MANAGEMENT OF RETAIL ASSETS IN BANKING: COMPARISION OF INTERNAL MODEL OVER BASEL

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Abstract

Retail Assets in Banks has grown among banks at a much faster space over the recent years. Unlike the commercial exposures banks manage retail assets on pooled basis. In this paper, we discuss the methodology of creating pools of revolving retail assets. Further, we compare the capital charges generated by the Basel's formula with the capital charges generated by one possible earnings-at-risk (Future Margin Income) internal capital allocation models. We find that in general, Basel's capital ratios are closer to those generated by our models for the groups with lower credit risk. We attribute the discrepancies to the different ways Basel and our models account for future margin income, to Basel's' assumptions about asset correlations.

JEL Classification Codes: G0, G2.

Key Words: Correlations, Capital Charge

I. INTRODUCTION

The most prominent issue in the context of banking these days are the implications arising out of the sub prime crisis and BIS [1] Basel II accord. Basel Committee on Banking Supervision (BCBS) announced the adoption of risk-based capital standards by banks in 1989. The Basel accord [2] proposes three alternative regimes: the "standardized", the "foundation IRB" (for internal ratings based) and the "advanced IRB." Banks that opt for the advanced regime have to provide internal estimates of expected losses and use the Basel formula for capital calculation. Bank's retail assets include all borrower relationships and relationships with small businesses and therefore will include credit cards, auto loans, mortgages, personal loans, and small business loans. Revolving retail assets include credit cards, home equity, ready cash or overdraft etc, where the customer borrower can revolve on the balance after paying a minimum due amount. Failure to pay back the drawn amount for subsequent billing cycles results in his delinquency and a potential loss to the Bank. Retail portfolios are very different from commercial portfolios, in terms of their number, ticket size and loss measures[3]. The number of accounts in case of retail lenders touches millions on their books. Exposures at default are typically much smaller for retail than for commercial lenders: for un-collateralized loans the size varies between about Rs.5, 000 to about Rs. 10, 00,000. Probabilities of default range from a few hundreds of a percent (0.01%) to sometimes greater than 30%. Therefore retail assets do provide wider distribution of default rates compared to banks' commercial assets.

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[1] The Bank for International Settlements (BIS) is an international organisation based out of Basel, Switzerland, which fosters international monetary and financial cooperation and serves as a bank for central banks.
[2] BCBS June (2006)
[3] Exposures at default, loss given default and probabilities of default.

The computation of Basel capital ratios for retail exposures in a bank portfolio typically depends upon a segmentation scheme separating borrower accounts into pools that are homogeneous with respect to the characteristics of the borrower, probably determining their default behavior. These pools then form the basis for estimating a probability of default (PD) for exposures in the pool. BCBS[4] (2006) requires that banks segment their retail assets portfolios into pools, so as to satisfy certain key requirements. There exist various challenges to the bank on the question of pooling. The level of differentiation across the pools has to ensure that the number of exposures in a given pool is sufficient so as to allow for meaningful quantification and validation of the loss characteristics at the pool level. There needs to be a meaningful distribution of borrowers and exposures across pools. Similarly, a single pool should not include an undue concentration of the bank's total retail exposure. There is no generally accepted definition of homogeneity that forms an objective basis for determining appropriate segmentation. Kelly (2003) defines homogeneity as exposures within a pool having a common relationship between the PD and exogenous economic drivers over the range of possible outcomes. The basic problem is homogeneity over PD behaviour does not necessarily imply homogeneity over risk characteristics. Nystr¨om and Skoglund (2004) describe an application of portfolio credit risk model into tranches and the assignment of appropriate ratings to the tranches, to retail and mortgage portfolios. The method of using PD is an objective segmentation approach where the segments of loss measures (Probability of Default) determine the creation of pools. In view of the above limitations, therefore, instead of an objective segmentation (using PD), a non objective segmentation method of natural grouping of data (natural clustering) using the risk

[4] Banks are needed to create pools with meaningful differentiation of risk across pools and stability of each pool's risk behavior so as to allow for accurate and consistent estimation of risk characteristics at a pool level.

characteristics of the borrowers may be an appropriate method of segmentation.

The next step in capital computation of retail assets is to use the homegenous default rates obtained from the above segments. The Basel (BCBS) capital ratio is the tail loss at 99.99% confidence interval, since the BCBS entails capital requirement for both expected and unexpected losses. However, we need to subtract our measure of Future Margin Income (FMI) from the tail loss at 99.99 % confidence interval and obtain an economic measure of capital. This is because while computing the capital charges against the segment specific loss measures it may be desirable to obtain an estimate of Future Margin Income. This is because banks price the revolving portfolios ex ante based on their expected loss measures. In other words, our capital definition is based on the tail economic loss, rather than the tail credit loss. The economic loss could be computed by the difference between income over one year minus the tail credit loss and minus the expenses during that period (Nayda & Perli 2001).

