Using Predictive Analytics to Support MBS Servicing and Loss Mitigation

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Given the economic landscape and continued deterioration in the housing market, mortgage servicers have aggressively worked to strengthen their risk management, collections, and loss mitigation strategies. The pressure to do so comes from all sides, from regulators to investors and shareholders. As the barrage of delinquencies continues, all stakeholders are increasingly sensitive to how—and how effectively—servicers deploy their resources to mitigate risk and minimize losses in their portfolios.

Within the parameters of individual pooling and servicing agreements (PSAs), servicers have employed various tactics to manage risk more successfully across the thousands of loans in mortgage-backed securities (MBS) portfolios. Understandably, investors expect servicing organizations to allocate loss mitigation resources where they can most effectively protect the pool from continued deterioration.

MOVING BEYOND HISTORICAL ANALYSIS

Servicers have access to vast stores of data on the properties, borrowers, and loans in their portfolios. By using a variety of analytical tools, they can leverage that data to help them identify loans that are more likely to go delinquent and more likely to stay delinquent, and, with no intervention, ultimately move to foreclosure and loss. The results from these tools allow them to apply their resources more effectively and improve their loss ratios.

For servicers to make the best use of their data, they must, however, move beyond simple historical analysis and deploy their data for loan-level predictive analysis and modeling. Roll-rate models that are based on recent trends in a portfolio focus on groups or cohorts of loans, but don't do a good job of discriminating among individual loans and implicitly assume that recent historical trends will continue. Models that base delinquency risk on historic payment timing patterns may provide some amount of discrimination, but they also assume recent historic trends will continue and rely on a single payment metric as opposed to looking at interactions among borrower, loan, and property information.

Sophisticated behavior-based predictive modeling has an important role to play in addressing the record-breaking levels of mortgage loan delinquencies we see today. Forward-looking analytics that draw upon observed borrower behaviors and robust loan data can project future outcomes for individual loans with a strong confidence factor. The resulting insights enable servicers to target their loss mitigation resources more effectively to triage troubled loans, make better decisions, improve results, and minimize losses.

PREDICTIVE ANALYTICS DELIVER GREATEST POTENTIAL

While mortgage servicers benefit from the use of many types of analytics, predictive analytics have the greatest untapped potential for addressing loss mitigation.

Today, the sheer number of delinquencies stretches servicer resources nearly to the breaking point, and the severity of losses looks like it will remain high for some time. In order to manage and mitigate risk more effectively, servicers must have a comprehensive understanding of the risks associated with each loan in a portfolio, have the ability to segment their portfolios into clear bands of risk, and then adjust their loss mitigation efforts accordingly.

The insights provided by predictive analytics can help to focus servicer resources where they will produce the most return. The goal should be to determine which loans in a servicing portfolio represent the greatest risk of delinquency and loss, rank them accordingly, and assign the most experienced loss mitigation professionals to address loans with the largest expected loss to the portfolio.

In addition, servicers can deploy predictive modeling to determine the projected performance of a variety of possible loan modification scenarios, including the probability of borrower re-default for each scenario as well as the future net present value (NPV) of each option. Comparing these to the costs and NPVs of alternatives, such as short sales or foreclosure, enables servicers to determine which course of action is optimal for both the borrower and the investor.

BEHAVIOR-BASED PREDICTIVE ANALYTICS

Behavior-based models have been used by mortgage investors, traders, and hedge funds for years as the predictive backbone for valuing whole loans, MBS, and CDOs. As their name suggests, these models are more than straightforward logistic regressions. They are based on intuitive "rules" about how borrowers will behave in different future economic environments, often defined by changing projected interest rates and house prices. In general, they try to model what borrowers feel—what hits them in their wallets—and how the various factors interact to predict delinquencies and losses. For example, changes in the prevailing interest rates can drive changes in payments on ARM loans, potentially impacting default probabilities, either up or down. They can also create incentives to refinance. If, however, we see in the data that a borrower missed a chance to refinance to a lower rate, this could mean he is facing stresses that prevented a refinancing and default probabilities can rise. Changing house prices impact the equity a borrower has in the house, driving both his propensity to default and the ultimate loss if he does.

