RESEARCH REPORT

PERSISTENCY PAYS OFF:
Prepayment Behavior of Affordable Homeownership

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Abstract

Accurate evaluation of the returns and risks of mortgages to low-income and minority households is vital for determining optimal housing finance practices and policies. One of the most important yet most unpredictable drivers of mortgage economics is the rate at which borrowers pay off their loans. It has been posited that loans made to low- and moderate- income borrowers have slower and more predictable prepayment rates than other prime mortgages, suggesting that more value should be attributed to these loans. Using a database of 38,000 mortgages made to low- and moderate-income borrowers through the Self-Help Community Advantage Program (CAP), we find that the CAP mortgages consistently prepaid slower than other comparable mortgage assets. Classic option theory explains much, but not all of this difference. By examining the drivers of prepayment behavior within the CAP portfolio, we find that risk-related constraints, borrower characteristics, and certain neighborhood characteristics contribute to the prepayment differential. Finally, we investigate drivers of refinancing and mobility using a subpopulation of borrowers who participate in an annual panel survey.

I. Introduction

The mortgage market is increasingly important in the US economy. As of the first quarter of 2006, total outstanding residential mortgage debt was $8.978 trillion,[1] more than 2.5 times its level a decade before. Origination volume peaked at a record level in 2003 at $3.9 trillion—a five times the volume of 1995—and remained strong from 2004 through 2006 at around $3 trillion in each year. (Inside Mortgage Finance 2007, Vol I, p.3). Today, more than two-thirds of mortgages are securitized in mortgage-backed securities (MBS) (Inside Mortgage Finance 2007, Vol II, p.3). Mortgage-related assets comprise the largest portion (23.7%) of US outstanding bond market debt, exceeding Corporate (19.6%) and Treasuries (15.8%) as of December 31, 2006 (SIFMA 2007).

Despite this flow of funds, lower income borrowers and communities continue to face challenges in accessing mortgage capital. In recent years, higher-cost lending has expanded rapidly, gaining its strongest foothold among low-income and minority households,[2] and previous concern over the lack of mortgage capital available in low-income areas has given way to worries about the disparity in the cost and terms of mortgage debt provided. Defenders of high-cost mortgages claim that they are "priced for the risk." Thus, better quantification of risks of loans to low-income and minority households is vital for determining appropriate intervention policies for the mortgage market and credit market in general.

The standard mortgage made to a homebuyer in the United States is a fixed-rate loan with a 30-year term.[3,4] From a lending perspective, the economics of this seemingly straightforward asset are complicated by two mutually exclusive risks: the risk of loss of principal from default,

[1] Federal Reserve Flow of Funds Report

[2] For example, HUD and Treasury (2000) present evidence that nationally, subprime loans on average are three times more frequent in low-income neighborhoods than in upper-income neighborhoods and five times more frequent in predominantly black neighborhoods than in predominantly white neighborhoods. Several empirical studies at the MSA-level provide further evidence of the geographic concentration of subprime mortgages in census tracts with high concentrations of low-income and minority households, see Deng, Pavlov and Yang 2005 for a summary.

[3] The conventional market share of 30-year mortgages for each year from 1997 through 2004 has ranged from 78% to 90% and averages 84% of all conventional mortgages (FHFB).

[4] From 1990 to 2006, the Federal Housing Finance Board reports that the annual share of fixed-rate mortgages in the conventional market was at least 60%, and for eleven of those years was 75% or higher. Fixed-rate mortgages are even more dominant in the non-jumbo market where they averaged 80% of loans originated over the 15-year period from 1990 through 2004 compared to 44% for conventional jumbo loans. (FHFB). In 2004 and 2005, adjustable rate mortgages surged to about half of *all* mortgage originations, but declined to 45% for 2006. (Inside Mortgage Finance 2007, p4); however, by the end of March, 2007, the Mortgage Bankers Association reported ARM share had fallen to 19% and projected a level more in line with its long range market position (MBA 2007).

and the risk attendant to the borrower's decision to exercise her option to pay the loan off at par at any point. Defaults typically account for a small share of terminations, but prepayment is almost sure to occur sometime before the end of the 30th year—the challenge lies in predicting when.[5] Because investors in rated mortgage backed securities (MBS) and especially those issued by Fannie Mae, Freddie Mac and Ginnie Mae, face little to no credit risk, prepayment risk is of paramount importance.

The most volatile element of prepayments is due to refinancing. When rates fall, borrowers switch to lower-rate mortgages, eroding asset values. Other causes of prepayment include cash-out refinances, prepayment, default and curtailment. Cash-out refinances can occur in response to appreciation gains and are less interest-rate sensitive than pure rate/term refinances. Unlike refinance, housing turnover rates tend to remain fairly stable from year to year, ranging between 5% and 6.5% of outstanding mortgages from 1984 to 1994. Less important elements of prepayment are default (generally less than .5% annually), borrowers making extra principal payments or "curtailments" (less than .5% annually), and full payoffs (negligible except in the case of very well-seasoned loans) (Hayre and Rajan 1995).

This paper seeks to analyze whether prime, fixed-rate mortgages to low-income and minority borrowers, hereinafter referred to as "affordable mortgages," pose different prepayment risks than other, similar loans. Affordable mortgages are characterized by features associated with higher default risk: low equity, blemished or non-traditional credit history, and high ratio of debt-to-income, for example. Yet many of these same factors also reduce prepayment risk. As a result, affordable mortgages could have a higher value than traditionally viewed, particularly in environments with falling interest rates, when mortgage-related asset values are most volatile.

First, we demonstrate the comparatively slower prepayment speeds of a large, geographically dispersed portfolio of affordable mortgages. Next we present evidence from the existing literature on the relative prepayment risks presented by low- and moderate-income borrowers. This is followed by an empirical analysis of the affordable mortgage portfolio in which we identify factors that drive slower prepayment behavior. We also introduce unique data obtained from a series of post-origination interviews of a panel of lower income mortgagors, to unpack these results even further.

[5] It should be noted that our analysis examines mortgages priced and funded through the prime market; loans with subprime terms and conditions exhibit different performance attributes; for example, they often feature hefty prepayment penalties, which alters the refinance paradigm.