Hence, FMI can cover credit losses before a bank has to use its capital. It can be mentioned here that segments with high default rates may exhibit higher income but the corresponding recovery rates against such segments will determine their effectiveness in capital allocation. Hence, it is interesting to compare the capital allocations resulting from internal models that could be used by banks. We believe that this exercise is useful for retail portfolios by subtracting a proxy for future margin income from the credit loss-based capital ratios. We present a one-factor model and calculate capital ratios for each segment based on the model and to the new Basel formula. We also attempt to identify factors that could account for the differences and the important policy implications of our findings including the need for further investigations.

II. Segmentation Method

The methodology comprises using the method of K-means nearest neighborhood clustering to create homogenous clusters of data which are heterogeneous across all clusters. The input to a k-means clustering would be the number of clusters which is refined iteratively. For natural grouping of data, clustering is used using two of the prominent techniques that includes; Hierarchal and K-Means methods. In case of larger number of attributes and bigger sample sizes or presence of continuous variables, K means is a superior method over Hierarchical. For the K means model, character attributes against the borrowers were transformed with suitable indicator transformations. Extreme Values of the numeric variables were transformed for outliers. Further, a multivariate collinearity check was also done for the variables within the model to eliminate any collinearity bias among the variables used.

III. One Factor Credit Risk Model with Future Margin Income

Perli and Nayda (2001) have followed the analysis in Schonbucher (2000) and Vasicek (1987) to propose a One Factor credit risk model of (Future Margin Income) FMI. We extend the above approach of Perli and Nayda (2001) to compute estimates of capital ratio from an internal model.

Here we assume in this model that there are borrowers belonging to i pools of exposures (from the above k means model) and that the default of a borrower occurs when the value of his/her assets, falls below a certain threshold. The borrowers might default not just because of a decline in the value of their assets, which is unobservable and can only be explained with the help of One Factor, for simplicity. Hence, the threshold below which a borrower defaults would then be related to the probability of default of that borrower.

Perli and Nayda (2001) assume that the value of all borrowers' assets is driven by a single common factor. The common factor and the defaults are also assumed independent. All borrowers within a homogenous risk segment have the same probability of default and, therefore, the same default threshold. The expected losses from each of the segments can be used to compute both the Basel capital charges and the capital charges with FMI. The details of the One Factor model including the method of computing FMI for each of the pools is also based on the assumptions (Perli and Nayda 2001), which is described in the Appendix .

For each risk segment, between the time of disbursal to the time of default the bank will collect some revenue and will have some expenses including losses. Revenue is due to the price income (interest income) and non price income (fees) on performing accounts. Expenses are incurred on accumulated losses, funds and operating and marketing expenses including collection expenses. Here we assume that non-interest income is a constant fraction of outstanding balances, even if fees are assessed in dollar terms rather than as a percentage of balances. We also assume that, at default, the losses are the outstanding balance net of the recovered amount. Hence a constant fraction of borrowers in each segment pays the annual fee, the late fee, etc. Total revenue, is therefore, the sum total of all price and non price income. Similarly, total expenses is the sum of interest and non interest expenses. Interest expenses are on account of cost of funds and non interest expenses are on account of servicing, marketing, etc.

Interest expense is also related to the initial outstanding balances, since that (minus the capital the firm holds) is the amount that needs to be financed. Since financing has to occur at the beginning of the period, any loss incurred after that still needs to be financed. As with non-interest income, we assume that non-interest expenses are incurred on a per-account basis and, therefore, are a constant percentage, of outstanding balances.

Due to the above simplified approach, for any given segment the bank loses, only if the outstanding balance at the time of default is below the outstanding balance in the beginning. The ratio of outstanding balance at the time of default to the outstanding balance at the beginning is called a profit ratio which is in fact a random variate, assumed to follow $G(F(x), c)$ for a given capital ratio c. The capital charge can be computed at a confidence interval of 99.99% assuming a $G(.)$ follows a Normal Distribution. In the event a segment generates a very high net income relative to its tail loss, c is zero or positive, hence all positive c could be made zero.

IV. EMPIRICAL FINDINGS

Because of confidentiality issues, we cannot disclose the identity of the bank and hence the information relative to the exact probabilities of default of each risk group, or to their income, expenses, and specific losses.

We calibrate our cluster model on the test portfolio which results in four significant risk groups. The risk segmentation drivers (characteristics) for each of the four groups include, Home Ownership, Occupation, Age of the Relationship, Balance Amount, Fees and Payment Amount, which includes a balanced mix of transaction, delinquency and demographic attributes[5]. These four groups are heterogeneous across other groups and homogenous within each group due to the clustering algorithm in k-means[6] model.