Probabilities of prepayment, delinquency, and default, as well as estimated current LTV and loss severity, can be determined at the loan level by using interest rate and MSA or ZIP Code-level house price forecasts as the variable economic drivers of behavior-based models. The fixed drivers include borrower, property and loan factors such as:

- Behavioral Drivers
  - Age of loan
  - Seasonality
  - Payment changes
  - Exposure to refinancing
  - Original LTV
  - Equity
  - Current LTV (calculated using ZIP/MSA-level HPI)
- Loan Data Drivers
  - Geography
  - Credit score
  - Loan size
  - Loan type
  - Purpose
  - Property type
  - Documentation
- Loss Severity Drivers
  - Property value
  - Lien position
  - Fixed costs
  - Variable costs
  - Lost interest

These types of models, which investors have used for years to value loans, can help servicers also. The results can be used to segment loans and develop mitigation strategies and tactics based on the probability of future delinquency; predict which currently delinquent loan is likely to cure; identify those loans that are most likely to proceed to foreclosure; and ultimately, determine the expected loss.

To illustrate the improved discrimination capability of this type of modeling, the relevant data points indicated above can be captured for an MBS portfolio in a randomly selected month and the associated risk metrics created. Loans can then be risk-ranked using those metrics and delinquency probabilities projected for three months into the future. By tracking the actual delinquency rates over the three-month period and comparing them against the model's projections for the same period, the discrimination "lift" provided by the model can be clearly demonstrated.

Exhibit 1 shows the results for a sample portfolio of 750,000 loans. In this example, 55% of loans that actually deteriorated over three months were identified in the first 14% of loans ranked by the predictive metric. Especially when compared to projections based on traditional factors such as FICO scores or current LTVs, the accuracy improvement produced through the use of predictive modeling is significant.

