The Mortgage Prepayment Decision: Are There Other Motivations Beyond Refinance and Move?

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October 2019

Abstract

Borrowers terminate residential mortgages for a variety of reasons. Prepayments and defaults have always been distinguishable, and researchers have recently distinguished between prepayments involving a move and other prepayments. But these categories still combine distinct decisions. For example, a borrower may refinance to obtain a lower interest rate or to borrow a larger amount. By matching mortgage servicing and credit bureau records, we are able to distinguish among several motivations for prepayment: simple refinancing, cash-out refinancing, mortgage payoff, and move. Using multinomial logit to estimate a competing hazard model for these types of prepayments plus default, we demonstrate that these outcomes are distinct, with some outcomes showing quite different relationships to standard predictive variables, such as refinance incentive, credit score, and loan-to-value ratio, than in models that combine outcomes. The implication of these findings is that models that aggregate prepayment types do not adequately describe borrower motivations.

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I. Introduction and Background

Mortgages are terminated for many reasons, some of which are quite straightforward. Mortgages include a call option for the borrower so mortgage prepayment can be triggered by a decline in interest rates. Mortgages are also usually without recourse, so defaulting on a mortgage can be triggered by a decline in the value of the house, such that the value of the house plus all the costs the borrower will bear as a result of the default is exceeded by the balance owed on the mortgage. So prepayment or default can be triggered by exogenous changes in interest rates and house prices. Given that many households are liquidity constrained, prepayment or default may also be triggered by unexpected changes in income or expenses.

Beyond these purely financial considerations, the close relationship of the mortgage to the consumption of housing services, and its place as one element in a portfolio of debt whose size and composition the household will seek to optimize, create additional reasons for mortgage prepayment. Incorporating these factors implies a much more complex decision space than that of a corporation with callable debt and the ability to declare bankruptcy. A nonexhaustive list of actions involving mortgage termination and the reasons for it would include:

- Refinancing with a new mortgage with the same balance to reduce the coupon interest rate because:
  - market interest rate have fallen,
  - the borrower's creditworthiness has improved, and the credit premium on a new mortgage would be lower.
- Refinancing with a new mortgage with a higher balance to:
  - finance additional housing consumption,
  - finance additional nonhousing consumption,
  - optimize the borrower's debt portfolio (e.g., replace a second mortgage, credit card, or other debt with mortgage debt),
  - increase financial leverage and invest in additional assets.
- Paying off a mortgage without replacing it because the savings in the mortgage interest paid exceeds the return on available investments.
- Paying off the mortgage and selling the house to:

- o optimize the supply of housing services,
  - o take a superior job,
  - o move to more suitable housing because of age or infirmity,
  - o respond to an unforeseen financial reverse that either reduces income or increases expenses to the extent that the borrower can no longer afford the mortgage payments but would realize some return by selling the house and paying off the mortgage,
  - o speculate on house prices when the borrower expects house prices to decline.
- Defaulting on the mortgage because:
  - o the foregone value of the house, plus the costs of default, is less than the balance of the mortgage,
  - o an unforeseen financial reverse either reduces income or increases expenses to the extent that the borrower can no longer afford mortgage payments but would not realize any return and would lose housing service for some period if he sold the house.
- Prepayments and defaults also occur because of a homeowner's death.

All empirical models of choice are necessarily simplifications of reality, but current models of the mortgage termination choice seem particularly so. Given the wide range of motives for terminating a mortgage, the universe of potential predictive variables is wide, but many of the factors that could affect the choice are not observed in available data sets. The birth of a child, the availability of a better job, the amount of liquid investments held by the borrower, the borrower's expectation about house prices, and preferences about financial leverage are just a few of the usually unobserved factors suggested by the typology of reasons for terminating a mortgage outlined previously.

Earlier empirical analyses have not been able to differentiate between reasons for terminations even at the top-most level of the typology. A few analyses have been able to differentiate between prepayments that involve a change of address and those that do not. These studies (Clapp, Goldberg, Harding, and LaCour-Little (2001); Deng, Pavlov, and Yang (2005); Clapp, Deng, and An (2006); and An, Clapp, and Deng (2010)) find differing predictors for moves versus other kinds of prepayments.

This study differentiates mortgage terminations into the five categories in the top level of the termination typology given previously. The differentiation is made possible by matching a mortgage servicing data set to corresponding credit bureau records. The credit bureau record indicates whether the borrower takes out a new mortgage after prepaying and gives the balance on the new mortgage.

The bureau data also indicate whether the borrower changed his address as of the prepayment. Based on these additional data elements, borrowers can be assigned to one of the five categories. This further differentiation of outcomes allows a more detailed study of borrower behavior.[3]

II. Data Set and Preparation

Data for this study consist of matched records from two sources:

- Black Knight McDash Data (McDash)

    This data set provides origination and monthly servicing records from several large mortgage servicers.

- The Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP)

    This panel data set represents a 5 percent random sample of credit bureau records. It contains information about mortgages and other debt, as well as encrypted address information.

    Records from these two databases were matched using a methodology that offered a high probability of true matches.

    Once a matched data set was produced, a number of additional selection criteria were applied:

- Mortgages must have been originated between January 2005 and December 2011 (with performance observed until May 2012).

- Information on address and on mortgage tradelines must have been complete in the CCP data so that address changes and any new mortgages taken out after prepayment of the selected mortgage would be observed.

- The mortgage servicing record must be complete until termination or the end of the observation period.

    See Appendix 1 for a description of the matching process and the development of the final data set.

    The final analysis data set was restricted to 30-year, fixed-rate prime mortgages. The restriction was imposed to ensure that all borrowers in the sample faced substantially the same structure for the financial incentive to prepay. Prime borrowers were defined following Hancock, Lehnert, Passmore,

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[3] However, several of these top-level categories have subcategories that could perhaps further differentiate behavior. Data limitations prevent separating terminations beyond the top level so the analysis presented here can claim to explore mortgage termination in more detail than was possible earlier, but terminations could be further differentiated if the appropriate data were available.

and Sherlund (2006) as those having a credit score at or above 660 and a loan-to-value (LTV) below 80 percent at origination, based on the credit score and LTV at origination provided in the McDash data. While this standard is arbitrary and does not capture all the criteria used in underwriting, subsequent analysis demonstrated that it distinguished a population in which underwriting seemed consistent over time and excluded mortgages where standards for underwriting seemed to vary before and after the credit crisis.

Two additional restrictions were imposed. First, a borrower's death was observable in the CCP data, and those observations in which prepayment or default was associated with death were excluded. Second, we suspect that some moves by older borrowers were for health reasons and involuntary, so we also excluded borrowers from the sample who were over 65 at the time of mortgage termination.

Mortgage status was observed monthly until termination. Monthly time series for interest rates, county-level unemployment rates, and zip code-level house price indices were merged into the data set.[4] The final data set consisted of 6,852,695 monthly records among which there were a total of 102,062 terminations of all types.

III.   Empirical model

Binary variables were created for each type of termination event (see Table 1):

- Default (code: D) for this study was defined as 90 or more days delinquent. The prepayment outcomes were defined as follows:
  - Regular refinance (code R): Remain at the same address and take out a new mortgage for an amount less than or equal to the mortgage balance at prepayment,
  - Cash-out refinance (code: C): Remain at the same address and take out a new mortgage for an amount greater than the balance at prepayment,
  - Payoff (code: P): Remain at the same address and do not take out a new mortgage,
  - Move (code: M): Change address following prepayment.

