Payment Changes and Default Risk:
The Impact of Refinancing on Expected Credit Losses

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Abstract

This paper analyzes the relationship between changes in borrowers' monthly mortgage payments and future credit performance. This relationship is important for the design of an internal refinance program such as the Home Affordable Refinance Program (HARP). We use a competing risk model to estimate the sensitivity of default risk to downward adjustments of borrowers' monthly mortgage payments for a large sample of prime adjustable-rate mortgages. Applying a 26 percent average monthly payment reduction that we estimate would result from refinancing under HARP, we find that the cumulative five-year default rate on prime conforming adjustable-rate mortgages with loan-to-value ratios above 80 percent declines by 3.8 percentage points. If we assume an average loss given default of 35.2 percent, this lower default risk implies reduced credit losses of 134 basis points per dollar of balance for mortgages that refinance under HARP.

Key words: refinancing, default

In early 2009, the Home Affordable Refinance Program (HARP) was announced by the U.S Department of Treasury as part of a suite of housing relief programs. HARP sought to reduce obstacles to refinancing such that borrowers with high loan-to-value (LTV) ratios could gain increased access to the lower prevailing market rate for prime conforming fixed-rate mortgages. Mortgage refinancing is one of the normal channels through which declining interest rates support economic activity, growth, and employment, by reducing the amount of income households have to spend on servicing their home mortgages, freeing up cash flow to spend on other goods and services. For homeowners with adjustable-rate mortgages (ARMs), the required monthly mortgage payment declines automatically as the interest rate resets on the mortgage. For homeowners with fixed rate mortgages – the vast majority of U.S. mortgage borrowers but not in most other developed economies – the reduction in monthly payments takes place when the homeowner refinances the existing mortgage into a new mortgage at the lower prevailing mortgage interest rate.

Despite the implementation of HARP, since 2009, refinancing activity has remained subdued relative to model-based extrapolations from historical experience. Since its inception, 1.1 million mortgages had been refinanced through HARP, compared to the initial announced goal of three to four million mortgages. If anything, this has vindicated the original rationale for HARP: the notion that following the housing bust borrowers need help refinancing

Over the last two and a half years, the HARP's lackluster results have provoked much discussion by market participants and policymakers of the frictions obstructing refinancing activity. Prominent among these frictions are credit risk fees, limited lender capacity, costly and time-consuming appraisal processes, restrictions on marketing refinancing programs, and legal risks for lenders. Ultimately, the HARP was revised, to better address these frictions.

Several concerns about revising the HARP have been raised, including doubts about its fairness and macroeconomic efficacy. The Federal Housing Finance Authority (FHFA), as the regulator of the GSEs, has the responsibility of evaluating any proposed changes to the implementation of the HARP in terms of the likely impact on the capital of the GSEs. This includes the likely impact on the fee income generated from the refinancing, on the interest income from the GSEs' holdings of MBS securities, on the expected revenues from put-backs of guaranteed mortgages that default, and finally on the impact of refinancing on expected credit losses to the GSEs. Analysis of leading proposals, however, have tended to provide only estimates of the first three of these impacts on the GSEs' capital.[1]

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[1] The exception is Remy *et al.* (2011) to be discussed below.

In this paper, we implement an empirical strategy to estimate the expected reduction in credit losses to the GSEs that would result from improvements to the HARP program. An outcome of an improved program would be a larger set of borrowers who are "in the money" to refinance. For these borrowers we can estimate the average percent reduction in their monthly mortgage payment that would result from a refinance. The question is how this mortgage payment reduction will affect the likelihood that the borrower defaults subsequent to the refinance. We would like to use that change in probability of default to determine the difference in expected credit losses from two identical borrowers with identical fixed-rate mortgages (FRMs) – where one borrower refinances to a lower monthly payment and the other borrower does not. The difficulty is that we do not observe changes in mortgage payments for borrowers with FRMs, since the lower payments are obtained by taking out a new loan and paying off the previous one and available data does not allow one to link together these two mortgages. So, this impact of a payment change on borrower performance must be inferred.

We work around these obstacles by extrapolating from the performance of prime ARM borrowers with similar observed credit characteristics as prime FRM borrowers. We use a competing risk model to estimate the sensitivity of default risk to downward adjustments to borrowers' monthly mortgage payments. A caveat regarding this approach is that prime borrowers who select ARMs may differ in unobserved ways from those who select fixed FRMs, and these unobserved differences may invalidate generalizing our estimates to FRMs borrowers. This inquiry is novel in that previous research on the sensitivity of default risk in ARMs to payment adjustments has primarily focused on upward adjustments associated with rate resets on non-prime hybrid ARMs. There has been little research on the sensitivity of default risk to downward adjustments to household borrowers' monthly mortgage payments.

The GSEs' pricing decision for refinances

The following figure illustrates a simplified version of the decision by the GSEs on setting the up-front fee for a refinance of an existing agency-guaranteed mortgage. These fees are set in terms of basis points charged against the mortgage balance that is to be refinanced. Given the distribution of active agency mortgages across different coupon rates, the other costs of refinancing and the payback period borrowers require to recoup these costs, there will be a downward sloping demand curve for

refinancing as a function of the fee charged by the GSEs.[2] All else the same, borrowers with higher mortgage rates are willing to pay a higher fee to the GSEs in order to be able to refinance at the lower prevailing mortgage interest rate.

Figure 1. GSE Refinance Pricing Decision
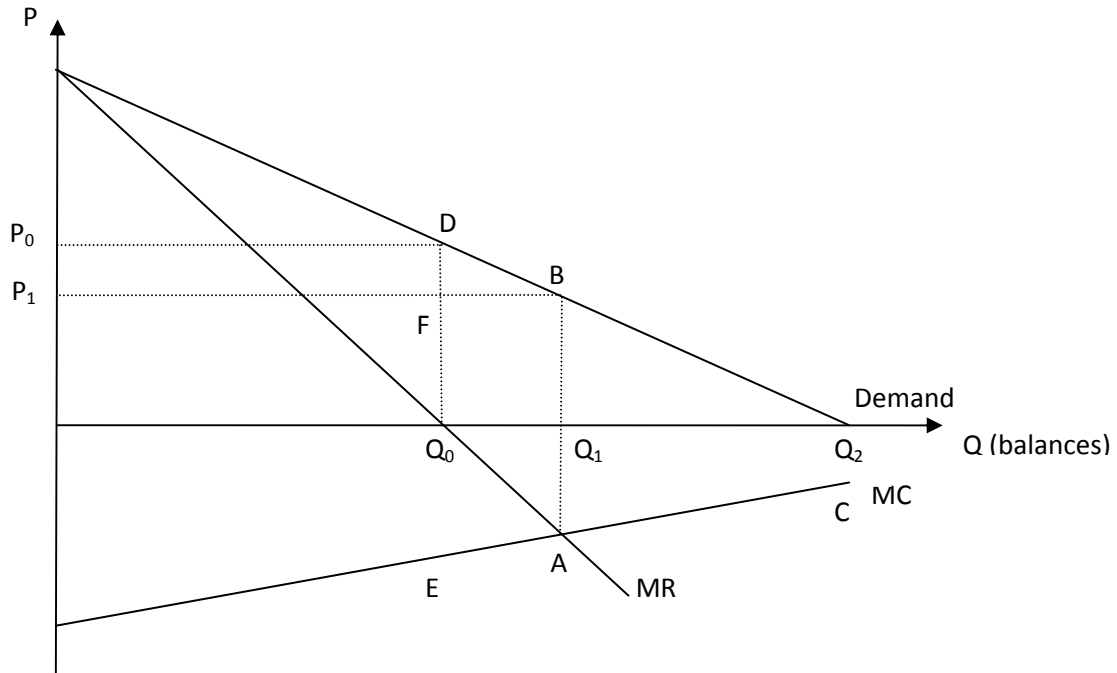
If lowering the borrower's monthly mortgage payment through a refinance reduces the expected credit losses for that borrower, then we can represent this as a negative marginal cost. The marginal cost is upward sloping since borrowers with a lower demand price face a smaller interest rate incentive to refinance and therefore would have a smaller percent reduction in their monthly payment from a refinance. This smaller percent reduction in the monthly payment implies a smaller reduction in the expected credit losses from a refinance.

