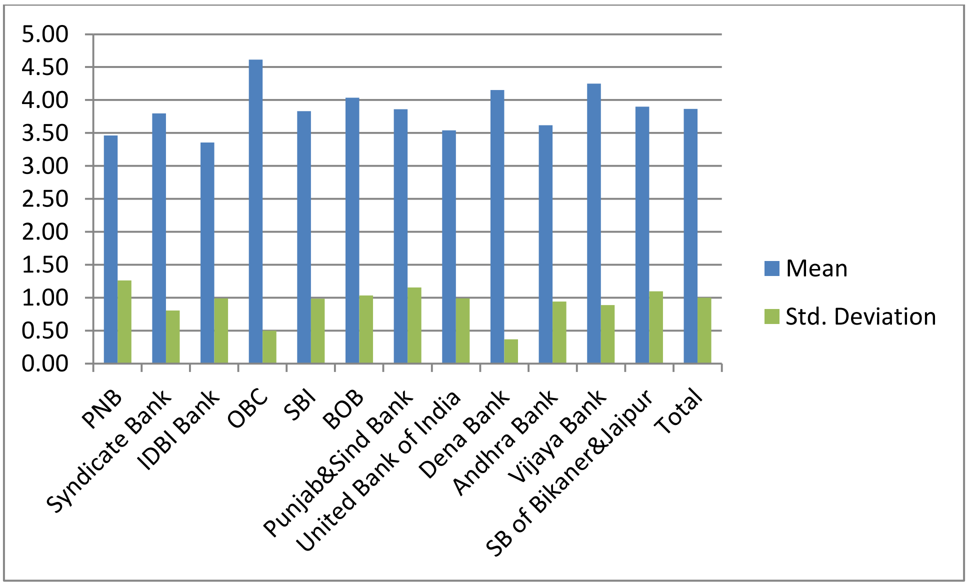

FIGURE 8.9: RELIANCE ON EXTERNAL RATINGS - MEAN & STANDARD DEVIATION

TABLE 8.23: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.21: Should the bank rely on the external credit ratings?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.193	1	.193	.193	.661
Within Groups	334.798	335	.999		
Total	334.991	336			

TABLE 8.24: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.21: Should the bank rely on the external credit ratings?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.615	2	.308	.307	.736
Within Groups	334.376	334	1.001		
Total	334.991	336			

TABLE 8.25: ANOVA BY LEVEL OF MANAGEMENT

Q.21: Should the bank rely on the external credit ratings?

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.261	2	.131	.130	.878
Within Groups	334.730	334	1.002		
Total	334.991	336			

Though three-fourth managers in our sample agree with the importance of external credit ratings in the internal credit-scoring models, favorable replies have come randomly from all groups of managers. Highest mean scores are from small banks' managers, from '8 to 20 years' experience group, and from senior level managers (Tables 8.13 to 8.15).

8.2.14 Evaluation of Credit Risk Assessment Framework

337 credit managers of sample banks who are dealing with business loans for different length of period, at various managerial levels, have been surveyed (Question

no. 23) on " Whether credit rating models of the bank are effective in capturing the credit risk?". Only 56.08 % agreed/ strongly agreed (Table 8.26). Largest number of respondents who agreed/ strongly agreed belonged to large banks, middle-level managers, and managers in the experience groups of 'Up to 7 years' and 'above 20 years' (Figures 8.10 to 8.12) (Tables 8.13 to 8.15).

TABLE 8.26: Q.23: CREDIT RATING MODELS OF THE BANK ARE EFFECTIVE IN CAPTURING THE CREDIT RISK

Responses	Frequency	Percent	Valid Percent	Cumulative Percent
Strongly disagree	3	.9	.9	.9
Disagree	70	20.8	20.8	21.7
Cannot say	75	22.3	22.3	43.9
Agree	163	48.4	48.4	92.3
Strongly agree	26	7.7	7.7	100.0
Total	337	100.0	100.0	

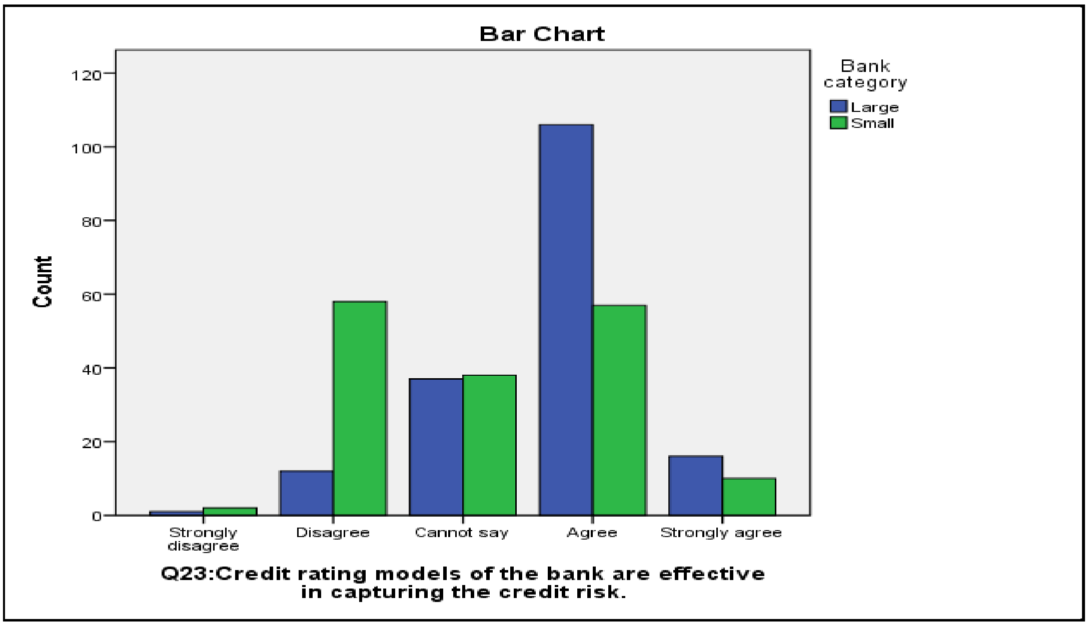

FIGURE 8.10: CREDIT RATING MODELS EVALUATION- BANK SIZE WISE

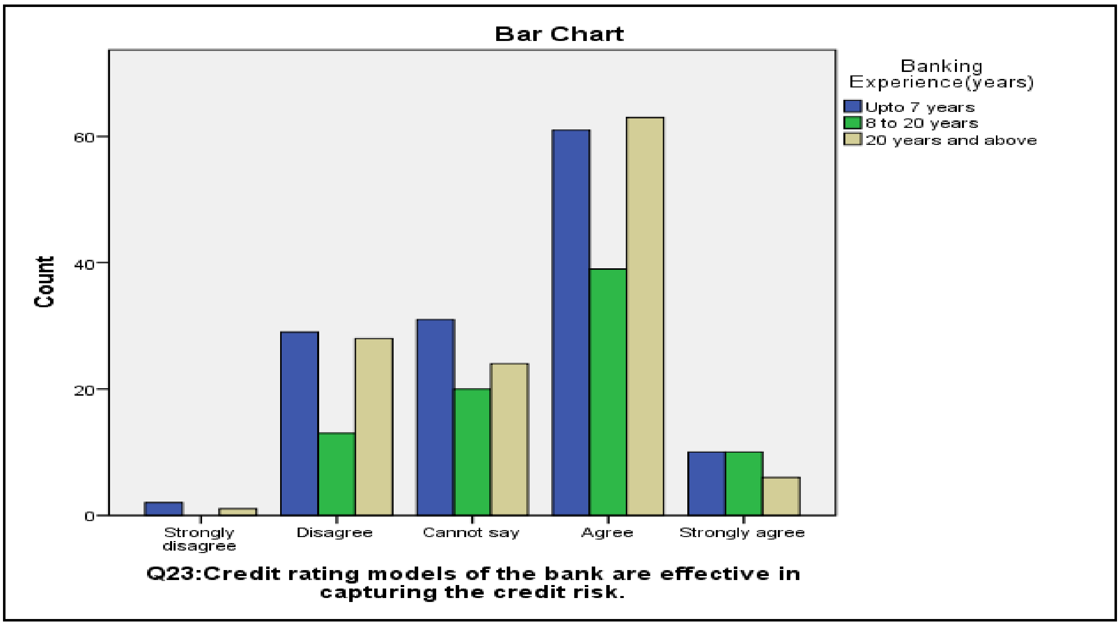

FIGURE 8.11: MANAGERS MANAGEMENT EXPERIENCE-WISE EVALUATION OF RATING MODELS

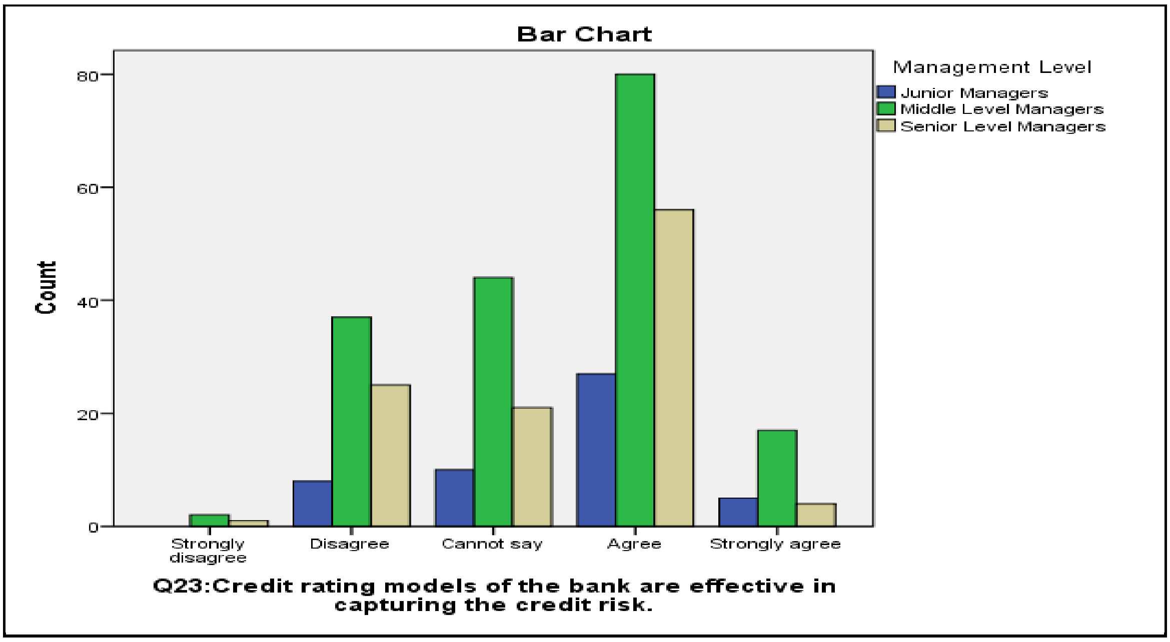

FIGURE 8.12: EVALUATION OF RATING MODELS BY MANAGEMENT LEVELS

Credit managers of the State Bank of India, Syndicate Bank, Bank of Baroda, and State Bank of Bikaner & Jaipur, Punjab National Bank and the IDBI Bank or in other words, credit managers of large public sector banks have been more satisfied, than the credit managers from other banks (Figure 8.13).

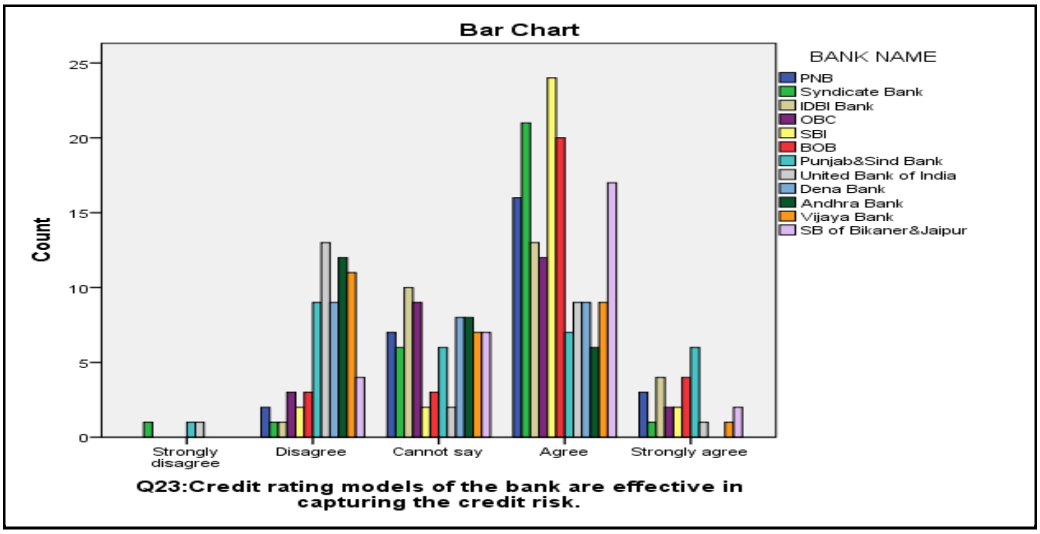

FIGURE 8.13: BANK-WISE EVALUATION OF RATING MODELS

TABLE 8.27: MEAN & STANDARD DEVIATION

Q.23: Credit rating models of the bank are effective in capturing the credit risk.

