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EXECUTIVE SUMMARY

This report basically highlights how the credit is rated in the bank of baroda and based on that rating how interest rate is charged from different customers based on their credit score.

To understand the various parameters that is taken into account while rating borrowers the report has been made. Since ratings are subjective in nature and the grades assigned by the rating officers are discretionary, the main factors which is deduced by surveying the rating officers at different branches of the Bank. This has been done by using a questionnaire and then applying Factor Analysis to the responses so obtained. On applying this tool seven important factors have been obtained which play a significant role in determining ratings. These are:

1.Gap between demand and supply

2. Ability of the borrower to raise debt

3.Managerial competence of the borrower

4.Financial strength of the borrower

5.Past Payment record

6.Net worth of the company

7.Adequacy of security coverage

Further, Analytical Hierarchy Process, an Operations Research tool, has been applied using Excel applied in order to obtain a hierarchy of factors which affect ratings of the different Borrower models namely Large Corporate model, Small and Medium Enterprise model, Infrastructure (Power) model and Trader model. The hierarchy so obtained gives an idea of the main risk factors which should be effectively managed so as to obtain improved ratings which in turn enable the borrower in negotiating interest rates.

CHAPTER 1 INTRODUCTION

The Scheduled Commercial Banks (SCBs) in India have shown an impressive growth from FY08 to the mid of FY13. Total deposits, advances and net profit grew at CAGR of 19.6%, 27.4% and 20.2% respectively from FY08 to FY13. Banking sector recorded credit growth of 33.3% in FY10 which was highest in last two and half decades and credit growth in excess of 30% for three consecutive years from FY11 to FY14, which is best in the banking industry so far. Increase in economic activity and robust primary and secondary markets during this period have helped the banks to garner larger increase in their fee based incomes. A significant improvement in recovering the NPAs, lowest ever increase in new NPAs combined with a sharp increase in gross advances for SCBs translated into the best asset quality ratios for banking sector in last two decades.

This significant transformation of the banking industry in India is clearly evident from the changes that have occurred in the financial markets, institutions and products. While deregulation has opened up new vistas for banks to augment revenues, it has also entailed greater competition and consequently greater risks.

Risk is an inherent part of Bank's business. Effective Risk Management is critical to any Bank for achieving financial soundness. In view of this, aligning Risk Management to Bank's organizational structure and business strategy has become integral in banking business.

In the financial services industry, the main risk exposures that a bank faces are **Market Risk**, **Operational Risk**, **Credit Risk** and **Liquidity Risk.**

Market risk is the exposure to adverse price movements of financial instruments arising as a result of changes in market variables such as interest rates, exchange rates and other asset prices.

Operational risk is the risk of loss on account of inadequate or failed internal process, people and systems or external factors.

Credit Risk is the risk that the counterparty to a financial transaction will fail to discharge an obligation resulting in a financial loss to the bank. Credit risk management processes involve identification, measurement, monitoring and control of credit exposures.

Liquidity risk is the risk that the bank either does not have the financial resources available to meet all its obligations and commitments as they fall due or has to access these resources at excessive cost.

1.1 COMPANY PROFILE

Bank of Baroda was established in the year 1908 in Baroda. Ever since its inception, the bank has been growing and expanding its branches successfully. At the turn of a century, the bank has its presence in 25 countries across the world. Bank of Baroda has progressively taken a step towards commitment and values by providing uncompromising standards of service to its customers, stakeholders, employees and the like.

Bank of Baroda is the third largest Public Sector Bank in India after State Bank of India and Punjab National Bank. BoB has total assets in excess of Rs. 2.27 lakh crores, a network of over 3000 branches and offices, and about 1100+ ATMs. It offers a wide range of banking products and financial services to its corporate and retail customers.

The Bank's performance has been improving over the years and is evident from the year on year growth as reported in the annual report and other financials. The improvement in financials in the year 2009-10 over 2008-09 can be seen from the table given hereunder:

Table 1: BoB Financials

PARTICULARS	2013-14	2014-15
Return on Average Assets (%)	1.21	1.09
Average Interest bearing liabilities (Rs. Crore)	2,15,886.21	1,71,666.55
Average Cost of Funds (%)	4.98	5.81
Average Interest Earning Assets (Rs crore)	2,16,735.54	1,75,818.59
Average Yield (%)	7.70	8.58
Net Interest Margin (%)	2.74	2.91
Cost-Income Ratio (%)	43.57	45.38
Book Value per Share (Rs)	378.44	313.82
EPS (Rs)	83.96	61.14

The Bank has approved policies and procedures in place to measure, manage and mitigate various risks that the Bank is exposed to. In order to provide ready reference and guidance to the various functionaries of the Risk Management System in the Bank, the Bank has in place Asset Liability Management and Group Risk Policy, Domestic Loan Policy, Off Balance Sheet Exposure Policy (domestic), Stress Test Policy and Stress Test Framework, Operational Risk Management Policy, Internal Capital Adequacy Assessment Process (ICAAP), Credit Risk Mitigation and Collateral Management Policy duly approved by the Board.

The Bank uses a robust rating model developed to measure credit risk for majority of the business loans (non personal loans). The rating model has the capacity to estimate probability of default (PD), Loss Given Default (LGD) and Expected Losses (EL) in a specific loan asset.

Apart from estimating PD and LGD, the credit rating model will also help the Bank in several other ways:

- To migrate to Rating Based Approaches of computation of Risk Weighted Assets
- To price a specific credit facility considering the inherent credit risk.
- To measure and assess the overall credit risk and to evolve a desired profile of credit risk.

1.1.1 CREDIT MONITORING AT BOB

Credit monitoring on a continuous basis is one of the most important tools for ensuring quality of advance assets. The Bank has the system of monthly monitoring of the advance accounts at various levels to prevent asset quality slippages and to take timely corrective steps to improve the quality of credit portfolio.

A separate department for Credit Monitoring function at the corporate level, headed by a General Manager, and one at the Regional/Zonal level, started functioning since September 2008. The Slippage Prevention Task Force formed at all Zonal/Regional offices in terms of the Bank's Domestic Loan Policy was activated for the purpose of arresting slippage and also for initiating necessary restructuring in potential sick accounts at an early stage in conformity with the laid down norms and guidelines. The Bank placed special focus on sharpening of the credit monitoring process for improving the asset quality, identifying areas of concern/branches requiring special attention, working out strategies and ensuring their implementation in a time bound manner.

The primary objectives of the Credit Monitoring Department at the corporate level are fixed as under:

- Identification of weakness/Potential default/incipient sickness in the loan accounts at an early stage;
- Initiation of suitable and timely corrective actions for preventing impairment in credit quality, whenever signals are noticed in any account, e.g. decline in credit rating, delay in meeting liabilities in LC/Guarantee and delay in servicing of interest/ installments.
- Prevention of slippage in the Asset Classification and relegation in Credit Ratings through vigorous follow up;
- identification of suitable cases for restructuring/rescheduling as well as further financing in deserving and genuine cases with matching contribution from the borrowers;
- Taking necessary steps/regular follow up, for review of accounts and compliance of terms and conditions, thereby improving the quality of Bank's credit portfolio;
- Endeavoring for upward migration of Credit Ratings

CREDIT SCORING MODELS

Over the last decade, a number of the world's largest banks have developed sophisticated systems in an attempt to model the credit risk arising from important aspects of their business lines. Such models are intended to aid banks in quantifying, aggregating and managing risk across geographical and product lines. The outputs of these models also play increasingly important roles in banks' risk management and performance measurement processes, including performance-based compensation, customer profitability analysis, risk-based pricing and, to a lesser (but growing) degree, active portfolio management and capital structure decisions. The Task Force recognizes that credit risk modeling may indeed prove to result in better internal risk management, and may have the potential to be used in the supervisory oversight of banking organizations. However, before a portfolio modeling approach could be used in the formal process of setting regulatory capital requirements for credit risk, regulators would have to be confident not only that models are being used to actively manage risk, but also that they are conceptually sound, empirically validated, and produce capital requirements that are comparable across institutions. At this time, significant hurdles, principally concerning data availability and model validation, still need to be cleared before these objectives can be met, and the Committee sees difficulties in overcoming these hurdles in the timescale envisaged for amending the Capital Accord (BIS, credit risk modeling, 19th April 1999). Credit scoring models use data on observed borrower characteristics either to calculate the probability of default or to categorize borrowers into different default risk classes (Saunders and Cornett, 2007).

