RISK MANAGEMENT – RETAIL VS WHOLESALE LENDING

By
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At the heart of credit risk measurement and management is a fear: what has gone shall not return. The process of risk management, therefore, becomes a series of mechanisms to pre-empt such an occurrence. The process of mitigation, in whatever form expressed, starts as early as the disbursement stage and continues till the money comes back to the lender—along with the interest.

The business of lending for single, large ticket transactions (usually referred to as 'wholesale lending') is structurally different from large volume homogeneous lending (usually referred to as 'retail lending'). It is important to understand the distinction since the modelling structures applied for risk measurement and monitoring of exposures take different forms to accommodate the differences.

The following peculiarities differentiate the management of retail credit risk visà-vis wholesale credit risk.

- The vehicles for retail lending are products that are homogeneous in nature while wholesale lending tends to have products tailor-made for custom purposes. The homogeneity of retail business products makes it imperative that demographic segmentation is accurate to achieve construction of portfolios which, in turn, are homogeneous.

- The customer takes a front seat in the understanding of retail credit risk, while product characteristics drive the understanding of the embedded credit risk in wholesale lending. Thus, capturing customer information (and possibly superimposing it with localized economic indicators) at every step of a relationship and integrating such information become the keys to effective credit risk management in the retail lending business.

- The "explanatory variable set" – and its myriad combinations – which explains risk at different phases of the credit lifecycle is much more for retail credit than it is for wholesale. This is because the demographics associated with a consumer (or consumer group) are many. This has created enormous scope for quantitative modellers and, as a result, the application of quantitative techniques in the measurement of retail credit risk has increased manifold. Unlike wholesale credit risk, where the concentration of the monitoring activity lies primarily in the account maintenance function, retail credit risk management and monitoring cuts across the entire credit lifecycle.

Retail Credit Lifecycle - Best Practices

Table 1 represents the retail credit lifecycle and the different activities that are part of each phase.

Table 1

<table>
<tr><td colspan="2" rowspan="2">CREDIT SCORING</td><td>CREDIT QUALITY MONITOR</td><td rowspan="2">CREDIT COLLECTIONS</td></tr>
<tr><td>LOSS FORECASTING</td></tr>
<tr><td>External</td><td>Internal</td><td>FORTFOLIO ANALYSIS</td><td>CREDIT RECOVERIES</td></tr>
<tr><td colspan="2">Origination</td><td>Acct Maintenance</td><td>Collection and Recovery</td></tr>
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Credit Scoring

The predominance of credit bureau information on retail credit scores has converted credit risk measurement at origination from a specialized function to a 'commoditized' task. The emergence of specialized organisations using tested odels to generate scores like FICO have found wide acceptance. However, prudent lenders tend to blend in-house rating scores with the external ratings to arrive at scores that are finally used in the credit approval process. Such techniques become important especially under the following situations.

- The lender, from its modelling of change of state or otherwise, has reasons to believe that the current demographic characteristics of the customer has a predictive risk profile (that is, a forecast of how such demographic accounts have behaved post credit disbursement) that merits adjustments to the current score.

- 'Look-back' analyses demonstrate that the scores given by external agencies were not representative of current status. Lenders regularly apply such techniques to gauge the efficacy of scoring models.

While the benefits of blending internal with external scores cannot be understated, the challenge lies in the ability to provide accurate and consistent demographic information to the scoring models. This has to be systematic in order to understand the changing nature of the demographic segmentation input and interpret the credit scores accordingly.

Credit Quality Monitor

Monitoring the health of an account is the main task of the Account Maintenance function at the lender institution. There is no one technique of measuring ongoing quality of credit but prudent lenders choose from multiple representation of the information to estimate the health of portfolios. This task is more onerous than it seems, largely because of the volume of the retail lending business. Lenders tend to create and monitor the health of homogenous portfolios rather than that of individual accounts. This poses a challenge in terms of drilling through from aggregated data (portfolios) to granular data (accounts) seamlessly.