II. A Demonstration of Prepayment Performance: Affordable Mortgages vs Comparable Assets

The Community Advantage Program

In 1998, Fannie Mae and the Ford Foundation invited the Center for Community Capitalism (CCC) to evaluate the Community Advantage Program (CAP), a mortgage secondary market program developed out of a partnership between the Ford Foundation, Fannie Mae, and Self-Help, a leading Community Development Financial Institution. The goal of CAP is to provide evidence to lenders, policy makers, and the secondary mortgage market that low-wealth borrows are "bankable," and that Fannie Mae (and, by implication, Freddie Mac) can significantly expand the purchase of affordable housing loans without compromising either balance sheets or safety and soundness concerns. With a Ford Foundation grant to underwrite a significant portion of the credit risk, Self-Help purchases affordable mortgages from participating lenders. These loans could not otherwise be readily sold in the secondary market because of such features as limited assets, lack of private mortgage insurance, and/or non-traditional employment or poor credit history. Self-Help retains recourse (assumes full credit risk) on these loans, enabling them to be securitized or sold to Fannie Mae and effectively creating a traditional outlet for otherwise illiquid loans. In turn, lenders can extend more home loans to households who may not qualify under traditional mortgage guidelines.

The agreement between Fannie Mae and Self-Help originally stipulated that Fannie Mae would purchase $2 billion in CAP mortgages over a five-year period. To support this level of risk, the Ford Foundation made a $50 million grant to Self-Help. By 2004, Self-Help reached its $2 billion target, leveraging the Ford grant 40 times over, and Fannie Mae agreed to extend the program.

To qualify for the CAP program, borrowers must have income of no more than 80% of the area median income (AMI), except in the case of minority borrowers or those borrowers purchasing a home in a high-minority (>30%) or low-income (<80% of AMI) census tract, in which case income may not exceed 115% of AMI. This mix of income- and location-based targeting gives participating lenders some flexibility in developing programs to meet the needs of

their markets. CAP loans are solely for the purpose of home purchase (not refinance).[6] None of the loans are assumable, and none have prepayment penalties. The preponderance are fixed-rate, 30-year mortgages, without prepayment penalties or balloons. It should be emphasized that, while many of the borrowers are somewhat credit impaired (with about one-fifth having credit scores below 620 at origination), the program cannot be characterized as subprime. The CAP portfolio features loans with prime terms and conditions, is predominantly made up of retail (vs. broker) originations, includes only purchase money mortgages only, and is limited to low- and moderate-income borrowers.

As of September 2006, Self-Help had purchased 42,694 loans totaling $3.79 billion. With an average loan of $88,773, participating lenders appear to be successfully serving the affordable market. Ninety-one percent of borrowers earned 80% of area median income or less; 45% are minority. Seventy-one percent of the loans had an original loan-to-value ratio above 95%, and more than 41% of the borrowers had FICO scores below 660 at the time of origination.

The CCC is undertaking in-depth research on CAP to evaluate performance and impacts of homeownership for low- and moderate-income borrowers. This research includes a six-year series of interviews of a panel of CAP borrowers to collect data on household dynamics and community characteristics. The large number of study participants and the panel design create a promising opportunity to understand not only the performance of CAP loans but also the social and wealth impacts of homeownership. The unique attributes of this portfolio make it possible to undertake focused analysis of affordable mortgages in the prepayment context.

We expect that the CAP borrowers will generally find refinancing less to their advantage under scenarios with similar interest rates than other borrowers in the conforming, conventional market. Several factors reduce the net benefits, characterized as the "option value", of refinancing typical affordable mortgages. First, there is the smaller average loan balance. Transaction costs can run over $1,500 in fixed costs plus 1% of the loan amount. This would amount to nearly 2.75% on an $86,000 loan, but only 1.7% on a $222,000 loan, the average US mortgage[7]. Additionally, most of the CAP loans were originated with high loan-to-value (LTV) and replacement loans may require mortgage insurance, which can add 50 to 75 or more basis

[6] The relative prepayment propensity of purchases vs refinances is open to debate. The Solomon Brothers Prepayment Model assumes a slightly higher refinance propensity for refinances to be conservative, but adds that "the data available for discount collateral originated after 1992 seems inconclusive." (Hayre and Rajan 1995). In an honors thesis project analyzing 136,663 loans issued by Prudential Home Mortgage Securities Corporation between 1988 and 1996, Jeff Grothe found that purchase loans were actually more likely to prepay than the refinances (Grothe n.d.).

[7] For conventional loans made in April 2006 (FHFB).

points to the effective cost of borrowing[8,9] Likewise, the somewhat weaker credit score profile of CAP borrowers may limit the benefit of refinancing. Today's risk-based pricing schemes may provide choices for more borrowers, but at higher costs. As of January 2006, about 35% of active CAP loans had a FICO score below 620, and borrowers whose scores fall below the 620 to 640 range can incur significantly higher borrowing rates.

While CAP loans have credit scores and LTV profiles more closely resembling FHA-insured loans, FHA's average loan balance is quite a bit larger, averaging $108,000 between 1998 and May 2005.[10] Thus, we hypothesize that CAP loans have slower prepayment rates than both other prime conforming loans and FHA loans, particularly in an environment of falling rates. To test this hypothesis, we first compare prepayment rates for the CAP portfolio with these two common mortgage types, conventional conforming mortgages and FHA-insured loans.

Comparative Prepayment Performance

While we have loan-level information on CAP loans, we did not have access to loan-level data on the two comparison groups. As a proxy, we look to GNMA MBS (securities representing FHA-insured loans) and Fannie Mae MBS (securities comprised of conventional loans meeting Fannie Mae criteria), whose monthly prepayment performance is reported by year of origination and pass-through rate. Likewise, we grouped the CAP portfolio into cohorts by year of origination and note rate range and compared like CAP cohorts with the GNMA and Fannie Mae MBS loans of similar vintage and note rate.[11] We selected the largest four cohorts among the CAP loans, and these represent a range of age and interest-rate profiles.

