

Credit Risk Modelling: A wheel of Risk Management

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Abstract

Banking institutions encounter two broad types of risks in their everyday business – credit risk and market risk. Credit risk may be defined as the risk that borrowers might default on their obligations, whereas market risk reflects the variability in the value of their financial position due to changes in interest rates, exchange rates, etc. Over the last decade, rapid strides have been made in developing Value at Risk (VaR) models for managing market risks in a portfolio context. Such models have also been recognized for regulatory capital setting for market risks. However, a similar approach to measure credit risk in a portfolio context was found difficult on account of certain crucial differences between credit risk and market risk.

In the last few years, credit risk models, which attempt to measure risk in a “Portfolio” context, and compute VaR due to credit, have emerged in the market. While significant hurdles, especially relating to data limitation and model validation, still need to be addressed before a VaR type model for credit risk can be accepted as an alternative to the standardized approach to the measurement of capital, such modeling techniques have caught considerable attention amongst the community of bankers and banking supervisors. The present study explores ball-by-ball description of credit risk modeling in reference to the Indian public sector bank

Keywords:

Credit risk, Risk Management, Credit Risk Models, Probability Density Function, Portfolio

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Introduction

Banking institutions encounter two broad types of risks in their everyday business – credit risk and market risk. Credit risk may be defined as the risk that borrowers might default on their obligations, whereas market risk reflects the variability in the value of their financial position due to changes in interest rates, exchange rates, etc. Over the last decade, rapid strides have been made in developing Value at Risk (VaR) models for managing market risks in a portfolio context. Such models have also been recognized for regulatory capital setting for market risks. However, a similar approach to measure credit risk in a portfolio context was found difficult on account of certain crucial differences between credit risk and market risk.

While market rates change from one second to the next, credit events are rare, and hence, the amount of credit data available is much smaller. Also, whereas the historic data necessary to calculate market rate correlations are readily available, correlations in credit quality cannot be readily observed and may have to be inferred from other sources like equity prices.

In the last few years, credit risk models, which attempt to measure risk in a “Portfolio” context, and compute VaR due to credit, have emerged in the market. While significant hurdles, especially relating to data limitation and model validation, still need to be addressed before a VaR type model for credit risk can be accepted as an alternative to the standardized approach to the measurement of capital, such modeling techniques have caught considerable attention amongst the community of bankers and banking supervisors.

Credit Risk Models: Definition and Advantages

Credit risk models attempt to measure and manage credit risk, taking into account the correlations in credit quality between difference borrowers by virtue of the fact that they may operate in the same industries and/or countries, and be influenced by the same economic forces.

The primary objective of credit risk models is to treat credit risk on a “Portfolio” a basis to address issues, such as, qualifying aggregate credit risk, identifying concentration risk, quantifying marginal risk, i.e., the effect on portfolio risk on account of the addition of a single asset, setting risk limits, and last but not least, quantifying economic and regulatory capital.

The traditional techniques for managing credit risk, the use of limits. The common limits used by banks are individual/group borrower limits, which seek to control the size of exposure, concentration limits, which seek to control concentration within industry, instrument type, country, tenor limits, which seek to control the maximum maturity of exposures to borrowers, etc. While the limit system takes care of the various factors, which contribute to the magnitude of credit risk, viz., size of exposure, concentration risk of the borrowers, the maturity of the exposure, etc., on a “stand-alone” basis, it does not provide a satisfactory measure of the “concentration risk” and “diversification benefits” of a portfolio of exposures.

Concentration risk refers to additional portfolio risk resulting from increased exposure to one borrower or groups of correlated borrowers. The common method

used to control concentration risk is exposure based credit limits (individual/group limits). However, such limits tend to be arbitrary in nature. Credit risk models have the potential to address concentration risk in a more systematic manner as they provide risk estimates, which give an idea of the ‘relative riskiness’ of the various exposures in a portfolio. Further, a portfolio view of credit risk facilitates a rational assessment of portfolio diversification. For example, the decision to take an ever higher exposure to a borrower will result in higher marginal risk, which will increase exponentially with increasing exposure to the borrower. On the other hand, a similar additional exposure to another borrower, although having a higher absolute risk, offers a relatively small marginal contribution to the overall portfolio risk due to diversification benefits. Credit risk models, therefore, help in quantifying marginal contribution to portfolio risk on account of addition/deletion of exposures, which in turn aid in quantifying portfolio diversification benefits.