Assume that the GSEs set a single refinancing fee in an attempt to maximize their return. If the GSEs ignore the impact that refinancing has on their expected future credit losses, then the profit-maximizing fee equates the marginal revenue with an assumed zero marginal cost. Here we treat the

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[2] The other costs of refinancing include the application fee charged by the lender, the appraisal fee (unless the appraisal is waived), title insurance, and any other taxes that might be imposed. Increases (reductions) in these other refinance costs would cause the demand curve to shift inward (outward).

two GSEs as if they act as a single monopoly in the provider of agency refinancing.[3] The GSEs would set their fee at P_0 and Q_0 of borrower balances would be "in the money" to refinance. By definition, in this simple example this is half of the total borrower balances that would be in the money to refinance if the GSEs set their fee to zero. The fee income to the GSEs is given by the rectangle $0P_0DQ_0$.

Now assume that the GSEs correctly recognize that refinancing reduces their expected future credit losses. This would incent the GSEs to lower their fee in order to increase the number of refinances. The profit maximizing fee would decline from P_0 to P_1. This new lower fee equates the marginal revenue with the (negative) marginal cost. By increasing the set of borrower balances that are "in the money" from Q_0 to Q_1, the reduction in fee income to the GSEs from the Q_0 of borrower balances that would have refinanced at the higher fee (area P_1P_0DF) is more than made up for by the fee income on the additional refinances as well as the reduction in expected future credit losses (area EFBA).

However, note that even in this case the GSEs would be charging a socially inefficient fee. If the GSEs were directed instead to set their pricing to maximize the sum of the expected profit to the GSEs and borrower surplus, then the GSEs would eliminate the refinance fee. By increasing the stock of borrower balances that are in-the-money to refinance from Q_1 to Q_2, this would increase overall welfare (by the area ABQ_2C). The magnitude of this welfare loss depends in part on the marginal impact of refinancing on reducing expected future credit losses at the fee P_1 and the number of incremental refinances that are priced out by this fee. In the remaining sections of the paper, we implement an empirical strategy for estimating this marginal impact via the sensitivity of borrower default to changes in the borrower's required monthly payment.

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[3] In reality, the GSEs have fees that are differentiated by the borrower's current loan-to-value ratio and current credit score. In addition, the implementation of the HARP program has differed somewhat between Freddie and Fannie. For specifics on Fannie Mae pricing see https://www.efanniemae.com/sf/refmaterials/llpa/and http://www.freddiemac.com/singlefamily/pdf/ex19.pdf

For general information on the HARP program see:
http://www.freddiemac.com/homeownership/educational/harp_faq.html

For information on the recent changes to HARP see: https://www.efanniemae.com/sf/mha/.

Literature review:

Recent advocates for a broad-based refinance program cite as one of the advantages the reduction in future defaults on mortgages that participate in the program. However, no estimates are provided as to the potential magnitude of the reduction in defaults and associated default costs.[4] A recent Congressional Budget Office working paper provides an estimate of the reduced credit losses from a refinance program that is assumed to produce an incremental 2.9 million refinances of agency and FHA mortgages [see Remy *et al* (2011)]. The authors estimate that such a program would reduce expected foreclosures by 111,000 (or 38 per 1,000 refinances) resulting in reduced aggregate credit losses of $3.9 billion. The authors use an estimated loan-level competing risk model of prepayment and default on fixed-rate mortgages to calculate the reduced expected credit losses. However, the estimated model is not provided in the paper, so it is difficult to fully assess their methodology.

An alternative empirical strategy is to estimate competing risk models of prepayment and default for prime ARMs. In this case, we can measure the impact of cumulative changes in the monthly mortgage payments from rate resets that have taken place since the origination of the mortgage on the future performance of the borrower. Using prime conforming ARMs focuses on a roughly similar set of borrowers as prime conforming FRMs in terms of their credit profiles and underwriting standards. However, prime borrowers will likely self-select between FRM and ARM products based on private information on their expected duration in the mortgage, among other factors. This selection process will generate unobserved differences between FRM and ARM borrowers.[5] The low initial mortgage rates that are typically offered on many ARMs may also be relatively attractive to borrowers who have to stretch more in their budget [Green and Shilling (1997)].

The empirical literature has focused relatively more on estimating default and prepayment models for FRMs as compared to ARMs. Calhoun and Deng (2002) provide a side-by-side comparison analysis of FRMs and ARMs using a comparable empirical specification. While FRMs and ARMs have similar baseline prepayment hazards, Calhoun and Deng show that ARMs have baseline default hazards that are higher over the first two years following origination. They speculate that this might reflect the fact that ARMs attract a more heterogeneous set of borrowers in dimensions that are not well captured

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[4] See for example Boyce, Hubbard and Mayer (2011).
http://www4.gsb.columbia.edu/null/download?&exclusive=filemgr.download&file_id=739308.
Also, Greenlaw (2010).
http://www.scribd.com/doc/35781758/US-Economics-Slam-Dunk-Stimulus-Morgan-Stanley-July-27
[5] See Brueckner and Follain (1988) and Dhillon, Shilling and Sirmans (1987).

by the observed borrower characteristics controlled for in the empirical specification. Calhoun and Deng do not include the change in the monthly payment as a control in their ARM specification.

The recent empirical literature on ARMs has focused relatively more on the impact of increases rather than decreases in the monthly payment on prepayment and default. This focus is motivated by the fact that most ARMs have an initial "teaser" rate in that the coupon rate is set below the rate that would be implied by the reference rate and margin at the origination date.[6] That is, if the reference rate (generally either a short-term Treasury or LIBOR) does not change between the origination and the first rate reset date, the monthly payment will increase at the rate reset date. In addition, many ARMs also include a prepayment penalty period that covers the period up to the first rate reset date.[7]

The combination of an initial teaser rate and a possible prepayment penalty will reduce the prepayment rate during the period leading up to the first rate reset. As a consequence, there tends to be a spike in prepayments at the rate reset [Ambrose and LaCour-Little (2001), Ambrose *et al* (2005), Pennington-Cross and Ho (2010)]. The challenge in identifying if the increase in the mortgage payment at the first reset leads to higher defaults is that there may also be a change in the composition of the remaining borrowers in terms of their unobserved characteristics. The spike in prepayments may have selected the better quality borrowers out of the sample, leaving relatively more risky borrowers remaining in the sample. An observed rise in defaults following the reset date could therefore reflect not only the impact of the payment increase, but also the change in the unobserved risk characteristics of the remaining borrowers. However, this story is not supported by the empirical literature. For subprime ARMs, Gerardi *et al* (2007) and Sherlund (2010) do not find evidence of a significant rise in the default risk following the expiration of the teaser rate for non-prime hybrid ARMs.[8]

There are two reasons we would not necessarily want to use the evidence on the impact of increases in mortgage payments on default risk to infer the impact of payment decreases. First, as noted above, there is often a significant change in the sample of borrowers at the time of the payment increase associated with the expiration of the initial teaser rate and the prepayment penalty. This is not likely to be a problem for reductions in the mortgage payment when the rate resets lower. In these cases, we would not expect to see a spike in prepayments so the sample composition remains relatively constant.

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[6] Ambrose and LaCour-Little (2001) report that 99% of their sample of conventional ARMs originated in the early 1990s had teaser rates with an average discount of 2.1%.

