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Unmasking Covid's Impact on Multiple Prepayment Models

An investigation into the behavior of prepayment models during the Covid Pandemic using machine learning

In today's ever-evolving economic environment, with fluctuating interest rates and rising inflation, the mortgage industry and the financial risks associated with mortgages are changing. During the Covid Pandemic, a spike in prepayments was observed in the United States, because customer deposits increased due to the inability of customers to spend money. This effect on prepayments is further compounded by market rates that were at historically low levels, causing an incentive for customers to refinance their mortgage against a lower rate. With the Covid Pandemic behind us, and rising mortgage rates, banks may be inclined to reevaluate their prepayment models.

Our research contributes to the aforementioned challenge by investigating different prepayment models, as well as the influence of different calibration periods, on the estimated prepayment amounts. In- or excluding the Covid period in data used to calibrate or test the model can have a significant effect on the model performance. Therefore, investigating this effect on the estimated prepayment amounts is the key focus of our research. By understanding this dynamic, financial institutions can make informed decisions about the optimal calibration strategy for their portfolio.

DATA

For our research, we use the publicly available Freddie Mac mortgage data. Figure 1 provides an overview of partial and full prepayments in percentage of USD outstanding. The 15 year mortgage rate is used as proxy for the rate against which lenders can refinance. The figure shows that the majority of the total USD prepayments are caused by full prepayments. A spike in both the full and partial prepayments is observed during the Covid Pandemic.

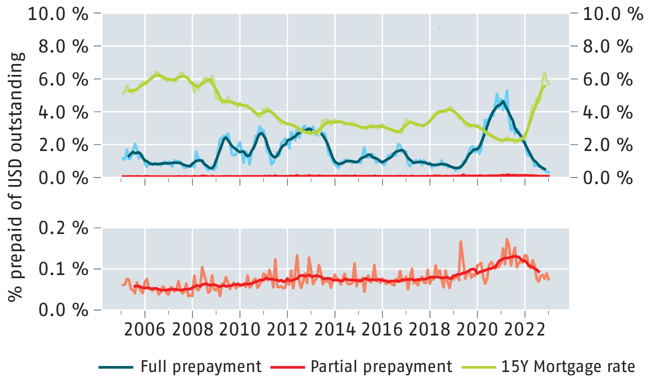

Figure 1: The percentage of USD outstanding prepaid through full and partial prepayments per period, and 15Y mortgage rates. Data is shown as centred six month moving average, original data is shown transparent.

PREPAYMENT RISK DRIVERS

For our research, we establish a long list of potential prepayment risk drivers. The performance of the long list is given by AUC scores and is shown in Figure 2. The results show that a large difference exists between the predictive performance of different variables. Interestingly, the same variable can be quite powerful for predicting a specific state but not for other states.

From left to right:

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This article has been shortened. The full article can be obtained via the authors:
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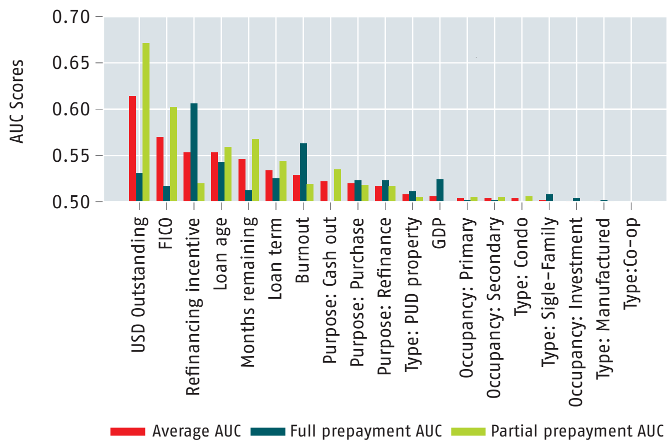

Figure 2: Overview of performance of models trained with a single variable. The average AUC is the average of the AUC for no, full and partial prepayments.

The refinancing incentive and the burnout show a high performance for full prepayments. The refinancing incentive is defined as the economic incentive of an obligor to refinance the existing contract, i.e. the difference between the contractual interest rate and the refinancing rate. The burnout, calculated as the difference between the current and maximum historical refinancing incentive, is intended to capture the diminishing impact of a continuous or repeated positive refinancing incentive.

Given our analysis, we select the following variables to be included: refinancing incentive, burnout, original loan term, remaining months, loan age and USD outstanding.

