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By

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Understanding the Effect of Concentration Risk in the Banks' Credit Portfolio: Indian Cases

Abstract:

Credit Concentration Risk has been the specific cause of many occurrences of financial distress of banks world wide. This paper analyzes the credit portfolio composition of a large and medium sized leading public sector Bank in India to understand the nature and dimensions of credit concentration risk and measure its impact on bank capita from different angles. In evaluating the bank wide measures in managing concentration risk, we demonstrate how economic capital approach may enable the bank to assess the impact of regional, industry and individual concentration. We also show how portfolio selection can be done through correlation, stress tests, marginal risk contribution vis-à-vis risk adjusted return that will enable the top management to manage portfolio concentration risk and accordingly plan its capital.

Keywords: Credit Concentration, Portfolio Risk, Bank's Economic Capital

JEL Classifications: G18, G21, G12

1. Introduction.

Internationally, there is lot of incidents of clustered defaults within industries as well as between industries. The failure of large borrowers like Enron, Worldcom and Parmalat were also the source of sizable losses in a number of banks. The agricultural loans in US mid-west, oil loans in Texas, East Asian Crisis and recent US mortgage crisis are examples of incidents of correlated defaults that jeopardized the health of many financial institutions. The reason being that in addition to very significant concentrations of lending in a particular industry (e.g. energy), the regional dependence and a strong correlation between the health of the industries. More than half of the US's foreclosures during 2007-08 took place in 35 counties, a sign that the financial crisis devastating the national economy may have begun with collapsing home loans in only a few corners of the country depicts ripple effect of geographic concentration. A geographic mapping of sub-prime & Alt-A loans in the Phoenix metropolitan area has revealed that sub-prime loans are heavily concentrated in lower to middle income group of population (or small business people who don't relish disclosing all their income), newly constructed houses (many of them are refinancing) especially in urban areas (Gwinner and Saunders, 2008). All these examples illustrate the importance of measuring concentration risk in credit portfolios of banks that arises not only from exposures to a single credit, or asset class, but also from linkages between asset classes across industries, regions, income class, group pf population etc. When two or more borrowers default simultaneously, the losses are more severe.

The emergence of concentration risk is closely linked to the business strategy orientation of banks. International experiences suggest concentration risk has direct impact on bank's portfolio loss and hence core capital and solvency position. 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. As a matter of legacy, most Banks in India 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. 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. A portfolio approach to credit risk analysis, which is a very new concept amongst Indian Bank, allows portfolio managers to quantify and stress test concentration risk along various dimensions. In this research paper, we address the credit portfolio composition of a large public sector bank in India to understand the nature of concentration risk and measure its impact on bank capital.

The literature on concentration measurement primarily proposes specific concentration indexes such as Herfindahl-Hirschman Index (HHI), the Gini-Lorenz curve method, Theil coefficient measure of inequality ((Kwoka, 1977, Gini 1921, Lorenz, 1905, Theil, 1967). Moody's Investors Service use expected loss based HHI for assessing the concentration risk associated with large balance residential mortgage loans in rating the securitizations pool.[1] Both loan concentration measurements and loan level review help them to identify the severity related to the entire pool risk. Furthermore, note that measuring concentration is not only relevant in primary lending but also of major importance for the securitization of loans. Typically, investors that face a noticeable degree of concentration in a loan pool will require additional credit enhancements that make the securitization transaction more costly for the originator. Accordingly, Moody's also has a diversity score approach to rating multisector Collateralized Debt Obligations (CDOs).[2] To derive diversity score for a pool of collateral assets with correlated default risk, they specify portfolio characteristics, including the rating profile, the maturity profile, the face value of each asset and their default correlations.

Traditionally, banks in India manage risk exposures that arise within the various risk category silos following the prudential norms set by RBI such as limit systems and internal reporting based on nominal exposure amounts. Banks often monitor exposures both against gross and net limits. Internationally, Banks monitoring of established credit limits has long been a part of credit risk management (Carey, 2000). Even the sub-prime lenders in US have had historically used dollar limits by borrower or a dollar limit by geography to manage credit risk exposure (Cowan and Cowan, 2004). However, consideration of how risk mitigation approaches may play out under stressful market conditions (i.e. unexpected loss)

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[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/Sizing RMBSLargeLoanConcentrationRisk.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

can not be explicitly captured in most measures. In this context, hidden layers of correlation (especially the systematic single risk factor) need to be well-understood to assess tolerance level of concentration risk in line with the bank's solvency target. Higher the correlation of default, greater is the concentration risk of the portfolio and lower the correlation of default, more diversified the portfolio. This has serious implications for credit risk capital requirements. Gordy (2000) finds that capital requirements based on industry credit risk models vary considerably based on average default correlations in the portfolio. Paper by Cowan and Cowan (2004) emphasized the significance of default correlation in understanding sub-prime loan portfolios risk. Their study provides empirical evidence that the significance of default correlation increases as the internal ratings of the borrower decline. Loffler (2003) finds that correlation uncertainty is a very significant factor for determining portfolio quality. Lucas et al. (2001) provide numerical results showing that for a given correlation, a higher portfolio quality lowers extreme credit loss quantiles. Lopez (2004) has used the structural model framework to empirically derive asset correlations for portfolios of USA, Japanese and European firms. His paper demonstrates that asset correlation for relatively highly rated, large sized companies is high. According to his explanation, this relationship arises because high credit quality firms are more likely to be influenced by common macro economic conditions. Lucas (1995), Nagpal and Bahar (2001) and De Servigny and Renault (2003), Bandyopadhyay et al. (2007) extract information about the joint behavior of rating migrations and defaults directly from historical bond data to calculate joint default probabilities.

Gordy (2003) developed a granularity adjustment factor to take care of concentration risk in his Asymptotic Single-Risk Factor (GA for the ASRF) model that underpins the IRB approach in the new Basel capital framework (BCBS 2004). Through this adjustment, originally omitted single-name concentration is integrated into the ASRF model. The GA can be calculated as the difference between unexpected loss in the real portfolio and in an infinitely granular portfolio with the same risk characteristics. Empirical evidence shows that the HHI is suitable as a measure of single-name concentration, in particular in view of its relatively simple calculation method. However, in the case of small portfolios, for which idiosyncratic risk plays a greater role, a GA holds out more promise for providing information than the HHI (Uberti and Figini, 2010). Still, the GA method was not much appreciated by the Bankers because of complex mathematical process and its difficulties in implementation and huge data requirements. Later, the revised Basel II IRB capital framework (BCBS 2006a) dropped this segment from regulatory capital estimation formula.

In practice, no portfolio can achieve perfect diversification, but the infinitely-fine-grained portfolio serves as a useful benchmark for measuring concentration risk. In an another paper, Düllmann and Masschelein (2007) using sectoral portfolio composition on credit information from the German central credit register have explored a simplified version of the credit value-at-risk approximation (C-VaR) which only requires risk parameters on a sector level. They measure the impact of credit concentrations in business sectors on the economic capital of credit portfolios and find that economic capital is a better measure of concentration than the regulatory capital as prescribed in Basel II IRB formula.

A group of researchers from the Research Task Force (RTF) of the Basel Committee on Banking Supervision undertook a project (see BCBS 2006b) with the goal of analyzing the ability of various methods to account for concentration risk in bank loan portfolios and to survey current best-practice in the industry. The empirical studies conducted by this group, all of which used data only on corporate portfolios, suggest that name concentration risk, albeit important in its own sake, is likely to represent a smaller marginal contribution to economic capital than sector concentration for a typical commercial bank with a medium to large sized loan portfolio. They find that the patterns of asset correlations both across and within sectors are key determinants of this impact. Reynolds (2009) examined the suitability of different measures of concentration risk in his case study based on a portfolio of 500 publicly traded and rated exposures. Her paper gives evidence that capturing correlation, along with the other key factors exposure, PD and LGD leads to a measure such as credit value at risk (CVaR) can uncover hidden information about a portfolio. She has shown that a concentration ratio measure (defined by CVaR divided by the absolute loss) provides great portfolio insight that enables a risk manager to identify names that would be good hedges (lowest concentration ratio) and which are good targets for increased monitoring or hedging (obviously with high concentration ratio).

Concentrations of credit exposure can pose risks to the earnings and capital of any financial institution in the form of unexpected losses. Economic capital can be used as a common currency for measuring diverse financial risk. Economic capital based limits has the advantage of taking into account the size, default risk, loss given default expectations and also the correlation risk. 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. While moving away from traditional approaches, his paper conceptually illustrates how a limit structure can be devised that incorporates and reflects variability in default, recovery, and drawdown rates, as well as the all-important correlation characteristics on a portfolio basis. Dev (2004) has shown in his book how economic capital can be used in decision making at financial institutions. He explains the key elements within economic capital and illustrates the role of economic capital in performance evaluation and highlights its strategic implementation. Helbekkmo (2006) has very lucidly illustrated the process of building an economic capital and risk adjusted return on capital (RAROC) framework that obliges retail banks to consider their concentration risk in relation to capital costs. His paper claims that banks with geographically diversified portfolio can gain benefits of up to 40% compared to the economic capital required for similar portfolios where the bank lacks any geographic diversification.

The amount of portfolio credit risk may change with macro economic condition. During periods of economic calm, concentrations in an institution's portfolio are unlikely to have any noticeable adverse effects on performance or credit quality as usually measured and, as such, can remain latent. However, the real threat arises in an adverse economic scenario, where connected or correlated exposures all show increased risk of default or actually default at the same time. As shown by Nickell et al. (2000), default probabilities depend strongly on the stage in the business cycle, and transition matrices tend to exhibit a higher frequency of downgrades during a recession and a higher occurrence of upgrades during booms. McNeil et al. (2005) have shown that extremes of default indicator distribution are very sensitive to variations in the multivariate normal assumption for systematic risk factors. Heitfield et al. (2006) examined the impact of systematic and idiosyncratic risk on credit portfolio losses for US banks in a simulation study. Bonti et al. (2006) provide methods for stress testing of credit risk concentration using the distribution of sector risk factors. Bangia et al. (2000) proposed that underlying macroeconomic volatility is a key part of a useful conceptual framework for stress testing credit portfolios, and that credit migration matrices provide the specific linkages between underlying macroeconomic conditions and asset quality. Utilizing an extensive database of S&P issuer ratings, they presented a systematic study of rating migration behavior and its linkages to the macroeconomic conditions and asset quality. Like them, Nickell, Perraudin and Varotto (2000) used Moody's data from 1970 to 1997 to examine the dependence of ratings transition probabilities on industry, country and stage of the business cycle using an ordered probit approach, and they find that the business cycle dimension is the most important in explaining variation of these transition probabilities. Zhou (1997) finds that default probabilities of bond issuers are positively correlated and their default correlations increase with the level of default risk in the economy, implying a business cycle effect on default correlations and hence portfolio concentration risk. Das et al. (2007) provide empirical evidence that corporate defaults cluster in time because firms' default intensity processes are correlated and because there could be contagion or unobserved macro covariates (like US industrial production) that are correlated across firms.

To our knowledge, no empirical study has been done on credit portfolio risk analysis of Banks in India. A more systematic portfolio approach of managing credit risk is also not popular amongst Indian Public Sector Banks mainly due to the scanty data. However, since Reserve Bank of India has released the Basel II guidelines in India (April 2007), the Banks have started their effort to build up proper information system to collect borrower wise, facility wise, industry wise, geography and product wise data and develop credit risk models to assess borrower level risk. Exploiting the detail Bank specific real loan portfolio information as well as external industry data, we for the first time measure borrower wise, group wise, size wise, industry wise and geography wise level of concentration in bank's credit portfolio. Next, we 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. We have used single risk correlation and marginal risk contributions based on bank's data history & industry/regional portfolio to find amount of capital required to cover concentration risk in a large Bank. This has been done under various scenarios (normal as well as non-normal condition) to assess additional capital requirement vis-à-vis the Bank's mandatory regulatory capital as per Basel II guidelines of Reserve Bank of India (RBI). In our Simulation Approach, we exploit the actual regional portfolio risk characteristics of the Bank and have estimated economic capital of the Bank using Credit Value at Risk (C-VaR). Here also we compare the estimated economic capital of the Bank with the mandatory Basel II regulatory capital under standardized approach to examine the impact on Bank's internal capital requirements. More importantly, the portfolio risk dimension may change during economic downtime and a Bank may experience capital erosion because of increase in concentration of lower quality of assets as well as increase in number of defaults. Consequently, using three historically generated scenarios, we stress test the large corporate loan pool of the Bank and examine their impact on capital erosion and Bank's Capital Adequacy Ratio.

