Refinancing Trends among Lower Income Homeowners during the Housing Boom and Bust

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ABSTRACT

This paper documents the difference in refinancing activity between Low- and Moderate-Income (LMI) and non-LMI homeowners during the housing boom and bust. Contrary to earlier evidence on mortgage terminations, homeowners in LMI areas prepaid their mortgages more frequently than their non-LMI counterparts during the boom. But following the 2007 collapse in real estate markets, LMI homeowners were again slower to prepay their mortgages.

To explain these trends, I estimate a multinomial logit model of mortgage terminations on a large sample of loan-level mortgage payment records spanning the years 2005 to 2010. I find that income and collateral constraints to the refinancing decision are important factors in explaining the discrepancy in mortgage prepayments between LMI and non-LMI households. But even after controlling for such factors, the residual effect of LMI status on probability of prepayment is statistically significant and large in magnitude. This indicates that other unobserved factors correlated with LMI status, on net, had an economically important effect on probability of prepayment.

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1. Introduction

Interest rates on mortgages in the U.S. fell dramatically in November 2008 following implementation of the Federal Reserve's large-scale asset purchase program (LSAP). This prompted a surge in mortgage refinance activity as many homeowners sought to take advantage of historically low rates. However, the increase in refinance loans was substantially less pronounced for homeowners in low- and moderate-income (LMI) areas relative to non-LMI areas, as illustrated in Figure 1.[1] After bottoming out over the period September to November 2008, by May 2009 refinance originations on properties in non-LMI areas increased by a factor of over four, while "merely" doubling in LMI areas over the same period.[2] There was a similar, albeit less striking, discrepancy in refinancing activity between LMI and non-LMI homeowners following an earlier dip in interest rates in January 2008. In contrast, during the height of the real estate boom in years 2005 and 2006, refinance activity among homeowners in LMI areas was high relative to non-LMI homeowners.

The goal of this paper is to document and explain trends in mortgage refinancing in recent years, with a focus on homeowners in LMI areas. Refinancing activity has important implications for homeowners and for public policy. A refinancing can lead to material benefit to a homeowner in the form of savings on monthly interest rate payments.[3] This increase in

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[1] Throughout this paper I refer to homeowners as LMI or non-LMI based on the geography of the property location and not based on borrower income. Community Reinvestment Act (CRA) and Home Mortgage Disclosure Act (HMDA) regulations classify census tracts by income level based on median family income of the tract as a percentage of median family income of the corresponding metropolitan area. Census tracts with median family income less than 50 percent are deemed "low" income, and tracts with median family income greater than 50 but less than 80 percent are deemed "moderate" income.

[2] Fuster and Willen (2010) make a related observation that the distribution of successful refinance applicants shifted dramatically toward more creditworthy borrowers (as measured by FICO score) following implementation of the LSAP.

[3] To illustrate the potential impact of a refinancing on a homeowner's budget, consider a typical homeowner with a mortgage of $150k (roughly 80 percent of the median home value in the U.S.). An interest rate reduction from 6.5 to 5.0 percent would reduce his monthly mortgage payment by over $140, or 15 percent. And given that LMI homeowners are disproportionately likely to hold a higher cost mortgage, they may be substantially more likely to benefit from a refinance than non-LMI homeowners.

household disposable income can lead to increased household consumption and economic growth in the local area (Caplin, Freeman, and Tracy, 1997). Further, public policy initiatives such as the Obama Administration's Making Home Affordable loan modification and refinance program have sought to reduce the tremendous social costs associated with the current foreclosure crisis. Foreclosure rates are particularly high in LMI areas (see Figure 2), in part because of concentrated subprime lending in these areas during the housing boom.[4] Understanding the factors that inhibit refinancing behavior of LMI households may help improve the effectiveness of public policy programs going forward, potentially helping such households to refinance out of risky subprime loans into a more stable loan product, reducing foreclosure risk.

According to the standard option based model of mortgage termination, a mortgage holder should exercise his option to refinance the mortgage when the benefit of doing so exceeds the costs. In practice, however, it is well known that borrowers do not exercise their option to refinance the mortgage as ruthlessly as the frictionless model implies. In order to obtain a new mortgage a homeowner must demonstrate that he is credit-worthy, has the financial capacity to make the new monthly payments, and that he has sufficient collateral for the loan (i.e. sufficient equity in the home). If there are systematic differences in economic conditions or in house price growth across homeowners in LMI and non-LMI areas, this may account for some of the observed differences in refinancing activity. Alternatively, the discrepancy may arise from other differences across borrowers in preferences or ability to refinance. For example, a borrower's level of financial literacy, or a lack of access to credit for certain geographic areas or demographic groups beyond that which can be explained by an individual's credit risk profile.

[4] Ding, Quercia, Li, and Ratcliffe (2008) find evidence suggesting that higher default rates on loans to LMI borrowers are mainly attributable to risky loan products and not to underlying borrower risk profile.

I analyze a large sample of loan-level mortgage payment records from Lender Processing Services, Inc. (LPS) spanning the months January 2005 to June 2010. I specify a multinomial logit (MNL) model of mortgage termination that accounts for the joint nature of the borrower's options to prepay or default.[5] My empirical approach is as follows. I first estimate the impact of residing in an LMI census tract on the probability of mortgage prepayment controlling only for factors related to the cost and benefit of refinancing. In this "base" specification the coefficient estimate on LMI reflects the effect of all omitted variables correlated with both LMI and with prepayment. I then sequentially add additional area- and loan-level control variables to the specification that characterize the presence of: (a) credit and income constraints; (b) collateral constraints; and (c) any other time invariant factors that differ across metropolitan areas that may impact a homeowner's decision to refinance. Thus in the fully specified model, factors (a) through (c) are controlled for and the estimate on LMI reflects the net effect of all remaining heterogeneity across borrowers in LMI and non-LMI areas in tastes or ability to prepay.

When analyzing the full 2005-2010 period, my estimation results indicate that the discrepancy in refinancing behavior between LMI and non-LMI households can be explained primarily by systematic differences in the influence of credit, income, and collateral constraints. In the specification that controls for such constraints, the coefficient estimate on LMI in the mortgage prepayment model is statistically insignificant and small in terms of economic magnitude.

However, my results differ when I stratify the sample based on the calendar years roughly corresponding to the real estate boom (2005 – 2006) and bust (2008-2010). Mortgage credit was easy and cheap during the boom years, fueled by the rise of private mortgage

[5] As in Caplin, Freeman, and Tracy (1997), I use mortgage prepayment as a proxy for a loan refinancing. I discuss the reasonableness of this proxy in Section 4 below.

securitizations and lax underwriting standards based on the premise that house prices were on a never-ending upward trajectory (Brunnermeier, 2009). Over this period, my estimates indicate that LMI status is associated with *increased* probability of prepayment, even after accounting for differences in mortgage terms and other constraints.[6] But in the wake of the mortgage and financial crisis, when availability of mortgage credit tightened substantially, I find that the impact of LMI status on probability of prepayment is negative, statistically significant, and large in terms of economic magnitude. The presence of income, credit, and collateral constraints remains important, and can account for roughly half of the disparity in prepayments between LMI and non-LMI households observed in the baseline model. Nonetheless, based on the fully specified model that controls for such factors, I estimate that LMI households are 28 percent less likely to prepay their mortgage in a given month between January 2008 and June 2010, other things equal.

Finally, to provide additional context on the impact that LMI status and other factors have on refinance activity, I provide a supplemental analysis focusing on mortgage prepayments in calendar year 2009. Avery, Bhutta, Brevoort, and Canner (2010) note that although there was a sharp increase in refinance loans in 2009, the magnitude of this growth was subdued compared with prior occurrences of a sharp drop in interest rates. My results indicate that although LMI status is associated with a lower probability of mortgage prepayment, in terms of explaining general trends in refinancing behavior it is of minor importance. This is perhaps unsurprising, given that lending to borrowers in LMI areas makes up a small share (roughly 15 percent) of overall home purchase and refinance lending in HMDA. I find that the muted growth of

[6] The finding that LMI borrowers were *more* likely to prepay over this period, even when controlling for differences in mortgage terms and other constraints, is novel and runs counter to evidence from earlier studies of prepayment behavior that show LMI and minority borrowers are slower to prepay their mortgages (e.g. Deng and Gabriel, 2006; Firestone, Van Order, and Zorn, 2007).

refinance mortgages in 2009 is attributable mainly to recent house price declines and the resulting erosion of home equity. I estimate that the volume of refinance loans would have been roughly 90 percent higher in 2009 if each homeowner in my sample experienced no change in house prices from the time their mortgage was originated.

The remainder of the paper is organized as follows. Section 2 provides context for this study and motivates the empirical specification described in Section 3. Data sources and variable definitions are detailed in Section 4, results are presented and discussed in Section 5, and Section 6 concludes.

2. Background

As noted above, the standard option based model of mortgage termination implies that a mortgage holder should exercise his option to refinance the mortgage when the benefit of doing so exceeds the costs.[7] The benefit from refinancing is driven primarily by the savings on interest payments achieved by lowering the contract rate. The present value of interest savings associated with a refinancing is a function of both (1) the spread between the borrower's current rate and the rate he can attain on a refinancing, and (2) the expected survival time (in months) of the new mortgage before termination. The latter factor may depend, among other things, on the homeowner's expected future tenure in the home (Caplin, Freeman, and Tracy, 1997) or on future interest rate movements. Costs of refinancing include both transactions costs (time costs, fees and points paid, etc.) as well as the loss associated with exercising the option, because a

[7] See Hendershott and Van Order (1987) or Kau and Keenan (1995) for a review of option based models of prepayment and default. Although the discussion in this section focuses on the factors that affect the decision to prepay (refinance), as described in the next section I account for the jointness of the prepayment and default options in my econometric specification.

choice to exercise the prepayment option today means the homeowner relinquishes the option of refinancing the loan in the future.[8]

Existing evidence demonstrates that borrowers do not exercise their option to refinance the mortgage as ruthlessly as the frictionless model implies. In particular, some studies have shown there are systematic differences across households in the likelihood of prepayment. For example, Campbell (2006), Deng and Gabriel (2006) and Firestone, Van Order, and Zorn (2007) find that borrowers with certain socio-economic characteristics (e.g. less educational attainment; lower income; minority) are slower to prepay their mortgages. Fuster and Willen (2010) show that low credit score borrowers made up a disproportionately small share of homeowners who refinanced their mortgages following the Fed's LSAP. There are several plausible explanations for these discrepancies.