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[4] The sources for these data are the Board of Governors of the Federal Reserve System (US), 30-Year Conventional Mortgage Rate (DISCONTINUED) [MORTG], retrieved from FRED, Federal Reserve Bank of St. Louis; CoreLogic Solutions Home Price Index; and Bureau of Labor Statistics, Local Area Unemployment Statistics.

IV.   Predictive Variables

Predictive variables used in the analysis are listed in Table 2. Several of these are the standard ones used in prepayment and default modeling: LTV ratio, credit score, age of the loan, and a variable measuring financial incentive to prepay. Because matched credit bureau data were available, the balance of any second mortgage could be used to calculate a combined LTV ratio as of each observation date. Financial incentive was measured as the difference between the mortgage index rate as of the month of origination and the index rate as of observation lagged five months. The LTV, age, and rate incentive variables were splined to allow for nonlinear impact with knot points at:

- LTV   60, 80, 90, 100, and 120 percent
- Age   12, 24, and 36 months
- Rate incentive   0, 1, and 2 percent

A second financial variable (spread at origination) was included measuring the difference between the mortgage index on the month of origination and the coupon rate on the loan. Borrowers whose interest rate on the original mortgage was relatively high should have an additional financial incentive to prepay as well as that provided by the change in the mortgage index rate.

Other variables indicated features of the mortgage, such as the type of documentation (low-, or no-doc versus full-doc), the channel through which the mortgage was originated (wholesale or correspondent versus originated by the institution servicing it), and whether the mortgage was used to purchase the property. Variables were also included indicating whether the mortgage met GSE (government-sponsored enterprise) standards for size (conforming or jumbo conforming) or not (jumbo nonconforming).[5]

Some variables related to the characteristics of the borrower, derived from the consumer credit data were also included. These included the borrower's age and an indicator showing whether the borrower currently had a second mortgage. Finally, the county unemployment rate was included as a partial measure of the likelihood that the borrower could experience financial distress.

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[5] The GSEs set a national conforming loan limit, but in some periods and for some areas, will purchase mortgages that exceed that limit. Such mortgages are called jumbo conforming because they have principal amounts larger than the national conforming loan limit.

V.   Methodology

Models were estimated by multinomial logit. Some models were nested, meaning that a first-stage model was estimated in which some outcomes were combined, and then a second-stage model was estimated distinguishing individual outcomes within the combined outcome. In the first-stage models, the "did not terminate" outcome is treated as the omitted category. Where models were nested, they were estimated using standard logistic regression for each stage rather than an overall maximum likelihood approach. Overall maximum likelihood estimation is sometimes difficult because of the lack of convergence. On the other hand, multinomial logit applied to nested models is not efficient, although it is statistically consistent.[6] Given the size of our sample and our intention to estimate several competing models, we chose to use multinomial logit.

VI.   Results — Model Comparisons

The data for the study enabled us to estimate a five-termination state model, so a natural question is whether the greater differentiation of prepayment produces a more accurate model. Equivalently, earlier models with less differentiation can be considered as restricted versions of the larger model and formally tested. A series of multinomial logit regressions was run with each representing a particular model with outcomes combined appropriately.

To present the results, it will be helpful to use a standardized notation for describing a model. Following An, Clapp, and Deng (2010), outcomes will be represented by letters, as indicated in Table 1. An estimated model will be represented by a set of letters in circumflexes, so:

(1)   {R,C,P,M,D,xN},

represents a model estimated with each of the five termination types treated as a distinct outcome and the left-out category is indicated by an "x" preceding it. (The code N indicates the outcome that the loan was not terminated.) Aggregation of outcomes is indicated by parentheses, so:

(2)   {(R,C,P,M),D,xN},

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[6] See Kenneth E. Train, *Discrete Choice Methods with Simulation*, Chapter 4, 2003.

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represents the standard two terminal state competing hazard model in which all types of prepayment are aggregated. Finally, nested models are indicated by the addition of notation describing the second-stage model, so:

(3)   {(R,C,P,M),D,xN} + {R,C,P,xM},

represents a model in which all types of prepayment are aggregated in the first stage, then disaggregated in the second-stage nested model, with M (Move) as the left-out category in the second-stage model.

It is important to note that the model in (2) differs from those in (1) and (3) in a fundamental way: It does not provide an estimated probability for each outcome. We will call the model in (2) *incomplete* to distinguish it from the *complete* models in (1) and (3). Likelihood functions for incomplete models are not comparable with those for the complete models because they do not cover the same set of outcomes. Thus, model (2) is not a restricted version of model (1) or (3), and the hypothesis that outcomes aggregated in (2) are indistinguishable cannot be tested using their estimated likelihood functions. The solution to this dilemma is to complete model (2) in a way that is consistent with the hypothesis. If the outcomes aggregated in model (2) are indistinguishable under the hypothesis, then they must be randomly assigned and equally likely. Our notation for that uses square brackets, so:

(4)   [R,C,P,M]

represents a second-stage model that randomly assigns the four outcomes. A complete version of model (2) would be:

(5)   {(R,C,P,M),D,xN} + [R,C,P,M].

Because it provides predictions for each outcome, the combined likelihood function for (5) is comparable with those of (1) and (3). For further details on testing hypotheses involving outcome

aggregation, see Appendix 2.

Based on that insight, the conditional likelihood function for the individual outcomes in an incomplete model can be calculated.

Using this notation and methodology, likelihood ratio tests for single-stage models based on aggregations are presented in Table 3. The table compares two models from the literature with a fully disaggregated model. The first is a standard prepayment/default competing hazard model. The second model, studied by Clapp et al. (2001), and An, Clapp, and Deng (2010), treats moving as a separate outcome from other types of prepayment. Both models with aggregated prepayment outcomes are strongly rejected in favor of the fully disaggregated model. These results demonstrate that the subcategories of prepayment defined previously and implemented in the data represent distinct behaviors.

A more nuanced question is whether a nested model in which the second stage separately differentiates among aggregated outcomes can perform as well as a fully disaggregated single-stage model. Table 4 addresses that question. Likelihood ratio tests cannot be used to compare these models because the nested models are not strictly restricted versions of the disaggregated model. As a result, model comparisons are based instead on the Akaike Information Criterion (AIC) shown in the far right column of the table. Rows A and B show results for models in which the Move outcome is and is not aggregated with the other prepayment outcomes. Row A corresponds to the standard competing hazard prepayment/default with all prepayment outcomes aggregated, while Row B differentiates Move from other prepayment outcomes. Row C represents an alternative treatment of the Move outcome suggested by An, Clapp, and Deng (2010) in their nested multinomial logit model (NMLM), where it is combined with the Default outcome in the first stage and then is separated in a second-stage model while the other prepayment outcomes remained combined. Both models which differentiate the Move outcome (B and C) perform better than the model that does not (A). Perhaps surprisingly, however, combining Move and Default in the first stage, then differentiating them in the second stage (model C), produces a substantially lower AIC than simply differentiating Move in the first stage (model B). The implication is the Move and Default share some behavioral similarity that differentiates them more from the other prepayment outcomes than they are different from each other.