One more crucial objective of the paper is to guide the Banks' top management to make portfolio selection such a way to diversify the concentration risk. In order to achieve this objective, we have estimated industry wise default risk by using Merton Model (1974). Next, using ten years' monthly equity return and idiosyncratic risks of these industries we find a 25-25 default correlation matrix both for the Bank and for the Banking industry as a whole. Using a longer credit history from CRISIL's 18 years of published bond rating movements of 572 corporates, we also estimate rating wise default correlation to guide the top management to better understand the nature of corporate portfolio risk in India which will also assist them to make portfolio selection. These two correlation matrices along with industry distance to default and expected default frequencies will enable the top management in Banks to have idea about the industry risk characteristics and level of concentration risk the may have in their credit portfolio. Such industry view of portfolio will guide them to do industry selection in a more conscious way while picking up large loans. Finally, we demonstrate how risk adjusted return on capital (RAROC) can be used to evaluate region and branch level performance and can be used as a common yardstick for systematic bank wide allocation of risk capital to manage concentration risk.

This paper is organized as follows. In section 2 we describe the credit portfolios of the Banks that have been studied and the External Data and variables on which we base our empirical analyses. In this section, in various subsection we describe our empirical methodologies and model assumptions. Section 4 discusses and presents our empirical results. Section 5 concludes the paper.

2. Data and Methodology

In this paper, we have used an exhaustive loan portfolio data of a large public sector bank located in western India and a medium sized south based bank (in India) to examine the nature of credit concentration risk and its implications on bank capital and performance. In doing so, we have studied industry wide zone-wise, region wide, rating wide entire advance portfolio of the two Banks for assessing concentration risk using their yearly loan histories from the Bank. We have also analyzed a dynamic pool of all internally rated large commercial exposures (corporate and SMEs with exposure above Rs. 1 Crore) by the western based large Bank. This rated sample data consists of 3,133 borrowers from 2002 to 2009.

It was also required to benchmark our study with the external information available from Reserve Bank of India and CRISIL (a leading rating agency in India). Accordingly we have used their historical industry default information and rating slippage data in our portfolio analyses. In our stress testing analyses, we have used CRISIL's published annual bond rating data sample of 572 corporates from 1998 till 2009 to study the pattern of rating migration in various economic cycles and have developed historical stress scenarios. We have also studied the impact of these scenarios on Bank's corporate loan portfolio and assess capital erosion the Bank is likely to face. The annual GDP at factor cost data series has been obtained from Reserve Bank of India data base.

In our industry portfolio risk assessment and industry wide default correlation exercise, we have used monthly equity index price data of 25 industries from February 1999 to March 2009. This has been obtained from CMIE Prowess data base. We have used RBI list of industries which are quite commonly used by all Public Sector Banks in reporting their industry distribution of advances as part of Basel II disclosures. The industry wise borrowing position, market capitalization data have been obtained from Prowess data source.

In assessing the risk adjusted return on capital (RAROC) of various regions and branches, we have exploited the item wise regional and top 20 branch balance sheet data of the large Bank (income, expenditure, provisions etc.). We have also looked at region wise as well as branch wise quarterly and yearly NPA movements to estimate default probabilities (PD) and loss given defaults (LGD).

The following steps have been followed 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/industry/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.
- Analysis of risk adjusted return on capital (RAROC) for optimal allocation of capital to internal businesses (capital budgeting) that links credit concentration with the bank's solvency position.

2.1. Heuristic Measures of Concentration Risk followed by Banks in India:

Traditionally, Banks in India manage risk exposures that arise within the various risk category silos following the prudential norms as set by RBI such as limit systems and internal reporting based on nominal exposure amounts. 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), **i**ndirect 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. We have observed that loan policy of these two Banks stipulates maximum exposure across various industries to avoid concentration risk. As a prudential measure aimed at better risk management and avoidance of concentration of credit risks, the Reserve Bank of India in its 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] These prudential exposure limits are presented in Table 1. Banks on quarterly basis monitor the individual borrower, group borrower and sectoral limits to mitigate concentration risk.

We begin by examining Bank specific ratio based prudential measures, next common portfolio-level index measures & then descriptive statistical measures of concentration risk before correlation and loss based measures. We find that the large western bank has great dependence on a major infrastructure group (37.67% of Capital Funds) and their top 20 borrower contributes to 27.02% of total credit risk exposure of the bank indicating significant amount of concentration. However, as far as prudential limits in terms of capital funds are concerned, these exposures are within the regulatory/prudential ceilings fixed except for an infrastructure firm. It is worthwhile to mention that in few cases borrower rating was at inadequate Safety level as mentioned in the scoring methodology of the Bank where the limit % to capital funds were also quite high (12% & 13% respectively).

[Insert Table 1 Here]

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[3] 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).

Next, we have used many 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.

2.2. Simple Straightforward Measures of Concentration:

In a search for simplicity, it is tempting to reduce concentration risk to a single number, or index. Various indexing techniques have been examined in the credit risk literature. All have a common approach: to identify the extent of the concentration in a portfolio through some simple and straight forward measures. One of the most straightforward indexes is the Herfindahl-Hirschman Index (HHI). Originally used in the context of quantifying diversification within an industry to assess the level of competition in the marketplace, the HHI can also be used to calculate portfolio concentration risk. The HHI is calculated by summing the squares of the portfolio share of each contributor. Two different decisions must be made: what is a contributor and from which measure should the shares be calculated. Likewise, Gini coefficient or Lorenz curve represents distribution of loans and popularly used as measure of inequality in loan distribution. To assess which industries/zones/Grades might be contributing concentration risk to the portfolio, we can examine their contribution to HHI & Gini-Lorenz curve methods based only on exposures.

2.2.1. Herfindahl-Hirschman Index (HHI)

The Herfindahl index is a commonly used ratio to measure concentrations. Originally used in the context of quantifying diversification within an industry to assess the level of competition in the marketplace, the HHI can also be used to calculate portfolio concentration risk. This is a very straight forward measure of concentration. The benefit of the Herfindahl index is that it gives a weight depending on the exposure to the counterparties. A loan pool with few loans will have a high level of concentration, while many loans of similar size results in low concentration.

The Herfindahl index measures concentration as the sum of the squared business share of each loan in the pool (or portfolio). i.e.,

$$HHI = \frac{\sum_{n=1}^{N} E_n^2}{\sum_{n=1}^{N} E_n} = \sum_{n=1}^{N} s_n^2 \qquad \text{Eq. 1}$$

Where E= Loan Exposure Amount (Rs. Cr.) and s= loan share to total. The HHI is calculated by summing the squares of the portfolio share of each contributor.

Theoretically, a perfectly diversified portfolio of 500 borrowers would have HHI = 0.002. In contrast, if the bank portfolio is divided amongst five zones in the ratio of 5:2:1:1:1, then the implied HHI by sector is 0.32, indicating a significant level of concentration. However, the HHI of 0.32 does not hint at ways to lower the concentration. This is perhaps a major drawback of this method. As a general rule, a HHI below 0.1 signals low concentration, while a HHI above 0.18 signals high concentration. Between 0.1 and 0.18 the industry is moderately concentrated.

However, the level of concentration risk is generally better understood if we look at the size wise loan distribution within a portfolio. This is why Gini Coefficient or Lorenz curve measures are quite popular.

2.2.2. 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 (everyone having exactly the same income) and 1 corresponds to perfect inequality (where one person has all the income, while everyone else has zero income).

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

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

Therefore, the Gini coefficient,

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

pi is the probability or frequency of no. of borrowers and zi is the loan share.

A value of Gini coefficient close to zero (45 degree diagonal line - no inequality) corresponds to a well diversified portfolio where all exposures are more or less equally distributed and a value close to one corresponds to a highly concentration portfolio. A Gini coefficient in the range of 0.3 or less indicates substantial equality, Gini>0.3 to 0.4 indicate acceptable normality. However, if Gini coefficient is above 0.4 means concentration is large or inequality is high.

A major drawback of Gini coefficient for the measurement of concentration risk is the fact that the portfolio size is not taken into account. Moreover, Gini coefficient can increase when a relatively small loan is added to a given portfolio although concentration would actually decrease. The problem with Gini co-efficient is that it is independent of portfolio size. Hence HHI is a better measure of concentration. However, it is necessary to use a set of methods in measuring concentration risk for checking the robustness. We have thus presented various techniques for measuring, assessing and presenting concentration risk, observing that the use of any single measure or representation can be misleading when analyzing concentration.

2.3. EL based Measure of Concentration Risk:

We have followed a simple metric to measure the risk-wise corporate loan concentration for the year March 2009 industry portfolio of the two Banks. Identifying the loss wise concentration can help to establish an acceptable industry basis tolerance level for loan concentration.

We again 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:

$$HHI = \sum \left(\frac{ELi}{ELp} \right)^2 \qquad \text{Eq.3}$$

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.

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

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.) The idea of correlation (mainly the systematic impact) enables us to estimate its contribution (marginal) to the tails of the overall credit loss distribution. Loss (or default) correlation has been estimated based on the historical data of losses (from the bank's NPA history).

Let us begin by considering the simple case of a portfolio of say n number of loans:

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.

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

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

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

Now 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

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

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 default correlation which will be more realistic number.

2.5. Estimating Multiple Default Correlation:

We have followed an Asset correlation approach to estimate industry wide default correlations. In this method, the loss correlation between industries is estimated based on the correlation between their equity prices which indicate their movement of asset values. This approach calculates the default correlation from the joint default probability. The relationship between Joint Default Probability and Default Correlation is expressed by the following equation.

$$JDP_{ij} = \Pr[A_i \leq K_i, A_j \leq K_j]$$
$$= N_2(K_i, K_j, \rho_{ij}^a) \qquad \text{Eq.7}$$

Where, *N2* (.) denotes the cumulative bivariate standard normal distribution, and, ρ_{ij}^a denotes the asset correlation between firm i and firm j. The joint default probability is the probability that both obligors default at a fixed time horizon (of say 1 year) that means their assets fall below a certain threshold as depicted in Merton Model (1974).

The Joint Default Probability across industries has been estimated from equation 10 using bivariate normal cdf: $BIVNOR[\phi^{-1}(PD_i), \phi^{-1}(PD_j).\rho_{ij}^a]$ function (see Crouhy, et. al., 2000; Gordy, 2000, Gordy and Heitfield, 2002). In this case, equity correlation of industry index return ($\rho_{\alpha\beta}$) has been taken as proxy for asset correlation.

We assume; when A_i falls below a critical default threshold say K_i (popularly known as distance to default), default is triggered.

Thus,

$$PD_i = \Pr[A_i \leq K_i]$$
$$\Rightarrow K_i = N^{-1}(PD_i) \qquad \text{Eq.8}$$

We substitute the asset correlation and default thresholds using industry PDs in the above bivariate joint distribution function and find joint default probabilities (*JDPs*).

Along with PDs, the Industry EDFs are estimated following the Merton Model (1974) using the principles of option pricing (Black and Scholes, 1973). Merton observed that giving a loan to a risky company is equivalent to writing a put option on the assets of the company. The payoff function to the debt holder is similar to writing a put option on the value of the borrower's assets with the face value of debt as the exercise price. The put option arises because if the value of the assets falls below the value of the debt, the shareholders of the firm can put the assets to debt holders, and in return, receive the right not to repay the full amount of the debt. The loan is repaid as long as the borrower does not default and the lender bank receives a fixed return which is the interest rate implicit in the fixed term loan similar to the premium on a put option. However, when asset value falls below the book value of debt, the borrower defaults and the lender stands to lose both interest and principal.

This observation led Merton to develop a pricing model for risky debt and allowed the calculation of the probability of default. In his seminal work (see Merton, On the Pricing of Corporate Debt") he has shown an elegant tool for extracting default probabilities by linking volatility of the firm's equity and that of its assets. It is really difficult to observe directly the total value of a company's assets but it is reasonable use Merton approach where loans are modeled as a claim on the value of the firm. The market value of the firm's assets equals the value of the debt plus equity. This assumption allows us to observe the changes in asset value from the changes in the equity price and can derive the asset volatility. The difference between the derived market value of assets and the book value of debt (or say default threshold) divided by the asset volatility is called the critical value or the distance to default (DD). For any given distance to default we calculate the expected default frequency (EDF) and map them with corresponding external rating to derive industry ratings.

Next, given the values of JDP_{ij} (empirically derived), we estimate PD implied default correlation across industries using the equation 9.

The correlation of default probability between two assets, i and j, can be derived by using the following expression:

$$\rho_{i,j}^{D,D} = \frac{JDP_{i,j} - PD_i PD_j}{\sqrt{PD_i(1-PD_i)PD_j(1-PD_j)}} \qquad \text{Eq.9}$$

The joint default probability between two industries, say i & j ($JDP_{i,j}$), is the probability that loans in the both industries 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. Here, equity correlation of industry index return ($\rho_{\alpha\beta}$) has been taken as proxy for asset correlation. There have been a number of studies on default-implied asset correlations in the literature. For an excellent discussion on this method see Zhang, Zhu and Lee (2008) MKMV working paper.

2.6. Estimation of Joint Default Probability (JDP) through equity correlation:

In the process of extracting default correlation from asset correlation, we estimate the equity return correlations of 25 industries by using the monthly industry stock index return data from February 1999 to March 2009.

Next, we convert the equity correlation into asset return correlation proxy by multiplying the respective industry specific idiosyncratic risk weights.