First, differences in refinancing patterns across borrowers may be attributable to the presence of credit, income, or collateral constraints. In order to obtain a new mortgage a homeowner must demonstrate that he is credit-worthy, has the financial capacity to make the new monthly payments, and that he has sufficient collateral for the loan. Existing evidence clearly demonstrates that homeowners who have poor credit history, insufficient income, or less collateral (i.e. low or negative equity in their home) are substantially less likely to exercise their prepayment option, other things equal.[9] LMI homeowners may be disproportionately affected by such constraints, especially to the extent that they have lower credit scores on average, are more likely to have suffered a job loss or other adverse shock to income, and have lower equity in the

[8] This loss is offset somewhat by the value of the call option associated with the new mortgage. Archer, Ling, and McGill (1995) model the net value of the loss associated with exercising the prepayment option as a function of the book value of the mortgage, probability of mortgage prepayment in future periods, future interest rates, and remaining loan term.

[9] See, for example, Archer, Ling, and McGill (1995); Caplin, Freeman, and Tracy (1997); Peristiani, Bennett, Monsen, Peach, and Raiff (1997); LaCour-Little (1999a); Campbell (2006); Deng and Gabriel (2006); Firestone, Van Order, and Zorn (2007).

home. In fact, some (but not all) studies have found that differences in income and home equity can account for the entire discrepancy across socio-economic groups in likelihood of refinancing (Archer, Ling, and McGill 1995; LaCour-Little 1999a).

Other proposed explanations for differences in prepayment behavior are compelling, but difficult to measure. For example, some borrowers may lack financial sophistication or interest, and thus fail to refinance even when it is optimal to do so. Campbell (2006) finds that likelihood of refinancing is lower among less educated and lower income households, characteristics that are likely correlated with financial sophistication. Fuster and Willen (2010) find that following the implementation of LSAP, search activity for new refinance loans is relatively low among low credit score borrowers.

Access to credit for homeowners in LMI areas is another potential factor. This may be of particular concern following the mortgage meltdown, when the private mortgage securitization market evaporated and FHA significantly tightened its lending standards.[10] HMDA data show that loan application denial rates are generally higher in LMI areas than non-LMI areas, although this discrepancy might be accounted for by other factors not observed in HMDA data that characterize a borrower's credit risk.[11]

Finally, there may be other unobservable heterogeneity across borrowers in transaction costs or benefits associated with a refinancing. For example, time costs may be high relative to the *level* of interest rate savings resulting from a refinancing for low income borrowers, especially if they are less integrated into the financial system and require more time or effort to secure a mortgage. Alternatively, Fuster and Willen (2010) note that price adjustments were

[10] To illustrate, from 2007 to 2010, the average credit score on owner occupied, 1-4 family mortgages increased from 713 to 761 for conventional loans, and from 626 to 702 for FHA loans (source: LPS data). FHA has recently introduced a minimum credit score of 580 on loans with less than 10 percent down payment.

[11] See Ladd (1998) or Lacour-Little (1999b) for alternative reviews of the literature on discrimination in mortgage lending.

central feature of the subprime loan market; less creditworthy borrowers were required to pay additional upfront "discount points" at closing to obtain a given interest rate on a new mortgage, other things equal.[12] Such adjustments were introduced into the Agency loan market in November 2007 when Fannie Mae introduced their Loan Level Price Adjustment (LLPA) program.[13]

3. Empirical Model

I specify a multinomial logit (MNL) model of mortgage terminations that accounts for competing risks of prepayment and default.[14] The probability of prepayment and default is modeled as follows:

$$Pr(\, PP_{ijt} = 1) = f_{PP} \{ LMI_j , R_{t-1} , M_{ijt-1} , Y_{it-1} , V_{it-1} \}$$

$$Pr(\, D_{ijt} = 1) = f_{D} \{ LMI_j , R_{t-1} , M_{ijt-1} , Y_{it-1} , V_{it-1} \}$$

where i indexes a loan, j indexes zip code, and t indexes time (in months). The data are organized into loan-month observations in which the dependent variable PP_{it} takes on a value of one if the loan is prepaid in month i, a value of two if the loan is defaulted upon in month i (i.e. $D_{ijt} = 1$) , and a value of zero otherwise.[15] All time-variant controls are lagged one month relative to the prepayment decision to approximate the length of time it typically takes to refinance a mortgage. I control for the age of the loan using a cubic function in age, age

[12] A "discount point" is a fee charged by the lender at closing, traditionally for a borrower to "buy down" the contract interest rate. One discount point is equivalent to one percent of the loan amount. An alternative way to finance discount points is to fold the fee into the loan balance, or to accept a higher interest rate.
[13] See Fuster and Willen (2010) for more on the evolution of LLPAs. Note that I include a control for LLPAs in my empirical analysis of refinancing behavior.
[14] Deng (1997) and Deng, Quigley, and Van Order (2000), among others, demonstrate the empirical importance of accounting for the jointness of the prepayment and default options. A closely related alternative to MNL is the proportional hazard model (PHL). Clapp, Deng, and An (2006) discuss the relative strengths and weaknesses of these alternatives, and find that in practice the MNL and PHL models yield estimates that are quite similar.
[15] I classify a mortgage as "in default" if it enters foreclosure. All loan-month observations following the initial entry into foreclosure are excluded from the sample. The results presented in this paper are qualitatively robust to using an alternative definition of mortgage default: the first incidence of a 90+ days delinquency.

dummies at 24, 36, 60, and 84 months from origination, and these age dummies interacted with an indicator variable equal to 1 if the loan is an Adjustable Rate Mortgage. The age dummies reflect the sharp increases in likelihood of prepayment observed in my data at these loan ages. In all regressions, I include quarterly fixed effects to control for national macroeconomic trends. Depending on specification, metropolitan area fixed effects are included to control for persistent differences across geographic areas in factors that affect refinance or default activity. Standard errors are clustered by zip code.

The vector R_{t-1} includes measures that characterize the current market price of a new loan, and M_{ijt-1} the terms of the mortgage currently held by the borrower. Following Richard and Roll (1989), I use the annuity value per dollar of principal outstanding to measure the homeowner's economic incentive to refinance in month *t-1*, approximated by the ratio of the interest rate on the current mortgage to the market interest rate. The vector Y_{it-1} includes measures of the borrower's credit quality as well as local economic conditions correlated with the likelihood that the borrower is income constrained, and V_{it-1} measures the homeowner's current equity in the home (i.e. LTV). The specific variables included in these control vectors and source data are described in detail in the next section.

The key independent variable is LMI_j, a set of indicators characterizing the likelihood that the property is located in an LMI census tract.[16] To the extent that all other controls in the model are well measured, the coefficient estimate (from the prepayment model) on LMI_j can be interpreted as the net effect that all remaining unobserved factors correlated with LMI status have on probability of prepayment. Thus a coefficient estimate on LMI_j that is not statistically different from zero would indicate that any disparity in prepayment behavior between LMI and

[16] I do not directly observe whether the loan is on a property located in an LMI tract. As described in the next section, I use the zip code of the property to characterize the likelihood the property is in an LMI tract.

non-LMI households can be entirely accounted for by differences across groups in the costs and benefits of refinancing, and by the presence of income, credit, and collateral constraints.

4. Data

I estimate the empirical model on a sample of mortgage loans from Lender Processing Services Inc. (LPS), formerly known as McDash. LPS data consist of loan-level information provided by participating mortgage servicing firms, including (by year-end 2009) nine of the ten largest firms and 16 in total, reporting on over 30 million active loans. A rich set of variables characterizing the loan at origination are included, as well as monthly payment records for each loan that can be used to determine in each month whether the loan has been prepaid, is delinquent, or is in foreclosure. Although its coverage of the U.S. mortgage market is strong overall, LPS does have some important limitations. Primarily, it is not a random sample of the market and some segments of the market, including subprime mortgages, are under-represented.[17]

I create an analytically tractable dataset by drawing a random 2.5 percent sample of loans from LPS. The analysis sample is restricted to owner-occupied, first-lien home purchase mortgages on 1-4 family homes.[18] The sample covers mortgages that were originated between years 2000 and 2008, and I examine mortgage terminations over the period January 2005 to June 2010. I only retain loans where the property is located in a zip code for which monthly zip code

[17] Immergluck (2008) reports that, as of year-end 2008, LPS covered roughly 58 percent of the total prime/near prime market and 32 percent of the subprime market.

[18] I exclude refinance loans from the analysis because the information on property value at origination for these loans, which is used to compute LTV, is often unreliable. An analysis of refinance loans in LPS yields results which are qualitatively similar to those presented in this paper.

level house price information from Case-Shiller is available, which effectively excludes all rural loans from the analysis sample.[19]

The Case-Shiller zip code level house price index, along with the original property value and the current loan balance, is used to estimate the current LTV for every loan-month observation in our sample. LTV enters the empirical specification (in the control vector V_{it-1}) as a series of indicator variables so that its effect on probability of prepayment is allowed to vary non-linearly. Because LPS does not include information on the presence of junior liens, I am able to compute a first-lien LTV measure only. Thus my LTV measure is understated relative to true (combined) LTV for some loans in the sample.[20] To proxy for possible presence of a second lien, I include a control for whether LTV at origination was equal to exactly 80 (as in Foote, Gerardi, and Willen, 2008).

As noted above, the vector R_{t-1} characterizes the current market price of a new loan. I use the national average rate on a conventional, conforming 30-year fixed-rate mortgages from the Freddie Mac Primary Mortgage Market Survey to measure the current "market" rate.[21] In addition, I control for the approximate Loan Level Price Adjustment (LLPA) that would be in effect if the borrower were to refinance into an agency mortgage in month *t-1*.[22]

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[19] Specifically, I draw the random sample as follows. First, I drop all loans from LPS that are not owner-occupied, first lien, 1-4 family, home purchase loans. I then remove all loans originated prior to year 2000 or that were not active in at least one month in January 2005 or later. Next, I remove loans for which no payment records are observed within the first 12 months from origination. Finally, I drop loans on properties not located within the set of 4,110 zip codes covered by the Case-Shiller zip-code level House Price Index. From these remaining loans I draw a random 2.5 percent sample.

[20] Based on a sample of mortgages from LPS of first-lien, fixed rate originations in 2005-06 matched with credit bureau records, Elul, Souleles, Chomsisengphet, Glennon, and Hunt (2010) find that 26% of borrowers have a 2nd mortgage. For these borrowers, combined LTV is approximately 15 percentage points higher than the LTV based on the first lien.

[21] I use the national average rate on a conventional, conforming 30 year fixed mortgage from the Freddie Mac Primary Mortgage Market Survey to measure the current "market" rate. In doing so I am assuming that all borrowers use some function of the current mortgage rate on prime loans when evaluating the potential benefit from refinancing.

