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# Internal Assessment of Credit Concentration Risk Capital: A Portfolio Analysis of Indian Public Sector Bank


### *Abstract:*

This paper aims at working out a more risk sensitive measure of concentration risk and captures its impact in terms of capital number that will help the bank's top management to manage it efficiently as well as meet the regulatory compliance. We have designed a more risk sensitive measures like expected loss based Hirschman-Herfindahl Index (HHI), loss correlation approach (single as well as multi factor), credit value at risk (C-VaR) based on bank's internal loss data history that would measure credit concentration and suggest the amount of capital required to cover concentration risk. Using detailed borrower wide, facility wide, industry and regional loan portfolio data of a mid sized public sector bank in India, our paper attempts to provide a detail insight into measurement of concentration risk in credit portfolio and understand its impact in terms of economic capital for the bank as a whole. Regulators and other stakeholders worldwide are asking for more accurate and precise measure of concentration risk in terms of capital numbers. The detailed analysis and methods used in this paper is an attempt to find out a solution in this direction.



Keywords: Portfolio Credit Concentration Risk, Bank Capital

JEL Classifications:  G32, G21

## 1. Introduction

Credit risk is a material risk for the Bank as it is most important in terms of potential losses. Credit risk is risk resulting from uncertainty in counterparty's ability or willingness to meet its contractual obligations. Credit risk is the probability of losses associated with changes in the credit quality or borrowers or counterparties. These losses could arise due to outright default by counterparties or deterioration in credit quality. This has recently been evidently shown again in the example of the US sub-prime crisis. The crisis occurred despite various improvements in credit risk management, for example the progress in the field of credit risk analysis applied by banks on the portfolio level – spurred by Basel II. Credit institutions are expected to conduct internal assessments of the adequacy of the capital they hold by utilizing credit risk models to account for portfolio concentration and correlation effects. The credit risk models assist in measuring the credit risk exposure and losses in loan portfolios. Generally, these models provide valuable information concerning risk concentrations, loan losses, capital adequacy, and return on capital. In particular, the new Basel Capital Accord is based on simplified credit risk models that align regulatory capital more closely with economic capital (the funds used by a bank to absorb unexpected losses).

As a matter of legacy, most Banks have originated and are holding loan exposures that are function of their geography and industry orientation. As a result, they do hold concentration risk. Over time, Credit portfolios might become increasingly concentrated in less creditworthy obligors not necessarily by choice but by chance. These two situations, on which banks have little control, may make them more vulnerable to economic downturns. Hence, measurement and monitoring of concentration risk by banks is a necessity. Banks with heavy correlation risks can make money and steer clear of trouble, so long as they hold enough risk capital to protect the bank against the higher level of unexpected losses and charge their customers accordingly (or exit markets where market pricing makes charging for concentration risks impossible). Where these skills are lacking, banks with strongly correlated portfolios suffer the double blow of heavy losses followed by the need to adjust ongoing business strategy. Thus, a portfolio approach to credit risk analysis allows portfolio managers to quantify and stress test concentration risk along various dimensions as under. The measurement of concentration risk in credit portfolios is also necessary for regulatory compliance under Pillar II of Basel II.

Concentration Risk in a Bank generally arises due to an uneven distribution of loan exposures in terms of inherent risks, either across regions or across sectors that is capable of generating increases unexpectedly losses large enough to threaten an institution's solvency. The emergence of concentration risk is closely linked to the business strategy orientation of banks. Managing concentration risk means mitigating the effects of systematic risk resulting from dependence in losses across loans and idiosyncratic risk associated with large exposures to individual obligors. Concentration Risk in credit portfolio of a Bank can be observed in a variety of ways: by borrower, risk rating, industry, sector, region and any other common factors leading to grouping of credits. For the regulator as well as the bank it is necessary to identify concentration based on common and or correlated risk factors and assess its impact of in terms of risk capital and bank solvency. This is possible if we have a process and system in identifying key risk variables and their correlations on a predictive basis. Moody's Investors Service use expected loss (EL) based Herfindahl-Hirschman Index (HHI) for assessing the concentration risk in rating residential mortgage loans pool for securitization purpose.[1] Assessment of EL based concentration risk and loan level reviews enable them to identify assets that are contributing to entire pool risk. Moody's also use diversity score measure for rating Collateralized Debt Obligations (CDOs).[2] For this, they use various portfolio characteristics like loans rating profile, maturity profile, asset value and their default correlations. Uberti and Figini (2010) proposed a new index that takes into account the risk of the loan to measure credit concentration risk. Düllmann and Masschelein (2007) have measured the potential impact of business sector concentration on economic capital through a simplified version of value at risk approach that avoids Monte Carlo Simulations. Reynolds (2009) examined the suitability of various measures such as exposure based HHI, expected loss measure and relative credit value at risk measures etc. in assessing portfolio concentration risk.

There is empirical evidence that support the idea that credit events are correlated like studies by Lucas (1995), Nagpal and Bahar, 2001; De Servigny and Renault, 2003;

[1] See Moody's Rating Methodology for Structured Finance in technical paper: "Sizing RMBS Large Loan Concentration Risk", February 24, 2006. Website: http://www.moodys.com/cust/content/Content.ashx?source=StaticContent/Free+Pages/ABS_East_Event/SizingRMBSLargeLoanConcentrationRisk.pdf

[2] See Moody's Approach to Rating Multisector CDOs, Special Report, September 15, 2000 (By Jeremy Gluck and Helen Rameza). Website: http://www.securitization.net/pdf/MoodysMultiSectorCDO.pdf

Bandyopadhyay, A., et al., 2007), Zhang, Zhu and Lee (2008) etc. that have estimated the dependence among borrower risks. Gordy (2003) and the Basel committee on banking supervision (2006) in IRB approach used asymptotic single risk factor model based value at risk (VaR) method for measuring concentration risk. The portfolio models used by them are very similar to Vasicek's (1977) single asset correlation model. In these models, credit risk in a portfolio is influenced by idiosyncratic risk and systematic risk. While idiosyncratic risk represents the effects of risk related to individual borrower, the systematic risk captures the effect of unexpected changes in macroeconomic and market conditions on creditworthiness of the borrower. The basic idea behind these models is that as the portfolio becomes more and more fine-grained (or less concentrated), where largest individual exposure account for a smaller and smaller share to total portfolio exposure, idiosyncratic risk is diversified away on the portfolio level. In such case, only systematic risks that affect many exposures in the loan pool have a material impact on portfolio losses. In our correlation approach, all systematic risks like industry or regional risk is modeled with only one systematic factor to derive the resulting portfolio loss percentage distribution to compute unexpected loss (UL) capital charge.

Based on micro structure information available in a bank Egloff et al. (2004) have business contagion significantly increases the correlation between debtors that affects on tail of loss distribution increases credit concentration risk. Fiori, Fogilia and Lannotti (2006) have linked historically observed sectoral default rates with macro economic variables. Their papers finds that although the explanatory power of macro factors for defaults is relatively limited, their estimate of residual cross section correlation of default rates suggests the presence of contagion effects through the impacts of sector specific risk on the default rates of the other sectors. This way, credit correlation and concentration influences bank capital.

Taylor (2002) examined the use of economic capital to manage portfolio concentration and discussed how to structure risk limits on individual obligors and concentration limits on portfolio segments rather than the simple exposure limits. Dev (2004) has shown in his book how economic capital can be used in decision making at financial institutions on a risk adjusted basis. Heitfield et al (2006) have simulated the distribution of portfolio credit losses for a number of real US syndicated loan portfolios to find that sector concentration risk is the main contributor to economic capital for portfolios of all sizes.

Gürtler et al. (2010) compares value at risk and expected shortfall methods with Basel II formula to test their suitability to assess concentration risk.

Using detailed borrower wide, facility wide, industry and regional loan portfolio data of a mid sized public sector bank in India, this paper attempts to provide a detail insight into measurement of concentration risk in credit portfolio and understand its impact in terms of economic capital for the bank as a whole. We have designed a more risk sensitive measures like expected loss based Hirschman-Herfindahl Index (HHI), loss correlation approach (single as well as multi factor), credit value at risk (C-VaR) based on bank's internal loss data history that would measure credit concentration and suggest the amount of capital required to cover concentration risk. Our results suggest that economic capital gives more conservative & realistic measure of real portfolio risk.

We have used a simplified measure of single correlation estimates using the Bank's internal loss history data and credit portfolio information. From the correlation, we estimate the region-wide marginal risk contribution and find economic capital estimates given the risk appetite of the Bank. While comparing the economic capital with the mandatory regulatory capital as prescribed by RBI under Basel II standardized approach, we also assess whether the Bank require any additional capital for maintaining its solvency or reputation in the market. This helps us to understand the region-wise contribution and directly links concentration risks to the Bank's internal capital requirement.

The rest of the paper is structured in the following manner. In section 2 we describe the data and variables that have been used in our empirical analyses. Section 3 describes our methodology and empirical results. Section 4 concludes the paper. The detailed methodologies and formulations have been shown in Appendix A. Tables and Charts are presented at the end of the paper.

## 2. Data, Variables and Approach

This paper has used detailed loan history files of a mid-sized public sector bank in India with almost 1,500 branches spread across India and has a business mix of more than Rs. 1 crore. The bank's business is mainly concentrated in Western part of India and has deeply penetrated under banked areas of among three most industrialized states of the country. We have used the bank's aggregate level information, business segment wise as well as detailed account wise granular data to study the extent of concentration risk in the bank's loan portfolio from various angles. We have examined the bank's rated large corporate pool, industry pool and regional pools to assess concentration risk from various angles. Simultaneously, we have also checked two peer bank's aggregate sectoral information from their Basel II disclosure reported in their respective websites for benchmarking purpose. Using historical CRISIL's (a leading external rating agency in India) bond rating migration data for 572 corporates from 1998 to 2009, we also estimate a system level default correlation for rated Indian corporates.

Following steps have been taken to assess the impact of concentration risk on respective banks' total portfolio risk capital:

- Identifying whether there is credit concentration in the portfolio through heuristic method (ratio based: exposure to capital ratios by checking the maintenance of prudential limits) and by using various statistical measures.
- Estimating and comparing the exposure arising from those risks.
- Applying expected loss based concentration measure to get a better picture of risk.
- Arriving at the default correlation among different borrowers in a portfolio and assess the marginal risk contribution that a particular credit/ region adds to total portfolio risk to guide the top management in Bank to do portfolio selection.
- Using their actual default history data, determining the expected and unexpected loss in the portfolio to link concentration to risk capital (or economic capital).
- Guiding the top management in understanding the additional capital requirement to cover concentration risk under normal as well as stress scenarios. This is also necessary for the determination of regulatory capital as prescribed in Internal Capital Adequacy Assessment Process (ICAAP) under Pillar 2 of Basel II.

