Commercial vehicle securitisation: Loss given default estimation using Transition Matrix (TM-LGD)

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Nearly 40% of households (Roy, 2011) and 92% of small enterprises (Ministry of MSME, India, 2011) in India are financially excluded. The total credit demand is estimated to be around INR32.5 trillion (IFC, 2012). A large share of these borrowers do not have sufficient credit history, income documents, collateral assets and sufficient proof to establish residential or business stability which is often required by traditional lending institutions to evaluate their creditworthiness. To meet this growing demand for credit, many lending institutions have entered the market with niche lending models. However, the risky profile of underlying borrowers makes it difficult for the lending institutions to access capital from mainstream capital-market players such as mutual funds, insurance companies, bank treasuries, other financial institutions and asset management firms who have different risk-return expectations.

Structured finance has enabled the access to capital markets for such lenders across different asset classes including microfinance, small business loan lenders, vehicle finance and affordable housing finance. IFMR Capital, an India-based non-banking financial institution, has successfully demonstrated how securitisation helps lenders across different asset classes to sustainably access capital at an affordable cost. MOSEC™ (multi-originator securitisation) has further allowed small lenders to pool their loans together to reach a critical size required to justify higher costs for a capital market transaction and has provided risk mitigation to investors through diversification across different originators-cum-servicers (Anand & Fernandes, 2012). Securitisation allows structuring of the investors cashflows to meet their risk-return requirements. Further, through different forms of credit enhancements such as cash collateral, excess interest spread (EIS), over-collateralisation and liquidity facilities, the securitisation structure can provide the required risk cover to investors.

However, it is important to determine the size and type of risk cover required. The appropriate credit enhancement is a function of the risk-return expectations of the investors, the credit behaviour of underlying portfolio and servicer risk among other things. This article discusses a methodology developed and used by IFMR Capital to understand the periodic credit behaviour of the underlying loans and to estimate the required credit enhancement to cover losses due to prepayment and default of underlying loans. This loss estimation methodology is called Transition Matrix & Loss Given Default (TM-LGD) Model. The article discusses the model and its implementation through a case study based on the loss estimation for a securitisation transaction with underlying commercial vehicle loans.

Repayment behaviour of certain secured asset class

Loan repayment behaviour differs across asset classes along with the borrower profile. In microfinance, under the joint liability group model (also known as the Grameen model discussed in detail by Fernandes (Fernandes, 2011)), the repayments are seen to be extremely regular with close to 99% periodic collection efficiency[1] (Fernandes, 2011). On the other hand, in small business loans, affordable housing finance and commercial vehicles loans the periodic collection efficiency may range from 90% to 95%. However, in these asset classes the ultimate loss on the portfolio may be significantly smaller as compared to the peak delinquency levels during the tenure of the portfolio. The key reason for such performance is that higher delinquency levels in secured asset classes are usually followed by higher recoveries and, possibly, prepayments. Such cycles, in turn, are driven by cash flow and income volatility of the underlying borrowers as well as delinquency management practices of the lenders.

It is important to capture the loss and periodic shortfalls due to such credit behaviour. The loss and default distribution estimated based on the ultimate performance of the portfolio, no matter how accurate, may not help in estimating the periodic shortfalls or windfalls in investor cashflows during the life of the transaction. In order to model cashflows accurately, the method should be able to model the transitions of loans across different delinquency levels during its tenure. The TM-LGD model does this by first converting the periodic credit behaviour of loans into a 'transition matrix' (or TM) and then estimating the periodic cashflows using Monte-Carlo simulations.