[22] The LLPA is computed as a function of current LTV, the borrower's credit score at origination of the previous loan, and the Fannie Mae LLPA schedule in effect in month *t-1*. In all months prior to Fannie Mae's introduction of

The vector M_{ijt-1} characterizes the borrower's mortgage in month *t-1*, including the current interest rate and current unpaid principal balance. I also include indicator variables for interest rate structure (fixed; adjustable with initial rate period 5 or more years; adjustable with initial interest rate period less than 5 years) and whether the loan has an interest-only payment option (IO).[23] Finally, I include a control for household mobility at the zip code level using Census' American Community Survey 2005-2009 five-year estimates.[24] This variable is included to control for average differences among borrowers in the expected length of tenure in the home, which as noted earlier impacts the potential benefit from refinancing.

The vector Y_{it-1} controls for the presence of credit and income constraints. Included are measures of the borrower's credit score at origination of the currently held mortgage ("low" if below 640; "middle" if between 640 and 719; "high" if 720 or more; "missing" if credit score is unknown), an indicator for whether the current loan was obtained with "low or no" documentation, and the debt-to-income ratio at origination of the current loan (DTI: less than 28; 28 to 35; 36 to 41; 42 or more; DTI information missing). Each of these variables may be associated with a homeowner having difficulty in demonstrating creditworthiness for a new loan. This vector also includes controls for local macroeconomic conditions that are likely positively correlated with adverse income shocks, including county-level unemployment rates from the Bureau of Labor Statistics' Local Area Unemployment Statistics, and quarterly county-level

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LLPAs in November 2007, LLPA takes on a value of zero. All LLPAs based on product features or terms other than the baseline credit score/LTV schedule are ignored.

[23] A homeowner with an ARM or IO mortgage may have a strong incentive to refinance in order to avoid incurring a sharp increase in the level future monthly mortgage payments. Such "payment shock" may occur due to a rate reset (particularly if the original mortgage had a 2 or 3 year teaser rate) or re-amortization of the loan at the expiration of the IO option period, often 5 years. An analysis of raw prepayment rates for the loans in my sample shows sharp spikes at 24 months, 36 months, and 60 months from origination, corresponding with these thresholds.

[24] Mobility is defined as the share of residents that did not live in the same house one year prior. ACS provides estimates at the census tract level; I converted to zip code level by taking the weighted average of the associated census tract mobility rates, where the weights are number of census tract residents in the zip code (based on the MABLE tract to zip code crosswalk file discussed below). Mobility rate data varies across zip codes but does not vary for a given zip code over time.

credit card 60+ day delinquency rates from TransUnion's TrenData (as in Bhutta, Dokko, and Shan, 2010).

Finally, the geographic LMI indicator is defined by CRA and HMDA regulations based on the census tract in which the property is located. LPS includes information on the zip code in which the property is located. I assign LMI indicators to loans in my sample as follows. First, for each zip code in my sample, I compute the percentage of its population that resides in an LMI tract based on the 2000 Census.[25] Next, I categorize each zip code into one of three LMI groups based on LMI population share: "Non-LMI" if zero; "Low LMI" if greater than zero and less 50; and "High LMI" if 50 or more. A loan in a "Non-LMI" zip code cannot be on a property located in an LMI tract, while a loan in a High LMI zip code is likely to be on a property located in an LMI tract.[26]

Table 1 presents descriptive statistics for the full analysis sample and separately by LMI group, based on the last observation for each loan in the sample. The final sample includes 115,565 unique loans and 3.59 million loan-month observations. There are some notable differences in mean characteristics of loans across the LMI groups. Prepayment rates decrease monotonically as LMI population share increases. For the Non-LMI group, 42 percent of loans ultimately end in prepayment over our period of observation, compared with 33 percent for the High LMI group. Unsurprisingly, the share of borrowers in the high credit score group falls as LMI population share rises; in the Non-LMI group 47 percent of borrowers have high credit score, compared with 33 percent in the High LMI group. Consistent with the discrepancy in

[25] To compute zip code LMI population share, I use census tract level LMI indicators published by Federal Financial Institutions Examination Council (FFIEC) and a census tract to zip code crosswalk file produced from the Missouri Census Data Center's MABLE program (available at http://mcdc2.missouri.edu/websas/geocorr2k.html). The crosswalk file also contains information on the distribution of tract population across zip codes, based on 2000 Census data.

[26] To the extent that some loans in the "High LMI" group are actually located in non-LMI tracts, my estimates will understate the difference in prepayment behavior of homeowners in LMI vs non LMI tracts.

share of lending that is high priced in HMDA data, in my sample the mortgage interest rate is higher on average for the High LMI group than for the Non-LMI group. Finally, the difference in current LTV across LMI groups is striking. In the last observed month of each loan, over 37 percent of High LMI borrowers were underwater on their primary mortgage loan, i.e. had first lien LTV equal to 100 or more. In contrast, 25 percent of Non-LMI borrowers were underwater. These numbers show that a large percentage of borrowers are constrained in their ability to refinance due to lack of home equity, particularly in LMI areas.[27]

Figure 3 shows prepayment rates by month for each of the LMI groups in my sample. Overall the trends in prepayment activity illustrated here are very similar to refinancing trends evident in HMDA (presented in Figure 1). This evidence supports the reasonableness of using prepayments as a proxy for refinancing activity. Over the earlier years of the sample period when the housing market was booming, prepayment rates are substantially higher on the loans most likely to be LMI compared with non-LMI loans. But by the end of 2007 prepayment rates were roughly equal, and in the post mortgage crisis period prepayment rates were generally higher among non-LMI loans. On all mortgages, regardless of geographic area, prepayment rates spiked upward after November 2008. However the magnitude of this increase is smaller in Low LMI zip codes compared with Non-LMI zip codes, and smaller still in High LMI zip codes.

5. Results

A. Multinomial Logit Estimates

[27] Further analysis reveals that the discrepancy in current LTV across LMI geographies is due primarily to differences in house price growth across areas. Higher LTV at origination in LMI areas relative to non-LMI areas also played a role. Average principal payments (measured as unpaid principal balance relative to original loan aount) were similar across LMI and non-LMI geographies and thus contribute little to the difference across groups in current LTV.

Table 2 summarizes the estimated impact of LMI status on the probability of prepayment. Each column in the table contains coefficient estimates from a separate model specification, as well as the estimated marginal effects implied by the estimates. All specifications include controls for the age of the loan, quarterly fixed effects, and variables that characterize the relative costs and benefits of refinancing the loan. (A more comprehensive set of coefficient estimates for both the prepayment and default outcomes is presented in Appendix Tables 1 and 2.)

In Panel A the model is estimated using the full analysis sample, covering months from January 2005 to June 2010. In Specification (1) in the first column, the negative and statistically significant estimate on High LMI indicates that for the set of loans most likely to be in LMI census tracts, likelihood of prepayment is lower than on non-LMI loans (the omitted category). In terms of economic significance, the marginal effect of the loan being located in a High LMI zip code (rather than a Non-LMI zip code) on probability of prepayment is -0.0015, or roughly 12 percent of the mean monthly prepayment rate for the sample (0.012). Since this model does not explicitly control for credit, income, or collateral constraints on the borrower's ability to refinance, or any other unobservable differences across borrowers, this estimate picks up the net effect of all such factors that differentially affect LMI borrowers relative to non-LMI borrowers.

In the next column of Table 2, Specification (2) adds controls for the county level unemployment rate and credit card delinquency rate, indicators for credit score at origination of the currently held mortgage, and other indicators presumably correlated with the presence of credit and income constraints to the homeowner's ability to refinance. In Specifications (3) and (4), indicators for current LTV and metropolitan area fixed effects are sequentially added to the model, controlling for collateral constraints and any other time invariant differences across areas that impact mortgage prepayments, respectively. As these controls are added to the model, the

coefficient estimate on High LMI declines substantially in magnitude, and is no longer statistically significant at the 10 percent level.[28] As shown in the fourth column, the marginal effect on probability of prepayment of being in a High LMI zip code instead of a Non LMI zip code is -0.0004. This is a 75 percent decline in magnitude from estimate of -0.0015 from Specification 1.

If taken at face value, the estimation results in Panel (A) indicate that over the full sample period being analyzed, the discrepancy in refinancing behavior of LMI and non-LMI can be explained primarily by systematic differences in the influence of credit, income, and collateral constraints among borrowers. On net, the remaining unobserved heterogeneity across borrowers in preferences or ability to refinance accounts for only a minor amount (25 percent) of the disparity across LMI geographies.

However, the dramatic change in the mortgage market following the collapse of the real estate market in 2007 suggests that estimating the model on the full 2005 to 2010 period may be problematic. Doing so imposes the restriction that the effect of being in an LMI area (and of all other covariates) on the probability of prepayment was the same in both the pre- and post-crisis period. But this assumption is tenuous. The boom years were characterized by easy credit with the proliferation of subprime mortgages fueled by the increase in private securitizations and expectations of ever-increasing house prices. However, as the subprime mortgage crisis unfolded in early to mid 2007, leading to a wider financial crisis in 2008, the availability of mortgage credit waned as lenders hoarded capital (Brunnermeier, 2009). Figure 3 suggests that this shift in the mortgage market affected prepayment behavior of LMI households differently than non LMI households, as LMI households were relatively more likely to prepay prior to

[28] Although I do not focus on the Low LMI coefficient here, it is worth noting that for all of the specifications presented in this paper, the magnitude of the estimated marginal effect on likelihood of prepayment monotonically decreases as the likelihood of the loan being in a LMI census tract declines from “High” to “Low” to zero.

2007, and relatively less likely to prepay after 2008. Thus it seems more appropriate to analyze the boom and bust periods separately, to see if this pattern holds after controlling for other factors.

Panels (B) and (C) of Table 2 present coefficient estimates where the sample has been stratified into two groups based on calendar month: January 2005 to December 2006, and January 2008 to June 2010, respectively.[29] For the earlier period, the coefficient estimates from specifications (1) and (4) both indicate that LMI status is associated with an *increased* probability of prepayment. Recall that specification (4) includes controls for the terms of the currently held mortgage, including whether the loan is a 2/28 or 3/27, whether the loan has an interest-only option, and other characteristics that might be associated with an impending payment reset and that were more prevalent in LMI areas. Although consistent with the raw data illustrated in Figure 3, the finding that LMI borrowers were *more* likely to prepay over this period, even after accounting for differences in mortgage terms and other constraints, is somewhat surprising and stands in stark contrast to evidence from earlier studies of prepayment behavior that show LMI and minority borrowers are slower to prepay their mortgages.[30]

Following the housing market collapse, however, my estimates indicate the impact of LMI status on probability of prepayment is negative and statistically significant. The associated marginal effects are large in terms of economic magnitude, as shown in Table 3 panel (C). When controlling only for the relative costs and benefits of refinancing (Specification 1), the probability of prepayment in any given month is lower by 46 percent (or 0.005 percentage

[29] The estimates presented in Panels (B) and (C) are robust to reasonable alternative definitions of the calendar months that define the boom and bust periods. Ultimately I chose to omit 2007 from the stratified analysis because it was a transition year in which the real estate bubble burst, leading to turmoil in the market.