## 3. Methodology and Empirical Results

### 3.1. Various Heuristic Measures of Concentration

Traditionally, Banks in India manage risk exposures that arise within the various risk category silos following the prudential norms as set by RBI in its 1999 and 2010 circular. [3 & 4] As a prudential measure aimed at better risk management and avoidance of concentration of credit risks, the Reserve Bank of India in its 1999 and recent ICAAP circular has advised the 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 India.[3&4] Banks often monitor exposures both against gross and net limits of large exposures to Individual clients or groups, Clients in the same economic or geographic region, Borrowers in a certain country, certain industries, clients of poor credit quality (low credit rating or sub-prime), Off balance sheet exposures particularly derivatives, credit substitutes etc., credit exposures to counterparties whose financial performance is dependent on the same activity or commodity (Automobile accessories / spare manufacturing), indirect credit risk concentration arising from credit risk mitigation techniques. Default on account of any such exposures can result in the erosion of the capital to the extent of such concentrated exposures.

The lending as well as risk management policy documents of the bank stipulates prudential limits on various types of credit exposures as per RBI circulars in 1999 and 2010. The maximum exposure limits to single/group borrower, ceilings in respect of sectors, individual industry, including exposure to sensitive sectors, sector/industry hurdle risk grades are presented in Table 1. These prudential limits across various individual borrower wise, sector wise, industry wise or risk grade level have been assigned to mitigate concentration risk. Banks on quarterly basis monitor the individual borrower, group borrower and sectoral limits to mitigate concentration risk. As far as specific industry ceilings are concerned, the bank maintains the following limits for the following industries in relation to the gross credit outstanding as shown in Table 2.

[Insert Table 1 & Table 2 here]

### 3.1.1. Industry Risk Concentration

Actual exposure positions are compared with the limits set by the bank's risk management and loan administration policies. Detail analyses of credit concentration assessment for various categories of advances across various industries are documented in Table 3.This table provides evidence that loan exposures are well within the industry ceilings

[3] See Annex to RBI Circular DBOD.No.BP.(SC).BC.98/ 21.04.103/ 99 dated October 7, 1999 regarding Risk Management System in Banks http://www.rbi.org.in/scripts/NotificationUser.aspx?Id=85&Mode=0

[4] See recent RBI Master Circular- Prudential Guidelines on Capital Adequacy and Market Discipline – New Capital Adequacy Framework (NCAF) ICAAP released on February 8, 2010 (pg. 116).

specified by the Bank. The gross NPA percentage in Automobile including trucks (55.33%) and Iron & Steel sector (21.09%) is significantly higher in comparison to peer banks. Thus, industry-wide risk comparative risk characteristics and exposure distribution give as depicted in table 3 gives us an idea about portfolio risk concentration in Bank's credit portfolio. It is however not clear why exposure limits are lower in Sugar (2% of gross bank credit), Textile (5%), Film Industry (1%) and in Software/IT industry (5%) that has been stipulated in previous table 2.

[Insert Table 3 here]

Next, we look at the sectoral portfolio position of the Bank. It is quite evident from table 4 that average risk position in personal loans segment is significantly higher than the other sectors.

[Insert Table 4 here]

**3.1.2. Bank's Approach in Managing Credit Portfolio Risk-Rating Monitoring**

The bank has eight rating models (effectively four) for credit risk rating of prospective borrowers which were introduced in July 2005. These four entry level credit risk rating models (for industrial & Hi tech agricultural activities, PSU firms, traders & services and for agricultural borrowers above Rs. 2 lac) are helpful in decision making process in respect of prospective borrowers. These models are based on activity of the borrower. The bank has developed in-house web based software for assigning risk rating to a borrower. Credit rating is done at least once in a year for exposures up tp Rs. 5 Cr. and twice a year for exposures above Rs. 5 crore.

For quantitative assessment of credit concentration risk and addressing the same, we have seen that the bank has fixed prudential / regulatory ceilings for various categories of advances. These limits are monitored at least on a quarterly basis and in some cases more frequently such as country risk exposure, counter party exposure etc. Actual positions are compared with the limits set and corrective action is taken for breaches/concentration if any.

The entry level minimum acceptable grades (or hurdle grades) are benchmarked by the bank's risk management policy pertaining lending to different industries. For industries like Sugar, Textile, Leather & Leather Products, Plastic Products, Electric Products with exposures above Rs. 1 crore, and Electronic products industry for exposures above 1 crore, entry level hurdle grade is A (medium risk). For Electric and Electronic products with exposures less than 1 crore, Readymade Garments, Information Technology enabled services (ITeS), Commercial Real Estate, Dyes and Pigments and Glass and Glass products, minimum acceptable entry level rating is BBB (average risk). However, minimum acceptable benchmark rating for a new entry level proposal other than these industries is BB (high risk/below average safety) which depicts higher risk appetite nature of the bank.

Portfolio credit risk (including concentration risk) is managed by the bank through sound appraisal and due diligence process, effective monitoring and recovery system and internal controls like framework for delegated authority, documentation, review / renewal, pre and post inspection of securities etc. The Bank has introduced following policies to manage the Credit Risk (including credit concentration risk), which are reviewed/revised from time to time.

**3.2. Quantitative assessment on credit concentration risk**

We begin by examining common straight forward portfolio-level index measures of concentration risk before moving on to more risk sensitive measures where we gauge credit concentrations in terms of risk capital and compare relative risk contributions using credit value at risk (CVaR) method. In some cases, comparing the relative shares of capital (or CVaR (with a confidence level say 99.9%)) against the relative shares of exposure along various dimensions such as rating, sector or region can yield portfolio management great insights. We also investigate which specific borrower/sector/region adds concentration and diversification to the Bank's credit portfolio

The steps involved in concentration analysis are:

- Identifying whether there is credit concentration in the portfolio
- Calculating the exposure arising from those risks
- Determine the expected and unexpected loss in the portfolio
- Arriving at the default correlation among different assets / borrowers in a portfolio
- Identifying the marginal contribution that a particular credit adds to risk capital and what return compensates the bank for it
- Assisting management in allocating economic capital to internal businesses (capital budgeting)

In doing so, we assess the Bank's credit concentration risk in the following areas using popular approaches/statistical models:

- Zone wise credit concentration
- Rating wise concentration
- Concentration in top 20 borrowal accounts
- Sector wise concentration
- Industry wise concentration
- Size wise loan concentration

We measure rating wise, industry wise and geography wise level of concentration in bank's credit portfolio. We also assess the impact of credit concentration risk on Bank capital as well as solvency. This will enable the top management in Banks to understand the implications of managing a credit portfolio. One more crucial objective of this exercise is to guide the Banks' top management to make portfolio selection such a way to diversify the concentration risk.

We have adopted following approaches in gauging credit concentration risk-

1) Lorenz-Gini Coefficient (exposure share vs. risk share or rating share vs. default share etc.)-lesser the value more uniform is the portfolio

2) Herfindahl-Hirschman Index (HHI)-sum of squares of relative portfolio share-lower the value, lesser the concentration.-Need to slice to credit portfolio according to size, rating grades, industry, geography (or region wise) etc to understand the nature of credit concentration and portfolio position.

3) Expected Loss Based measure of credit concentration

4) Correlation Approach (Rating history/Credit Loss History/Equity index/Asset correlation)-We have designed a correlation framework based on bank's data history as well as from external rating history to measure credit correlation concentration and suggest the amount of capital required to cover concentration risk.

The details of these methods are explained in the Appendix A.

**3.2.1. Rating wise Portfolio Concentration:**

The ability of the bank to manage its geographic or sectoral concentration depends on how it is able to manage the risk in its credit portfolio. This further depends on rating wise profile of risk characteristics in its credit portfolio. Accordingly, we look into the rating wise distribution of the bank's corporate credit portfolio. We also examine how the portfolio composition is changing over time.

**3.2.2.** ***Single Default Correlation for Bank's Commercial Loan Pool:***

We first study the yearly rating migration pattern of borrowers above Rs. 2 lac from 2003-04 till 2008-09 using exhaustive dynamic pool of 1757 borrower rating data obtained from various branches/regions of the bank. Next we construct one year average migration matrix including rating wide PDs and also track the PD fluctuations across 6 yearly cohorts.

To find out sub-group default correlation for rated commercial portfolio of the Bank we assume default correlation is simply the relation of variability of default rate over time periods relative to the total variability. This relationship has been established in appendix A. The one year average of five yearly rating migrations and default rates variability are reported in tables 5 & 6. It is quite evident from both these tables that internal risk classifications of the bank appears to fairly capturing the credit risk. The likelihood of default monotonically increases as the risk category decreases. Notice that single default correlation almost monotonically increasing with decrease in rating grade. The default correlations obtained in lowest two risk grades B and C are quite high indicating high portfolio concentration risk of the bank in these grades. The increase in default correlation at B and C suggests that high risk borrowers are also vulnerable to systematic events. It also warns that bad tail loss rates are understated by estimating portfolio loss distributions by equally weighting such events. Hence, the hidden layers of correlation risk need to factor into portfolio loss estimation for computation of actual risk capital of the bank.

[Insert Table 5 & 6 here]

**3.2.3.** ***Rating wise Multiple Default Correlation for the Entire Indian Corporate Industry:***

We also derive industry benchmark default correlation estimates for large corporate loans. Such correlation estimates may guide the banks to benchmark their rated portfolio to understand the extent of concentration risk. For this, we divide 572 corporate bonds rated by CRISIL from 1992 till 2009 into homogenous subgroups to create a rating wise corporate portfolio for the Indian banking industry. Then using the multiple default correlation method as discussed in the methodology section, we estimate their default correlation using rating migration history of these bonds. The basic idea is that borrowers with similar default probabilities and pair-wise default correlations would exhibit similar default correlations. The higher the correlation numbers, greater is the concentration risk in the portfolio. The lower the correlation of default more diversified the portfolio.

Table 7 reports grade group wised default correlation estimates for all industries putting together. The default correlation methodology is shown in appendix A. The rating grades are either grouped in Investment Grades (IG: AAA-BBB) and Non-Investment Grades (NIG: BB, B & CCC) to better capture the portfolio movements. We find that IG-IG grade correlation is lower than IG-NIG and NIG-NIG correlation. Thus, as far as external bond rating is concerned, there is a diversification benefit within IG grades.

[Insert Table 7 here]

Next, we look deeper into the bank's March 2009 rated large commercial loan pool (current limit above Rs. 1 Crore) to examine the extent of it's' portfolio risk.