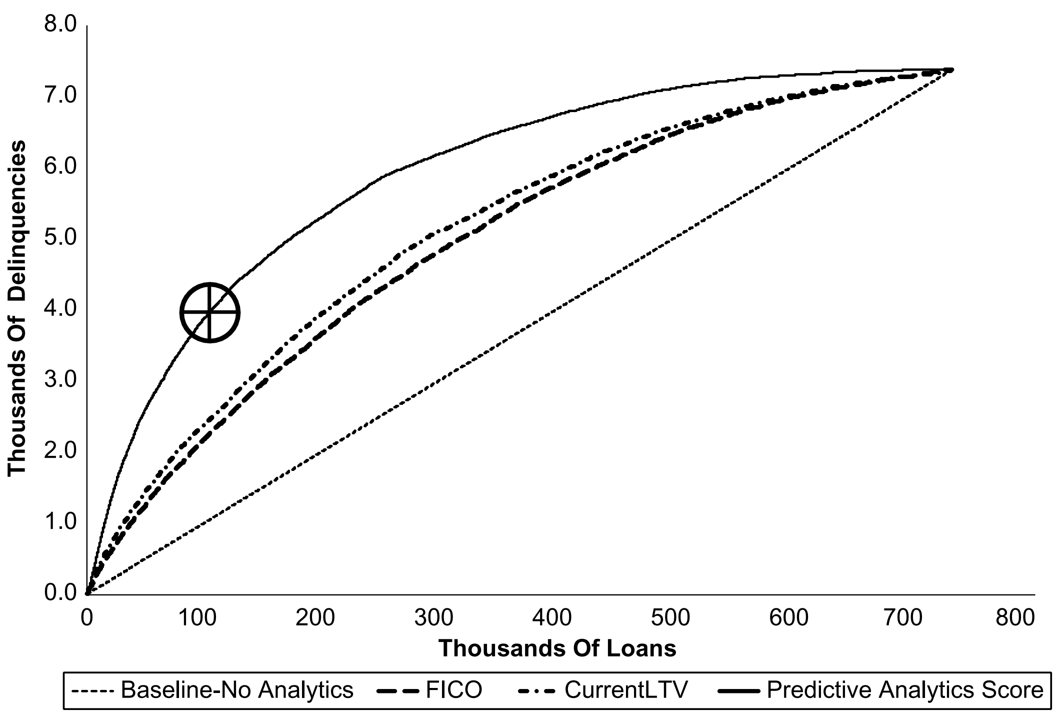
OPERATIONALIZING PREDICTIVE ANALYTICS

The key to minimizing losses and managing portfolio risk is to put the analytics into operation by allowing the results to drive loss mitigation strategies. A servicer must adopt a probability-of-deterioration metric, combine that with dollars at risk, and then segment the portfolio accordingly.

By utilizing a probability measure that combines the probability of serious delinquency and the probability of ultimate default, the discrimination capabilities of the models are maximized in the near term while differentiating loans that will, absent intervention, work their way through to foreclosure and loss over the next 12–24 months.

While the probability that a loan will be delinquent or will ultimately default is important, the severity of the potential loss is also key. Servicers need to focus their resources where they can have the most impact. By

EXHIBIT 1
Example of Discrimination Lift Provided by a Predictive Model



using house price projections at the most granular level into the models, they can calculate the loss severity at a chosen point in the future. Multiplying the probability metric and this severity produces a probability-weighted severity akin to expected loss and produces a dollar-weighted, risk-ranking metric, or "quasi-expected loss" (QEL), that can be used to segment the portfolio. While loss severity and unpaid principal balance (UPB) are often correlated, some servicers have decided to utilize UPB as an additional segmentation factor to make sure they are balancing quasi-expected loss with the size of loan. Exhibit 2 shows an example of how a segmentation might be performed based on the interaction of these metrics on a normalized basis.

Exhibit 3 provides an example of how, by implementing risk-based segmentation, servicers can develop communication and workout strategies that are better targeted to effectively address the issues associated with each segment rather than deploying the same treatment approach irrespective of risk. They can also then assign the appropriate loss mitigation personnel based upon the complexity and severity of the loans in each segment.

DETERMINING WHAT AND HOW TO MODIFY

Once loans have been analyzed, risk-ranked, and segmented, if a given loan doesn't qualify for a government program such as HAMP or a specific approved investor program, other modification possibilities come into play, and the analytic findings are invaluable here as well. Servicers can gain a clear picture of how changing the structure of any particular loan through interest rate reduction, principal forgiveness or forbearance, or loan term extension will impact the probability of re-default and resulting NPV.

By testing different "what if" modification scenarios, servicers can determine how best to improve the value and the collectability of the loan. The servicer begins by modeling the current loan, property, and borrower characteristics to determine how the probabilities look prior to any modification. Then the servicer can manipulate