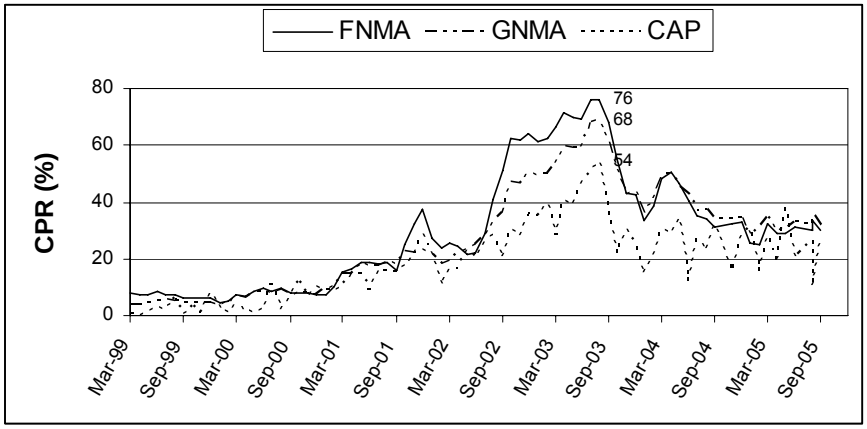
For each cohort, we calculated the Single Monthly Mortality Rate and an annualized Conditional Prepayment Rate (CPR). The prepayment ratios reflect terminations from both prepayment and default. We then compared the Self Help CPR with GNMA and Fannie Mae 30-

[8] This assumes 25% coverage on 90% LTV loan and 30% coverage on 95% LTV loan.
[9] Rates as shown on AIG United Guaranty annual premium rate card, effective May 1, 2006, accessed 29 June 2006 at https://www.ugcorp.com/rates/20060501/AllPlans.pdf.
[10] Calculated from data provided in the 2005 FHA Actuarial Review (An Actuarial Review of the Federal Housing Administration's Mutual Mortgage Insurance Fund for Fiscal Year 2005, Exhibit IV-2) http://www.hud.gov/offices/hsg/comp/rpts/actr/2005actr.cfm
[11] Note that we compare by note rate, not pass-through rate. Both Fannie Mae and GNMA MBS pass-through rates are about 50 basis points (bp) lower than the note rate on the loans in those MBS. For GNMA-backed securities, the following are deducted from the borrowers' gross interest rate: 44 bp for servicing and 7 bp guarantee fee. For Fannie Mae MBS, the servicing fee is 25 bp and a typical guarantee fee is between 20 bp and 25 bp. In both cases, these fees would result in a difference of 50 basis points between borrower gross note rate and net pass-through rate to investors. For details on the method used to calculate prepayment rates for the Self-Help portfolio, see www.ccc.unc.edu, "Calculating PSAs and CPRs for CAP Mortgages".

year MBS of like year and note rate (figure 2 below). Mortgage rates dropped in 1998 and then rose through 1999. After peaking in 2000, they started falling to a long-range low in 2003. Rates were generally rising or stable from 2004 to 2005, with some dips.

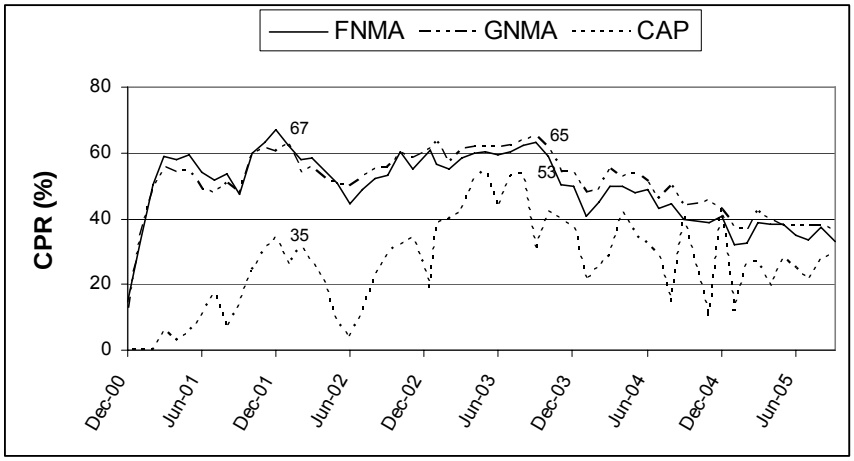
Figure 1. Prepayment Speeds of Self-Help v.s. GNMA and Fannie Mae MBS

1998: 7% CPR for Self-Help vs GNMA and Fannie Mae MBS
Calculated monthly from March 1999 through September 2005 (peak values labeled)



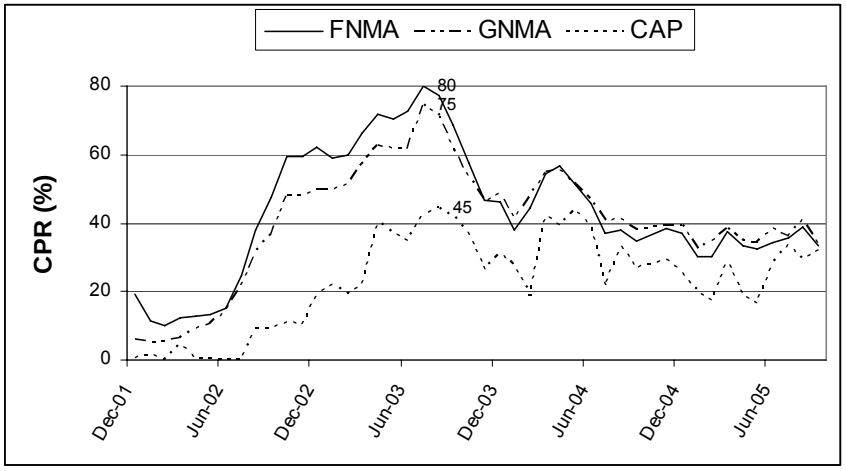
GNMA & FNMA 6.5% pass-through

2000: 8.5% CPR for Self-Help vs GNMA and Fannie Mae MBS
Calculated monthly from December 2000 through September 2005 (peak values labeled)



