# USING RATE LOCK VOLUME TO PREDICT MORTGAGE PREPAYMENT SPEEDS

WHITE PAPER

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# USING RATE LOCK VOLUME TO PREDICT MORTGAGE PREPAYMENT SPEEDS

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## Summary

Black Knight captures origination rate lock data as an output of its Optimal Blue[SM] Product, Pricing and Eligibility (PPE) engine. The data is accessible through Optimal Blue's Mortgage Lock Data product. Using this data set, let's examine rate lock volume as a predictor for prepayment speeds.

## Introduction

Prepayment modeling is the most important aspect of predicting a loan's future cash flow, which is the primary driver of value for both mortgage-backed securities (MBS) and mortgage servicing rights (MSR). As prepayment activity increases, interest received on an MBS investment and servicing fees that a servicer collects on payments from borrowers decrease. Typically, prepayments are predicted with a statistical model using historical loan prepayment data to establish predictive coefficients between loan risk characteristics, market activity and prepayment speeds.

Data that informs prepayment models is limited to what's observable—either proprietary or publicly available sources. Through Optimal Blue's Mortgage Lock Data, modelers have a new class of data relevant to mortgage lock activity. The Mortgage Lock Data records the key attributes of a loan application at the moment it's locked. Unlike other model inputs, which attempt to predict borrower behavior, rate locks are an indication of a decision already made by the borrower to pursue new home financing. That makes rate lock activity a leading indicator of prepayments to the extent that a new mortgage, identified by the rate lock, will be replacing an existing loan. This paper demonstrates how rate lock activity can be used to accurately forecast short-term prepayment speeds.

## Methodology

A rate lock is a commitment by a lender to a borrower that it will honor the current mortgage rate for a specified period, typically 30, 45 or 60 days. The lock protects the borrower against rising interest rates from the time of rate lock to the time of closing. In most cases, the lock will occur at roughly the same time as the application is submitted to the lender. The timing of the lock makes it the most reliable, initially observed event in the mortgage process. Rate locks are therefore uniquely positioned to be a leading indicator of mortgage and housing metrics, including prepayment. Approximately 40% of U.S. residential mortgages are priced and locked on the Optimal Blue PPE. Given this market share, the Mortgage Lock Data provides a representative indication of activity in the broader market across products (e.g., Conforming, FHA, VA), geographies (e.g., states, MSAs), amounts, property occupancy (e.g., primary residence, second home, investment property) and more. This is critical for forecasting purposes as observations within this sample can be used to infer prepayment activity across market segments and the market as a whole.

The Optimal Blue PPE is used by more than 1,200 lenders, including +60% of the top 500 lenders by volume, to determine product eligibility and pricing for residential mortgages and, ultimately, to document rate lock commitments with borrowers. Each rate lock on the Optimal Blue PPE documents detailed information about the borrower's risk profile, property and proposed loan. These variables enable rate locks to be separated into cohorts to match investors' MBS pools or MSR loan portfolios.

It is worth noting that interest rate movements remain the strongest leading indicator of prepayment rates. As rates fall, borrowers are incentivized to refinance their loans, leading to higher prepayments. Conversely, as rates rise, the incentive to refinance and the risk of prepayment to investors declines. However, other variables, including equity in the home, originator capacity, state laws and loan-level pricing adjustments, prevent a consistent, causal relationship. Rate lock activity can enhance prepayment forecasting efforts because it reflects a decision already made by the borrower, not an external factor that may or may not lead to certain behavior.

Although the rate locks are anonymized and are therefore not able to be matched one-to-one to an existing loan, the rate lock volume within a specific cohort can be assumed to be paying off loans from that same cohort (e.g., a rate lock to refinance a property in New York can be assumed to be paying off a New York loan). We used this connection to conduct this research, which includes an analysis of conforming (as defined by Fannie Mae and Freddie Mac), fixed-rate lock volume filtered by loan amount, occupancy and state. In addition to stratifying across non-temporal loan attributes, the rate locks were grouped by the month in which they are most likely to close (i.e., result in a prepayment). Once the rate locks were grouped into cohorts, the relative size of the groups was tracked as a percent of the market overall. If the overall percentage of a particular cohort increased, that indicated that more rate locks were occurring and that there would be a relative increase for that cohort compared to other cohorts in the market overall. To control for the client growth on the Optimal Blue PPE, only locks from lenders that were on the platform prior to 2018 were included. The equation below was used to derive a projection based on the Optimal Blue (OB) Cohort Ratio.