[Insert Table 8 here]

Table 8 shows asset size distribution of all 1,200 rated borrowers across 32 regions of the bank. Though in terms of number share the portfolio risk seems to be well diversified, however, few large loans in the lower graded assets is increasing the risk of concentration. While it is intuitive to think that a portfolio that is more evenly distributed across ratings or sectors or regions may be less subject to the effects of idiosyncratic and systematic risk, the difference between portfolio credit concentration and portfolio credit loss need to be understood. In this context, simple exposure based concentration indexes may not be helpful unless we understand the dependence of credit losses across exposures. This can be done by linking the exposure share with expected loss share which can be adopted by the central office to manage concentration risk at regional or industry level. The basic idea of expected loss based concentration measure is that the large number of borrowers in a pool will reduce the credit risk via diversification. However, if there are a few borrowers in the pool that are significant in size relative to the entire pool balance, this diversification benefit can be lost, resulting in a higher level of default risk. In such instances, the bank may set concentration risk limits based on expected loss percentage for regions or branches or sectors and will be monitored closely. We have tried to demonstrate this in the bank's regional portfolio.

### 3.2.4. Geographic Concentration:

Here, we compare the region inequality to understand their extent of geographic concentration. When measuring the degree of geographical concentration the total position in shares and credits in a region should be taken into account, since geographical concentration can arise in all loan categories.

When measuring the degree of geographical concentration the total position in shares and credits in a region should be taken into account. This is because geographical concentration can arise in all loan categories.

[Insert Table 9 here]

It is quite evident from the above Table 9 that Mumbai city (24.75%); Delhi (16.84%) and Pune city (11.87%) are the top 3 regions of the bank in terms of exposure size. In terms of both exposure and EL HHI the bank seems to be well diversified. However, this is just an overall aggregate view and does not factor each zone wise size and risk wide distribution of assets and details pattern of asset quality. A better approach may be to look into distribution pattern of assets and their risk rating and hence EL share in accordance with various size classes within each region/industry and then compare HHI. Accordingly, we looked into he original pattern of loan distribution within each region which may significantly influence the concentration result.

### 3.2.5. The Loan Distribution based Measure of Concentration:

The concentration risk is generally better understood if we look at the size of the loan distribution within each region. Using the bank's internally rated large commercial loan portfolio data (exposures above 1 crore), estimate loan size wise distribution and compare regional risk concentration. The results are documented in Table 10.

[Insert Table 10 here]

One can notice that loan exposure distribution is more unequal in Ahmedabad, Bangalore and Mumbai region due to recent addition of few large loans by the bank in March 2010. This inequality can be seen by looking at the difference between 75 and 99 percentiles, their skewed-ness and kurtosis. However, risk wise these regions are less concentrated as can be observed by their median rating, deviation of grades and coefficient of variation. The variation of the grades in all these three regions range from AA to BBB. The risk wise as well as size wise concentration is relatively higher in Chandigarh, Kolkata, Thane, Chennai and Nasik regions in comparison to overall bank position. This is observed by incorporating the size wise distribution and rating wise distribution of assets. A Risk rating based limits that take into account the risk rating of the borrower as well as industry risk characteristics and need to be weighted with exposure limits. For example, bank may set policy such that no more than 10% of exposures are in a region where the weighted average risk rating is equal to or less than BBB. Likewise, industry limits may be established. However, this view is based average risk expectation. A more risk sensitive approach would be to estimate regional marginal risk contribution to total portfolio loss of the bank based on their unexpected losses and correlation with systematic factors. It is therefore necessary to use a set of methods in measuring concentration risk for checking the robustness since the use of any single measure or representation can be misleading when analyzing concentration.

Moving from a single number to a ranked list of 'high risk' items is a logical step towards more actionable, granular information. It is important to understand the sources of risk in the portfolio at a more granular level. This can be done through the process of capital attribution. Accordingly, in order to link credit concentration with risk capital, we need to measure the hidden layer of default correlation.

### 3.2.6. Single Default Correlation Measure for the Bank:

The best way to measure the risk of a concentrated portfolio is to find correlation between Bank's loss volatility vis-à-vis segments volatility and their increased capital requirements by estimating their marginal risk contributions. Economic capital concepts can then be used to put rupee costs against the concentration risk. The idea of correlation (mainly the systematic impact) enables us to estimate its contribution (marginal) to the tails of the overall credit loss distribution.

Default correlation is a measure of the dependence among risks. Along with default rates and recovery rates, it is a necessary input in the estimation of value of the portfolio at risk in bank loan. In general, the concept of default correlation incorporates the fact that systematic events cause the default event to cluster. This joint dependence in default among borrowers may be triggered by common underlying factors (call it systematic factor like changes in unemployment rate, changes in raw-material prices, input price changes etc.). There is enough historical evidence that support the idea that credit events are correlated (like studies by Nagpal and Bahar, 2001; Servigny and Renault, 2003; Bandyopadhyay, A., et al., 2007).

Here, we have followed a simple methodology from historical default or loss based on the assumption that all loans within the risk class have identical default rates. The single loss correlation method has already been discussed in methodology section given in the appendix A. The bank level default correlations estimates as measured by fresh slippage rate have been shown in Table 11. The loss percentage obtained from the annual NPA movement data of the Bank. The historical percentage Unexpected Loss of the portfolio ($UL_P$) is the standard deviation of fresh slippage rates. The total Unexpected Loss assuming same correlation=$N \times UL_i$ (assuming LGD has no volatility and ignored LGD variation). The default (or loss) correlation is the ratio of Portfolio loss volatility over and above total volatility ($=UL_p^2/UL_{total}^2$).

While computing single default correlation for the bank as a whole (as reported in table 11), it is assumed that total variance of defaults comes from either systematic factor or idiosyncratic risk. If Bank can manage the idiosyncratic risk through rating and through its due diligence in lending, this single loss correlation will actually capture the systematic risk. As it is capturing if economic condition deteriorates, how the default risk in the Banks' credit portfolio will go up.

[Insert Table 11 here]

However, this loss correlation estimates the bank's aggregate historical data does not differentiate between differences in risk characteristics of various loans and therefore it may be less risk sensitive. Accordingly as a next step of complication, we now exploit the region wise historical loss data of these banks as we have an idea of the distribution of creditworthiness of the loans across the regions. This more risk sensitive correlation method has also been discussed in the appendix A. The results of this correlation estimate has been discussed in the following section where we have economic capital computation for the bank as well as for its regions.

### 3.2.7. Linking Concentration Risk to Bank Capital: Credit VaR Approach in Bank's Regional Portfolio

At the top of the house, economic capital gives a clear answer to the most pressing question of all: Does bank's capital (available capital) equal or exceed the capital necessary to ensure our survival (economic capital) with a given level of confidence (the bank's solvency target) after taking account of its credit concentration risks? To answer this question, we convert the portfolio concentration and their marginal contribution into Economic capital to find out the risk tolerance level for credit concentration.[5]

In order to capture the concentration risk in terms of capital, we have to estimate the marginal risk contribution (MRC) which is the contribution of each rating grade/borrower/sector to the unexpected loss of the portfolio of the bank. To calculate the marginal risk contribution of each rating grade it is essential to know the default correlation (with the systematic factor) across rating grades. It is a measure to dependence among risks due to serial correlation with the common risk factor (This can be proved).

*Marginal risk contribution* $MRC_i = \sqrt{r_i} \times UL_i \times Exposure_i$

The regional risk profile of the bank's entire advance portfolio has been summarized in Table 12. One can compare the regional positions in terms of PD%, LGD%, and Exposure Share as well as EL share. Using, regional portfolio distribution of advances of the bank as documented in the Table 12 and also their bank level loss variance (reported in Table 11), we re-estimate single default correlation and report in Table 12. The marginal risk contributions of 32 regions in percentage terms and in rupee amount have also been reported in Table 12. Risk contribution measures the portion of individual region's unexpected loss contributes to the bank's portfolio risk. This captures the incremental risk caused by the region to the bank portfolio. The regions whose EL share and MRC share are higher are adding more cost to the bank in terms of risk capital.

[Insert Table 12 here]

[5] Economic capital is the amount of internal capital needed to provide a cushion against the unexpected loss incurred in the credit portfolio. Credit Value at Risk method (C-VaR) considered worldwide as a standard approach to estimate risk capital. A financial institution sets a confidence level, say 99.9%; it then estimates a 'worst case' loss that will not be exceeding during one year with the chosen confidence level. Economic capital is the difference between this worst case loss and the expected loss. It is the estimate of the level of capital that a bank requires to operate its business with a desired target solvency level.

As a next step, we convert the portfolio unexpected loss of the bank and the regions into economic capital number to assess their impact on bank capital. The necessary amount of Economic Capital of Bank to sustain a target debt rating (solvency rating) is derived from portfolio unexpected losses which have been further estimated by adding their regional marginal risk contributions. These estimates have been documented in the later section of the report.

Economic capital is the tail percentile (as illustrated in the in chart 1) that represents the total amount of risk (value-at- risk) less the expected loss covered by the loan loss reserve. Chart 1 illustrates the nature of credit loss distribution. As one can see that the loss distribution is negatively skewed indicating fatness of the default tail which means large losses have very less frequency and they are located in the tail. The bank requires keeping economic capital to cover this tail or maximum loss with certain probability.

[Insert Chart 1 here]

To calculate the unexpected default rate it is usual to calculate the standard deviation (sigma) of annual default rates on loans and then multiply by sigma by a factor such that 99 percent (or higher) of defaults are covered by capital. For example, if loss distribution was normally distributed, then sigma (or volatility) of default rates would be multiplied by 2.33 to get the extreme 99 percent default rate. For many Fis, default rates are skewed to the right and have fat tails suggesting a multiplier much larger than 2.33. For example, to get coverage of 99.97 percent of defaults, Bank of America has historically used a multiplier of 6 (Walter, 2004). Finally, the denominator can also be adjusted for the degree of correlation of the loan with the rest of the FI's portfolio. Under standard normal distribution assumption, $EL_p=0$; however, we will adjust if the Bank is making any provisions for standard assets and we this from $k \times UL_p$. From Credit VaR, we arrive at capital at risk which is also termed as “Economic Capital”. It is a broader concept than unexpected loss because depending upon the nature of the loss distribution, unexpected loss variation will be higher (i.e., $k \times UL_p$).

The concept of economic capital (EC) is a widely used approach for managing credit risk in Banks. To prevent insolvency, economic capital must cover unexpected losses to a high degree of confidence. Banks often link their choice of confidence level to a standard of solvency implied by a credit rating of A or AA for their senior debt. If the Bank targets AA rating, the confidence level will change depending upon the nature of tail of the default distribution. A higher multiplier (more than 3) will assume portfolio loss has fat tail as 99.9% of the area of a normal loss distribution is captured by 3 standard deviation (or k=3). Therefore, higher the k, heavier is the tail of the distribution which cannot be captured by the normal distribution. Accordingly, we estimate the economic capital for the Bank as whole from risk characteristics of its regional credit portfolio and compare with the regulatory capital under Basel II standardized approach. The economic capital estimates based on the bank's historical credit VaR under various scenarios are reported in Table 13.