Table 1: Parameters for Calculating One Factor Model Capital Ratios

r	average annual interest rate over balance	34%
λ_i	average fraction of non interest income over opening balance	2%
γ_i	loss given default (1- recovery ratio)	50%
cof	cost of funds (interest expenses)	15%
ψ	average fraction of non interest expenses over opening balance	15%

Table 1 provides the parameters for calculating the FMI for each of the risk groups. For the purpose of simplicity the above parameters are assumed equal across all risk groups.

[5] Para 460 of BCBS (June 2006)

Table 2: Profile of Segments

Risk Group	Probability of Default	Asset Correlation Factor	Loss Given default	Future Margin Income
Group1	p1	constant	constant	Constant
Group2	p2 >p1	constant	constant	Constant
Group3	p 3>p2	constant	constant	Constant
Group4	p4 >p3	constant	constant	Constant

Table 3: One Factor Model Capital Ratio Comparison

Risk Group	Probability of Default	Basel Capital Ratio	One Factor Model Capital Ratio	Difference
Group1	p1	2.48%	0.00%	2.48%
Group2	p2 >p1	2.59%	0.00%	2.59%
Group3	p 3>p2	2.78%	0.04%	2.74%
Group4	p4 >p3	3.88%	2.87%	1.00%

Parameters of the k means model (viz, Centroid Distance, Nearest neighbourhood Distance, etc).

However, it is true that the Bank has already made provision for higher APRs (annualized percentage rates) for high default groups and so on. Table 2 gives a brief profile of four groups in the form of increasing default rates across 4 segments against a constant asset correlation factor and loss given default. The capital ratio computation results using both the Basel formula and FMI formula is discussed in the next section. In practice, the bank would charge varying interest rates to varying groups. For the purpose of making the computations simple, asset correlation factor, non interest income factor, non interest expense factor, recovery factor, loss given default factor, etc are all assumed to be constant across all the groups. The One Factor Model capital ratios adjusted for Future Margin Income at Tail Loss is also depicted in Table2. As is evident from the increasing default rates *p1-4*, the Basel capital ratio for each of the groups are increasing from 2.5% to 3.9%. The FMI factor for each of the groups was constant. After adjusting for the FMI factor, One Factor capital ratios were found to be nil for bottom two groups. Similarly, the difference between the Basel capital ratio and One Factor capital ratio was maximum only for the top default group. This is due to the fact that even when the future margin income factor is constant for all groups, the tail loss decreases substantially when the default rates are relatively lower. The One Factor capital requirements are higher only for high default groups.

V. POLICY IMPLICATIONS & CONCLUSIONS

We presented a simple but advanced approach towards building an internal model for recognizing the margin income due to revolving portfolios and the results of capital ratio calculation. Further, we also compared the two ratios computed by the Basel method and the

FMI method. As is evident from the model, when the margin income is realized at the tail, the requirements of capital ratios, is lower than that of Basel. It is possible, that a certain risk group displays higher net income relative to its tail loss and hence the capital requirement may be zero. Similarly, the capital ratios of risk segments with high probability of default may be lower than those for segments with low probability of default, if the loss-given-default for the former is significantly lower and the revenue they generate significantly higher.

Credit-risk segments should hold less capital than high-credit-risk segments. In addition, the capital ratios obtained from the multi-factor model could indicate that Basel's assumptions about how asset correlations change with the probability of default might be inaccurate, especially at the low and high end of the credit spectrum.

VI. REFERENCES

Alfred Hamerle, Thilo Liebig, Daniel RÖsch; *Credit Risk Factor Modeling and the Basel II IRB Approach*, Discussion Paper Series 2: Banking and Financial Supervision, No 02/2003

Elizalde, Abel; *Do We Need to Worry about Credit Risk Correlation*; Journal of Fixed Income, December 2005

Lyods Bank: *Comments Relating to Segmentation of Retail Credit Portfolios* http://www.bis.org/bcbs/cp3/allandsha.pdf); April 2003

Michael B. Gordy; *A Comparative Anatomy of Credit Risk Models*; Board of Governors of the Federal Reserve System, December 1998,

Michel Crouhy, Dan Galai , Robert Mark; *Prototype risk rating system*; Journal of Banking & Finance 25 (2001) 47 – 95

Michel Crouhy, Dan Galai, Robert Mark; *A comparative analysis of current credit risk models*; Journal of Banking & Finance 24 (2000) 59 – 117

Perli Roberto and Nayda, William, 2004; *Economic and Regulatory Capital Allocation for Revolving Retail Exposures*, Journal of Banking & Finance, Elsevier, vol. 28(4), pages 789-809 April.