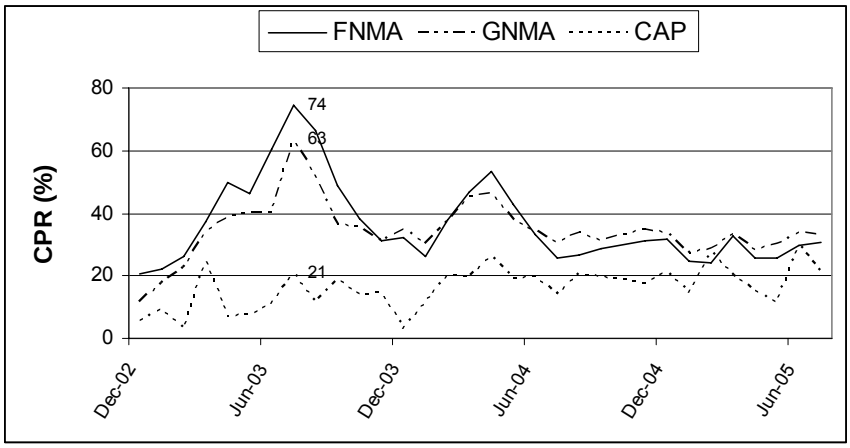
GNMA & FNMA 8% pass-through

2001: 7% CPR for Self-Help vs GNMA and Fannie Mae MBS
Calculated monthly from December 2001 through September 2005 (peak values labeled)



FNMA & GNMA 6.5% pass-through

2002: 6.5% CPR for Self-Help vs GNMA and Fannie Mae MBS
Calculated monthly from December 2002 through July 2005 (peak values labeled)



FNMA & GNMA 6% pass-throughs; CAP pool becomes too small after 7/05.

Across vintages and rates, CAP prepayments were consistently less sensitive to interest rate declines than the comparison loan types. In most of the cohorts shown, the average CAP prepayment rates were around half those of the Fannie Mae and GNMA pools. The absolute gaps were greatest in times of high prepayments. Sustained, lower prepayment speeds make a considerable difference in pool size over time; a pool with a steady 30% CPR will fall to half the size of the pool with a steady 15% CPR within five years; the difference would be much greater if the CPRs were 80% and 40%, respectively. This suggests that investors and servicers investing in CAP-type loans experience less volatility in asset value, particularly during times of high prepayments.

The next task in our research was to identify the factors driving this difference, beginning with a review of the existing research.

III. Literature Review

Theories on Prepayment and Default risks

The theories used to study default and prepayment risks propose three main factors are at work: option value, borrower heterogeneity, and transaction costs.

Option Value

Option theory has been widely applied to the study of the prepayment and default risks of mortgage loans. Most American mortgages are, in effect, callable bonds with two embedded options: a default option (a put option to sell the property to the lender at the unpaid balance of the mortgage), and a prepayment option (a call option to purchase the loan at par). According to option theory, the default option (the put) or the prepayment option (the call) will be exercised when such an option is "in the money." It follows that a borrower will default on a mortgage when the value of the mortgage exceeds the value of the house; a borrower will prepay and refinance when the market value of the loan exceeds par, i.e., when interest rates fall below the note rate. Exercising either option means giving up the opportunity to exercise the other option later, making these competing risks. For a review of literature on the option-based model of default, see Quercia and Stegman (1992). Papers that mainly adopt option theory to study mortgage performance are Hendershott and Van Order (1987), Kau and Keenan (1995), Deng, Quigley and Van Order (2000). Downing, Stanton, and Wallace (2003) further examine the importance of including property price changes as well as interest rate in the calculation of option value.

Borrower Heterogeneity

Borrowers do not mechanically default or prepay strictly because an option is "in the money." According to Deng, Quigley, and Van Order (2000, 303), "there exists significant heterogeneity among mortgage borrowers, particularly regarding prepayment." Factors influencing prepayment behavior might include household composition, income and job situation, culture, education levels, and information availability. Borrower heterogeneity is especially useful in explaining the decision to move, which will also lead to prepayment (see Clapp, Goldberg, Harding, and LaCour-Little 2001). Other papers testing the impacts of

borrower heterogeneity include Deng, Pavlov, and Yang (2005), and Van Order and Zorn (2004).

Transaction Costs and Institutional Constraints

Even with the same option value and same observed borrower characteristics, different transaction costs and institutional constraints could limit a borrower's default and prepayment decisions. The literature particularly highlights the role of transaction costs in the case of default: even when a borrower's property price declines below the mortgage balance, she may not default since by defaulting she will incur a bad credit history, be forced to move, and suffer loss in foreclosure. Institutional constraints include such factors as post-origination income and collateral constraints on prepayment behavior as in Archer, Ling, and McGill (1996); trigger events such as unemployment and divorce, as in Deng, Quigley and Van Order (1996); declining property markets as in Caplin, Freeman, and Tracy (1997); and variance in house-price dynamics as in Mattey and Wallace (2001) and Downing, Stanton, and Wallace (2005).

Estimation Methods

The existing literature uses several main estimation methods, including the Cox proportional hazard model (PHM), the competing risks proportional hazard model (CRPHM), and the multinomial logit model (MNL).

Clapp, Deng and An (2005) detail and compare the econometric efficiency, the likelihood functions, and the technical details of the PHM, CRPHM, and MNL models. The PHM by Cox (1972) is a continuous time duration model. It assumes the hazard rate—the probability of an event happening at time t given that it hasn't happened through time t-1—is composed of a baseline hazard and the hazard is explained by the independent variables. The baseline hazard in the PHM is given no particular parameterization. In the PHM model, the hazard function is constructed in a path-dependent framework: The hazard function in a proportional hazard model is conditioned on the subject surviving up to time t-1, therefore any event between t and t-1 is not an i.i.d (independent identically distributed) assumption. In the PHM estimation, when modeling prepayment risks, loans that default are treated as censored, and vise versa.