[Insert Table 13 here]

We see that as bank targets AA rating under non-normal situation, multiplier increases and accordingly, economic capital and the gap between economic and regulatory capital also increases. Finally, we have chosen capital multiplier of 6 because credit losses are generally not normally distributed. Bank of America historically used a multiplier of 6. Bank of America's reference points for the allocation of economic capital are a target rating of AA and the related 99.97% confidence level for solvency. This confidence level requires that economic capital be sufficient to cover all but the worst three of every 10,000 possible risk scenarios with a one-year horizon. Following this Credit Value at Risk methodology, we estimate bank level as well as regional economic capitals. We find that with a multiplier of 6, in our credit VaR method, economic capital is below the regulatory capital. This amount of targeted economic capital requirements results in additional capital requirement of Rs. 329.97 crore over and above existing Basel II minimum regulatory capital for covering credit risk. However, in terms of available capital, the bank has surplus position. Following the same method, we have also estimate the economic capital for each regions from their marginal risk contributions. At the sub regional portfolio level, hard limits can be placed on notional exposure such that the economic capital as a percentage of exposure does not exceed a certain threshold. This way, bank can follow risk criteria rather than size criteria as a basis for managing concentration risk.

One may still argue that the choice of multiplier of six may not be enough to capture the fat tail of default loss distribution. To mitigate this problem, exploiting the bank's regional portfolio risk characteristics to fit into a beta distribution using Monte Carlo simulation method (discussion is in the appendix A). We have done 10,000 simulations by plugging in regional level portfolio expected loss and unexpected loss as inputs. We use these two inputs to derive location and scale parameters of beta distribution and then integrate numerically to simulate the loss distributions through Monte Carlo method in the following section.

**3.2.8.** ***Estimation of Economic Capital through Simulation Based C-VaR Model:***

The credit losses are typically assumed to be a Beta distribution (with positive skewness and kurtosis>3 shaped similar to the distributions that have been observed for historical credit losses globally). Using Beta distribution has another advantage; it only requires two parameters $EL_p$ and $UL_p$ to determine the shape. Moreover, it also restricts loss percentages to be in between 0% to 100%.

Using the above formula, we plug in empirically derived values of $EL_p$ (=0.97%) and $UL_p$ (=1.64%) in the zonal portfolio to obtain $a$=0.337 and $b$=34.40.

As next step, we use these to parameters to fit beta distribution and use Monte Carlo simulation method to generate 10,000 likely loss values in %. The fitted loss distribution is shown in the chart 2.

[Insert Chart 2 here]

Through simulation we basically generate ten thousand likely loss probable values after fitting with the beta distribution as it requires only two parameters. The simulation method helped us to check the tail pattern of the loss distribution. The fitness of the distribution has been tested using Quantile-Quantile and chi square fitness tests

As a next step, from the tail of the beta distributions, we try to obtain estimates of economic capital required for the portfolio under various confidence levels. Here, we are estimating the economic capital using Credit Value at risk method (C-VaR) which is the maximum probable loss minus the expected loss:

$$EC_p = MPL_p - EL_p \qquad \text{Eq.10}$$

The Simulated economic capital numbers are reported in Table 19. Next, we compare the economic capital numbers with the Basel II minimum regulatory capital position (under standardized approach) of the bank. This has been done under various confidence level and then figure out the gap in terms of capital and tier I %. Further, in our simulation based C-VaR approach, we observe more conservative loss estimates for the bank.

Table 14 documents our simulation based C-VaR results. We find that if a bank targets to get CRISIL rating of AA/A (with a PD% of 0.70%), to obtain a possible 99.30% confidence level to protect itself from default tail, it requires to have economic capital of 7.95% of gross advances. This means additional capital requirement of Rs. 348.29 crore by the bank over and above its existing credit risk regulatory capital of Rs. 2929.42 crore. Thus, in terms of amount, the bank's economic capital obtained at 99.30% confidence level is of Rs. 3277.71 crore. Accordingly, we obtain the bank's required economic capital over risk weighted assets equals 10.07% which is well above its existing Tier I capital % of 6.44%. Jokivuolle and Peura (2010) through various simulations have shown minimum rating targeting may have explained many US banks' actual capital level. They argued that on average Eco-cap/RWA would be higher than Tier I% depending on the rating target of the bank. They find that median tier I% in AA rated US Banks is: 9.2%. When the bank's minimum target is single A or better, the amount of economic capital necessitated by the rating target should be higher than the bank's pillar I regulatory capital requirement. Their paper mentions casual observations from US market suggest that A or AA rated banks typically report economic capital figures that exceeds Pillar 1 minimum capital charges.

[Insert Table 14 here]

If actual credit losses have fat tail of this nature, targeting AA in such stress time would mean they have to keep enough surpluses to cover losses are a challenging exercise and accordingly they have to plan their business growth and plan to raise further capital. For example, if the bank decides to meet this additional Rs. 348.29 crore capital (as estimated in simulated credit VaR in Table 14) to achieve AA/A CRISIL rating, and also target to maintain 21.4% return on equity (ROE), their minimum targeted net profit in March 2011 would be at least Rs. 469.96 crore (ROE×Eco-cap=21.4%×Rs.3277.71 cr & after adjusting by 67% due to corporate tax). This is because, future earnings also gets added to the core capital.

We also estimate the amount of risk capital the bank may have to keep as a cushion against its top 20 large borrower concentration risk. For this, we estimate the marginal risk contribution of these large borrowers based on their rating and correlation estimates reported in table 15. We first rank the borrowers in terms of their share to total advances in a descending order. Then we map their PD and correlation to bank portfolio from Table 5 & 6 to estimate unexpected loss share and marginal risk capital (MRC). We assume LGD for the entire top 20 pool will be the overall bank LGD rate of 78.07% obtained from its regional portfolio average in Table 9. After adding the marginal risk capital of top 20 borrowers we obtain the total economic capital required by the bank by multiplying the sum of MRCs (equals Rs. 22.4673 crore) by 6 which totals up to approximately Rs. 134.80 crore. This is the estimated additional capital the bank needs to keep as cushion to counter large borrower concentration risk which may be added to its Pillar II capital requirement. In our analysis, if the bank decides to meet additional Rs. 348.29 crore capital through profit or equity capital, then that may also cover up top 20 borrower concentration risk capital as well.

[Insert Table 15 here]

## 4. Conclusions.

In this paper, using a medium sized Indian bank's detailed credit exposure and loss history data, we assess region wide, sector wide, borrower wide concentration risk and demonstrate its impact in terms of capital. Using our correlation based marginal risk capital measure; we demonstrate how a more risk sensitive economic capital approach may enable the top management to manage concentration risk to remain solvent. Given an appetite for risk, economic capital based measures may enable the bank to set a profit and target and draw capital raise plan to meet the additional capital requirement under pillar II of Basel II regulation.

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## Appendix: A

***Methodology for Estimation of PD & LGD***

Two most important drivers of credit risk of any given credit position are probability of default (PD) over a given horizon and expected loss-given-default (LGD). Given our Bank data set, the historical PDs for the Bank as a whole as well as across industries and regions have been computed by tracking the historical NPA movements and Gross Advances data (yearly movements). We estimate yearly marginal PDs by using a moving average method as shown in the equation.

$$MPD_t = \frac{1}{3}\sum_{t=1}^{3}(\Delta GNPA_t / Advances_t)$$
$$PD = \sum_{t=1}^{T}\frac{MPD_t}{T} \qquad \text{Eq. 1}$$

Where T is the total number of periods. In this method, we divide the fresh NPA slippage (or NPA additions) amount in Rs.Cr. in a year (denoted by $\Delta GNPA_t$) by the 3 years average gross advances. Next, we estimate the long run average PD by taking five or ten year weighted average of yearly marginal PDs (or MPDs). This gives us rupee weighted average long run PDs for banks as well as zones and it is a more conservative measure than frequency based measure of PDs (Davis et al., 2004).

Similarly, bank and region level Loss Given Default (LGDs) have been estimated using the aggregate level recovery workout history of the bank obtained from yearly historical NPA movements data at various sub portfolio level. The recovery rate in a year or quarter is the total amount cash recovered in that year (or quarter) divided by the 3 years (or quarter) average of gross NPA amount that the bank has opened with. Next, we estimate long run LGD by taking these yearly (or quarterly) average. This pooling method has been used in the absence of account wise LGD data.

***EL based Measure of Concentration Risk:***

We apply a Herfindahl-Hirschman index measure to quantify the potential large loan concentration risk in corporate loan pool. This loss concentration measure is calculated using

Expected Rupee loss share (ELi) to portfolio loss share (ELP). This EL based measure is summarized in the following formula:

$$HHI = \sum \left( \frac{ELi}{ELp} \right)^2 \qquad \text{Eq.2}$$

EL=EAD×PD×LGD

EAD=Exposure at default (both fund based and non fund based after adjusting credit conversion factor). Exposure indicates in the event of default, how large will be the outstanding obligations if the default takes place. PD=Yearly Probability of Default calculated by a pooled method (tracking NPA movements over gross advances. LGD=Annualized Loss Given Default obtained from bank's historical aggregate recovery data.

***Gini Coefficient Measure of Inequality***

The Gini coefficient or Lorenz ratio is a standard measure of inequality or concentration of a group distribution. It is defined as a ratio with values between 0 and 1. A low Gini coefficient indicates more equal income or distribution of loan assets with different industries/groups, sectors, etc., while a high Gini coefficient indicates more unequal distribution. 0 corresponds to perfect equality.

For a portfolio of $N$ loans with exposure shares *s1, s2,…., sN*, the empirical Gini coefficient is defined as

$$G(s_1, s_2, \ldots\ldots\ldots, s_N) = \frac{\sum_{n=1}^{N} (2n-1)s_n}{N} - 1 \qquad \text{Eq. 3}$$

Therefore, the Gini coefficient,

$$G = 1 - \sum p_i (z_i + z_{i-1})$$

$p_i$ is the probability or frequency of no. of borrowers and $z_i$ is the loan share.

***Methodology for Estimation of Loss (or single Default) Correlation:***

The unexpected loss (standard deviation of portfolio loss due to NPA volatility mainly measures the risk of potential credit loss) for the portfolio is:

$$UL_P = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\rho_{i,j}^{d} \times UL_i \times UL_j} \qquad \text{Eq. 4}$$

Where ρ is the default correlation

We can get an estimate for the correlation if we assume that the correlation between each loan is identical (assuming 0 within correlation).

That is $\rho_{i,j} = \overline{\rho}_i$ for all i and j

Given the assumption of s fixed correlation, we can separate two summations because they no longer depend on each other.

$$UL_P^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\overline{\rho}UL_iUL_j$$

$$= \overline{\rho}\sum_{i=1}^{N}UL_i\sum_{j=1}^{N}UL_j$$

$$= \overline{\rho}\left(\sum_{i=1}^{N}UL_i\right)^2$$

If we assume that each loan has the same UL, we can estimate the Bank-wide single default correlation as follows:

$$\overline{\rho} = \frac{UL_P^2}{\left(\sum_{i=1}^{N}UL_i\right)^2}$$

$$= \frac{UL_P^2}{(N \times UL_i)^2} \qquad \text{Eq. 5}$$

Here, N is the total number of loans clubbed in the portfolio.