[30] For example, Deng and Gabriel (2006) find that mortgages held by LMI and minority borrowers are less likely to terminate due to prepayment, based on a sample of FHA loans originated between 1992 and 1996. Firestone, Van Order, and Zorn (2007) also note that LMI and minority borrowers tend to prepay more slowly, using a sample of loans originated between 1993 and 1997 and purchased by Freddie Mac. However the authors note that in the latter years of their study, 2004-05, the relationship between income/minority status and prepayment probability weakens.

points) for borrowers most likely to be in an LMI area, relative to non-LMI borrowers. And when controls for income, credit, and collateral constraints are included in Specification (4), the estimated marginal effect of being in an LMI area on mortgage prepayment remains negative and large in the fully specified model. "High LMI" households are 28 percent less likely to prepay their mortgage in a given month, other things equal.

The estimated effects of the other covariates on probability of prepayment are generally of the expected sign so I discuss them only briefly here. See Appendix Table 2. From the fully specified model (Specification 4) estimated on the January 2008 to June 2010 period, the following covariates have a statistically significant and positive effect on the probability of prepayment: the ratio of the mortgage interest rate to the current market rate, Unpaid Principal Balance, and ARM loans (relative to fixed rate loans). And the following covariates have a statistically significant and negative effect on prepayments: LLPAs, I/O loans, lower credit scores, low or no documentation, credit card delinquency rate in the local area, and LTV ratio. The same is true for the earlier period (January 2005 to December 2007), with the notable exception of the indicators for lower credit score, lack of loan documentation, and lower DTI. Here these variables are associated with *higher*, not lower, probability of prepayment.[31]

The coefficient estimates on the default models presented in Appendix Tables 1 and 2 are also consistent with prior expectations and with the existing literature on mortgage defaults. A homeowner being located in an LMI area is associated with a higher likelihood of mortgage default. Variables that reflect higher credit risk (e.g. low credit scores, no or low loan documentation, higher DTI) are also associated with higher default rates, as is a higher current LTV ratio.

[31] The positive coefficient estimates on these variables is counterintuitive if interpreting these variables as measures of income and credit constraints. But over this period of easy credit, these constraints were much less likely to bind in practice.

B. Discussion

To summarize my main results, I find that credit, income, and collateral constraints to the refinancing decision have an important effect on the probability of mortgage prepayment. Over the full 2005 to 2010 period, such constraints can account for 75 percent of the difference in prepayment behavior between LMI and non-LMI households, and the residual effect of LMI status is statistically and economically insignificant. When I stratify the sample into periods corresponding to the housing boom and bust, credit, income, and collateral constraints can explain roughly half of the discrepancy in prepayment behavior. However, in the stratified analysis I find that even when all control variables are included in the specification, the effect of LMI status on prepayment is statistically significant and large in magnitude. LMI households were relatively more likely to prepay their mortgage during the mortgage bubble, and less likely to prepay after the bust.

Why might this be the case? As discussed earlier, there are at least two plausible explanations that are not accounted for in my model: (1) LMI borrowers may, on average, have less financial sophistication and therefore be slower to recognize or act on a beneficial refinancing opportunity, and (2) LMI borrowers may have a relative lack of access to credit, beyond that which is justified based on their individual risk profiles.

First, consider financial sophistication. Past evidence on this topic has typically shown that covariates likely correlated with financial sophistication (e.g. education, income) are also associated with *lower* rates of refinance activity (e.g. Campbell 2006, Fuster and Willen 2010). Following the real estate bust, I also find that LMI borrowers were less likely to refinance. My finding that LMI borrowers were *more* likely to refinance during the housing boom is a novel result. But a higher rate of refinancing is not necessarily inconsistent with lack of financial

sophistication, at least to the extent that less educated, less financially sophisticated borrowers were more willing to accept a risky subprime loan, or more likely to be "sold" into an unfavorable refinancing by a pushy (or predatory) mortgage lender.[32]

Second, consider access to credit. That LMI borrowers were more likely to refinance during a period of easy credit (the mortgage boom) and less likely to refinance during a period of restricted credit availability (the mortgage bust) provides circumstantial evidence that access to credit might be an important explanatory factor. This concern is supported by HMDA data which shows that following the mortgage crisis, the disparity in conventional refinance loan application denial rates on properties in LMI tracts grew relative to non-LMI tracts. See Figure 4(a). Over the 2005-06 period, the denial rate was roughly 41 percent on LMI applications, compared with 32 percent on non-LMI applications. In 2008-09, the denial rate on LMI applications grew to 46 percent, while falling to 27 percent on loans in non-LMI areas. However, Figures 4(b) through 4(d) show that for FHA/VA refinance loans, and for conventional and FHA/VA home purchase loans the pattern of increasingly higher denial rates in LMI areas either does not hold or is much weaker. Consequently, the evidence from HMDA data in support of the hypothesis that access to credit generally declined more severely for lower income homeowners after the financial crisis is mixed.[33]

C. Economic Impact of LMI Status and Other Covariates on Probability of Prepayment in 2009

In order to provide additional context for the economic impact of LMI status and other factors on the propensity to refinance, I now present a supplemental analysis in which I focus on

[32] Spader and Quercia (2009) find that among lower income borrowers who refinanced their mortgages, those who were initially approached by a mortgage broker were more likely to: (1) refinance through a mortgage broker and (2) obtain a riskier adjustable rate mortgage.

[33] HMDA data on denial rates may not tell the whole story in terms of access to credit. Anecdotal evidence cited by Fuster and Willen (2010), and corroborated in my own conversations with retail loan officers, suggests that when mortgage brokers and lenders are at capacity, borrowers with poor credit may be 'rationed out' of the market. Borrowers in such cases are unable to even complete a loan application.

prepayments in the calendar year 2009. Avery, Bhutta, Brevoort, and Canner (2010) note that although refinancing activity increased sharply in 2009 following the LSAP, the magnitude of this increase was subdued compared with what has been historically observed when mortgage rates sharply decline. The authors present a descriptive analysis showing that prepayment rates are lower on average for borrowers in areas with steeper house price declines, and for borrowers who had missed at least one payment on their mortgage, suggesting that collateral constraints and economic conditions may have dampened refinance activity.

To explore this further, I estimate a modified version of the MNL model presented in Section 3. I restrict the analysis sample to include only loans that were still active as of December 2008. Each observation in the sample represents a single, unique loan (as opposed to the prior analysis in which the sample included observations at the loan-month level). The dependent variable takes on a value of 1 ("prepaid") if the loan prepaid at any point in 2009; a value of 2 ("default") if the loan entered foreclosure at any point in 2009; and 0 otherwise.

MNL estimates from this specification, presented in Appendix Table 3, are qualitatively similar to my earlier results for the January 2008 to June 2010 period. Conditional on the loan still being active in December 2008, a homeowner in an LMI area was less likely to prepay their mortgage in 2009 than a non-LMI homeowner. Variables associated with collateral constraints (higher current LTV) and credit and income constraints (lower credit scores; no or low loan documentation; local unemployment rate; local credit card delinquency rate) were also associated with lower probability of prepayment.

Figure 5 illustrates the economic impact that each of these factors had on mortgage prepayments in 2009, based on a series of counterfactual simulations. The first counterfactual scenario examines the impact that the fall in house prices and resulting high current LTVs have

had on prepayment. For each loan in my sample I compute a counterfactual LTV in which house prices are assumed to have remained unchanged since origination. Specifically, counterfactual LTV is equal to the unpaid principal balance divided by property value at origination. All other variables take on their actual values. Based on the MNL coefficient estimates I generate a counterfactual predicted 2009 prepayment rate equal to 25.8; this is 88 percent higher than the baseline predicted prepayment rate of 13.8 percent for the full sample. Looking at the sample separately by LMI status, the impact of high LTVs on prepayment is especially large for the subset of loans in High LMI zip codes (counterfactual prepayment rate is 143 percent higher than baseline) compared with the Non-LMI zip codes (70 percent). This reflects the relatively high share of loans in LMI areas that have high current LTVs, and are thus disproportionately affected by collateral constraints to refinancing.

The next counterfactual scenario examines the effect of economic conditions on 2009 prepayments. For each loan in the sample, I set the unemployment rate and credit card delinquency rate equal to their December 2005 level (for the corresponding county). All other variables take on their actual values. In this scenario the counterfactual predicted probability of prepayment is 14.4 percent, just 5 percent (or 0.7 percentage points) higher than the baseline rate. And in the final counterfactual scenario, I examine the role of LMI status. When I set the "Not LMI" indicator equal to one (and the "Low" and "High" LMI indicators equal to zero) for all loans in the sample, the counterfactual 2009 prepayment rate is 7 percent higher than baseline for the full sample. Of course, the difference in predicted probability of prepayment in this scenario is limited to the loans that are in High and Low LMI areas (41 percent and 9 percent higher than baseline, respectively). For the loans that are not in LMI areas, the counterfactual scenario is equivalent to the baseline (actual) scenario, so the effect is zero.

These results indicate that the primary explanation for the relatively muted level of refinance activity in 2009 is the low level of home equity held by borrowers due to house price declines. My estimates suggest the refinance rate in 2009 would have been nearly twice as high had house prices remained stable and borrower's home equity not eroded. Adverse local economic conditions, at least to the extent they are well measured in my model, appear to have had very little effect. And although LMI status is associated with a lower probability of mortgage prepayment, in terms of explaining market-level trends in refinancing behavior it is of minor importance.

6. Conclusion

In this paper I document the disparity in refinance activity across LMI and non-LMI homeowners during the housing boom and bust. I show that, contrary to earlier evidence on mortgage prepayment behavior, during the real estate boom homeowners in LMI areas prepaid their mortgages more frequently than their non-LMI counterparts. But following the 2007 collapse in real estate markets, LMI homeowners were again slower to prepay their mortgages.

To investigate these trends, I estimate a MNL model of mortgage terminations on a large sample of loan-level mortgage payment records spanning the years 2005 to 2010. My results indicate that income and collateral constraints to the refinancing decision are important factors in explaining the discrepancy in mortgage prepayments between LMI and non-LMI households. Systematic differences across borrowers in the likelihood of being affected by an adverse economic shock and in the level of home equity currently held by the borrower can account for roughly half of the observed discrepancy in likelihood of prepayment. But even after controlling for these constraints to the refinancing decision, I find that a mortgage held by a homeowner in

an LMI area is 28 percent less likely to terminate due to prepayment over the 2008-09 period. Thus other unobserved factors correlated with LMI status, on net, had an economically important effect on probability of prepayment. I note that the observed trends in prepayments among LMI households are consistent with the likely impact of two such factors: financial literacy, and lack of access to credit. Determining just how important these (and other) factors are remains a topic for future research.