**OB Cohort Ratio = Rate Lock Volume of Cohort / Rate Lock Volume of All Conforming Fixed-Rate Loans**

In order to demonstrate the predictive quality of rate lock activity, we observed the correlation between monthly rate lock volumes in the Mortgage Lock Data compared to Single Monthly Mortality (SMM) as calculated from Black Knight's McDash[SM] loan performance data set. The McDash data is contributed by mortgage servicers and accounts for roughly 70% of all active residential mortgages in the U.S. The performance data is released monthly and is widely used as a source of truth for prepayment speeds.

The purpose of this exercise was to present rate lock activity as a forecasting tool for relative prepayment speeds among different specified pools. Using the McDash data, SMM Factors were calculated to represent the relative monthly prepayment speeds of each cohort. The equation for the SMM Factor used for correlation purposes is presented below.

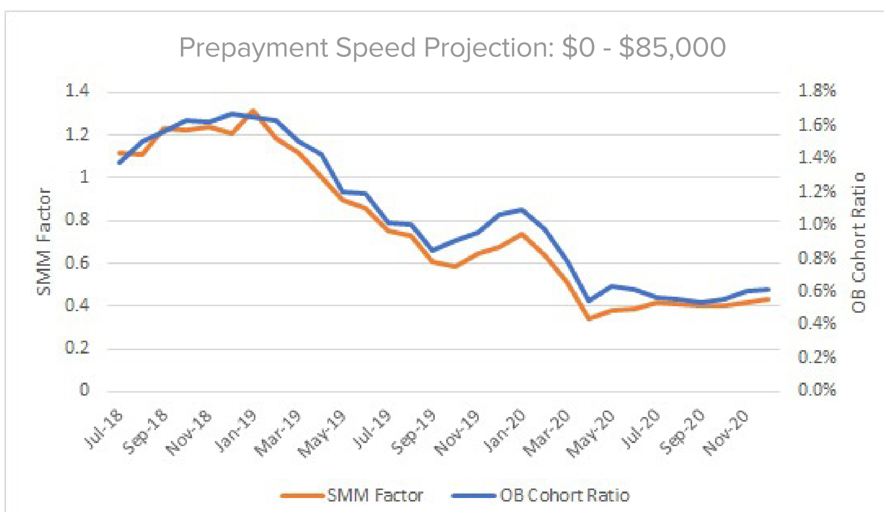
**SMM Factor = SMM of Cohort / SMM of All Conforming Fixed-Rate Loans**

Correlations between the month-over-month (MoM) changes of the OB Cohort Ratio and SMM Factors are presented in the next section.

## Results

The samples tested include cohorts of loans separated based on loan amount ($0–$85,000, $85,000–$110,000, $110,000–$125,000), occupancy (investor owned) and state (Florida, Texas, New York and California). The samples were analyzed for the 30-month period from July 2018 to December 2020.

For example, the correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for loans of $0–$85,000 was 86.7% from July 2018 through December 2020, based on a closing assumption of 41 days. The chart to the right displays the correlation during that period.



The correlation for all cohorts, as well as the days to close assumption, are provided in the table below. We used a single time-to-close assumption for each cohort; however, actual closing periods fluctuate over time and across loan purpose (e.g., purchase, rate/term refinance, cash-out refinance). We are confident that leveraging a more dynamic assumption for time to close would produce improvements on the correlations we observe. For the charts specific to each cohort, please see the Appendix.

| COHORT | DAYS TO CLOSE ASSUMPTION | CORRELATION JUL 2018 – DEC 2020 | APPENDIX CHART # |
|---|---|---|---|
| $0–$85,000 | 41 | 86.7% | 1 |
| $85,000–$110,000 | 36 | 80.8% | 2 |
| $110,000–$125,000 | 35 | 75.0% | 3 |
| Investor Owned | 36 | 82.7% | 4 |
| Florida | 37 | 73.7% | 5 |
| Texas | 38 | 52.3% | 6 |
| New York | 34 | 44.9% | 7 |
| California | 28 | 47.1% | 8 |

The table demonstrates the effectiveness of predicting prepayment by observing in-stratification lock activity. Even on a state level, there is a meaningful level of demonstrable correlation, suggesting that including combinations of selected cohorts into a predictive prepayment model could prove quite fruitful.