[7] Mayer, Pence and Sherlund (2009) report that 70% of their sample of subprime ARMs had prepayment penalties. In addition, in 2005 the average teaser discount was 3.5%.

[8] Sherlund (2010) does report higher default risks following a large payment increase (greater than 5%) when the borrower also has little equity (current LTV of 95 or higher).

Second, even if we could better control for changes in the unobserved heterogeneity of the borrowers, there is no reason to expect that the impact of mortgage payment changes on default and prepayment are symmetric with respect to payment increases and decreases.[9] On the contrary, it is a well-established principle of mortgage pricing that prepayment risk, at least, is asymmetric with respect to the prevailing level of mortgage interest rates; for credit risk, the question of symmetry with respect to payment changes is less settled. In our analysis, described below, we allow for asymmetric impacts.

A refinance is similar to a modification where the rate of the mortgage is lowered and the term is extended. The emerging literature on modifications offers additional insight into the effects of payment reductions on expected credit losses. Initial research focused on modifications that pre-dated the government's Home Affordable Modification Program (HAMP). Haughwout *et al* (2010) use LoanPerformance data to estimate a competing risk model using over 53 thousand modifications of subprime loans that were originated between December 2005 and March 2009. They exclude capitalization modifications where the borrower's monthly payment can increase. They find that a 10 percent reduction in the monthly payment lowers the 12-month re-default rate by 13 percent.[10] Agarwal *et al.* (2011) analyze mortgages originated between October 2007 and May 2009 from the OCC-OTS Mortgage Metrics data. They report that a 10 percent reduction in the monthly mortgage payment reduces the re-default rate by 3 percent.[11] As a note of caution, findings from studies of re-default of modification may not generalize to HARP due to differences in borrower risk characteristics and delinquency status: HARP borrowers are current in their mortgages whereas borrowers receiving modifications tend to be seriously delinquent.

Data and empirical specification:

To conduct our competing risk analysis we select a 10 percent random sample of all first-lien, GSE-held prime, owner-occupied ARMs from the LPS data that were originated from January 2003 onwards. This produced an initial sample of 279,124 ARMs. We drop 87,816 of these loans because we

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[9] Ambrose *et al.* (2005) impose symmetry in the competing risk specification estimated on a sample of 3/27 hybrid ARMs.

[10] They define re-default as the borrower becoming 90-days delinquent within the first year following the modification.

[11] In this study, a mortgage re-defaults if it becomes 60-days delinquent within 6 months of the modification. As such, the two results are not directly comparable.

do not observe them within two months of origination. We drop 6,801 loans because they had no servicing data beyond the second month or the initial observation for the mortgage indicates a liquidation, transfer, prepayment, or default. We trimmed the bottom 1 percent based on origination loan balances as well as balances that exceeded the standard conforming loan limit – dropping mortgages with balances below $50,825 (1,450 mortgages) or with balances above $417,000 (10,914 mortgages). We further restricted the estimation sample to mortgages with origination LTV ratios between 20 and 105 (2,166 mortgages were dropped for an origination LTV below 20 and 2,458 mortgages were dropped for an origination LTV above 105). Finally, we dropped 7,454 loans because they had at least one monthly payment below $200, or because they had at least one month where their cumulative monthly payment increase was greater than 150 percent. All told, these criteria led to the elimination of 105,857 loans (note, there was overlap among the groups being excluded for different criteria), leaving 173,267 loans in our estimation sample.

We define our "default" event as the first time that a mortgage reaches 90 days delinquent. This choice is measured consistently in the data and does not depend on state laws governing foreclosure. In addition, borrowers who reach 90 days delinquent have a reasonably low "cure" rate – that is, the probability that the borrower will catch up on the missed payments and or pay off the mortgage. This can be seen in Table 1 where we compare transition rates into a credit loss (end of a foreclosure) as well as cure rates for different delinquency triggers. There is a reduction in the cure rates moving from a default definition of 60 days delinquent to 90 days delinquent. For mortgages that ever reach 60 days delinquent, 27.7 percent are either now current or have paid off. The cure rate declines to 23.3 percent for mortgages that ever reach 90 days delinquent. Finally, the cure rate declines to 14.7 percent if we define default as a mortgage ever entering the foreclosure process. For all three default definitions, conditional on the mortgage being terminated, over 80 percent of the mortgages that reach that default trigger result in a credit loss.[12]

Another consideration for the choice of the default definition is the variability in time from the initial delinquency to the time that the default trigger is reached. The higher this variability, the more difficult it becomes for the model to capture the timing of economic conditions that may have contributed to a borrower initially going delinquent and, ultimately, defaulting. Table 2 provides information on the mean and variance of the time between the initial delinquency in an unbroken string of delinquencies and the default trigger. There is a 50 percent increase in the standard

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[12] For the 60-day, 90-day and foreclosure start default triggers these conditional loss rates are 80.1 percent, 85.2 percent and 88.5 percent respectively.

deviation moving from a default definition of 60 days delinquent to 90 days delinquent, but the standard deviation increases by 150 percent going from 90 days delinquent to a foreclosure start. Taken together, the results from Tables 1 and 2 suggest that defining the default event as the first time a borrower reaches 90 days delinquent provides a good balance between consistent timeliness of the default trigger and a high transition rate to a final claim.

The key variable of interest is the percent change in the monthly payment from the initial monthly payment to the current monthly payment. Our aim is to use the estimated impact that these monthly payments changes have on the ARMs borrowers' risk of default and prepayment to infer the impact on expected credit losses from refinancing borrowers who have fixed-rate mortgages. We allow for the possibility that decreases in monthly payments may have asymmetric effects on default and prepayment from increases in monthly payments, and that these asymmetric effects may further differ for borrowers with high versus low current LTV. We define a "unit" change in each monthly payment variable as a 10 percent change in the indicated direction. The monthly payment change variables are dynamic variables in that their values vary over time for a mortgage. The payment changes are dictated by the terms of the mortgage contract regarding the index, the spread, the dates the rates adjust, any triggers or caps on adjustments, and changes in the reference rate since the mortgage was originated. One distinction between payment reductions for FRM borrowers through a refinance and for ARM borrowers through a rate reset is that the payment changes are permanent for the FRM borrowers and can be reversed for ARM borrowers. A consequence may be that the impact of these payment reductions on future credit losses will be attenuated in moving from FRM to ARM borrowers.[13]

The LPS data provide information on a variety of borrower, loan, and property risk factors. We supplement these with additional data on economic factors and state legal requirements that may impact loan performance. Summary statistics on these variables for loans in the estimation sample are given in Table 3. The summary statistics are presented separately for the static variables whose values do not change over the life of the mortgage and for the dynamic variables whose values are time-varying. For the categorical variables, the left-out group is selected to be the high-quality or relatively more common mortgage type.

Appendix Table A1 provides a comparison set of static summary statistics for a sample of prime FRMs from LPS over the same time period. The adjustable and fixed-rate prime mortgage

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[13] We thank Mitch Remy for highlighting this point to us.

samples are similar in terms of their origination LTVs and credit scores. The purchase share is higher and the origination balance is larger for the ARM sample. Finally, the FRM sample has a higher fraction of mortgages with terms shorter than 30 years.

The borrower's updated LTV is an important risk factor. We update each mortgage's LTV using the origination LTV, the amount of debt amortization to date, and the cumulative change in metropolitan area house prices to date. For fully underwritten loans, we observe the initial mortgage balance and for each month the mortgage balance that reflects amortization and any accelerated payments made by the borrower.[14] We also observe the appraisal value at origination which we update each month using the CoreLogic house price index for the loan's metropolitan area. Combining these data gives us a monthly updated LTV on the mortgage. We control for the updated LTV in the hazard analysis by entering a series of indicator variables for different LTV intervals. The left-out category corresponds to a mortgage with a current LTV below 80.