Prominent amongst the credit scoring models is the **Altman's Z-Score.** The Z-score formula for predicting Bankruptcy of Dr. Edward Altman (1968) is a multivariate formula for measurement of the financial health of a company and a powerful diagnostic tool that forecast the probability of a company entering bankruptcy within a two year period with a proven accuracy of 75-80%.

The Altman's credit scoring model takes the following form:

Z=1.2X1+ 1.4X2 + 3.3X3 + 0.6X4 +1.0X5.. (2)

Where,

X1 = Working capital/ Total assets ratio

X2 = Retained earnings/ Total assets ratio

X3 = Earnings before interest and taxes/ Total assets ratio

X4 = Market value of equity/ Book value of long-term debt ratio

X5 = Sales/ Total assets ratio.

The higher the value of Z, the lower the borrower's default risk classification. According to Altman's credit scoring model, any firm with a Z-Score less than 1.81 should be considered a high default risk, between 1.81-2.99 an indeterminate default risk, and greater than 2.99 a low default risk.

Use of this model is criticized for discriminating only among three borrower behaviours; high, indeterminate, and low default risk. Secondly, there is no obvious economic reason to expect that the weights in the Z-Score model – or, more generally, the weights in any credit-scoring model- will be constant over any but very short periods. Thirdly, the problem is that these models ignore important, hard to quantify factors (such as macroeconomic factors) that may play a crucial role in the default or no-default decision.

THE BOBRAM MODEL

The BOBRAM model is the CRISIL rating model designed for the purpose of rating borrowers of the Bank. All commercial advance customers enjoying credit facility of Rs. 25 lacs and above are to be rated using this model. It is a scientific model that generates rating grades when scores are assigned to various predetermined rating parameters. This model came into effect in the year 2006. Initially, borrowers enjoying credit facility of Rs. 5 crores and above were only rated. This policy was revised in the year 2007 and the credit limit was reduced to Rs. 25 lacs both fund based and non fund based.

The BOBRAM Model recognizes 11 borrower categories. These are:

1. Large Corporate Model
2. SME (Manufacturing sector) incl. Commercial Enterprises
3. SME (Services)
4. Traders
5. Banks
6. Non Banking Finance Company
7. Brokers
8. Infrastructure (Power)
9. Infrastructure (Roads and Bridges)
10. Infrastructure (Ports)
11. Infrastructure (Telecom)

The Model lays down certain criteria for determining the category to which a borrower belongs (Refer Appendix). It is of utmost importance to recognize the correct borrower category as ratings can drastically differ between any two categories. The BOBRAM Model for Commercial Advances which is based on two dimensional rating method specified under Basel II accord norms. The rating process of credit risk as per New CRISIL Rating Method involves three types of ratings for each credit facility viz. **1) Obligor (Borrower) Rating** – for credit worthiness indicating the **Probability of Default (PD), 2) Facility Rating** – representing the **Loss Given Default (LGD)** and **3) Composite Rating** – which is indicative of the **Expected Loss (EL).**

BORROWER RATING

This is measures the credit worthiness of the borrower and is based on the assessment of the past records of the borrower, past financials etc. Four types of risks are analyzed here, namely:

Industry risk consists of parameters like Government Policy, Industry Averages, demand and supply gap etc. In case of Large Corporate Model scores for these parameters are already fed into the system by the Risk Management Department at the Head Office after a thorough survey of the economy and the macro economic factors affecting a particular industry. In case of all other models the industry risk score is assigned by the rating officers handling the particular accounts.

Business Risk consists of parameters like Multi locational advantages, research and development activities, capacity utilization etc.

Financial Risk consists of factors like financial ratios, net worth, borrowers' ability to raise debt etc.

Management Risk consists of factors like past payment record, labour relations, management competency, brand name etc.

In addition to these two more categories of risks are analyzed in case of Infrastructure projects only:

1. **Project Implementation risk** consisting:
    - **Buildup Risk**
    - **Liquidity Risk**
2. **Post Implementation Risk** consisting:
    - **Industry Risk**
    - **Business Risk**
    - **Financial Risk**
    - **Management Risk**

Obligor rating Grades range from BOB-1 to BOB-10. The definitions of various Obligor grades are given in Annexure-IA.

FACILITY RISK RATING

Facility rating involves assessment of the security coverage for a given facility and indicates the Loss Given Default (LGD) for a particular facility. Facilities proposed/sanctioned to a company are assessed separately under this dimension of rating.

Facility Rating Grades range from FR-1 to FR-8. The definitions for various facility rating grades have been stated in Annexure IB**.**

COMPOSITE RATING

The Composite Rating (CR), which is the matrix or the combination of PD and LGD; indicates the Expected Loss in case the facility is defaulted. The Composite Rating is worked out automatically by the software based on the matrix of Obligor (Borrower) Grade (BOB Rating) and facility Rating Grade (FR) as per details stated in Annexure III.

Composite rating grades range from CR-1 to CR-10. The definitions for carious composite rating grades have been stated in Annexure – IC

CUT OFF GRADE FOR ACCEPTANCE

Bank has accepted BOB-6 as the cutoff point for the acceptance of an Obligor (borrower) based on Obligor (Borrower) rating carried out as per appropriate model.

TECHNOLOGY USED

The credit risk rating application is centre server based. For doing the rating of various advance accounts, software already loaded on the main server can be accessed/ used through internet. Thus the computers used by various users in our banks like officers, validators, sanctioning authorities etc. located at various places must have internet connection. The internet explorer (minimum 5.5 version) can be used as the browser for the purpose of credit risk rating.

There are no formats for manual ratings under the New CRISIL Rating Models and hence the rating has to be done only by using the technology/ software available at the central server provided for the purpose.

The process of allotting the log in name and password has been decentralized. Authority has been given to identified IT Officers/Risk Officers posted at Regional /Zonal offices. Branches having single party commercial exposure of Rs.25 lacs and above (FB+NFB) are required to contact respective regional office for obtaining the log in name and password.

STEPS INVOLVED IN CARRYING OUT THE CREDIT RATING OF COMMERCIAL ADVANCES

Step 1: Selection of Appropriate Model

Based on the criteria as issued in the guidelines issued by the Risk management department at Baroda Corporate Centre (BCC), the applicable model is to be selected for the rating purpose.

Step 2: Data Sheet Preparation (off line mode)

Having selected one of the applicable models for rating purpose, only the prescribed CMA data based input sheet and/or project profitability data input sheet is to be used. This sheet is to be filled in by the credit officers in the offline mode after due diligence of the CMA, project financials etc. by the appropriate authority for that particular borrower.

Step 3: Rating Exercise

A credit officer is supposed to have done prior study of company's operations and should have analyzed rating parameters which are to be rated/scored for that particular company under different modules. Prior study is essential, as the allotted score for a particular parameter has to be supported with proper justification at the space provided for the said purpose on the computer screen.

Rating of Industry Risk Score (except for SME/trading) – the credit rating officer has to select the relevant industry sub sector at the activity page during the rating process. Industry Risk Score for all applicable parameters are already uploaded for all 118 applicable industry sub sectors and the same is automatically filled in for the selected industry sub sector at the industry risk module during the rating process. The credit risk rating officer or the validator will not be able to change the industry risk score.

Rating of Industry Risk Score (For SME/trading) – the credit rating officer has to carry out the rating of all parameters after selecting the dependent industry and risk scores under various parameters are not made available as in the case of other models.

Financial Risk Assessment – Data sheet for that particular borrower is to be uploaded at appropriate prompt. While most of the parameters are scored automatically, only certain subjective parameters like comments on Obligor's (Borrower's) ability to raise debt/equity etc. are required to be scored with proper justification.

