Credit Risk in Banking: Managing the Impact of COVID-19

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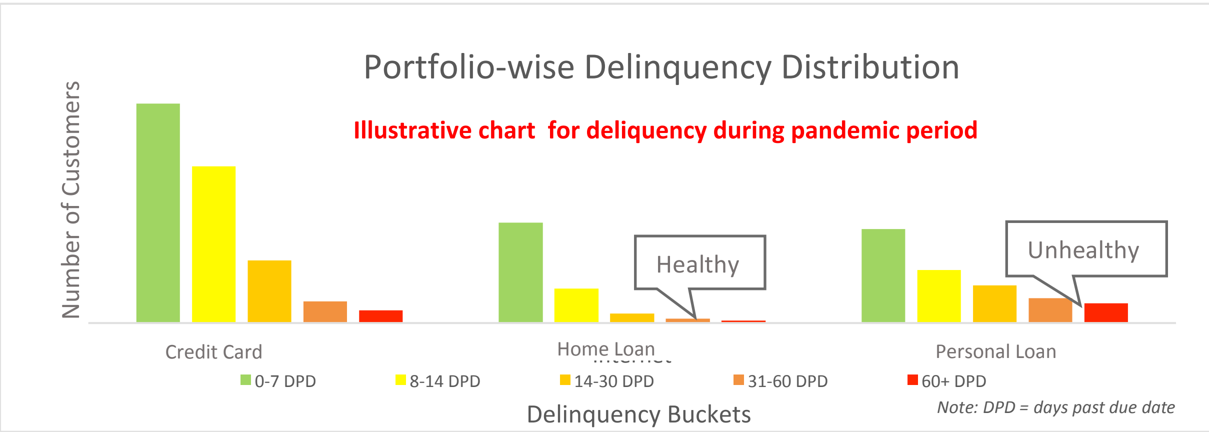
Introduction

COVID-19 has quickly emerged as a global health crisis, affecting the lives of everyone. The lifestyle restrictions necessary to stop the spread of the disease have taken a toll on many industries – which are seeing diminished business. Many individuals have either lost employment or faced a reduction in wages. A significant proportion of the population is finding it hard to pay their rents, utility bills and other loan obligations and the rate of default is rising.

The banking industry is also facing increased credit risk across a variety of portfolios, such as personal loan, home loan, auto loan, credit card service, overdrafts and ready credit services. It is important for banks to assess existing credit risk management systems to make the right decisions in these testing times.

Monitoring the Right KPIs

It is important to continuously track delinquencies, and non-payments for each portfolio. Delinquency rates are expected to increase during the coronavirus pandemic but the magnitude may vary across portfolios. Visualizing the evolution of late payments across different delinquency buckets can indicate portfolio health.



Furthermore, delinquency distribution should also be visualized across different customer segments (based on utilization or usage patterns) and geographic locations. Once again, the extent of COVID's impact on different groups of people and different geo-locations may vary and quantifying it can yield useful information.

Dealing with Delinquency

The Reserve Bank of India (RBI) had allowed a three-month moratorium (or temporary pause) on payment of all term loans from March 1st to May 31st extending the window further to August/September. Around half of the loan customers in India had availed of the option of deferring their loan installments. Financial Stability Report released by the RBI in July-20 showed that state-owned banks accounted for a large chunk (62%) of the total wholesale credit under moratorium, compared to their private peers (29%).

In present times, it is important to differentiate the customers who are not paying dues on time. For example, these customers can belong to one of the following categories:

- Customers who are unable to pay due to financial stress (unintentional delinquency)
- Customers who have a history of delinquency and late payment (habitual late payment)
- Customers who are not paying intentionally due to dispute (CRM issue)
- Customers who do not intend to pay at all (fraud)

It is important to correctly identify which customer belongs to which group and this can be done with the help of historical data. For example, if a customer with no history of late payments in the last 12 months has suddenly become delinquent, it is likely circumstantial. On the other hand, a customer with a history of habitual late payment may just be behaving as usual.

Dealing with all delinquencies in the exact same way would be ineffective and loyal customers may be aggrieved.

Credit Risk Modeling

It is vital to reconsider the approach for building credit risk models. Generally, 6 to 24 months of historical payment and credit score data is used for building credit scoring models for bank customers. However, the COVID pandemic has brought about a sudden and drastic change in the landscape, rendering the data from before the pandemic response mostly obsolete for the purpose of model building.

It is advisable to build early warning credit-scoring models from scratch using recent short-term data. It is possible to build reasonably accurate models with 3 to 6 months of recent data. It is also recommended that these models be refreshed on a weekly or fortnightly basis for best results. It is desirable to have real-time data processing capabilities for quick model refresh using latest data.

Furthermore, the model variables must be carefully selected. Usual variables like credit score may not be updating fast enough to reflect a customer’s immediate situation. It may be necessary to look deeper into the usage data and find new relationships and trends, which may indicate a higher or lower credit risk. External data related to payment and utilization, features internally + externally (bureau) should be used more exhaustively. This may continue for next 3 to 6 months till the economic environment get stable and all portfolios get stable.

Lastly, due to pandemic and its effect most of the pre-build models are not working effectively, so in this tough time, banks need to build some rule-based models supported with statistical testing. Due to this short-term volatile this approach will be more stable and less time consuming.