Models D, E, and F are versions of A, B, and C, in which a second-stage model is added to

differentiate among all prepayment outcomes. The greater differentiation in the second stage improves the AIC for each model, as would be expected, and again the best model is the NMLM combing Move and Default in the first stage.

Row G shows another way to generalize the NMLM model: Differentiate the other prepayment outcomes in the first-stage model rather than in a nested second-stage model. This model further lowers the AIC, implying that, while Move and Default have something in common that suggests combining them in the first stage, the other prepayment outcomes are distinct.

Finally, Row H provides a complete differentiation of all outcomes. Its AIC is higher than that of Row G, giving additional support to the idea that the Move and Default outcomes share some common features and validating the result originally reported by An, Clapp, and Deng (2010). These authors suggest that the reason why Move and Default should be combined in the first stage is that both outcomes are affected by unmeasured mobility characteristics. This argument implies that a family with a high propensity to mobility will default on their mortgage to move if they are not able to sell their house.

An alternative explanation may be the two-trigger theory first proposed by Vandell (1995). Here, terminating tenure in the house is motivated by an unexpected adverse financial event that leaves the family unable to continue mortgage payments. If the mortgage balance exceeds the value of the house at that point, a default results. But if the house value exceeds the mortgage balance, it will be optimal to sell the house and move. While not all moves occur in this way, if a sufficient fraction of them do, then Move and Default could be related as we have found. This is because unexpected adverse financial events are unmeasured in typical mortgage data sets, including ours. Because we do not distinguish between types of Move outcomes, it is not possible to test these two explanations. Therefore, we turn to the results for individual outcomes; however, this would be a fruitful area for additional research.

VII.   Results — Estimated Parameters

This section presents the results for the disaggregated model (Row H, Table 4), which treats each of the four prepayment outcomes as distinct. We chose to present the completely disaggregated model rather than the better-performing nested model (Row G, Table 4) because the results were qualitatively similar and because this permits a comparison of Move and Default outcome estimated

parameters directly to the other prepayment outcomes. Table 5 presents coefficient estimates for this model. Overall, nearly all coefficients are significantly different from zero, and only one variable, the LTV spline with knot point at 100 percent is not significant for any outcome.

For variables that were splined, it is difficult to calculate the net contribution to the model's linear form by reviewing the coefficients in the table, so a graph of the total contribution of all the splines for a particular variable as a function of the level of the variable is provided. Figure 1 shows the LTV ratio contribution to the model linear form for each of the five separately modeled outcomes. As would be expected, there is a strong positive relationship with Default (a higher LTV implies a higher probability of default). All prepayment outcomes are less likely for high LTVs. The Regular Refinance and Move outcomes show little impact until about 80 LTV, and then a moderate negative trend as LTV increases further. The Cash-Out outcome is more sensitive, beginning to turn down at 60 LTV and declining more than Regular Refinance for high LTVs. This may reflect higher underwriting standards being applied to Cash-Out Refinances. By far, the most sensitive prepayment outcome is payoff, where the trend in the relationship is negative through the whole range, presumably because a higher LTV implies a higher balance and therefore a higher financial hurdle to paying off the mortgage.

The impact of loan age on the probability of all outcomes is shown in Figure 2. Here, age impact increased for all outcomes over the first 12 months, and then it diverges from there. The change in impact over the first 12 months is small for the payoff outcome, and there is little subsequent change. The increase over the first 12 months is greater for the Regular Refinance and Move outcomes, but they also change little after 12 months. The largest effect of loan age is for the Default outcome, and it continues to rise until month 24. The greater sensitivity of this outcome to age may reflect the success of the mortgage underwriting process in accurately assessing the borrower's ability to make the monthly payments as of the mortgage origination. As time passes and the borrower's financial condition evolves, the original assessment becomes less relevant and default probability rises. Uniquely, the relationship with age seems to reverse at month 12 for the Cash-Out Refinance outcome. The decline is initially rapid, reversing the initial increase around month 30, but eventually it becomes more gradual. There is no reason to expect that Cash-Out Refinance becomes less attractive as time passes, so this result may reflect self-selection in Cash-O Refinance, based on factors not included in the model. If this were true, the proportion of borrowers with a propensity for Cash-Out Refinance would decline over time, creating the negative relationship observed.

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Figure 3 illustrates the impact of the refinance incentive upon each model outcome. An increase in this variable implies that market mortgage rates have declined. Two of the outcomes modeled are solely related to financial motives with respect to the existing mortgage: Regular Refinance and Payoff. With Regular Refinance separated from other prepayment outcomes, the impact of the refinance incentive seems quite consistent with the view of Regular Refinance as the exercise of a call option on the mortgage. The relationship is upward sloping throughout its range, and the steepest part is where the mortgage rate has increased relative to the rate at origination. Thus, relative to no change in the mortgage interest rate, a 1 percent rise in the rate reduces the probability of Regular Refinance by more than a 3 percent reduction in the rate increases it. The Payoff relationship is also upward sloping for rate declines but flat for rate increases. The Cash-Out Refinance relationship shows an even greater change than Regular Refinance for rate declines up to 2 percent, but then it reverses direction. This is consistent with a burnout explanation: Those considering a Cash-Out Refinance responded rapidly to declining rates so that many who still had not refinanced after rates had fallen more than 2 percent are self-selected against prepayment. The Move and Default outcomes, as expected, show less sensitivity than the other outcomes to mortgage rate changes.

Turning to the nonsplined variables, from Table 5, a higher credit score at origination increases the probability of the four prepayment outcomes and decrease the probability of the Default outcome. This relationship is expected and consistent with other studies: Less creditworthy borrowers are more likely to default, and therefore, less likely to prepay. However, our results show considerable differences among the four prepayment outcomes. To explain these, we believe it is necessary to consider an additional role for the credit score: as a prediction of future credit scores. A borrower who wishes to refinance her mortgage must have an acceptable credit score to do so. And so must a borrower who wishes to move and purchase a new house. If the credit score at origination is at least a somewhat accurate prediction of future credit score, we would expect it to have a larger impact on those prepayment outcomes that involve getting a new mortgage and a smaller impact on the outcome that does not: Payoff. And this is the pattern we find. The one surprising result is the small magnitude of the coefficient for Cash-Out Refinance.

While LTV, the age of the loan, the refinance incentive, and the credit score at origination represent the primary drivers of prepayment and default, the other variables in the model measure

smaller differences among borrowers. For these, a few relationships deserve some discussion. The spread at origination variable is meant to represent the lender's assessment of the borrower's riskiness, but it also represents a component of the cost of the mortgage. Its positive sign for Default and all prepayment outcomes is consistent with these two factors: A riskier loan is more likely to default, and higher cost should also motivate prepayment. Low Doc and No Doc mortgages should, all else being equal, be riskier than mortgages with full documentation (the omitted category), and therefore, more difficult to refinance and more likely to default. This pattern can be seen for Low Doc mortgages, but signs for the prepayment outcomes are reversed for No Doc loans. Also, the Default coefficient is much smaller for No Doc than for Low Doc mortgages, although a No Doc mortgage should be, ceteris parabis, more risky than a Low Doc mortgage. This pattern suggests that underwriting standards may have been higher for No Doc loans in dimensions not reflected in the model.