Business Risk/Management Quality Risk Assessment – Necessary information/data input required by way of industry profiles/updates etc. is already circulated as well as uploaded on the INTRANET. Only the parameters relevant to the industry of operations of the obligor

(Borrower) are automatically made available for scoring. The other subjective parameters are required to be scored by the credit officer with proper justification.

Step 4: Facility Rating:

After completing the obligor rating as above, facility rating is to be carried out. For this purpose the security value is to be appropriated first against the respective facilities and thereafter the excess security over the outstanding amount of facility enjoyed is to be worked out. The excess security is distributed over the remaining facilities in proportion to the availment [This methodology is explained at Annexure – V with the help of two cases viz. 1. Review of existing facilities (sole banking), 2. Review with increase/ additional facilities (sole banking)].

The limit amount of each of the facilities considered/ under consideration and the amount of securities, existing/proposed are to be worked out by above stated method by allocation of excess security and then filled in at appropriate pages during the facility rating process as the case may be. After filling up the data as stated above the facility rating, separate for each facility is worked out by the system.

Step 5: Composite Rating (CR Rating)

The rating is automatically worked out, once the obligor rating and the facility rating are in place.

With the completion of the above five steps, the credit risk rating process is over.

Step 6: Submission of credit rating to the Validator

The credit rating officer is required to comply with the following steps:

1. Get 2 hard copies print out of the “Interim Company Report” from the reports section in the online mode. The relevant PDF file for “Interim Company Report” has also to be saved in the system by the credit rating officer on his computer for any reference.

2. One copy of the above stated “Interim Company Report” is to be sent to the appropriate validator. A credit officer has also to submit the hard copies of the financial data (audited or provisional) along with the relevant records, which have been used during the risk rating process to the validator for further processing. The second copy of the “Interim Company Report” has to be kept by the credit rating officer for records.

3. Whenever a proposal for certain credit facilities is submitted to the sanctioning authority, one hard copy of the latest validated “Interim Company Report” received from the validator is required to be sent to the sanctioning authority.

Step 7: Validation

The validator is required to comply with the following steps:

1. The validator is required to validate the credit risk rating based on the financial data (audited or provisional) and other relevant records, which have been used during the credit risk rating process by the rating officer

2. After due validation the validator is required to take out 3 hard copies print out of the "Interim Company Report" and send one copy to the credit rating officer, the other copy to the sanctioning authority and the third copy may be kept for records.

3. Validator is required to submit the validated credit rating to the appropriate sanctioning authority through the system.

With the completion of seven steps as described above, the credit risk rating and validation process stands completed.

Step 8: Submission of Validated Credit Risk Rating Report and other MIS Reports to the Sanctioning Authority.

The sanctioning authority has no role during the process of credit risk rating as also during the process of validation.

After the completion of validation process, the concerned credit officer at the office of the sanctioning authority will receive a hard copy of the validated rating from the validator as also a soft copy through the system. A copy of the validated rating report is to be attached to the proposal.

1.2 OBJECTIVE AND SCOPE OF THE STUDY

The aim of the project is to study and analyze the Credit Rating Method adopted by different branches of Bank of Baroda. It is model developed by CRISIL. The CRISIL BOBRAM model is used for the purpose of rating borrowers whose total credit facility exceeds Rs. 25 Lacs. On the basis of the ratings obtained, the premium interest rate is decided and the final interest rate is then charged.

The objective of the study is to understand the parameters that play the key role in enhancing the ratings of borrowers obtained by this model. The project attempts to find the drivers of a good rating and how this information can be used by borrowers in reducing their interest burden.

The study focuses on the credit rating process undertaken by Bank of Baroda for the purpose of giving out loans and deciding upon the rate of interest to be charged. Responses to the questionnaire for Factor Analysis and Analytical Hierarchy Process will be obtained from credit officers at the various branches of Bank of Baroda and its scope is therefore limited to these respondents.

CHAPTER 2 REVIEW OF LITERATURE

Three main variables that affect the credit risk of a financial assets are (i) the probability of default (PD), (ii) the "loss given default" (LGD), which is equal to one minus the recovery rate in the event of default (RR), and (iii) the exposure at default (EAD). While significant attention has been devoted by the credit risk literature on the estimation of the first component (PD), much less attention has been dedicated to the estimation of RR and to the relationship between PD and RR. This is mainly the consequence of two related factors. First, credit pricing models and risk management applications tend to focus on the systematic risk components of credit risk, as these are the only ones that attract risk-premia. Second, credit risk models traditionally assumed RR to be dependent on individual features (e.g. collateral or seniority) that do not respond to systematic factors, and therefore to be independent of PD.

"This traditional focus only on default analysis has been reversed by the recent increase in the number of studies dedicated to the subject of RR estimation and the relationship between the PD and RR (Fridson, Garman and Okashima [2000], Gupton, Gates and Carty [2000], Altman, Resti and Sironi [2001], Altman, Brady, Resti and Sironi [2003 and 2005], Frye [2000a, 2000b and 2000c], Hu and Perraudin [2002], Hamilton, Gupton and Berthault [2001], Jarrow [2001], Jokivuolle and Peura [2003] and Acharya, Bharath and Srinivasan (2007). This is partly the consequence of the parallel increase in default rates and decrease of recovery rates registered during a substantial part of the 1999-2009 periods. More generally, evidence from many countries in recent years suggests that collateral values and recovery rates can be volatile and, moreover, they tend to go down just when the number of defaults goes up in economic downturns. Indeed, first half results in 2009 (8.0% year-to-date) indicate that the default rate on high-yield bonds will reach a record high level in 2009 and recovery rates will fall to perhaps the lowest level in history, at least in the modern high yield bond era (22.5% year-to-date, Altman and Karlin (2009) and Keisman and Marshella (2009)".

The first category of credit risk models are the ones based on the original framework developed by Merton (1974) using the principles of option pricing (Black and Scholes, 1973). In such a framework, the default process of a company is driven by the value of the company's assets and the risk of a firm's default is therefore explicitly linked to the variability of the firm's asset value. In addition to Merton (1974), first generation structural-form models include Black and Cox (1976), Geske (1977), and Vasicek (1984). Each of these models tries to refine the original Merton framework by removing one or more of the unrealistic assumptions. Black and Cox (1976) introduce the possibility of more complex capital structures, with subordinated debt; Geske (1977) introduces interest-paying debt; Vasicek (1984) introduces the distinction between short and long term liabilities which now represents a distinctive feature of the KMV model. Longstaff and Schwartz (1995) argue that, by looking at the history of defaults and the recovery rates for various classes of debt of comparable firms, one can form a reliable estimate of the RR. In their model, they allow for a stochastic term structure of interest rates and for some correlation between defaults and interest rates. They find that this correlation between default risk and the interest rate has a significant effect on the properties of the credit spread.

Smithson et al. provide a report (2002) of international survey amongst 41 global banks about their practices of credit portfolio management. Most notable points are that the largest exposures in the credit portfolios of the surveyed banks are attributed to large and middle market corporations and banks. The instruments behind these exposures are mainly undrawn lines of credit, bilateral bank loans and syndicated bank loans.

During the last several years, new approaches explicitly modeling and empirically investigating the relationship between PD and RR have been developed. These models include Bakshi et al. (2001), Jokivuolle and Peura (2003). Frye (2000a and 2000b), Jarrow (2001), Hu and Perraudin (2002). Bakshi et al. (2001) enhance the reduced-form models to allow for a flexible correlation between the risk-free rate, the default probability and the recovery rate. Based on some evidence published by rating agencies, they force recovery rates to be negatively associated with default probability. They find some strong support for this hypothesis through the analysis of a sample of BBB-rated corporate bonds: more precisely, their empirical results show that, on average, a 4% worsening in the (risk-neutral) hazard rate is associated with a 1% decline in (risk-neutral) recovery rates.

A rather different approach is the one proposed by Jokivuolle and Peura (2003). The authors present a model for bank loans in which collateral value is correlated with the PD. They use the option pricing framework for modeling risky debt: the borrowing firm's total asset value triggers the event of default. However, the firm's asset value does not determine the RR. Rather, the collateral value is in turn assumed to be the only stochastic element determining recovery. Because of this assumption, the model can be implemented using an exogenous PD, so that the firm's asset value parameters need not be estimated.