## Conclusion

The data presented demonstrates the predictive power of the Optimal Blue Mortgage Lock Data. Unlike other model inputs, which try to predict borrower behavior, rate locks present a unique observation that reflects an action already taken by the borrower to seek home financing. Certainly, those concerned with mortgage prepayments have long considered application activity as a precursor for prepayments, but never before have they been able to segment this early activity to predict prepayments on specific cohorts of MBS or MSR investments. Rate lock data can be used as both a model input and a benchmark against which to compare existing prepayment assumptions.

In conclusion, this study leads us to recommend that prepayment analysts test the value of incorporating rate lock data into their prepayment forecasting models. Our research suggests it will improve the predictive capability of prepayment models above and beyond the standard inputs, particularly modeling prepayments in the short term.

## Appendix

**Chart 1:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for loans of $0–$85,000 was 86.7% from July 2018 through December 2020, based on a closing assumption of 41 days.

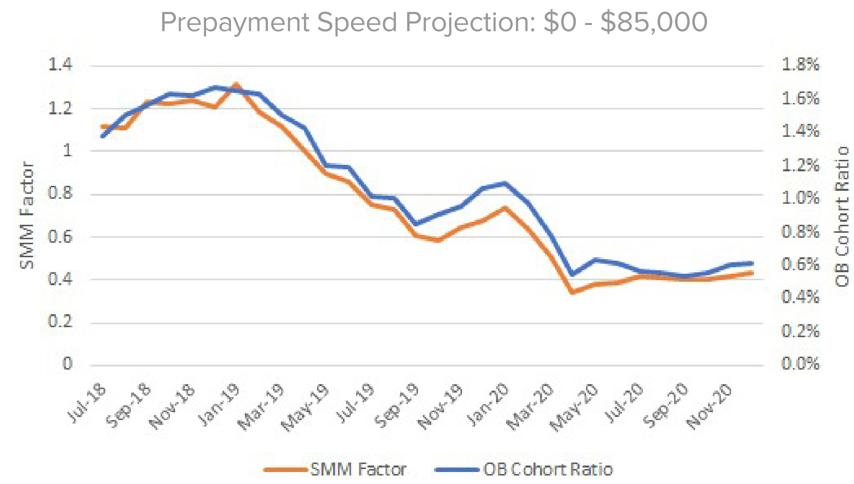



**Chart 2:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for loans of $85,000–$110,000 was 80.8% from July 2018 through December 2020, based on a closing assumption of 36 days.

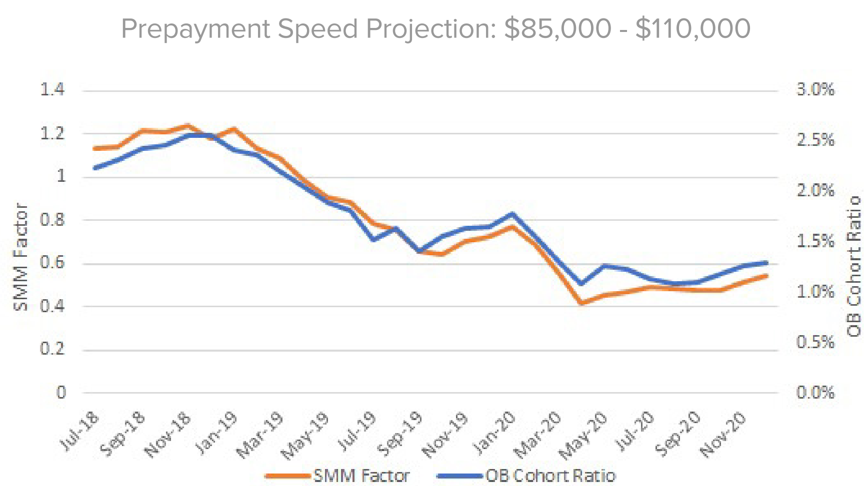



**Chart 3:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for loans of $110,000–$125,000 was 75% from July 2018 through December 2020, based on a closing assumption of 35 days.