Jumbo Conforming mortgages are those that meet GSE underwriting requirements but exceed the GSE loan size limits. Jumbo Nonconforming mortgages are large and do not meet GSE underwriting requirements. The omitted category is conforming mortgages. Jumbo Conforming mortgages are more likely to prepay and less likely to default, but there are noticeable differences among the coefficients for the prepayment outcomes. Jumbo Nonconforming mortgages are about as likely to default as conforming mortgages, and prepayment impacts are more mixed. These patterns do not seem to have a simple explanation. Wholesale loans are originated by others and purchased by the ultimate owner. The positive sign on that variable for the Default outcome indicates that wholesale mortgage originators may have used lower underwriting standards in some unmeasured dimensions than lenders who originated for their own mortgage book (the omitted category). Correspondent loans are originated by others but under the purchaser's underwriting guidelines. The negative sign for that variable for the Default outcome seems to imply that correspondents underwrote more strictly than the institutions for which they originated, perhaps implying that the purchasing institutions set higher standards for correspondents than for themselves.

Mortgages used to purchase a house are less likely to default than those used to refinance an existing mortgage or to have a Regular Refinance but more likely to pay off. Again, the explanation for this pattern is unclear. Borrower Age could be a proxy for geographic mobility, which is consistent with the negative sign and relatively large size of the coefficient for Move. For the Default outcome, the

positive coefficient implies that older borrowers, all else equal, are less financially secure. Taking on a second mortgage is likely to increase a borrower's total mortgage payment. (It will not necessarily increase the payment because the most common form of second mortgage is a line of credit and need not have a positive balance.) A higher mortgage payment ought to raise the likelihood that a financial reverse would lead the borrower to default.

However, to obtain a second mortgage, the borrower must be underwritten and approved by a new lender, providing more recent evidence for her continued creditworthiness that is not available for a borrower who does not take out a second mortgage. This signal should imply a lower likelihood of default. These two effects are in the opposite direction, so the coefficient for the variable should measure the net impact. The negative coefficient for the Default outcome implies that the validation of continued creditworthiness implicit in the appearance of the second mortgage is the stronger of the two impacts. The presence of a second mortgage also increases the likelihood of all prepayment outcomes, presumably because consolidation into a large first mortgage can produce a lower overall average interest rate and lower payment.

Finally, higher county unemployment rates increase the probability of default and reduce the probability of the prepayment outcomes except for Regular Refinance. Assuming that the unemployment rate variable indicates a greater probability that the borrower will have a job loss, the positive sign for Regular Refinance is counterintuitive.

VIII.   Results — Differences Among Prepayment Outcomes

Looking across the four types of prepayment, the model results support the idea that different motivations drive different prepayment outcomes. Regular Refinance is the outcome implicit in the standard description of prepayment behavior: Prepayment is a financial option more likely to be exercised the further it is in the money. The same motivation should affect Cash-Out Refinance, but the borrower must have an additional motivation that requires that he raise cash. Often, the additional cash will be used for investments, such as home improvement or to purchase another property. Thus, Cash-Out Refinance should often be motivated by a desire to increase real estate investment. The differences between the Regular Refinance and Cash-Out Refinance support this interpretation. Cash-Out Refinance reacts more strongly to small rate incentives to prepay but less strongly to larger rate incentive, and negative rate incentives do not reduce it.

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Further, Cash-Out Refinance seems to occur sooner after the mortgage is originated than Regular Refinance, and the impact of loan age is negative after about 30 months of age. And those who obtained mortgages from wholesale loan brokers are much more likely to do a Cash-Out Refinance, as are those who obtained a second mortgage. These results suggest that Cash-Out Refinance, in contrast to Regular Refinance, is driven by an interest in increasing financial leverage, as well as exercising the mortgage call option.

Those who prepay and move may also be affected by the rate incentive, but they clearly have other important reasons for their behavior. Consistent with this view, the Move outcome is affected less strongly by rate incentive than any other prepayment outcome. Most of the reasons homeowners might choose to move are not represented directly in the data. However, Borrower Age may proxy for mobility, since its coefficient is the most negative among prepayment outcomes.

Borrowers can only pay off a mortgage if they have sufficient other assets. Thus, the Payoff outcome should be more likely the smaller the remaining balance of the mortgage relative to other assets. Borrower asset data are not available, but payoff should be more likely the lower the LTV. The estimated model is consistent with this expectation, exhibiting a negative impact of increasing LTV on the probability of Payoff, which is both large and quite different from the LTV relationship for other prepayment outcomes. Further, borrowers who are capable of paying off their mortgage would be more likely to do so if their alternate uses for the funds generate a lower return than the interest rate on the mortgage. Thus, Payoff should be affected by rate incentive in the same way as other prepayment outcomes. That behavior is seen in the estimated model, although Payoff is less sensitive to rate incentive than Regular Refinance or Cash-Out Refinance.[7]

IX.   Results — Prediction

While the statistical tests show conclusively that the different prepayment outcomes are driven by different variables, and parameter estimates are generally consistent with expectations about the behavior affecting different outcomes, the practical impact for users of mortgage prepayment and default models is unclear. Do models that disaggregate prepayment produce overall predictions of

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[7] The gain from prepayment is determined both by the current rate differential and the current balance of the loan. If, for most borrowers, payoff is only feasible when the mortgage balance is small, then the impact of a given rate incentive should be smaller for Payoff than for Regular Refinance and Cash-Out Refinance prepayments where balances are often large.

prepayment that differ materially from models that aggregate prepayment outcomes? And does the disaggregation of prepayment outcomes have any effect on default predictions? To address these questions, the disaggregated model with four prepayment outcomes and the standard model aggregating prepayment outcomes were used to predict cumulative prepayments and defaults for two newly originated mortgages under three economic scenarios.

The two mortgages were to chosen to differ as much as possible while still meeting the prime definition used here. The "Better" mortgage had an 800 credit score, and an initial LTV of 60 percent, while the "Worse" mortgage was set at 80 percent LTV and a 680 credit score. The Worse mortgage was also given a 0.5 percent higher coupon interest rate and was assumed be a low documentation mortgage originated in the wholesale channel. All variable values for the two mortgages are presented in Table 6.

The mortgages were simulated over three years under three different economic scenarios. Two scenarios were historic: January 2000 through January 2003, and January 2006 through January 2009. The third scenario was the Supervisory Severely Adverse Scenario used by the Federal Reserve for bank stress testing in 2018.[8] This scenario envisions a fast and deep recession with a slow recovery near the end of the three-year period. Time paths for the mortgage interest rate, the house price index[9], and the unemployment rate are shown in Figures 4–6.

Table 7 gives the cumulative default and prepayment rates using the two-outcome model, which aggregates all prepayment outcomes and the five outcome model that models each prepayment outcome separately. For the Better mortgage, cumulative prepayment is lower for the five outcome model in the benign 2000–2003 scenario and higher in the other two more stressful scenarios. Cumulative default is low and differs little between the two-outcome and five-outcome models. Larger differences are seen with the Worse mortgage. As expected, cumulative prepayment rates are generally lower for the Worse mortgage, and cumulative default rates are much higher. Again, the five-outcome model has lower cumulative prepayments in the 2000–2003 scenario and higher prepayments in the other scenarios.