The following are popular methods of monitoring credit quality:

- Delinquency-based analysis (both coincidental and lagged delinquencies)
- State Transition matrices (both volume and accounts)
- Credit Score Transition matrices
- Loan-to-value analysis

The emerging solution has to provide a choice of models, possessing a proven power for explaining the dependant state.

Loss Forecasting

Risk assessment techniques and methodology, as applied to retail portfolios, are quite different from those applied to corporate portfolios mainly because of the non-efficacy of a case-by-case judgmental effort and the unavailability of a rich default history to base statistical models of potential loss.

Banks, especially those with advanced systems and techniques, tend to adopt most loss concepts (Probability of Default, Expected Loss and Delinquency), and a computation of Expected Loss (EL) based on Probability of Default (PD), Loss Given Default (LGD) and Exposure at Default (EAD) is clearly the norm amongst sophisticated banks. Table 2, excerpted from a study by ISDA, shows the relative popularity of different loss forecasting methods employed by a sample of internationally diversified banks with significant retail exposures.

Table 2

Bank	Historical loss	Roll Rate	Application score	Behavior score	Markov matrix	Other
1	*					
2		*				Manual Adjustment
3			*	*		
4	*	*	*	*	*	
5	*	*	*	*		Transition matrix
6	*					
7				*		
8	*	*	*	*	*	
9	*		*			Trend analysis
10	*			*		
11			*			Trend analysis
12	*					
13	*	*				Vintage analysis
14	*	*		*		Customized scores

Note: Bank names have been masked to retain anonymity

From the table, it is evident that Historical Loss analysis still remains the most popular method of loss forecasting. This poses a challenge to data management. Data management implies ensuring appropriate information at demanded granularity over user-chosen time periods, pre-modelled for timely and accurate analysis.

In addition to the techniques mentioned, Delinquency Flow models and Segmented Vintage analysis are now commonly used to identify portfolio dynamics and behaviour patterns. A large measure of the credit for ushering in this sophistication must lie with credit card companies with their massive segmentation profiles and advanced analytical models.

The last logical step in loss forecasting, and certainly not least in terms of importance, is the validation of the loss forecasting model. In the case of retail credit risk, this process is relatively simple as the loss behaviour is modelled with internal historical information, making ongoing validation and calibration of models that much easier. Several statistical techniques are popular as validation/ calibration models. For example, scorecard performance is monitored against predicted performance to enable review of the choice of parameters by means of well-known statistical techniques such as Discriminant Analysis.

Credit Portfolio Modelling

Until recently, lenders and regulators have tended to push for loss modelling of commercial and industrial portfolios, with relatively little focus on retail credit risk modelling. The over-emphasis on modelling idiosyncratic risks of a large commercial portfolio possibly made more economic sense. However, over the last decade, a push from regulators and the dominance of the retail business, as a consequence of lower industrial activity, has seen hectic activity in the retail portfoliomodelling scene. Based on their levels of sophistication, lenders follow either of the two methods for credit portfolio modelling.

Descriptive or Non-causal Models

Being a simple model, this is popular as well. In this method, portfolio loss standard deviation is computed either based on historical distribution or based on standalone computation of PD and LGD (most lenders do not complicate computations by introducing correlations between the two). Subsequently, a multiplicative factor is chosen to represent a confidence interval and the resultant is recognized as the economic capital.

Some lenders do adopt techniques that use fixed form distributions for default events (e.g.,beta or gamma distributions) and deriving loss distributions considering LGD as a separate variable. From this distribution, the loss corresponding to a given percentile is extracted.

Though not a necessity for lenders adopting this approach, calibrating models for greater accuracy demands that initiatives are undertaken to develop independent causal models for default and LGD rates.

Causal Models

Lenders at the highest grade of sophistication employ causal modelling that invariably tends to take the form of factor models. These models allow lenders to anticipate changes in default rates and their distributions due to macro-economic changes, and model default correlation across portfolio segments.