Case study

Commercial vehicle financing

Commercial vehicles (CV) are the vehicles used by businesses either to transport goods or to transport passengers. The CV segment comprises of medium and heavy CVs (MCV and HCVs) used for heavy transportation typically over long distance, and light CVs (LCVs) which are multi-purpose vehicles and preferred for intra city transportation and end-point connectivity. The borrower segment typically consists of transporters, drivers and first time users (FTUs) and first time borrowers (FTBs). Transporters can be categorised as large, medium and small transporters based on the size of their fleet. FTUs and driver-cum-owners own a single vehicle which they drive themselves. FTBs are borrowers with prior experience managing a commercial vehicle borrowing to purchase a CV for the first time. FTBs and FTUs are generally not financed by large lenders who view them as risky borrowers. Banks and large non-bank financial companies prefer to fund new vehicle purchases. Used vehicle purchases are funded by many small and medium non-bank financial companies and some large non-bank financial companies.


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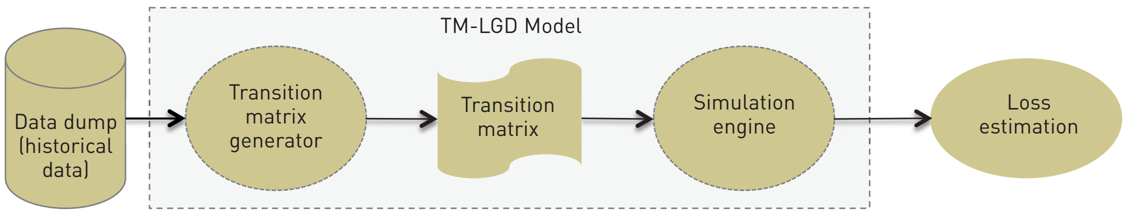
TM-LGD model schema **Exhibit 1**



Source: IFMR Capital

CV securitisation

IFMR Capital structures, arranges and co-invests securitisation transactions, among other financial products, to enable capital market access to high quality originators. It invests in the subordinate securities issued under securitisation to ensure its skin-in-the-game and align interest with those of the investors. IFMR Capital structured and arranged the first microfinance securitisation in October 2009. Since then it has completed more than 200 structured finance transactions in microfinance, small business loan, vehicle finance and affordable housing finance companies. The first commercial vehicle (CV) securitisation was completed in October 2013 and since then IFMR Capital has completed 11 CV securitisation deals with more than INR2.7bn principal.

The article discusses an illustrative CV portfolio with underlying principal of INR280m to be securitised. The illustrative transaction, named here IFMRC CVX, has close to 2,000 CV loans originated by a vehicle finance company based in India. The underlying portfolio has loans originated in different districts across different commercial vehicle types, loan-to-value, borrower types, tenure and loan amount among other factors.

The investor cashflows in IFMRC CVX are structured as senior and junior tranches. The interest and expected principal cashflows to the senior investors are promised at every payout period, which is monthly. The cashflows to the junior tranche are paid only after the senior tranche is completely paid after which the interest cashflows to junior tranche are promised at every payout date but the principal amount is promised only at maturity. In order to meet the shortfall at every payout period as well as at maturity, credit enhancement in the form of cash collateral, excess interest spread and over collateral are provided. However, in order to determine the minimum credit enhancement to cover credit losses, it is important to understand the credit behaviour of the underlying loans. In the next section we describe how we use TM-LGD to gain insight into the borrower credit behaviour and estimate periodic as well as ultimate losses on the portfolio.

TM-LGD model

Motivation for TM

Based on the repayment behaviour, a loan may move to different states (delinquent, current, prepaid or pre-closed). The states referred to in this article are defined as follows: If a loan defaults on a monthly repayment for the first time, it moves to a delinquent state of ‘days past due more than 0’ (or PAR0) which means that the loan is delinquent for more than 0 (zero) days. If the same loan defaults another monthly repayment, it moves to PAR30, and so on. Similarly, a loan can move back to lower delinquency states if overdue repayments are made. If a loan pays more than the due amount, it moves to 'prepaid' state. Similarly, if the borrower prepays the total principal outstanding before the maturity date, the loan is said to be pre-closed. Capturing this movement is helpful in estimating the periodic cash flows and ultimate loss on a portfolio. TM captures these loan transitions across different states using the historical repayment behaviour of the borrowers. IFMR Capital uses a proprietary algorithm to estimate the TM from the historical repayment data.