Cumulative default rates are much higher over the three-year period for the Worse mortgage in all three scenarios and are higher for the five-outcome model in all scenarios. On a percentage

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[8] See the Board of Governors of the Federal Reserve System, "2018 Supervisory Scenarios for the Dodd–Frank Act Stress Testing, Rules and the Capital Plan Rule," February 2018, Table 4.1, p. 15.

[9] The house price indices have each been normalized to 100 at the start of the simulation.

basis, the differences between the two models is not great (4 percent to 6 percent), but the difference in default rates is larger in each case than the three-year cumulative default rate for the Better mortgage. These differences in default rates would translate into noticeably larger loss forecasts if these models were used in stress testing. Thus, although the purpose of differentiating among prepayment outcomes was to assess and understand the motivations associated with different prepayment outcomes, these simulations demonstrate that such models could actually provide some additional accuracy in default and loss predictions.

X.   Conclusion

Performing a statistical match combining servicing data with credit bureau data for a large sample of 30-year, fixed-rate mortgages, we have been able to separately identify several types of prepayment: a straight refinance, refinance with cash out, mortgage payoff, and move. Multinomial logit and nested multinomial logit models were estimated for these four outcomes plus default and compared with a standard prepayment/default model in which all types of prepayment are lumped into a single outcome. Likelihood ratio tests demonstrate that the greater differentiation of prepayment outcomes produces a more accurate model than either the standard two outcome model, or a model in which just Moves are analyzed separately. The results demonstrate that borrowers prepay for several distinguishable reasons and that their reason for prepayment is influenced in understandable ways by variables relating to their mortgage, the value of their house, interest and unemployment rates, and their personal characteristics such as credit score. Differentiating prepayment outcomes also modestly improves default prediction, raising cumulative default predictions over three years.

Finally, while this study increases the differentiation of prepayment outcomes substantially compared with earlier research, a review of the probably incomplete typology of prepayment presented at the beginning of the paper indicates that further differentiation would be justified if the data to implement it were available. As data sets and matching algorithms improve, further differentiation could offer new insights and provide a more detailed understanding of mortgage borrower behavior.

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Appendix 1

Construction of the Matched Data Set

Mortgage records from a mortgage servicing database (Black Knight McDash) and a credit bureau database (Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP)) were matched and merged based on four variables common to both. The match was done with the goal of minimizing the chance of incorrect matches, so nonunique records in each database were discarded before matching, and only one-to-one matches were retained. Steps in the merger and subsequent selection of matched records to be used are described next.

- Within each database, select only those records that are unique within the database based upon four variables: origination date, property zip code, original loan amount, and monthly payment range.

- Compare the mortgage servicing records with the credit bureau records and create a merged data set of matched records.

- Although the payment ranges used were narrow, there were a few cases in which the match between the two databases were not one to one.

- Compare status codes for the last joint record from the two sources and eliminate all merged records in which status codes do not agree.

- Select records meeting standards for inclusion in the analytic data set:
  - Fixed-Rate, First Mortgages, 30-Year Term, Primary Occupancy,
  - Originating from January 2005 through December 2011 (performance through May 2012),
  - Determine if the family changed addresses and/or took out a new mortgage after termination,
  - Document type known,
  - Servicing not transferred to another servicer,
  - No missing information for model variables.

Figure 7 is a waterfall chart illustrating these steps, showing the number of loan-level records surviving each step in the matching and selection process. From these loan-level records, monthly records for each month in the loan's history were constructed.

Testing the Hypothesis That Outcomes Can Be Combined in a Multinomial Logistic Model

Suppose that, in a multinomial logistic regression, the researcher wishes to test the hypothesis that two or more outcomes should be combined. This is logically equivalent to the hypothesis that, given the combined event occurs, which of the individual events occurs is completely unpredictable and, therefore, under the hypothesis, equally as likely. With this understanding of the null hypothesis, the likelihood for an observation in which one of the combined outcomes occurs can be calculated. Suppose there is data set in which j outcomes are possible, and the researcher wishes to test the hypothesis that k of them can be combined into a single outcome designated as outcome C. Assume a multinomial regression has been estimated based on the combined outcome. Define $L(m \in C)_i$ as the estimated probability that outcome m, which is one of those included in C, occurred for observation i. Then, under the null hypothesis, with each of the k outcomes in C equally likely, that

$$L(m \in C)_i = L(C)_i * \left(\frac{1}{k}\right)$$

and

$$log(L(m \in C)_i) = log(L(C)_i) + log\left(\frac{1}{k}\right).$$

The first term on the right-hand side of this equation is the corresponding term in the log likelihood function for observation i from a multinomial logit model estimated based on the combined outcome. So the overall likelihood function for predicting individual outcomes under the null hypothesis, based on an estimated model that combines k outcomes into C, is just the estimated likelihood function for that model plus the term $N_C * log(\frac{1}{k})$, where N_C is the total number of observations in which any of the outcomes in C occurred. This likelihood function can be compared in a likelihood ratio test with the likelihood function from a model in which the outcomes in C are not combined.

Table 1

Observations and Outcomes by Loan-Month

Outcome	Code	Number	Frequency
Regular Refinance	R	50,430	0.74%
Cash-Out Refinance	C	26,132	0.38%
Payoff	P	6,720	0.10%
Move	M	12,184	0.18%
Default	D	6,596	0.10%
No Change	N	6,750,633	98.51%
Total		6,852,695	

Table 2

Predictive Variables

Name	Definition
LTV, LTV > 60, LTV > 80, LTV > 90, LTV > 100, LTV > 120	Current Combined Loan-to-Value Ratio Lagged 5 Months (Splined with knot points at 60%, 80%, 90%, 100%, and 120%)
Credit Score	Credit Score at Origination
Loan Age, Loan Age > 12, Loan Age > 24, Loan Age > 36	Age of Loan (Splined with knot points at 12, 24, and 36 months)
Rate Incentive, Rate Incentive > 0, Rate Incentive > 1, Rate Incentive > 2	Interest Rate Incentive to Prepay (Rate at Origination Minus Current Rate) lagged 2 months
Spread at Origination	Mortgage Coupon Spread at Origination
Low Doc	Low Doc Indicator
No Doc	No Doc Indicator
Jumbo Conforming	Jumbo Conforming Indicator
Jumbo Nonconforming	Jumbo Nonconforming Indicator
Wholesale	Wholesale Channel Indicator
Correspondent	Correspondent Channel Indicator
Purchase	Purchase Mortgage Indicator
Borrower Age	Borrower Age at Termination
Second Mortgage	Second Mortgage Indicator
Unemployment Rate	County Unemployment Rate Lagged 2 Months

Table 3

Likelihood Ratio Tests for Single Stage Models

	Model	Description	-2log(likelihood)	Degrees of Freedom	H_0	Additional likelihood term to represent H_0	-2log(likelihood) under H_0	Likelihood ratio test statistic	Likelihood ratio test degrees of freedom	Likelihood ratio test significance level
A	{R,C,P,M,D,xN}	Five termination state model	1,222,656	130						
B	{(R,C,P,M),D,xN} + [R,C,P,M]	Standard two termination state model	1,026,598	52	All prepayment terminations can be combined	264,688	1,291,286	68,630	78	0.000
C	{(R,C,P),M,D,xN} + [R,C,P]	An, Clapp, Deng "MNL" model	1,094,812	78	All prepayment terminations except moves can be combined	182,989	1,277,801	55,145	52	0.000