The competing risks proportional hazard model (CRPHM) by Han and Hausman (1990) Sueyoshi (1992) and McCall (1996), built on the basis of Cox proportional hazard model, considers the joint survival probability and estimates the conditional probability of termination

risks over time. The competing risks model acknowledges only the duration associated with the type of termination that is first observed and adjusts the equations for the probability of competing risks considering this effect.

The multinomial logic (MNL) model is a discrete time[12] duration model. It directly models the probability of observing one risk versus another. At each observation, the probability of refinance, move, default, and continue-to-pay sum to one. An increase in one risk directly causes a decrease in at least one other risk. The MNL cannot allow correlation among the termination risks through unobservable variables, as implied by the independence from irrelevant alternatives (IIA) assumption. In addition, the MNL requires the i.i.d. assumption for a given agent observed over time. Following standard practice, the observations of historical events for each agent are stacked into the likelihood function. This logic also requires complicated formulation of variables measuring duration dependency.

Findings and Results

Deng, Quigley and Van Order (2000) were the first to apply the competing risks model to analyze mortgage prepayment and default risks simultaneously. In their study tracking 1.5 million Freddie Mac mortgages, they find evidence to support the option theory. They also find that borrower willingness to exercise financial options may be triggered or hindered by other conditions, such as high LTV. Unexpected depreciation or appreciation of property values, as well as borrowers' tastes or abilities, lead to borrower heterogeneities, as shown by the mass point estimation result. If the prepayment risks are estimated without accounting for heterogeneity, the result will be substantial underestimation of option-driven prepayment behavior. They also find that liquidity constraints (indicated by the proxies high unemployment and divorce rates) could keep borrowers from exercising an in-the-money call option.

Pennington-Cross (2003) applies similar models to compare prepayment and default performance of nonprime versus prime mortgages, using data on 66,000 nonprime (mostly A-minus and Alt-A loans) and 24,000 prime loans. His findings highlight the importance of FICO score in both default and prepayment behavior. Further, he finds that nonprime borrowers prepay at higher rates than prime borrowers, and that the prepayment rates of nonprime borrowers are less responsive to "in the money-ness" than they are to credit scores.

[12] The difference between discrete time and continuous time models depends on whether the dependant variable is a continuous or discrete categorical variable.

Archer, Ling, and McGill (2001) compare relative mortgage termination rates of affordable housing households (those with incomes at or below 80% AMI) with those of other homeowners. They also examine differentials in factors influencing the termination rates of each group by constructing five two-year panels of data from the American Housing Survey (AHS). They find that the propensity for mortgage prepayment by low- to-moderate income households is no less responsive to interest rate changes than among higher income households. Rather, they note that the lower income borrowers appear more constrained by high LTV and high debt-to-income burden than the higher income borrowers, while a number of demographic variables largely appear insignificant.

Van Order and Zorn (2004) studied the performance of fixed-rate low-income and minority loans (LIMLs) originated in the 1990s and purchased by Freddie Mac. In their review, they use proportional hazard modeling but allow for fixed effects of borrower heterogeneities. They find that LIMLs prepay less rapidly than other loans whether the option is in the money or out of the money, and suggest that when the option is most valuable to the borrowers, the LIMLs will have the most relative value to investors. Conversely, LIMLs may be less valuable in a rising yield-curve environment, when the option is less likely to be in the money. LIMLs' slightly higher default costs appear to be at least offset by the value created by slower prepayment speeds. Van Order and Zorn find the effect of race and ethnicity on prepayment to be stronger than that of income, when controlling for loan characteristics (LTV, purpose, age, size), borrower characteristics (credit history, debt-to-income), and neighborhood characteristics (tract income, tract minority population, state). They also find that LIMLs default at a higher rate than base-case loans. This, along with higher loss severity rate, implies higher default costs. However, after controlling loan characteristics, they find borrower race/ethnicity has little effect, though borrower income and neighborhood minority composition and income have some explanatory power.

Deng and Gabriel (2004) apply the competing risks model on FHA-insured home purchase loans. They find the option value to be highly predictive of both default and prepayment, but like Van Order and Zorn (2004), they note the importance of borrower and loan characteristics as well. They too find that, while having low credit quality and being a minority borrower carry higher default risks, the overall termination rate is greatly dampened by slower repayment speeds of those loans, resulting in markedly lower loan termination probability among underserved borrower groups. They suggest that these damped termination risks should translate

into sizable reductions in prepayment risk premiums to investors in lower credit quality mortgage pools and that such pooling and risk-based pricing of FHA-insured mortgages could serve to substantially reduce housing finance costs among underserved borrowers.

To measure the effect of unobserved borrower heterogeneities, Deng, Pavlov, and Yang (2005) use neighborhood location to represent the borrowers' characteristics in the competing risks model using a three-stage maximum likelihood estimation approach. They find that neighborhood location produces significant implications for mortgage termination behavior, in this case within Los Angeles County from 1988 to 2001. Notably, borrowers in affluent communities both refinance and move at a higher rate than predicted by the standard maximum likelihood estimation method; conversely, borrowers from lower-valued neighborhoods tend to hold their mortgages and properties longer than the standard model predicts.

The importance of mobility in the prepayment equation, and the notion that the decision to move is influenced by factors different from the decision to refinance, is highlighted by Clapp, Goldberg, Harding, and LaCour-Little (2001). Among the mortgages they examined, 44% of the non-default terminations were attributed to mobility. Using both multinomial logit and Cox proportional hazard models to analyze refinance, move, or default, they highlight how certain factors can have a different magnitude or even opposing effects on each decision. For example, minority borrowers were significantly less likely to refinance, but even less likely to move, than non-minority borrowers; income is negatively correlated with refinancing but positively with moving; low credit scores increase the likelihood of refinancing but lack significance for moving.

Summary of Literature Review

In summary, the existing literature provides ample reasons why affordable mortgages have a different prepayment risk profile than non-affordable mortgages. The smaller average loan size means that rates have to fall more for the refinance option to be in the money. Higher LTV and income constraints can be expected to further dampen refinancing propensity. To the extent that affordable mortgages are secured by properties situated in weaker real estate markets, prepayment options may be further limited. The literature also points to borrower characteristics that can be expected to contribute to slower prepayments because of mobility or refinancing, such as a greater representation of minority borrowers or borrowers with lower credit scores.