BANK NAME	Mean	N	Std. Deviation
PNB	3.71	28	.763
Syndicate Bank	3.67	30	.758
IDBI Bank	3.71	28	.763
OBC	3.50	26	.812
SBI	3.87	30	.629
BOB	3.83	30	.791
Punjab& Sind Bank	3.28	29	1.222
United Bank of India	2.85	26	1.084
Dena Bank	3.00	26	.849
Andhra Bank	2.77	26	.815
Vijaya Bank	3.00	28	.943
SB of Bikaner &Jaipur	3.57	30	.817
Total	3.41	337	.932

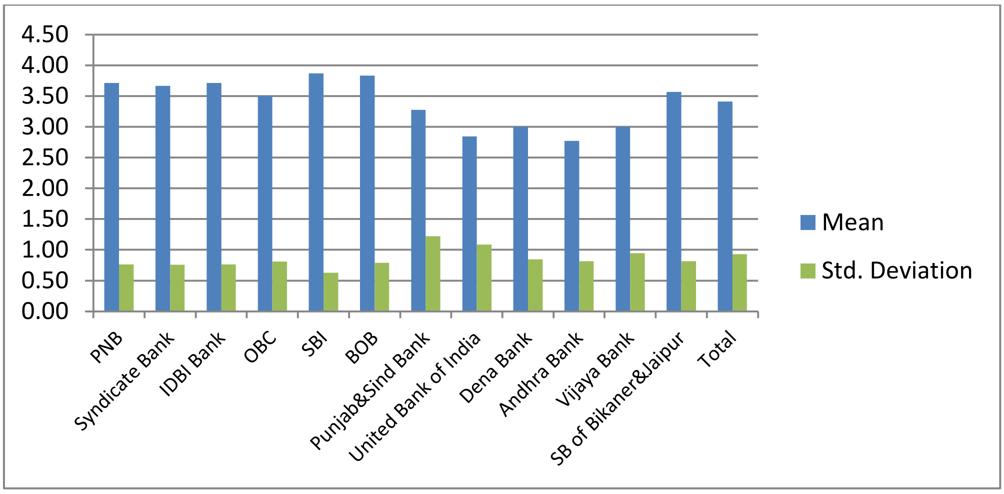

FIGURE 8.14: EVALUATION OF CREDIT RATING MODELS- MEAN AND STANDARD DEVIATION

In terms of mean scores and standard deviation values also (Figure 8.14) (Table 8.27), those who are in favor of effectiveness of credit rating models, belong to SBI, BOB, PNB, IDBI Bank, Syndicate Bank, and the State Bank of Bikaner & Jaipur (SBBJ). Five are from large banks category, and one bank is an associate bank of SBI i.e., SBBJ which is following the SBI's credit rating models.

One-way analysis of variance (ANOVA) has been undertaken to test the statistical significance of mean score differences between and within three managerial groups, large and small banks; managers of three experience groups; and managers at junior, middle and senior levels (Tables 8.28 to 8.30). Results of ANOVA indicate significant difference in mean scores between large and small public sector banks with F statistic equal to 43.362 (d f 1,335), at p=0.000 (Table 8.28). The credit managers of large banks (mean score 3.72) are more satisfied with credit risk rating framework in their banks in measurement of credit risk in business loan transaction than of small banks (mean score 3.09).

However, ANOVA results are not significant for managers of different experience groups or between various managerial levels. In other words, differences in their managerial perception about effectiveness of banks' credit rating models in capturing credit risk are random or only chance occurrence. Though among different experience groups, middle experience groups are most satisfied and little experience groups are least satisfied. Among different managerial levels, junior managers are most satisfied and senior managers are least satisfied.

TABLE 8.28: ANOVA BY BANK SIZE (LARGE BANKS VS. SMALL BANKS)

Q.23: Credit rating models of the bank are effective in capturing the credit risk.

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	33.427	1	33.427	43.362	.000
Within Groups	258.241	335	.771		
Total	291.668	336			

TABLE 8.29: ANOVA BY LEVEL OF MANAGERIAL EXPERIENCE

Q.23: Credit rating models of the bank are effective in capturing the credit risk.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.605	2	1.303	1.505	.223
Within Groups	289.062	334	.865		
Total	291.668	336			

TABLE 8.30: ANOVA BY LEVEL OF MANAGEMENT

Q.23: Credit rating models of the bank are effective in capturing the credit risk.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.888	2	.944	1.088	.338
Within Groups	289.780	334	.868		
Total	291.668	336			

8.3 RESULTS AND DISCUSSION

1. Most of the Indian public sector banks have elaborate internal credit risk assessment models to measure transactional credit risk.

2. However, use of theoretical or statistical models could not be established.

3. One of the positive aspects of credit risk assessment by the public sector banks is that they are aware of strength and weaknesses of other banks' risk management systems. This knowledge would have helped them to improve their operations and increase their bargaining power against the competing banks.

4. Nearly two-third of bank managers (sample) were for disclosure of rating models to borrowers. This will increase transparency in credit ratings, will encourage full disclosures of credit information by borrowers, and in case of SMEs, it will help them to improve their credit history and encourage them to have good accounting practices. Though there will also be problem of window dressing of credit information.

5. Credit risk assessment models have both quantitative and qualitative risk parameters. In case of qualitative risk factors which are mainly part of business, industry, and management risk valuation, there is high scope of subjectivity by credit analysts.

6. Only half of the respondents were aware of stress testing on credit risk models undertaken by the banks. This exercise is possibly conducted by banks only at top management levels.

7. There was, however, more participation by credit managers, at all levels, in conducting sensitivity analysis in credit risk assessments.

8. Nearly 75 percent respondents agreed on importance of external ratings in credit risk measurement. Statistical significance of differences in group-wise responses, however, could not be established.

9. Credit managers of large public sector banks are more satisfied with their credit risk rating models. Highest satisfaction has been perceived in credit managers of State Bank of India, Syndicate Bank, and Bank of Baroda. Though in total, only 56 percent of respondents agreed that their banks' credit risk rating models are effective in capturing credit risk.

10. The evaluation of credit rating models on various dimensions highlighted the statistically significant differences in perceptions of junior managers and senior managers; and managers in all experience groups. Since credit risk assessment is highly judgmental system, there is a need for more participation of managers at all levels, in sharing of risk information and decision making. Increased participation will improve managerial skills and motivation, and will also reduce subjectivity or bias in ratings

8.4 CONCLUSIONS

Credit risk assessment is the core risk management system in banks to assess the creditworthiness of their borrowers. The Indian PSBs have comprehensive, different, and software-driven internal risk rating models. They have moved way forward from simple judgmental 5 Cs approach to risk factors based credit rating or scoring models. However, only about half of the survey respondents agreed that their banks' credit risk rating models were effective in capturing credit risk. Though, the large bank credit managers were more satisfied with their bank's rating models than those of the small bank managers.

The next chapter attempts to design a credit risk assessment model for banks based on a comparison of existing and theoretical credit-scoring or rating models.

CHAPTER 9
MODELING TRANSACTIONAL CREDIT RISK IN BUSINESS LOANS USING DISCRIMINANT ANALYSIS

9.1 INTRODUCTION

The purpose of this chapter is to develop a credit risk assessment model for predicting default risk in the grant of commercial loans by Indian public sector commercial banks. Asset quality of Indian public sector banks is deteriorating because of rising burden of non-performing assets. Since business loans are a major part of bank credit, credit appraisal and risk assessment of every loan transaction is important. This chapter aims to develop a model based on multiple discriminant analysis (MDA) for correct borrower classification using both financial and non-financial characteristics of commercial firms in India.

9.2 SAMPLE

The study uses a sample of 47 bank loans to SMEs and mid-corporates, by an Indian public sector bank, to design a three group discriminant model, based on 13 financial ratios and four non-financial factors for predicting credit risk in grant of each business loan.

The sample of 47 firms has 40 performing and seven restructured/non-performing bank loans and has been collected from loan documents of few Delhi branches (Level VI/IV, DGM/AGM managed) of an Indian public sector bank (from the sample) during June to December 2013. Due to technical reasons including non-availability and incomplete information about sub-standard loans, only seven such cases with usable data were available. It is a mixed sample of manufacturers, trading firms and service providers. The borrowers in the database are either **SMEs or mid-corporates** with loan exposures from Rupees 50 lakh to Rupees 100 crore. The data pertains to the period from 2008 to 2013.

For designing MDA model, the sample data has been divided into two samples, analysis, and validation samples. Analysis or estimation sample (40) has thirty-six performing loans and four problem loans whose debts have been either restructured or listed as sub-standard assets. The hold-out or validation sample (7) has four performing loans and three bad loans. Firms have been divided in estimation and validation samples on a random basis.

Different statistical tests for normality, the goodness of fit, and multicollinearity have been performed using SPSS.

9.3 INDEPENDENT VARIABLES SELECTION

For Independent or predictor variables selection, both quantitative and qualitative factors of sample borrowers have been considered. The final variable selection includes 13 financial variables and four non-financial variables. The thirteen **financial variables** and four **non-financial variables** that are part of our MDA model building are listed in Tables 9.1 and 9.2. Thus, total 17 variables are the base of model building for classification of borrowers in different risk groups.

The financial predictors which are part of this model are fundamental solvency, profitability, liquidity and leverage ratios. Total Outside Liabilities/Tangible Net Worth ratio (TOL/TNW) and Debt/Equity ratio are the two solvency and leverage ratios.

TOL/TNW is the ratio of total outside liabilities to tangible net worth of the firm. Total outside liabilities include both long-term debt as well as current liabilities, whereas tangible net worth includes paid-up capital, reserves and surplus (excluding revaluation reserves) less intangible or fictitious assets. Debt/ equity ratio, however, takes into consideration only long-term debt. Security Coverage ratio is the ratio of the value of securities/collaterals/guarantees offered by the borrower to the amount of loan sanctioned to him by the bank. The securities may be financial collaterals/movable collaterals/immovable collaterals. Good security coverage ratio, at least 1:1.5, ensures recoveries in case of default or lowers 'Loss Given Default' or facility risk.

TABLE 9.1: LIST OF FINANCIAL VARIABLES

Sl. no.	Financial Variables
1.	Net Sales/Total Assets Ratio.
2.	Retained Earnings/Total Assets Ratio.
3.	Net Working Capital/Total Assets Ratio.
4.	Earnings Before Interest and Tax (EBIT)/Total Assets.
5.	Total Outside Liabilities/Tangible Net Worth (TOL/TNW).
6.	Debt/Equity Ratio.
7.	Current Ratio.
8.	Profit Before Taxes /Net Sales Ratio.
9.	Profit After Taxes / Net Sales Ratio.
10.	Book Value of Equity/Long- term Debt Ratio.
11.	Securities Coverage Ratio.
12.	Net Working Capital to Total Current Assets Ratio.
13.	Return on Capital Employed (ROCE).

TABLE 9.2: LIST OF NON-FINANCIAL VARIABLES

Sl. no.	Non-financial Variables
1.	Banking Relations.
2.	Kind of Firm.
3.	Since in Business (experience in the industry).
4.	The Level of Group Support.

The four non-financial variables (Table 9.2) selected on the basis of review of literature and experience of bank officers, are:

(a) Banking Relations: Banking relations signify the trust between the borrower and lender. Longer relationships mostly vouchsafe the track record of previous payments and conduct of loan account by borrowers such as regular submission of financial statements, stock statements, no claims dishonored, no guarantees revoked, etc. Bank's experience with the borrower always improves his credit desirability. In our model design, we have taken banking relations in actual years.

(b) Kind of firm: A survey (Question no. 11) on 337 bank managers directly associated with business loan processing in public sector banks, revealed that 43% found trading as more risk prone as they have no fixed assets base, 34% found manufacturing riskier and 22 % considered services sector loans more hazardous. This variable has thus, discriminatory power and has been included in the model design.

(c) Since in business: Since in business means experience or expertise in the industry. Expertise in the industry reduces chances of default. Experience/expertise has been measured as the age of the firm or company since establishment.

(d) Group support: Group support reduces the possibility of financial crisis and the probability of default. Group support of the borrower has been classified as no group support, weak group support, high group support.

9.4 DEPENDENT VARIABLE IDENTIFICATION

The **dependent variable** in the multiple discriminant analysis is the Z score. In our MDA model for credit risk assessment, the lending bank situation is considered as a multinomial problem where its borrowers are considered as 'High Safety' group, 'Moderate Safety' group, and 'Inadequate Safety' group.

High Safety: Borrowers have a fundamentally strong position, and the bank has the high safety of timely payment. There is no or very little credit risk.

Moderate Safety: Borrowers are presently in a good position though they may be marginally in a difficult situation in near future. They may turn into high credit risk and need continuous loan monitoring.

Inadequate Safety: Borrowers are facing adverse business/economic conditions and very susceptible to default or had defaulted. There is the highest credit risk.

In analysis sample, for estimation of discriminant functions and Z-scores, the borrowers have been divided into these three categories, by credit risk ratings awarded by the bank. For monitoring credit risk, larger the number of risk categories the better, as rating transitions can be carefully tracked. Downward movement of credit ratings during the term of the loan will indicate increasing probability of default. Most borrowers do not default overnight. Borrowers credit- worthiness and asset quality decline gradually and warning signals start appearing in his financial statements, external ratings, and share prices. Broad credit rating framework is also important to avoid simplistic classification of loans into the good or bad category (RBI, 2011).