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Table 4

Estimated Model Comparisons

	Model	Description	-2log(likelihood) First stage model	First Stage Number of Parameters	-2log(likelihood) Second stage model(s)	Second Stage Number of Parameters	-2log(likelihood) Total	Total Number of Parameters	Akaike Information Criterion
A	{(R,C,P,M),D,xN} +[R,C,P,M]	Standard competing hazard prepayment/default model	1,026,598	54	264,688	0	1,291,286	54	1,291,394
B	{(R,C,P),M,D,xN} +[R,C,P]	An, Clapp, Deng model (MNL)	1,094,812	81	182,989	0	1,277,801	81	1,277,963
C	{(R,C,P),(M,D),xN} + [R,C,P] + {xM,D}	An, Clapp, Deng nested model (NMNL)	1,081,211	54	196,244	27	1,277,454	81	1,277,616
D	{(R,C,P,M),D,xN} + {R,C,P,xM}	Standard competing hazard prepayment/default model with second stage R,C,P model	1,026,598	54	196,603	81	1,223,200	135	1,223,470
E	{(R,C,P),M,D,xN} + {R,C,xP}	An, Clapp, Deng model (MNL) with R, C, P disaggregated in second stage	1,094,812	81	128,389	54	1,223,201	135	1,223,471
F	{(R,C,P),(M,D),xN} + {R,C,xP} + {xM,D}	An, Clapp, Deng nested model (NMNL) with R, C, P disaggregated in second stage	1,081,211	54	141,644	81	1,222,854	135	1,223,124
G	{R,C,P,(M,D),xN} + {xM,D}	An, Clapp, Deng nested model (NMNL) with R, C, P disaggregated in first stage	1,209,055	108	13,254	27	1,222,309	135	1,222,579
H	{R,C,P,M,D,xN}	Completely disaggregated model	1,222,656	135	0	0	1,222,656	135	1,222,926

Table 6: Variable Values for Two Mortgages

Table 7

Better Mortgage Cumulative Outcomes

	2 Outcome Model	5 Outcome Model
Default		
2000-2003	0.3%	0.4%
2006-2009	0.3%	0.3%
Fed Sev. Adv.	0.6%	0.7%

	2 Outcome Model	5 Outcome Model
Prepayment		
2000-2003	72.2%	71.9%
2006-2009	27.3%	28.5%
Fed Sev. Adv.	21.2%	22.7%

Worse Mortgage Cumulative Outcomes

	2 Outcome Model	5 Outcome Model
Default		
2000-2003	12.3%	13.1%
2006-2009	13.4%	14.0%
Fed Sev. Adv.	33.6%	34.9%

	2 Outcome Model	5 Outcome Model
Prepayment		
2000-2003	54.8%	53.1%
2006-2009	20.5%	21.3%
Fed Sev. Adv.	11.6%	11.8%

Figure 1

Loan-to-Value Ratio Contributions to Model Linear Forms
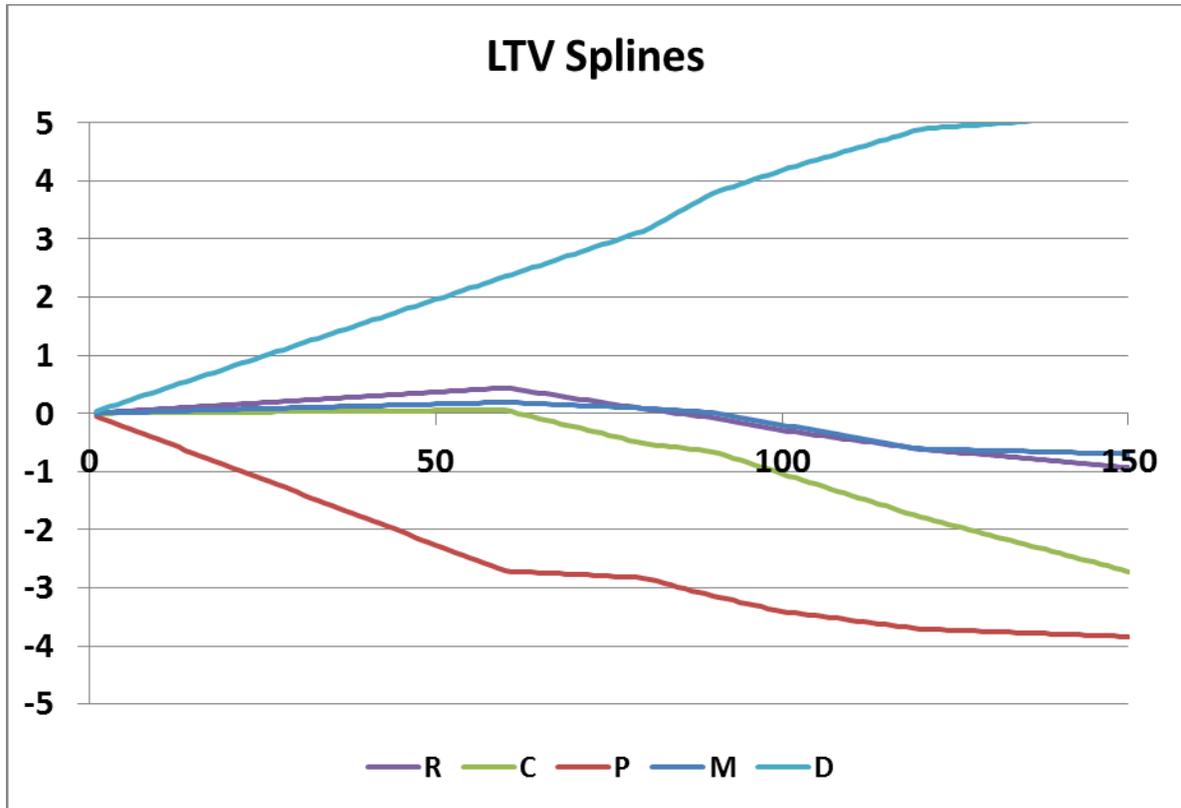
Figure 2