Two additional important borrower risk factors are the credit score (FICO) and the debt-to-income (DTI) ratio. In contrast to the LTV, which is a dynamic variable that varies over the duration of the mortgage, both FICO and DTI are static variables. We include a series of indicators for different intervals of FICO scores as well as an indicator for a missing FICO. The left-out category corresponds to a FICO score of 780 or higher (a high credit quality borrower). The DTI variable is meant to capture what is called the "front-end" ratio, which is defined as the sum of the borrower's annual mortgage payments (principal and interest), property taxes, and house insurance premium incurred divided by the borrower's income. However, the data provider (LPS) confirmed that some servicers report "back-end" ratios which include in addition payments on home equity loans, auto loans, student loans and minimums on credit cards. We were unable to identify what type of DTI was being reported for each mortgage, so we had to omit the DTI variable from the analysis.

There are several loan-specific factors that we control for in the analysis. The first category is the loan purpose. We include indicators for three different types of refinances: cash-out, non-cash-out, and unknown purpose. Here, the left-out category is a purchase mortgage. Other loan-specific factors that we control for are whether the mortgage is not fully documented, the documentation status is unknown, and if the mortgage does not have a 30-year term. We also include the origination mortgage balance measured in $10,000 increments to capture any

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[14] We do not include in the mortgage balance arrears due to past missed payments. Doing so would induce a mechanical positive correlation between the updated LTV and borrower default.

independent effect of loan size. Our final loan-level variable is a measure of the incentive to refinance a mortgage measured by the difference between the current interest rate on the mortgage and the current average prevailing rate for 30-year fixed rate mortgages, if this difference is positive.[15] We allow this interest rate incentive to have a differential effect for current low- and high-LTV borrowers. To help control for any systematic unobserved differences in underwriting standards across time, we include indicators for the year the mortgage was originated.

Local economic factors, which proxy for unobserved loan-level indicators, may also exert a strong influence on mortgage performance. A traditional trigger for a default is an unemployment spell experienced by the borrower. We include the 12-month change in the local unemployment rate lagged six months. We find that the change in the local unemployment rate is a better predictor of default than the level of the unemployment rate. We lag by six months the 12-month unemployment rate change to account for the time lag between when the borrower loses his/her job and when the borrower may become 90 days delinquent. The unemployment rate variable should be thought of as a proxy variable for the unobserved indicator for whether the borrower becomes unemployed. If we had dynamic data on the borrower's employment status, we would likely drop the unemployment rate from the specification.[16] As a proxy, we expect that the estimated impact of the unemployment rate on default will be attenuated due to a low correlation of the unemployment rate with the borrower's actual employment status.[17]

Variation in house prices over time within a metropolitan area and across metropolitan areas is an important factor in affecting the distribution of updated LTVs for active mortgages. Rising or falling house prices may also be correlated with other local economic shocks that are not well controlled for by the other variables in the specification and which may impact the prepayment and default behavior of borrowers. For example, the current LTV effects may reflect both the direct effect of the borrower's equity position on the prepayment and default decision, as well as the indirect effects due to economic shocks that are correlated with changing area house prices. To

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[15] We use the monthly average rate on conventional 30-year mortgages from the FHLMC weekly survey (available at http://www.freddiemac.com/pmms/).

[16] Given an indicator for whether the borrower is unemployed, the area unemployment rate would be included in the empirical specification only if the risk of unemployment (conditional on the borrower currently being employed) affected the likelihood that the borrower would prepay or default on the mortgage.

[17] See Haughwout *et al.* (2010) for a more detailed discussion.

mitigate any possible omitted-variable bias on the current LTV estimates, we include the 12-month percentage change in the area house prices as an additional dynamic variable.

Local contagion may affect a borrower's decision to default as well. A recent survey [Fannie May (2010)] finds that borrowers who know someone who has experienced a foreclosure are more than twice as likely to seriously consider default as those who do not.[18] We control for the possibility of a contagion effect by including the number of distressed sales per 10,000 households in the metropolitan statistical area (MSA). We calculate a three-month moving average of MSA distress sales using CoreLogic data. The number of households in the MSA is taken from the 2008 American Community Survey.[19] Given the long time lag between the events that trigger a default and the eventual foreclosure sale, this measure is unlikely to pick up contemporaneous economic shocks that may be affecting current default decisions.

Finally, the legal environment that governs how mortgage delinquencies are handled varies by state. A potentially important factor is whether the mortgage is originated in a state with a judicial foreclosure process, which lengthens the expected time to complete the foreclosure. Longer delays in the foreclosure process could provide an incentive to borrowers to strategically default.[20] A second legal consideration is whether mortgages are considered as recourse or non-recourse loans in a state. Recourse loans provide potentially more security to the lender, since the lender has the ability to pursue a defaulted borrower with a deficiency judgment for any unpaid balance. As a result, borrowers in a recourse state may be less likely to default if the property is underwater – that is, if the mortgage balance exceeds the current market value of the property. We include indicators for judicial foreclosure states as well as for recourse states.

Econometric Specification:

We use a competing risk model to analyze the impact of the borrower risk characteristics, mortgage and property characteristics, and economic factors on prepayment and default outcomes. We assume these risks are independent. We model each risk using a proportional hazard framework. The prepayment (*p*) and default (*d*) hazard rates since origination at duration *t* are given by:

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[18] A similar result is also found in Guiso *et al.* (2009).

[19] http://factfinder.census.gov/servlet/DTSelectedDatasetPageServlet?_lang=en&_ts=286380818796)

[20] See for example discussions of strategic default in Foote *et al.* (2008) and Haughwout *et al.* (2010).

$$h^p(t|X_t^p) = \exp(g^p(t)) \exp(X_t^p \beta^p) \qquad (1a)$$

$$h^d(t|X_t^d) = \exp(g^d(t)) \exp(X_t^d \beta^d) \qquad (1b)$$

where $g(t)$ is the baseline hazard function of the time since the mortgage was originated. We approximate the baseline hazard using a step-function where the steps are monthly.[21] The key assumption is that the explanatory variables X_t shift the baseline hazard proportionally.[22]

With the estimated prepayment and default hazards we can calculate the probability that any active ARM mortgage will prepay or default over a specified horizon, and consequently, the probability that the mortgage is still active (or "survives") at the end of the horizon. Let S denote the estimated joint survivor function, given by:

$$S(t) = \exp\left(-\sum_{j=1}^{t}(h^p(j) + h^d(j))\right) \qquad (2)$$

where t indexes the number of months into the forecast period and $S(0)$ equals one.

With the estimated prepayment and default hazards we can evaluate the impact of a payment reduction of the size expected for mortgages that refinance through HARP on the cumulative default rate over any forecast horizon. We select a five-year horizon for this analysis.[23] For forecasting default and prepayment probabilities, we need to specify the path of the dynamic variables over the forecast horizon. To calculate the marginal effect of monthly payment reductions on cumulative default rates, we hold all variables constant over the forecast horizon except for the mortgage's duration and its dynamic LTV. The estimated probability that an active ARM mortgage with current duration t will default over the next T months is given by:

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[21] See Meyer (1990) for an early example of using step-function approximations to the baseline hazard.

[22] See Kalbfleisch and Prentice (2002) for details.

[23] While a longer forecast horizon would provide a more complete measure of the change in the cumulative default probability, going out beyond five years would involve extrapolating the baseline hazard rates well outside of the observed range in the estimation data.

$$\Pr^{D}(t,T) = \sum_{j=t+1}^{t+T} \left(S(j) h^{d}(j) \right)$$

We compute the cumulative default projections for all active mortgages with updated LTVs of 80 or higher at the end of our ARM data. We first assume no change in the monthly payment. This gives us a baseline cumulative default rate. We then redo the calculation assuming a 26 percent reduction in the monthly payment (the average we estimate for HARP refinances) to generate a counterfactual cumulative default rate assuming a refinance. The difference between these two cumulative default rates averaged across the active high LTV mortgages is the marginal effect of the refinancing on the portfolio default rate.