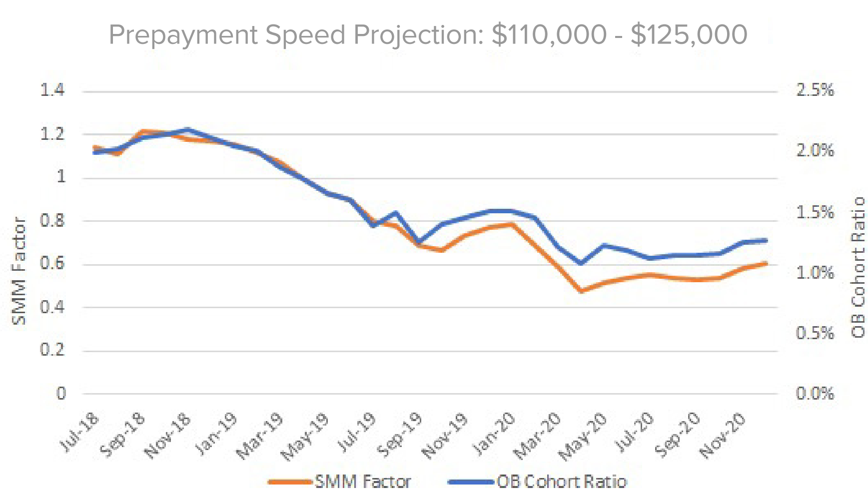


**Chart 4:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for investor-owned loans was 82.7% from July 2018 through December 2020, based on a closing assumption of 36 days.

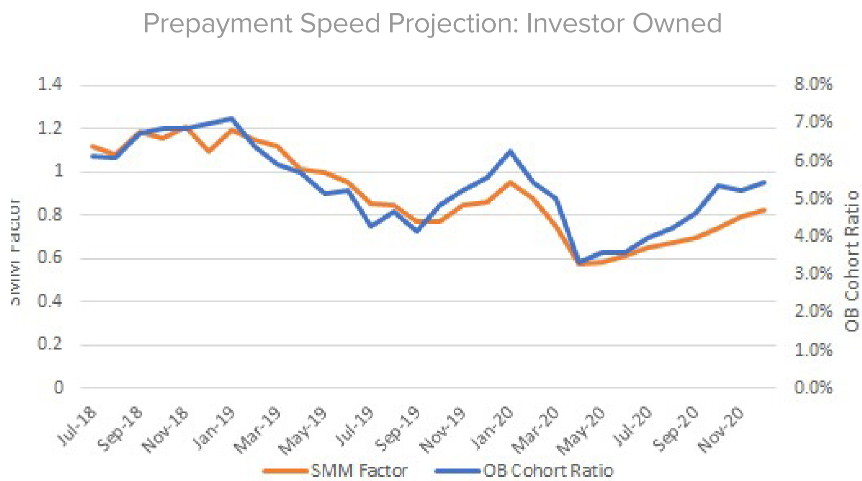



**Chart 5:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for Florida loans was 73.7% from July 2018 through December 2020, based on a closing assumption of 37 days.