$UL_P^2$ is estimated from the volatility (or annual data series).

In estimating the loss correlation from historical data of the Bank, we have assumed that all the loans were identical in terms of risk characteristics to create a single pool. However, in real life portfolio, this is not the case and we have an idea of the distribution of the creditworthiness of the loans in the portfolio. Accordingly, we use region wise/industry wise loan distribution and estimate sum of the ULs of the individual loans according to their allocation to each region/industry group

$$\sum_{i=1}^{N} UL_i = w_1 \sum_{i=1}^{G1} UL_i + w_2 \sum_{i=G1+1}^{G2} UL_i + w_2 \sum_{i=G2+1}^{G3} UL_i + ....... + w_n \sum_{i=Gn+1}^{N} UL_i \qquad \text{Eq. 6}$$

$W_i$ is the proportion of the portfolio's exposure that is in each sector or region. G represents region or industry groups.

$$w_i = \frac{\sum_{i=1}^{G1} E_i}{E_{Total}}$$

Using equation 5 and 6, we can estimate single default correlation which will be more realistic number.

***Estimating Multiple Default Correlation:***

From the joint migration of bond grades using CRISIL's published bond rating data history for 18 years, we estimate IG-IG, IG-NIG and NIG-NIG default correlation using the following formula:

$$\rho_{i,j}^{D,D} = \frac{JDP_{i,j} - PD_i PD_j}{\sqrt{PD_i(1-PD_i)PD_j(1-PD_j)}} \qquad \text{Eq.7}$$

The joint default probability between two industries, say i & j ($JDP_{i,j}$), is the probability that loans in the these rating grades (say IG and NIG) will default at the same time. Clearly, the correlation will be positive if the JDP is larger than the product of the univariate probabilities. The main difficulty is to estimate the JDP. We have used historical yearly rating migration being tracked to estimate JDP.

$$JDP_{ij} = \sum_t w_t \frac{D_t^i D_t^j}{N_t^i N_t^j} \qquad \text{Eq.8}$$

where $w_t = \frac{N_t^i N_t^j}{\sum N_i N_j}$; $D_t^i$ & $D_t^j$ are the number of defaults in a given year from respective grades and $N_t^i$ and $N_t^j$ are the number of borrowers in the beginning of the year in each grade. We also estimate rating wise long run PDs by taking weighted average of 18 yearly cohort movements of these grades towards defaulted grade. Next, we estimate rating wise default correlations by using these inputs in equation 7.

**Loss Simulation Approach using Beta Distribution**

The formula for the beta probability density function for % losses (L) is as follows:

$$\beta(L) = \frac{L^{a-1}(1-L)^{b-1}}{\int_0^1 L^{a-1}(1-L)^{b-1}\,dL} \qquad \text{Eq.9}$$

The beta function has been integrated numerically using Palisade @RISK statistic package. To use it for Monte Carlo simulation, the parameters *a* and *b* are expressed in terms of the required mean (ELp) and standard deviation (ULp):

$$a = (1-EL_p)\left(\frac{EL_p}{UL_p}\right)^2 - EL_p$$

$$b = \frac{a(1-EL_p)}{EL_p}$$

| **Table 1: Position of Exposure Ceilings Internally Fixed by the Bank for Various Categories of Borrowers as per RBI guidelines** | |
|---|---|
| ***Exposure Category*** | ***Prudential Limit*** |
| ***a. Individual and Group Borrowers:*** | |
| i. For Individual Borrowers-NBFC (other than AFC) | 10% of capital funds |
| ii. Others including NBFC-AFC | 15% of capital funds |
| iii. Oil Companies who have been issued oil bonds (which do not have SLR status) by Government of India | 25% of capital funds |
| iv. For individual borrowers for **infrastructure projects**-NBFC (other than AFC) | 25% of Capital funds |
| v. For **group borrowers** including NBFC-AFC | 40% of capital funds |
| vi. For **group borrowers** for **infrastructure projects** | 50% of capital funds |
| ***b. Substantial Exposure Limits:*** | |
| SEL limits | Threshold limit is 10% of the total capital funds and the bank restricts aggregate credit exposure under such substantial to 750% of bank's capital funds. |
| ***c. Ceilings in respect of sectors:*** | |
| Industry/Sector | 10% of total bank credit |
| Real Estate Sector | 32.5% of gross credit |
| Of which- Housing Loans to Individual | 12.5% of gross bank credit |
| NBFCs | 25% of gross bank credit |
| HFCs | 12% of gross bank credit |
| Infrastructure | 35.5% of gross bank credit |
| Of which power sector | 17.5% of gross bank credit |
| Roads including highways | 5% of gross bank credit |
| Telecom | 6% of gross bank credit |
| Advances to Stock Brokers | 15% of net-worth |
| Non Fund Business | 30% of gross bank credit |

Note: Capital funds means total of tier I and tier II capital of the bank in a particular year (say in March 2010).

| Table 2: Industry Limits set by the Bank's Risk Management Policy | | |
|---|---|---|
| **SL#** | **Industry** | **Exposure Limits** |
| 1 | Sugar Industry | 2% of gross bank credit |
| 2 | Textile Industry | 5% of gross bank credit |
| 3 | Film Industry | 1% of gross bank credit |
| 4 | Software/IT industry | 5% of gross bank credit |
| 5 | Auto and Auto Ancillary | 10% of gross bank credit |
| 6 | Any other industry | 10% of gross bank credit |

| Table 3: Industry wide Loan Distribution of the Bank under study vis-à-vis other banks | | | | | |
|---|---|---|---|---|---|
| SL# | INDUSTRY | % age of Gross Advances | GNPA% | GNPA% Large Bank | GNPA% Mid sized Bank |
| 1 | Coal | 0.004% | 8.78% | 2.77% | 9.05% |
| 2 | Mining | 0.57% | 0.81% | | |
| 3 | Iron and steel | 0.42% | 21.09% | 2.02% | 1.78% |
| 4 | Other metal and metal product | 0.23% | 7.50% | 5.88% | 1.40% |
| 5 | All Engineering | 8.19% | 0.58% | 4.55% | 2.12% |
| 6 | Electricity | 3.56% | 0.01% | 6.66% | 0.14% |
| 7 | Cotton textiles | 0.97% | 0.51% | 8.50%@ | 3.61%@ |
| 8 | Jute textiles | 0.01% | 2.74% | | |
| 9 | Other textiles | 1.03% | 3.55% | | |
| 10 | Sugar | 0.67% | 0.20% | 1.58% | 3.61% |
| 11 | Tea | 0.00% | 2.47% | 21.03% | 1% |
| 12 | Food processing | 1.95% | 0.96% | 5.02% | 7% |
| 13 | Vegetable oil and vanaspaty | 0.01% | 5.13% | 8.89% | 3.40% |
| 14 | Tobacco and tobacco product | 0.05% | 0.94% | | |
| 15 | Paper and paper products | 0.76% | 2.04% | 9.05% | 2.12% |
| 16 | Rubber and rubber products | 0.18% | 0.70% | 10.25% | 5.64% |
| 17 | Chemical, dyes , paints | 1.39% | 0.89% | 15.26% | 2.17% |
| 18 | Cement | 0.51% | 2.07% | 0.37% | 1.20% |
| 19 | Leather & leather products | 0.05% | 5.65% | 7.55% | 1.69% |
| 20 | Gems and jewellery | 0.73% | 0.04% | 0.90% | 2.92% |
| 21 | Construction | 4.95% | 0.04% | 0.30% | 1.03% |
| 22 | Petroleum | 1.67% | 0.01% | 0.40% | 0.01% |

| | | | | | |
|---|---|---|---|---|---|
| 23 | Automobile including trucks | 0.01% | 55.33% | 0.26% | 1.86% |
| 24 | Computer software | 0.14% | 1.05% | 33.08% | 1.31% |
| 25 | Infrastructure of which | 17.86% | 0.15% | | |
| 25.1 | Power | 6.09% | 0.00% | | |
| 25.2 | Telecommunication | 1.64% | 0.00% | 0.002% | 0.004% |
| 25.3 | Roads and ports | 1.55% | 0.12% | 3% | 3.61% |
| 26 | NBFCs | 19.76% | 3.18% | 0.001% | 0.001% |
| 27 | Residual Advances (includes Trading) | 32.48% | 5.27% | 4% | 1.60% |
| 31 | Other Industries | 1.83% | 17.33% | | |
| | TOTAL | 100.00% | | | |

Note: @ For Textile industry overall

**Table 4: Sector wise Risk Characteristics of the Bank-Non Food Credit**

| | **March 2010** | | **March 2009** | |
|---|---|---|---|---|
| **Sector** | **% Share** | **Gross NPA%** | **Gross Advances** | **Gross NPA%** |
| Agriculture & allied activities | 15.57% | 3.70% | 15.94% | 2.86% |
| Industry (Small, Medium & Large) | 28.18% | 1.00% | 30.36% | 1.50% |
| Services | 5.58% | 5.31% | 7.24% | 3.43% |
| Personal Loans | 0.50% | 30.95% | 0.79% | 20.14% |
| Housing Loans | 9.04% | 4.17% | 8.69% | 3.24% |
| Real Estate Loans | 2.57% | 5.77% | 5.23% | 1.28% |
| Auto Loans | 1.63% | 17.30% | 1.55% | 28.69% |
| Trade | 6.15% | 10.40% | 2.70% | 0.20% |
| Loan to Capital Market | 0.48% | | 0.82% | |
| Others | 30.29% | | 26.66% | |
| Total Non-Food Credit | 100.00% | | 100.00% | |

| Table 5: One Year Rating Transition Matrix: 2003-2009 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **AAA** | **AA** | **A** | **BBB** | **BB** | **B** | **C** | **D** |
| **AAA** | **61.30%** | 24.96% | 10.77% | 2.08% | 0.28% | 0.39% | 0.11% | 0.11% |
| **AA** | 28.95% | **40.45%** | 20.50% | 7.12% | 1.80% | 0.47% | 0.47% | 0.23% |
| **A** | 17.20% | 26.95% | **35.98%** | 14.63% | 3.05% | 0.37% | 0.98% | 0.85% |
| **BBB** | 7.95% | 15.64% | 24.10% | **29.49%** | 14.10% | 3.85% | 1.79% | 3.08% |
| **BB** | 4.44% | 8.15% | 14.07% | 27.41% | **21.48%** | 11.11% | 7.41% | 5.93% |
| **B** | 3.13% | 4.69% | 10.94% | 21.88% | 6.25% | **21.88%** | 6.25% | 25.00% |
| **C** | 2.00% | 4.00% | 0.00% | 6.00% | 8.00% | 2.00% | **28.00%** | 50.00% |