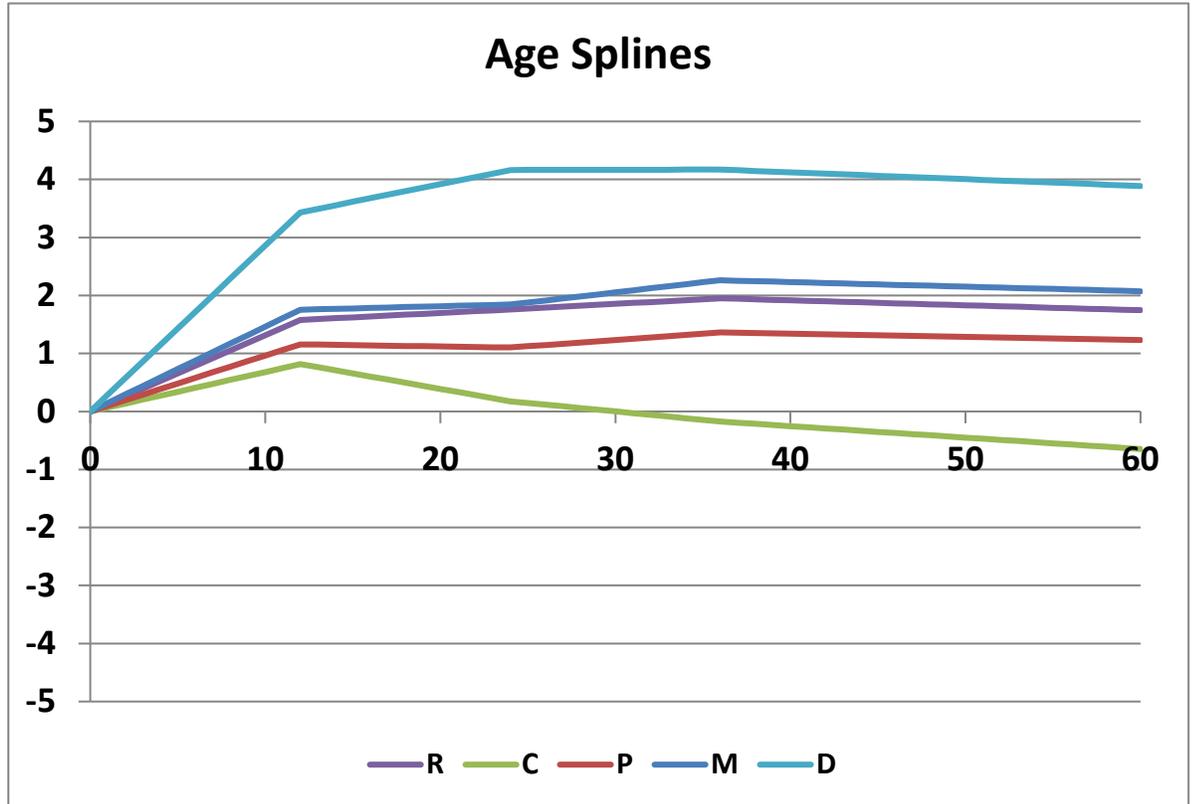**Loan Age Contributions to Model Linear Forms**