9.5 DEVELOPMENT OF THE Z-SCORE MODELS

Given the estimation sample of 36 performing loans and four non-performing loans, the multivariate linear discriminant functions have been estimated to obtain Z-scores that will help to predict the credit risk involved in new loan proposals. Our MDA models have two purposes, to look for predictor variables which have high discriminatory power and least misclassification rates, and second, which have improved prediction accuracy in our hold-out sample.

The discriminant analysis is a useful method to assess differences in groups and to find on which variables are they most different. It answers the question whether a combination of variables may be used to predict group membership or which variables are contributing the most to discriminate between the groups. Discriminant coefficients make the groups differ as much as possible. This occurs only when the ratio of the between-group sum of squares to a within-group sum of squares for the discriminant scores is at a maximum. The assumptions in discriminant analysis are that each of the group is a sample from a multivariate normal population, and all the populations have the same covariance matrix.

The linear discriminant analysis model involves combination of the following form:

Z=a+b1*x1+b2*x2+b3*x3+..…..bk*xk

Where

Z= discriminant score.

a= a constant.

b= discriminant co-efficient or weight of variable.

x= predictor or independent variable.

The general objective of multivariate discriminant analysis (MDA) within a credit assessment procedure is to distinguish between solvent and insolvent borrowers as accurately as possible using a function which contains several independent creditworthiness criteria. Qualitative creditworthiness criteria, which come in the form of ordinal values, may not be normally distributed. However, rescaling the qualitative criteria in a suitable manner can fulfill the theoretical prerequisites of MDA (Oesterreichische National Bank, 2004).

9.6 TESTING ASSUMPTIONS

Based on the above methodology, two models have been tested.

The **Model I** comprises of a set of four predictor or independent variables, based on the **Altman's Emerging Markets Z- Score Model** (1995) with re-estimated discriminant scores.

The **Model 2** is ours and has been named **All Variables Z-Score Model.** It comprises of thirteen financial and four non-financial predictor variables. Both the MDA models have been tested using the step-wise and direct (separate and within) methods through SPSS program.

Before model tests, some general statistical tests regarding equality of covariance matrices, the goodness of fit and multicollinearity were performed. We are using a level of significance of .01 for testing assumptions and .05 for evaluating the statistical relationships. Box's M statistic assesses conformity to the assumption of homogeneity of group variances. If the Box's M shows probability (p)>.01 or equal to, the covariance is not statistically different, and the null hypothesis is accepted, and the assumption of homoscedasticity is upheld. In our test sample, the Box's M test value 28.546 is at p=.001, which means the null hypothesis is not accepted. Box's M test is extremely sensitive to violation of normality, and many researchers check it at p=.001, which holds good in our sample for Model 2 (Table 9.3). Some researchers also find that the violation of the normality is not 'fatal', and the resultant significance tests are still reliable as long as non-normality is caused by skewness (Tabachnick, 1996).

TABLE 9.3: BOX'S M TEST OF EQUALITY OF COVARIANCE MATRICES OF CANONICAL DISCRIMINANT FUNCTIONS

Test Results

Box's M		28.546
F	Approx.	3.936
	df1	6
	df2	550.331
	Sig.	.001

Multicollinearity in MDA has the same effect as it does in multiple regression analysis. Multicollinearity in the discriminant analysis is identified by examining tolerance values. If a tolerance problem occurs in direct method, SPSS includes a table title "Variables Failing Tolerance Test", not included in this study. Otherwise multicollinearity is indicated when the tolerance value for an independent variable is less than 0.10. In our sample, tolerance values for all the independent variables are larger than 0.10 (Tables 9.4 and 9.5). Multicollinearity is thus not a problem in this discriminant analysis. The primary criteria for a successful discriminant analysis are:

- The existence of statistically significant discriminant functions to distinguish among the groups defined by the dependent variable.
- An accuracy rate that substantially improves the accuracy rate obtainable by chance alone.

TABLE 9.4: TOLERANCE VALUES-VARIABLES IN THE ANALYSIS (STEP-WISE OUTPUT)

Step		Tolerance	Sig. of F to Remove	Min. D Squared	Between Groups
1	Security Coverage Ratio(%)	1.000	.003		
2	Security Coverage Ratio(%)	.995	.004	.279	High Safety and Moderate Safety
	EBIT/Total Assets(%)	.995	.005	.583	High Safety and Inadequate Safety
3	Security Coverage Ratio(%)	.785	.000	.279	High Safety and Moderate Safety
	EBIT/Total Assets(%)	.869	.046	1.338	High Safety and Moderate Safety
	Debt/Equity Ratio(%)	.721	.018	1.578	High Safety and Moderate Safety

TABLE 9.5: TOLERANCE VALUES-VARIABLES NOT IN THE ANALYSIS (STEP-WISE OUTPUT)

Step		Tolerance	Min. Tolerance	Sig. of F to Enter	Min. D Squared	Between Groups
0	Kind of business	1.000	1.000	.149	.107	High Safety and Moderate Safety
	Since in Business	1.000	1.000	.922	.002	High Safety and Inadequate Safety
	Banking relations(years)	1.000	1.000	.644	.002	High Safety and Moderate Safety
	Net Sales/Total Assets(%)	1.000	1.000	.258	.006	High Safety and Inadequate Safety
	Retained Earnings/Total Assets(%)	1.000	1.000	.117	.134	High Safety and Inadequate Safety
	Net Working Capital/Total Assets(%)	1.000	1.000	.052	.016	High Safety and Moderate Safety
	EBIT/Total Assets(%)	1.000	1.000	.004	.279	High Safety and Moderate Safety
	Book Value of Equity/Debt(%)	1.000	1.000	.274	.165	High Safety and Inadequate Safety

	TOL/TNW(%)	1.000	1.000	.013	.120	High Safety and Moderate Safety
	Debt/Equity Ratio(%)	1.000	1.000	.023	.017	High Safety and Moderate Safety
	Current Ratio(%)	1.000	1.000	.148	.062	High Safety and Moderate Safety
	Net Profit Before Taxes/Net Sales(%)	1.000	1.000	.234	.093	High Safety and Moderate Safety
	Net Profit After Taxes/Net Sales(%)	1.000	1.000	.345	.118	High Safety and Moderate Safety
	Security Coverage Ratio(%)	1.000	1.000	.003	.583	High Safety and Inadequate Safety
	Group Support	1.000	1.000	.737	.005	Moderate Safety and Inadequate Safety
	Net Working Capital/Current Assets(%)	1.000	1.000	.242	.000	High Safety and Moderate Safety
	ROCE(%)	1.000	1.000	.039	.035	High Safety and Moderate Safety
	Kind of business	.950	.950	.064	1.555	High Safety and Moderate Safety
	Since in Business	1.000	1.000	.929	.587	High Safety and Inadequate Safety
1	Banking relations(years)	.988	.988	.771	.742	High Safety and Inadequate Safety
	Net Sales/Total Assets(%)	.961	.961	.134	.636	High Safety and Inadequate Safety
	Retained Earnings/Total Assets(%)	1.000	1.000	.161	.712	High Safety and Inadequate Safety
	Net Working Capital/Total Assets(%)	.935	.935	.145	1.233	High Safety and Moderate Safety
	EBIT/Total Assets(%)	.995	.995	.005	1.578	High Safety and Moderate Safety

	Book Value of Equity/Debt(%)	.947	.947	.113	.939	High Safety and Inadequate Safety
	TOL/TNW(%)	.784	.784	.001	1.242	High Safety and Moderate Safety
	Debt/Equity Ratio(%)	.826	.826	.002	1.338	High Safety and Moderate Safety
	Current Ratio(%)	.999	.999	.239	1.255	High Safety and Moderate Safety
	Net Profit Before Taxes/Net Sales(%)	1.000	1.000	.301	1.107	High Safety and Inadequate Safety
	Net Profit After Taxes/Net Sales(%)	1.000	1.000	.472	.821	High Safety and Inadequate Safety
	Group Support	1.000	1.000	.753	.678	High Safety and Inadequate Safety
	Net Working Capital/Current Assets(%)	.984	.984	.347	1.229	High Safety and Moderate Safety
	ROCE(%)	.950	.950	.126	1.212	High Safety and Moderate Safety
	Kind of business	.941	.941	.097	2.000	High Safety and Moderate Safety
	Since in Business	.998	.993	.926	1.593	High Safety and Moderate Safety
	Banking relations(years)	.965	.965	.564	1.609	High Safety and Moderate Safety
2	Net Sales/Total Assets(%)	.950	.950	.123	2.362	High Safety and Moderate Safety
	Retained Earnings/Total Assets(%)	.922	.917	.055	2.553	High Safety and Moderate Safety
	Net Working Capital/Total Assets(%)	.879	.879	.561	1.578	High Safety and Moderate Safety
	Book Value of Equity/Debt(%)	.947	.943	.121	2.106	High Safety and Moderate Safety

	TOL/TNW(%)	.667	.667	.015	1.786	High Safety and Moderate Safety
	Debt/Equity Ratio(%)	.721	.721	.018	1.960	High Safety and Moderate Safety
	Current Ratio(%)	.953	.949	.455	1.705	High Safety and Moderate Safety
	Net Profit Before Taxes/Net Sales(%)	.682	.679	.176	2.237	High Safety and Moderate Safety
	Net Profit After Taxes/Net Sales(%)	.662	.659	.122	2.291	High Safety and Moderate Safety
	Group Support	.899	.894	.889	1.580	High Safety and Moderate Safety
	Net Working Capital/Current Assets(%)	.798	.798	.950	1.596	High Safety and Moderate Safety
	ROCE(%)	.507	.507	.533	1.813	High Safety and Moderate Safety
	Kind of business	.941	.721	.143	2.398	High Safety and Moderate Safety
	Since in Business	.998	.721	.923	1.978	High Safety and Moderate Safety
	Banking relations(years)	.958	.716	.664	2.012	High Safety and Moderate Safety
3	Net Sales/Total Assets(%)	.943	.716	.117	2.847	High Safety and Moderate Safety
	Retained Earnings/Total Assets(%)	.909	.711	.052	3.100	High Safety and Moderate Safety
	Net Working Capital/Total Assets(%)	.850	.698	.371	1.971	High Safety and Moderate Safety
	Book Value of Equity/Debt(%)	.900	.685	.365	2.325	High Safety and Moderate Safety
	TOL/TNW(%)	.179	.179	.491	1.980	High Safety and Moderate Safety

Current Ratio(%)	.939	.710	.362	2.149	High Safety and Moderate Safety
Net Profit Before Taxes/Net Sales(%)	.648	.648	.213	2.439	High Safety and Moderate Safety
Net Profit After Taxes/Net Sales(%)	.624	.624	.112	2.476	High Safety and Moderate Safety
Group Support	.899	.721	.911	1.962	High Safety and Moderate Safety
Net Working Capital/Current Assets(%)	.755	.668	.692	2.041	High Safety and Moderate Safety
ROCE(%)	.507	.499	.584	2.174	High Safety and Moderate Safety

9.7 MODEL 1: ALTMAN'S EMERGING MARKETS Z-SCORE MODEL

Altman (1968) developed his classic multivariate insolvency prediction model (MDA) for publicly traded manufacturing firms in the USA. In the original Z-score formula for predicting bankruptcy (with cut-off score 1.81), Altman employed 5 ratios, Working Capital/Total Assets, Retained Earnings/Total Assets, Earnings Before Interest and Taxes (EBIT)/Total Assets, Sales/Total Assets, and Market Value of Equity/Book Value of Total Debt Ratios, with given discriminant weights. The model was subsequently revised and called Zeta model by Altman et al. (1977). Again 1n 1995, Altman et al. modified his Z-score model to emerging market corporations, especially Mexican firms that had issued Eurobonds denominated in US dollars. In this enhanced Z-score model, he dropped Sales/Total Asset Ratio and used book value of equity in place of the market value of equity to make it suitable for private firms whose securities were not quoted in the stock exchange. Since our model building data set has several such companies, we are using Altman's Emerging Markets Z-score model, with re-worked discriminant scores, for estimation of discriminant functions and classification accuracy.

9.7.1 Discriminant Functions

With the given sample of 40 loan applicants consisting of 36 performing and four non-performing or restructured loans, we have performed the multiple discriminant analysis with three dependent credit risk categories, High Safety, Moderate Safety, and Inadequate Safety. The predictor or independent variables are Net Working Capital/Total Assets, EBIT/Total Assets, Retained Earnings/Total Assets, and Book Value of Equity/Long- term Debt Ratios. Against three dependent groups, the model has generated two discriminatory functions (Table 9.6).

TABLE 9.6: CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS- MODEL 1 (ALTMAN)

Variables	Function*	
	1	2
Retained Earnings/Total Assets (%)	.014	-.013
Net Working Capital/Total Assets (%)	.015	.031
EBIT/Total Assets (%)	.128	-.004
Book Value of Equity/Debt (%)	.000	.001
(Constant)	-1.231	-.850

*Unstandardized coefficients.

The results are:

Function 1

Z= -1.231 +0.014 (Retained Earnings/Total Assets) +0.015 (Net Working Capital/Total Assets) + 0.128 (EBIT/Total Assets) +0.000(Book value of Equity/Debt).

Function 2

Z= -0.850 -0.013(Retained Earnings/Total Assets) +0.013(Net Working Capital/Total Assets) -0.004(EBIT/Total Assets) +0.001(Book Value of Equity/Debt).