MODEL BACKGROUND

Prepayment models usually estimate the probability that there is a prepayment. However, for practical applicability, we are interested in the height of the prepayment:

Prepayment USD = Prepayment probability· Prepayment size · Exposure

The difficulty of prepayment models mainly lies in the first term. For this, we take three approaches: a logistic regression, a random forest, and a neural network. The second term is equal to 100% for full prepayments. For partial prepayments we use a linear regression to determine the proportion that is prepaid. The third term is the exposure of the mortgage the moment before prepayments are made.

MODEL PERFORMANCE

To accurately compare the performance of the different models we assess their performance by out-of-time tests on a time interval in- and excluding the Covid Pandemic. Figure 3 shows that when the Covid Pandemic is included in the test period, none of the models are able to completely capture the peak in prepayments. When the Covid Pandemic is excluded from the test period, we observe that all model predictions fit the testing data significantly better. The machine learning models perform better than the logistic regression, although the difference is small.

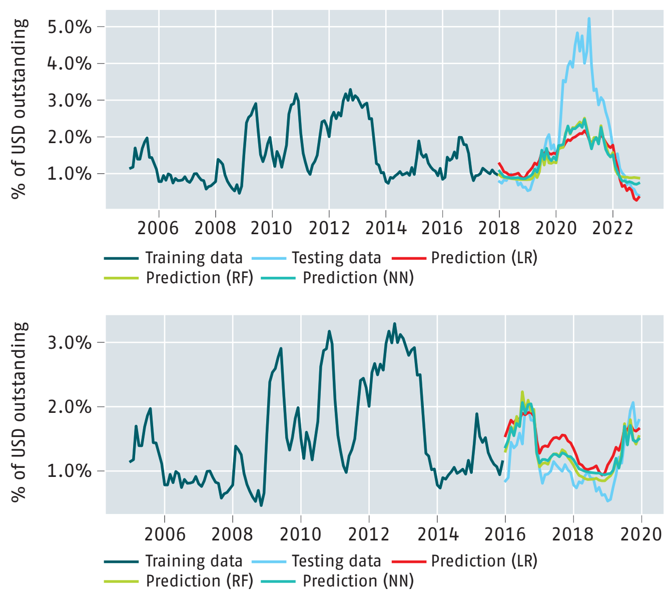

Figure 3: Model comparison where the testing is performed on a time interval in- and excluding the Covid Pandemic (top and bottom, respectively).

A major challenge that banks must tackle when developing a prepayment model after the Covid Pandemic is the treatment of data from that period. To assess the influence the Covid Pandemic has on modelling, we have trained a neural network on two periods of the same length, one in- and excluding the Covid Pandemic. The results are shown in Figure 4.

The figure shows that training a model on a period including the Covid Pandemic (light blue) leads to a considerable overestimation of the prepayment rate in a period without the pandemic. Since the spike in the training period does not completely stem from macroeconomic factors or changing characteristics of mortgages, it is very difficult, if not impossible, to accurately capture its behaviour. In this case, the effect of the Covid Pandemic, is incorrectly attributed to the model variables, which causes endogeneity. On the contrary, the model trained on a period without Covid Pandemic (red) predicts a prepayment rate very close to the observed rate.

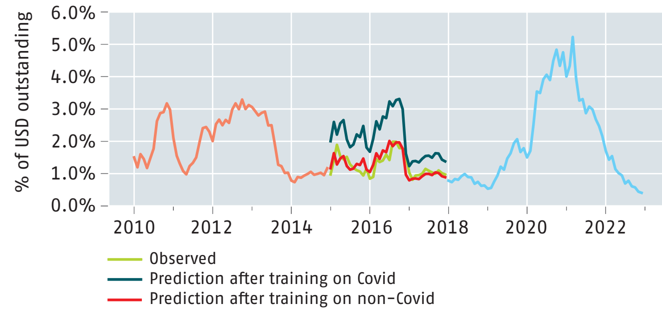

Figure 4: A comparison of two Neural Networks, one trained on a period including the Covid Pandemic and one trained on a period without pandemic influences. Data shown transparent is used to train the model of which the prediction is shown in the same color.

CONCLUSION

Our study highlights the impact of the Covid Pandemic on prepayment models. We found that including the pandemic in the calibration data leads to an overestimation of prepayments, and the effect of the Covid Pandemic is incorrectly attributed to the other variables in the model. This emphasizes the need for financial institutions to adapt prepayment models to such anomalies and maintain accuracy in risk assessments. Our findings underscore the importance of selecting appropriate calibration periods and offer valuable insights for improving prepayment models in the mortgage industry. ■