Perhaps, the most significant objective, which the output of a credit risk model can address is in the estimation of the amount of capital needed to support a bank’s credit risk, termed as ‘economic capital’ it is now a well-recognized fact, that the current risk-based capital standards for banks established by the 1988 Basle Accord have significant shortcomings inasmuch as the quantum of capital arrived at under the standard may not be a true measure of the riskiness of a bank’s business. A notable weakness under the current regime is that the risk-weighted assets in the denominator of the capital ratio may not represent the true risk, as all commercial credits are assigned 100 percent risk weight, and therefore, the methodology ignores the crucial difference in credit risk

among different borrowers. The methodology also ignores the effect of portfolio diversification on credit risk. In addition the current risk-based capital standards have provided incentives to banks to indulge in regulatory capital arbitrage – a prime example is the use of asset securitization by banks in the United States to achieve significant reduction in capital requirements without materially reducing the credit risk in their books (although this is not relevant in the Indian context as the securitization market is yet to take off).

Credit risk models facilitate computing a measure of economic capital reflecting more closely the perceived riskiness of the underlying assets of an institution.

Types of Credit Risk Models

Essentially, credit risk models can be classified into two types based on the definition of credit loss. First, Default Mode (DM) models, also called as “two-state” models, recognize credit loss only if a borrower defaults within the planning horizon, i.e., in such models only two outcomes are relevant – non – default and default. Such models are useful in situations, where secondary loan markets are not sufficiently developed to support a full mark-to-market approach. Second, Mark-to-market (MTM) models, also called “multi-state” models, recognize that ‘default’ is the only one of the several possible credit rating grades to which the instrument could migrate over the planning horizon. Therefore, a credit loss under the MTM paradigm is defined as an unexpected reduction in portfolio value over the planning horizon due to either deterioration in credit ratings on the underlying loans or a widening of credit risk spreads in financial markets.

Credit Risk Model: Building

Blocks Type of Model

As described above, there are two types of models to choose from DM models and MTM models, and the approach to the measurement of credit loss depends on the type of model chosen. While the MTM modeling technique is conceptually attractive, as it recognizes the fact that changes in an asset's creditworthiness and its potential impact on a bank's financial position can occur not only on account of defaults but also due to events short of defaults (rating downgrade), its adoption in countries, which do not have a well-developed secondary market for loans (to support a full MTM approach), is difficult.

Choice of Planning Horizon

Along with deciding on the conceptual definition of credit loss, a bank has to choose a time horizon over which to measure this loss. Generally, a constant time horizon, such as, one-year or a hold-to-maturity time horizon under which each facility is assessed according to its maturity is chosen. Normally, a uniform one-year

planning horizon is favoured by banks on account of the fact that (a) accounting statements are prepared on a yearly basis, (b) credits are normally reviewed on a yearly basis, and (c) one year is a reasonable time over which new capital could be raised and / or other loss mitigating action could be taken to eliminate future risk from the portfolio.

Internal Credit Rating and

Transition Matrices

A reliable internal credit rating system is a key component needed to implement a credit risk model, as the probability of a credit facility defaulting within the planning horizon is determined solely on the basis of its internal rating.

Another component required is a 'rating transition matrix', which indicates the probability of a customer migrating from the current rating category to any other category within the time horizon. A sample one-year transition matrix showing the credit rating one year in the future is shown in the **Table** below:

Table 1
 Sample credit rating transition matrix
 (Probability of migrating to another rating within one year as a percentage)
 Credit rating one-year in the future
 Transition Matrix

Initial Rating	Rating at year end (%)							
	AAA	AA	A	BBB	BB	B	CCC	Default
AAA	85.50	13.10	0.40	0.60	0.15	0.14	0.10	0.01
AA	0.70	88.50	7.43	2.05	1.10	0.11	0.10	0.01
A	0.25	1.40	89.40	7.28	1.46	0.12	0.07	0.02
BBB	1.60	1.76	4.55	85.04	6.60	0.27	0.13	0.05
BB	0.05	2.85	3.43	5.04	74.50	8.81	4.04	1.28
B	0.20	0.39	9.17	8.30	2.28	64.34	10.04	5.28
CCC	0.08	0.27	1.87	2.07	12.35	25.87	40.01	17.48

Note: The credit rating transition matrix is based on the historical migration frequencies of publicly rated corporate bonds.

Proprietary rating transition matrices of the above type are prepared by external rating agencies like the Standard & Poor and the Moody's based on historical migration frequencies of publicly rated corporate bonds. Above the transition matrix indicates, for example, that the likelihood of an AA-rated loan migrating to single A within one year would be 7.43%. For DM models, only the last column would be relevant, as such models recognize only two states, viz., default and non-default.