Thus, Model 1 has generated two significant discriminant functions with a Wilks' Lambda of 0.503 and chi-square value of 24.403 (Table 9.7). Eigenvalues associated with the functions are, however, very small 0.560/0.275 (Table 9.7). Other statistics relating to Model 1(Altman's) are Test of Equality of Group Means (Table9.8), Group Statistics (Table 9.9), Standardized Canonical Discriminant Function Coefficients (Table 9.10), Structure Matrix (Table 9.11), Functions at Group Centroids (Table 9.12), Prior Probabilities for Groups (Table 9.13), and Fisher's Classification Function Coefficients (Table 9.14).

TABLE 9.7: WILKS' LAMBDA AND EIGENVALUES- MODEL 1(ALTMAN)

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.503	24.403	8	.002
2	.784	8.626	3	.035

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.560[a]	67.0	67.0	.599
2	.275[a]	33.0	100.0	.464

(First 2 canonical discriminant functions were used in the analysis.)

TABLE 9.8:TESTS OF EQUALITY OF GROUP MEANS- MODEL 1 (ALTMAN)

Variables	Wilks' Lambda	F	df1	df2	Sig.
Retained Earnings/Total Assets (%)	.890	2.277	2	37	.117
Net Working Capital/Total Assets (%)	.852	3.201	2	37	.052
EBIT/Total Assets(%)	.742	6.448	2	37	.004
Book Value of Equity/Debt (%)	.932	1.342	2	37	.274

TABLE 9.9: GROUP STATISTICS- MODEL 1(ALTMAN)

Credit Risk Rating		Mean	Std. Deviation	Valid N (list-wise)	
				Un-weighted	Weighted
High Safety	Retained Earnings/Total Assets(%)	25.6148	20.88065	25	25.000
	Net Working Capital/Total Assets(%)	20.8160	18.70858	25	25.000
	EBIT/Total Assets(%)	8.8080	8.10992	25	25.000
	Book Value of Equity/Debt(%)	290.6452	328.68241	25	25.000
Moderate Safety	Retained Earnings/Total Assets(%)	-11.1691	86.27650	11	11.000
	Net Working Capital/Total Assets(%)	23.1100	18.29920	11	11.000
	EBIT/Total Assets(%)	5.1682	3.94602	11	11.000
	Book Value of Equity/Debt(%)	554.2055	978.88642	11	11.000
Inadequate Safety	Retained Earnings/Total Assets(%)	8.0225	9.22754	4	4.000
	Net Working Capital/Total Assets(%)	-2.2100	8.06739	4	4.000
	EBIT/Total Assets(%)	-4.2300	2.90059	4	4.000
	Book Value of Equity/Debt(%)	57.8575	64.75539	4	4.000
Total	Retained Earnings/Total Assets(%)	13.7400	49.51999	40	40.000
	Net Working Capital/Total Assets(%)	19.1443	18.95406	40	40.000
	EBIT/Total Assets(%)	6.5033	7.79984	40	40.000
	Book Value of Equity/Debt(%)	339.8455	578.93746	40	40.000

TABLE 9.10: STANDARDIZED CANONICAL DISCRIMINANTFUNCTION COEFFICIENTS – MODEL 1 (ALTMAN)

Variables	Function	
	1	2
Retained Earnings/Total Assets(%)	.670	-.615
Net Working Capital/Total Assets(%)	.275	.557
EBIT/Total Assets(%)	.879	-.027
Book Value of Equity/Debt(%)	-.141	.775

TABLE 9.11: STRUCTURE MATRIX – MODEL 1(ALTMAN)

Variables	Function	
	1	2
EBIT/Total Assets(%)	.767*	.268
Net Working Capital/Total Assets(%)	.388	.568*
Book Value of Equity/Debt(%)	.009	.513*
Retained Earnings/Total Assets(%)	.329	-.477*

TABLE 9.12: FUNCTIONS AT GROUP CENTROIDS- MODEL 1 (ALTMAN)

Credit Risk Rating	Function*	
	1	2
High Safety	.498	-.176
Moderate Safety	-.510	.737
Inadequate Safety	-1.707	-.926

*Unstandardized canonical discriminant functions evaluated at group means

TABLE 9.13: PRIOR PROBABILITIES FOR GROUPS- MODEL 1(ALTMAN)

Credit Risk Rating	Prior	Cases Used in Analysis	
		Unweighted	Weighted
High Safety	.333	25	25.000
Moderate Safety	.333	11	11.000
Inadequate Safety	.333	4	4.000
Total	1.000	40	40.000

TABLE 9.14: CLASSIFICATION FUNCTION COEFFICIENTS- MODEL 1 (ALTMAN)

Variables	Credit Risk Rating*		
	High Safety	Moderate Safety	Inadequate Safety
Retained Earnings/Total Assets(%)	.021	-.005	-.001
Net Working Capital/Total Assets(%)	.060	.072	.003
EBIT/Total Assets(%)	.187	.054	-.092
Book Value of Equity/Debt(%)	.001	.002	.000
(Constant)	-2.898	-2.695	-1.292

*Fisher's linear discriminant functions

9.7.2 Classification Accuracy

The model's classification accuracy is 75 percent by original group, 62.5 percent by cross-validation. Since the model's accuracy is 25 percent more than the chance accuracy (33 percent), it has otherwise satisfactory results (Table 9.15).

TABLE 9.15: CLASSIFICATION ACCURACY- MODEL 1(ALTMAN)

Credit Risk Rating			Predicted Group Membership			Total
			High Safety	**Moderate Safety**	**Inadequate**	
Original	Count	High safety	20	3	2	25
		Moderate Safety	4	6	1	11
		Inadequate Safety	0	0	4	4
	%	High safety	80.0	12.0	8.0	100.0
		Moderate Safety	36.4	54.5	9.1	100.0
		Inadequate Safety	.0	.0	100.0	100.0
Cross-validated	Count	High safety	19	3	3	25
		Moderate Safety	7	2	2	11
		Inadequate Safety	0	0	4	4
	%	High safety	76.0	12.0	12.0	100.0
		Moderate Safety	63.6	18.2	18.2	100.0
		Inadequate Safety	.0	.0	100.0	100.0

Notes:

1. 75.0% of original grouped cases correctly classified.

2. 62.5% of cross-validated grouped cases correctly classified.

9.8 MODEL 2: ALL VARIABLES Z-SCORE MODEL

This MDA model is based on thirteen financial ratios and four non-financial factors. Because there are three groups, two discriminant functions are estimated. The eigenvalue associated with function 1 is 4.134, and it accounts for 65.7% of the explained variance (Table 9.16). The canonical correlation associated with this function is 0.897. The square of this correlation, 0.804 indicates that 80% of the variance in the dependent variable (credit rating) is explained or accounted for in this model, under function 1.The second function has a small eigenvalue of 2.155, and accounts for only 34.3% of the explained variance. The value of the Wilks' Lambda for function 1 through 2 is 0.062 (Table 9.16). This transforms to a chi-square of 80.759 with 34 degrees of freedom which is significant (.000) beyond the .05 level. Thus two functions together significantly discriminate among the three groups. However, when function 1 is removed, the Wilks' Lambda associated with function 2 is only 0.317, though it is also significant at 0.05 level. Thus the second function does not contribute as significantly to group differences, as function 1.

Table 9.16: Wilks' Lambda and Eigenvalues- Model 2 (All Variables)

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.062	80.759	34	.000
2	.317	33.318	16	.007

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	4.134[a]	65.7	65.7	.897
2	2.155[a]	34.3	100.0	.826

The higher eigenvalue and chi-square value indicate the goodness of fit of discriminant functions. The smaller Wilks' Lambda followed by, the higher chi-square values imply that there are differences among 'High Safety', 'Moderate Safety' and 'Inadequate Safety' groups, and variability within groups is relatively small. This has helped in correctly classifying a case belonging to a particular group and therefore, minimized misclassification errors.

TABLE 9.17: STRUCTURE MATRIX-MODEL 2 (ALL VARIABLES)

Variables	Function	
	1	2
EBIT/Total Assets(%)	.270*	.147
TOL/TNW(%)	-.244*	-.092
Debt/Equity Ratio(%)	-.233*	-.026
ROCE(%)	.209*	-.071
Net Working Capital/Total Assets(%)	.201*	-.052
Current Ratio(%)	.150*	-.087
Kind of business	.141*	-.110
Net Working Capital/Current Assets(%)	.139*	-.007
Net Profit Before Taxes/Net Sales(%)	.120*	-.102
Banking relations(years)	.075*	-.018
Security Coverage Ratio(%)	.158	-.350*
Retained Earnings/Total Assets(%)	.028	.236*
Net Sales/Total Assets(%)	.033	-.182*
Book Value of Equity/Debt(%)	.079	-.147*
Net Profit After Taxes/Net Sales(%)	.088	-.112*
Group Support	-.038	-.070*
Since in Business	.012	-.042*

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

Variables ordered by absolute size of correlation within function.

*. Largest absolute correlation between each variable and any discriminant function

9.8.1 The Structure Matrix

In Structure Matrix (Table 9.17), the variables EBIT/Total Assets, TOL/TNW, Debt/Equity Ratio, Net Working Capital/Total Assets Ratio, ROCE, Current Ratio, Kind of Business, Net Working Capital/Current Assets Ratio, PBT/Net Sales, Banking Relations, Net Sales/Total Assets, Since in business, have larger coefficients for function 1. Whereas, variables, Security Coverage Ratio, Retained Earnings /Total Assets, Book Value of Equity/Debt, PAT/Net Sales, and Group Support have larger coefficients for function 2. Structure coefficients are simple Pearsonian correlations, also called discriminant loadings. These correlations serve like factor loadings in factor analysis, by identifying the largest absolute correlations associated with each discriminant function. Thus, borrowers with high EBIT/Total Assets, low TOL/TNW, low Debt/Equity ratio, high Net Working Capital/Total Assets Ratio, high ROCE, high Current Ratio, longer banking relations, high Sales/Total Assets Ratio and longer business life tend to have lower credit or default risk, and vice-versa.

TABLE 9.18: TESTS OF EQUALITY OF GROUP MEANS- MODEL 2 (ALL VARIABLES)

Variables	Wilks' Lambda	F	df1	df2	Sig.
Kind of business	.902	2.008	2	37	.149
Since in Business	.996	.081	2	37	.922
Banking relations(years)	.976	.445	2	37	.644
Net Sales/Total Assets(%)	.929	1.408	2	37	.258
Retained Earnings/Total Assets(%)	.890	2.277	2	37	.117
Net Working Capital/Total Assets(%)	.852	3.201	2	37	.052
EBIT/Total Assets(%)	.742	6.448	2	37	.004
Book Value of Equity/Debt(%)	.932	1.342	2	37	.274
TOL/TNW(%)	.790	4.907	2	37	.013
Debt/Equity Ratio(%)	.815	4.189	2	37	.023
Current Ratio(%)	.902	2.012	2	37	.148
Net Profit Before Taxes/Net Sales(%)	.924	1.512	2	37	.234
Net Profit After Taxes/Net Sales(%)	.944	1.095	2	37	.345
Security Coverage Ratio(%)	.732	6.789	2	37	.003
Group Support	.984	.307	2	37	.737
Net Working Capital/Current Assets(%)	.926	1.473	2	37	.242
ROCE(%)	.840	3.531	2	37	.039

The significance of the univariate F ratios (Tests of Equality of Group Means-Table 9.18), indicates that when predictors are considered individually, only Security Coverage Ratio, EBIT/Total Assets Ratio, TOL/TNW Ratio, Net Working Capital/Total Assets Ratio, Debt/Equity Ratio significantly differentiated between borrowers with high, moderate and inadequate safety.

Other statistics relating to Model 2 are Group Statistics (Table 9.19), Standardized Canonical Discriminant Function Coefficients (Table 9.20) and Fisher's Classification Function Coefficients (Table 9.21).