TM interpretation

A TM is an *n-by-n* matrix with rows denoting the initial states and columns denoting the future states after a transition. A single TM gives the probability of transition over a single repayment period, i.e. over a month for loan with monthly repayment frequency. However, theoretically one can construct a TM for transitions over multiple repayment periods or even the complete tenure of the loans. The ICMFC CVX pool has loans with only monthly repayments and the article refers to the TM with transition probabilities over a single month only. An illustrative TM for transition during a particular month *m* is shown in Exhibit 2. The circled number A (1.9%) denotes the probability of a loan to miss one repayment and move from Current or Normal state at the end of month *m-1* to PAR0 at the end of the month *m*.

It is intuitive to think that credit behaviour may change based on the age of the loan, i.e. based on the value of *m*. Hence, in order to capture the transitions of loan with tenure of 24 months, one would need as many as 23 TMs, i.e. month 1 to month 2, month 2 to month 3,..., month 23 to month 24. As a result, for a portfolio the TM denotes a set of multiple transition matrices based on the tenure of underlying loans (Exhibit 3).

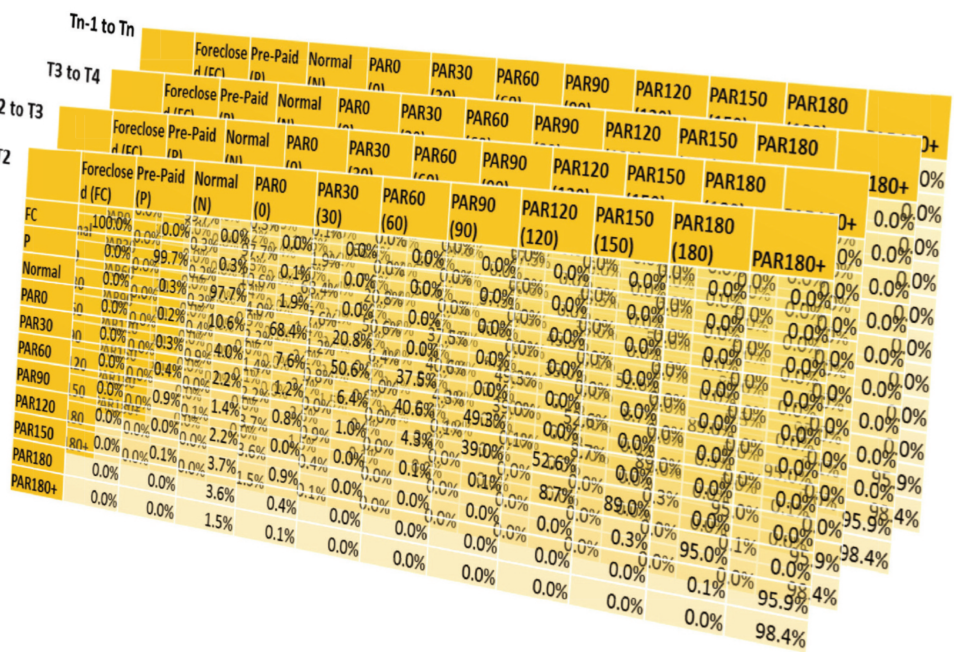
Credit behaviour and resulting losses may further vary based on borrower profile, type of vehicle financed, loan-to-value, and loan amounts among other factors. For example cashflows for HCV borrowers may have higher correlation with business cycles and industrial activity, as compared to those of LCV borrowers. Similarly, certain vehicle types may have higher demand in the used vehicle market resulting in higher recoveries to the lender from sale of vehicles repossessed from delinquent borrowers. Certain borrower profiles such as drivers with temporary contracts may face higher volatility of cashflows. A preliminary analysis of historical data may help in identifying key factors. Separate TMs should be generated for loans which fall in 'similar' credit behaviour categories.

