Abstract

Banks are in the business of lending, investment and offering services which exposes them to credit risk, market risk and operational risk. With the advent of deregulation, technological innovations and globalization, understanding and managing risk in banks across the world has become complex. The understanding of credit risk in banks was simplified in 1988 when the Basel Committee on Banking Supervision (BCBS) published Basel I Capital accord to provide 8% capital of predefined risk weighted assets commonly known as Capital Adequacy Ratio (CAR). In 1996, BCBS amended the Basel I norms by including market risk and in 1999 included operational risk. The drafting of the new accord, led to framing of Basel II in 2006. (BCBS document-2006a)

The various aspects of credit risk model development and its validation, a methodology for estimating Value at Risk (VaR) for market risk on Government securities, its validation and operational VaR estimation for operational risk as also Basel-II implementation issues in a public sector bank is the focus of the present study. The scope of this research work is limited to Basel-II implementation issues in public sector banks in India. Primary Data from one public sector bank has been used to carry out data driven analysis of credit risk and market risk. The public sector bank selected represented the universe of all public sector banks as its important financial ratios were similar to all public sector banks in aggregate. For operational risk, secondary data has been used.

Despite significant research works found in literature, review of literature on research done for Indian banks indicate that very little work has been undertaken to model and estimate credit risk, market risk and operational risk in public sector banks and study the Basel II implementation issues in the said banks. A questionnaire survey was carried out to investigate and assess the detailed nature of problems faced by Indian public sector banks in implementing advanced approaches of Basel-II. The Reserve Bank of India has been postponing implementation of the advanced approaches of Basel-II several times. This study indicated that public sector banks are unable to estimate probability of default of borrowers due to delay in computerization which prevented availability of data for previous five years. The credit scoring models used by the public sector banks were unable to assess credit risk correctly due to non-inclusion of certain

parameters and improper risk weightages to different attributes. The existing models of two chosen public sector banks were studied indicating certain drawbacks relating to management and financial evaluation in the models. Based on the study, a revised credit scoring model has been developed after including impact of PLR and MIBOR on credit risk. The model has been validated using data of 1000 corporate borrowers from the chosen public sector bank. We find that the model is reliable and stable for out of sample and out of time parameters. The probability of default of 100 personal loan borrowers from the chosen public sector bank has been estimated using Logit Model. Assuming normal distribution, the unexpected losses in the said portfolio has been estimated. We find that the capital requirement for the portfolio is lower than the prescribed regulatory capital for the portfolio resulting in savings in capital. Further, a multi-regression analysis has been carried out to ascertain the impact of macroeconomic variables on credit risk in the chosen public sector bank. We find that PLR and MIBOR are the major variables which significantly impact credit risk of the bank.

As regards market risk, most of the public sector banks do not compute VaR for Government securities as it is not mandatory. The different approaches for an internal VaR model for the bank have been studied for estimation of market risk in Government securities. The methods studied were normal VaR, also known as Variance-Covariance approach, Historical Simulation and EVT methods. The model was back tested for validation and implementation in banks. Further banks ignore diversification effect of their investment portfolio leading to higher capital requirement. The diversification effect of the portfolio indicated that estimated VaR is reduced.

Further, for operational risk, public sector banks use Basic Indicator Approach for computing operational risk as there is no framework to record operational losses resulting in its inability to shift to Advanced Measurement approaches.

The operational VaR in a bank has been estimated based on portfolio of lending, investment and services activities of the chosen bank using Delta methodology. Delta is based on error propagation, a technique for measuring uncertainty due to errors and omissions. It enables losses to be predicted even though there is no comprehensive loss data. A bank faces operational risk in lending, investment and services activities. Error contribution in lending

came from standard errors in credit scoring, default and recovery. Errors in investment come from standard errors in valuation, settlement and reconciliation. Similarly errors in services activities came from volume, margin in earnings and its errors and reconciliation error.

High frequency minor losses occur frequently and extreme losses are rare events in any bank. Banks normally do not record these minor losses. Hence no historical record is easily available with the banks. Reserve Bank of India states that any loss above Rs.10,000 would be considered as large loss. This can be considered as a threshold beyond which all losses in a year are to be captured. A hypothetical loss data is developed for a year. These data are classified into events which can happen in different months. Extreme value theory has been applied to determine extreme losses. Using Peak Over Threshold (POT) method a Generalized Pareto Distribution (GPD) is fitted to this data using maximum likelihood fitting to generate ξ, the shape parameter and β, the scale parameter. A Poisson distribution is fitted to the loss events which do not rely on historical events. The Poisson frequency and GPD severity is combined to generate a loss distribution using Monte Carlo Simulation. Using the yearly cumulative loss figures, the excess loss distribution gives the maximum yearly loss at a chosen confidence level.

Keywords : Basel-I, Basel-II, Credit scoring model, Validation, Probability of default, Logit Model, Credit Risk, Standardized Duration Method, Value at Risk, Marker Risk, Back-testing, Delta-EVT methodology, Operational risk.