Finally, I examine potential explanations for the relatively muted growth in refinancing activity in 2009 (following the Federal Reserve's implementation of LSAP in November 2008) documented by Avery, Bhutta, Brevoort, and Canner (2010). I find that the primary drag on new refinance loans in 2009 was the decline in home equity of borrowers resulting from falling house prices; my estimates suggest the refinance rate in 2009 would have been nearly twice as high had house prices remained stable. This suggests that recently introduced public policy initiatives that give underwater borrowers the option to refinance, such as FHA's Short Refinance Option and Obama's Home Affordable Refinance Program, should be of great value to homeowners if designed appropriately.

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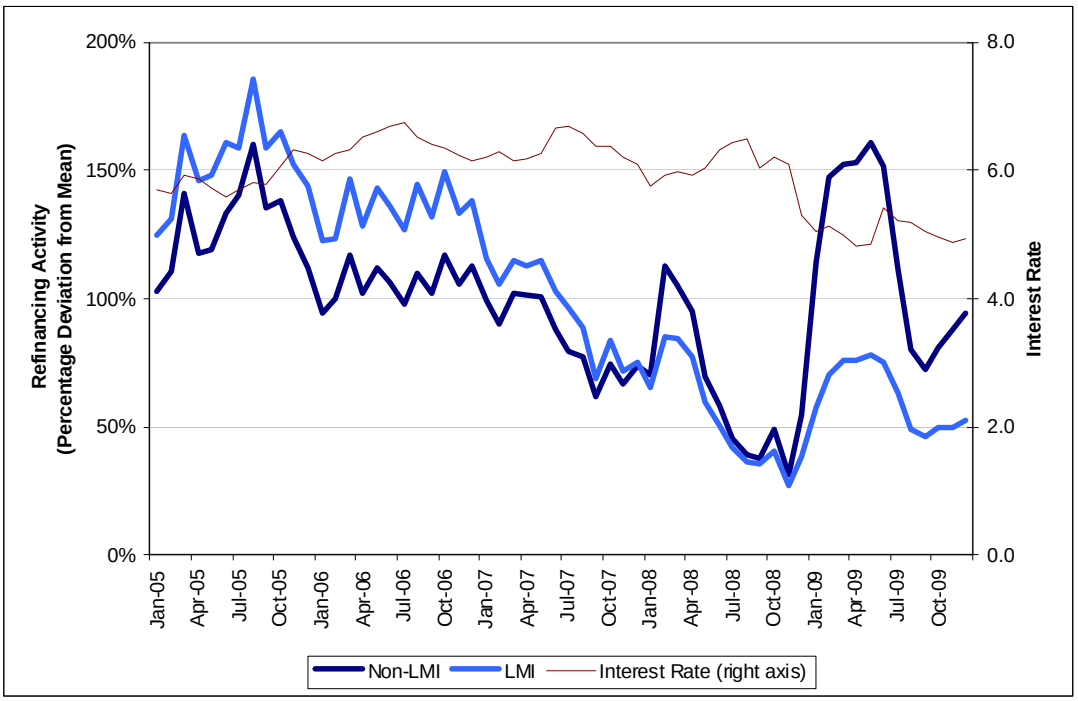
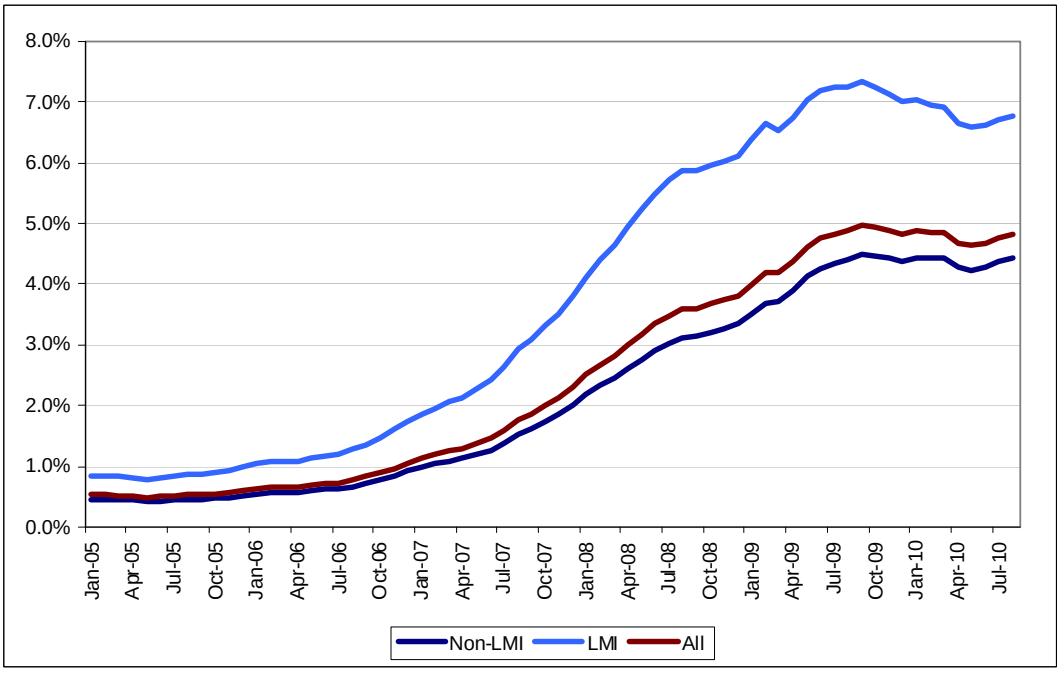
Figure 1: Refinance Activity by Census Tract LMI Status



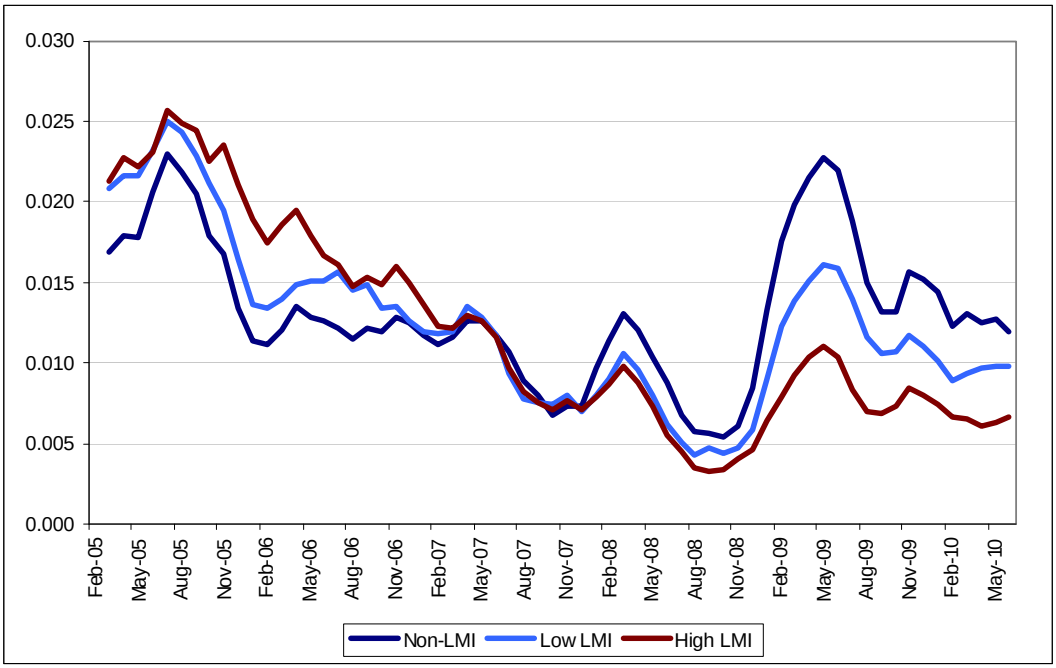
Notes: Based on author's calculations using Home Mortgage Disclosure Act (HMDA) data on owner occupied, 1-4 family refinance mortgage originations. Refinancing activity is expressed as a percentage of the mean monthly count of refinance loans from 2005 to 2009. In Non-LMI tracts the mean was 346,163 loans, and in LMI tracts the mean was 55,562 loans. Interest Rate data is from Freddie Mac's Weekly Primary Mortgage Market Survey.

Figure 2: Foreclosure Rate by LMI Status



Notes: Based on author's calculations using loan-level data from Lender Processing Services, Inc. Sample includes owner occupied, 1-4 family, purchase and refinance first lien mortgages. Foreclosure rate is defined as the share of active loans in any stage of foreclosure. Property zip code information in LPS is used to infer whether the property is located in an LMI or non-LMI census tract. In the many cases where the property zip code associated with the loan maps to more than one census tract, the loan is fractionally allocated to the associated census tracts using the share of zip code population that resides in each census tract, based on 2000 Census population.

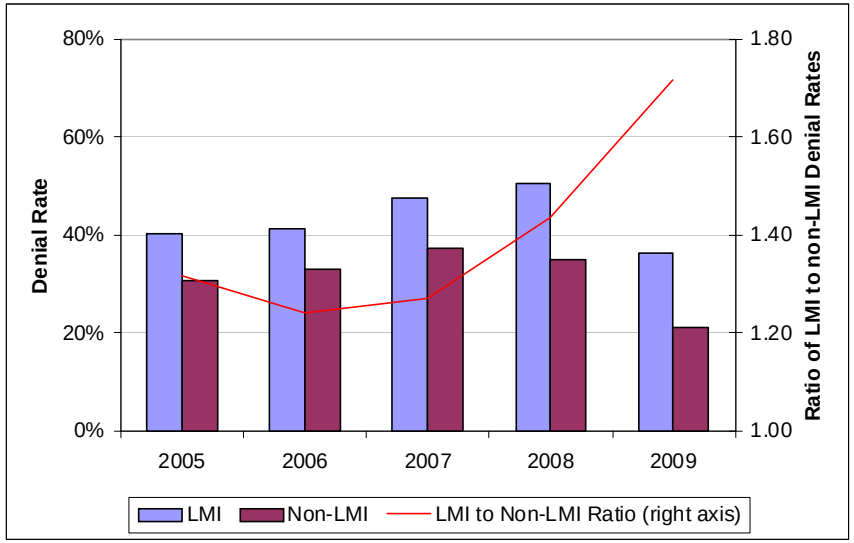
Figure 3: Mean Prepayment Rates by Month and Zip Code LMI Population