The correlation of asset returns between two industries (A & B) is:

$$\rho(A, B)= \omega_1^{A} \times \omega_1^{B} \times \rho_{\alpha\beta} \qquad \text{Eq. 10}$$

Weights are the obligor specific risk which has been estimated using regression methods.

We have used regression equation on equity return of industry stock indexes over the market index (BSE 500) return and find obligor specific risk weight (or idiosyncratic) by using: $1\text{-}R^2$; where R^2 (captures systematic risk) is the ESS/TSS. For this, we have used 10 years of monthly equity returns data from February 1999 till March 2009.

2.7. Methodology for Estimation of PD, LGD, Rating-wise Multiple Default Correlation and Loss Distribution

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.

$$MPD_t = \frac{1}{3}\sum_{t=1}^{3}(\Delta GNPA_t / Advances_t)$$
$$PD = \sum_{t=1}^{T}\frac{MPD_t}{T} \qquad \text{Eq. 11}$$

Where T is the total number of periods. Some case we have taken 5 years average and some cases 10 years average) depending upon the data availability.

In this method, we divide the fresh NPA slippage 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.

However, for the corporate loan pool analyses, rating wise PDs have been estimated based on historical performance of credits grouped by internal as well as external rating. For this, we have studied the yearly rating migration pattern (or cohort behavior) of various grades through transition matrix analyses. We have used a historical bond rating data of 572 corporates rated by S&P's CRISIL and studied their migration patterns from 1998 to 2009. We have followed the concept of mortality rate as retained by S&P and estimated marginal mortality rates through yearly cohort analysis and constructed the one year average transition matrix as expressed by the following equation.[4]

$$PD_i = \sum_{t=1}^{n} w_i^t \frac{D_t^i}{N_t^i} \qquad \text{Eq. 12}$$

where D^i_t is the number of accounts migrating from i^{th} grade to default (D) grades within a year; N^i_t is the matching number of accounts in the i^{th} rating grade over a one year period. w^t_i is the weight representing the relative importance of a given year.

The third dimension in portfolio credit risk measure is to estimate default correlation from the rating migration history of 572 corporate bonds in India. To estimate rating wise default correlation, we pair the borrowers into IG, NIG groups and in different grades assigned by CRISIL. We assume all borrowers in the same group or grade have the same default probability and then estimate the default correlation. For joint default probability (JDP), we track the ratio of number of defaulted pairs to the total number of possible pairs between as well for within each grade for each year and then take weighted average of these ratios. This has been shown in equation 13. The weights represent the relative importance of the sample in a given year.

i.e. $$JDP_{ij} = \sum_t w_t \frac{D_t^i D_t^j}{N_t^i N_t^j} \qquad \text{Eq.13}$$

where $w_t = \dfrac{N_t^i N_t^j}{\sum N_i N_j}$; 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

[4] For more detailed discussions about this method, see A. de Servigny and O. Renault, "Measuring and Managing Credit Risk", Chapter 2.

yearly cohort movements of these grades towards defaulted grade. Next, we estimate rating wise default correlations by using these inputs in equation 9.

2.8. Estimation of Economic Capital and RAROC:

Economic capital EC for a given confidence level k is defined as the Value-at-Risk at level k of the portfolio unexpected loss (UL) minus the expected loss (EL) of the portfolio. Using the historical regional portfolio of these two banks we have actually worked out the amount of true risk capital of the bank under normal and non-normal condition using the Credit VaR method:

Credit VaR or Economic Capital=k×ULp-ELp Eq. 14

Bank-wide portfolio unexpected loss is estimated by adding the marginal risk contribution of all the regions of the Bank.[5] Using the default correlation, we can now determine the contribution of that loan to the portfolio as a whole:

$$MRC_i = \sqrt{\rho_i} UL_i \qquad \text{Eq. 14.a}$$

For a confidence level k=99.9%, the EC can be interpreted as the appropriate capital the Bank has to keep for the next year to cover unexpected losses in 999 events out of 1000 possible events of losses. As if it is the difference between maximum possible standard deviation of loss over and above average loss. This deviation depends on the actual nature of the loss distribution. Under normal condition, k=3 has been used. However, to estimate economic capital in case of non-normal loss distribution, higher multiplier has been used since deviation will be larger. The economic capital also depends on the bank's target debt rating in the market.

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

We are further interested to see the probability distribution of the portfolio's losses in a covariance model (with the presence of single correlation input). 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%.

[5] It can be proved that portfolio unexpected loss (ULp) is the summation of individual or subgroup marginal risk contributions (MRCs)

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

$$\beta(L) = \frac{L^{a-1}(1-L)^{b-1}}{\int_0^1 L^{a-1}(1-L)^{b-1}\,dL} \qquad \text{Eq.15}$$

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):

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

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

Using the above formula, we plug in empirically derived values of EL_p and UL_p in the zonal portfolio to obtain *a* and *b* parameters. As next step, we use these to parameters to fit beta distribution to the portfolio data and use Monte Carlo to generate 10,000 likely loss values in percentages.

The EC method also relates a bank's whole portfolio of risk to the amount of capital the bank must hold if it is to achieve a particular solvency target. If a bank is targeting higher rating in the market (to stakeholders e.g.) they should use a higher multiplier (that represents higher confidence level) to reserve the capital to limit the loss. The key drivers of portfolio risk: correlation, exposure, PD and LGD are in-built in this measure of concentration risk and hence economic capital is more risk sensitive measure than only exposure based methods.

The ultimate focus of the Bank to manage concentration risk should be to bring each client/product/business into RAROC-EVA efficiency axes to improve their overall risk adjusted profitability of the entire credit portfolio. This will also enable them to get a balance between holding enough capital to maintain good solvency rating even in times of economic depression, on the one hand, and minimizing economic capital to make profits, on the other hand. We have used credit risk adjusted return on capital (RAROC) to evaluate and compare profitability of various regions and top 20 branches. The RAROC is the risk adjusted post tax income divided by economic capital or credit VaR. Using the detailed balance sheet as well as historical loss data of various regions and top 20 branches of a leading mid sized bank in India we have estimated the region wide and branch wide RAROC for the Bank using the following formula:

$$RAROC = \frac{(Intr\_Inc + Fee\_Inc - CoF - CoO - EL) \times (1-t)}{EC} \qquad \text{Eq. 16}$$

Where *Intr_Inc*: Interest income on advances; *Fee_Inc*: Fee income related to advances; *CoF*: Cost of Funds (mainly deposit cost); *CoO*: Cost of Operations; *EL*=expected loss=$EAD \times PD \times LGD$; *EC*=Economic capital and *t*=corporate tax rate=33% in India.

Once calculated RAROC is to be compared with some hurdle rate reflecting the bank's cost of funds or the opportunity cost of stockholders in holding equity in the bank. If RAROC exceeds the hurdle rate, then the region's performance is viewed as value adding (i.e. Economic Value Added or EVA>0).

Thus, *economic profit or EVA =Risk Adjusted Income-HR×EC* Eq. 16a

Where, Risk Adjusted Income is the first component within bracket of the numerator of RAROC expression as depicted in Equation 15.

Hurdle rate is computed using Capital Asset Pricing Model (CAPM):

$$HR = r_f + \beta \times (\pi - r_f) \qquad \text{Eq. 17}$$

Where r_f is the risk free rate (we have used 364 T Bills rate as risk free rate); β=equity beta estimated for the Bank using the daily closing stock price data of the bank vis-à-vis the index return (BSE 500 index closing), π=average market index return over 10 years (we find average stock market return=12.16% on an annual basis).

Finally, we have compared post tax RAROC of regions or branches with post tax hurdle rate of the bank to compute EVA.

3. Empirical Results

In this section, we present and discuss the main results of our detailed empirical investigation of portfolio concentration risk position in Indian banking sector. We are basically trying to find out a more risk sensitive measure of concentration risk in Banks' credit portfolio. Using detailed credit portfolio data of two Indian banks as well as external sectoral information, we examine the contributions and interactions of sector, region, rating, borrower in total portfolio risk.

3.1. Industry Portfolio Position:

We first compare the industry portfolio concentration of two banks. Twenty five industry wide exposure shares as well risk positions have been reported in Table 2. One can notice that the medium sized bank's advances portfolio size is 55.15% of its large bank counterpart. One may expect that large bank portfolio is more diversified than a smaller one Here we find in terms of Herfindahl index, the large sized bank portfolio is more concentrated (HHI=0.1321) in comparison to the medium sized bank (HHI=0.079). A fully diversified portfolio could have resulted in HHI=0.04. The reason for higher HHI is due to significant exposure concentration in NBFCs and Construction & Infrastructure sectors by the large bank. The sector wise risk profiles of these two banks under study also have been documented in terms of gross non performing assets (GNPA) percentage to gross advances (See Table 2, col. 5 & 8). We also report the overall industry PD percentage (see col. 9) that we have obtained from CRISIL and RBI database.

It is quite evident that in terms of credit risk, large bank sectoral portfolio concentration is higher than the medium sized bank. The gross NPA percentages of the large bank is quite high in sectors like computer software, chemical, rubber and rubber products and tea etc. in comparison to the industry average. The industry distance to defaults (col. 10 of Table 2) predicts the expected default risk of these industries for the period of 2009-10. We also observe that industry sector specific risks are higher in case of Coal & Mining & Lignite, Leather & Leather Products, Paper & Paper Products, Rubber & Rubber Products, Processed or Packaged Foods, and Vegetable Oil & Products (see col. 11 of Table 2). The overall industry PDs are also high in these sectors. This means if the bank has larger exposure in these industry sectors, the portfolio concentration risk will be higher. The industry concentration level for the large Bank suggests that the Bank should take extra care in managing the relationship with the large clients or counterparties; more diligence is exerted in monitoring industry level risk positions.

[Insert Table 2 Here]

To get a better insight about industry wide portfolio risk position in Indian loan market, we have constructed a 24 by 24 industry default correlation matrix which has been reported in Table 3. These default correlation have been estimated by taking input from monthly industry index equity correlation, overall industry PD percentage and industry idiosyncratic risk weights (as documented in Table 2). The correlation estimation methodology has been illustrated in section. Default correlation describes the degree to which the default risk of one borrower one industry depends on the default risk of another borrower in another or same industry. Therefore, default correlation risk represents the risk that several borrowers default together in clusters. Since two industry's risk position may be affected by common macroeconomic factors either because they are located in the same geography or purchase the raw material from the same source or serve the same market or due to input-output linkage effects and that is why we have dependence between their defaults.

[Insert Table 3 Here]

The higher the default correlation, higher is the sectoral concentration risk. Here, default correlation is measuring clustered defaults within sector as well as across sector. The correlation coefficient is capturing the effect of one borrower default in one industry to another borrower default in the same industry (within sector correlation) or in the different industry (cross-sectoral correlation). Like cross sectoral correlation between Automobile and Coal & Lignite sector (SL1-SL4) is 2.6% which means if one borrower defaults in SL1 sector, the probability of another borrower default in SL4 sector goes up by 260 basis point. As far as within sector correlations are concerned, we observe higher concentration risk in Processed Foods, Rubber & Rubber Products, and Vegetable Oils & Products. On the other hand, the Bank may have diversification opportunities within Chemical, Petroleum, and Transport Services. This is however, an indicative industry benchmark portfolio for the year 2009-10 that will guide the Banks' top management to design its portfolio.

It is worthwhile to mention that default dependencies may be more pronounced in during macro economic stress condition. Default correlations have a strong impact on the tail portion of the credit loss distribution for a large portfolio because of common systematic factors.

3.2. Rating wise 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.

[Insert Table 4 & 5 Here]

Table 4 reports grade group wised default correlation estimates for all industries putting together. 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.

However, the grade wise correlation estimates provide us more detailed picture to understand the effect of concentration risk in the credit portfolio. From Table 5 results we see that default correlation monotonically increases as we move down to the rating scale. However, between grades correlation figures reveals that there is a diversification of risk between A-AA, AA-BBB, A-BBB, AA-B, A-B and even in B-BB. The rating-wise historical correlation matrix documented in Table 4 & 5 may also help the Bank management to make portfolio selection. For example, if B assets are already there in their portfolio, it is better to lend BB or Investment grade assets rather than keeping more of similar B or BBB assets. Similarly, for BB assets, it better to mix them with AAA assets. Again, for BBB assets, concentration risk may be reduced if one lends to AAA, AA or A rather than lending more to BBB. It is obvious that Keeping CCC assets in the portfolio not only increase idiosyncratic risk but also more default correlation risk.

Next, we focus on regional portfolio composition of the large Bank and examine the extent of its' geographic concentration risk from various angles.

3.3. Geographic Concentration Risk:

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. In Table 6, all nineteen regions of the two Banks have been ranked in descending order in terms of their percentage share of loan outstanding to total loan outstanding of the Bank. It is quite evident that Delhi, Mumbai metro region, corporate region (which is also in Mumbai) and Chennai are the key regions of the Bank as these 4 regions contribute almost 60% of gross advances of the Bank. The Mumbai area covers almost 32% of the total lending business of the large bank. According to

HHI index, mid-sized bank is slightly more geographically concentrated than the large bank. However, the concentration levels in both the cases are at moderate level.