Estimation results:

We report the exponentiated default and prepayment hazard coefficients in Table 4. Values above (below) one indicate that the variable shifts upwards (downwards) the baseline hazard. We use monthly duration indicators for the first four years after the mortgage is originated and a single indicator for durations beyond four years. The first "at-risk" month for a mortgage to be 90 days delinquent is the third month following the origination month. We initialize both the prepayment and default hazards at the third month. Also not reported in the table are the coefficients on the origination vintage year effects and three property type indicators: condo, two-to-four family, and other property type. The left-out category of ARM for our analysis is a fully documented 30-year new-purchase mortgage on a single family residence with a current LTV below 80 and a borrower FICO score above 780 originated in 2003.

The key hazard coefficients of interest are those associated with payment reductions for the default and for the prepayment hazards for borrowers with current LTVs above 80. The impact of a 10 percent reduction in the monthly payment is to lower the default risk regardless of whether the borrower has a high or low current LTV. For borrowers with a current LTV above 80, a 10 percent reduction in the monthly payment is associated with a 22.5 percent reduction in the monthly default risk. For borrowers with a low current LTV, the same reduction in the monthly payment is associated with a 16.6 percent reduction in the monthly default risk. The same payment reduction

14

has a much smaller impact on the monthly prepayment risk for low LTV borrowers – the estimated reduction is less than 7 percent. In contrast, for high LTV borrowers, a ten percent payment reduction lowers the prepayment hazard by 25.4 percent. For the high LTV borrowers, the net impact on the cumulative default rate will depend on whether the marginal effect on the monthly default hazard outweighs the marginal effect on the monthly prepayment hazard.[24]

Before turning to the default forecast exercise, it is useful to quickly summarize some of the other key empirical findings from the competing risk model. Default and prepayment risks are very sensitive to the estimated current LTV on the mortgage. The monthly default risk rises by a factor of 8 comparing ARMs with an estimated current LTV below 80 to those above 120. Looking at the prepayment hazard, the data indicates that the monthly prepayment rate declines by 90 percent as we increase the estimated current LTV from below 80 to above 120. This illustrates the "collateral constraint" on refinancing identified earlier by Caplin *et al* (1997). Absent special refinance programs such as HARP, borrowers with high current LTVs have low prepayment speeds because they cannot fund the downpayment necessary for a refinance using equity in their current house.[25] In interpreting the current LTV hazard results, it is important to note that we are controlling for the percent change in metro area house prices over the prior year.[26]

A borrower's FICO score is also an important determinant of default and prepayment. A limitation of our data is that we only observe the borrower's FICO score at the time of the origination of the ARM. Despite the static nature of the credit score variable, the predicted monthly default risk increases by a factor of 12 comparing a borrower with an origination FICO of above 780 to a borrower below 580. FICO scores have a much smaller impact on the likelihood that a borrower prepays. Comparing borrowers with an origination FICO of above 780 to below 580 the monthly prepayment risk declines by only 10.5 percent.

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[24] The data also reject symmetry of the effect of payment increases and payment decreases on the default and prepayment hazards. Payment increases have smaller effects on the default hazard than payment decreases for both high and low LTV borrowers.

[25] Deng *et al.* (2000) control for the probability that a prime FRM is in negative equity. They find that the probability of negative equity raises the default hazard and lowers the prepayment hazard.

[26] Dropping the 12-month change in area house prices results in the negative equity LTV indicators rising by roughly 11 percent in the default hazard and decline by roughly 9 percent in the prepayment hazard. The unemployment hazard coefficients are not meaningfully impacted.

Turning to the remaining loan-specific characteristics, ARMs that are not fully documented have higher monthly default rates but also higher monthly prepayment rates. Refinances have a higher default risk than new-purchase mortgages – regardless of whether the borrower took cash out or not in the refinance. Very few ARMs in our sample do not have a 30-year term. Those with shorter terms, though, have higher monthly default risks than similar ARMs with a 30-year term. Loans with larger origination balances have higher default and prepayment hazards. Increasing the loan balance by $100,000 raises the default and prepayment hazards by 8 percent and 5 percent respectively. Finally, increasing the financial incentive to refinance as measured by the spread between the current rate on the mortgage and the prevailing rate on 30-year fixed rate mortgages increases the monthly prepayment rate. The data indicates that mortgages with a current LTV below 80 have a stronger prepayment response to changes in the financial incentive to refinance.

Several local economic factors are controlled for in the analysis. As already discussed, we control for the percent change in metro area house prices over the past 12 months. Holding the borrower's current LTV constant, falling house prices both increase the default risk and decrease the prepayment risk. The fact that, controlling for an estimate of the borrower's current LTV, area house prices impact default and prepayment behavior likely reflects correlations between changes in house prices and other local economic conditions that are left out of the empirical specification.[27]

Increases in the local unemployment rate raise the default risk. The magnitude indicates that a one percentage point increase in the unemployment rate raises the monthly default hazard by 12 percent. As discussed earlier, this marginal effect is likely seriously understated, due to the measurement error in using the area unemployment rate as a proxy variable for whether a particular borrower experiences an unemployment spell. The share of distressed sales in the metro area does not impact either the default or prepayment hazards in any economically meaningful manner. This could be interpreted as a lack of evidence in this data of "contagion" from strategic default. Finally, we find that the legal environment in the state does impact the estimated hazards. Judicial foreclosure states are associated with 25.3 percent higher monthly default hazards.[28] In contrast, states where mortgages are recourse loans have a 15.6 percent lower monthly default hazards.

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[27] One possibility is that credit availability may be more restricted in housing markets that have experienced greater house price declines.

[28] The higher estimated default rate in judicial foreclosure states may reflect the longer foreclosure delays that exist in these states. These delays increase the incentive to strategically default.

Impact of refinancing on future credit losses:

Using the estimated default and prepayment hazards, we can estimate the impact that increased refinancing under the HARP program would likely have on future credit losses to the GSEs. The first step in the analysis is to identify a set of prime conforming FRM where the borrower would likely qualify for a HARP refinance. For this set of borrowers, we can calculate the average percentage reduction in the required monthly payment associated with a HARP refinance. We can use this average percent reduction in our forecast exercise to predict the average reduction in the cumulative five-year default rate. Given an assumed loss given default, we can estimate the implied reduction in expected credit losses.

We use data from LPS on prime conforming FRMs. For each mortgage, we know the origination LTV and location of the property. The servicing data for each mortgage gives the current mortgage balance over time. We update the LTV over time using the current mortgage balance and an updated house value based on CoreLogic house price indices for that metro area. To identify the set of HARP-eligible borrowers, we select all borrowers where the estimated current LTV exceeds 80 and where the borrower has been current for the past 12 months. To identify the subset of these borrowers who would have an incentive to refinance under an improved HARP program, we use a rule that the borrower is "in the money" to refinance if the estimated all-in cost of the refinance would be recovered within two years.[29] Using the identified set of in-the-money HARP-qualified borrowers, we calculate that refinancing would reduce the required monthly payment on average by 26 percent.