TABLE 9.19: GROUP STATISTICS- MODEL 2(ALL VARIABLES)

Credit Risk Rating		Mean	Std. Deviation	Valid N (list-wise)	
				Un-weighted	Weighted
High Safety	Kind of business	1.7200	.84261	25	25.000
	Since in Business	16.1600	9.38385	25	25.000
	Banking relations(years)	9.2000	9.28260	25	25.000
	Net Sales/Total Assets(%)	119.9492	126.59346	25	25.000
	Retained Earnings/Total Assets(%)	25.6148	20.88065	25	25.000
	Net Working Capital/Total Assets(%)	20.8160	18.70858	25	25.000
	EBIT/Total Assets(%)	8.8080	8.10992	25	25.000
	Book Value of Equity/Debt(%)	290.6452	328.68241	25	25.000
	TOL/TNW(%)	300.2000	223.75694	25	25.000
	Debt/Equity Ratio(%)	121.1600	150.71404	25	25.000
	Current Ratio(%)	155.0800	55.47140	25	25.000
	Net Profit Before Taxes/Net Sales(%)	3.6432	26.48189	25	25.000
	Net Profit After Taxes/Net Sales(%)	.8744	26.40999	25	25.000
	Security Coverage Ratio(%)	194.8292	100.26417	25	25.000
	Group Support	.9600	.97809	25	25.000
	Net Working Capital/Current Assets(%)	30.0876	24.06891	25	25.000
	ROCE(%)	7.7220	38.56433	25	25.000
Moderate Safety	Kind of business	2.0000	1.00000	11	11.000
	Since in Business	17.9091	20.35905	11	11.000
	Banking relations(years)	9.5455	6.20264	11	11.000
	Net Sales/Total Assets(%)	486.5427	1196.09319	11	11.000
	Retained Earnings/Total Assets(%)	-11.1691	86.27650	11	11.000
	Net Working Capital/Total Assets(%)	23.1100	18.29920	11	11.000
	EBIT/Total Assets(%)	5.1682	3.94602	11	11.000
	Book Value of Equity/Debt(%)	554.2055	978.88642	11	11.000
	TOL/TNW(%)	432.9091	518.92205	11	11.000
	Debt/Equity Ratio(%)	155.4545	293.29008	11	11.000
	Current Ratio(%)	171.1818	87.90201	11	11.000
	Net Profit Before Taxes/Net Sales(%)	11.7300	30.10763	11	11.000
	Net Profit After Taxes/Net Sales(%)	9.3791	24.46157	11	11.000
	Security Coverage Ratio(%)	422.6364	366.98236	11	11.000
	Group Support	1.1818	.87386	11	11.000
	Net Working Capital/Current Assets(%)	29.9745	22.59135	11	11.000
	ROCE(%)	13.8100	14.29912	11	11.000
Inadequate Safety	Kind of business	1.0000	.00000	4	4.000
	Since in Business	15.5000	9.03696	4	4.000
	Banking relations(years)	5.2500	3.86221	4	4.000
	Net Sales/Total Assets(%)	72.6375	29.72187	4	4.000
	Retained Earnings/Total Assets(%)	8.0225	9.22754	4	4.000
	Net Working Capital/Total Assets(%)	-2.2100	8.06739	4	4.000
	EBIT/Total Assets(%)	-4.2300	2.90059	4	4.000
	Book Value of Equity/Debt(%)	57.8575	64.75539	4	4.000

	TOL/TNW(%)	942.7500	714.59283	4	4.000
	Debt/Equity Ratio(%)	529.2500	618.59485	4	4.000
	Current Ratio(%)	96.0000	29.69848	4	4.000
	Net Profit Before Taxes/Net Sales(%)	-15.1450	6.51063	4	4.000
	Net Profit After Taxes/Net Sales(%)	-11.3750	2.85651	4	4.000
	Security Coverage Ratio(%)	36.5400	24.04714	4	4.000
	Group Support	1.2500	.95743	4	4.000
	Net Working Capital/Current Assets(%)	8.7200	22.83820	4	4.000
	ROCE(%)	-35.1900	22.77286	4	4.000
Total	Kind of business	1.7250	.87669	40	40.000
	Since in Business	16.5750	12.94146	40	40.000
	Banking relations(years)	8.9000	8.09812	40	40.000
	Net Sales/Total Assets(%)	216.0313	636.73130	40	40.000
	Retained Earnings/Total Assets(%)	13.7400	49.51999	40	40.000
	Net Working Capital/Total Assets(%)	19.1443	18.95406	40	40.000
	EBIT/Total Assets(%)	6.5033	7.79984	40	40.000
	Book Value of Equity/Debt(%)	339.8455	578.93746	40	40.000
	TOL/TNW(%)	400.9500	419.57029	40	40.000
	Debt/Equity Ratio(%)	171.4000	283.36113	40	40.000
	Current Ratio(%)	153.6000	66.11753	40	40.000
	Net Profit Before Taxes/Net Sales(%)	3.9883	26.86596	40	40.000
	Net Profit After Taxes/Net Sales(%)	1.9883	24.85551	40	40.000
	Security Coverage Ratio(%)	241.6473	236.05556	40	40.000
	Group Support	1.0500	.93233	40	40.000
	Net Working Capital/Current Assets(%)	27.9198	23.86414	40	40.000
	ROCE(%)	5.1050	34.63841	40	40.000

TABLE 9.20: STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS-MODEL 2 (ALL VARIABLES)

Variables	Function	
	1	2
Kind of business	.320	-.474
Since in Business	.405	.427
Banking relations(years)	.378	.192
Net Sales/Total Assets(%)	-.204	-.616
Retained Earnings/Total Assets(%)	.306	1.267
Net Working Capital/Total Assets(%)	-.144	.472
EBIT/Total Assets(%)	-.214	1.002
Book Value of Equity/Debt(%)	-.006	-.765
TOL/TNW(%)	.419	-.376
Debt/Equity Ratio(%)	-1.319	.482
Current Ratio(%)	1.493	.749
Net Profit Before Taxes/Net Sales(%)	6.925	-1.786
Net Profit After Taxes/Net Sales(%)	-9.738	1.502
Security Coverage Ratio(%)	.072	-.940
Group Support	.470	.036
Net Working Capital/Current Assets(%)	-.249	-.521
ROCE(%)	3.113	-.293

TABLE 9.21: CLASSIFICATION FUNCTION COEFFICIENTS- MODEL 2 (ALL VARIABLES)

Variables	Credit Risk Rating*		
	High Safety	**Moderate Safety**	**Inadequate Safety**
Kind of business	4.387	6.103	2.359
Since in Business	.440	.330	.214
Banking relations(years)	.302	.218	-.019
Net Sales/Total Assets(%)	-.004	-.001	-.001
Retained Earnings/Total Assets(%)	.173	.086	.110
Net Working Capital/Total Assets(%)	-.137	-.220	-.105
EBIT/Total Assets(%)	.603	.140	.693
Book Value of Equity/Debt(%)	-.003	.001	-.002
TOL/TNW(%)	.032	.035	.026
Debt/Equity Ratio(%)	-.052	-.057	-.020
Current Ratio(%)	.319	.276	.157
Net Profit Before Taxes/Net Sales(%)	1.013	1.178	-.651
Net Profit After Taxes/Net Sales(%)	-1.858	-1.975	.676
Security Coverage Ratio(%)	-.010	.005	-.008
Group Support	4.817	4.595	1.531
Net Working Capital/Current Assets(%)	-.276	-.203	-.189
ROCE(%)	.547	.557	-.074
(Constant)	-39.334	-37.740	-19.637

*Fisher's linear discriminant functions

9.8.2 The Step-wise Discriminant Analysis

The data set in analysis sample was also subjected to **step-wise discriminant analysis**. A step-wise discriminatory analysis is used in an exploratory situation to identify those variables from among a larger number that have more discriminatory power. In this analysis, predictors are entered sequentially based on their ability to discriminate between the groups, on an optimizing criterion. The order in which variables are selected indicates their importance. In our All Variable Z-Score model (Model 2), the step-wise procedure selected Security Coverage Ratio, EBIT/Total Assets Ratio, and Debt/Equity Ratio as the most discriminatory variables. The findings in the step-wise analysis agreed with the conclusions reported in the direct method. But the classification accuracy of step-wise analysis has been found to be less than of the direct method (Table 9.22).

TABLE 9.22: CLASSIFICATION RESULTS (STEP-WISE METHOD)- MODEL 2(ALL VARIABLES)

Credit Risk Rating			Predicted Group Membership			Total
			High Safety	Moderate Safety	Inadequate Safety	
Original	Count	High Safety	21	3	1	25
		Moderate Safety	4	7	0	11
		Inadequate Safety	0	0	4	4
	%	High Safety	84.0	12.0	4.0	100.0
		Moderate Safety	36.4	63.6	.0	100.0
		Inadequate Safety	.0	.0	100.0	100.0
Cross-validated	Count	High Safety	20	4	1	25
		Moderate Safety	6	5	0	11
		Inadequate Safety	2	0	2	4
	%	High Safety	80.0	16.0	4.0	100.0
		Moderate Safety	54.5	45.5	.0	100.0
		Inadequate Safety	50.0	.0	50.0	100.0

Notes:

a. 80.0% of original grouped cases correctly classified.

b. Cross-validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 67.5% of cross-validated grouped cases correctly classified.

Figure 9.1 defines the scattering of Group Centroids (step-wise method).

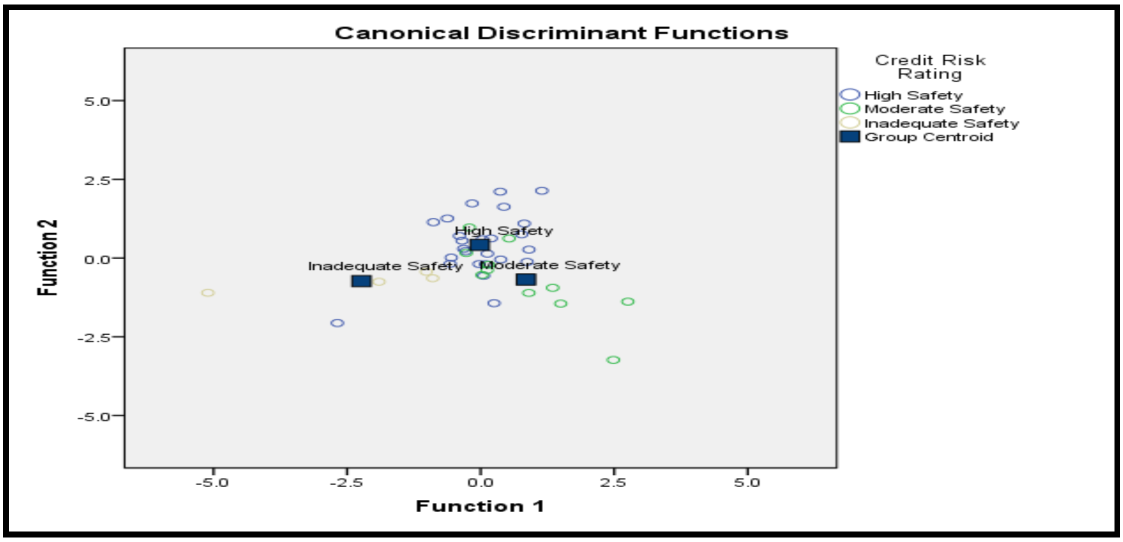

FIGURE 9.1: SCATTER PLOT OF GROUP CENTROIDS – MODEL 2

9.8.3 Territorial Map

A territorial map is a graphic presentation of the cutting scores on a two-dimensional graph. When combined with the plots of individual discriminant score paired values for each particular case, the dispersion of each group can be viewed, and the misclassification of individual cases can be identified directly from the map.

Each group centroid is indicated by an asterisk, with clear group boundaries are shown by the numbers corresponding to the group (Figure 9.2). Thus High Safety group (1) centroid is bounded by 1s, Moderate Safety group(2) centroid is bound by 2s, and Inadequate Safety group(3) centroid by 3s. The group centroid is the mean value of the discriminant score of a given category of a dependent variable. There are as many centroids as there are groups or categories.

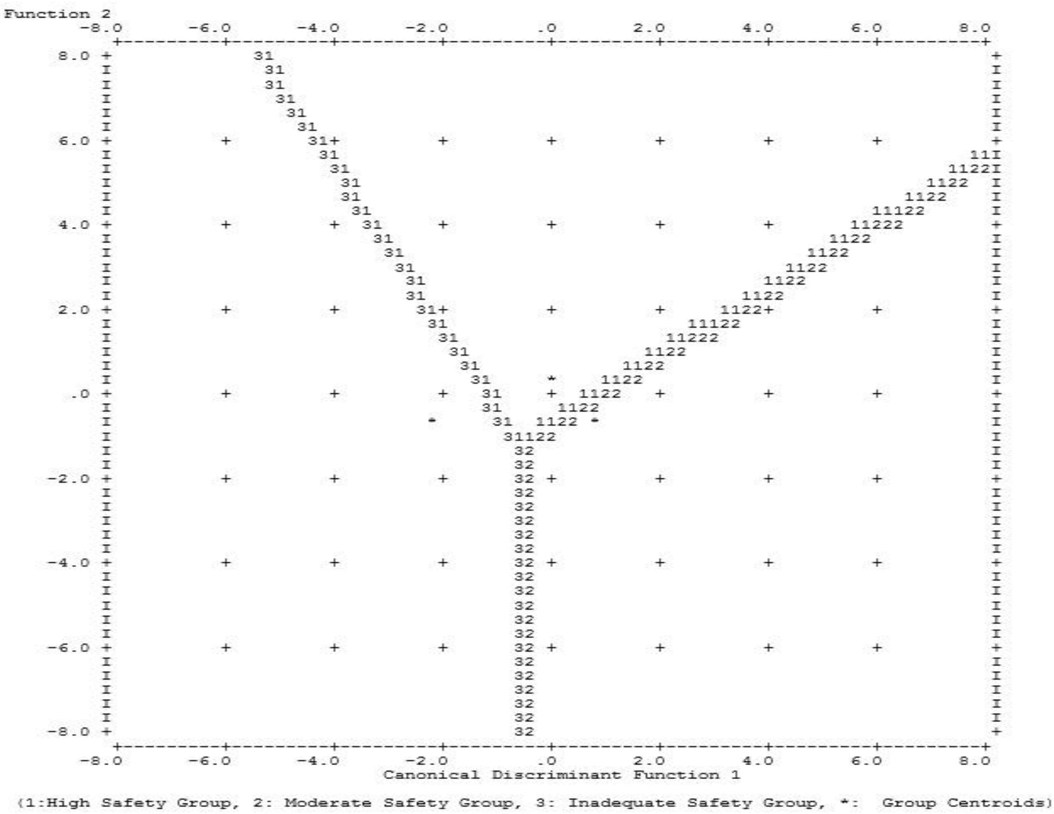

FIGURE 9.2: TERRITORIAL MAP-MODEL 2

9.8.4 Discriminant Functions

A discriminant function also called a canonical root, is a latent variable which is created as a linear combination of discriminating (predictor or independent) variables. There will be two discriminant functions for 3-group discriminant analysis. The first function will be the most powerful differentiator, but later functions may also represent additional differentiation. The functions and group centroids of Model 2 are displayed in Table 9.23 and 9.24.