[Insert Table 6 Here]

However, it is not clear the actual nature of distribution of loans across different zones. One can clearly see that in top four regions, ranked in descending orders in terms of size of outstanding, there is a significantly large difference between percentage of number of loans and Exposure percentage share. This is happening for both the banks. Accordingly, in order to better capture the regional inequality in advances, Gini coefficient can be used to measure uneven distribution. The derived Gini coefficient however indicates the presence of concentration risk in the credit portfolio of both the banks since derived Gini>0.40 as specified in the worldwide industry benchmarks.

The concentration risk is generally better understood if we look at the size of the loan distribution within each region and then compare the zonal positions. This is because both Gini and HHI are generally used by the researchers as relative indicators of concentration. Accordingly, we look at size wise distribution of loans across geographic operations of these two banks. To better understand the overall geographic concentration risk we look into zone-wise distribution of assets. It is important to note that the banks' regions operate under each zone.

3.3.1. Zone-wise inequality comparison: by Decile Groups of Borrowers (10 Equal Slices:

The borrower wide detail loan information was available only in the case of large bank. So we could capture the actual nature of the distribution through 10 decile group of 3,133 corporate borrowers only for the large bank case. The zonal comparison will give us a broad perspective about credit concentration risk.

Table 7 represents the detailed summary statistics of loan distribution across nine zones.p25, p50, p75,…p50 p75 are the percentile values of actual size of the loans. Like p50 measures the median loan size. The tail side of the loan distribution is captured by p99 percentile. It captures the presence of few numbers of very large sized loans which are the primary concern in measuring concentration risk. The coefficient of variation (CV=SD/Mean), Kurtosis capture the inequality in loan distribution along with Gini and HHI. One can see that the deciles method give us more conservative estimate of concentration risk as measured by Gini and Herfindahl Index. All these measures tell us that there is a significant presence of geographic concentration in the corporate loan portfolio of the bank.

[Insert Table 7 Here]

Next, we compare the zonal inequality within the Bank to understand their extent of concentration in relative terms. Figure 1 shows the Lorenz curve position of nine zones of the Bank under study.

Longer the distance of the Lorenz curve from the diagonal line, greater is the presence of inequality (or higher is the concentration level of that region). Similarly, shorter the distance of the Lorenz curve from the 45^0 diagonal line, lower is the concentration ranking of that region. Using this as criteria, one can easily read the Figure 1 and compare the zones in terms of concentration ranking. One can easily make out that loan distribution in the North Zone, Mumbai Zone and West Zone I are more un-equal compared to East Zone, Central Zone I, Central Zone II and West Zone II. Thus, the deciles based inequality measure gives us more realistic measure of concentration.

[Insert Figure 1 Here]

3.3.2. Assessing the Effect of Large accounts on Portfolio Concentration:

We have analyzed the contribution of large exposures on concentration. For example, in case of East Zone, if we drop two large loans of size (Rs. 1251 Cr. and Rs. 260 Cr.) from the zone pool, the Gini coefficient falls from 0.792 to 0.724 and HHI falls from 0.60 to 0.42. It is interesting to see that change in concentration is better captured by Herfindahl Index than the Gini. This is because Gini is also influenced by the presence of large number of small sized loans. Thus, even if we drop 2 large loans, the change in Gini is not very significant.

3.4. Rating wise Portfolio Concentration for the Large Bank:

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 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.

Table 8 documents the rating wise portfolio risk position of the bank. The reported transition matrix summarizes the frequency and magnitude of rating changes in the bank's corporate credit portfolio. This average transition matrix is derived by tracking the 7 yearly transitions of rated corporates through 4 one year cohort wise mortality analysis. The cross-diagonal cell captures the rating stability and off-diagonal cells capture down-ward (towards right) and up-ward (towards left) migrations. The transition matrix also reveals that although the bank's internal rating process has discriminatory power, however, upper grades have very low stability (especially CR1-CR3). This may be because of point in time (PIT) nature of the internal rating model used by the Bank. In such case, the newer upper graded loans/projects every year may be in the watch list for one or two years before it is added to the existing transition matrix. Thus, migration matrix tool may be applied by the Bank across industries, zones and also across branches to get early warning signal and also to more granularly capture credit risk. This will also enable the Bank to migrate towards Basel II advanced approaches.

[Insert Table 8 Here]

3.4.1. Default Correlation for Corporate Pool:

To find out sub-group default correlation (like for rated commercial portfolio of the Bank) we assume default correlation is simply the relation of variability of default rate over time periods (like UL_P assuming in any block if any loan defaults, they all default) relative to the total variability (like the summation of UL) assuming 0 correlation. This has been discussed in methodology section (see section 2.4).

It is quite evident from table 8 & 9 that internal risk classifications of the bank appears to fairly capturing the credit risk (excepting the top most grades). The likelihood of default monotonically increases as the risk category decreases. However, the default correlation does not monotonically increase as the internal risk classification decreases till CR6. A relatively higher correlation at CR1 level (coefficient=0.0108) may be capturing the unexpected failure of CR1 borrowers due to adverse macro economic condition. The increase in default correlation from CR7 to CR8 suggests that high risk borrowers are also vulnerable to systematic events and the Bank's lower graded loan portfolio (CR7 & 8) are not only risky but also have high correlation risk . It also warns that bad tail loss rates are understated by estimating portfolio loss distributions by equally weighting such events.

[Insert Table 9 Here]

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 is a very simplistic approach. A better approach is to find out correlation of credit losses across sectors or regions and their contribution to total portfolio loss (correlation-based approach).

3.5. EL based Concentration: comparison of regional portfolio of two banks:

The Expected Loss based HHI measure reported in Table 10 shows the medium size Bank has more diversification benefits in terms of risks as HHI is =0.0767 is at lower than its large bank counterpart. In large bank, EL based concentration is coming higher contribution Kolkata, Lucknow and Chennai regions are having higher contributions.

[Insert Table 10 Here]

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.

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.

3.6. Single Default Correlation Measure for Banks:

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.

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[6].

Marginal risk contribution $MRC_i = \sqrt{r_i} \times UL_i \times Exposure_i$ Eq.4a

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.)[7]. 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. 8 The single loss correlation method has already been discussed in methodology section. 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 ($=UL_p^2/UL_{total}^2$).

As can be seen in Table 11, we find that loss correlation for large bank as a whole is lesser than the medium sized bank giving the large bank some risk diversification benefit. 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. However, this loss correlation estimates from two banks' historical data does not

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6 This relationship can be proved.

7 Such geographic specific events are modeled by Calem and LaCour-Little (2001), Federal Reserve Board, Financial and Economics Discussion Series-60, November.

8 The real challenge, however, is finding a robust, defensible way to estimate the correlation parameters for each sub-portfolio. It is quite practical to estimate default correlations directly from bank history of individual defaults—the data within each bank is too scarce to support the analysis.

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 has been shown in section.

[Insert Table 11 Here]

One can notice that this time loss correlation is lower for medium sized bank in comparison to its large bank counterpart. Thus, the medium sized bank is having a better region wide diversified portfolio than the large bank. In the next section, we will see how this converts into lesser portfolio risk capital requirement to the mid-sized bank when we will link concentration risk to economic capital using their regional portfolio risk characteristics including correlation input.

3.7. Linking Concentration Risk to Bank Capital: Credit VaR Approach

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.[9]

The necessary amount of Economic Capital of these two Banks 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 Table 12.

As can be seen from the table 12, the two bank's regional portfolio risk in terms of their marginal risk contributions are significantly different which is affecting their total portfolio risk position. We find that mid-sized bank has greater geographic risk diversification benefit and hence portfolio concentration risks in significantly lesser than its large bank counterpart. Accordingly, it default correlation is lower, regional marginal risk contributions are more granular and hence overall portfolio unexpected loss is lower.

[9] 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.

[Insert Table 12 Here]

Using, regional portfolio distribution of advances of the two banks and also their bank level loss variance (reported in Table 11), we re-estimate single default correlation and report in Table 12. One can compare Table 11 and Table 12 results to find that the magnitude of default correlation for the total pool of loans was quite low, but an examination of subgroups shows that default correlation are different if we consider regional portfolio distribution. This is also true in case of correlations across rating grades for the large bank (already has been shown in Table 9). In order to more granularly measure portfolio credit risk and understand the ways for diversification, it is necessary to estimate different correlations for grades and industries rather than depending upon single correlation numbers. More insight will be available about the nature of concentration if we know further granular information (like rating-wise distribution across zones or industry etc.).

As a next step, we convert the portfolio concentration risks of these two banks into economic capital number to assess their impact on bank capital. From Credit VaR, we arrive at capital at risk which is also termed as "Economic Capital". Economic Capital is the amount of capital needed to provide a cushion against the Unexpected Loss incurred in the credit portfolio. Economic capital 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×ULp). The concept of economic capital (EC) is a widely used approach for managing credit risk in Banks. It is worthwhile to note that the VaR is reduced by EL due to the common decomposition of total risk capital (or VaR) into a part covering expected losses and another part goes as reserve for unexpected loss.[10] To prevent insolvency, economic capital must cover unexpected losses to a high degree of confidence.[11] We have chosen capital multiplier of 5 because credit losses are generally not normally distributed and obtain economic capital number for large bank (7.28%) and mid-sized bank (6.88%). All these results have been reported in Table 12.

We have also done 10,000 simulation of two banks portfolio using their historically obtained regional level portfolio expected loss and unexpected loss as inputs. We then 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 (discussed in

[10] Even under standard normal assumption of loss distribution series, ELp=0; however, we will adjust if the Bank is making any provisions for standard assets and we have deducted this percentage k×ULp.

[11] 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 almost covered 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.

section). 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.

Next, we compare the economic capital numbers with the Basel II minimum regulatory capital position (under standardized approach) of these two banks. We find that the capital gap is significantly high for the large bank (the gap between economic capital and existing Basel II credit risk regulatory capital is 12.31% of the regulatory capital). On the other hand, the mid-sized bank is having a capital surplus as its Basel II credit risk regulatory capital (under the standardized approach) is 22.66% higher than the economic capital. Further, in our simulation based C-VaR approach, we observe more conservative loss estimates of these two banks. We find that for the large bank case, using beta distribution, a 99.50% confidence level require economic capital of 8.30% which means additional capital requirement of 28.13% (The results have not been reported to conserve space). On the other hand, in case of mid-sized south based bank, for the same confidence level, the required economic capital proportion is 9.75% and the capital gap will be 7.45% over and above its Basel II existing regulatory capital for credit risk.

In our large bank case, even if it may not be able to cover up such a very high capital gap, but it gives some idea about largeness of the loss sizes the Bank may incur in most unlikely but plausible events. If actual credit losses are 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 large bank decides to meet additional 12.31% capital which amounts to Rs. 686 crore (as estimated in Table 12) should be aware that if they target a 15.27% return on equity (ROE), they minimum targeted profit in March 2010 would be at least Rs. 955.5 crore (ROE×Eco-cap=15.27%×Rs.6257.30 crore). This is because, future earnings also gets added to the core capital.

In this context, adoption of a Risk Assessment and Performance Management (RAPM) framework will enable the top management to meet this profit target. Accordingly we estimate unexpected losses and marginal risk contribution of various regions of the two banks. The region wise risk position (in terms of unexpected loss) would help us to compare performance and allocate capital to minimize concentration risk. The regions, whose risk contributions are higher, should ensure adequate return to ensure stability in the Bank's overall solvency position.

3.8. Risk vs. Return: Regional RAROC position of two Banks:

Risk-Adjusted Return on Capital (RAROC), by definition, is the ratio of risk adjusted net income to the level of risk the asset or portfolio has. It is a powerful risk measurement tool that assists banks and financial institutions both in measuring solvency and evaluating the performance of different business activities. While regulatory capital focuses on satisfying the objectives of the regulator, economic capital looks at internal management of the business to maximize shareholder return. RAROC and EVA are credible tools and key drivers for conscious decision-making for managing portfolio concentration risk since this has the ability to allocate banks' scarce capital among their expanding array of activities.

Consequently, we compute the risk adjusted return on economic capital or RAROC for all the regions of these two banks to identify the regions who are having higher RAROC in comparison to a hurdle rate (which we have computed using CAPM). We have taken the regional unexpected losses in the denominator of RAROC formula as expressed in equation 16 and also use region wide income and expenditure data to compute region-wide RAROC numbers. The bank wide estimated economic capital reported in Table has been used in estimating bank-wide RAROC.

Figure 2 and Figure 3 illustrate the region wide RAROC and EVA positions of two banks. The banks will make profit from those regions where RAROC is above the bank level hurdle rates. We have estimated the RAROC of all the regions of these two banks. We find that for the large bank case (see Figure 2), only five out of nineteen regions's RAROC (Ahmedabad, Delhi, Guwahati, Mumbai Main and Corporate region) are above the hurdle rate of 10.89% depicting these regions are adding value to the shareholders and hence making economic profit. Two regions Agra and Bhopal are just marginally below the hurdle rate. However, seven regions of this bank: Chennai, Hyderabad, Kolkata, Lucknow, Nagpur, Pune and Card Region are making economic losses (i.e. EVA<0) as their RAROC values are well below the benchmark hurdle rate.