Shashi Bhattarai and Shivjee Roy Yadav (2009) review application of Analytic Hierarchy Process (AHP) in the finance sector with specific reference to banking. They also give a detailed account of the feedback from bankers' community in Nepal on utility of AHP as a decision support tool in the situation of global financial crisis. The relationship between problem loans and the economic cycle is also analysed by Salas and Saurina (2002). Using panel data, they report that the business cycle (proxied by the current and lagged growth of GDP) has a negative and significant impact on bad loans. They also find that credit risk was significantly influenced by individual bank level variables, after controlling for macro-economic conditions.

In 2001 Boston Consulting Group study confirmed the general impression that North American banks have a clear lead on most of their European and Asian competitors. Institutions in the U.S. and in Australia too for that matter were pursuing risk management not to comply with regulatory requirements but to enhance their own competitive positions. Arpa et al., (2001) study the effects of the business cycle on risk provisions and earnings of Austrian banks in the 1990s. They conclude that risk provisions increase in period of falling real GDP growth, confirming the pro-cyclical tendencies in bank behaviour. Moreover, rising real estate prices lead to higher provisions, whereas falling inflation depresses them. They also find that some macro-economic variables such as interest rates, real estate and consumer prices are useful in explaining the profitability of Austrian banks.

Meyer and Yeager (2001) employ a set of county macro-economic variables to test if rural bank performance is affected by the local economic framework. They fit an OLS model when the return on assets and the net loan losses are the dependent variables and a bit specification for the nonperforming loans. They find that none of the county-level coefficients is significant, suggesting that county economic activity does not have a relevant effect on bank performance; in contrast, state-level data are significant. Eichengreen and Arteta (2000) carefully analyze the robustness of the empirical results on banking crises using a sample of 75 emerging markets in the period 1975-1997 and considering a huge range of explanatory variables mentioned in previous works. Their findings confirm that unsustainable boom in domestic credit is a robust cause of financial distress; macro-economic policies leading to rapid lending growth and financial overheating generally set the stage for future problems. Domestic interest-rate liberalization often accompanies these excessive lending activities. On the other hand, they point out that there is little evidence of any particular relationship between exchange-rate regimes and banking crises; the role of the legal and regulatory framework is also uncertain.

Gambera (2000), using bivariate VAR systems, tries to understand how economic development affects bank loan quality. He points out that, since systemic financial conditions help predict the soundness of the single intermediaries; it may be interesting to predict the systemic financial conditions themselves. In particular, he uses the ratio of delinquencies to total loans and the ratio of non-performing loans to total loans as alternative dependent variables and he estimates a bivariate system for each series of macro-economic variables. Survey on the “Implementation of the Capital Adequacy Directive” by the Banking Federation of the European Union, April 1998 (covering 17 countries) revealed that very few banks are using sophisticated models for managing their risks. Most banks which use it at first place use it for internal risk management purposes only. Ajit and Bangar (1998) present a tabulation of the performance of private sector banks vis-à-vis public sector banks over the period 1991-1997, using a number of indicators: profitability ratio, interest spread, capital adequacy ratio, and the net NPA ratio. The conclusion is that Indian private banks outperform public sector banks. What is of interest, however, is that they find Indian private banks have higher returns to assets in spite of lower spreads.

Shaffer (1998) shows that adverse selection has a persistent effect on the banks which are new entrants in a market. Salas and Saurina (1999) have modeled the problem loans ratio of Spanish banks in order to gauge the impact of loan growth policy on bad loans. According to their empirical estimation results (which were achieved using a panel data of commercial and savings banks from 1985-1997), the cycle (measured through the current and lagged-one-year GDP growth rates) has a negative and significant impact on problem loans. The current impact is much more important. It is also shown that problem loans ratio differs by type of loan. Households and firms have different levels of bad loans. On an average, the former is lower than the latter. Among households, mortgages have very low delinquency levels compared to consumer loans, credit loans or overdrafts.

Demirguc-Kunt and Detragiache (1998) estimate a logit model of banking crises over the period 1980-1994 in order to understand the features of the economic environment in the periods preceding a banking crisis and, therefore, to identify the leading indicators of financial distress. The 1998 study by Demirgue-Kunt and Huizinga (DKH) is a cross-country study of variations in bank performance, using two performance indicators separately regressed on a set of explanatory factors; the interest spread (used as an efficiency indicator) and bank profitability. The data set is at bank level for 80 countries over the period 1988-95. The most important finding pertains to the differences in the impact of foreign ownership between developed and developing countries. In developing countries foreign banks have greater interest margins and profits than domestic banks. In industrial countries, the opposite is true. The first finding bears out the better NPA performance by foreign banks in India by country of origin. Among the macro variables reported by DKH that affect bank profitability positively although not net interest margins (the efficiency indicator), is per capita GDP. These results suggest that per capita GDP may be less a correlate of banking efficiency or superior banking technology, and more a correlate of banking opportunities and the operating environment generally.

The Sarkar, Sarkar and Bhaumik (1998) cross-bank study for India regresses two profitability and four efficiency measures (one of which is the net interest margin) on pooled data for two years, 1993- 94 and 1994-95, for a total of 73 banks, using single-equation OLS estimation for each. The study focuses exclusively on an examination of the prediction from the property rights literature about the superiority of private ownership in terms of performance. Private banks are divided into traded and non-traded categories; the control variables include the (log of) total bank assets, the proportion of investment in government securities, the proportion of loans made to the priority sector, the proportion of semi-urban and rural branches and the proportion of non interest income to total income.

Berger and Deyoung (1997) address a little examined intersection between the problem loan literature and the bank efficiency literature. They employ Granger-casualty techniques to test four hypotheses regarding the relationship among loan quality, cost efficiency, and bank capital. The data suggest that the inter temporal relationships between problem loans and cost efficiency ran in both directions for U.S. commercial banks between 1985 and 1994. The data suggest that high levels of nonperforming loans Granger-cause reductions in measured cost efficiency, consistent with the hypothesis that the extra costs of administering these loans reduces measured cost efficiency ('bad luck'). The data also suggest that low levels of cost efficiency Granger-cause increases in nonperforming loans, consistent with the hypothesis that cost-inefficient managers are also poor loan portfolio managers ('bad management'). In the paper by Mario Quayliariello (1997), the relationship between bank loan quality and business cycle indicators is studied for Italy. A distributed lag model (which is estimated using ordinary least squares) and bivariate Granger-causality tests are used in order to evaluate the importance of macroeconomic factors in predicting the quality of bank loans measured by the ratio of non-performing loans to total loans. The main target of the research is to understand the contribution that macro-data can offer in capturing the evolution of credit quality and to select a reasonably manageable set of indicators which can act as early warning signals of the banking system fragility.

Kaminsky and Reinhart (1996) in their well-known paper on twin-crises study about 25 episodes of banking crises and 71 balance of payments crises in the period 1970-1995. Regarding the influence of business cycle on the episode of financial instability and the possibility to identify macro-variables that act as early warning, they find that recessionary conditions such as economic activity decline, weakening of the export sector, high real interest rates, falling stock market, usually precede banking as well as currency crises. They also find that Credit expansions, an abnormally high money growth and the decline in the terms-of-trade anticipate many of the banking crises.

CHAPTER 3 RESEARCH METHODOLOGY

For this study the following approach has been adopted:

- Two structured questionnaires – one containing those factors that may influence rating and the other containing hierarchy of risk factors that influence the various business models as recognized by the BOMRAM model – are prepared in consultation with the persons in-charge.
- Then, the rating officers and validators at various branches of Bank of Baroda were surveyed through questionnaires, face to face interactions and interview regarding parameters, according to them, that can help in generating good ratings for borrowers.
- The responses so received were analyzed with the help of quantitative tools such as Factor Analysis and Analytical Hierarchy Process (AHP) to arrive at the drivers of good ratings.