IV. Modeling Prepayment Behavior in the CAP Portfolio

To ensure that we employ the latest developments in estimation techniques in our analysis and that our results are robust to the different estimation methods chosen, we apply two estimation methods—proportional hazard model (PHM) and multinomial logic model (MNL)—to our data set. We did not run the competing risks PHM (CRPHM) model because the MNL model fully captures the competing risks effect in CRPHM and has similar nonparametric character (by assuming the likelihood function as a step function) as CRPHM. Secondly, in the comparison between PHM and MNL, since only a small portion of the loans default, treating defaulted loans as censored in the prepayment risk estimation won't significantly alter the results. Therefore, we expect that PHM and MNL will give very similar results in the prepayment risk estimation, and PHM will give good estimates in terms of the signs and magnitudes of the effects analyzed before. Finally, the focus of this paper is termination due to prepayment, and treating default as censored or as one of the competing risks won't alter the estimates significantly. Therefore, we interpret in detail models that focus on prepayment risks by treating default as censored, and use these models to further investigate the interaction effects and data from panel surveys.

The Data

After narrowing down the CAP dataset to fixed-rate, 30-year mortgages originated between 1998 and 2004 with payment data through December 2005 and eliminating 1,799 loans with missing information, we were left with 20,970 mortgages in our sample. The composition of the sample, the missing data and the overall population is presented in Table 1, which shows that the sample is fairly representative. The geographic coverage of the 20,970 loans is extensive as well, including 46 states and the District of Columbia.

All loans in the CAP portfolio were originated for the purpose of home purchase (not refinancing), and are, by design, concentrated among low-income and minority households. As shown in Table 2, the average loan in the CAP sample is $86,146. Three-quarters of the loans have an original LTV above 95%, with 30% originated with LTV over 97%. Mean annual income is $32,010, with more than 90% of the borrowers having household income below 80% of AMI. Thirty-eight percent are first-time homebuyers; and 47% are minorities. More than 40%

of borrowing households are headed by females, and 20% of the borrowers had origination credit scores under 620. The properties are located in 46 states and the District of Columbia, though just over a quarter are in North Carolina.

By December 2005, 10,640 of the loans (50.7%) had terminated because of prepayment, and 831 loans (4.0%) had terminated because of "default" (in this case, defined as loans that either entered into the foreclosure process or were returned to the originating lender because they were non-performing). The remaining 9,499 loans (45.3%) were still active as of December 2005.

Table 2 further shows how prepayments substantially changed the profile of the sample. Higher credit score and higher income borrowers were more likely to prepay, as were homeowners whose loans had lower original LTV. In a particularly stark contrast, half the white borrowers and 68% of the Hispanic borrowers paid off the loans, while only 31% of African American borrowers prepaid. A negligible share of the prepayments (1.5%) were made when a loan was delinquent (often referred to as distressed prepayment).

Choice of Explanatory Variables

Table 3 provides a list of explanatory variables included and the expected sign of the impact of each. The value of the option is mostly determined by the interest rate spread and loan amount. Borrowers may face certain additional limitations based on current loan-to-value (CLTV) and creditworthiness. The ultimate decision to prepay is made by individual borrowers with different characteristics and perceptions of the value of and the barriers to refinancing. The selected variables are categorized as loan characteristics, borrower characteristics, and neighborhood characteristics:

Loan Characteristics

The original loan balance captures the scale effect of loan size. We expect a positive relationship between loan balance and prepayment propensity. Homeowners with larger loans are more likely to refinance, because a large mortgage with a positive option value provides a larger dollar incentive to exercise than does a small mortgage at the same rate. Fixed costs of refinancing disproportionately reduce the option value for refinancing smaller loans.

The spread between the note rate and the current market rate drives the option value. Prepayments are expected to increase with this spread. Some studies use a ratio of current market

interest rate to the market rate at origination (Pavlov 2001), while others actually estimate the value of the option using the net present value of the loan at the current market rate relative to that of the loan at the contract interest rate (Deng, Quigley, and Van Order 2000). We first use a variable for the gap between note rate and current market rate. In further iterations we decompose that gap into two parts: the gap between note rate and market rate at the time of origination (which may indicate underlying credit risk by measuring the borrower's initial ability to obtain a market-rate loan) and the gap between market rate at origination and market rate at each monthly period (a macro-level variable that would be the same for all loans originated in the same month). For market interest rate, we use the 30-year fixed rate shown in Freddie Mac's weekly interest rate survey.[13]

We construct a measure of the borrower's equity in the property, the current loan-to-value ratio (CLTV), by dividing unpaid balance by current house value.[14] Since we have the original house prices and the estimated market values of the houses as of January 2006, we interpolate the appreciation rate for each house to estimate the value at any point in time. Consistent with the literature, we expect borrowers with high CLTV to be more likely to default but to be constrained in moving and refinancing. In fact, if the CLTV exceeds 80%, a higher note rate or mortgage insurance premium will reduce the benefits of prepayment. This effect is expected to be particularly apparent in the CAP portfolio, since most borrowers received loans with LTV ratios above 80% at origination without mortgage insurance but may incur mortgage insurance costs if they refinance. Further, since tapping home equity is a refinancing benefit not captured in the option value, loans with more built-up equity could also see more cash-out refinance activity.

[13] This data can be found at http://www.freddiemac.com/dlink/html/PMMS/display/PMMSOutputYr.jsp Accessed January 30, 2006.