[Insert Figure 2 & Figure 3 Here]

On the other hand, regional RAROC & EVA positions are much better for mid-sized bank as shown in Figure 3. We observe that bank is making economic profits from almost all its regions except three regions. Only Hassan, Vijayawada and Bhopal regions are generating low returns in comparison to their risk that makes their RAROC values far below the bank's hurdle rate (9.73%).

Here, RAROC attempts to address the issue of capital allocation from the perspective of improving performance. The bank can use this analysis to target the performance of individual regions and may attempt to bring them above the hurdle. Such RAROC-EVA exercise also facilitates the bank in setting return targets, deposit mix, rates and volumes, advance, mix, rates and volumes, target other income, set recovery targets while planning their business growth. It also prods the bank to move away from the traditional 'Transfer Pricing Mechanism (TPM)' to 'Fund Transfer Pricing Mechanism (FTP) to generate the desired business profile to augment its performance.

The destructive power of credit concentrations depends on the degree of correlation among borrowers under various economic conditions. Researchers have shown that credit migration matrices provide the specific linkages between underlying macroeconomic conditions and asset quality. Stress tests are a tool adopted to help identify and manage a broad spectrum of risks (including concentration risk). To better understand the portfolio risk dimension, we create a more realistic stress testing framework and examine the impact of macro changes on the portfolio risk of the Bank's externally rated corporate loans.

3.9. A Realistic Stress Testing Framework on Bank's Corporate Loan Portfolio:

The most crucial input to do stress testing and capital simulation exercise depends upon choosing/identifying realistic scenarios. By scenario we mean an event (for example, an increase in interest rates) and, possibly, its broader implications that are believed to represent abnormal operating conditions. Scenarios can be chosen based on historical experience, or they can be hypothetical. The gloomy macro scenario and the change in outlook, may lead to a significant deterioration of their small and medium enterprise and the corporate loan books of Indian Banks during if economy gets caught under trough of the business cycle. This may significantly impact the bank's capital level and solvency position (i.e. capital adequacy). In this paper, we have generated three historical scenarios using CRISIL's published data of 572 corporate bonds studied over 18 years: 1998-2009. Next, we study the impact of these scenarios on Bank's corporate loan portfolio and assess capital erosion the Bank is likely to face. Such stress tests would enable banks to assess the risk more accurately and, thereby, facilitate planning for appropriate capital requirements in future.

As we clearly see from Figure 4, CRISIL's corporate Bond rating moves with India's GDP growth rate. The dark shaded bars are capturing year-wise number of downgrades and lighter bars are showing number of upgrades and the smooth line is the ratio of number of downgrades to the number of upgrades from 1993-94 till 2008-09. The dotted line is the annual GDP growth rate in percentages. It is quite evident from the Figure 4 that whenever GDP growth rate was high, downgrade to upgrade ratio was low and when GDP growth rate was down, the downgrade-upgrade ratio also peaked up. As a result, the amount of portfolio credit risk changes with the economic cycle.

[Insert Figure 4 Here]

During periods of economic calm, concentrations in an institution's portfolio are unlikely to have any noticeable adverse effects on performance or credit quality. However, the real threat arises in an adverse economic scenario. In order to capture the effect of economic stress on Banks' loan portfolio composition and its capital position, we have created three scenarios: Moderate Depression time, Severe Stress time and recent depression time caused by sub-prime crisis in US.

Notice that scenario 1 (severe depression time) actually lead to more number of downgrades in corporate ratings awarded by rating agency CRISIL during 1997-99 (See Tables 14, 15 and 16) in comparison to their average migration pattern as reported in Table 13. Scenario 2 captures period 2000-02 when GDP growth rate was again down at around 4.35%-5.81%; but that the crisis was over and government had also taken stabilization policies to improve the growth rate. One can notice that the net slippage rate (downgrade rate minus upgrade rate) was not as severe as scenario 1 (compare Table 15A with Table 14A). This situation has been taken as moderate stress scenario. Table 16 shows (scenario 3) recent economic condition which prevailed during 2007-09 and GDP growth rate was 8.62% which fell down to 6.8% in the aftermath of US sub-prime crisis. The slippage statistics have been documented in Table 16A.

[Insert Table 13, 14, 14A, 15, 15A, 16 & 16A Here]

We then take the first two stress scenarios and examine how they impact on corporate credit portfolio composition of these two banks in terms of capital adequacy. For example, an economic downturn could lead to a downgrade in the credit ratings awarded to a bank's counterparties by rating agencies. This might lead to a consequent increase in the risk weights for these exposures which will have an impact on the bank's capital adequacy (CRAR) position.

3.9.1. Taking These Economic Scenarios to Study the Impact on Bank's Credit Portfolio:

We now use these historical economic scenarios and apply on the Bank's corporate credit portfolio. At the moment, we have incorporated Scenario 1 and Scenario 2 and examine how the portfolio composition and hence risk position of the Bank will change if such situations arises. We assume Bank's credit supply remain constant during this time. Scenario 3 looks quite similar to Scenario 2 especially in terms of movement from rated to unrated categories. However, in the unrated category, it was not possible to know what percentage of them are actually defaulting and because of less information on Bond default we have not finally used this scenario 3.

Table 17 & 18 present the rating wise (external) distribution of Corporate Loan Portfolio of two Banks. All ratings are solicited rating provided by External Rating Agency Institutions (ECAIs). We find that the mid sized bank is more vulnerable to economic downturn than its large bank counterpart. Our stress results reveal that the additional capital requirement (in absolute term) under both mild and severe stress scenarios is higher for the mid sized bank than the large bank. Accordingly, the capital erosion effect on CRAR due economic stress is more pronounced in case of mid sized bank (from 13.61% to 13.01% in scenario 1 and to 12.33% in scenario 2) than the large bank (from 13.12% CRAR to 12.85% and 12.52%). It is also interesting to note that the additional capital requirement in proportion to existing Basel II minimum regulatory capital for the large bank under stress scenario 1 is 9.85% and 22.69% under scenario 2 where it is 7.05% and 15.99% for the mid sized bank.

[Insert Table 17 & 18 Here]

This is happening because of two reasons: first, the mid-sized bank's corporate portfolio size is bigger than that of large bank (almost 3 times) and second, the unrated portion of loan assets are higher (63.68%) compared to the large bank (28.16%). Therefore, we may conclude that though the mid sized bank has diversification benefit in terms of economic capital in comparison to the large bank, the gap between economic capital and Basel II regulatory capital (under standardized approach) may reduce significantly under adverse economic condition. On the contrary, the large bank tend to have concentration risk due to overexposure to some sectors or regions but are less vulnerable to economic downturn as long as their asset quality is good.

4. Conclusion

In this paper, we have made an attempt to examine the difference between credit concentration and concentration risk. In order to accomplish this objective, we have analyzed in detail the credit portfolio composition of two leading public sector banks in India and have assessed the impact of credit concentration risk on bank capital. In evaluating the bank wide measures in managing concentration risk, we demonstrate how economic capital approach may enable the bank to assess the impact of regional, industry and individual concentration. For this, using bank's loss history, external rating migration history as well as equity return history, we estimate regional, rating wide and industry wide default correlation matrices to understand the nature of portfolio risk of bank assets in India. Next, we show how portfolio selection can be done through correlation analysis, estimation of marginal risk contribution vis-à-vis risk adjusted return that will enable the top management to manage portfolio concentration risk and accordingly plan its capital.

We empirically find that a large bank does not necessarily have risk diversification benefit in its credit portfolio in comparison to mid-sized bank. The bank's portfolio risk depends upon sectoral and regional performance of credit. On the other hand, the mid sized banks' portfolio risk may be less but its portfolio risk characteristics may be more vulnerable in the economic downturn and experience more pressure on its capital adequacy position. Hence, stress testing may reveal previously undetected linkages between different elements of an institution's portfolio. In this context, well designed, comprehensive and regular stress tests of institutions' portfolios may serve as a useful tool in managing concentration risk. Our historically generate stress scenarios would help the banks to understand how much shock it can absorb in changing economic condition and accordingly can set its leverage position. For this, we had to study the CRISIL's eighteen years of 572 corporate rating migration patterns under various economic cycles. This stress testing exercise will also equally help the regulator to check whether banks are healthy and stable and how much capital does the bank need in order to meet the credit needs of borrowers in the Indian economy.

Finally, through region-level risk adjusted return on capital (RAROC) & economic value added (EVA) analysis, we have tried link risk contribution with desired return contributions that will assist the top management in banks to optimally allocate capital and minimize the concentration risk capital. One of the fundamental limitations in the existing business growth strategies of Indian banks, especially public sector banks, is their disconnect with riskiness. The finalization of business targets should no longer remain a mundane 'volume-mix' targeting exercise but should incorporate inherent risk-return dimensions like we have shown in our RAPM exercise.

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Table: 1 Details of Ceilings Fixed for Various Categories of Borrowers	
Exposure Category	***Prudential Limit***
For Individual Borrowers For individual borrowers for infrastructure projects	15% of capital funds 20% of capital funds
Group Borrower Exposure For group borrowers for infrastructure projects	40% of capital funds 50% of capital funds
Substantial Exposure Limit (SEL)	Aggregate SEL of 600% of bank's capital funds.
Industry/Sector	10% of total bank credit
Infrastructure	20% of total bank credit

Table 2: Industry-wise Portfolio Concentration of two Banks:

SL #	Industry	Western Side Large Bank			South Side Medium Bank			Overall		
		Exposure Share%	**HHI weight**	**GNPA %**	**Exposure Share%**	**HHI weight**	**GNPA %**	**Industry PD%**	**Industry DD**	**Idiosyncratic Risk (1-R2)**
1	Automobile	2.78%	0.077%	0.26%	2.57%	0.066%	1.86%	2.70%	3.60	34.45%
2	Cement	1.45%	0.021%	0.37%	3.63%	0.132%	1.20%	1.22%	3.77	52.06%
3	Chemical	2.40%	0.058%	15.26%	5.39%	0.290%	2.17%	3.47%	4.42	14.69%
4	Coal & Mining & Lignite	0.12%	0.000%	2.77%	0.20%	0.000%	9.05%	3.73%	1.53	54.90%
5	Computer Software	0.03%	0.000%	33.08%	0.32%	0.001%	1.31%	2.64%	5.56	43.19%
6	Construction & Infrastructure	14.27%	2.037%	0.30%	13.59%	1.847%	1.03%	3.09%	2.13	41.02%
7	Electricity	0.21%	0.000%	6.66%	0.00%	0.000%	0.14%	1.16%	2.44	34.26%
8	Engineering/Machinery	3.78%	0.143%	4.55%	5.84%	0.341%	2.12%	2.70%	4.06	34.00%
9	Ferrous Metals	6.19%	0.384%	2.02%	5.47%	0.299%	1.78%	1.90%	2.46	49.02%
10	Gems & Jewellery	1.31%	0.017%	0.90%	4.39%	0.193%	2.92%	2.94%	2.20	51.75%
11	Leather & Leather Products	0.23%	0.001%	7.55%	1.15%	0.013%	1.69%	1.99%	3.14	57.93%
12	NBFCs	24.13%	5.822%	0.001%	4.00%	0.160%	0.00%	7.72%	2.46	48.89%
13	Non Ferrous Metals	1.34%	0.018%	5.88%	5.49%	0.301%	1.40%	1.75%	3.79	46.64%
14	Paper and Paper Products	0.51%	0.003%	9.05%	1.35%	0.018%	2.12%	1.54%	2.73	57.95%
15	Petroleum Products	2.37%	0.056%	0.40%	11.78%	1.388%	0.01%	0.39%	3.72	32.40%
16	Processed or Packaged Foods	2.13%	0.046%	5.02%	1.84%	0.034%	7.00%	8.89%	2.27	64.02%
17	Rubber & Rubber Products	0.31%	0.001%	10.25%	1.54%	0.024%	5.64%	6.66%	2.22	72.09%
18	Sugar	1.53%	0.023%	1.58%	0.17%	0.000%	0.58%	1.16%	1.67	62.34%
19	Tea	0.56%	0.003%	21.03%	0.00%	0.000%	1.00%	4.43%	2.76	59.08%
20	Telecom	4.87%	0.237%	0.002%	6.23%	0.388%	0.004%	0.77%	4.05	50.32%
21	Textiles	2.98%	0.089%	8.50%	10.51%	1.104%	3.61%	4.63%	2.54	55.63%
22	Transport Services	6.83%	0.467%	3.00%	3.67%	0.135%	3.00%	0.39%	2.03	34.74%
23	Vegetable Oil & Products	0.42%	0.002%	8.89%	0.15%	0.000%	3.40%	1.60%	2.17	68.04%
24	Others	19.25%	3.705%	4.00%	10.73%	1.151%	1.60%	4.55%	2.30	44.41%
	Total	100%			100%					
	HHI		0.1321			0.079				