The next step is to estimate the impact that this 26 percent reduction in the monthly payment would have on the average default rate. We use the estimated ARM default and prepayment hazards to do a five-year cumulative default forecast. We select the ARMs with current LTVs above 80 that are still active at the end of our estimation period (July 2011) and that have not prepaid or reached 90 days delinquent. For each of these mortgages, we generate five years of additional data to be used in the forecast exercise. We assume that the local unemployment rate and local house prices remain at their current levels over the forecast period – that is, we set their values to zero since they

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[29] We use two years instead of three years for the payback period to account for possible risk aversion by borrowers to invest in a refinance given the high risk of a job loss. If the borrower becomes unemployed during the payback period, then the borrower would likely not be able to recoup the full cost of the refinance.

are in change form. We allow the mortgage's duration and current LTV to vary over the forecast period. The only factor impacting the current LTV is debt amortization. We first do a baseline default forecast for each mortgage assuming no change in the monthly payment. We then redo the default forecast for each mortgage assuming a 26 percent reduction in the monthly payment. We construct cumulative default curves by averaging the estimated cumulative default probabilities over all of the mortgages. The results of this forecast exercise are displayed in Figure 1. The baseline cumulative default curve is shown in red. At five years, the estimated hazard models imply that the expected cumulative default rate would be 17.3 percent. When we repeat the exercise reducing the monthly payments by 26 percent, the expected five-year default rate is reduced to 13 percent – a 24.8 percent reduction.[30]

We assume that a borrower with a prime conforming FRM who refinances under HARP would experience the same proportionate decline in the expected cumulative default rate. The next step is to generate predicted 5-year cumulative default rates for prime conforming FRM borrowers with current LTVs of 80 or higher who are current in their payments. To do this, we constructed a "roll-rate" matrix of monthly transition rates between payment statuses for prime conforming FRMs with current LTV of 80 or higher. We estimate this matrix using LPS data on a 5 percent random sample of prime FRMs for the six-month period from June of 2011 through November 2011.[31] We use this roll-rate matrix to simulate the five-year cumulative default rate for our target borrowers – current LTV of 80 or higher and current in mortgage payments as of June 2011. We define the default rate to be probability that the mortgage is in foreclosure, REO or has been liquidated. The data indicated a predicted 5-year cumulative default rate of 15.2 percent.[32]

Our earlier ARMs-based forecast exercise predicts that facilitating refinances for these HARP-eligible borrowers would reduce their cumulative 5-year default rate by 24.8 percent. Applying this to the estimated 5-year cumulative default rates for HARP-eligible FRMs implies a reduction from 15.2 percent to 11.4 percent – a decline of 3.8 percentage points. This estimate of a 3.8 percentage point reduction in the default rate is identical to the estimate reported in Remy *et al.*

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[30] Holding the prepayment hazard constant and changing the default hazard alone the cumulative default rate declines to 11.2 percent – a 34.9 percent reduction. In contrast, holding the default hazard constant and changing the prepayment hazard alone the cumulative default rate increases to 19.5 percent – a 12.9 percent increase.

[31] The sample consisted of approximately 254 thousand prime conforming FRMs and 1.5 million monthly transitions.

[32] An estimated 45.3 percent are prepaid by the end of the 5-year period.

(2011). In comparing the two estimates, it is important to keep in mind that the Remy *et al.* estimate includes the effect of borrowers with current LTVs below 80 who refinance while our estimate is restricted to borrowers with current LTVs above 80.

To convert this reduced default rate into an estimated reduction in credit losses for the HARP program, we need to estimate a loss given default (LGD). We start with the average LGD reported in their Table 2 of Qi & Yang (2009) for different LTV intervals.[33] For example, they report an average LGD of 30.5 percent for mortgages with current LTVs between 100 and 110, which increases to 37.0 percent for mortgages with current LTVs between 110 and 120. To estimate our LGD input, we generate a weighted-average LGD based on the share of the aggregate 5-year predicted cumulative default probability that falls into each of Qi & Yang's LTV intervals. We then adjust these default probability shares to reflect the different distribution of LTVs between our ARM forecast sample and a FRM sample that we estimate would be "in the money" to refinance under the revised HARP program. The resulting share-weighted LGD is 35.2 percent. Combining the 3.8 percent lower probability of a default with an estimated average LGD of 35.2 percent translates into a reduction in expected credit losses of around 134 basis points of the principal balance on each mortgage that is refinanced.

The expected reduction in credit losses for any given refinance is a function of the magnitude of the decline in the monthly mortgage payment and the current LTV. The monthly payment decline determines the reduction in the probability of default and the current LTV determines the expected loss given default. In Figure 1 we indicate that the negative marginal cost curve reflecting these lower expected default costs is upward sloping. To calibrate the slope of this curve we divided our estimated in-the-money HARP refinances into deciles based on the percent reduction in the monthly payment from a refinance.[34] For each decile, we calculated the balance-weighted percent reduction in the mortgage payment and the balance-weighted loss given default. We then calculated the implied expected reduction in credit losses for each decile. The results indicated that the reductions in credit losses varied from 186 basis points to 47 basis points going from the highest to the lowest decile.

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[33] Their loss given default numbers include estimates for foreclosure expenses and property maintenance expenses. Around 91 percent of their defaulted loans are conforming.

[34] For this exercise, we calculate whether the mortgage is in the money to refinance using the same 2-year payback rule as discussed earlier but assume no GSE refinance fee.

Our estimate of an average 134 basis point reduction in expected credit losses is likely conservative due to a likely understatement of the expected LGD. The LGD estimates are derived from data from 1990 to 2003 when housing markets were much less stressed than they are today. This higher degree of stress would result in larger average losses for the same range of current LTVs.

Application

We use the estimates to illustrate the implications for pricing from incorporating the impact of refinances on future expected credit losses. We conduct a simple pricing exercise to show for different category of prime borrowers the magnitude of the difference between the refinancing fee that maximizes fee income for that category of borrowers from the refinancing fee that maximizes the combination of the fee income and the reduction in the expected future credit losses. We adopt the pricing categories used by the GSEs in their loan level pricing adjustments (LLPAs).

The GSE pricing categories for HARP are delineated by LTV and FICO scores. The reduction in future expected credit losses will vary by borrowers across LTV in our model due to the impact of LTV on the estimated loss given default. However, our baseline model discussed above does not generate differences in expected credit loss reductions by the borrower FICO scores. In order to investigate how FICO differences should affect the fee for internal refinances, we generalize our baseline model for the purpose of this pricing exercise. We allow the impact of lower monthly mortgage payments on the default and prepayment hazard to vary not only by high and low LTV as before but also by low, medium and high FICO scores. We define the three ranges of FICO scores as below 680, 680 to 720, and above 720. We find these FICO interactions to be significant in both the default and prepayment hazards. When we redo the five year default exercises for each FICO interval we find that the percent reduction in the cumulative default rate for a typical HARP refinance payment reduction is 21.9 percent for borrowers with high FICO scores, 22.6 percent for medium FICO scores and 42.4 percent for low FICO scores.

In order to convert these monthly payment impacts into an implied reduction in five year default rates for HARP eligible FRMs, we generate separate payment transition matrices for each of the three FICO intervals. We use these payment transition matrices to compute implied five year cumulative default rates assuming that the borrower is current on the mortgage. These cumulative default rates are 8.7 percent for HARP eligible FRM borrowers with high FICO scores, 17 percent

for medium FICO scores, and 21.4 percent for low FICO scores. Combining these results, the generalized model indicates that the average HARP refinance would reduce the expected default rate by 1.9 percentage points for a borrower with a high FICO score, by 3.8 percentage points for a borrower with a medium FICO score, and by 9.1 percentage points for a borrower with a low FICO score. The differential impact of a HARP refinance on the probability of default by FICO score and on the loss given default by LTV implies that incorporating the impact of expected credit losses into the pricing decision should generate higher price discounts for weaker credit borrowers as measured by FICO score and LTV.