Illustrative transition matrix **Exhibit 2**

	Pre-closed (PC)	Pre-Paid (P)	Normal (N)	PAR0 (0)	PAR30 (30)	PAR60 (60)	PAR90 (90)	PAR120 (120)	PAR150 (150)	PAR180 (180)	PAR180+
PC	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
P	0.0%	99.7%	0.3%	0.1% A	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Normal	0.0%	0.3%	97.7%	1.9%	0.0% B	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
PAR0	0.0%	0.2%	10.6%	68.4%	20.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
PAR30	0.0%	0.3%	4.0%	7.6%	50.6%	37.5%	0.0%	0.0%	0.0%	0.0%	0.0%
PAR60	0.0%	0.4%	2.2%	1.2%	6.4%	40.6%	49.3%	0.0%	0.0%	0.0%	0.0%
PAR90	0.0%	0.9%	1.4%	0.8%	1.0%	4.3%	39.0%	52.6%	0.0%	0.0%	0.0%
PAR120	0.0%	0.0%	2.2%	0.0%	0.0%	0.1%	0.1%	8.7%	89.0%	0.0%	0.0%
PAR150	0.0%	0.1%	3.7%	0.9%	0.0%	0.0%	0.0%	0.0%	0.3%	95.0%	0.0%
PAR180	0.0%	0.0%	3.6%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	95.9%
PAR180+	0.0%	0.0%	1.5%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	98.4%

Source: IFMR Capital

TM as a set matrices to capture transitions over the tenure of loans **Exhibit 3**



Source: IFMR Capital

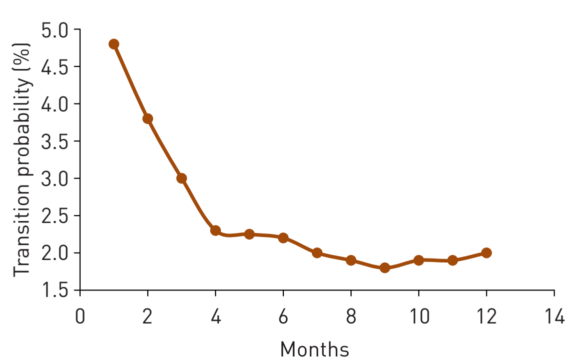
Visualising the TM

Transition probabilities from a given state to another can be seen as line or curve as shown in Exhibit 4. However, transition probabilities for multiple state transitions form a surface which guides the loan transition during the tenure (Exhibit 5).

Estimating loss-given-default (LGD) using TM

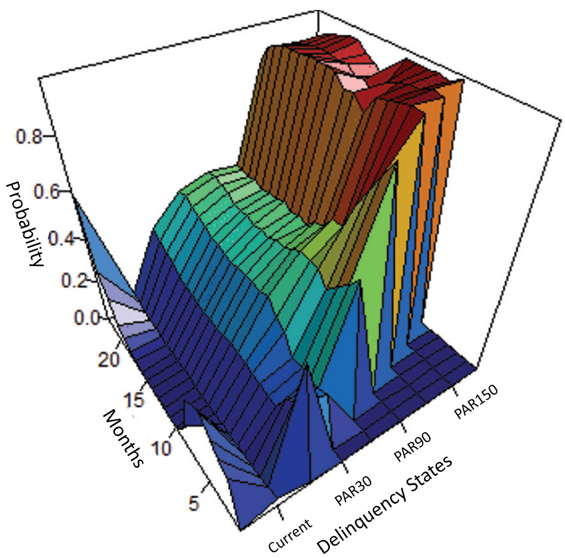
There are close to 2,000 loans in the underlying portfolio for IMFRC CVX securitisation. In order to estimate the periodic cashflows, the TMs generated earlier are used to simulate the possible states for all the loans in the portfolio. Based on TMs, path of each loan in the portfolio is simulated a large number of times (~ a million times). Each simulation represents a set of paths for all the loans, which denotes a single state of the universe of all the

Transition probability curve for single transition (from 'Current' to 'PAR') **Exhibit 4**