Table 3: Industry Default Correlation Matrix (%) in India

	Industry Name	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SL#	Industry																								
1	Automobile	**2.2%**																							
2	Cement	2.0%	**4.3%**																						
3	Chemical	0.7%	0.7%	**0.4%**																					
4	Coal & Lignite	2.6%	3.1%	1.1%	**8.6%**																				
5	Computer Software	1.9%	2.2%	0.7%	2.2%	**3.8%**																			
6	Construction	2.2%	2.9%	0.8%	3.4%	2.5%	**3.6%**																		
7	Electricity	1.3%	1.5%	0.5%	2.1%	1.3%	1.7%	**1.3%**																	
8	Engineering	1.8%	2.1%	0.7%	2.6%	2.4%	2.4%	1.3%	**2.1%**																
9	Ferrous Metals	2.4%	3.4%	0.8%	3.8%	2.7%	3.3%	1.8%	2.6%	**4.5%**															
10	Gems & Jewellery	2.7%	3.1%	0.9%	3.7%	3.6%	3.7%	1.9%	3.1%	4.2%	**6.6%**														
11	Leather & Pdcts	2.4%	3.2%	0.9%	3.4%	3.4%	3.7%	1.6%	2.9%	3.6%	5.1%	**7.7%**													
12	Misc Manuf	2.7%	3.5%	1.0%	3.8%	3.7%	3.9%	1.9%	3.2%	4.1%	4.8%	5.0%	**5.4%**												
13	NBFCs	3.2%	3.9%	1.2%	4.8%	4.3%	4.5%	2.5%	3.8%	5.2%	5.7%	5.3%	5.9%	**8.8%**											
14	Non Ferrous Metals	2.2%	3.0%	0.8%	3.0%	2.4%	3.1%	1.7%	2.3%	3.4%	3.6%	3.5%	3.7%	4.2%	**3.7%**										
15	Paper & Paper Pdcts	2.5%	3.9%	0.8%	3.7%	3.0%	3.6%	1.8%	2.9%	4.3%	4.4%	4.4%	5.2%	5.4%	3.8%	**6.8%**									
16	Petroleum Products	0.7%	1.0%	0.3%	1.2%	0.9%	1.0%	0.6%	0.8%	1.1%	1.2%	1.3%	1.3%	1.5%	1.0%	1.2%	**0.5%**								
17	Processed Foods	3.6%	4.9%	1.4%	5.8%	5.6%	5.5%	2.7%	4.6%	5.5%	7.3%	7.5%	7.4%	8.5%	4.6%	6.5%	1.7%	**18.4%**							
18	Rubber & Rubber Pdcts	3.6%	4.4%	1.4%	5.5%	4.8%	5.1%	2.4%	4.4%	5.6%	6.0%	5.8%	6.9%	8.2%	5.2%	6.7%	1.6%	9.4%	**23.5%**						
19	Sugar	2.1%	3.6%	0.8%	3.0%	2.2%	3.0%	1.6%	2.3%	3.6%	3.6%	3.8%	3.7%	4.5%	3.2%	3.8%	1.1%	4.7%	5.1%	**7.8%**					
20	Tea	3.1%	4.3%	1.2%	4.9%	4.0%	4.4%	2.3%	3.7%	5.0%	5.6%	6.1%	6.0%	6.7%	4.3%	6.0%	1.5%	8.6%	7.5%	5.3%	**11.4%**				
21	Telecom	1.3%	1.6%	0.5%	2.0%	2.3%	1.8%	1.1%	1.7%	2.0%	2.2%	2.3%	2.4%	3.2%	1.7%	2.2%	0.7%	4.1%	3.4%	1.7%	2.7%	**3.0%**			
22	Textiles	3.5%	4.6%	1.1%	5.0%	4.3%	4.9%	2.5%	4.1%	5.9%	6.7%	6.3%	6.5%	7.9%	4.9%	6.6%	1.6%	9.1%	9.0%	5.2%	7.8%	3.2%	**9.9%**		
23	Transport Services	0.9%	0.9%	0.3%	1.5%	0.8%	1.0%	0.6%	0.8%	1.1%	1.1%	1.1%	1.2%	1.5%	1.0%	1.1%	0.4%	1.6%	1.8%	1.0%	1.4%	0.6%	1.6%	**0.6%**	
24	Vegetable Oils & Pdcts	2.4%	2.9%	0.9%	3.8%	2.2%	3.2%	1.7%	2.4%	3.4%	3.3%	3.6%	3.9%	4.5%	3.0%	3.4%	1.0%	5.7%	5.2%	3.7%	4.8%	1.8%	4.9%	1.0%	**12.2%**

Table 4: Default Correlation: All Industries (%)		
	IG	NIG
IG	**3.58%**	12.10%
NIG	12.10%	**19.30%**

Table 5: Default Correlation Across Rating Grades							
	AAA	AA	A	BBB	BB	B	CCC
AAA	**0.00%**						
AA	0.00%	**1.46%**					
A	0.00%	3.14%	**4.46%**				
BBB	0.00%	3.90%	3.90%	**6.23%**			
BB	0.00%	10.24%	14.16%	20.49%	**32.93%**		
B	0.00%	-2.02%	-5.35%	11.64%	**-2.88%**	**30.02%**	
CCC	0.00%	5.35%	9.22%	20.60%	17.29%	2.19%	**22.14%**

Period: 1992-93 to 2008-09

Table 6: Comparative Geographic Concentration Risk Position of Two Banks						
	Large Bank			**Mid-Sized Bank**		
Rank	**Region Name**	**% of Loans (pi)**	**Exposure% Share**	**Region Name**	**% of Loans (pi)**	**Exposure % Share**
1	Delhi	3.72%	22.26%	Greater Mumbai	4.00%	28.61%
2	Corporate Region	0.01%	17.86%	Delhi	3.80%	21.42%
3	Mumbai Metro Region	1.72%	11.81%	Bangalore	5.40%	10.72%
4	Chennai	12.25%	7.49%	Chennai	7.00%	4.80%
5	Hyderabad	7.56%	6.32%	Coimbatore	2.50%	4.80%
6	Kolkata	7.45%	5.03%	Gujarat	6.00%	4.34%
7	Chandigarh	4.23%	4.42%	Hyderabad	3.00%	4.30%
8	Bhopal	8.87%	4.19%	Pune	12.00%	4.11%
9	Lucknow	8.16%	3.75%	Kolkata	7.00%	2.93%
10	Ahmedabad	4.83%	3.49%	Udupi	4.00%	2.81%
11	Pune	4.46%	2.32%	Hassan	8.00%	2.30%
12	Muzzafarpur	9.07%	2.09%	Kerala	9.90%	1.50%
13	Mumbai Main Region	0.08%	2.01%	Chandigarh	4.00%	1.34%
14	Raipur	6.28%	1.99%	Vijaywada	6.00%	1.24%
15	Agra	4.49%	1.67%	Hubli	7.00%	1.16%
16	Patna	7.07%	1.59%	Belgaum	4.00%	1.09%
17	Nagpur	6.40%	1.07%	Bhopal	2.00%	1.07%
18	Guwahati	2.61%	0.63%	Goa	3.00%	0.86%
19	Card Region	0.74%	0.01%	Lucknow	1.30%	0.61%
Total		100.0%	100.0%		100.0%	100.0%
HHI			0.1163			0.152
Gini			0.493			0.531

Note: Ranks are based on Exposure% share in descending order

Table: 7 Size wise Zonal Portfolio Concentration

Units in Rs. Cr.

Zonal group	p25	p50	p75	p90	p95	p99	min	max	range	mean	CV	Kurto	Gini	HHI
Central_Z_I	1	1.68	3	7.67	11.15	84.79	0.01	90.89	90.9	4.042	2.57	56.47	0.634	0.356
Central_Z_II	0.99	1.43	2.54	6.97	13.71	107.7	0.01	211.43	211.4	5.410	3.83	76.68	0.724	0.519
East_Z	1.35	2.39	10.8	30.5	55.84	260	0.01	**1251**	1251.0	20.703	**4.70**	**137.38**	0.792	0.598
Mumbai_Z	1.48	4.14	15	49.6	133.7	560	0.004	1204.4	1204.4	27.815	3.30	67.32	0.786	0.572
North_Z	1.2	2.22	5.49	13.4	41.45	183.3	0.01	731.03	731.0	10.620	**4.20**	**159.31**	0.739	0.519
South_Z_I	1.31	2.4	6.41	24.3	38.27	97.3	0.02	380.5	380.5	8.735	2.73	**155.87**	0.701	0.421
South_Z_II	1.37	3.11	9.74	29	59	272.4	0.04	400	400.0	13.249	2.85	67.84	0.720	0.442
West_Z_I	1.53	3.27	11	29.7	105.5	225.1	0.12	385.4	385.3	18.296	2.67	31.59	0.759	0.547
West_Z_II	1.23	2.34	4.93	13.7	27.16	50.32	0.07	99.54	99.5	6.108	1.89	32.66	0.619	0.299
Overall	1.24	2.51	7.94	26.1	52.41	250	0.004	1251	1251.0	15.505	4.02	163.61	0.771	0.578

Figure: 1

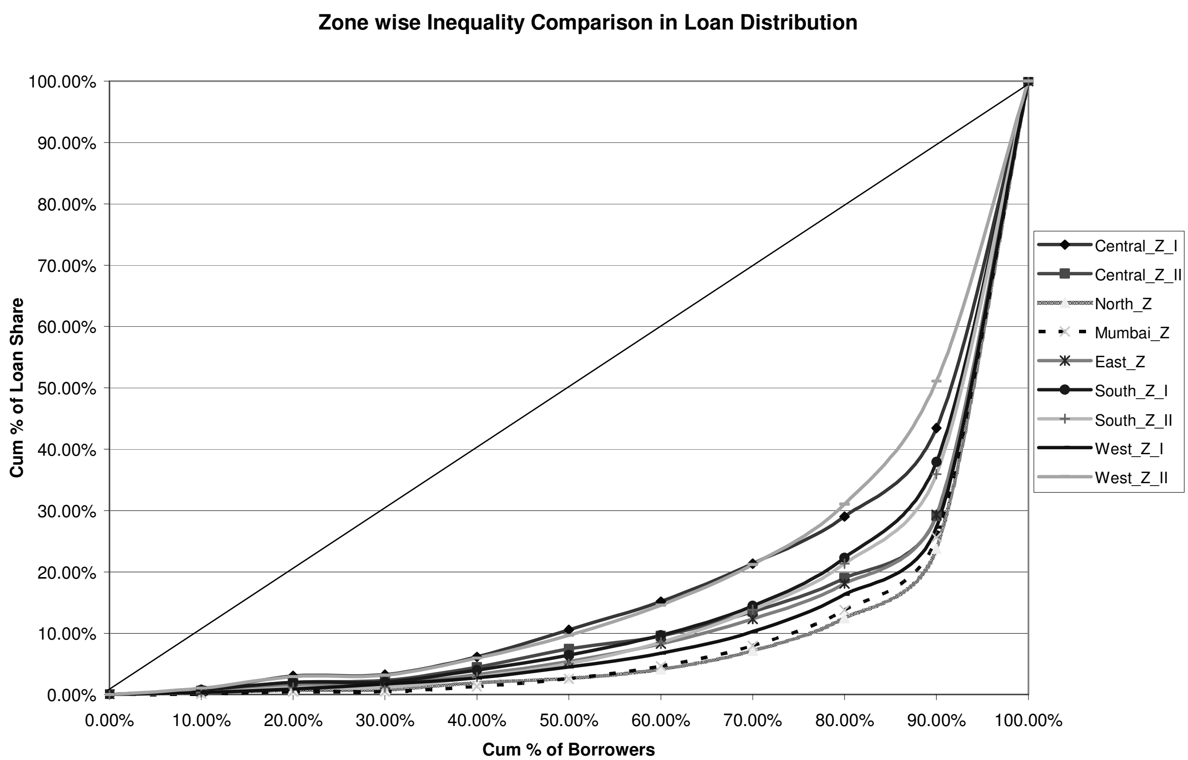

Table 8: One year Average Transition Matrix for Corporate Loan>5 Cr.