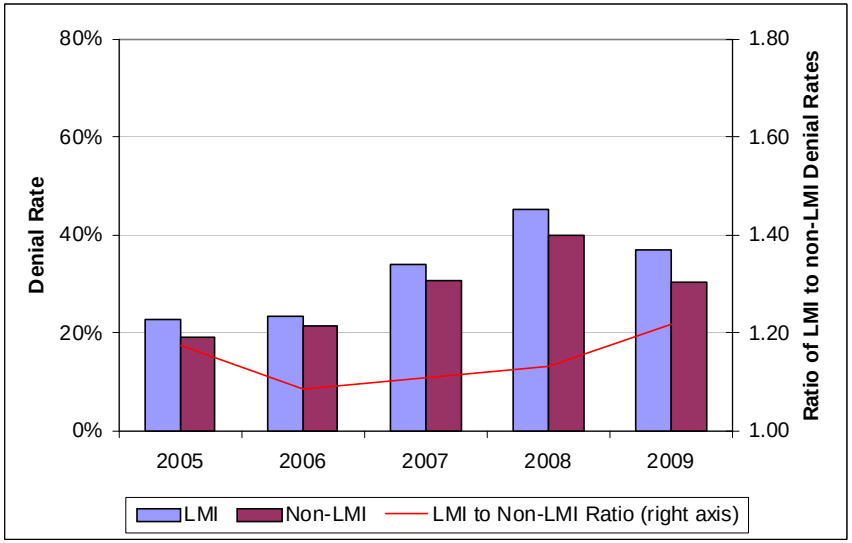
Notes: Mortgages are categorized into one of three LMI groups based on the likelihood that the property is in a LMI census tract. A loan is classified as "High LMI" if at least 50 percent of the zip code population resides in an LMI tract ("Low LMI" if between 0 and 50 percent; "Non-LMI" if zero percent).

Figure 4: Loan Application Denial Rates by LMI Status

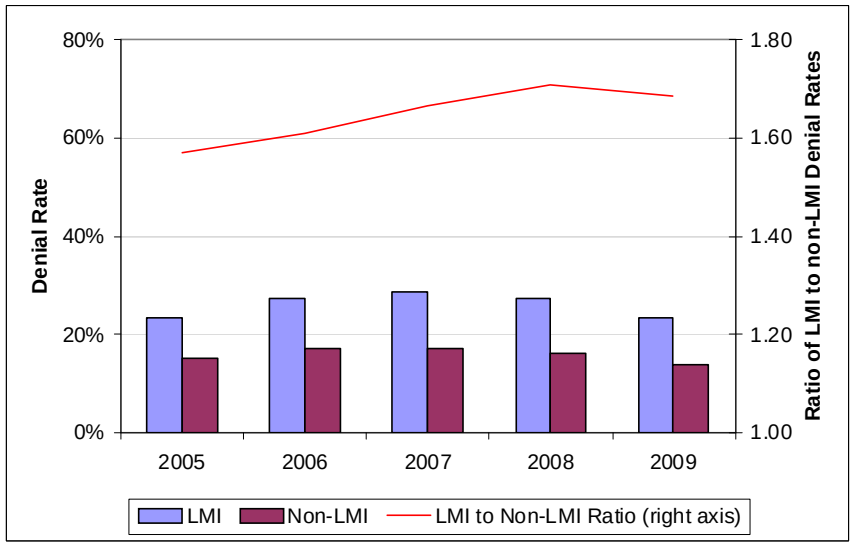
(a) Refi Conventional



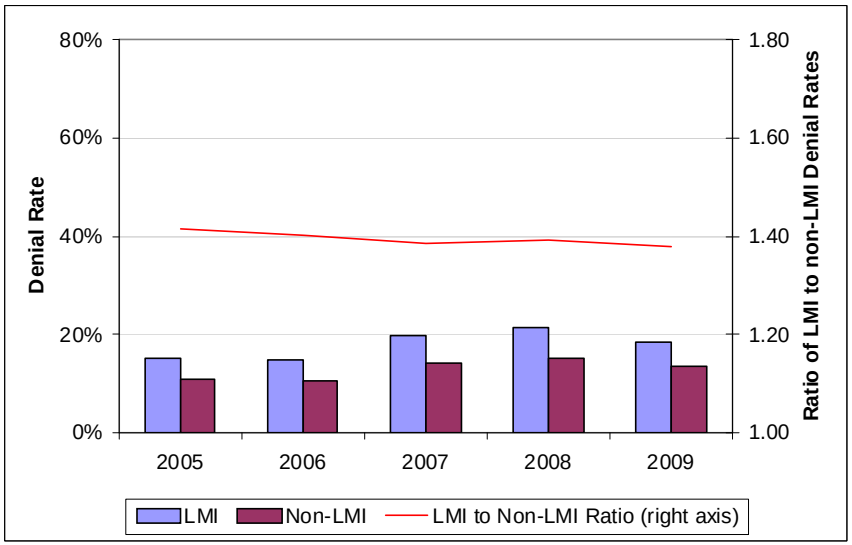
(b) Refi FHA/VA



(c) Purchase Conventional

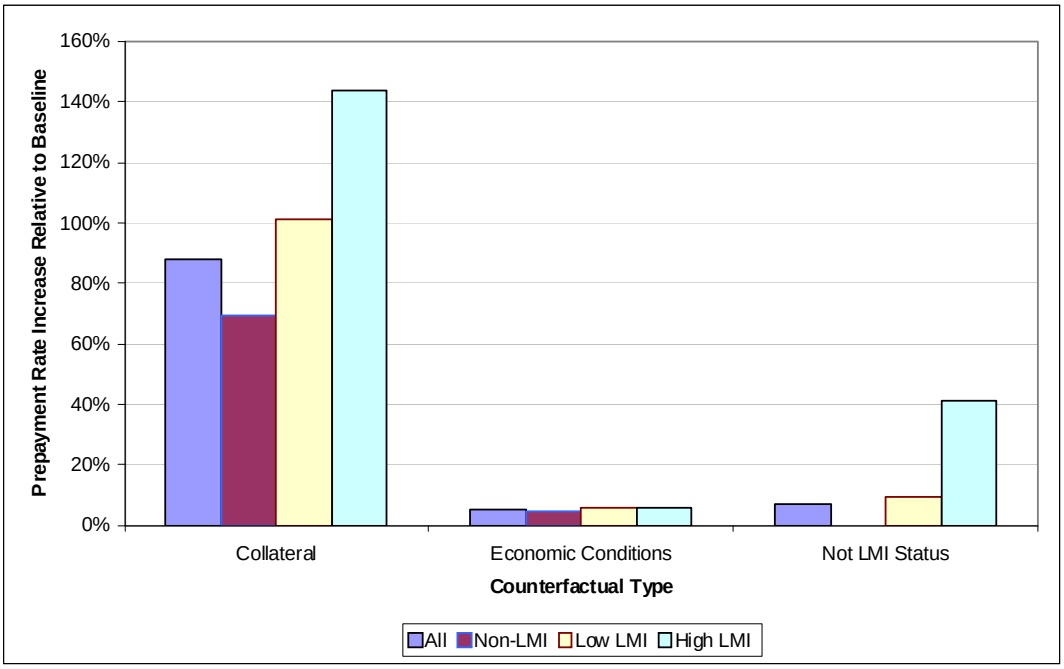


(d) Purchase FHA/VA



Notes: Based on author's calculations using HMDA data on home purchase and refinance, 1-4 family, owner occupied loans. Denial rate is defined as the number of loan applications denied by the financial institution divided by the sum of loans originated, loans approved but not accepted by the borrower, and loans denied by the financial institution. LMI status is based on the census tract of the property, and not based on borrower income.

Figure 5: Counterfactual Prepayment Rate in 2009 by LMI Status



Notes: Each column represents the increase in predicted probability of prepayment in 2009 in the counterfactual scenario relative to baseline. Predictions are based on the MNL estimates presented in Appendix Table 3.

Table 1: Descriptive Statistics

Variable	Full Sample		Zip Code LMI Population Group					
			Non-LMI		Low LMI		High LMI	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Loan Count	115,516		48,027		48,826		18,663	
Prepayment Rate	38.3	(48.6)	41.7	(49.3)	36.9	(48.3)	33.0	(47.0)
Default (Foreclosure) Rate	13.2	(33.9)	9.7	(29.6)	14.1	(34.9)	19.9	(39.9)
Loan Age (in months)	36.3	(21.8)	37.6	(22.0)	35.9	(21.7)	33.6	(21.2)
Mortgage Rate / Market Rate	1.14	(0.21)	1.12	(0.21)	1.14	(0.21)	1.16	(0.22)
Mortgage Interest Rate	6.16	(1.12)	6.04	(1.06)	6.19	(1.12)	6.40	(1.24)
Market Interest Rate	5.46	(0.64)	5.42	(0.63)	5.46	(0.64)	5.54	(0.66)
Loan Level Price Adjustment	0.66	(1.06)	0.59	(0.63)	0.70	(0.62)	0.78	(0.61)
Unpaid Principal Balance	259.7	(191.3)	291.4	(221.5)	247.2	(171.3)	211.2	(134.5)
Int Rate: Fixed	62.6	(48.4)	63.4	(48.2)	62.4	(48.4)	61.0	(48.8)
Int Rate: < 5 Year Hybrid ARM	9.7	(29.6)	7.4	(26.2)	10.2	(30.2)	14.4	(35.1)
Int Rate: >= 5 Year Hybrid ARM	13.7	(34.4)	14.5	(35.2)	13.6	(34.2)	12.1	(32.6)
Int Rate: ARM Init. Pd. Unknown	14.0	(34.7)	14.7	(35.4)	13.9	(34.5)	12.5	(33.1)
Not Interest Only	84.3	(36.4)	85.3	(35.4)	84.1	(36.5)	82.2	(38.3)
Interest Only	14.7	(35.4)	13.6	(34.2)	14.9	(35.6)	17.1	(37.6)
Unknown if Interest Only	1.0	(10.0)	1.1	(10.6)	1.0	(9.8)	0.8	(8.7)
Mobility Rate	15.6	(5.6)	13.3	(5.0)	16.5	(5.3)	18.9	(5.8)
Credit Score Low	11.8	(32.3)	9.1	(28.7)	12.5	(33.1)	17.3	(37.8)
Credit Score Middle	30.8	(46.2)	28.7	(45.2)	31.7	(46.5)	33.6	(47.2)
Credit Score High	42.0	(49.4)	47.0	(49.9)	40.6	(49.1)	33.1	(47.0)
Credit Score Missing	15.3	(36.0)	15.3	(36.0)	15.2	(35.9)	16.0	(36.6)
Full Documentation	30.5	(46.0)	29.0	(45.4)	31.0	(46.3)	32.8	(47.0)
Low or No Documentation	27.7	(44.8)	27.4	(44.6)	28.1	(44.9)	27.8	(44.8)
Missing info on Documentation	41.8	(49.3)	43.5	(49.6)	40.9	(49.2)	39.4	(48.9)
DTI Less Than 28	13.6	(34.2)	14.8	(35.5)	13.0	(33.6)	11.9	(32.4)
DTI 28 to 35	12.8	(33.4)	12.7	(33.3)	12.7	(33.3)	13.1	(33.7)
DTI 36 to 41	14.2	(34.9)	14.0	(34.7)	14.2	(34.9)	14.5	(35.2)
DTI 42 or More	21.8	(41.3)	20.4	(40.3)	22.5	(41.8)	23.3	(42.3)
DTI Missing	37.7	(48.5)	38.1	(48.6)	37.6	(48.4)	37.3	(48.4)
Unemployment Rate	7.91	(3.22)	7.82	(3.08)	8.06	(3.37)	7.76	(3.16)
Credit Card 60+Days Delinq.	2.29	(0.72)	2.16	(0.67)	2.37	(0.74)	2.40	(0.74)
LTV Equal to 80 at Orig.	27.8	(44.8)	26.9	(44.4)	28.4	(45.1)	28.6	(45.2)
LTV less than 70	29.0	(45.4)	32.0	(46.6)	27.8	(44.8)	24.7	(43.1)
LTV 70 to 80	15.8	(36.5)	16.7	(37.3)	15.2	(35.9)	15.1	(35.8)
LTV 80 to 90	13.9	(34.5)	15.3	(36.0)	13.0	(33.6)	12.5	(33.1)
LTV 90 to 100	11.4	(31.8)	11.7	(32.1)	11.3	(31.6)	11.0	(31.3)
LTV 100 to 110	9.0	(28.6)	8.6	(28.0)	9.3	(29.0)	9.2	(28.9)
LTV 110 or more	21.0	(40.7)	15.8	(36.5)	23.5	(42.4)	27.5	(44.7)