TABLE 9.23: CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS- MODEL 2 (ALL VARIABLES)

Variables	Function	
	1	2
Kind of business	.374	-.555
Since in Business	.031	.032
Banking relations(years)	.046	.023
Net Sales/Total Assets(%)	.000	-.001
Retained Earnings/Total Assets(%)	.006	.026
Net Working Capital/Total Assets(%)	-.008	.026
EBIT/Total Assets(%)	-.031	.145
Book Value of Equity/Debt(%)	.000	-.001
TOL/TNW(%)	.001	-.001
Debt/Equity Ratio(%)	-.005	.002
Current Ratio(%)	.023	.012
Net Profit Before Taxes/Net Sales(%)	.261	-.067
Net Profit After Taxes/Net Sales(%)	-.393	.061
Security Coverage Ratio(%)	.000	-.005
Group Support	.495	.038
Net Working Capital/Current Assets(%)	-.011	-.022
ROCE(%)	.096	-.009
(Constant)	-5.412	-.771

Unstandardized coefficients

TABLE 9.24: FUNCTIONS AT GROUP CENTROIDS- MODEL 2 (ALL VARIABLES)

Credit Risk Rating	Function	
	1	2
High Safety	.712	.965
Moderate Safety	.513	-2.262
Inadequate Safety	-5.861	.189

Unstandardized canonical discriminant functions evaluated at group means

Function 1

Z= -5.412+0.374(Kind of Business) +0.031(Since in Business)+0.046(Banking Relations) +0.000(Net Sales/Total Assets) +0.006(Retained Earnings/Total Assets)-0.008(Net Working Capital/Total Assets)-0.031((EBIT/Total Assets) +0.000(Book Value of Equity/Debt)+0.001(TOL/TNW)-0.005(Debt/Equity)+0.023(Current Ratio)+0.261(PBT/Net Sales)-0.393(PAT/Net Sales)+0.001(Security Coverage Ratio) +0.495(Group Support)-0.011(Net Working Capital/Current Assets) + 0.096 (ROCE).

Function 2

Z= -0.771-0.555(Kind of Business) +0.032(Since in Business) +0.023(Banking Relations)-0.001(Net Sales/Total Assets) +0.026(Retained Earnings/Total Assets) +0.026(Net Working Capital/Total Assets) +0.145(EBIT/Total Assets)-0.001(Book Value of Equity/Total Assets)-0.001(TOL/TNW) +0.002(Debt/Equity)+0.012(Current Ratio)-0.067(PBT/Net sales) +0.061(PAT/Net sales)-0.005(Security Coverage Ratio) +0.038(Group Support)-0.022(Net Working Capital/Current Assets) – 0.009 (ROCE).

9.8.5 Classification Accuracy

The training sample data set was also subjected to leave-one-out cross-validation option. In this option, the discriminant model is re-estimated as many times as there are respondents in the sample. Each re-estimated model leaves out one respondent, and the model is used to predict for that respondent. When a large hold-out sample is not possible, as in our case, this gives a sense of robustness of the estimates using each respondent, in turn, as a hold-out. It is a less biased estimation of the accuracy of classification. Most researchers suggest that classification accuracy achieved by discriminant analysis should be at least 25% greater than that obtained by chance. In our All Variable Z-Score model, the improvement (97.5% / 72.5%) over chance (33.33% -Table 9.25) is more than 25%, and the validity of our all variable model is satisfactory (Table 9.26). The results demonstrate that the discriminants were fairly accurate in predicting credit risk.

TABLE 9.25: PRIOR PROBABILITIES FOR GROUPS- MODEL 2 (ALL VARIABLES)

Credit Risk Rating	Prior	Cases Used in Analysis	
		Un-weighted	Weighted
High Safety	.333	25	25.000
Moderate Safety	.333	11	11.000
Inadequate Safety	.333	4	4.000
Total	1.000	40	40.000

9.9 MISCLASSIFICATION ERRORS

Misclassification may arise due to type I and type II errors. Type I error occurs when the model incorrectly classifies a bad (Inadequate Safety) business as good (High Safety or Moderate Safety). Type II errors occur when the model identifies a good firm as dangerous. Type I error is more costly for banks than the type II error because it will cause non-performing loans, consequently lost profits, higher provisions, and higher credit costs. **In Model 2**, the model records 97.5% classification accuracy. Since both High Safety and Moderate Safety groups have performing loans (there is one misclassification case in between these two categories), both type I and II errors are zero. However in cross-validation, type I errors are high and type II errors very small. As regards **Model 1**, in original count, type I error is zero and type II errors are 8.33% (three firms out of 36 good firms have been classified as bad). Thus both in terms of classification accuracy and misclassification costs, the second model with all variables performed better.

TABLE 9.26: CLASSIFICATION ACCURACY- MODEL 2 (ALL VARIABLES) (DIRECT METHOD)

Credit Risk Rating			Predicted Group Membership			Total
			High Safety	Moderate Safety	Inadequate	
Original	Count	High safety	25	0	0	25
		Moderate Safety	1	10	0	11
		Inadequate Safety	0	0	4	4
		High safety	100.0	.0	.0	100.0

	%	Moderate Safety	9.1	90.9	.0	100.0
		Inadequate Safety	.0	.0	100.0	100.0
		High safety	21	3	1	25
	Count	Moderate Safety	4	6	1	11
Cross-validated		Inadequate Safety	2	0	2	4
		High safety	84.0	12.0	4.0	100.0
	%	Moderate Safety	36.4	54.5	9.1	100.0
		Inadequate Safety	50.0	.0	50.0	100.0

Notes:

1. 97.5% of original grouped cases correctly classified.

2. 72.5% of cross-validated grouped cases correctly classified.

9.10 HOLD-OUT SAMPLE VALIDATION

A hold-out sample of seven loans, consisting of four performing and three non-performing/ problem loans requiring restructuring was taken for validation of Model 1(Altman's Emerging Market Model) and Model 2(All Variables Z-Score Model). The first discriminatory function, in both the models, had higher discriminatory power among the three groups, and hence used to test the validity of models in hold-out or test samples. The Model 1 was able to classify four out of seven records correctly, whereas Model 2 was able to classify five out of seven records correctly (Table 9.27).

TABLE 9.27: HOLD-OUT SAMPLE - COMPARISON OF MODELS PERFORMANCE

Case No.	Bank's Rating	Model 1 (Altman) Rating	Model 2 (All Variable) Rating	Actual Loan performance
1	High Safety	High Safety	High Safety	Performing
2	Moderate Safety	High Safety	Moderate Safety	Performing
3	High Safety	High Safety	Moderate Safety	Performing
4	High Safety	High Safety	High Safety	Performing
5	Inadequate Safety	Moderate Safety	Moderate Safety	Non-performing
6	Inadequate Safety	Inadequate Safety	Inadequate Safety	Non-performing
7	Inadequate Safety	Moderate Safety	Inadequate Safety	Non-performing

The predictive power of Model 1 is 57.1 %, and of Model 2 is 71.4 %. Misclassification errors are also lower in Model 2. Type I errors in Model 1 are 67%, and in Model 2 are 33%. Type II errors are zero in both cases. For calculation of misclassification errors, we have compared performing loans (High and Moderate Safety groups) with non-performing loans (Inadequate Safety group). Thus Model 2 (All Variables Z-Score Model) has performed better in analysis sample as well as in the hold-out sample.

9.11 RESULTS AND DISCUSSION

The results demonstrate that multi-discriminant analysis is fairly accurate in predicting transactional credit risk in business loans. In both training and hold-out samples, the original and cross-validated classification accuracy surpassed by chance accuracy criteria, supporting the utility of All Variables Z-score Model.

Borrowing firms with low credit risk (High Safety group), medium credit risk (Moderate Safety group) and high credit risk (Inadequate Safety group) could be differentiated in terms of their balance sheet and profit and loss account variables as well as various non-financial factors. The combination of quantitative and qualitative risk factors improved credit risk assessment, and the model had high classification accuracy.

Utmost important is discrimination of bad loans from good loans, and our MDA model has been found quite accurate in the existing samples. With a larger sample base, primarily with a more extensive analysis and hold-out samples, MDA model will perform better.

The results confirm that by using multiple discriminant analysis, banks can predict credit risk in each loan transaction, and can also map rating transition matrix to develop early warning signals of default. When the MDA model is applied to quarterly or half-yearly financial results of the borrowers, it can also generate rating migrations or rating transitions to work as warning signals to detect approaching defaults.

Further in case the banks are also able to score borrowers in terms of all important subjective factors like their managerial competence, integrity of management, key input risk, marketing opportunities, environmental clearances, external ratings, ability to raise debts, accounting quality, industry prospects, labour relations, capacity utilization, etc., MDA model will have higher discriminatory power on multiple dependent variable bases and will be useful to Indian public sector commercial banks in grant of business loans and predict default.

9.12 CONCLUSIONS

Presently, Indian public sector banks are considering more than eighty risk factors in the categories of financial risk, business risk, industry risk and management risk for each segment of business loans. Within the existing samples, the Security Coverage Ratio, EBIT/Total Assets Ratio, and Debt/Equity Ratio have been found to be the most discriminatory variables. By using the multi-discriminant analysis, Indian public sector banks can test the discriminatory power of the various predictor risk factors suitable to a different category of borrowers like SMEs, mid-corporates, large corporations, new projects, etc., in the categories of financial and non-financial factors, for credit risk specialization and for tracking the credit risk.

Further, the inability of the companies to service their loans has affected most Indian banks with a majority of their loans turning bad. It is highly imperative that the banks' credit risk assessment models capture the probability of default and migration in credit ratings during the loan maturity taking into account both objective and subjective risk factors. The study has shown that the multi-discriminant analysis would be highly accurate in credit scoring of transactional credit risk in business loans.

CHAPTER 10
CONCLUSIONS AND RECOMMENDATIONS

10.1 INTRODUCTION

The Times of India had reported on 14 February, 2016 that the cumulative losses of the eight public sector banks crossed Rupees 10,000 crore in the third quarter of 2015-16, the highest ever in absolute terms, and the most nationalised banks reported gross non-performing assets (bad loans) in the range of 8 percent to as high as 12 percent. Thus, indicating high credit risk in these banks. This study has empirically investigated the credit risk management practices of the Indian public sector banks (PSBs) to identify and examine the characteristics and causes of credit risk in these banks, to compare the credit risk management practices of large and small PSBs, to analyze the implementation of Basel norms by them and their credit risk assessment framework. The study has also designed a credit risk assessment model for these banks based on multivariate discriminant analysis, for accurate classification of business borrowers in risk categories.

10.2 MAJOR FINDINGS

This empirical study of credit risk management practices of Indian public sector banks has the following main findings:

1. Banking loans to business and industry account for more than two-third of total advances by the Indian banking industry and since public sector commercial banks dominate the Indian banking, these loans are the main channel or source of credit risk in these banks. Since March 2011, because of the stressful economic

environment and increasing loan defaults, the public sector banks are reducing annual credit to the commercial sectors. There is both risk aversion by banks and slack in demand from business and industry.

2. Both micro and macroeconomic factor are changing the credit risk spectrum of borrowers' industries in a different manner. Presently aviation, iron & steel, textiles, infrastructure, mining, power generation, coal, and telecommunication are highly stressful. This makes it essential for banks to undertake in-depth industry studies for assessing the credit risk. Further survey respondents have found that trading activities (43%) in any industry have more default risk as compared to manufacturing (35%) and services (22%). Thus, differential credit risk exists in different industries as well as in different activities in the same industry.

3. The Indian public sector banks are under high stress on account of growing non-performing assets and increased restructuring of loans to business and industry. During the study period of 2008-2015, all indicators of credit risk like GNPA/Gross Advances Ratio (GNPA Ratio), NNPA/Net Advances Ratio (NNPA Ratio), Restructured Standard Advances/Total Advances Ratio, Stressed Assets Ratio (Restructured Assets + GNPAs/Total Advances Ratio), Exposure to Sensitive Sectors Ratio, Net Interest Margin, ROA have shown high pressure on public sector banks. Though their capital adequacy ratios (Capital to Risk-weighted Assets Ratio or CRAR) are above the regulatory requirement, they are least capitalized in the Indian banking industry and with the highest risk-bearing assets. Since CRAR is an indicator of financial leverage risk and since financial

leverage risk and credit risk reinforce each other, the Indian public sector banks have the highest credit risk in the industry. The linear regression analysis of sample banks (2008-2015) has also statistically established the significant inverse relationship between CRAR and NNPA Ratio.

4. The asset quality of the Indian public sector banks has been continuously deteriorating. In terms of individual public sector banks, mean Gross NPA Ratio (2008-15) was at an alarming rate in United Bank of India (5.17%), and in State Bank of India (4.09 %), and thus, these banks had the highest credit risk. The Bank of Baroda (2.21%) and Punjab & Sind Bank (2.29%) had the lowest credit risk during this period, regarding GNPAs.