This has been constructed after tracking 7 Years of Rating Transition from 2002-03 to 2008-09 using the Bank's Internally Rated 3133 Borrower Rating Sample

Rating Year: T	CR 1 T+1	CR 2	CR 3	CR 4	CR 5	CR 6	CR 7	CR 8	Default
CR 1	**55.00%**	12.86%	10.50%	8.42%	7.97%	4.53%	0.36%	0.00%	0.36%
CR 2	4.52%	**74.80%**	13.79%	4.26%	2.40%	0.00%	0.00%	0.00%	0.23%
CR 3	1.76%	4.60%	**72.27%**	14.10%	5.00%	1.57%	0.10%	0.00%	0.60%
CR 4	1.21%	3.71%	11.13%	**56.86%**	17.90%	7.42%	0.82%	0.04%	0.91%
CR 5	0.52%	1.87%	6.25%	14.36%	**62.82%**	11.63%	1.04%	0.22%	1.30%
CR 6	0.35%	1.29%	4.43%	9.01%	15.14%	**62.35%**	3.09%	0.90%	3.44%
CR 7	0.00%	0.00%	1.94%	3.40%	8.25%	19.90%	**52.43%**	5.34%	8.74%
CR 8	0.00%	0.00%	0.00%	0.00%	2.03%	12.50%	12.50%	**52.00%**	20.97%

Table 9: Default Rates of corporate loans by internal risk class

	Risk Grade							
Year cohort	**CR1**	**CR2**	**CR3**	**CR4**	**CR5**	**CR6**	**CR7**	**CR8**
2002-03	0.00%	0.00%	0.00%	0.00%	0.63%	5.35%	8.57%	30.00%
2003-04	0.00%	0.00%	0.00%	0.00%	0.59%	3.24%	21.33%	30.77%
2004-05	1.37%	0.72%	0.29%	0.27%	0.26%	3.76%	8.47%	25.93%
2005-06	0.00%	0.60%	0.52%	0.00%	0.70%	3.30%	5.90%	12.50%
2006-07	0.00%	0.42%	0.21%	1.24%	2.16%	3.04%	10.71%	16.67%
2007-08	1.20%	0.00%	0.68%	1.06%	0.66%	2.10%	6.00%	50.00%
2008-09	0.00%	0.00%	0.83%	1.01%	1.56%	4.99%	7.69%	14.29%
Portfolio vol. (σ_{PD}^{P})	0.63%	0.32%	0.33%	0.57%	0.67%	1.14%	5.34%	13.04%
Total vol. (σ_{PD}^{T})	6.05%	4.99%	6.01%	7.13%	9.64%	18.83%	29.75%	43.72%
Def, Corrln. = $\overline{\rho}=\frac{(\sigma_{PD}^{P})^2}{(\sigma_{PD}^{T})^2}$	0.0108	0.0042	0.0029	0.0063	0.0048	0.0037	0.0322	0.0890

Table: 10 EL-based concentration measure for Regional Portfolio of the Large Sized Bank vs. Medium Sized Bank: **Units in Rs. Lac, others in %**								
	Large Bank				**Medium Sized Bank**			
SL #	**Region**	**PD%**	**LGD%**	**EL-share %**	**Region**	**PD%**	**LGD%**	**EL-share %**
1	Agra	2.29%	78.77%	3.10%	Pune	1.70%	62.53%	4.83%
2	Ahmedabad	0.95%	79.86%	2.73%	Hyderabad	2.70%	70.33%	6.23%
3	Bhopal	1.08%	85.50%	4.00%	Bangalore	0.89%	71.90%	9.61%
4	Chandigarh	1.32%	81.94%	4.92%	Chennai	1.94%	70.81%	6.43%
5	Chennai	2.20%	83.19%	14.18%	Hubli	2.70%	68.38%	3.09%
6	Delhi	0.26%	74.30%	4.40%	Udupi	1.37%	66.67%	3.57%
7	Guwahati	2.52%	86.26%	1.42%	Kerala	3.48%	70.39%	5.77%
8	Hyderabad	1.55%	83.44%	8.43%	Kolkata	0.81%	73.77%	2.06%
9	Kolkata	3.87%	91.49%	18.39%	Delhi	0.89%	69.28%	15.28%
10	Lucknow	2.99%	90.68%	10.49%	Goa	0.42%	65.69%	0.38%
11	Mumbai Main Region	0.02%	90.87%	0.05%	Gujarat	1.47%	75.58%	6.10%
12	Mumbai Metro Region	0.42%	86.71%	4.39%	Hassan	2.92%	76.06%	7.32%
13	Muzaffarpur	2.28%	89.55%	4.41%	Vijaywada	4.14%	76.10%	5.22%
14	Nagpur	1.90%	90.05%	1.88%	Greater Mumbai	0.38%	83.33%	10.45%
15	Patna	3.23%	89.64%	4.75%	Belgaum	3.27%	67.19%	3.29%
16	Pune	2.91%	90.12%	6.27%	Coimbatore	1.44%	64.48%	5.63%
17	Raipur	3.48%	85.49%	6.12%	Lucknow	2.15%	83.87%	1.26%
18	Corporate Region	0.00%	87.63%	0.01%	Chandigarh	1.31%	78.37%	1.77%
19	Card Region	11.55%	74.32%	0.07%	Bhopal	2.64%	74.14%	1.71%
	Total		83.68%					
	Risk Based HHI:			0.0941				0.0767

Table: 11 Bank Level Credit Risk Loss Position

Units in Rs. Cr., others in %

Period	Fresh Slippage%		Recovery Rate(RR)%	
	Large Bank	Medium Sized Bank	Large Bank	Medium Sized Bank
1999-00	4.50%	5.83%		
2000-01	6.50%	1.77%	16.69%	13.67%
2001-02	4.15%	2.59%	18.81%	13.46%
2002-03	3.25%	1.60%	25.62%	17.54%
2003-04	3.31%	1.77%	35.41%	16.44%
2004-05	3.02%	1.21%	42.35%	21.97%
2005-06	2.37%	1.11%	24.93%	25.74%
2006-07	1.99%	1.09%	35.73%	30.05%
2007-08	1.21%	0.55%	37.74%	28.55%
2008-09	1.23%	0.60%	39.15%	46.58%
LRPD%	3.15%	1.81%		
Real Unexpected Loss (UL_p)	1.62%	1.54%		
Recovery Rate (RR %)			30.72%	23.78%
Loss Given Default (LGD %)			69.28%	76.22%
Total Unexpected Loss (UL-total)	10.40%	10.17%		
Single Default Correlation	0.0241	0.028		

Table: 12 Linkage between Concentration and with Risk Capital: Marginal Risk Contribution and Zonal Unexpected Loss (Large Bank Case) Units in Rs. Cr., others in %										
	Large Bank					**Mid Sized Bank**				
SL #	**Region Name**	**Expos. wtd. UL%**	**Region MRC %**	**Region MRC**	**Region -wide UL%**	**Region Name**	**Expos. wtd. UL%**	**Region MRC %**	**Region MRC**	**Region wide UL%**
1	Agra	0.20%	2.62%	37.56	11.77%	Pune	0.33%	3.11%	11.53	8.09%
2	Ahmedabad	0.27%	1.72%	51.65	7.74%	Hyderabad	0.49%	6.33%	14.88	11.39%
3	Bhopal	0.37%	1.97%	70.86	8.84%	Bangalore	0.72%	2.05%	22.95	6.76%
4	Chandigarh	0.41%	2.08%	78.96	9.33%	Chennai	0.47%	4.25%	15.34	9.76%
5	Chennai	0.91%	2.72%	175.02	12.22%	Hubli	0.13%	3.25%	7.38	11.09%
6	Delhi	0.84%	0.84%	160.45	3.77%	Udupi	0.22%	2.37%	8.52	7.76%
7	Guwahati	0.09%	3.01%	16.34	13.52%	Kerala	0.19%	3.48%	13.77	12.91%
8	Hyderabad	0.65%	2.29%	124.66	10.30%	Kolkata	0.19%	2.40%	4.92	6.63%
9	Kolkata	0.89%	3.93%	169.92	17.65%	Delhi	1.40%	2.40%	36.50	6.52%
10	Lucknow	0.58%	3.44%	110.79	15.44%	Goa	0.04%	1.14%	0.91	4.27%
11	Mumbai Main Region	0.03%	0.32%	5.51	1.43%	Gujarat	0.39%	3.03%	14.56	9.08%
12	Mumbai Metro Region	0.66%	1.24%	126.06	5.58%	Hassan	0.30%	3.80%	17.49	12.82%
13	Muzaffarpur	0.28%	2.98%	53.45	13.37%	Vijaywada	0.19%	4.83%	12.47	15.16%
14	Nagpur	0.13%	2.73%	25.09	12.28%	Greater Mumbai	1.46%	1.85%	24.95	5.10%
15	Patna	0.25%	3.53%	48.18	15.85%	Belgaum	0.13%	3.68%	7.85	11.95%
16	Pune	0.35%	3.37%	67.16	15.14%	Coimbatore	0.37%	2.59%	13.44	7.69%
17	Raipur	0.31%	3.49%	59.80	15.67%	Lucknow	0.07%	4.46%	3.02	12.16%
18	Corporate Region	0.04%	0.05%	7.18	0.21%	Chandigarh	0.12%	2.97%	4.22	8.93%
19	Card Region	0.002%	5.29%	0.34	23.76%	Bhopal	0.13%	6.17%	4.09	11.89%
	TOTAL	7.26%		1389.00			7.34%		743.36	
	Default Correlation			0.0495					0.0438	
	Portfolio UL%			1.62%					1.54%	
	Multiplier (k)			5					5	
	Provisioning %			0.80%					0.92%	
	Portfolio EL %			0.97%					0.49%	
	Economic Capital %			7.28%					6.88%	
	Regulatory Capital			5571.30					4305.22	
	Deficit in % of Regulatory Capital			12.31%					-22.66%	

Figure 2: Risk Adjusted Return on Capital by Regions-Large Bank Case

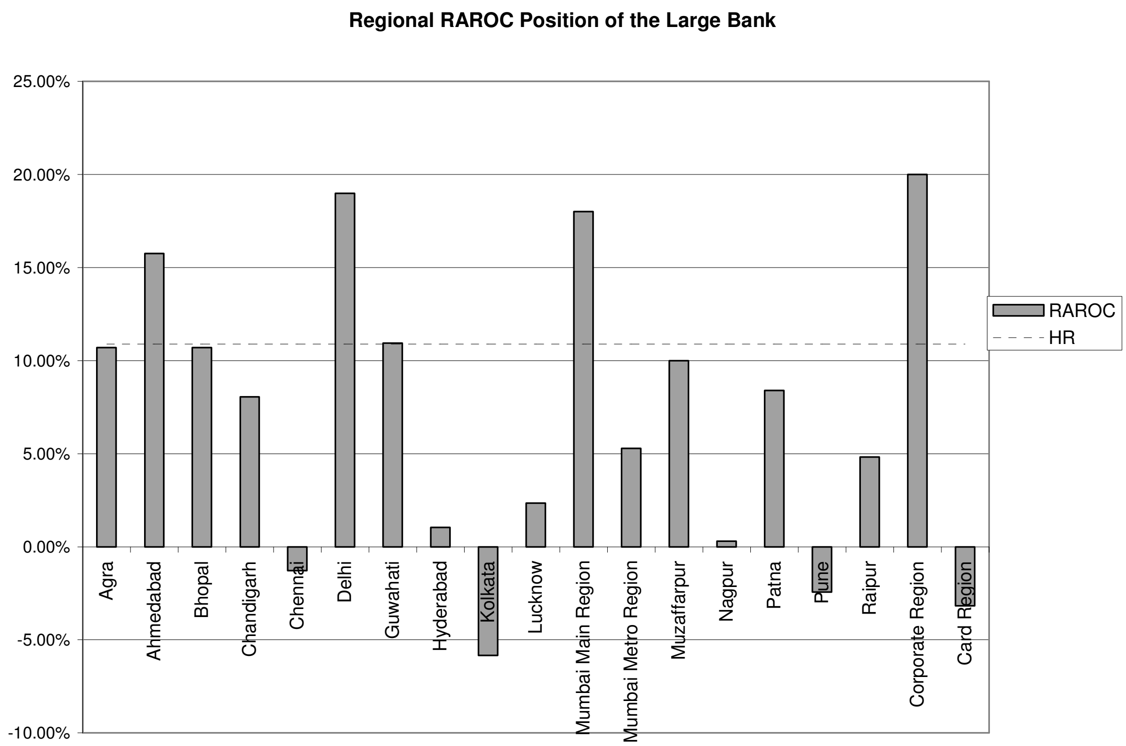

Figure 3: Risk Adjusted Return on Capital by Regions-Mid Sized Bank Case

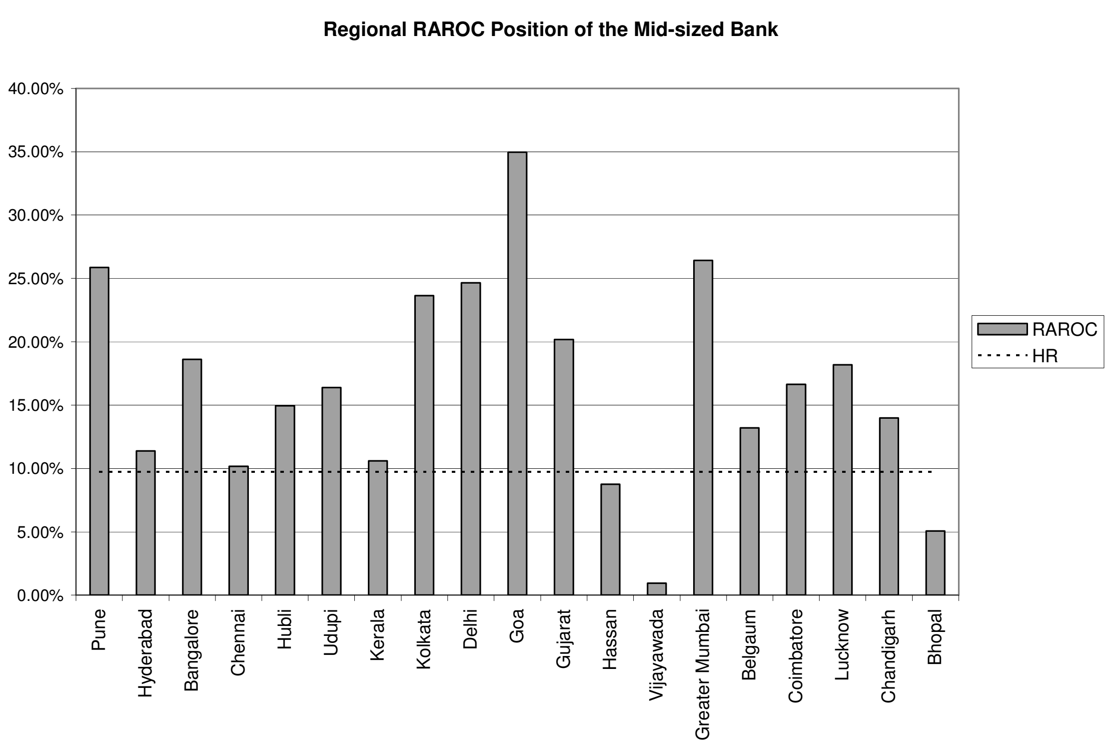

Figure 4: Rating Revisions due to Economic Changes: Require Stress Testing of Bank Capital