Shannon Kelly, Federal Reserve Bank of Philadelphia; *Using Cluster Analysis for Retail Portfolio Segmentation in an Economic Capital Model: Homogeneity by Common Default Behavior over Time* NESUG03 September 2003

APPENDIX

Let N_i be the number of customers borrowers in each of the i pools.

A borrower j in pool i defaults when the value of his/her assets at time T, denoted by V_{ij} (T), falls below a certain threshold K_{ij}.

Since, all borrowers within a homogenous risk segment have the same probability of default p, therefore, the default threshold $K_{ij}=K$.

We assume that the value of all borrowers' assets is driven by a single factor Y.

Building upon the approach of Nayda and Perli (2001) the One Factor Model is described below.

Since, defaults happen independently of each other, as the number borrower tends to infinity, the default rate will be equal to the default probability:

$$Pr(X = p(y)|Y = y) = 1, \qquad (1)$$

where X is a random variable indicating the fraction of defaulted accounts.

The One Factor Model Probability Distribution Function of the fraction of losses is given by:

$$F(x) = \Phi\ (\ 1\ \surd\rho\ (\surd 1 - \rho\Phi^{-1}\ (x) - \Phi^{\ -1}\ (p))) \qquad (2)$$

Where ρ is the correlation factor and p is the probability of default.

For the purpose of calculating FMI we proceed over Nayda and Perli (2001) as follows;

Let B_i be the total outstanding balance amount against all borrowers in pool i.

Therefore, the total outstanding balances B' as the sum of outstanding balances for pool i where $B= \Sigma\ B_{ij}$, where B_{ij} is the outstanding amount against each borrower.

Let the recovery rate be γ_i for a given pool i, then the loss amount at time T implied by a fraction x of borrowers defaulting is:

$$L_i = (1 - \gamma_i)\ B_i\ x \qquad (3)$$

Suppose the bank lends B_{0i} dollars to a pool 'i' at the beginning of the time horizon.

It is unlikely that the borrowers would have been offered the same interest rate on their balances, however we assume it to be fixed. If the rate applied to outstanding balances is fixed and is r, and collected interest income by I_i,

we have:

$$I_i = r B_{0i} - r L_i = r \ (B_{0i} - (1 - \gamma_i)B_{0i} x) = r (1 - x(1 - \gamma_i))B_{0i} \qquad (4)$$

We denote the constant fraction of non interest income by λ_i

$$NI_i \ = \lambda_i B_{0i} - \lambda_i L_i = \lambda_i(B_0 - (1 - \gamma_i)B_0 x) = \lambda_i(1 - x(1 - \gamma_i))B_{0i} \qquad (5)$$

Total revenue:

$$R_i = I_i + N_i = (r_i + \lambda_i)*(1 - x(1 - \gamma_i))B_{0i} \qquad (6)$$

If cof be the average cost of funds, interest expense $\mathrm{IE_i}$ will therefore be:

$$IE_i = cof\, B_{0i} - cof\, C = cof\,(B_{0i} - C) \qquad (7)$$

We assume that non-interest expenses are incurred on a per-account basis and, therefore, are a constant percentage, denoted as ψ, of outstanding balances. Again, recoveries and losses are not assumed to affect ψ.

Non-interest expenses are therefore $NE_i = \psi\, B_{0i}$, and

Total expenses are: $E_i = IE_i + NE_i = cof\,(B_{0i} - C) + \psi\, B_{0i}$ (8)

Hence

$$\begin{aligned} B_{Ti} &= B_{0i} - L_i + R_i - S_i \\ &= B_{0i} - x\,(1 - \gamma_i)\, B_{0i} + (r + \lambda_i)\,(1 - x\,(1 - \gamma_i)\, B_{0i} - cof\,(B_{0i} - C) - \psi B_{0i} \\ &= B_{0i}\,((1 + r + \lambda_i)(1 - x(1\ \gamma_{ii})) - cof - \psi) + cof\, C \qquad (9) \end{aligned}$$

Hence the profit ratio is

$$\pi_i = (B_{Ti} / B_{0i} - 1) \text{ where } \pi_i \text{ is assumed to follow } G(F(x),c) \tag{10}$$

where $G(F(x),c)$ is the probability distribution of π and $c = C/B_0$.

The capital charge will be given by the left tail of $G\ (F(x),\ c)$ at an appropriate percentile.

It follows that the capital ratio c for each segment is:

$$c = \text{Minimum}\left[\ \frac{(r+\lambda_i - cof - \psi) - (1 + r + \lambda_i)(1-\gamma_i)x_\alpha}{(1-cof)},\ 0\ \right] \tag{11}$$

Here c is the α (99.99%) revenue distribution in (6)