Loan Valuation

The current and future values of each credit instrument at the beginning and end of the planning horizon have to be computed under both DM and MTM models. In the DM model, the current value of a loan is its book value and the future value depends on whether or not the borrower defaults during the planning horizon. If the borrower does

not default, the future value would be the book value at the end of the planning horizon, after adding back the interest and principal payments received during the planning horizon. The future value of a defaulting loan would be the recovery rate measured as the loan's book value multiplied by (1-its loss rate given default). Computation of loss rate give defaults (LGDs) is a difficult task. Banks compute LGDs from a variety of sources which include: a) internal data on the bank's own LGD, wherever available, b) loss rate from external reports like publicly available regulatory reports, c) intuitive judgments of experienced lending officers, etc.

In respect of many types of credit instruments, a bank's exposure is not known with certainty, but will depend on the occurrence of future random events. In respect of a committed line of credit, for example, the customer's drawdown rate would tend to increase as his credit quality

deteriorates, reflecting the higher costs of alternative sources of funds.

Credit risk models treat such ‘credit related optionality’ associated with a line of credit by treating the draw-down rate as a known function of the customer’s end-of-period credit rating. For example, consider a one-year line of credit that is initially undrawn. Then, depending on the customer’s credit grade at the end of the planning horizon, assumed end-of-period draw-down rate would be based on the average historical draw-down experience of customers having that future grade. In the DM framework, the undrawn facility is converted into a loan equivalent exposure (LEE) to make it comparable to a term loan. The LEE is calculated as the expected draw-down under the line in the event the customer becomes insolvent by the end of the period (if the customer remains solvent, the size of the draw-down is irrelevant in a DM model, as credit losses would be Zero).

Credit Events Correlation

After determining the current and future values of each credit instrument, the next step is to consider the correlation among the factors determining credit-related losses. According to modern portfolio theory, portfolio credit risk is not just the summation of the credit risk of the individual credit instruments comprising the portfolio, there is also an element of system risk on account of joint movements in loan values arising from their dependence on common influences. Across customers, correlations exist among (a) rating migrations/default events (b) loss rate given defaults (LGDs) and (c) term structure of credit spreads and LGDs. (Under DM models, of course, credit spreads are irrelevant). For example, it is well known

that the fortunes of the tyre industry are linked to that of the automobile industry. Therefore, a rating downgrade of an exposure in the automobile sector is very likely to trigger off a similar downgrade amongst borrowers in the tyre industry. However, while bankers are well aware of such correlation, its quantification is difficult in practice. Quantification of such correlations is the most challenging and the least evolved area in credit risk modeling. Under the current generation of credit risk models, correlation between details/rating migrations and LGDs, between LGDs and term structure of credit spreads and between rating migrations and changes in credit spreads are assumed to be zero. The only correlation effects considered are the correlation between defaults/rating migrations of different customers.

One of the methods used to estimate the correlation among defaults/rating migrations of different customers is to represent each customer’s credit migration at the end of the planning horizon in terms of a future realization of a migration risk factor (e.g., customer asset value or net worth). Thus, a customer might be assumed to default if the underlying value of its assets falls below some threshold, such as, the level of his liabilities. For MTM models, the change in the value of a customer’s assets in relation to the various thresholds is often assumed to determine the change in its risk rating over the planning horizon. It is the correlation between these migration risk factors, which determines, implicitly, the correlation among borrowers’ defaults/rating migrations.

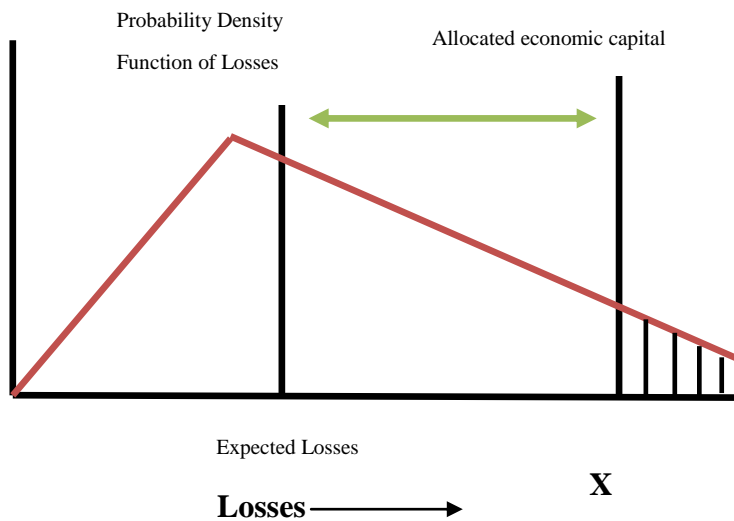
Probability Density Function

Once all the parameters are specified as described in the above paragraphs, the credit