For each cell of the pricing matrix we calculate a price that maximizes the fee income and a second price that maximizes the combination of the fee income and the expected reduction in credit losses. We start by selecting active HARP eligible FRMs that fall in range of LTVs and FICOs for that cell of the matrix. For each mortgage, we calculate the maximum fee that the borrower would be willing to pay and still refinance.[35] In addition, for each mortgage we calculate the impact that a refinance would have on the expected credit losses for that mortgage. For each cell of the pricing matrix we construct the demand curve for refinancing as a function of the fee charged by the GSEs as well as the negative marginal cost curve. The fee income maximizing fee sets the marginal revenue curve in each cell equal to zero, and the profit maximizing fee sets the marginal revenue curve equal to the marginal cost curve. We also estimate the total fee revenue and total profits generated from both pricing rules assuming that there is a full take up of the in-the-money borrowers.

The results from this pricing exercise are reported in Table 5. Weighting the results across cells of the pricing matrix by the number of mortgages in each cell, we find that incorporating into the pricing decision the impact of refinancing on the expected future credit losses on average lowers the desired price by 17 basis points.[36] Looking at the averages by LTV intervals, we see that the average pricing impact is 15 basis points for mortgages with a current LTV of 80 to 85 and increases to 24 basis points for mortgages with a current LTV of 105 or higher. Comparing high to low FICO score borrowers, we find that while the pricing impact is not monotonic, the implied impact for

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[35] We use the same decision rule as earlier that a borrower will refinance only if the total costs can be recovered within two years from the reduction in monthly mortgage payments. We also use the same costs for a refinance outside of the fee charged by the GSEs.

[36] If we weight each cell by mortgage balances rather than mortgages we obtain the same 17 basis point average price reduction.

borrowers with a FICO score of below 640 is considerably higher than the overall average.[37] In our exercise, reducing the prices from the fee income maximizing values to the optimal values increases the overall return by 2.1 percent.

Conclusion

Our competing risk model, incorporating a set of loan-specific and macroeconomic variables, indicates that the cumulative five-year default rate on prime conforming ARMs with LTVs above 80 percent declines significantly if the average monthly payment is reduced. The average HARP refinance would result in an estimated 3.8 percentage point lower default rate. Assuming a conservative average loss-given default of 35.2 this indicates an expected reduction in future credit losses of 134 basis points of a refinanced loan's balance.

This inquiry is novel in that previous research on the sensitivity of default risk in ARMs to payment adjustments has focused on upward adjustments associated with rate resets on non-prime hybrid ARMs. There has been little research on the sensitivity of default risk to downward adjustments to household borrowers' monthly mortgage payments. Traditionally, refinancing – or exercising the no-penalty prepayment option – has been a privilege of high-quality borrowers, and there has been little research on the sensitivity of default risk to ability or inability of borrowers to exercise the option to refinance. This lack went little noticed, in part because most large-scale refinancing waves of recent decades often occurred without widespread concerns about either household default rates or financial institutions' basic solvency.

As we noted earlier, the impact of refinancing on the future default risk of the borrower is an important element of the current debate over the fee structure set by the GSEs for the HARP program. These results suggest that refinancing can be fruitfully employed as a tool for loss mitigation by investors and lenders. The optimal refinance fee will be lower if this reduction in credit losses is recognized. Reducing these fees will increase the set of borrowers with the incentive to refinance, but at the cost of current fee income to the GSEs. Our analysis shows, however, that there is an offset to this lower fee income today which is lower credit losses in the future.

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[37] This is the opposite effect from optimal pricing of guarantee fees for new credit risk from purchase mortgages. In this case, the guarantee fees should increase as the LTV on the mortgage rises and as the FICO score on the borrower falls.

Incorporating this trade-off requires accurate estimates of impact of payment reductions and the expected future credit losses. In producing our estimate, we relied on earlier research on the sensitivity of loss given default to the borrower's current LTV. The severity of the recent housing crisis may have altered this sensitivity. Updating an empirical model of loss given default for prime borrowers should be a priority for policy research going forward.

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Table 1. Definition of "Default" and Likelihood of a Credit Loss

Trigger Definition	Reached Trigger	Delin as Last obs (%)	Current as Last obs (%)	Servicing Transferred (%)	Paid Off (%)	Liquidated & REO (%)
60+	24,640	8,073	4,664	934	2,181	8,788
		(32.8)	(18.9)	(3.8)	(8.8)	(35.7)
90+	22,104	7,428	3,621	766	1,523	8,766
		(33.6)	(16.4)	(3.5)	(6.9)	(40.0)
Foreclosure start	16,995	5,630	1,387	392	1,104	8,482
		(33.1)	(8.2)	(2.3)	(6.5)	(49.9)

Notes: REO stands for real estate owned. Percentages relative to total that reached the trigger are given in parentheses.

Table 2. Time from 1st Missed Payment to "Default" Trigger for Loans with Credit Loss

Trigger Definition	Mean	Std Dev	25th	50th	75th
60+	2.6	1.6	2	2	2
90+	3.9	2.4	3	3	4
Foreclosure start	7.8	6.0	4	5	9

Notes: Authors calculations.

Table 3. Summary Statistics

Variable	a) Static Variables			
	Mean	Std Dev	Minimum	Maximum
Origination LTV	72.2	15.5	20	105
Credit Score (FICO):	731	51	300	896
Less than 580	0.003	0.060	0	1
580 – 619	0.014	0.118	0	1
620 – 679	0.132	0.338	0	1
680 – 719	0.199	0.399	0	1
720 – 780	0.376	0.484	0	1
780 or higher	0.176	0.381	0	1
Missing	0.100	0.300	0	1
Loan purpose:				
Cash out refinance	0.112	0.316	0	1
Non-cash out refinance	0.031	0.174	0	1
Unknown refinance	0.289	0.453	0	1
Purchase	0.419	0.494	0	1
Other loan-specific:				
Not full documentation	0.313	0.464	0	1
Unknown documentation	0.348	0.476	0	1
Not 30-year term	0.008	0.090	0	1
Origination balance ($10k)	22.5	8.82	5.09	41.7
State-specific				
Judicial foreclosure	0.363	0.481	0	1
Recourse	0.644	0.479	0	1

Table 3. Summary Statistics (continued)

Variable	b) Dynamic Variables			
	Mean	Std Dev	Minimum	Maximum
Loan-to-value (LTV):	72.36	23.86	0.0001	250
Less than 80	0.686	0.464	0	1
80 – 84	0.079	0.271	0	1
85 – 89	0.061	0.240	0	1
90 – 94	0.044	0.206	0	1
95 – 99	0.031	0.175	0	1
100 – 104	0.022	0.148	0	1
105 – 109	0.017	0.128	0	1
110 – 114	0.012	0.111	0	1
115 – 119	0.010	0.097	0	1
120 or higher	0.037	0.188	0	1
Economic determinants:				
Lag unemployment rate change	0.48	1.52	–15.7	17.7
House price change (12 months)	–0.06	1.21	–3.86	4.67
Distress sales share (1 percent)	5.55	5.73	0	56.36
Interest rate differential (100 bp)	0.24	0.50	0	5.72
Increase in monthly payment (10 pct)	0.16	1.02	0	14.96
Decrease in monthly payment (10 pct)	0.14	0.59	0	9.00
Duration at risk (months)	27.40	20.46	1	101

Notes: Summary statistics for the dynamic variables vary slightly between the prepayment and default as well as unlinked and linked data files. Percent increase (decrease) in monthly payments are cumulative from initial payment to current payment.