[14] Current market-value estimate are from Fannie Mae's automated valuation model (AVM). Fannie Mae's AVM model consists of three individual models that independently estimate property values based on repeat sales data, property characteristics, and tax assessments, respectively. Fannie Mae then uses a value reconciliation model to compute a best value estimate in the case of multiple model predictions where valuations vary. This aggregation of independent estimates also allows the AVM system to rank order prediction accuracy at the property level. (Scores are grouped into five buckets that categorize the confidence level of predictions, where each successive bucket is characterized by a flatter and more widely dispersed distribution. Because of substantially higher mean and median rate and variance of price appreciation for the least reliable confidence category, we chose to omit those loans from our analysis.) Each of these models depends both on Fannie Mae's own proprietary loan data as well as public tax record and purchased deed data, and each has been tested out of sample in ongoing Fannie Mae research efforts. Because of its use in risk management, AVM is also examined annually by Fannie Mae's regulator, the Office of Federal Housing Enterprise Oversight (OFHEO), which has consistently awarded high grades in regulatory audits.

Borrower Characteristics

We factor in borrower credit score at origination using categorical variables: no score, less than 620, 621-660, and over 660, which serves as the comparison group and is a score level that typically would qualify the borrower for a prime, conventional loan. Borrowers with weak credit are more likely to be constrained in their ability to refinance and move. Based on the empirical literature, we expect a positive correlation between credit score and the probability of prepayment and an inverse correlation with probability of default.

We include borrower age, race, gender, and income in the model. Based on the literature, we expect negative effects of minority status on prepayment. We expect high-income borrowers are more likely to prepay and less likely to default.

All the variables mentioned previously can be found in the origination data. The CAP research project also includes a panel, a subset of CAP borrowers who are interviewed annually and who provide richer detail. We use additional variables from the panel, including education level, employment status, availability of medical insurance, number of dependents, level of emergency assets, and whether the borrower is partnered or single, in a supplemental analysis.

Neighborhood Variables

We include neighborhood racial composition and median income variables in the model, determined at the block group level. The dummy variables we used are for high African-American neighborhoods (greater than 50% African-American residents), African-American neighborhoods (31-50% African American residents), very low-income neighborhoods (median income below 50% AMI) and low-income neighborhoods (between 51% and 80% AMI). We include dummies for the three states with the most loans—North Carolina, Oklahoma, and California; they work to isolate the effects of local market conditions and market-specific loan features in different markets.

Estimation Results

Cox PHM Estimation

The Cox PHM model is widely used in estimation of prepayment and default risks. It assumes no parametric form of the baseline hazard; that is, the function of the time until an event—either prepayment or default—occurs could be increasing, decreasing, or constant. But it does assume the baseline hazard is the same for everyone, and one subject's hazard is a

multiplicative shift of the baseline hazard. The direction and magnitude of the multiplicative shift depend on the covariates. The estimation of the covariates is still possible even after leaving the baseline hazard function unspecified. The Cox PHM has several features that boost its popularity in this field, such as the concept of conditional probability, the recognition of the duration dependence of status change, and its allowance of time-varying covariances. Table 5 presents the Cox PHM estimates of coefficients for the prepayment and default models, respectively.

As explained before, the difference between Cox PHM and MNL is that in PHM, the loans that default are treated as censored in prepayment risk estimation, and vise versa, but in MNL, the two risks are estimated jointly as competing risks. However, in the CAP portfolio, only a very small percentage of loans default. Hence, we expect the PHM and MNL to give very similar results in the prepayment risk estimation, and PHM should give good estimates regarding the signs and magnitudes of the postulated effects.

The results in Table 4 confirm our expectation and are consistent with the postulated effects in Table 3. Not surprisingly, the rate spread is very influential in both the prepayment and default models. A loan with a note rate 1% higher than the prevailing interest rate has a prepayment risk that is 61% higher than one with a note rate equal to the prevailing rate. Deng, Pavlov, and Yang (2005) use the difference between prevailing interest rate at origination and contemporaneous prevailing rate, which captures the market valuation of the prepayment options. They argue that the individual rate typically contains a risk premium or discount specific to that of borrower or property. Table 5 demonstrates the results of decomposing the interest rate into two variables: one for the difference between note rate and market rate at origination (variable “Loan rate spread”), and one for the difference between market rate at origination and market rate at each point in time (variable “Market rate spread”). Both variables are significant and increase the likelihood of prepayment by a similar magnitude, which suggests the underlying cause of the interest spread, whether specific to that borrower or because of macro economic dynamics, does not matter in the process of making the decision to prepay.

As expected, loan amount is also a key driver of prepayment behavior. Loan amount, when controlling for income, has positive and significant effects on both prepayment risk and default risk. We attribute these effects to the fact that a large mortgage with a premium price provides a larger absolute dollar incentive to prepay or to default than does a small mortgage at the same price, which should have more relative value for lower-income borrowers or when

controlling for income. This verifies previous findings about the importance of the *relative* value of the option.

CLTV is significant and strongly negatively correlated with prepayment. We choose to use CLTV categories—below 60%, 60% to 84%, 85% to 95%, and over 95%, with the 60% to 84% category as baseline—rather than treating CLTV as a continuous variable, since the CLTV ratios are based on estimates,[15] and borrowers are not likely to make their decisions based on a 1% change in the estimated data. We selected these cohorts because the below-60% cohort is considered almost "bullet proof" and the 85%-to-95% cohort is in the range where, it is safe to assume, a borrower would need either mortgage insurance or increased credit enhancement on the new loan. The over-95% cohort calls for even further credit enhancements and limits the borrower's ability to sell or take cash out for closing costs or other purposes. All categories turned out to be significant and of the expected sign and order of magnitude. These results confirm the previous findings reported by Clapp et al (2001) regarding the constraints of limited housing equity on prepayment. On the default risk side, the positive correlation of high LTV with default is well established (see Vandell et al 1993 for a detailed review).

We find a strong credit score effect in both equations. The low credit score indicator is significantly and negatively correlated to prepayment and positively related to default, consistent with the conventional wisdom on credit scoring.

We find strong effects of borrower income in the CAP population: The higher the household income, the less likely the borrower will default and the more likely the borrower will prepay. Borrower age variables are insignificant in the default model, but the results show that younger borrowers (<35 years old) are more likely to prepay, which we are later able to conclude is entirely due to mobility. The first-time borrower variable appears not be significant in the prepayment model and only marginally significant (10%) in the default model.