Notes: Values are based on the last observation for each loan, whether it was prepaid, in default, or still active. Mortgages are categorized into one of three LMI groups based on the likelihood that the property is in a LMI census tract. A loan is “High LMI” if at least 50 percent of the zip code population resides in an LMI tract (“Low LMI” if between 25 and 50 percent; ““Non-LMI” if zero percent). All variables are binary indicators except for Loan Level Price Adjustment (expressed in terms of the number of discount points charged at origination), Unpaid Principal Balance (in $1000s), and unemployment, credit card delinquency, and mobility rates (all in percentages). Credit Score less than 640 is "Low"; between 640 and 720 is "Middle"; 720 or more is "High". With the exception of “Low or No Documentation”, “DTI 28 to 35”, “DTI 36 to 41”, and “Unemployment Rate”, for all variables listed the difference in the mean value of the High LMI group and the Non-LMI group is statistically different from zero at the five percent level.

Table 2: Estimated Impact of LMI Status on Probability of Prepayment

	(A) Full Sample				(B) Jan 2005 to Dec 2006		(C) Jan 2008 to Jun 2010	
Model Specification	(1)	(2)	(3)	(4)	(1)	(4)	(1)	(4)
Multinomial Logit Coefficient Estimates								
High LMI	-0.119***	-0.100***	-0.041*	-0.028	0.199***	0.103***	-0.498***	-0.302***
	(0.023)	(0.024)	(0.022)	(0.019)	(0.035)	(0.028)	(0.044)	(0.034)
Low LMI	-0.068***	-0.041***	-0.014	-0.005	0.126***	0.061***	-0.245***	-0.101***
	(0.016)	(0.016)	(0.014)	(0.013)	(0.027)	(0.021)	(0.028)	(0.019)
Implied Marginal Effects								
High LMI	-0.0015	-0.0012	-0.0005	-0.0004	0.0032	0.0016	-0.0049	-0.0030
Low LMI	-0.0009	-0.0005	-0.0002	-0.0001	0.0020	0.0010	-0.0027	-0.0011
Marginal Effect as a Percentage of Baseline Prepayment Rate								
High LMI	-11.8%	-9.9%	-4.1%	-2.9%	19.5%	10.0%	-45.6%	-27.7%
Low LMI	-6.9%	-4.1%	-1.4%	-0.5%	12.0%	5.9%	-25.2%	-10.2%
Specification Includes Controls for:								
Loan Age	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Refinancing Costs and Benefits	Y	Y	Y	Y	Y	Y	Y	Y
Area Macroeconomic Conditions		Y	Y	Y		Y		Y
Credit Score		Y	Y	Y		Y		Y
Current LTV			Y	Y		Y		Y
Metropolitan Area Fixed Effects				Y		Y		Y
Pseudo R2	0.0546	0.0642	0.0797	0.0824	0.0455	0.0663	0.0522	0.0883

Notes: Coefficient estimates on LMI status are from a multinomial logit model where the dependent variable in month *t* is equal to one if the loan prepaid, equal to two if the loan defaulted, and equal to zero otherwise. Standard errors clustered by zip code. Full sample covering January 2005 to June 2010 has 3,593,411 loan-month observations; the January 2005 to December 2006 period has 1,078,055 observations; the January 2008 to June 2010 period has 1,758,924 observations. See Appendix Tables 1 and 2 for the full set of coefficient estimates for the prepayment and default models. The symbol *** indicates the estimate is statistically significant at the one percent level (** = five percent; * = ten percent). See Appendix Tables 1 and 2 for the complete set of estimation results, including estimates on probability of default. Across all specifications, the estimated marginal effect of High LMI status on probability of prepayment is computed by taking the difference of (1) the predicted probability of prepayment when the High LMI indicator is set equal to one for all loan-month observations in the sample and (2) the predicted probability of prepayment when the High LMI indicator is set equal to zero for all loan-month observations in the sample. All other variables take on their actual values. Marginal effects for Low LMI are computed similarly. The baseline prepayment rate is 1.23 percent for the full sample, 1.65 percent for the 2005-06 sample, and 1.07 percent for the 2008-10 sample.

Appendix Table 1: Multinomial Logit Estimates, Full Sample

	Specification (1)		Specification (2)		Specification (3)		Specification (4)	
	Prepay	Default	Prepay	Default	Prepay	Default	Prepay	Default
High LMI	-0.119***	0.542***	-0.100***	0.450***	-0.041*	0.348***	-0.028	0.351***
	(0.023)	(0.046)	(0.024)	(0.039)	(0.022)	(0.033)	(0.019)	(0.032)
Low LMI	-0.068***	0.293***	-0.041***	0.188***	-0.014	0.126***	-0.005	0.123***
	(0.016)	(0.039)	(0.016)	(0.031)	(0.014)	(0.026)	(0.013)	(0.025)
Mortgage Rate / Market Rate	1.261***	2.545***	1.217***	2.174***	1.519***	1.954***	1.537***	1.973***
	(0.031)	(0.059)	(0.032)	(0.056)	(0.034)	(0.055)	(0.034)	(0.054)
Loan Level Price Adjustment	-0.320***	0.309***	-0.366***	0.057***	-0.175***	-0.083***	-0.174***	-0.083***
	(0.009)	(0.010)	(0.010)	(0.013)	(0.010)	(0.014)	(0.010)	(0.014)
Unpaid Principal Balance	0.000**	0.000***	0.000	0.000***	0.000***	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Int Rate: < 5 Year Hybrid ARM	0.565***	1.236***	0.494***	1.095***	0.531***	0.917***	0.497***	0.881***
	(0.020)	(0.037)	(0.020)	(0.035)	(0.021)	(0.032)	(0.021)	(0.032)
Int Rate: >= 5 Year Hybrid ARM	0.463***	0.771***	0.439***	0.719***	0.527***	0.486***	0.502***	0.457***
	(0.015)	(0.031)	(0.016)	(0.031)	(0.016)	(0.031)	(0.015)	(0.031)
Int Rate: ARM Unknown Init. Pd.	0.030*	0.751***	0.041**	0.692***	0.146***	0.498***	0.118***	0.480***
	(0.018)	(0.028)	(0.018)	(0.028)	(0.018)	(0.027)	(0.018)	(0.027)
Interest Only	-0.093***	0.123***	-0.105***	0.112***	-0.083***	0.125***	-0.076***	0.138***
	(0.016)	(0.026)	(0.016)	(0.025)	(0.016)	(0.024)	(0.016)	(0.024)
Unknown if Interest Only	0.422***	0.206*	0.488***	0.244**	0.424***	0.360***	0.452***	0.358***
	(0.040)	(0.105)	(0.040)	(0.114)	(0.041)	(0.125)	(0.041)	(0.126)
Mobility Rate	-0.312**	1.093***	0.159	0.213	0.295**	-0.281	-0.159	-0.157
	(0.152)	(0.287)	(0.151)	(0.259)	(0.138)	(0.230)	(0.143)	(0.253)
Credit Score Low			0.238***	1.083***	0.175***	1.255***	0.186***	1.289***
			(0.021)	(0.039)	(0.021)	(0.041)	(0.021)	(0.041)
Credit Score Middle			0.119***	0.745***	0.092***	0.793***	0.090***	0.791***
			(0.013)	(0.025)	(0.013)	(0.026)	(0.013)	(0.026)
Credit Score Missing			0.250***	0.725***	0.127***	0.906***	0.133***	0.910***
			(0.017)	(0.035)	(0.017)	(0.038)	(0.017)	(0.038)
Low or No Documentation			-0.004	0.407***	-0.007	0.358***	-0.007	0.341***
			(0.013)	(0.023)	(0.013)	(0.023)	(0.013)	(0.023)
Missing info on Documentation			-0.226***	-0.032	-0.224***	-0.035	-0.210***	-0.033
			(0.014)	(0.029)	(0.014)	(0.028)	(0.014)	(0.028)
DTI 28 to 35			-0.044**	0.386***	0.025	0.268***	0.007	0.262***
			(0.018)	(0.038)	(0.019)	(0.038)	(0.019)	(0.038)
DTI 36 to 41			-0.049**	0.457***	0.041**	0.320***	0.013	0.310***
			(0.019)	(0.039)	(0.019)	(0.039)	(0.019)	(0.039)
DTI 42 or More			-0.034**	0.568***	0.068***	0.425***	0.043**	0.414***
			(0.017)	(0.035)	(0.017)	(0.035)	(0.017)	(0.035)
DTI Missing			0.331***	0.630***	0.380***	0.552***	0.361***	0.542***
			(0.017)	(0.039)	(0.017)	(0.038)	(0.017)	(0.038)
Unemployment Rate			-0.007	0.025***	0.018***	-0.014**	-0.008	0.014
			(0.004)	(0.007)	(0.004)	(0.007)	(0.007)	(0.011)
Credit Card 60+Days Delinq.			-0.266***	0.443***	-0.134***	0.257***	-0.209***	0.122***
			(0.013)	(0.018)	(0.012)	(0.017)	(0.017)	(0.028)
LTV Equal to 80 at Orig.					-0.057***	0.220***	-0.089***	0.206***
					(0.012)	(0.019)	(0.012)	(0.019)
LTV 70 to 80					-0.319***	0.932***	-0.280***	0.996***
					(0.014)	(0.046)	(0.014)	(0.047)
LTV 80 to 90					-0.527***	1.365***	-0.485***	1.448***
					(0.018)	(0.046)	(0.018)	(0.047)
LTV 90 to 100					-0.927***	1.652***	-0.885***	1.744***
					(0.023)	(0.049)	(0.023)	(0.050)
LTV 100 to 110					-1.097***	1.961***	-1.067***	2.039***
					(0.030)	(0.052)	(0.030)	(0.054)
LTV 110 or more					-1.908***	2.488***	-1.887***	2.533***
					(0.035)	(0.050)	(0.035)	(0.052)
Metro Area FE	N		N		N		Y	
Pseudo R2	0.0546		0.0642		0.0797		0.0824	