EXHIBIT 2

Example of Loan Segmentation Heat Map

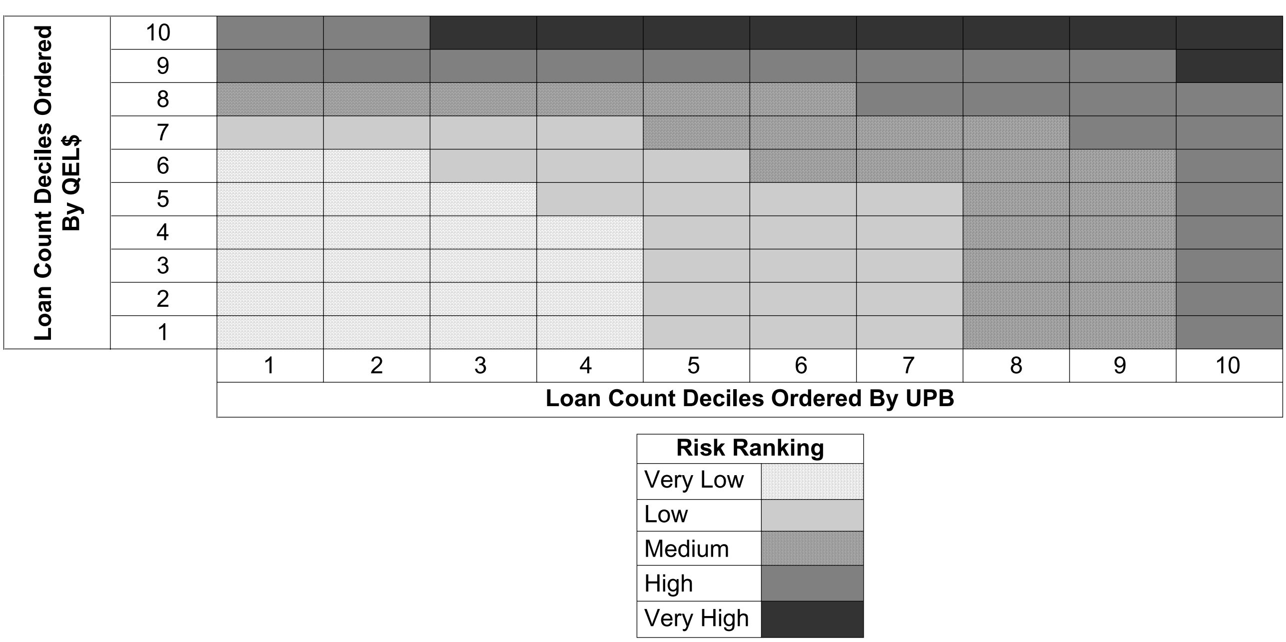


EXHIBIT 3

Example of Segmented Contact Strategies (Activity on Day in Month)

Risk Segment	Calling Entry Day	Blaster Message	Letter Day	Text Day	Email Day	No Contact = Door Knock	No Contact = Reassign/ Reroute
Very High	3		5	9	12	20	15
High	7		9	13	16	25	18
Medium	10	5	12	8	14		16
Low	14	7	16	10	12		20
Very Low	19	9	16	12	14		25

various factors like interest rates and term to determine what impact those changes would have on the probability of delinquency and the associated loss severity.

Ultimately, predictive modeling allows servicers to define their own criteria, such as maximizing NPV or minimizing the probability of re-default, and to select the modification parameters that are most appropriate for a given scenario. These parameters can be varied by portfolio, risk level, segment, sub-segment, etc. Given the unique servicer-defined constraints, the predictive models can determine the optimal combination of revisions to the loan to meet the chosen goals, in either a batch process or in real time for individual loans.

Predicting the impact of various potential adjustments helps the servicer optimize modifications to find that sweet spot where the highest probability of sustainability for the borrower and the maximum benefit for the lender coincide. This helps borrowers move out of delinquency status and stay in their homes, enables investors to protect their returns, and allows servicers to maintain their servicing asset—a true win-win-win.

CONCLUSION

In order to minimize losses, mortgage servicers must identify and prioritize those troubled loans that pose the greatest risk to their portfolios. Drawing upon the rich stores of loan-level data residing in their servicing platforms, servicers can easily identify their highest-risk loans though predictive analysis.

By segmenting their portfolios according to loss severity, mortgage servicers can more effectively target their limited resources where they have the potential to have the most impact and successfully mitigate risk. Predictive modeling allows servicers to project the impact that a wide variety of corrective measures may have on the probability and severity of loss and choose their mitigation strategies accordingly. By developing servicer-defined or investor-defined goals and constraints, predictive modeling also enables servicers to structure optimized loan modifications.

As delinquencies and foreclosures continue to move through both servicing and investment portfolios, servicers must make every possible effort to reduce losses. Predictive analytics can be a powerful tool in the mortgage servicer's arsenal. When they are effectively put into operation, the resulting intelligence can drive loss mitigation strategies and support appropriate resource allocation. These are critical tools that the mortgage industry needs to deal with today's loss mitigation challenges and to dramatically improve results.