Source: IFMR Capital

Transition probability surface for multiple state transitions **Exhibit 5**



Source: IFMR Capital

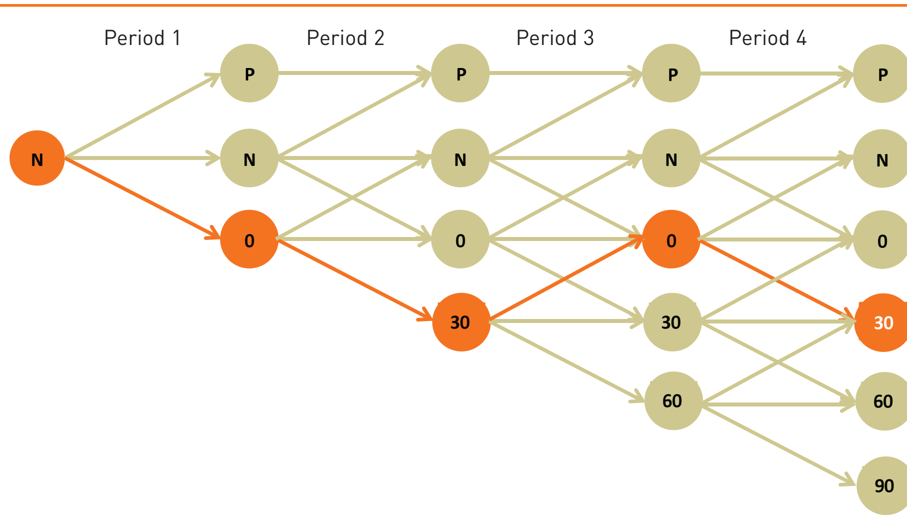
possible states through which the portfolio can evolve during its life. So a large number of simulations are done to theoretically cover as many states of the universe as possible (Exhibit 6).

With each transition, there is an associated cash flow which could be zero (default), one repayment instalment (normal payment), more than one repayment instalment (partial prepayment) or all the amount outstanding (full prepayment leading to pre-closure of the loan). Periodic cashflows are estimated using these transitions for each simulation. Exhibit 7 shows a comparison between the simulated and original scheduled cashflows for the portfolio for a single simulation. Using these periodic shortfall (or excess) and ultimate loss on the portfolio is estimated.

Estimating loss in the transaction

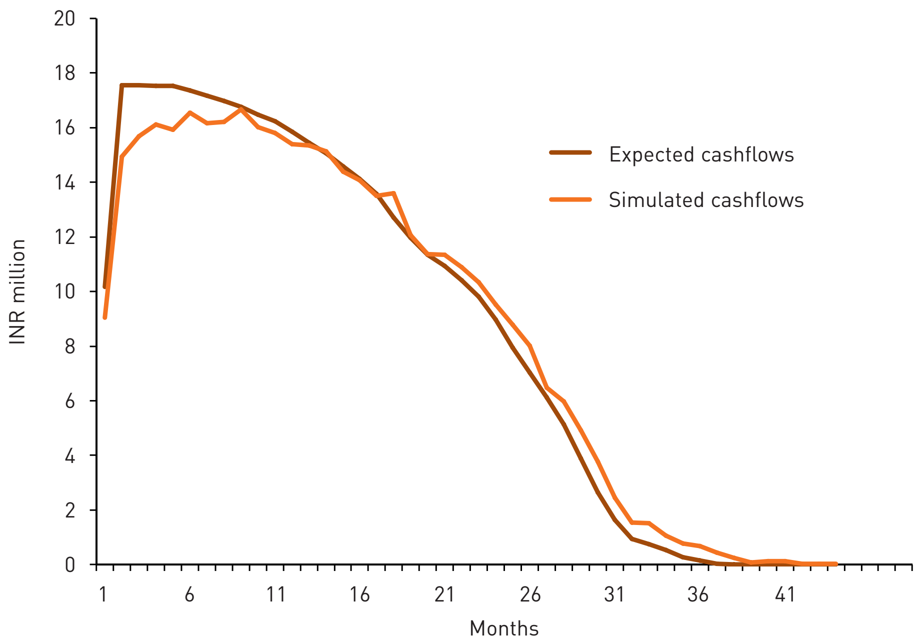
The average loss on the illustrative IFMRC CVX portfolio using the TM-LGD model is 2.6% of the pool size. The model also enables us to estimate the probability distribution of the loss as shown in Exhibit 8. The portfolio loss at 95% and 99% confidence level is close to 3.1% and