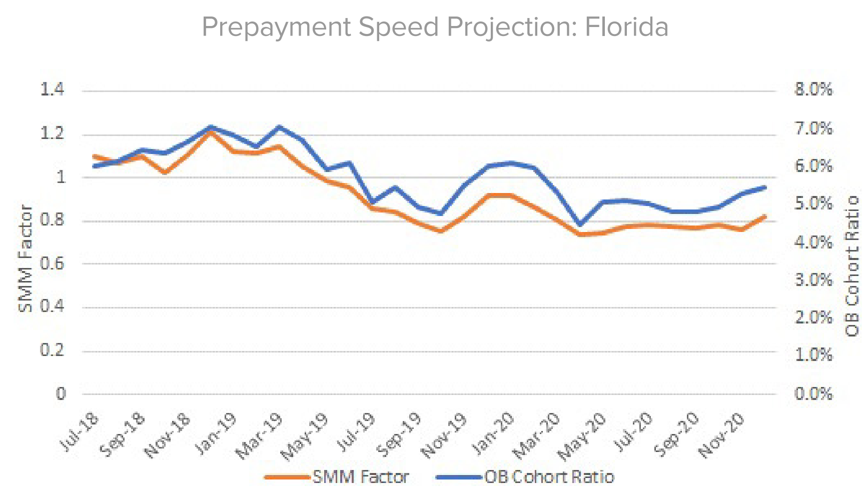



**Chart 6:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for Texas loans was 52.3% from July 2018 through December 2020, based on a closing assumption of 38 days.

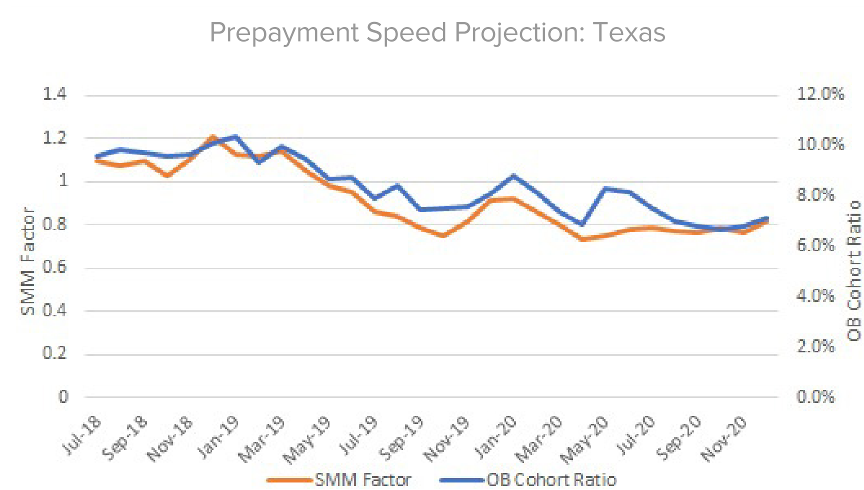


**Chart 7:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for New York loans was 44.9% from July 2018 through December 2020, based on a closing assumption of 34 days.

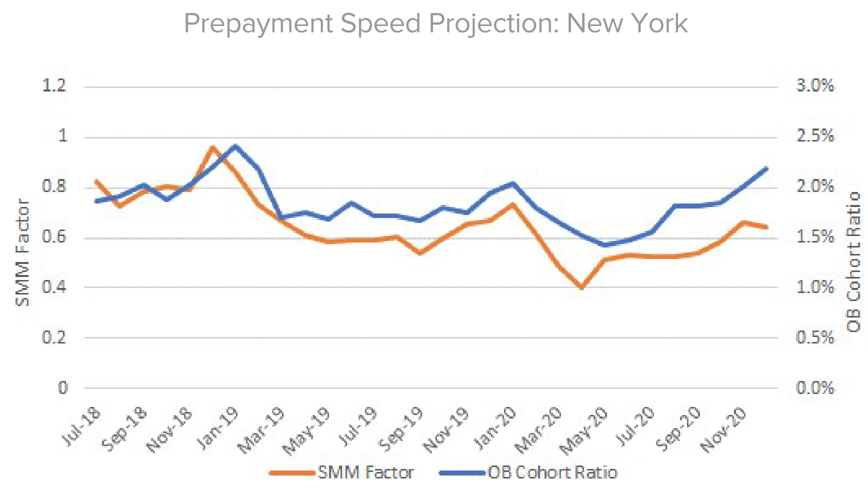



**Chart 8:** The correlation between the MoM changes in the OB Cohort Ratio and SMM Factor for California loans was 47.1% from July 2018 through December 2020, based on a closing assumption of 28 days.