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

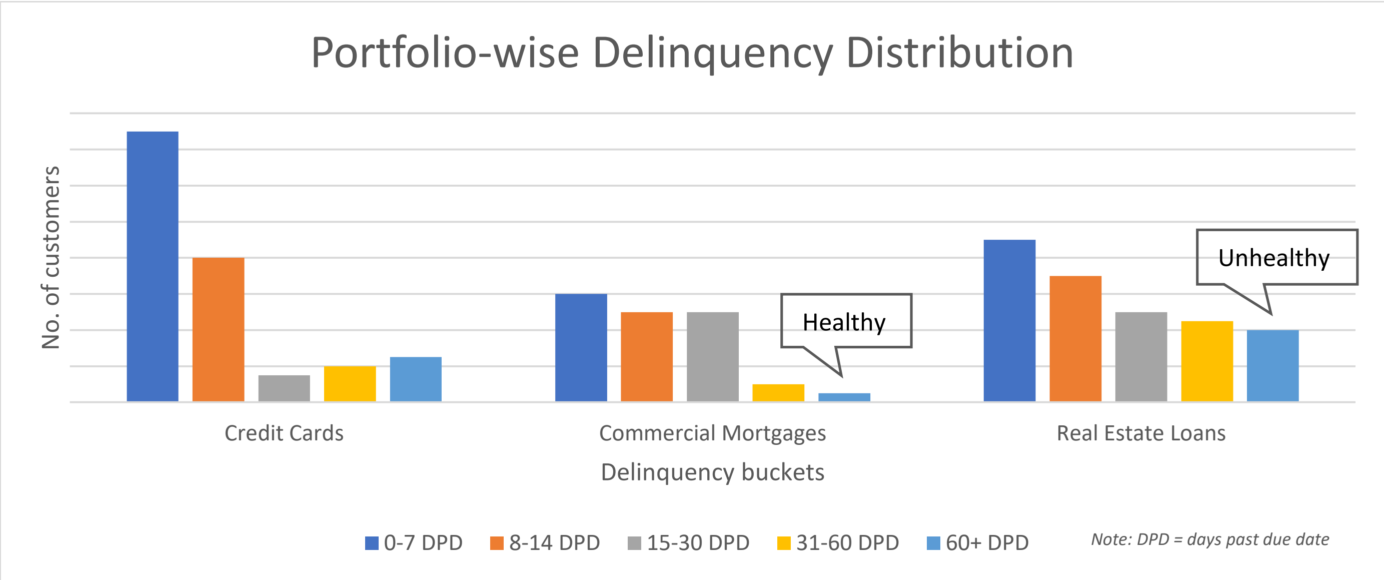
Introduction

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 facing increased credit risk in various financial instruments such as commercial loans, personal loans, credit cards, commercial mortgages, bonds, and in the extension of commitments and guarantees, and the settlement of transactions. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions.

Monitoring the Right KPIs

It is important to continuously track delinquencies, and non-payments for each portfolio. And also, to monitor Value at Risk (VaR) and expected credit loss. 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 APRU 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

In present times, it is important to differentiate the customers who are not paying bills 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.

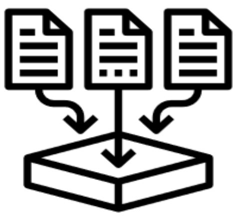
Credit Risk Modeling

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 telecom 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 rebuild credit-scoring models from scratch using recent short-term data. It is possible to build reasonably accurate models with 3 to 4 months of recent data. It is also recommended that these models be refreshed on a daily or weekly 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 COVID, like number of active cases per capita in different geographies can also boost the predictive power of the models.

Lastly, it is strongly recommended that advanced machine learning algorithms like gradient boosting be used to for model building. Modern algorithms will generally outperform traditional algorithms like logistic regression when using short-term data with novel trends.



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 total amount at risk was of the order of $ 30 million. 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.

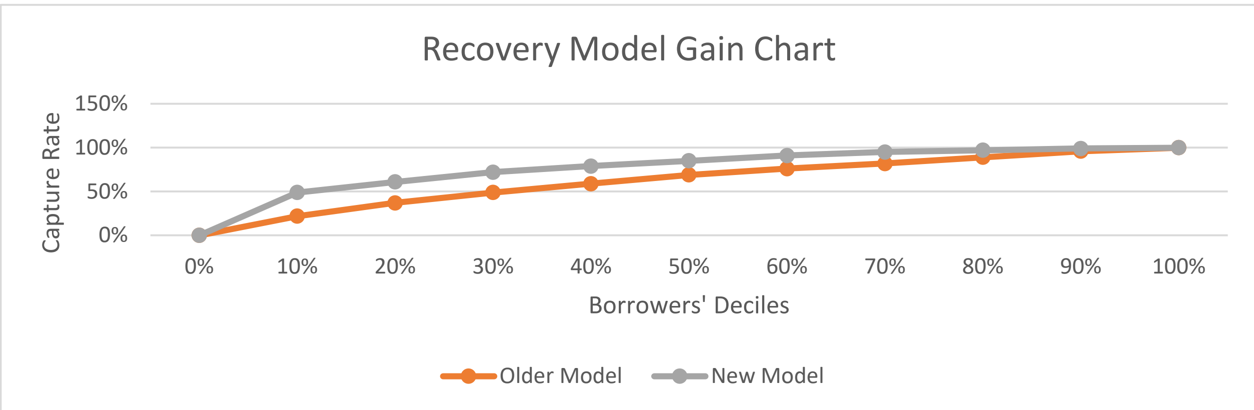
Risk Bucket/Amounts	< 30k	30 – 70 K	70 – 150 K	> 150 K
Very Low	Xxx	xxx	xxx	xxx
Low	Xxx	xxx	xxx	xxx
Medium	xxx	xxx	xxx	xxx
High	xxx	xxx	xxx	xxx
Very High	xxx	xxx	xxx	xxx

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.

In our experience, regulatory relaxations to customers (e.g., moratoria) warrant re-bucketing of the borrowers based on whether they avail moratoria facilities or not. Similarly, the basic minimum service pledges from regulators do call for a rehash of collections bucketing accompanied by aggressive last mile tactics such as one-time settlement, bargain to shift the product/customer category to lower rung product, converting due amount in EMIs (Equated Monthly Installments), etc.

Since these schemes from the governments/regulators are most likely to end after a few months, 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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