Table 4. Competing Risk Hazard Estimates:

Variable	(1) Default	(2) Prepay
Cumulative monthly payment change		
Increase (above 80 LTV)	1.030**	0.980**
	(0.005)	(0.004)
Increase (below 80 LTV)	1.134**	1.009*
	(0.012)	(0.004)
Decrease (above 80 LTV)	0.775**	0.746**
	(0.013)	(0.014)
Decrease (below 80 LTV)	0.834**	0.932**
	(0.026)	(0.005)
Loan-to-Value:		
80 – 84	2.327**	0.805**
	(0.074)	(0.012)
85 – 89	2.995**	0.652**
	(0.092)	(0.011)
90 – 94	3.661**	0.524**
	(0.115)	(0.011)
95 – 99	4.245**	0.428**
	(0.138)	(0.011)
100 – 104	4.799**	0.360**
	(0.163)	(0.011)
105 – 109	5.148**	0.264**
	(0.185)	(0.010)
110 – 114	5.747**	0.238**
	(0.216)	(0.011)
115 – 119	6.489**	0.190**
	(0.253)	(0.011)
120 or higher	8.335**	0.078**
	(0.258)	(0.004)
Credit Score (FICO):		
Less than 580	12.119**	0.895*
	(1.043)	(0.050)
580 – 619	6.199**	0.919**
	(0.317)	(0.027)
620 – 679	3.985**	0.877**
	(0.128)	(0.011)
680 – 719	2.916**	0.868**
	(0.091)	(0.009)
720 – 780	1.872**	0.934**
	(0.058)	(0.009)
Missing	1.941**	1.185**
	(0.074)	(0.017)

Table 4. Competing Risk Hazard Estimates: continued

Variable	(1) Default	(2) Prepay
Loan purpose:		
Cash-out refinance	1.246**	0.785**
	(0.028)	(0.010)
Non-cash-out refinance	1.484**	0.835**
	(0.059)	(0.019)
Unknown refinance	1.111**	0.883**
	(0.020)	(0.007)
Other loan-specific:		
Not full documentation	1.268**	1.311**
	(0.025)	(0.010)
Unknown documentation	1.433**	0.668**
	(0.027)	(0.006)
Not 30-year term	1.406**	0.987
	(0.082)	(0.037)
Origination balance ($10k)	1.008**	1.005**
	(0.001)	(0.000)
State-specific:		
Judicial foreclosure	1.253**	1.032
	(0.024)	(0.008)
Recourse	0.844**	0.940**
	(0.015)	(0.008)
Economic determinants:		
Lag unemployment rate change	1.120**	0.998
	(0.005)	(0.003)
House price change (12 months)	0.881**	1.130**
	(0.007)	(0.004)
Distress sales share (1 percent)	1.000	1.008**
	(0.001)	(0.001)
Interest rate differential		1.493**
(above 80 LTV) (1 percent)		(0.017)
Interest rate differential		1.654**
(below 80 LTV) (1 percent)		(0.016)
Number of "at risk" months	6,515,425	6,584,747

Notes: Exponentiated hazard coefficients and standard errors in parentheses. Default event defined to be initial 90 days delinquency. Hazard specifications contain three property type indicators, seven vintage year indicators in the prepayment hazard (2004-2010), eight vintage year indicators in the prepayment hazard (2004-2011), and monthly duration indicators for months 3 to 24 and 3-month duration indicators for months 25 to 48, and an indicator for durations longer than 48 months.
** significantly different from one at 1% level of significance
 * significantly different from one at 5% level of significance

Table 5. Difference Between Revenue and Profit Maximizing Refinance Fee

FICO	Loan-to-Value						Avg
	80-85	85-90	90-95	95-97	97-105	>105	
>740	0.14	0.06	0.09	0.10	0.10	0.18	**0.11**
720-740	0.19	0.20	0.27	0.14	0.30	0.18	**0.22**
700-720	0.17	0.16	0.00	0.26	0.22	0.23	**0.17**
680-700	0.11	0.19	0.19	0.40	0.24	0.22	**0.21**
660-680	0.04	0.27	0.17	0.23	0.39	0.36	**0.27**
640-660	0.40	0.25	0.44	0.24	0.15	0.17	**0.25**
620-640	0.05	0.23	0.18	0.28	0.25	0.42	**0.27**
<620	0.21	0.21	0.24	0.12	0.32	0.38	**0.30**
Avg	**0.15**	**0.13**	**0.14**	**0.17**	**0.19**	**0.24**	0.17

Notes: LPS data, authors' calculations. Mortgage weighted averages (percent), by row (FICO), column (LTV) and overall. The dark lines delineate the FICO and LTV intervals where impact of these variables on the probability of default (FICO) and the loss given default (LTV) are allowed to vary.

Figure 1. Five-year cumulative default curves: impact of a refinancing
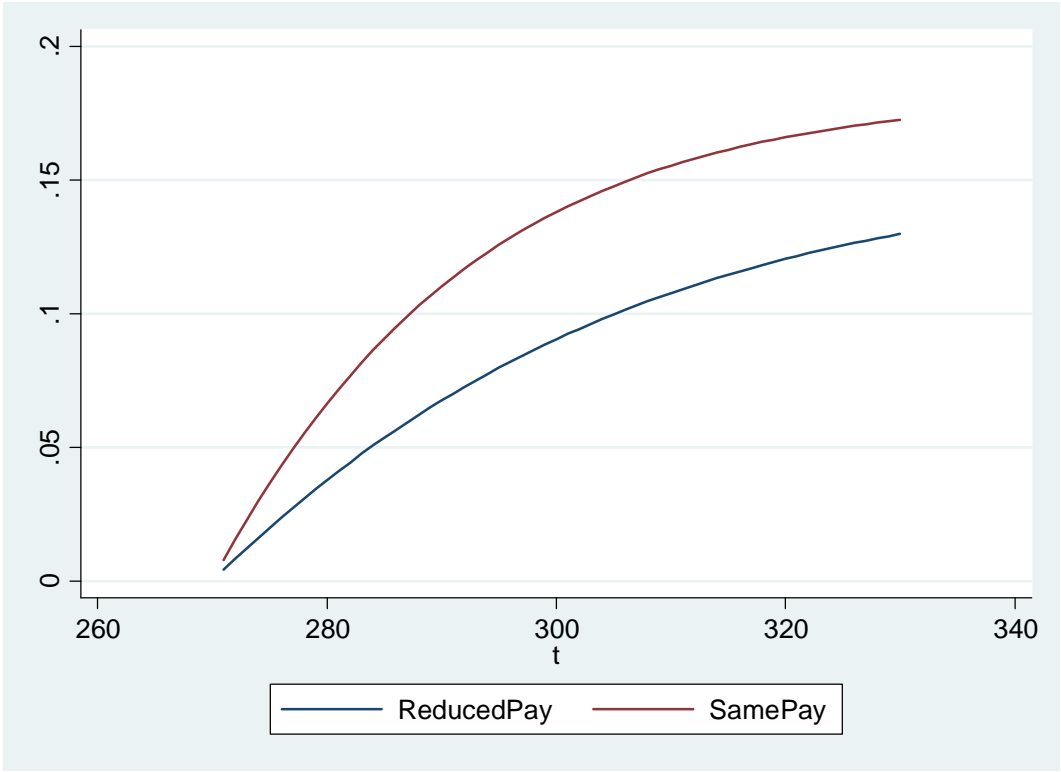
Appendix Table A1. Summary statistics for prime fixed-rate mortgages

Variable	FRM Sample		ARM Sample	
	Mean	Std Dev	Mean	Std Dev
Origination LTV	69.6	17.4	72.2	15.5
Credit Score (FICO)	734.1	55.5	731.2	50.9
Loan purpose:				
Cash out refinance	0.119	0.324	0.112	0.316
Non-cash out refinance	0.044	0.205	0.031	0.174
Unknown refinance	0.311	0.463	0.289	0.453
Purchase	0.285	0.451	0.419	0.493
Other loan-specific				
Not full documentation	0.190	0.393	0.313	0.464
Unknown documentation	0.400	0.489	0.348	0.476
Not 30-year term	0.277	0.448	0.008	0.090
Origination balance ($10k)	18.3	8.66	22.5	8.82

Notes: Authors calculations, Lender Processing Services data.