Reassess Data Sources
- Use Recent Data
- Use External Data

Data Exploration
- Identify new trends
- Create new KPIs

Visualize KPIs
- Create dashboards to track KPIs

Build Risk Models
- Use advanced algorithms
- Refresh models frequently

Case Study – Collections Modeling for a Bank

The bank wanted to create a collections strategy for different segment of its credit card customers who had failed to clear their payments. The window of observation was of three months.

Our team built a model at the credit card account level that predicted the probabilities with which a borrower would migrate to the next riskier bucket (by not paying the due amount). The end outcome was, thus, a risk spectrum of the borrowers – the one end being those would most likely migrate to the next riskier bucket and the other end, those who would rather normalize, by paying either the full or part amounts.

The above spectrum was divided into five risk-buckets for the purpose of collections. The table below shows the high-level strategy of collection. It is a two-dimensional-table with risk as one dimension and the amount-at-risk the other. Using the business judgment then, the table cells were color coded for respective collections strategies (shown in the legend beside the table).

The last mile collection tactics were up to the individual collection teams based on whose feedbacks the high-level strategy was further recalibrated.

Risk Bucket/Amounts	< 30k	30 – 70 K	70 – 150 K	> 150 K
Very Low	Xxx	Xxx	Xxx	Xxx
Low	Xxx	Xxx	Xxx	Xxx
Medium	Xxx	Xxx	Xxx	Xxx
High	Xxx	Xxx	Xxx	Xxx
Very High	Xxx	Xxx	Xxx	Xxx

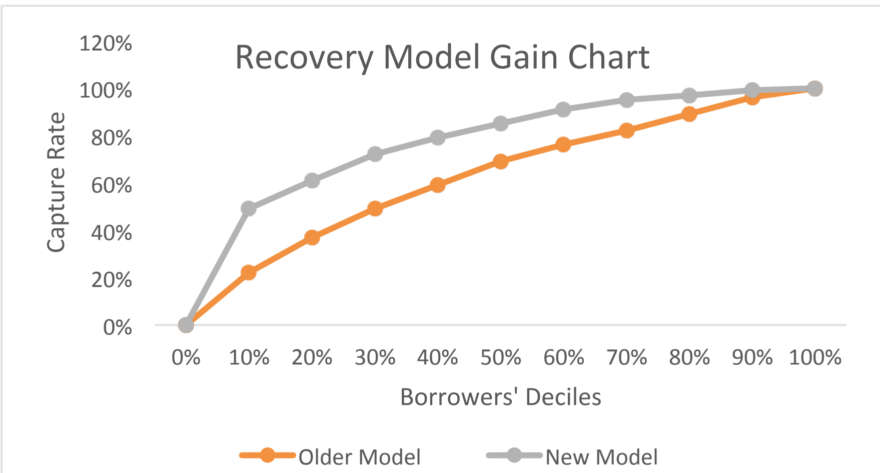
Legend
Only Calling
Calling for 15 days
Field
Focus Field

XXX denotes the number of customers under each category (removed numbers due to confidentiality)

Top variables that came out as influencing the repayment propensity in the decreasing order of importance were as under:

1. Amount paid in the last 3 months
2. Differentials of current balance and a moving average of previous 6 months' dues
3. Months since charge off
4. Months since last 30 DPD default
5. Total amount of arrears for open trades
6. Total number of tele-calling reminders
7. Total number of attempts of field collections

Gain Chart showing improvement over the previous model



Impact of moratoria and minimum service guarantee mandates from the regulators

After the COVID-19 outbreak, the client has made changes to both their risk profiling as well as collections strategies based on various norms on moratoria as well as regulatory restrictions from various regulators. They are also aggressively innovating their last mile recovery tactics to close as many risky accounts as possible.

Because of moratorium, there was a high shift of population from low risk to high risk, which made currently live models useless, So to tackle this for the entire moratorium customer pool for August end, interim risk bands were created based on customer's intent to pay, ability to pay and customer disposition.

Intent to Pay	Behaviour scorecard tagging, number of months in moratorium and payments made (internally or as per bureau data)
Ability to Pay	Net free income of customer: Imputed Income - (all debts + cost of living)
Customer Disposition	Feedback from collections contact, e.g. refused to pay, promised to pay or no contact with customer

Since these schemes from the governments and regulators are short term, the consequent customer behavior is characteristically different during the time such schemes are in force. Therefore, it is particularly important to build and refresh the models on a weekly or biweekly basis. Once this period is over, and the last iteration of collections based on this strategy is complete, one should ideally do away with the models that were used in this period, and try to build new models using the new data – and if possible try using a slice of pre-COVID data.

Therefore, the COVID-specific alterations in the entire process of delinquency modeling and consequent collections should be done at the following stages:

1. **Including COVID specific variables** as a part of basic customer demographics (e.g. variables related to per capita COVID cases in customer locality, unemployment claims or any other Mediclaim related to COVID etc.)
2. **Reclassifying the delinquents** specifically for the moratorium scheme, for the duration it is in force. Divide the borrowers into those who avail and those who do not avail the moratorium. Then recalibrating the risks under both the categories.
3. **At the collections stage,** accounting for regulatory mandates and company's own brand commitment to its customers, **monitor and reshuffle the borrowers' risk categories** based on their repayment behaviors for the time such regulatory mandates or company pledges are in force. At the end of such a period, execute the collections strategy based on the new risk categories.

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