| Table 6: Default Rates of Commercial Loans>Rs. 2 Lac | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Year Cohort** | **AAA** | **AA** | **A** | **BBB** | **BB** | **B** | **C** |
| 2003-04 | 0.00% | 0.00% | 3.90% | 0.00% | 5.00% | 10.00% | 14.29% |
| 2004-05 | 0.00% | 0.00% | 0.00% | 2.44% | 9.09% | 12.50% | 54.55% |
| 2005-06 | 0.34% | 1.36% | 0.97% | 2.08% | 0.00% | 10.00% | 100.00% |
| 2006-07 | 0.00% | 0.00% | 0.85% | 6.25% | 0.00% | 25.00% | 66.67% |
| 2007-08 | 0.00% | 0.00% | 0.00% | 2.78% | 4.35% | 33.33% | 33.33% |
| 2008-09 | 0.28% | 0.27% | 0.79% | 3.45% | 10.81% | 50.00% | 0.00% |
| | | | | | | | |
| Portfolio vol. | 0.1627% | 0.5442% | 1.44% | 2.04% | 4.49% | 16.04% | 36.58% |
| Total vol. | 3.35% | 4.84% | 9.20% | 17.27% | 23.61% | 43.30% | 50.00% |
| Def. corrln | 0.236% | 1.265% | 2.460% | 1.395% | 3.617% | **13.725%** | **53.518%** |

| Table 7: Corporate Default Correlation in India: All Industries (%) | | |
|---|---|---|
| | IG | NIG |
| IG | 3.60% | 12.14% |
| NIG | | 17.31% |

| Table 8: Rating wide Loan Distribution of the Bank for Exposures above Rs. 1 Cr. (Unit-Rs. Lac) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Grade** | **N** | **% Share** | **mean** | **p25** | **p50** | **p75** | **p99** | **sd** | **cv** | **sk** | **kurt** |
| AAA | 343 | 28.58% | 1319.82 | 79.17 | 159.41 | 462.61 | 29999.89 | 4685.93 | 3.55 | 6.02 | 42.70 |
| AA | 362 | 30.17% | 1339.80 | 107.07 | 216.32 | 641.35 | 24035.76 | 4176.50 | 3.12 | 6.14 | 48.37 |
| A | 295 | 24.58% | 1693.15 | 127.06 | 262.05 | 927.67 | 22328.67 | 3952.21 | 2.33 | 3.75 | 17.86 |
| BBB | 124 | 10.33% | 1490.47 | 145.56 | 304.84 | 1137.82 | 26515.36 | 3983.30 | 2.67 | 5.47 | 35.85 |
| BB | 41 | 3.42% | 585.01 | 121.91 | 264.91 | 659.11 | 5537.19 | 961.00 | 1.64 | 3.85 | 19.15 |
| B | 8 | 0.67% | 3080.15 | 144.06 | 503.38 | 2600.47 | 18087.95 | 6204.06 | 2.01 | 2.09 | 5.63 |
| C | 8 | 0.67% | 389.33 | 82.65 | 185.89 | 428.74 | 1719.81 | 563.78 | 1.45 | 1.88 | 5.15 |
| D | 19 | 1.58% | 1.84 | 0.00 | 0.00 | 0.00 | 31.35 | 7.60 | 4.12 | 3.75 | 15.06 |
| Total | 1200 | | | | | | | | | | |

| Table 9: Regional Risk Position of the Bank<br>Units in Rs. Lac, others in percentage | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **SL#** | **Region Name** | **Exposure Share** | **Borrower no. Share** | **Avg. PD%** | **Avg. LGD%** | **EL Amt.** | **EL Share** | **EL-based HHI weight** |
| 1 | AHMEDABAD | 3.68% | 1.49% | 2.70% | 85.60% | 3514.144 | 12.11% | 1.467% |
| 2 | AHMEDNAGAR | 0.84% | 2.75% | 2.99% | 78.22% | 807.924 | 2.78% | 0.078% |
| 3 | AKOLA | 0.76% | 6.07% | 4.20% | 81.71% | 1074.095 | 3.70% | 0.137% |
| 4 | AMRAVATI | 0.72% | 5.13% | 2.92% | 75.67% | 658.866 | 2.27% | 0.052% |
| 5 | AURANGABAD | 1.45% | 9.04% | 4.16% | 81.98% | 2037.260 | 7.02% | 0.493% |
| 6 | BANGALORE | 4.50% | 2.58% | 0.91% | 81.11% | 1370.188 | 4.72% | 0.223% |
| 7 | BHOPAL | 0.61% | 2.41% | 8.58% | 79.32% | 1713.746 | 5.91% | 0.349% |
| 8 | CHANDIGARH | 5.31% | 0.86% | 0.85% | 81.05% | 1501.662 | 5.18% | 0.268% |
| 9 | CHANDRAPUR | 0.64% | 3.82% | 2.55% | 78.45% | 527.810 | 1.82% | 0.033% |
| 10 | CHENNAI | 2.03% | 1.09% | 2.55% | 82.58% | 1759.126 | 6.06% | 0.368% |
| 11 | DELHI | 16.84% | 1.23% | 0.32% | 82.28% | 1855.210 | 6.39% | 0.409% |
| 12 | GOA | 0.65% | 1.39% | 1.98% | 65.83% | 351.552 | 1.21% | 0.015% |
| 13 | HYDERABAD | 3.48% | 2.59% | 0.86% | 78.00% | 963.511 | 3.32% | 0.110% |
| 14 | INDORE | 0.76% | 2.41% | 3.24% | 72.48% | 737.384 | 2.54% | 0.065% |
| 15 | JABALPUR | 0.47% | 1.89% | 4.02% | 74.57% | 587.577 | 2.03% | 0.041% |
| 16 | JAIPUR | 2.31% | 0.44% | 0.08% | 61.40% | 44.136 | 0.15% | 0.000% |
| 17 | JALGAON & DHULE | 0.63% | 2.55% | 2.05% | 83.61% | 447.320 | 1.54% | 0.024% |
| 18 | KOLHAPUR | 1.46% | 5.32% | 4.44% | 80.11% | 2139.041 | 7.37% | 0.543% |
| 19 | KOLKATA | 2.16% | 0.80% | 4.04% | 90.73% | 3269.588 | 11.27% | 1.270% |
| 20 | LATUR | 1.23% | 5.67% | 4.06% | 84.63% | 1747.569 | 6.02% | 0.363% |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 21 | LUCKNOW | 0.84% | 0.58% | 4.35% | 76.83% | 97.483 | 0.34% | 0.001% |
| 22 | MUMBAI CITY | 24.75% | 3.00% | 0.73% | 79.14% | 401.085 | 1.38% | 0.019% |
| 23 | NAGPUR | 1.70% | 3.45% | 2.42% | 86.37% | 91.518 | 0.32% | 0.001% |
| 24 | NASIK | 2.67% | 5.39% | 2.15% | 75.47% | 146.102 | 0.50% | 0.003% |
| 25 | PUNE CITY | 11.87% | 7.55% | 1.35% | 79.71% | 293.555 | 1.01% | 0.010% |
| 26 | PUNE RURAL | 1.67% | 4.58% | 3.81% | 80.21% | 137.120 | 0.47% | 0.002% |
| 27 | RAIGAD | 0.47% | 1.33% | 4.79% | 74.56% | 81.333 | 0.28% | 0.001% |
| 28 | RAIPUR | 0.38% | 1.36% | 2.63% | 78.31% | 20.268 | 0.07% | 0.000% |
| 29 | RATNAGIRI | 0.51% | 1.39% | 4.46% | 63.00% | 145.775 | 0.50% | 0.003% |
| 30 | SATARA | 1.32% | 4.95% | 4.89% | 75.53% | 221.705 | 0.76% | 0.006% |
| 31 | SOLAPUR | 1.33% | 4.44% | 3.93% | 75.95% | 179.438 | 0.62% | 0.004% |
| 32 | THANE | 1.95% | 2.43% | 2.83% | 73.71% | 92.373 | 0.32% | 0.001% |
| | Total | 100.00% | 100.00% | | 78.07% | 29015.466 | 100.00% | |
| | Exposure based HHI | 0.116 | | | | | | |
| | EL based HHI | | | | | | | 0.0636 |