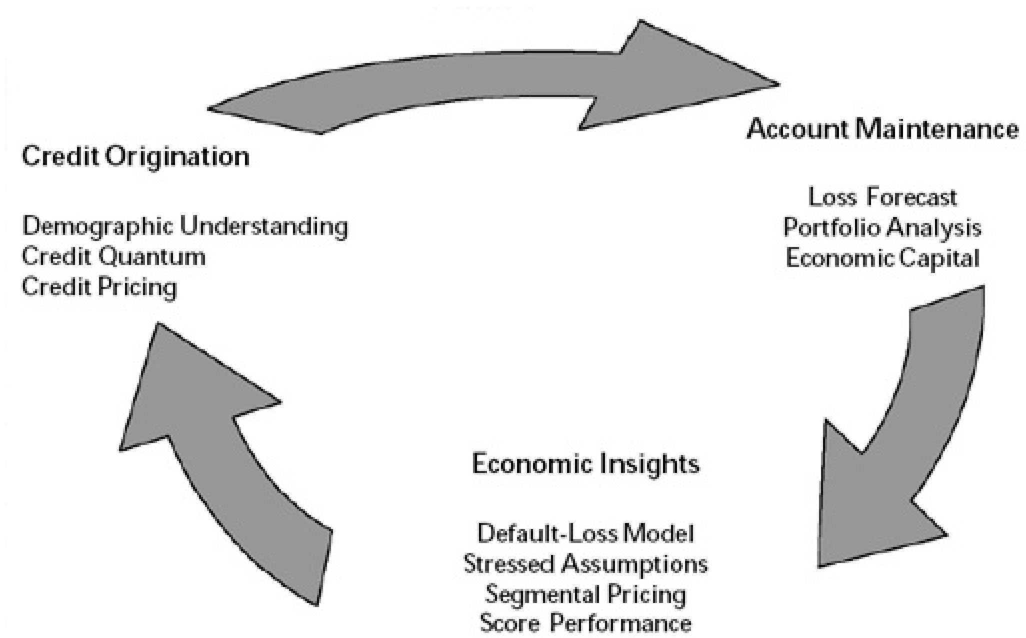
Similar causal relationships can be developed for LGD. For example, a codependency between LGD and default probabilities may be introduced by modelling LGD using risk drivers identical to those (or at least some of those) retained for default rates. This is a particularly desirable feature for those classes of assets where a general dowturn in the economy affects both default and loss rates (for instance, via loan to value ratios).

Validating deployed models against the actual (back-testing) and subjecting the model assumptions to extreme situations (stress-testing) go a long way in understanding out-of-tail situations and model efficacy. In fact, allowing subsequent state-representation analysis by stressing the factors could be a big incentive for lenders to develop factor models. Validating retail portfolios as compared to corporate lending is simpler because default events are more frequent in retail portfolios, portfolios are more homogenous and stable through time, and longer loss time series are available as data is predominantly internal.

The Federal Reserve Board of Philadelphia, in its recent initiative to foster greater sophistication in retail credit risk monitoring observes: '…the future of consumer credit risk management lies in organizing portfolio performances and account level details into databases and then applying refined analytical models to discern pattern or trends.'

Credit Risk for Strategic Decisioning

Herding is seen as a common phenomenon amongst retail lenders—that is, the propensity to follow the herd in pricing of loans. However, information computed in some of the credit lifecycles described earlier, especially in the area of loss forecasting and credit portfolio modelling, has the potential to provide strategic inputs to pricing. Economic capital understanding for portfolios assumes significant importance in order to be able to deliver superior risk adjusted pricing to different segments within portfolios or sub-portfolios. Such demographic segmentation can only be achieved if the information repository is deep and rich, and able to support multiple segmentation models. For an information ecosystem, the challenge lies in the possibility of analytical applications 'closing the loop' with the origination information systems so that credit cycle end-state economic insights are pumped back towards origination (Figure 1). The success of such a 'virtuous cycle' would, in-turn, result in superior risk-segmented pricing.



Technology the Enabler

Profit motives and regulatory directives (notably Basel II, which provides incentives by way of lower capital set-asides for adopting superior risk management techniques) have and shall continue to drive best practices in credit risk management for retail lending. Advances in technology provide the necessary impetus for these models to bridge the gap between academic articulation and actual deployment in production environments.

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