5. Another problem with PSBs is that they have the highest loan restructuring in the banking industry. Though the Reserve Bank of India reports do not publish how many rescheduled and restructured loans have turned into bad loans, these loans are under a high pressure and with high probability of turning into non-performing. The linear regression analysis of sample banks (2008-2015) has statistically established the direct and positive significant relationship between restructured standard advances and GNPA Ratios. Thus, the study takes both the GNPA Ratio and Restructured Standard Advances Ratio together as Stressed Assets Ratio, to indicate the credit risk in PSBs. Stressed Assets Ratio of the sample public sector banks has been continuously growing from 4.33% in 2008-09 to 14.19% in 2014-15. During 2008-15, the highest Stressed Asset Ratio was of the United Bank of India (10.03%). Other banks with high credit risk in our sample are OBC (9.996%), PNB (9.697%), Andhra Bank (9.51%), and the

Punjab & Sind Bank (9.13%). SBI, the largest PSB had a mean Stressed Assets Ratio of only 6.51% (SD 1.746) and ranks 10th among the sample banks. Bank of Baroda had the lowest credit risk (5.67%) in terms of this ratio.

6. Mean Stressed Assets Ratio (2008-15) of large public sector banks was 7.94% and of small public sector banks 8.77%, indicating a higher degree of credit risk in small PSBs.

7. During 2014-15 also, the United Bank of India had the highest credit risk among the sample banks with the highest GNPA Ratio (9.49%), the highest NNPA Ratio (6.22%), the highest Stressed Assets Ratio (22.51%), and the second lowest ROA (0.21%). Other banks under high stress on their asset quality during this year were OBC (19.1%), Punjab & Sind Bank (17.95%), PNB (16.82%), Andhra Bank (16.56%) and Dena Bank (15.68%). Mean Stressed Assets Ratio during 2014-15 was 14.19%.

8. The survey respondents find the SARFAESI Act (The Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest Act), 2002 and OTS (One -Time Settlement) scheme, the most efficient methods to recover defaulted loans.

9. The study investigated the various causes of credit risk in Indian PSBs. Five credit risk variables - TOL/TNW Ratio, the track record of past payments; integrity of management; current ratio and managerial competence were found with the highest risk component to measure borrower's creditworthiness. Thus, taking all the credit risk variables under consideration, a business borrower would have the highest chances of default in terms of his ability and willingness

to service debt if he has low TOL/TNW (Total Outside Liabilities/ Tangible Net Worth), low current ratio, poor payment record or banking discipline, low managerial integrity, incompetent management, low ROCE (Return on Capital Employed), capacity underutilization and industrial disputes.

10. Among various categories of risk factors of a commercial borrower, the study observed that the strongest cause of credit risk was the liquidity and solvency risk category (Current Ratio and TOL/TNW Ratio). Thereafter, the management risk category (managerial competence, integrity of management, payment record, length of banking relations, and ability to raise debt) and business and industry risk category (capacity utilization by the borrowers, state of their technology, level of competition, key input risk, marketing opportunities, and government policy towards the industry) also caused high credit risk.

11. The study also observed that the most challenging risk to manage for the Indian public sector banks is the industry risk of their borrowers. More experienced credit managers (experience 20 years and above) have found industry and business risk group of factors of the borrowers, to be the highest risk category. Management of this risk group would require regular industry studies and market intelligence. Since risk factors affecting each industry or business line may be strategically different, it would necessitate precise identification of critical risk factors and differential credit risk assessment practices to measure and control credit risk for various industries or business groups.

12. Indian public sector banks' credit managers agree (77.1%) with RBI observation that inadequate appraisal of business borrowers, is causing high non-performing

loans. They also believe (63.8%) that the economic slowdown is stressing firms and industries, and causing weak loan recoveries, and bad loans.

13. The study empirically compared the credit risk management practices of large and small public sector banks and found significant differences in managerial perceptions in these two bank categories about the effectiveness of their credit risk management systems, policies, and procedures. Small public sector banks do not perceive their CRM systems as well designed as that of large banks. They are facing more problems and obstacles in managing credit risk and shall be requiring better risk inputs, and restructuring of their various credit appraisal and loan monitoring processes. The small banks' credit and risk managers have scored higher for all the obstacles or constraints surveyed, in design and implementation of CRM systems and procedures. The more severely felt barriers by them are lack of specialized training for credit and risk managers, poor risk awareness, the lack of resources for proper risk management, poorly designed credit risk assessment framework causing inconsistencies in risk-rating approaches. The credit officers of large PSBs are, however, feeling more in support of weak loan appraisals in their banks. Against the question, whether inadequate appraisal of borrower's creditworthiness is causing higher NPAs, the mean score from large banks was 3.73 (S.D 1.055), and from small banks was 3.72 (S.D .999).

14. Most of the Indian public sector banks have elaborate internal credit risk assessment models to measure transactional credit risk. However, use of theoretical or statistical models could not be established, because of software-

driven credit rating models. A key differentiating factor in these banks' credit rating models was the calculation of RAROC or risk-adjusted return on capital on each loan transaction. RAROC is the most rational basis for risk-based pricing and measurement of loan performance and within RBI guidelines for banks. Punjab National Bank, which has pioneered the advanced credit rating models in Indian banking industry, was found not calculating RAROC. Other banks not measuring this ratio are four small banks – Punjab & Sind Bank, Dena Bank, United Bank of India and Andhra Bank.

15. Only 56.1% of the survey respondents agreed that the credit rating models in their banks were effective in capturing the credit risk of their business borrowers. The study observed that the credit managers in large PSBs were more satisfied with their credit risk assessment framework than the credit managers in small banks. The highest favorable perception has been observed from the State Bank of India, the Syndicate Bank and the Bank of Baroda. These three banks have thus, benchmark credit rating models. Andhra Bank and the United Bank of India's credit managers are least satisfied with their credit rating/scoring models.

16. Credit risk assessment by public sector banks has been found to be highly subjective. Credit rating models of banks have both quantitative and qualitative risk parameters. The qualitative risk parameters are larger in number though their weightage is lesser than the quantitative factors. Business, industry, and management risk valuation have mostly these qualitative or experiential factors and as such there is a huge scope of subjectivity in this part of credit risk assessment of the borrowers. Further the study has observed statistically

significant disagreement between junior, middle and senior level credit managers, and between ‘up to 7 years’ and ‘20 years and above’ category of managers. Since other than for financial risk factors, credit risk assessment of other factors is highly subjective, there shall be an emergent need for regular discussions, sharing of risk information, job-related training, and continuous watch on the compliance of credit risk policy and procedures at all levels in banks’ credit departments. These measures will reduce subjectivity and inconsistencies in credit risk assessment, and thereby help in controlling and mitigating credit risk.

17. Other than being a source of subjectivity or bias in risk assessment, significantly different perceptions observed in various managerial groups on various dimensions of credit risk management practices, can create other obstacles. These obstacles may be in integration of work-groups, goal alignment, team work, quick decision making, sharing of information, and may cause both interpersonal conflicts and misinterpretation of risk. Thus, there shall be a need for clear goals identification, high risk sensitivity, and efficient communication and feedback systems. These steps will also lead to skill or potential development in credit risk management.

18. The study examines the preparedness of the Indian PSBs to migrate to the Internal Rating Based Approach (IRB) of Basel II through the perceptions of their credit managers and finds that the large banks have higher mean scores which are statistically significant as well, showing the better implementation in these banks. The managerial perception in credit departments of all PSBs, about the utility of Basel II guidelines as a business enhancement skill in risk

management, is quite encouraging (76.5% agree). Credit managers also agree that Basel II has helped banks in credit risk mitigation (78.8% agree). Though many of them also find the quantitative framework of these guidelines complex (51% agree). The positive feedback for these prudential guidelines might have facilitated their implementation.

19. One of the positive aspects of credit risk assessment by the public sector banks is that they are aware of strength and weaknesses of other banks' risk management systems. This knowledge may have helped them to improve their systems. The majority of bank managers are also for disclosure of rating models to borrowers. This disclosure would increase transparency in credit ratings, encourage full disclosures of credit information by borrowers, and in the case of SMEs, it would help them to improve their credit history and motivate them to have fair accounting practices.

20. The size of the bank has been found to be a key discriminating factor in credit risk management among large and small public sector banks. First, in terms of stressed business loans (GNPA and Restructured Assets), smaller public sector banks have higher credit risk than the large public sector banks. Second, for large banks, business and industry risk factors of the borrowers are posing serious credit risk, whereas for small banks, management, and financial risk factors of borrowers are the primary causes of credit risk. Third, smaller banks are facing more problems and obstacles in managing credit risk. Fourth, large banks have better compliance with Basel II guidelines in developing internal credit risk rating models. Fifth, credit managers of large public sector banks, are found to be

more satisfied with their credit risk rating/scoring models. Thus, bank size itself is a critical credit risk variable in credit risk management in public sector banks.

21. The study evaluates two MDA models to predict transactional credit risk in business loans. Model 1 has four financial ratios (Altman, 1995) and Model 2 has 13 financial ratios and four non-financial factors. Model 2 is found to have higher classification accuracy (97.5% in estimation sample and 71.4% in the hold-out sample). Thus, the combination of quantitative and qualitative risk factors improved credit risk assessment. The results confirm that by using multi-discriminant analysis, banks can predict credit risk in each loan transaction, and can also map rating transitions to develop early warning signals of default. When the MDA model would be applied to quarterly or half-yearly financial results of the borrowers, it can generate warning signals of approaching defaults.

10.3 MANAGERIAL IMPLICATIONS OF THE STUDY

Credit risk is one of the significant risks that a commercial bank faces, and it has a direct impact on its profitability, liquidity and solvency. The study has important implications for bank management in Indian public sector commercial banks to manage and reduce transactional credit risk in business loans and improve asset quality. The findings are in tune with the RBI Report on Trends and Progress of Banking in India, 2014-15. RBI (2014-15) observed that the public sector banks (PSBs) witnessed deceleration in credit growth in 2014-15. Private sector banks (PVBs) and foreign banks (FBs), however, indicated higher credit growth. Further banks GNPA and NNPA ratios were increased during this year also indicating stress on their asset quality. The deterioration in the asset quality of banks in general, and

PSBs in particular continued during the year with a rise in volume and proportion of stressed assets (Paras 1.2,2.1 &3.5 of RBI Trends, 2014-15).

The study has investigated the managerial perceptions of different categories of risk & credit managers directly involved in commercial bank credit in Indian PSBs. Their perceptions/opinions have been studied on evolving characteristics and causes of credit risk in their banks, on problems/ obstacles in credit risk management in large and small banks and on effectiveness of their risk mitigation measures, their credit risk assessment framework, and regulatory compliance.

Understanding perceptual processes is fundamental in understanding the impact perception has on decision-making. Aligning CRM practices with perceptions and intrinsic knowledge of managerial groups will enhance their effectiveness and help in risk mitigation. Since credit risk management is highly subjective area and risk managers relying largely on experiential and judgmental factors, the study has contributed in gathering feedback from a large number of credit managers of Indian public sector banks and statistically analyzing that to find the areas which need more concerted effort in managing credit risk.

The empirical findings will also have significant implications for banks' strategic planners in the restructuring of various credit appraisal and loan review processes where they are feeling short. For example on risk awareness, potential HR development, business related training, data management and IT support, or on reducing disintegration across departments and inconsistencies in risk rating approaches, or requiring a reorganization of responsibility framework for loan approvals, separation of risk assessment from loan sanctions, and focused attention on problem loans. The risk managers should be conscious that every part of the CRM processes is necessary, and even a little complacency in the lending decision, such as in loan documentation, collateral valuation, or even in surprise plant visits, may result in loan defaults.

Further, in an environment of economic slowdown, weak credit growth, and least product differentiation between banks, efficient credit risk management practices of a public sector bank will act as a key differentiator to ensure good quality assets and competitive advantage. The study has contributed in empirical evaluation of these practices.

10.4 LIMITATIONS OF THE STUDY

The present study confines to an empirical investigation into the credit risk management practices of Indian public sector banks during 2008- 2015. In its pursuits, the study is subject to certain limitations which are discussed below:

1. The present study is limited to Indian public sector banks only. Private sector and foreign banks in the Indian banking industry are not part of this study.

2. The study uses the judgment or non-probability sampling method to select the 12 public sector banks out of total 26 such banks. Further, selection of 337 credit managers in data collection through a structured questionnaire has also been undertaken on convenience sampling method. Thus, the sample may not be fully representative of the population.

3. At the time of sample selection and data collection, there were only 26 public sector banks. However, at the date of reporting results, there are 27 public sector

banks as Bharatiya Mahila Bank has also been set up. As such this bank is not part of the study.

4. The study is limited to Delhi and areas in and around Delhi.

5. Since the large part of the study was related to internal credit risk systems and procedures of the public sector banks, the researcher did not have full access to information regarding their loans to business and industry. However, efforts have been made to cover all aspects in the study.

6. The study uses multivariate discriminant analysis in developing credit rating model for transactional credit risk. Lack of multivariate normality, homogeneity of group variances and linearity among the predictors may decrease the statistical power of the discriminant analysis procedure (Tabachnick & Fidell, 2000). The model developed by the study also has these limitations. Moreover, the results of discriminant analysis have limited generalizability. Usually, they generalize only to those populations from which the sample are obtained (Tabachnick & Fidell, 2000).

10.5 SUGGESTIONS AND RECOMMENDATIONS

The objective of credit risk management in Indian public sector banks is to maintain asset quality while maximizing risk-adjusted return on capital. In this pursuit, they shall require better risk inputs and restructuring of various credit appraisal and loan review processes. For better credit risk management, their immediate concern shall be in the following areas:

1. All efforts shall be made for HR potential development in credit departments through well-designed professional training modules. They shall need skill up-

gradation in credit risk identification, measurement, and mitigation tools through in-bank and specialized credit experts, to understand the financial data of borrowers, and adopt new and innovative risk strategies.