3.1 RESEARCH DESIGN

DESIGN

The design of the study undertaken is exploratory and descriptive in nature. The research tools used are Factor Analysis and Analytical Hierarchy Process (AHP).

The factors that influences the credit rating of borrowers are extremely varied and perception specific. In order, to arrive at a reliable and valid conclusion it was very important that an exploratory research should be carried out so that all the variables could be taken into account.

AHP has been used to determine which borrower model is most affected by which risk factor viz. Industry, Business, Financial and Management Risk and to establish a hierarchy for each. This will be useful in understanding which type of risk is more prevalent in the different kinds of borrower models.

UNIVERSE OF THE STUDY

The universe of the undertaken study consists of the various branches of Bank of Baroda in the Kolkata Metropolitan Region. Since, the study aims at the factors influencing the ratings of borrowers which are done by the credit officers at the various branches of the Bank it was apt that the respondents should be these officers who have been doing such ratings and also the erstwhile credit officers and validators.

SAMPLE

The respondents are the credit officers and validators of Bank of Baroda. The effective sample size is 40 in the case of Factor Analysis. In the case of Analytical Hierarchy Process the responses collected are 15.

TOOLS OF DATA COLLECTION

There are various tools of data collection that can be used while collecting data from the respondents. One such tool is a Questionnaire that has been used in this project. Following are the points that were taken into consideration while designing the questionnaire:

- ***Length of the Questionnaire***: The questionnaire for Factor Analysis was restricted to only 15 questions and a lengthy questionnaire was avoided. Only those questions were included in the questionnaire that comprised factors which have a significant impact on the ratings of obligors. The questionnaire was approved by the faculty guide as well as the industrial guide. Lengthy questionnaire can negatively impact the response rates as well as the representation of the sample.

  For AHP, an attempt was made to keep the questionnaire simple and easy to understand since filling up of responses can be very tedious in this case.

- ***Questions***: Repetitive questions were avoided in the questionnaire so that the respondent enjoys filling the questionnaire and can fill it using all his knowledge without getting irritated. Apart from this, while framing the questions, only relevant factors were taken into consideration. The relevance of the factors was determined on the basis of the discussions held with the mentors. The factors included are those that affect all the eleven borrower models explained in the banking guidelines relating to credit rating. In the process, for every factor, both positive and negative questions were designed so as to probe the respondent and get a true picture.

  Since AHP requires pair-wise comparison of criteria and alternatives, it was not required of frame questions. Only a table was made which required the respondent to fill up the ratings on the basis of the scale provided. Main focus was to keep the questionnaire understandable.

  The questionnaire for Factor Analysis and AHP has been provided in Exhibit 5 and 6 respectively.

- ***Scale of the Questionnaire*:** A Likert scale was used for the questionnaire for Factor Analysis covering all the possible answers to the questions asked so that the respondent has a say in his answer. The respondent should never feel that the answer he actually wants to give is not present in the questionnaire.

  For AHP a scale consisting of values from 1 to 9 were provided. This is a scale which is commonly used for AHP. The meaning of these values has been explained in the questionnaire.

- ***Structure of the Questionnaire***: The questionnaire used in the study was structured in a manner that it reflects a train of thought, so that the respondent feels connected to the questionnaire as if it is a logical conversation. Another important feature that was taken into consideration while structuring the questionnaire is the order of questions. If the questions are not properly ordered, it would result in the problem of Habituation. It means that some people will usually start giving the same answer, without really considering it, after being asked a series of similar questions. Respondents tend to deliver more accurate answers if the questions pertaining to a particular factor are not asked in a series. The third important feature that was considered during the formulation of questions is avoidance of multiple concepts in a single question. So, after taking all the aforementioned variables into mind the questionnaire was formulated and consequently designed.

- ***Avoidance of Errors*:** While the questionnaire was designed, full attention was paid that all possible errors that can be avoided. There are two types of errors that could arise while constructing a questionnaire:

  - ***Errors of Commission***, where the questions involved are worded poorly so that they are unclear and ambiguous.

- ***Errors of Omission***, where in some questions representing a factor are left out and hence omitted from the study.

3.1.1 FACTOR ANALYSIS

Factor analysis is a collection of methods used to examine how underlying constructs influence the responses on a number of measured variables. It is used mostly for data reduction purposes:

- To get a small set of variables (preferably uncorrelated) from a large set of variables (most of which are correlated to each other)
- To create indexes with variables that measure similar things (conceptually).

There are basically two types of factor analysis:

- Exploratory factor analysis (EFA) attempts to discover the nature of the constructs influencing a set of responses, i.e. when we do not have a pre-defined idea of the structure or how many dimensions are there in a set of variables.
- Confirmatory factor analysis (CFA) tests whether a specified set of constructs is influencing responses in a predicted way, i.e. it is confirmatory when we want to test specific hypothesis about the structure or the number of dimensions underlying a set of variables.

Both types of factor analyses are based on the Common Factor Model. This model proposes that each observed response is influenced partially by underlying common factors and partially by underlying unique factors. The strength of the link between each factor and each measure varies, such that a given factor influences some measures more than others.

Factor analyses are performed by examining the pattern of correlations (or co variances) between the observed measures. Measures that are highly correlated (either positively or negatively) are likely influenced by the same factors, while those that are relatively uncorrelated are likely influenced by different factors.

CHAPTER 4 DATA ANALYSIS

The data analysis tool used in the study undertaken is Factor Analysis, through which we are trying to identify the factors that most affect credit ratings. The aim of the study is to locate the most influential ones and ignore the redundant factors.

These factors have been decided upon on the basis of the fact that they are representative of all the five types of risks faced by the bank viz. Industry risk, Business risk, Financial risk, Management risk and Facility risk. Moreover, these factors feature in almost all the 11 borrower models as laid down by the guidelines i.e. these factors are common to all the 11 obligor models like Large corporate model, Trader model, Infrastructure Model etc.

The 13 factors were subjected to principal components analysis (PCA) using SPSS. Prior to performing PCA the suitability of data for factor analysis was assessed. Inspection of the correlation matrix revealed the presence of all coefficients of .3 and above. The Kaiser-Meyer-Oklin value was .515, exceeding the recommended value of .5 (Kaiser, 1970, 1974). The Barlett's Test of Sphericity (Bartlett, 1954) reached statistical significance, supporting the factorability of the correlation matrix. Principal components analysis revealed the presence of five components with eigen values exceeding 1 (5th component not very important), explaining 73.726 per cent of the variance.

Kaiser-Meyer-Olkin (Kmo) Test:

A useful statistic for factor analysis is the KMO test which measures the sampling adequacy. This index compares the magnitudes of observed correlation coefficients to the magnitudes of the partial correlation coefficients. Small values of KMO statistic indicate that the correlations between pairs of variables cannot be explained by other variables and that factor analysis may not be appropriate. Generally a value greater than 0.5 is desirable.

Value of KMO statistic in this case is 0.515; hence the data qualifies for further factor analysis.

Exhibit 1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.515
Bartlett's Test of Sphericity	Approx. Chi-Square	415.828
	Df	105
	Sig.	0.000

Anti-Image Correlation Matrix: Bartlett's Test for Sphericity

H0: the variables are un-correlated in the population

H1: the variables are correlated.

The null hypothesis, in other words can be stated as when the population correlation matrix is an identity matrix i.e. all its diagonal terms are 1 and off-diagonal terms are 0. The test statistic for sphericity is based on chi square transformation of the determinant of the correlation matrix. A large value of the test statistic will favour the rejection of null hypothesis, which in this case happens to be true as all the diagonal elements have a value which is greater than 0.5 suggesting that all the variables are valid and can be taken as such for factor analysis.

Total Variation Explained:

Here we see that out of the total 13 variables taken initially can be ideally reduced to 4 components contributing to approximately 73.726% variation.

Based on rotated component matrix and applicability of the factors the following factors and their respective variables have been extracted as mentioned in the findings.

4.1 FINDINGS

The above results have been obtained by applying 10 iterations. The factors can be compressed into four components in the following manner

Factors have been grouped into four components on the basis of their loadings. The factor having the maximum loading (ignoring the negative sign) in each component has been grouped under that component.