Simulating the loan path using TMs **Exhibit 6**



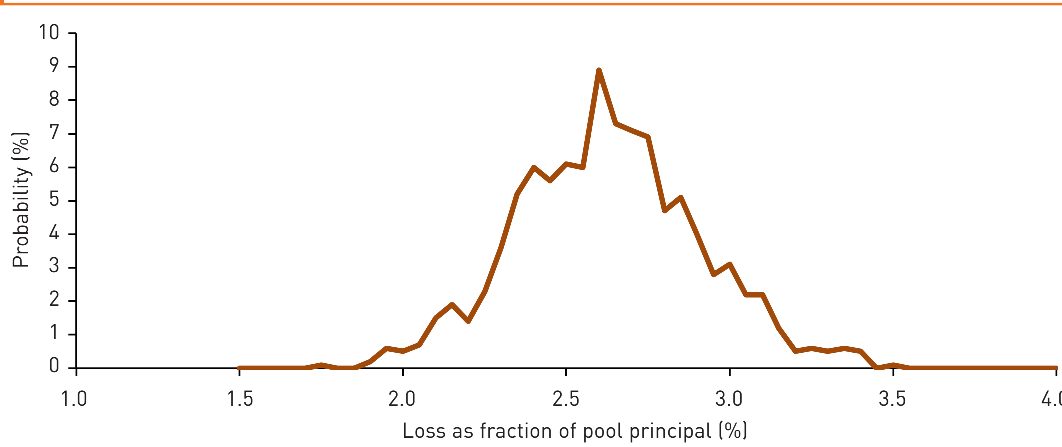
Source: IFMR Capital

Comparison between simulated and scheduled cashflows **Exhibit 7**



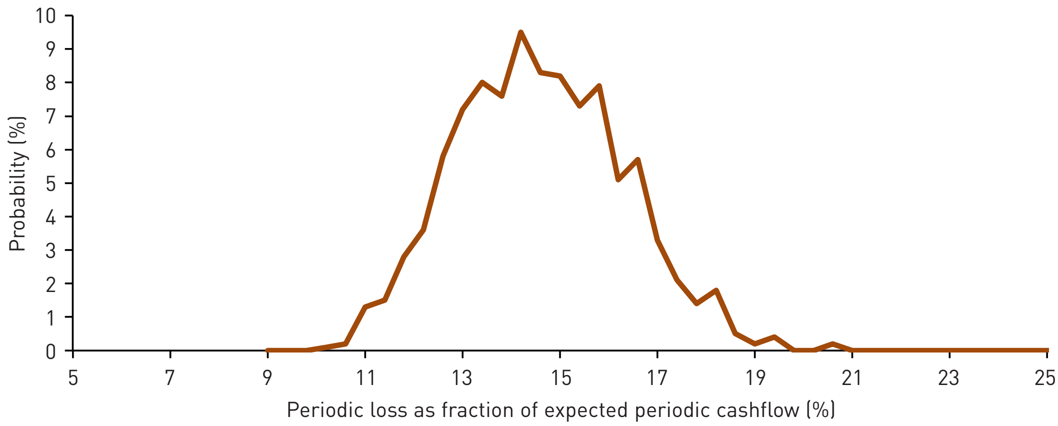
Source: IFMR Capital

Loss distribution on the illustrative portfolio using TM-LGD **Exhibit 8**



Source: IFMR Capital

Probability distribution of maximum periodic shortfall **Exhibit 9**



Source: IFMR Capital

3.5% respectively. The loss at certain confidence level can be used to determine the required credit enhancement to cover credit losses.