Age Splines

Figure 3

Refinance Incentive Contribution to Model Linear Forms

Figure 4

30 Year Fixed Rate Mortgage Rate

Figure 5

House Price Index

Legend: 2000-2003, 2006-2009, Fed 2018 Severely Adverse Scenario

Figure 6

Unemployment Rate
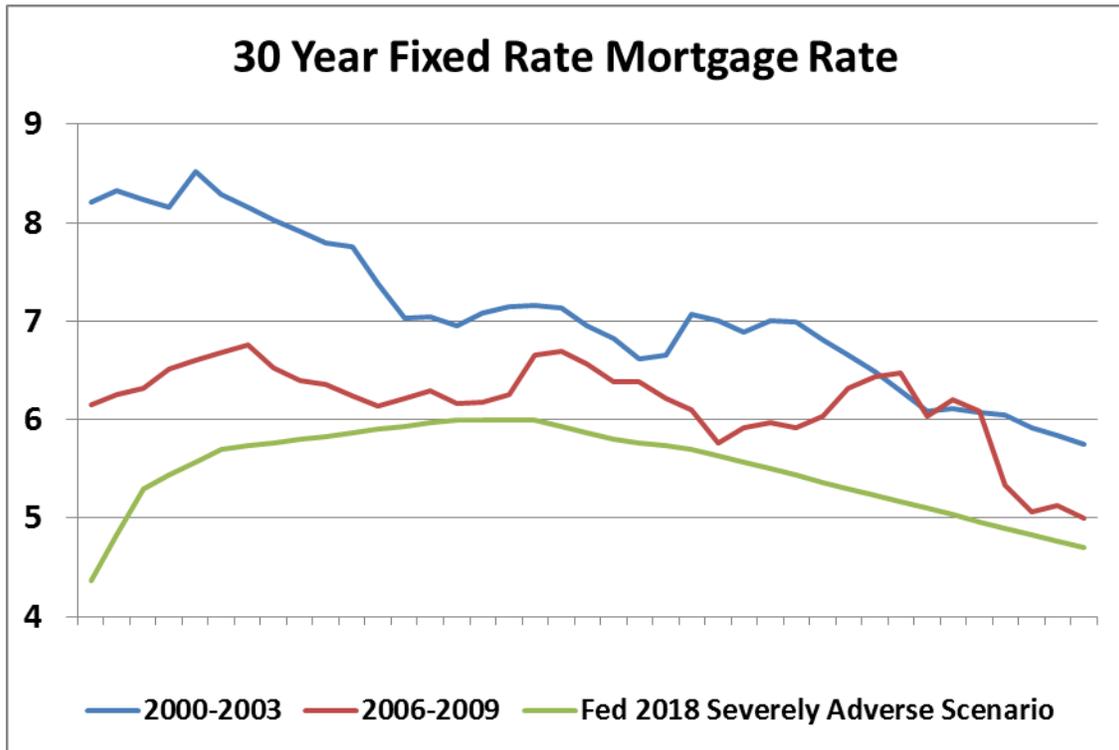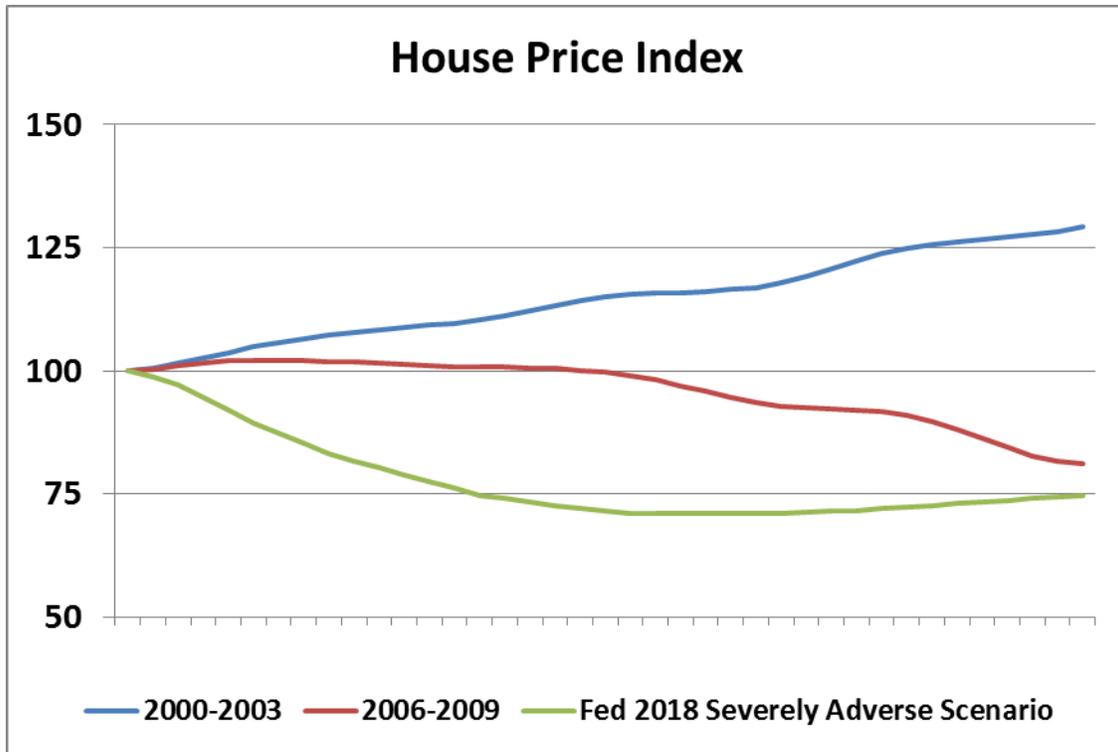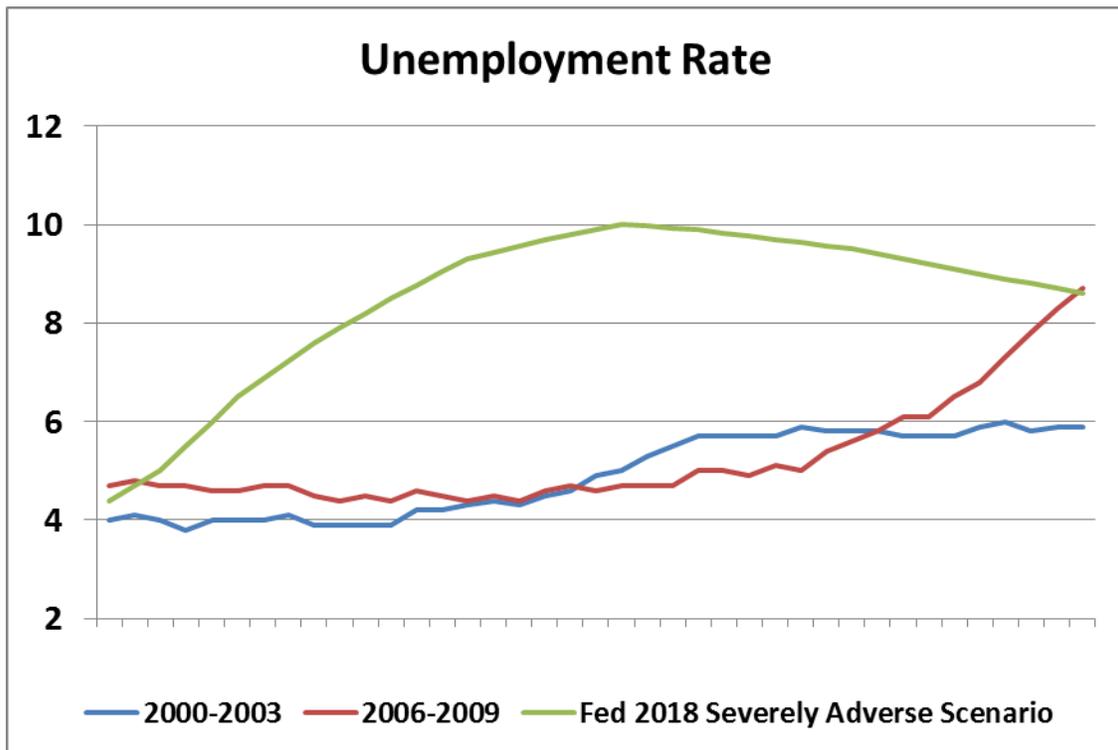
Legend: 2000-2003, 2006-2009, Fed 2018 Severely Adverse Scenario
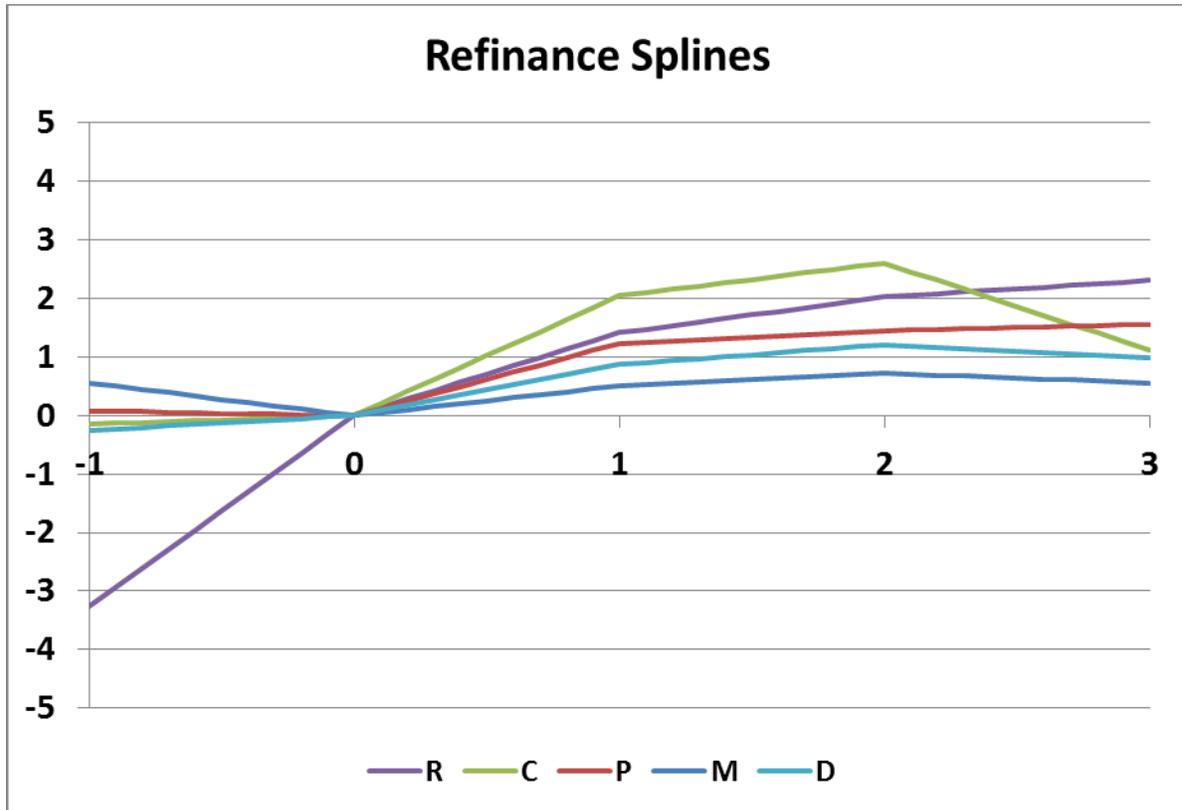
Figure 7

Waterfall for the Construction of the Matched Data Set

McDash
Fixed-Rate, First Mortgages
Opened in 2000–2011
(49,095,990)

CCP
First Mortgages
Opened in 2000–2011
(11,229,468)

McDash
Mortgages with Unique Zip Code, Origination Date, Original Amount, and Payment Range
(43,470,971)

CCP
Mortgages with Unique Zip Code, Open Date, High Credit, and Payment Range
(10,331,456)

Original Merge
McDash mortgages with same Zip Code, Origination Date, Original Amount, & Payment Range as those in CCP
(1,603,413)

One-to-One Matches
The one-to-one matches from Merge
(1,603,046)

Loan Status Merge
Mortgages which have agreeing status codes in last joint record in McDash and CCP
(1,551,511)

Final Data Set
Matched loans with complete information and that met additional criteria
(229,752)