It can be seen that eight factors form part of component 1, two factors form part of component 2, four factors form part of component 3 and only one factor forms part of component 4. Therefore it can be deduced that component one and three are more reflective of factors affecting ratings and have therefore been taken up for further analysis.

Component 1 mainly consists of financial and industrial risk factors like financial strength, government policy, security coverage etc. signifying the correlation between the two. In other words industrial risk can have a major impact on the financial aspects of a borrower enterprise.

On the other hand component 3 mainly consists of business and management risk factors like research and development activities, past payment record, managerial competence etc. This signifies that the internal aspects of a business enterprise are closely linked. That is to say, business and management risk are internal to an enterprise and have strong correlation.

Therefore, the four identified risk factors can be grouped into two components which constitute the main sub-divisions of each.

Further for the purpose of analysis it is assumed that only the factors with loadings exceeding 0.6 are significant for determining ratings and therefore these factors have been extracted. The factors so extracted are as follows:

Factor	Loadings
1.Ability to raise debt	0.868
2.Demand and supply gap	0.772
3.Managerial competence of the borrower	0.749
4.Financial strength	0.737
5.Past Payment record	0.720
6.Net worth of the company	0.639

7.Adequacy of security coverage	0.619

ANALYTICAL HIERARCHY PROCESS

The foundation of the Analytic Hierarchy Process (AHP) is a set of axioms that carefully delimits the scope of the problem environment (Saaty 1986). It is based on the well-defined mathematical structure of consistent matrices and their associated right eigenvector's ability to generate true or approximate weights, Merkin (1979), Saaty (1980, 1994). The AHP methodology compares criteria, or alternatives with respect to a criterion, in a natural, pair-wise mode. To do so, the AHP uses a fundamental scale of absolute numbers that has been proven in practice and validated by physical and decision problem experiments. The fundamental scale has been shown to be a scale that captures individual preferences with respect to quantitative and qualitative attributes just as well or better than other scales (Saaty 1980, 1994). It converts individual preferences into ratio scale weights that can be combined into a linear additive weight w(a) for each alternative a. The resultant w(a) can be used to compare and rank the alternatives and, hence, assist the decision maker in making a choice. Given that the three basic steps are reasonable descriptors of how an individual comes naturally to resolving a multi criteria decision problem, then the AHP can be considered to be both a descriptive and prescriptive model of decision making. The AHP is perhaps, the most widely used decision making approach in the world today. Its validity is based on the many hundreds (now thousands) of actual applications in which the AHP results were accepted and used by the cognizant decision makers (DMs), Saaty (1994b).

In the late 1960’s, Thomas Saaty, one of the pioneers of Operations Research, and author of the first Mathematical Methods of Operations Research textbook and the first queueing textbook, was directing research projects for the Arms Control and Disarmament Agency at the U.S. Department of State. Saaty's very generous budget allowed him to recruit some of the world’s leading economists and game and utility theorists. In spite of the talents of the people Saaty recruited (three members of the team, Gerard Debreu, John Harsanyi, and Reinhard Selten, have since won the Nobel Prize), Saaty was disappointed in the results of the team's efforts.

Years later, while teaching at the Wharton School, Saaty was troubled by the communication difficulties he had observed between the scientists and lawyers and by the apparent lack of a practical systematic approach for priority setting and decision making. Having seen the difficulty experienced by that the world’s best scientists and lawyers, Saaty was motivated to attempt to develop a simple way to help ordinary people make complex decisions. The result was the Analytic Hierarchy Process – a synthesis of existing concepts that attests to Saaty's genius through its power and simplicity.

THE AHP CALCULATIONS

There are several methods for calculating the eigenvector. Multiplying together the entries in each row of the matrix and then taking the nth root of that product gives a very good approximation to the correct answer. The nth roots are summed and that sum is used to normalise the eigenvector elements to add to 1.00. In the matrix below, the 4^{th} root for the first row is 0.293 and that is divided by 5.024 to give 0.058 as the first element in the eigenvector.

The table below gives a worked example in terms of four attributes to be compared which, for simplicity, we refer to as A, B, C, and D.

	A	B	C	D	n^{th} root of product of values	Eigenvector
A	1	1/3	1/9	1/5	0.293	0.058
B	3	1	1	1	1.316	0.262
C	9	1	1	3	2.279	0.454
D	5	1	1/3	1	1.136	0.226
Totals					5.024	1.000

The eigenvector of the relative importance or value of A, B, C and D is (0.058, 0.262, 0.454, 0.226). Thus, C is the most valuable, B and D are behind, but roughly equal and A is very much less significant.

The next stage is to calculate λmax so as to lead to the Consistency Index and the Consistency Ratio.

We first multiply on the right the matrix of judgements by the eigenvector, obtaining a new vector. The calculation for the first row in the matrix is:

1*0.058+1/3*0.262+1/9*0.454+1/5*0.226 = 0.240

And the remaining three rows give 1.116, 1.916 and 0.928. This vector of four elements (0.240,1.116,1.916,0.928) is, of course, the product Aω and the AHP theory says that $A\omega=\lambda_{max}\,\omega$ so we can now get four estimates of λ_{max} by the simple expedient of dividing each component of (0.240,1.116,1.916,0.928) by the corresponding eigenvector element. This gives 0.240/0.058=4.137 together with 4.259, 4.22 and 4.11. The mean of these values is 4.18 and that is our estimate for λ_{max}. If any of the estimates for λ_{max} turns out to be less than n, or 4 in this case, there has been an error in the calculation, which is a useful sanity check.

The Consistency Index for a matrix is calculated from (λ_{max}-n)/ (n-1) and, since n=4 for this matrix, the CI is 0.060. The final step is to calculate the Consistency Ratio for this set of judgements using the CI for the corresponding value from large samples of matrices of purely random judgments using the table below, derived from Saaty's book, in which the upper row is the order of the random matrix, and the lower is the corresponding index of consistency for random judgements.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

For this example, that gives 0.060/0.90=0.0677. Saaty argues that a CR > 0.1 indicates that the judgements are at the limit of consistency though CRs > 0.1 (but not too much more) have to be accepted sometimes. In this instance, we are on safe ground.

A CR as high as, say, 0.9 would mean that the pair-wise judgements are just about random and are completely untrustworthy.

DATA ANALYSIS

Analytical Hierarchy Process (AHP) has been used for the purpose of establishing the borrower model which is most affected by the 4 risk factors namely Industry Risk, Business Risk, Financial Risk and Management Risk and also the hierarchy of risk factors in terms of importance. The Bank recognizes 11 borrower models. Of these 11 models only four models have been used, namely:

- Large Corporate Model
- Small and Medium Enterprise
- Infrastructure (Power) and
- Trader model

These models have been shortlisted for the purpose of analysis on the basis of the fact that these mainly constitute the borrower categories handled by the Bank in the Kolkata region.

The goal of AHP here is to determine the model which is most affected by risk factors and the bearing of each risk factor on such model.

The criteria constitute the 4 risk factors viz. Industry Risk, Business Risk, Financial Risk and Management Risk.

The alternatives are the four borrower models explained above.

20 responses were obtained from the validators and credit officers working in the bank. The questionnaire for AHP has been provided as Exhibit 6. The responses so obtained had been put in Excel for the purpose of analysis. A sample Excel sheet is provided in Exhibit 8.

First, the criteria are rated against each other in a pair- wise manner. Ratings ranging from 1-9 are provided for each pair. The criteria ratings remain constant for all the responses. In this case, the criteria ratings assigned by the first respondent have been considered.

For each criteria the respondent is then required to rate the different models in a pair-wise manner again. The matrix so obtained is normalized and the consistency is determined by calculating the consistency ratio, which is a ratio of the Consistency Index (CI) and Random Index (RI). On establishing consistency the final matrix for each response is prepared. At this point, all the comparisons for Criteria and alternatives have been made, and the AHP has derived the priorities for each group at each level.

FINDINGS

It can be seen from the table below that it is the Large Corporate model which has the highest average value closely followed by Infrastructure (Power) model. The Small and medium Enterprises and the Trader model fill up the third and fourth spots.