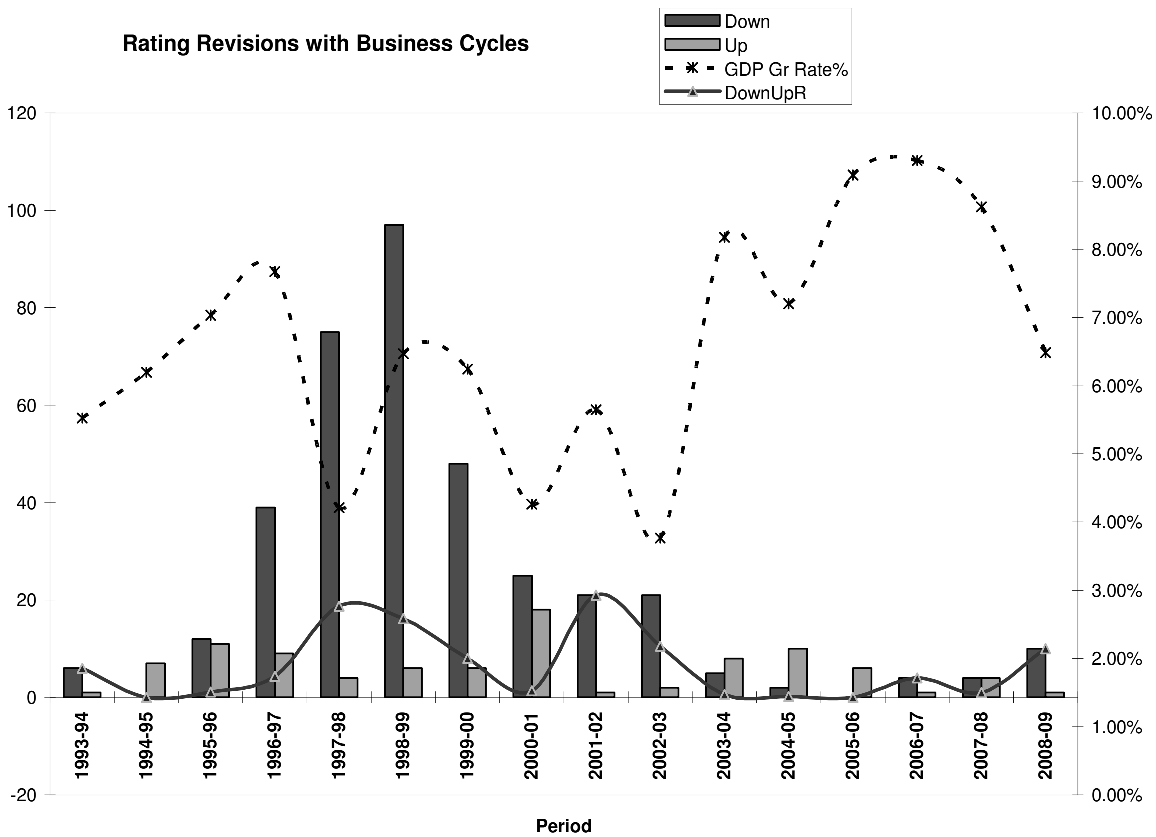

Table: 13 One Year Average Rating Transition Matrix for the Period 1992-2009 in %

		Year T+1							
		AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**
Year T	**AAA**	**96.05%**	3.95%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	AA	2.81%	**89.74%**	6.20%	0.68%	0.39%	0.10%	0.00%	0.10%
	A	0.00%	3.99%	**83.71%**	7.12%	2.70%	0.32%	0.54%	1.62%
	BBB	0.00%	0.51%	5.09%	**75.83%**	10.69%	1.53%	2.80%	3.56%
	BB	0.00%	0.70%	0.00%	1.41%	**59.86%**	3.52%	7.75%	26.76%
	B	0.00%	0.00%	0.00%	7.41%	0.00%	**40.74%**	22.22%	29.63%
	CCC	0.00%	0.00%	0.00%	2.13%	0.00%	0.00%	**53.19%**	44.68%

Scenario 1: Corporate Rating Transition under Severe Depression Time

Table: 14 Studying the Corporate Rating Migration under Severe Stress Scenario:

Period: 1997-98 & 1998-99; GDP growth @ 4.21%-6.47% coupled with East Asian Crisis Period

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	**91.30%**	8.70%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
AA	1.91%	**73.89%**	17.83%	3.18%	2.55%	0.00%	0.00%	0.64%
A	0.00%	2.07%	**70.95%**	14.11%	7.05%	0.83%	0.83%	4.15%
BBB	0.00%	0.00%	2.60%	**54.55%**	24.68%	2.60%	7.79%	7.79%
BB	0.00%	0.00%	0.00%	0.00%	**45.65%**	4.35%	6.52%	43.48%
B	0.00%	0.00%	0.00%	0.00%	0.00%	**80.00%**	0.00%	20.00%
CCC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**50.00%**	50.00%

Table: 14A Slippage Statistics

	Downgrade %	Upgrade %	Net-Downgrade %	Rated to Unrated %	%Slippage to D
AAA	8.70%	0.00%	8.70%	8.70%	0.00%
AA	24.20%	1.91%	22.29%	8.28%	0.64%
A	26.97%	2.07%	24.90%	14.11%	4.15%
BBB	42.86%	2.60%	40.26%	37.66%	7.79%
BB & Below	50.79%	0.00%	50.79%	7.94%	42.86%

Scenario2: Corporate Rating Transition under Moderate Depression Time

Table: 15 Studying the Corporate Rating Migration under Mild Stress Scenario:

Period: 2000-01 & 2001-02; GDP growth @ 4.26%-5.65% coupled with Stabilization Policy
Announced by the Indian Govt.

	AAA	AA	A	BBB	BB	B	CCC	D
AAA	**96.51%**	3.49%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
AA	3.79%	**89.39%**	6.06%	0.76%	0.00%	0.00%	0.00%	0.00%
A	0.00%	7.53%	**81.72%**	6.45%	1.08%	0.00%	2.15%	1.08%
BBB	0.00%	2.50%	5.00%	**72.50%**	2.50%	7.50%	0.00%	10.00%
BB	0.00%	4.00%	0.00%	4.00%	**72.00%**	4.00%	0.00%	16.00%
B	0.00%	0.00%	0.00%	18.18%	0.00%	**45.45%**	0.00%	36.36%
CCC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	**56.25%**	43.75%

Table: 15A Slippage Statistics					
	Downgrade %	**Upgrade %**	**Net-Downgrade %**	**Rated to Unrated %**	**%Slippage to D**
AAA	3.49%	0.00%	3.49%	2.33%	0.00%
AA	6.82%	3.79%	3.03%	10.61%	0.00%
A	10.75%	7.53%	3.23%	31.18%	1.08%
BBB	20.00%	7.50%	12.50%	45.00%	10.00%
BB & Below	30.77%	7.69%	23.08%	28.85%	28.85%

Scenario 3: Indian Corporate Rating Transition in Recent Downtime

Table 16: Studying the Corporate Rating Migration under Recent Downtime Scenario: Post Subprime Crisis Period: 2007-08 & 2008-09 GDP growth @ 8.62% & fell down to 6.8% along with Sub-prime crisis								
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**
AAA	**91.18%**	8.82%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
AA	2.73%	**95.45%**	1.82%	0.00%	0.00%	0.00%	0.00%	0.00%
A	0.00%	10.53%	**84.21%**	5.26%	0.00%	0.00%	0.00%	0.00%
BBB	0.00%	0.00%	0.00%	**80.00%**	20.00%	0.00%	0.00%	0.00%
BB	0.00%	0.00%	0.00%	0.00%	**66.67%**	0.00%	0.00%	33.33%
B								
CCC								

Table: 16A Slippage Statistics					
	Downgrade %	**Upgrade %**	**Net-Downgrade %**	**Rated to Unrated%**	**%Slippage to D**
AAA	8.82%	0.00%	8.82%	9.80%	0.00%
AA	1.82%	2.73%	-0.91%	10.00%	0.00%
A	5.26%	10.53%	-5.26%	21.05%	0.00%
BBB	20.00%	0.00%	20.00%	40.00%	0.00%
BB & Below	33.33%	0.00%	33.33%	0.00%	33.33%

Table 17: Stress Testing Corporate Portfolio (Long Term Loans> Rs. 5 Cr.) as on March-2009: Large Western Bank Case Units in Rs. Cr.							
	Original Corporate Portfolio of the Bank			**Scenario 1: Mild Stress**		**Scenario 2: Severe Stress**	
Grades	**Exposure %**	**RW**	**RWA**	**Changed Exposure %**	**Changed RWA**	**Changed Exposure %**	**Changed RWA**
AAA	14.04%	20%	641.98	13.98%	639.20	11.98%	547.76
AA	19.94%	30%	1367.88	18.11%	1242.53	14.73%	1010.47
A	20.61%	50%	2356.38	12.35%	1411.67	15.65%	1789.04
BBB	14.46%	100%	3305.55	5.67%	1296.82	5.98%	1368.16
BB & Below	2.80%	150%	959.44	5.61%	1925.19	11.34%	3890.61
D with<20%provision		150%		0.87%	299.90	6.20%	2127.41
D with prov>20% of outstanding but<50%		100%		1.67%	380.82	1.16%	265.93
D with prov at least 50%		50%		1.62%	185.65	0.39%	44.32
Un Rated (UR)	28.16%	100%	6438.55	40.11%	9172.59	32.56%	7446.17
Total	100.00%		15069.79	100.00%	16554.37	100.00%	18489.86
Basel II Regulatory Capital			1356.28		1489.89		1664.09
Additional Capital Requirement					133.61 (9.85%)		307.8 (22.69%)
Effect on Bank's overall CRAR			13.12%		12.85% (0.27%)		12.52% (0.60%)

Table 18: Stress Testing Corporate Portfolio (Long Term Loans> Rs. 5 Cr.) as on March-2009: Mid Sized Southern Bank Case Units in Rs. Cr.							
	Original Corporate Portfolio of the Bank			**Scenario 1: Mild Stress**		**Scenario 2: Severe Stress**	
Grades	**Exposure %**	**RW**	**RWA**	**Changed Exposure %**	**Changed RWA**	**Changed Exposure %**	**Changed RWA**
AAA	10.39%	20%	641.98	10.11%	932.14	8.75%	806.29
AA	8.66%	30%	1367.88	8.15%	1127.32	6.81%	941.48
A	10.79%	50%	2356.38	6.29%	1449.18	7.84%	1806.77
BBB	6.19%	100%	3305.55	2.49%	1146.61	2.84%	1310.88
BB & Below	0.29%	150%	959.44	6.80%	4701.47	9.82%	6790.63
D				4.64%			
D with<20%provision		150%		0.97%	673.77	8.55%	5910.77
D with prov>20% of outstanding but<50%		100%		1.86%	855.58	1.60%	738.85
D with prov at least 50%		50%		1.81%	417.10	0.53%	123.14
Un Rated (UR)	63.68%	100%	6438.55	61.52%	28361.41	53.26%	24551.22
Total	100.00%		15069.79	100.00%	39664.59	100.00%	42980.02
Basel II Regulatory Capital			3334.83		3569.81		3868.20
Additional Capital Requirement					234.99 (7.05%)		533.38 (15.99%)
Effect on Bank's overall CRAR			13.61%		13.01% (0.59%)		12.33% (1.28%)