**Table 10: Region wide Loan Size Distribution**

**Units in Rs. Crore, others in percentage**

| **Region name** | **N** | **mean** | **p50** | **p75** | **p99** | **cv** | **skew** | **kurt** | **Median Rating** | **Worst Dev of Grade*** | **rating cv** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **AHMEDABAD** | 57 | 16.24 | 1.03 | 3.40 | **600.00** | **4.91** | 7.05 | **52.00** | **AA** | **BBB** | 0.51 |
| AHMEDNAGAR | 16 | 3.47 | 1.00 | 2.80 | 24.70 | 1.86 | 2.50 | 8.54 | BBB | B/C | 0.48 |
| AKOLA | 2 | 21.79 | 21.79 | 42.52 | 42.52 | 1.34 | 0.00 | 1.00 | AA | BBB | 0.46 |
| AMRAVATI | 7 | 1.19 | 1.09 | 1.94 | 1.98 | 0.50 | 0.23 | 1.68 | AA | A | 0.41 |
| AURANGABAD | 40 | 2.89 | 0.91 | 3.07 | 27.86 | 1.81 | 3.28 | 14.88 | AA | BB | 0.69 |
| **BANGALORE** | 72 | 9.55 | 1.57 | 6.72 | 150.00 | 2.53 | 4.09 | **20.69** | AA | BBB | 0.50 |
| BHOPAL | 3 | 5.07 | 0.87 | 14.34 | 14.34 | 1.59 | 0.70 | 1.50 | **A** | **B** | **0.85** |
| CHANDIGARH | 20 | 62.49 | 14.97 | 82.63 | 402.19 | 1.74 | 2.17 | 6.76 | **A** | **BB** | 0.54 |
| CHANDRAPUR | 4 | 1.15 | 0.90 | 2.29 | 2.78 | 1.21 | 0.24 | 1.31 | B | D | 0.64 |
| CHENNAI | 56 | 5.54 | 1.28 | 2.71 | 53.96 | 2.16 | 3.00 | 11.13 | A | BB | 0.44 |
| **DELHI** | 128 | 29.34 | 1.62 | 7.89 | 401.68 | 2.76 | 3.41 | 14.00 | AA | BBB | 0.47 |
| GOA | 21 | 4.94 | 0.83 | 2.65 | 46.12 | 2.40 | 2.75 | 9.21 | AAA | A/BBB | **0.76** |
| HYDERABAD | 141 | 4.41 | 1.15 | 3.43 | 40.32 | 2.14 | 3.43 | 15.39 | AA | BBB | 0.64 |
| INDORE | 22 | 3.26 | 1.16 | 2.51 | 24.27 | 1.75 | 2.78 | 10.03 | AA | A | 0.42 |
| JABALPUR | 11 | 1.86 | 1.64 | 3.15 | 4.47 | 0.77 | 0.45 | 1.98 | AAA | AA/A | 0.56 |
| **JAIPUR** | 17 | 22.09 | 1.83 | 27.02 | 151.35 | 1.92 | 2.16 | 6.57 | AA | BBB | 0.50 |
| JALGAON | 17 | 2.33 | 1.48 | 2.67 | 13.05 | 1.30 | 2.76 | 10.47 | AA | A | 0.51 |
| KOLHAPUR | 49 | 2.18 | 1.23 | 1.95 | 13.95 | 1.34 | 2.23 | 7.94 | **AA** | **BB** | 0.66 |
| KOLKATTA | 40 | 9.02 | 1.29 | 2.06 | 103.01 | 2.66 | 3.21 | 12.22 | **A** | **BB** | 0.47 |
| LATUR | 40 | 1.47 | 1.17 | 1.94 | 6.07 | 0.88 | 1.53 | 5.71 | AA | A | 0.56 |
| LUCKNOW | 14 | 15.53 | 0.83 | 2.33 | 189.55 | 3.24 | 3.29 | 11.89 | AA | BBB/BB | 0.55 |
| **MUMBAI** | 319 | 14.03 | 1.43 | 5.02 | **211.33** | 3.54 | 7.07 | **65.49** | AA | BBB | 0.52 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| NAGPUR | 37 | 4.02 | 1.89 | 4.69 | 45.97 | 1.94 | 4.41 | 23.84 | AA | BBB | 0.53 |
| NASIK | 105 | 3.42 | 1.44 | 3.03 | 36.98 | 2.19 | 5.43 | 37.02 | **AA** | **BB** | 0.69 |
| PUNE CITY | 457 | 6.46 | 1.13 | 3.18 | 120.51 | 3.27 | 6.24 | 48.27 | AA | BBB | 0.55 |
| PUNE RURAL | 36 | 1.84 | 0.96 | 1.94 | 12.89 | 1.45 | 2.51 | 9.77 | AA | BB | 0.65 |
| RAIGAD | 15 | 2.32 | 1.01 | 3.92 | 8.78 | 1.15 | 1.16 | 3.28 | A | BB | 0.35 |
| RAIPUR | 19 | 2.83 | 1.40 | 4.12 | 17.71 | 1.48 | 2.61 | 9.65 | AA | A/BBB | 0.47 |
| RATNAGIRI | 7 | 0.70 | 0.62 | 0.93 | 1.89 | 0.92 | 0.70 | 2.84 | AA | BBB | 0.56 |
| SATARA | 29 | 2.32 | 1.11 | 2.11 | 20.85 | 1.80 | 3.59 | 15.46 | AA | BB | 0.65 |
| SOLAPUR | 28 | 1.52 | 1.01 | 2.12 | 6.91 | 1.07 | 1.61 | 5.56 | AA | BBB | 0.57 |
| THANE | 64 | 3.80 | 1.25 | 3.07 | 100.02 | 3.34 | 7.04 | 53.63 | **A** | **B** | 0.64 |
| Total | 1893 | 9.30 | 1.25 | 3.40 | 189.55 | 4.08 | 8.74 | 98.74 | AA | BBB | 0.57 |

Note: *It captures maximum downside deviation of grade at 95% confidence

**Table: 11 Historical Loan Loss at Bank Portfolio Level**

**Units in Rs. Crore**

| **Period** | **Gross Advances** | **Additions in GNPA** | **MPD** | **Total NPA Recovery** | **Recovery Rate (RR)** |
|---|---|---|---|---|---|
| 1997-98 | 3620.46 | | | | |
| 1998-99 | 4061.83 | 220.94 | | | |
| 1999-00 | 5252.20 | 197.17 | | | |
| 2000-01 | 7097.41 | 345.37 | 6.31% | 95 | 12.32% |
| 2001-02 | 8255.12 | 241.88 | 3.52% | 107 | 13.13% |
| 2002-03 | 9508.1373 | 267.45 | 3.23% | 102 | 11.40% |
| 2003-04 | 11731.508 | 220.81 | 2.25% | 132 | 14.27% |
| 2004-05 | 13061.64 | 222.71 | 1.95% | 137 | 14.27% |
| 2005-06 | 17080 | 274.52 | 1.97% | 137 | 14.39% |
| 2006-07 | 23462 | 306.57 | 1.72% | 234 | 25.80% |
| 2007-08 | 29798 | 252.11 | 1.08% | 188 | 22.24% |
| 2008-09 | 34817 | 357.05 | 1.22% | 164 | 20.64% |
| 2009-10 | 40926.15 | 851.11 | 2.42% | 229 | 24.71% |
| LRPD% | | | 2.56% | | |
| ULp% | | | 1.53% | | |
| ULtotal% | | | 13.07% | | |
| Default Corrln | | | 1.37% | | |
| Avg. RR | | | | | 17.32% |
| Avg.LGD | | | | | 82.68% |

**Table 12: Regional Portfolio Economic Capital Estimation**

**Units in Rs. Crore, others in percentage**

| SL# | Region Name | Exposure Share | Avg. PD% | Avg. LGD% | EL Share% | UL% | Expos. wtd. UL% | Regional MRC % | Regional MRC Amt. | Region EC % |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | AHMEDABAD | 3.68% | 2.70% | **85.60%** | 12.11% | 13.88% | 0.511% | 2.35% | 3575.731 | 14.12% |
| **2** | AHMEDNAGAR | 0.84% | 2.99% | 78.22% | 2.78% | 13.32% | 0.112% | 2.26% | 780.304 | 13.56% |
| **3** | AKOLA | 0.76% | 4.20% | 81.71% | 3.70% | 16.40% | 0.124% | 2.78% | 869.47 | **16.69%** |
| **4** | AMRAVATI | 0.72% | 2.92% | 75.67% | 2.27% | 12.73% | 0.092% | 2.16% | 644.664 | 12.96% |
| **5** | AURANGABAD | 1.45% | 4.16% | **81.98%** | 7.02% | 16.37% | 0.237% | 2.78% | 1658.348 | **16.66%** |
| **6** | BANGALORE | 4.50% | 0.91% | 81.11% | 4.72% | 7.70% | 0.346% | 1.31% | 2423.803 | 7.84% |
| **7** | BHOPAL | 0.61% | **8.58%** | **79.32%** | 5.91% | 22.21% | 0.136% | 3.77% | 948.710 | **22.60%** |
| **8** | CHANDIGARH | 5.31% | 0.85% | 81.05% | 5.18% | 7.42% | 0.394% | 1.26% | 2757.408 | 7.55% |
| **9** | CHANDRAPUR | 0.64% | 2.55% | 78.45% | 1.82% | 12.37% | 0.079% | 2.10% | 553.239 | 12.59% |
| **10** | CHENNAI | 2.03% | 2.55% | **82.58%** | 6.06% | 13.01% | 0.264% | 2.21% | 1844.859 | 13.24% |
| **11** | DELHI | **16.84%** | 0.32% | **82.28%** | 6.39% | 4.68% | 0.788% | 0.79% | 5512.344 | 4.76% |
| **12** | GOA | 0.65% | 1.98% | 65.83% | 1.21% | 9.18% | 0.0600% | 1.56% | 418.984 | 9.34% |
| **13** | HYDERABAD | 3.48% | 0.86% | 78.00% | 3.32% | 7.21% | 0.2501% | 1.22% | 1752.834 | 7.33% |
| **14** | INDORE | 0.76% | 3.24% | 72.48% | 2.54% | 12.83% | 0.098% | 2.18% | 683.307 | 13.06% |
| **15** | JABALPUR | 0.47% | 4.02% | 74.57% | 2.03% | 14.65% | 0.0700% | 2.49% | 486.694 | 14.91% |
| **16** | JAIPUR | 2.31% | 0.08% | 61.40% | 0.15% | 1.69% | 0.039% | 0.29% | 272.499 | 1.71% |
| **17** | JALGAON & DHULE | 0.63% | 2.05% | **83.61%** | 1.54% | 11.85% | 0.075% | 2.01% | 524.386 | 12.05% |
| **18** | KOLHAPUR | 1.46% | 4.44% | 80.11% | 7.37% | 16.50% | 0.241% | 2.80% | 1682.689 | **16.79%** |
| **19** | KOLKATA | 2.16% | 4.04% | **90.73%** | 11.27% | 17.87% | 0.386% | 3.03% | 2701.478 | **18.18%** |
| **20** | LATUR | 1.23% | 4.06% | 84.63% | 6.02% | 16.70% | 0.206% | 2.83% | 1441.116 | **16.99%** |
| **21** | LUCKNOW | 0.84% | 4.35% | 76.83% | 0.34% | 15.66% | 0.132% | 2.66% | 921.867 | 15.94% |
| **22** | MUMBAI CITY | **24.75%** | 0.73% | 79.14% | 1.38% | 6.73% | 1.667% | 1.14% | 11658.469 | 6.85% |
| **23** | NAGPUR | 1.70% | 2.42% | 86.37% | 0.32% | 13.28% | 0.225% | 2.25% | 1574.750 | 13.51% |
| **24** | NASIK | 2.67% | 2.15% | 75.47% | 0.50% | 10.94% | 0.292% | 1.85% | 2042.063 | 11.13% |
| **25** | PUNE CITY | **11.87%** | 1.35% | 79.71% | 1.01% | 9.21% | 1.094% | 1.56% | 7648.861 | 9.37% |
| **26** | PUNE RURAL | 1.67% | 3.81% | 80.21% | 0.47% | 15.36% | 0.257% | 2.61% | 1795.299 | 15.63% |
| **27** | RAIGAD | 0.47% | **4.79%** | 74.56% | 0.28% | 15.92% | 0.076% | 2.70% | 528.940 | 16.20% |
| **28** | RAIPUR | 0.38% | 2.63% | 78.31% | 0.07% | 12.53% | 0.047% | 2.13% | 329.135 | 12.75% |
| **29** | RATNAGIRI | 0.51% | **4.46%** | 63.00% | 0.50% | 13.00% | 0.067% | 2.20% | 466.569 | 13.23% |
| **30** | SATARA | 1.32% | 4.89% | 75.53% | 0.76% | 16.29% | 0.215% | 2.76% | 1500.885 | **16.57%** |
| **31** | SOLAPUR | 1.33% | 3.93% | 75.95% | 0.62% | 14.77% | 0.197% | 2.50% | 1376.286 | 15.03% |
| **32** | THANE | 1.95% | 2.83% | 73.71% | 0.32% | 12.22% | 0.238% | 2.07% | 1666.667 | 12.43% |
| | Total | 100.00% | | 78.07% | 100.00% | | 9.013% | | 63042.659 | |
| | Default Correlation | | | | | | | | 2.876% | |