It was further analyzed that 10 out of 20 respondents feel that the LCM model is most affected by all risk categories. Whereas, 8 feel that it is the Infrastructure (Power) model. This forms a majority in the case of LCM model proving that the findings are consistent. A pie chart has been drawn which displays the frequency distribution of the responses in sync with the highest average value of priorities. The bar graph represents the average values of the variables which are highest in the case of LCM mode

Figure 1: Pie Chart

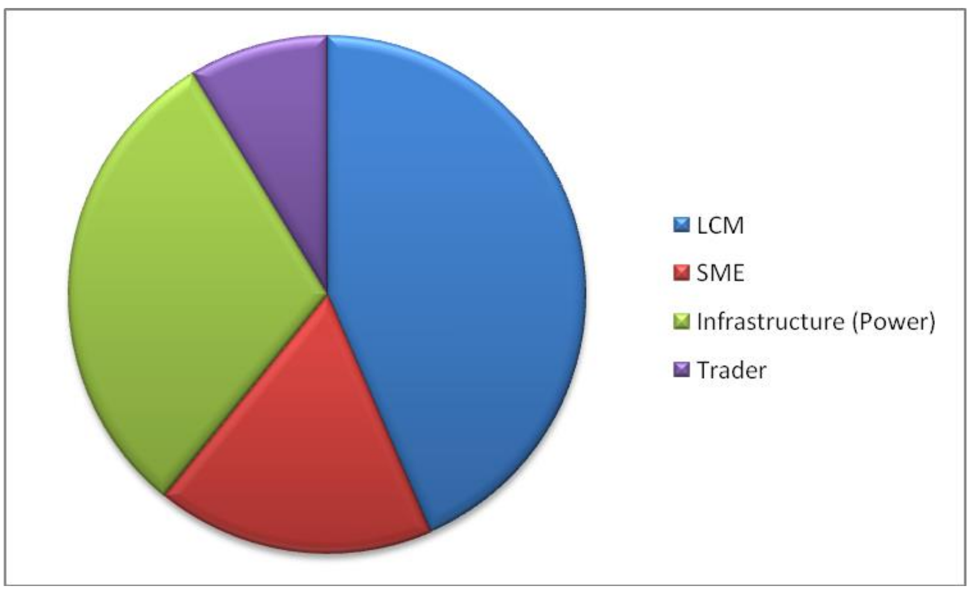
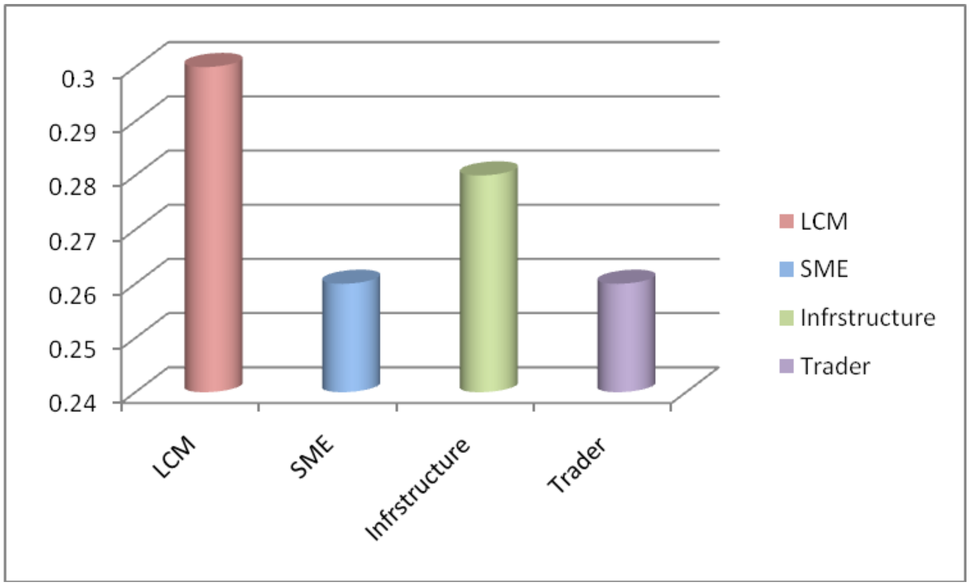


Figure 2: Bar Graph



Further analysis shows that 55% of the respondents feel that Industry Risk most affects LCM Model and 45% feel that Financial Risk is more significant in this case.

In case of SME model, 55% feel that Financial Risk is most important, whereas, 15%, 20% and 10% feel that Industry Risk, Business risk, management risk are most significant respectively.

In case of Infrastructure (Power) model, 75% of the respondents are of the opinion that Financial Risk is most significant here signifying the high investment risk involved in Infrastructure projects.

In case of Trader model, 60% of the respondents are of the opinion that Management Risk is most important for this model signifying that there is higher potential of internal risk in case of small business models like the trader model.

LIMITATIONS

This project has been undertaken in Bank of Baroda and is, therefore, specific to the accounts handled by the rating officers of this Bank and their level of experience.

A very significant limitation of Factor Analysis and AHP is the subjectivity involved. Scoring of questions and assigning weights constitutes subjectivity and is therefore specific to the opinions and views of the individual respondents.

The sample size is also very limited, being 45 in case of Factor Analysis and 15 in case of AHP.

In case of factor analysis, only 13 of the risk factors were used, for sake of convenience, instead of all the factors as explained in the Bank's guidelines. These factors were taken up for analysis due to the fact that they are common to all types of business models as recognized by the Bank.

In case of AHP only four borrower models were used instead of all eleven for sake of convenience. Moreover, these models were decided upon on account of the fact that they comprise majority of accounts handled by the Bank in Kolkata region.

RECOMMENDATIONS AND CONCLUSION

Factor analysis has helped in recognizing the main factors which play an important role in determining ratings of obligors. These factors are the following:

1.Ability to raise debt

2.Demand and supply gap

3.Managerial competence of the borrower

4.Financial strength

5.Past Payment record

6.Net worth of the company

7.Adequacy of security coverage

This has been established on the basis of the value of loadings. Higher the loading, higher is the importance of the factor. In other words, when a borrower approaches the bank for commercial credit, these are the factors which mainly determine whether loan should be granted or not and the rate of interest which should be charged to the borrower. A rating officer should be very careful while assigning ratings to the borrowers on these factors. A thorough analysis of the state of affairs of the borrower enterprise should be done before carrying out ratings.

This report is also helpful to borrowers seeking credit from Bank of Baroda. The above mentioned seven factors can give a borrower an idea as to the type of criteria which are researched by the bank before giving out ratings and the also the criteria which play an important role in determining ratings. If the borrower’s position is strong in the case of these factors, there can be scope for negotiation with respect to the amount of loan sanctioned and the rate of interest.

With respect to the findings of Analytical Hierarchy Process it can be said that it is the Large Corporate Model which is most affected by all risk categories. This is closely followed by Infrastructure (Power) model, followed by Small and Medium Enterprises then the Trader model.

Also the risk that most affects the LCM model is the Industry Risk. Therefore, factors external to the borrower company play an important role in determining ratings. On the other hand in the case of SME and Trader models internal risk factors like Financial Risk and Management Risk are more relevant due to the small size of the enterprise. In the case of Infrastructure (Power) model it is the Financial Risk and Industry Risk that are most significant.

The hierarchy so formed with the help of AHP can enable a borrower to recognize the risk factors, in order of importance, which are most significant to it and work towards eliminating the underlying constituents of such risk in order to be able to obtain better ratings and also obtain maximum benefit with respect to rates of interest.

In case of LCM model, Industry risk is rated by the Baroda Corporate Centre and is available to the credit officers on the intranet. For this purpose the Bank recognizes certain industries which by and large cover all the major categories of industrial enterprises. But many a times it so happens that certain companies have businesses which overlap between two or more industrial categories. This causes confusion to the rating officer and if the industries are chosen wrongly, the entire rating may change. Since this risk is most significant in case LCM model it is recommended that this practice be done away with or a very comprehensive list of categories of industries with proper ratings be provided to the rating officers or comprehensive guidelines on the selection of industrial category be provided.