Notes: All coefficients are estimates from a multinomial logit model where the dependent variable in month *t* is equal to one if the loan prepaid, equal to two if the loan defaulted, and equal to zero otherwise. Standard errors clustered by zip code; 3,593,411 loan-month observations. All specifications include quarterly fixed effects, metropolitan area fixed effects, a cubic function in age of the loan, age dummies for ages 12 to 14, 24 to 26, 36 to 38, or 58 to 62 months from origination, and these age dummies interacted with an indicator that the loan is an ARM. All time-variant controls (Interest Rate Ratio, LLPA, Unpaid Principal Balance, Unemployment Rate, Credit Card Delinquency Rate, and LTV indicators) are lagged one month. The symbol *** indicates the estimate is statistically significant at the one percent level (** = five percent; * = ten percent).

Appendix Table 2: Multinomial Logit Estimates, Sample Stratified by Time Period

	Housing Boom: January 2005 to December 2006				Housing Bust: January 2008 to June 2010			
	Specification (1)		Specification (4)		Specification (1)		Specification (4)	
	Prepay	Default	Prepay	Default	Prepay	Default	Prepay	Default
High LMI	0.199***	0.551***	0.103***	0.599***	-0.498***	0.515***	-0.302***	0.314***
	(0.035)	(0.086)	(0.028)	(0.084)	(0.044)	(0.053)	(0.034)	(0.036)
Low LMI	0.126***	0.192***	0.061***	0.252***	-0.245***	0.312***	-0.101***	0.118***
	(0.027)	(0.073)	(0.021)	(0.071)	(0.028)	(0.043)	(0.019)	(0.028)
Mortgage Rate / Market Rate	1.666***	3.560***	1.322***	2.660***	0.922***	2.244***	1.514***	1.871***
	(0.053)	(0.142)	(0.056)	(0.165)	(0.049)	(0.067)	(0.054)	(0.062)
Loan Level Price Adjustment					-0.286***	0.361***	-0.048***	0.085***
					(0.009)	(0.010)	(0.015)	(0.018)
Unpaid Principal Balance	0.000***	-0.000	-0.000	0.001***	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Int Rate: < 5 Year Hybrid ARM	0.725***	1.244***	0.479***	0.941***	0.242***	1.003***	0.301***	0.776***
	(0.031)	(0.092)	(0.032)	(0.100)	(0.043)	(0.046)	(0.046)	(0.039)
Int Rate: >= 5 Year Hybrid ARM	0.662***	0.042	0.591***	0.034	0.102***	0.995***	0.295***	0.645***
	(0.023)	(0.100)	(0.023)	(0.099)	(0.031)	(0.037)	(0.032)	(0.036)
Int Rate: ARM Unknown Init. Pd.	0.352***	-0.413***	0.262***	-0.234	-0.008	0.825***	0.175***	0.532***
	(0.032)	(0.142)	(0.032)	(0.147)	(0.026)	(0.031)	(0.026)	(0.030)
Interest Only	0.103***	0.135*	0.123***	0.124	-0.139***	0.072**	-0.095***	0.105***
	(0.027)	(0.079)	(0.026)	(0.083)	(0.026)	(0.031)	(0.026)	(0.027)
Unknown if Interest Only	0.439***	0.392	0.609***	0.377	0.178	0.029	0.098	0.183
	(0.048)	(0.239)	(0.050)	(0.242)	(0.123)	(0.156)	(0.124)	(0.181)
Mobility Rate	0.371	0.409	-0.019	0.081	-0.829***	1.208***	-0.198	-0.295
	(0.244)	(0.534)	(0.228)	(0.651)	(0.293)	(0.329)	(0.217)	(0.285)
Credit Score Low			0.311***	1.826***			-0.219***	0.759***
			(0.027)	(0.115)			(0.048)	(0.058)
Credit Score Middle			0.259***	1.061***			-0.226***	0.530***
			(0.019)	(0.103)			(0.024)	(0.035)
Credit Score Missing			0.160***	1.392***			-0.129***	0.421***
			(0.025)	(0.121)			(0.032)	(0.050)
Low or No Documentation			0.184***	0.137*			-0.130***	0.408***
			(0.022)	(0.079)			(0.021)	(0.026)
Missing info on Documentation			-0.298***	0.080			0.008	0.011
			(0.022)	(0.080)			(0.023)	(0.034)
DTI 28 to 35			0.095***	0.314**			-0.030	0.251***
			(0.031)	(0.133)			(0.028)	(0.043)
DTI 36 to 41			0.093***	0.244*			-0.028	0.336***
			(0.032)	(0.136)			(0.028)	(0.043)
DTI 42 or More			0.134***	0.362***			-0.049*	0.391***
			(0.030)	(0.121)			(0.025)	(0.039)
DTI Missing			0.694***	0.514***			-0.003	0.491***
			(0.028)	(0.128)			(0.027)	(0.044)
Unemployment Rate			0.005	-0.009			0.016*	0.009
			(0.017)	(0.058)			(0.009)	(0.013)
Credit Card 60+Days Delinq.			-0.057*	0.031			-0.089***	0.024
			(0.030)	(0.081)			(0.030)	(0.036)
LTV Equal to 80 at Orig.			-0.060***	0.298***			-0.082***	0.146***
			(0.018)	(0.068)			(0.019)	(0.022)
LTV 70 to 80			-0.130***	0.763***			-0.230***	0.794***
			(0.023)	(0.086)			(0.025)	(0.086)
LTV 80 to 90			-0.113***	1.077***			-0.517***	1.320***
			(0.034)	(0.103)			(0.026)	(0.078)
LTV 90 to 100			-0.302***	1.260***			-0.933***	1.687***
			(0.059)	(0.129)			(0.029)	(0.077)
LTV 100 to 110			-0.018	1.973***			-1.069***	1.954***
			(0.228)	(0.259)			(0.033)	(0.078)
LTV 110 or more			-0.725	2.877***			-1.712***	2.483***
			(1.094)	(0.702)			(0.038)	(0.076)
Metro Area FE	N		Y		N		Y	
Pseudo R2	0.0455		0.0663		0.0522		0.0883	

Notes: The January 2005 to December 2006 period has 1,078,055 observations. The January 2008 to June 2010 period has 1,758,924 observations. LLPA is omitted from the empirical specification estimated on the 2005 to 2006 period because it takes on a value of zero for all loan-month observations. See Appendix Table 1 for additional notes.

Appendix Table 3: Multinomial Logit Estimates, Mortgage Termination in 2009

	Prepay	Default
High LMI	-0.396***	0.471***
	(0.051)	(0.065)
Low LMI	-0.107***	0.191***
	(0.030)	(0.047)
Mortgage Interest Rate	0.229***	0.263***
	(0.019)	(0.028)
Loan Level Price Adjustment	0.028	0.187***
	(0.031)	(0.051)
Unpaid Principal Balance	0.000***	-0.000
	(0.000)	(0.000)
Int Rate: < 5 Year Hybrid ARM	-0.275***	0.656***
	(0.097)	(0.090)
Int Rate: >= 5 Year Hybrid ARM	0.149***	0.764***
	(0.053)	(0.070)
Int Rate: ARM Unknown Init. Pd.	-0.019	0.721***
	(0.044)	(0.058)
Interest Only	-0.091**	0.189***
	(0.045)	(0.052)
Unknown if Interest Only	-0.201	-0.447
	(0.231)	(0.470)
Mobility Rate	-0.297	-1.524***
	(0.305)	(0.486)
Credit Score Low	-0.409***	0.371**
	(0.085)	(0.147)
Credit Score Middle	-0.410***	0.365***
	(0.041)	(0.076)
Credit Score Missing	-0.281***	0.283***
	(0.053)	(0.108)
Low or No Documentation	-0.153***	0.516***
	(0.035)	(0.051)
Missing info on Documentation	0.037	0.144**
	(0.038)	(0.066)
DTI 28 to 35	-0.078*	0.426***
	(0.045)	(0.085)
DTI 36 to 41	-0.024	0.514***
	(0.045)	(0.084)
DTI 42 or More	-0.080**	0.549***
	(0.041)	(0.081)
DTI Missing	-0.067	0.687***
	(0.044)	(0.089)
Unemployment Rate	0.001	-0.048
	(0.042)	(0.070)
Credit Card 60+Days Delinq.	-0.159**	0.068
	(0.066)	(0.091)
LTV Equal to 80 at Orig.	-0.093***	0.106**
	(0.031)	(0.044)
LTV 70 to 80	-0.436***	0.905***
	(0.043)	(0.148)
LTV 80 to 90	-0.872***	1.118***
	(0.045)	(0.141)
LTV 90 to 100	-1.231***	1.498***
	(0.048)	(0.144)
LTV 100 to 110	-1.293***	1.695***
	(0.055)	(0.147)
LTV 110 or more	-2.223***	2.169***
	(0.074)	(0.143)
Metro Area FE	Y	
Pseudo R2	0.1328	

Notes: All coefficients are estimates from a multinomial logit model where the dependent variable is equal to 1 if the mortgage was prepaid in 2009, equal to 2 if the mortgage defaulted in 2009, and zero otherwise. Estimation sample includes loans that had not terminated or prepaid as of December 2008, 63,530 loan level observations. The empirical specification is analogous to Table 3 Specification 4, with one exception: instead of including a control for the ratio of the mortgage interest rate to the market interest rate, this specification controls simply for the mortgage interest rate as of December 2008.