risk model can be used to quantify credit risk through a concept called ‘probability density function (PDF)’ of credit losses over the chosen time horizon. PDF is computed essentially using either of the two methods (a) Monte Carlo Simulation, or (b) Approximation using a mean/standard deviation approach.

The concept of PDF and the process of setting economic capital using the same is explained with the help of the graph below:

Graph 1: PDF and Economic Capital



While a standard shape of PDF is yet to emerge unlike in the case of market risk models (where the normal distribution has evolved as the standard), observed portfolio credit loss distributions are typically skewed towards large losses as shown in the graph – the PDF of a risky portfolio has a relatively long and fat tail. An important property of the PDF is that the probability of credit losses exceeding a given amount X (as shown in the graph) is equal to the shared area under the PDF to the right of X. while

provisions are made to take care of expected losses (which represent the amount of losses a bank expects to incur in the normal course), economic capital covers unexpected credit losses (which is the amount by which actual losses exceed the expected losses). The amount of economic capital depends on the target credit loss quintile chosen. Due to the long-tailed nature of distribution of credit losses, a target quintile in the range of 99.0-99.8% interval is chosen when compared to 95.0-99.0% interval chosen in market models. Thus, if the confidence interval is set at 99.97% (which corresponds to a target insolvency rate of 0.03%), it means that there is only a 0.03% estimated probability that the unexpected credit losses would exceed the amount of economic capital set aside by a bank corresponding to the chosen insolvency rate.

Under the mean/standard deviation approach (which is mainly used in the context of DM models), the PDF is assumed to take the shape of a beta or normal distribution and the economic capital allocation process generally simplifies to setting capital at some multiple of the estimated standard deviation of the portfolio’s credit losses. The overall portfolio risk under the method is summarized as follows:

The portfolio expected credit loss (u) over the chosen time horizon equals the sum of the expected losses for the individual credit facilities:

$$u = \sum_{i=1}^a EDF_i \times LEE_i \times LGD_i$$

Where, for the i facility,

EDF i is the facility’s expected probability of default,

LEE i is the bank’s expected credit exposure, and

LGD i is the expected loss rate given default.

The portfolios expected standard deviation of credit losses (σ) can be expressed as:

$$\sigma = \sum_{i=1}^a \sigma_i \times p_i$$

Where, σ_i is the stand-alone standard deviation of credit losses for the i facility, and p_i denotes the correlation between credit losses on the i facility and those on the overall portfolio.

Further, the stand-alone standard deviation of credit losses for the i facility can be expressed as:

$$\sigma_i = \sqrt{LEE \times EDF_i \times (1 - EDF_i) \times LGD_i^2 + EDF_i \times VOL^2}$$

Where VOL is the standard deviation of the facility's LGD.

The mean/standard deviation method attempts to approximate the PDF analytically and does not take much time for execution. Monte Carlo simulation technique, on the other hand, characterizes the full distribution of portfolio losses. However, it is computationally burdensome and can take several days for execution. The technique, which is used in MTM models, involves generating scenarios, with each scenario corresponding to a possible credit rating of each of the obligors in the

portfolio. For each scenario, the portfolio is revaluated to reflect the new credit ratings. Thus, a large number of possible future portfolio values are generated, with which the distribution of portfolio values is estimated. Thereafter, a target insolvency rate is chosen and the corresponding quantum of economic capital is computed.

Conclusion

While credit risk models are not a substitute for sound credit appraisal systems, it is now generally accepted that such models have the potential to contribute significantly to enhancing the internal risk management systems in banks. The future scenario in this regard is articulated in the consultative paper issued by the Basel Committee on Banking Supervision on the new capital adequacy framework. The Committee intends to explore ways in which such models could play an explicit part in the regulatory capital setting process. The Indian banks, especially those which are internationally active, would do well to critically study the credit risk models available in the market (the two prominent models for which extensive technical documentation is available are Credit Metrics by J.P. Morgan and Credit Risk⁷ by Credit Suisse Financial Products), and prepare themselves for a model-based approach to the measurement of risk capital in the future.

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