Exhibit 2: Final Matrix
Priorities

	LCM	SME	Infrastructure (Power)	Trader
Industry	0.11	0.05	0.08	0.03
Business	0.04	0.06	0.03	0.04
Financial	0.15	0.05	0.10	0.04
Management	0.08	0.05	0.05	0.04
	0.38	0.22	0.26	0.14

Annexure – I – A

OBLIGOR RATING GRADES AND DEFINITION:

Grade No.	**Nature of Grade**	**Description**	**Definition of Obligor Grade**
1	BOB-1	Investment Grade-Highest Safety	Companies rated BOB-1 are judged to offer highest safety of timely payment. Thought the circumstances providing this degree of safety are likely to change, such changes as can be envisaged are more unlikely to affect adversely the fundamentally strong position of such issues.
II	BOB-2	Investment Grade High Safety	Companies rated BOB-2 are judged to offer high safety of timely payment. Changes in circumstances providing this degree of safety have low impact on the fundamentally strong position of such issues.
III	BOB-3	Investment Grade High Safety	Companies rated BOB-3 are judged to offer high safety of timely payment. They differ in safety from BOB-2 only marginally.
IV	BOB-4	Investment Grade Adequate Safety	Companies rated BOB-3 are judged to offer adequate safety of timely payment however changes in circumstances can adversely affect such issues more than those in higher rated grades.
V	BOB-5	Investment Grade Moderate Safety	Companies rated BOB-3 are judged to offer moderate safety of timely payment of interest and Principal for the present. However, changing circumstances are likely to lead to a weakened capacity to repay interest and principal than for

			companies in higher rated grades.
VI	BOB-6	Investment Grade Moderate Safety	Companies rated BOB-3 are judged to offer moderate safety of timely payment of interest and Principal for the present. There is only marginal difference in the degree of safety provided by issues rated BOB-5
VII	BOB-7	Sub Investment Grade Inadequate Safety	Companies rated BOB-7 are judged to carry inadequate safety of timely payment while they are less susceptible to default than other speculative grades in the immediate future, the uncertainties that the issuer faces could lead to inadequate capacity to make timely payments.
VIII	BOB-8	Sub Investment Grade High Risk	Companies rated BOB-8 have a greater susceptibility to default. While currently payments are met, adverse business or economic conditions can lead to lack of ability or willingness to repay.
IX	BOB-9	Default Substantial Risk	Companies rated BOB-9 are vulnerable to default. Timely payment of interest and principal is possible only if favorable circumstances continue.
X	BOB-10	Default	Companies rated BOB-10 are in default or are expected to default. Such investments are extremely speculative and returns from these may be realized only on reorganization or liquidation.

ANNEXURE – I – B

Facility rating grades and Definition:

Grade	Nature of grade	Description
I	FR-1	Highest Safety
II	FR-2	Higher Safety
III	FR-3	High Safety
IV	FR-4	Adequate Safety
V	FR-5	Reasonable Safety
VI	FR-6	Moderate Safety
VII	FR-7	Low Safety
VIII	FR-8	Lowest Safety/Clean Loans/Totally Unsecured

ANNEXURE – I – C

Composite Rating Grades and Definitions:

Grade No.	Nature of Grade	Definition of Composite / Combined Rating
I	CR-1	Minimum (Lowest) Expected Loss
II	CR-2	Lower Expected Loss
III	CR-3	Low Expected Loss
IV	CR-4	Reasonable Expected Loss
V	CR-5	Adequate Expected Loss
VI	CR-6	Moderate Expected Loss
VII	CR-7	Extra Expected Loss
VIII	CR-8	High Probability Loss

IX	CR-9	Higher Probability Loss
X	CR-10	Highest Probability Loss

ANNEXURE – II

RISK GRADATION FOR VARIOUS MODELS

A) Borrowers/Obligors eligible for rating under LCM, Banks, NBFCs, Broker Models, infrastructure projects under operations phase and expansion/diversification projects in case of existing companies

Large Corporate Model:

From Score	To Score	Grade	Common Scale
Above 8.5	10.0	I	BOB-1
Above 7.5	8.5	II	BOB-2
Above 6.5	7.5	III	BOB-3
Above 5.75	6.5	IV	BOB-4
Above 5.0	5.75	V	BOB-5
Above 4.25	5.0	VI	BOB-6
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

Bank Model:

From Score	To Score	Grade	Common Scale

Above 8.5	10.0	I	BOB-1
Above 7.5	8.5	II	BOB-2
Above 6.5	7.5	III	BOB-3
Above 5.75	6.5	IV	BOB-4
Above 5.0	5.75	V	BOB-5
Above 4.25	5.0	VI	BOB-6
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

NBFC Model:

From Score	To Score	Grade	Common Scale
Above 8.5	10.0	I	BOB-1
Above 7.5	8.5	II	BOB-2
Above 6.5	7.5	III	BOB-3
Above 5.75	6.5	IV	BOB-4
Above 5.0	5.75	V	BOB-5
Above 4.25	5.0	VI	BOB-6
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

Broker model:

From Score	To Score	Grade	Common Scale
Above 8.5	10.0	I	BOB-1
Above 7.5	8.5	II	BOB-2
Above 6.5	7.5	III	BOB-3
Above 5.75	6.5	IV	BOB-4
Above 5.0	5.75	V	BOB-5
Above 4.25	5.0	VI	BOB-6
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

B) Borrowers / Obligors eligible for rating under SME (Manufacturing) / SME (Services) and Traders model in case of existing companies:

SME (Manufacturing Model):

From Score	To Score	Grade	Common Scale
Above 8.5	10.0	I	BOB-3
Above 7.5	8.5	II	BOB-4
Above 6.5	7.5	III	BOB-5
Above 5.75	6.5	IV	BOB-5
Above 5.0	5.75	V	BOB-6

Above 4.25	5.0	VI	BOB-7
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

SME (Services) Model:

From Score	To Score	Grade	Common Scale
Above 8.5	10.0	I	BOB-3
Above 7.5	8.5	II	BOB-4
Above 6.5	7.5	III	BOB-5
Above 5.75	6.5	IV	BOB-5
Above 5.0	5.75	V	BOB-6
Above 4.25	5.0	VI	BOB-7
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

Trader Model:

From Score	To Score	Grade	Common Scale
Above 8.5	10.0	I	BOB-3
Above 7.5	8.5	II	BOB-4
Above 6.5	7.5	III	BOB-5

Above 5.75	6.5	IV	BOB-5
Above 5.0	5.75	V	BOB-6
Above 4.25	5.0	VI	BOB-7
Above 3.5	4.25	VII	BOB-7
Above 2.5	3.5	VIII	BOB-8
Above 1.5	2.5	IX	BOB-9
0	1.5	X	BOB-10

C) Project Borrowers / Obligors eligible for rating under infrastructure (Build Phase) / Green field Projects (LCM/SME):

Large Corporate Model (With Project):

From Score	To Score	Grade	Common Scale
Above 4.5	5	BOBPR-1	BOB-6
Above 3.5	4.5	BOBPR-2	BOB-7
Above 2.5	3.5	BOBPR-3	BOB-8
Above 1.5	2.5	BOBPR-4	BOB-9
0	1.5	BOBPR-5	BOB-10

SME (Mfg. /Services) Model (with project):

From Score	To Score	Grade	Common Scale
Above 7	8	BOBPR-1	BOB-6
Above 5	7	BOBPR-2	BOB-7
Above 3	5	BOBPR-3	BOB-8

Above 1	3	BOBPR-4	BOB-9
0	1	BOBPR-5	BOB-10

Infrastructure (Power/Port/Telecom) Model – Build Phase:

From Score	To Score	Grade	Common Scale
Above 4.5	5	BOBPR-1	BOB-6
Above 3.5	4.5	BOBPR-2	BOB-7
Above 2.5	3.5	BOBPR-3	BOB-8
Above 1.5	2.5	BOBPR-4	BOB-9
0	1.5	BOBPR-5	BOB-10

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