The model also enables us to estimate the distribution of periodic cashflow shortfall to the investors and collection efficiency. Though the maximum loss on portfolio appears to be close to 3.5%, the maximum periodic shortfall can be significantly higher as shown in Exhibit 9. So, the total loss as well as periodic shortfall plays an important role in determining the required credit enhancement based on the investor risk-return expectations.

Backtesting

Once the future cashflows and shortfalls have been estimated using the TM-LGD model for a portfolio, it is important to validate the TM and other model assumptions using the actual portfolio performance at regular intervals. Estimated levels of delinquency on the portfolio and estimated periodic cashflows should be compared with the actual performance to evaluate if the model is an acceptable reflection of the actual credit behaviour. Significant deviations in credit behaviour and origination practices may warrant change in TM or the model assumptions. Actual performance of portfolio and repayment behaviour should provide a feedback loop to the TM and the updated TM and assumptions should be used to recalculate the loan paths and future cashflows on the portfolio.

Limitations

The TM-LGD model is not without its limitations. These should be taken into account while implementing the model and interpreting the results. The model is dependent on the past repayment behaviour of the borrowers in the asset class. Unless explicitly corrected for, the TM assumes that the borrowers will continue to behave in the same way towards economic stress, repayment fatigue and other known events. Further, the model assumes that the origination and collection processes of the originator-cum-servicer will continue to reflect the historical practices. Such an assumption should be verified through a field visit, study of originator's underwriting process or through a management discussion.

Preparation of TM is a data intensive process and may require significant cleaning and pre-processing of historical repayment data. The TM is as good and reliable as the base repayment data. However, getting sufficient data covering the loan life cycle as well as business cycles in an industry can be challenging. Further, as the number of observed transitions falls in the historical data, the error associated with derived transition probabilities increases. Also, the estimated TM, and hence portfolio simulations based on it, are strictly based on the repayment information available in the historical portfolio. Any recovery or loss incurred but not reflected in the historical billing and collection information may not be incorporated in the TM and its derivative loss estimations.

Further, the repayment volatility of the past may have a significant impact on future credit behaviour of the loans. However, the TM-LGD model discussed in the article does not factor in the path taken by a loan to estimate its future transition probabilities.

Conclusion

TM-LGD is a powerful yet flexible methodology to understand the credit behaviour of portfolio at a granular level, to estimate periodic cashflows and loss distributions for the portfolio. It allows capturing the differences in loan transition probabilities based on seasoning[2], tenure, borrower profile and type of asset financed among other factors. TMs can be built using the historical repayment data and can be adjusted for new repayment observations. TM-LGD can be used to estimate the efficacy of the available credit enhancement on a portfolio. Further, TMs can be used to construct stress scenarios by selectively increasing or decreasing the forward and backward transition probabilities based on observed credit behaviour during periods of stress such as economic shocks and natural disasters. IFMR Capital uses TM-LGD model to gain insight into the credit behaviour and estimate portfolio losses across multiple asset classes including vehicle finance, small business loans and microfinance. However, the model has its limitations. Underlying historical repayment data and the evaluated portfolio should be similar in credit behaviour as well as lending and collections practices. Otherwise adjustments to the TM and LGD assumptions should be made to reflect the variances.

Bibliography:

- Anand, V., & Fernandes, K. (2012). Multi-originator Securitisation in Microfinance. *The Euromoney Securitisation and Structured Finance Handbook 2012/13*, pp. 29-37.
- Fernandes, K. (2011). A Structured Finance Approach to Microfinance. *The Euromoney Securitisation & Structured Finance Handbook 2011/12*, pp. 56-64.
- IFC. (2012). *MSME Finance in India*. IFC.
- Ministry of MSME, India. (2011). *Forth All India Census of MSME*. New Delhi: Development Commissioner, MSME.
- Roy, D. (2011). *Financial inclusion in India: Emerging profitable models*. Chennai: Indian Banks' Association.

Notes:

1 Collection efficiency is defined as the ratio of the actual collections to expected collections for a period.

2 Seasoning is defined as the number of repayment periods a loan has already been serviced by the borrower.

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