**Chart 1: Credit Loss Tail**

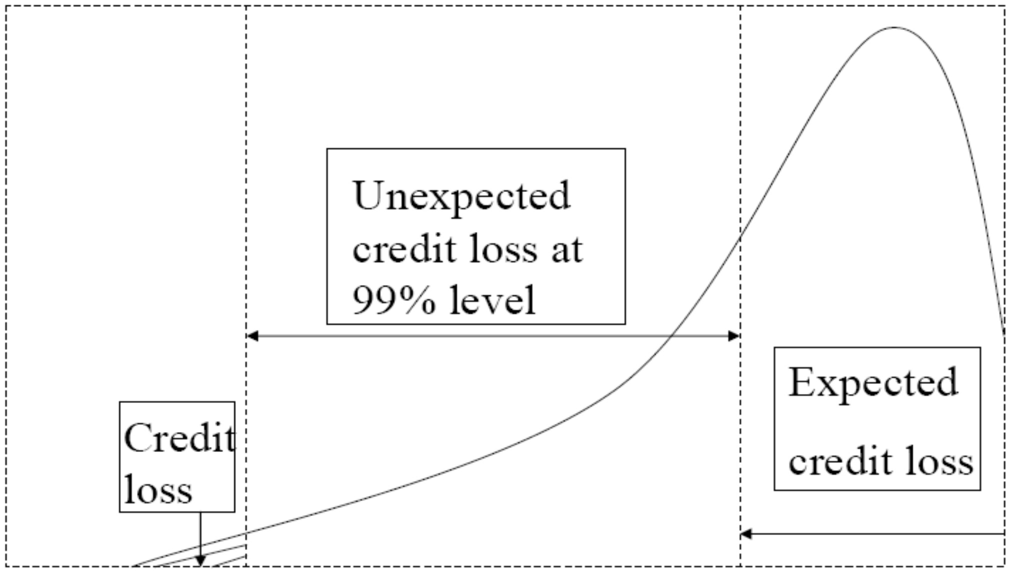


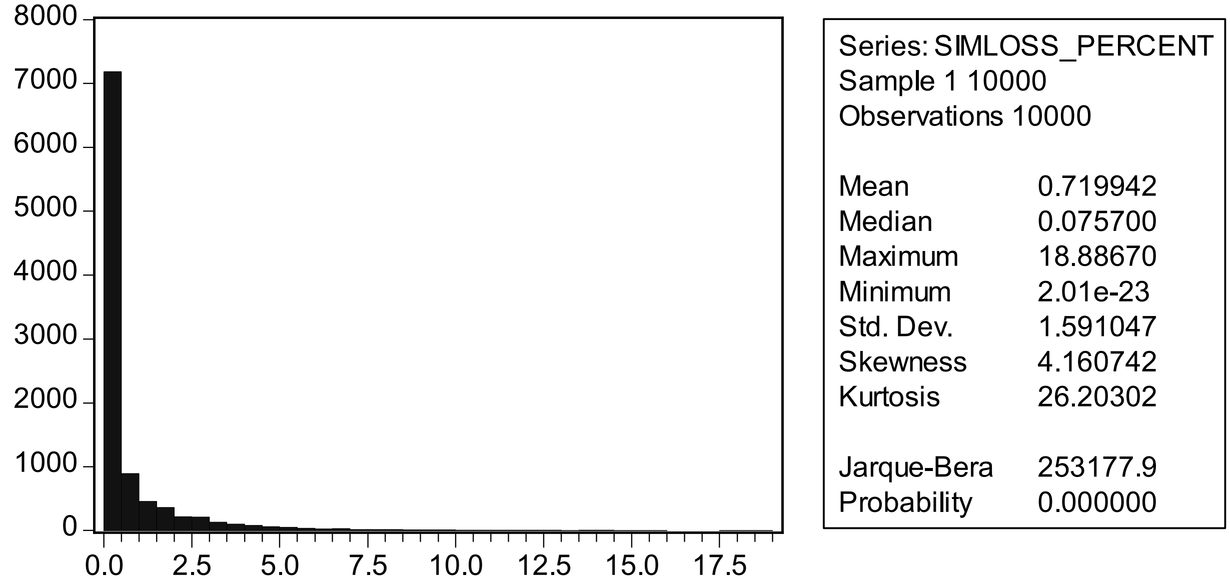

**Table 13: Regional Economic Capital under various scenarios using historical C-VaR method**

**Units in Rs. Crore others in %**

| SL# | Items | Normal Condition | Non-Normal Condition: Scenario 1 | Non-Normal Condition: Scenarios 2 |
|---|---|---|---|---|
| 1 | Default Correlation | 2.876% | | |
| 2 | Portfolio UL (Rs.Cr.) | 630.427 | | |
| 3 | Portfolio UL% | 1.53% | | |
| 4 | Portfolio EL% | 0.70% | | |
| 5 | NPA Provisioning% of gross advances | 1.27% | | |
| 6 | Target Rating | | AA | AA |
| 7 | Capital Multiplier (k) | 3 | 5 | 6 |
| 8 | Economic Capital % | 3.32% | 6.37% | 7.90% |
| 9 | Economic Capital (Rs.cr.) | 1368.12 | 2628.97 | 3259.40 |
| 10 | Credit Risk Regulatory Capital | 2929.42 | 2929.42 | 2929.42 |
| 11 | Capital Deficit | -1561.31 | -300.45 | 329.97 |
| 12 | Total Avalable Capital (Rs.cr.) | 4716.86 | 4716.86 | 4716.86 |

Note: The Bank's available Tier I & Tier II capital in March 2010 was Rs. 2364.18 crore and Rs. 2352.68 crore (total: Rs. 4743.64 crore)

**Chart 2:** Beta Distribution of Bank's Credit Losses (derived from Regional Portfolio)




The simulated loss distribution has been shown in Chart 2.

**Table 14: Simulation based C-VaR Results**

**Units in Rs. Cr., others in %**

| **Rating Target** | **Mapped PD%** | **Conf. Level** | **EL$_P$%** | **NPA Prov. %** | **UL$_P$%** | **Eco-cap%** | **Eco-cap** | **Deficit over & above Reg. Capital** | **Eco-Cap/ RWA** | **Tier I%** |
|---|---|---|---|---|---|---|---|---|---|---|
| AAA | 0.03% | 99.97% | 0.72% | 1.27% | 17.65% | 16.38% | 6755.73 | 3826.31 | 20.76% | 6.44% |
| AA | 0.10% | **99.90%** | 0.72% | 1.27% | 15.58% | 14.31% | 5904.25 | 2974.83 | 18.14% | 6.44% |
| AA/A | 0.50% | 99.50% | 0.72% | 1.27% | 10.05% | 8.78% | 3622.90 | 693.48 | 11.13% | 6.44% |
| AA/A | 0.70% | 99.30% | 0.72% | 1.27% | 9.22% | 7.95% | 3277.71 | 348.29 | 10.07% | 6.44% |
| AA/A | 1% | 99% | 0.72% | 1.27% | 8.12% | 6.85% | 2825.36 | -104.06 | 8.68% | 6.44% |
| A | 1.62% | **98.38%** | 0.72% | 1.27% | 6.65% | 5.38% | 2219.32 | **-710.10** | 6.82% | 6.44% |
| BBB | 3.56% | **96.44%** | 0.72% | 1.27% | 4.48% | 3.21% | 1322.915 | **-1606.51** | 4.06% | 6.44% |

Note:
i) The bank's minimum credit risk weighted assets in March 2010 was Rs. 32549.16 crore and min regulatory credit risk capital (under Basel II standardized approach) was Rs. 2929.42 crore.
ii) Total available capital in March 31, 2010 was Rs. 4716.86 crore. Out of which Tier I: Rs. 2364.18 crore and Tier II: Rs. 2352.68 crore.
iii) We assume credit loss follows beta distribution in Monte Carlo simulation
iv) Basel II under IRB specifies 99.9%
v) In USA, "A" rating target implies an approximately 99.96% confidence level for the bank's solvency (source: Jokivuolle and Peura, summer 2010, "Rating targeting and dynamic economic capital", The Journal of Risk, vol. 12/No. 4, pp. 3-13).
vi) Mapping of target rating and corresponding PD% is done using CRISIL's corporate bond rating transition matrix reported in Table 20.

| Table 15: Top 20 Borrower Concentration Risk Capital | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Borrower Rank** | **Sector** | **Rating** | **Limit % to Capital Funds** | **% to Total Adv.** | **UL%** | **Exposure Wtd. MRC%** | **MRC capital** |
| 1 | Power & Infrastructure | AAA | | 0.98% | 2.61% | 0.0012% | 0.5079 |
| 2 | Electricity Distribution-State Govt. | | | 0.95% | 2.61% | 0.0012% | 0.4952 |
| 3 | Infrastructure-Industrial | | | 1.00% | 2.61% | 0.0013% | 0.5175 |
| 4 | State Cooperative | BBB | 10.27% | 0.98% | 2.61% | 0.001248% | 0.5109 |
| 5 | Housing Construction | AAA | 10.27% | 0.85% | 3.78% | 0.003602% | 1.4742 |
| 6 | NBFCs | AAA | 11.55% | 1.10% | 3.78% | 0.004671% | 1.9118 |
| 7 | Housing Construction | | | 0.88% | | | |
| 8 | Power Sector | AAA | | 0.93% | 2.61% | 0.0012% | 0.4841 |
| 9 | Infrastructure Finance | AAA | 12.84% | 1.23% | 2.61% | 0.0016% | 0.6375 |
| 10 | Housing Finance | AAA | 12.84% | 1.22% | 2.61% | 0.0016% | 0.6350 |
| 11 | Power & Infrastructure | AAA | 10.27% | 0.98% | 2.61% | 0.0012% | 0.5079 |
| 12 | Housing and Development Finance | AAA | 14.64% | 1.39% | 2.61% | 0.0018% | 0.7245 |
| 13 | Petroleum Sector | AAA | 10.27% | 0.98% | 2.61% | 0.0012% | 0.5079 |
| 14 | NBFCs | | | 0.98% | | | |
| 15 | Infrastructure | AA | 10.27% | 0.98% | 2.61% | 0.0012% | 0.5105 |
| 16 | Infrastructure | AA | 11.30% | 0.99% | 2.61% | 0.0013% | 0.5168 |
| 17 | Petroleum Sector | AAA | | 1.40% | 17.27% | 0.0287% | 11.7279 |
| 18 | Housing Finance | AAA | 10.91% | 1.04% | | | |
| 19 | Petroleum | AAA | | 1.40% | | | |
| 20 | Infrastructure-Central Govt. | AAA | 16.05% | 1.53% | 2.61% | 0.13% | 0.7976 |
| | | | | 21.81% | | Total | 22.4673 |
| | | | | | | Reqd. EC | 134.80 |