2. Banks shall revamp performance appraisal systems in credit departments. Rewards of credit manager shall not be linked with business or loans secured by them for their banks but on the quality of risk assessment, mitigation, and control undertaken by them.

3. Establishing a transparent staff accountability framework to ensure due diligence and compliance with credit policy and procedures. There is a high possibility of connivance of bank staff with willful defaulters.

4. Banks shall thoroughly review their internal audit systems. All cases pending compliance to audit should be seriously considered. There shall be a continuous audit of loans above pre-decided limits even when they are standard and preforming.

5. Risk audit or external audit of banks' risk management systems and procedures can provide banks with good feedback for the reduction in processing effort, managing subjectivity in ratings, on the restructuring of risk departments, and develop IT resources.

6. Many cases of loan defaults have occurred in Indian PSBs on account of weak compliance with KYC norms, legal deficiencies in loan documentation, and inadequate surveillance at the time of loan disbursements. As such, banks suffered credit losses even with secured loans. Banks, therefore, must develop a checklist of actions for their credit and risk managers for every step in credit

approvals, disbursement, and loan recoveries to ensure compliance with policies and procedures.

7. Post-sanction, loan disbursement has been observed to be the weakest link in CRM processes. The credit managers shall be adequately trained to detect diversion of funds by the borrowers at this stage, for the promotion of their sister or associate concerns or expansion/diversification of their existing concerns beyond the terms of loan agreement. Banks can tighten their control on willful defaulters through effective credit risk management practices.

8. The efficiency of NPA recovery systems is very crucial to manage defaulted loans and minimize credit losses. Banks shall make full use of the SARFAESI Act. One- time settlement or compromise schemes, though very popular among banks and borrowers, shall be employed only as a last resort.

9. Adopting advanced approaches of Basel II will increase the competitive advantage of banks, and therefore, all public sector banks shall strengthen their internal risk management systems in tune with Basel norms.

10. Growth potential of SMEs is higher than the big companies and will continue to provide business to banks even during slow economic growth. Bank shall continue to have a greater focus on SME segment.

11. Small public sector banks shall develop credit risk strategies with clear implementation schedules and which are suitable to their resources and may reduce their competitive disadvantage. Updating data management and IT capabilities shall be their priority. Improved IT systems will increase the

efficiency of operative procedures, data analysis and prediction of both counterparty and portfolio credit risk.

12. Banks shall coordinate with Assets Reconstruction and Securitization Companies to offload their bad debts, in a risk-sharing or other available mechanism, to release funds back into the business, instead of fighting protracted legal battles to recover bad loans.

13. The credit policy shall be regularly updated with industry studies, field research, and there should be constant liaison within the banking sector.

10.6 SCOPE FOR FUTURE RESEARCH

The extent of this study is limited to evaluating credit risk management practices of Indian public sector banks in relation to transactional credit risk in firms and mid-corporate bank loans. Further research on credit risk management practices in Indian banks may be conducted in following areas:

1. The research may be carried out on comparative credit risk management practices of public and private sector banks.

2. Another area of possible research is portfolio management of credit risk by Indian banks, covering asset correlation, concentration risk and computation of economic capital.

3. Stress testing of credit risk models by Indian banks is another unsearched area. With the help of historical time series data, individual banks can stress test their credit risk measurement models through historical or hypothetical scenario building. Through stress testing, banks can assess the sensitivity of critical risk

factors to extreme or tail events, like the default of all primary borrowers, economic downturn, the impact of the recession on main borrowers, etc.

4. The research may be extended to study the IT systems and data management by Indian banks to support their credit risk management systems and procedures.

5. The high credit losses from non-performing assets have resulted into a high scale of debt rescheduling and restructuring of business loans, in particular by the public sector banks. There is a scope of research into nature and impact of debt restructuring on credit risk position of the banks.

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APPENDIX 1

LIST OF SAMPLE BANKS

1. State Bank of India
2. Punjab National Bank
3. Bank of Baroda
4. IDBI Bank
5. Syndicate Bank
6. Oriental Bank of Commerce
7. Andhra Bank
8. United Bank of India
9. Vijaya Bank
10. Dena Bank
11. Punjab and Sind Bank
12. State Bank of Bikaner and Jaipur

APPENDIX 2

QUESTIONNAIRE

Dear Respondent,

I am doing a survey on **'Evaluation of Credit Risk Management Practices – An Empirical Study of Indian Public Sector Commercial Banks'** as part of a Ph.D. research study through Delhi School of Management, Delhi Technological University, New Delhi. The objective of the research is to understand the credit risk management environment of the public sector banks in the grant of **business loans (SMEs/Firms and Mid-corporates)**. I request you for your kind cooperation. I assure that the information given by you will be kept confidential and will be used for educational purpose only.

Renu Arora

Bank_______________ Respondent No_________ Date of Survey_________

Part I: General details of the respondents

(a) Experience in the banking operations ☐ Years

(b) Educational Qualifications ☐ **(c)** Professional Qualifications ☐

(d) Management level
- ☐ Junior Managers (Asstt. Managers/ Officers).
- ☐ Middle Level Managers (Managers and Sr. Managers).
- ☐ Senior Level Managers (Chief Mgr, AGM and above).

(e) Area of operations ☐ Loan approval process. ☐ Loan recovery process.

Part II: Credit Risk Management Practices

Kindly tick (or write ok) the appropriate responses:	Strongly agree	Agree	Cannot say	Disagree	Strongly disagree
1. The bank has a well-designed credit risk policy and strategy					
2. Responsibility for credit risk management is clearly set- out and understood throughout the bank.					
3. Bank is aware of strength and weakness of its risk management system vis-á-vis, other banks.					
4. Public disclosures of credit risk rating models shall be undertaken to match risk perceptions of lenders and borrowers.					
5. Experience and judgment of risk managers are more important than to apply the sophisticated techniques of credit risk management.					
6. Credit risk systems and procedures of bank need review and change to increase effectiveness of credit risk management.					
7. For effective credit risk systems and procedures, the human resource needs better skill, training and movtivation.					

8. Which are more effective instruments of credit risk management in your bank:	Score each out of 5. 1 for least effective, 5 for most effective.
(a) Loan appraisal mechanism.	
(b) Prudential limits.	
(c) Risk-rating or credit-scoring.	
(d) Risk-based pricing.	
(e) Portfolio management.	
(f) Loan review mechanism.	
(g) Industry studies.	
(h) Periodic plant visits.	
(i) Surprise inspections.	
(j) Sharing experience with other lenders.	
(k) Securitisation of loans.	
(l) Issue of credit derivatives.	
(m) Consortium lending	
(n) Covenants for sensitive sectors.	
(o) Controls on related party lending/insider loans.	

9. Which are obstacles in implementation of credit risk management systems in your bank	Very much	Some What	Cannot say	A little Bit	Not at all
(a) Lack of resources.					
(b) Lack of risk awareness.					
(c) Insufficient training.					
(d) Disintegration of systems across departments.					
(e) Inconsistencies in risk-rating approaches.					
(f) Data management.					
(g) Inappropriate IT support.					
(h) Lack of comprehension of Basel guidelines.					
(i) Lack of standardization of risk-rating and review processes.					
(j) Overload.					
(k) Stringent regulatory requirements.					

10. How you score the following risk mitigation measures in your bank:	Very good	Good	Average	Below Average	Bad
(a) Regular discussions, reviews and feedback reports.					
(b) Restriction on responsibility for volume-based credit approvals and reviews.					
(c) Independence of credit risk assessment from credit sanctioning process.					
(d) Reduction in processing effort per loan application.					

(e) Regular rating reviews. ☐ ☐ ☐ ☐ ☐

(f) Reduction of subjectivity in credit rating. ☐ ☐ ☐ ☐ ☐

(g) Internal audits. ☐ ☐ ☐ ☐ ☐

(h) Risk-based appraisal and sanctions. ☐ ☐ ☐ ☐ ☐

(i) Independence of loan review mechanism. ☐ ☐ ☐ ☐ ☐

(j) Implementation of KYC norms. ☐ ☐ ☐ ☐ ☐

(k) Multi-tier credit approval process. ☐ ☐ ☐ ☐ ☐

(l) Focused attention on problem/weak credit exposures. ☐ ☐ ☐ ☐ ☐

11. Which sector is more risk prone? Manufacturing ☐ Services ☐ Trading ☐

12. Is the stress testing a part of credit risk models? Yes ☐ No ☐ Not sure ☐

13. Is the sensitivity analysis a part of credit risk rating models? yes ☐ No ☐ Not sure ☐

14. Which risk is more challenging to predict:	Strongly agree	Agree	Indifferent	Disagree	Strongly disagree
(a) Financial risk is easy to predict.	☐	☐	☐	☐	☐
(b) Industry risk is unpredictable and more challenging to manage.	☐	☐	☐	☐	☐
(c) Business risk can be predicted to a good accuracy.	☐	☐	☐	☐	☐
(d) Management risk is difficult to predict.	☐	☐	☐	☐	☐

15. Is the bank using any of the following credit risk models:

	Yes	No	Not Sure
(a) Altman's Z-score model.			
(b) KMV Credit Monitor model.			
(c) Credit Risk+.			
(d) Mckinsey's Credit Portfolio View.			
(e) Black and Scholes option pricing model.			

16. Do the credit risk assessment models of the bank are capable to calculate, as per Basel II:

	Yes	No	Not Sure
(a) Probability of Default (PD).			
(b) Loss Given Default (LGD).			
(c) Exposure at Default (EAD).			
(d) Capital Adequacy Requirement.			
(e) Portfolio credit risk.			
(f) Rating Transition Matrix.			
(g) Risk-adjusted Return on Capital (RAROC)			

	Strongly agree	Agree	Indifferent	Disagree	Strongly Disagree
17. Basel II is a business enhancement skill in risk mgt. and not merely a compliance issue.					
18. The quantitative framework of Basel II regulatory guidelines is complex and difficult to train the staff.					
19. Basel II has helped in credit risk mitigation in bank .					

20. The post-sanction loan monitoring in the bank is as strong as the loan approval process.					
21. Should the banks rely on the external credit ratings?					
22. Economic slowdown is the main cause of credit losses in banks.					
23. Credit rating models of the bank are effective in capturing the credit risk.					
24. Inadequate appraisal of borrower's creditworthiness is causing higher NPAs.					

25. Which method is more effective to recover/resolve NPAs?	Very much	Some What	Cannot say	A little Bit	Not at all
(a) One-time compromise settlement scheme.					
(b) Recovery through Debt Recovery Tribunals.					
(c) Recovery through recovery agents.					
(d) Recovery through Lok Adalats.					
(e) Recovery through SARFAESI Act.					
(f) Writing off (partial)					
(g) Restructuring of debt.					

(h) Any other, may specify. ______________________

26. How can the banks control willful defaults?	Strongly agree	Agree	Indifferent	Disagree	Strongly Disagree
(a) Ban on financing new ventures of defaulters.					
(b) Making their names public.					
(c) Filing of criminal charges against them.					

(d) Any other, may specify

27. There are sufficient internal controls to eliminate the tendency to postpone identification of NPAs?

Part III: Credit Risk Factors Score Sheet

Please give scores to each from 1 to 5. 1 for least importance. 5 for highest importance.

What shall be the importance of these borrower related factors in credit rating models of banks, as a cause of credit risk?

(1) Total outside liability/Total Net worth ratio.	
(2) Current ratio.	
(3) Return on capital employed.	
(4) PBDIT/Interest ratio.	
(5) Profit after taxes/Net sales ratio.	
(6) Net cash accruals/Total debt.	
(7) Industry prospects.	
(8) Industry averages/ratios.	
(9) Regulatory risk/government directives or policy.	
(10) Competition/threat of substitutes.	
(11) Capacity utilization.	
(12) Access to cost-effective technology.	
(13) Key input risk.	
(14) Marketing opportunities.	
(15) Managerial competence.	
(16) Ability to raise debt.	
(17) Length of exposure in the industry.	
(18) Integrity of management.	
(19) Labour relations.	
(20) Adequacy of collaterals/facility ratings.	
(21) Environmental risks/clearances.	
(22) Retained earnings.	

(23) Market value of equity.	
(24) Payment record/conduct of loan account.	
(25) Length of the banking relationship.	
(26) Amount of the loan.	
(27) Maturity period of loan.	
(28) Rate of interest charged.	
(29) Constitution of the borrower, like a co., partnership, proprietorship.	
(30) Group support/financial support from group companies.	

Name: (optional) Branch: (optional)

Tele: (optional)

APPENDIX 3

BIO-DATA OF THE AUTHOR

Name: Mrs. Renu Arora

Designation: Assistant Professor (Senior- Scale)

Institution: Mata Sundri College for Women, University of Delhi.

Educational Qualifications: M.Com (Delhi University- 1982) - 67%.

Professional Qualifications: MBA (IGNOU – 1999) with B Grade (5 point scale), UGC- NET, 1998.

Work Experience: 1. Administrative experience in IGNOU (SO/ Assistant Registrar – Nine years.

2. Teaching experience (Commerce & Management) – University of Delhi, 19 Years.

Publications (From this research work)-11

Research Papers (International) Published

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