In terms of race and ethnicity, both the African-American variable and the Hispanic variable are significant and negatively correlated with prepayment risk, particularly the African American variable. However, in the default model, the African-American variable is insignificant yet the Hispanic variable is significant and highly negatively correlated with default risks.

[15] Periodic values of homes owned by CAP households are obtained from Fannie Mae's proprietary automated valuation system, which enables us to estimate changes in accumulated home equity in the absence of a sale. While these estimates of paper gains and losses are just that, they are derived from the same models that Fannie Mae uses for internal asset valuation purposes.

Female borrowers are less likely to default, but we do not find a significant impact of gender on the behavior of prepayment.

Neighborhood racial variables have a significant impact on both default and prepayment. Specifically, borrowers in African-American neighborhoods are less likely to prepay and more likely to default. Once we control for the share of African-American population at the neighborhood level and other variables, the dummy variable for African-American borrowers becomes insignificant in the default model, as mentioned previously. But in the prepayment model, even after we control for the share of African-American population at the neighborhood level, African-American borrowers are still much less likely to prepay than white borrowers.

Macro-economic conditions can sometimes affect both equations. In the location variables, North Carolina is significant—and negative—for both prepayment and default; California as significant for default (negative); and Oklahoma significant for prepayment (negative). The variation in behavior is likely driven by prevailing economic conditions, such as appreciation, availability of refinancing options, and the effects of the limited number of lenders and loan programs represented in each market in our dataset.

In summary, several variables that increase the default risk of affordable mortgages simultaneously decrease prepayments: lower equity, credit scores and income, and location in very high-minority neighborhoods. Lower loan amounts and larger rate spreads increase both risks, while Hispanic status reduces both. Variables that influence prepayment behavior without effecting default include, for homeowners, being a younger and being African American, and for property, being in a 30%-to-50% minority neighborhood. African-American borrowers always exhibit significant and strong effect of slower prepayment. Even after we control for neighborhood characteristics, credit score, LTV, and income, African American borrowers are 60% less likely to prepay than the baseline group of white male borrowers.

MNL Estimation

Next we use the MNL model to estimate the prepayment and default risks simultaneously as competing risks. We use the same set of explanatory variables for easy comparison. The results of our MNL estimation are shown in Table 6. They are consistent with those of the Cox PHM, since most of the significant variables are similar in sign and magnitude. The MNL estimates confirm the effects of credit score, CLTV ratio, loan amount, and interest rate as explained above in the PHM. The MNL estimation found the state dummy for California to be a

significant predictor of prepayment, which is different from the Cox PHM estimation. In addition, being in a very low income (less than 50% AMI) neighborhood significantly reduces prepayment risk. We also find first-time homebuyer in a low income neighborhood (50-80% AMI) to be a significant variable for both prepayment and default, but the magnitudes are very small and can be neglected.

As terminations due to default were a small share of the total terminations, treating default as censored (as in PHM) or as one of the competing risks (as in MNL) will not make much difference in the coefficient estimates. We hence chose the former method and model prepayment risks alone. Logit model is thus the appropriate estimation method and is used to investigate the interaction effects.

We tested a number of interaction variables hoping to figure out factors driving the distinctively strong effect by African-American borrowers on slower prepayment. The results are shown in Table 7. For example, since many African-American borrowers are also female borrowers, we tried an interaction variable for female African-American borrowers that turned out not to be significant, indicating that female African-American borrowers do not respond differently to prepayment conditions than their male counterparts. Another interaction variable that did not prove significant was that between the categories African-American and age. An interaction that was more fruitful was that between the categories African-American and first-time homebuyer; among identified first-time homebuyers, African Americans were less likely to prepay than white borrowers.

The interaction of African-American borrower with CLTV cohorts turns out to be interesting. Within the CLTV cohort of less than 60%, African-American borrowers are less likely to prepay than whites. Within the same race, borrowers with CLTV below 60% are more likely to prepay than the base group with CLTV 60% to 85%. However, African Americans with CLTV less than 60% have almost the same likelihood of prepayment as the base group of whites with CLTV 60% to 85%. Hence, the effects of race and CLTV seem to offset each other.

To further explore the responsiveness of racial group to rate spread, and the interaction of individual race with neighborhood composition on prepayment behavior, we added more interaction terms and dropped the interactions of African American with CLTV cohorts because of collinearity.

Importantly, the interaction of rate spread (between current market rate and market rate at origination date) and African-American borrowers was significant even at the 1% level with a negative coefficient, suggesting that African-American responsiveness to rate spread is significantly lower than similarly situated white borrowers. Since rate spread is considered the core driver of option-based prepayment behavior, this interaction points to the heart of the matter. Since we controlled for certain credit risk indicators, this suggests that discrimination, either experienced or expected, may be at work. The interaction of rate spread and Hispanic borrowers was also significant at the 1% level; however, the magnitude was very small, indicating a slightly slower prepayment responsiveness to rate change by Hispanic borrowers compared with the base group of whites.

Another significant interaction was between neighborhood racial composition and African-American borrowers—that is, African-American borrower status in both very-high (>50%) and high (30% to 50%) African-American neighborhoods was significantly and negatively correlated to likelihood of prepayment. This suggests that within similar neighborhoods, African Americans are less likely to prepay than whites. However, perhaps more importantly, the African-American borrowers in neighborhoods with a higher share of African-American residents are less likely to prepay than African-American borrowers living in other neighborhoods. This may be a result of less availability of financing in high-minority neighborhoods or perceptions that such financing may be more difficult to obtain. Furthermore, collateral constraints along with actual or perceived discrimination may play a role. These finding may also reflect a weaker "media effect" (Hayre and Rajan 1995), which is created when falling rates generate publicity about refinancing opportunities, mortgage lenders increase their solicitations, and opportunity spreads by word of mouth as acquaintances refinance. It is possible that less buzz is generated if prime lenders are less active in targeting minorities living in high-minority communities and as fewer of these households are acting on the opportunity.

Once we controlled for these interaction terms, the neighborhood racial composition otherwise largely loses its significance. In fact, in 30% to 50% African-American neighborhoods, residents' responsiveness to rate spread actually has a positive sign. Consistent with the very small magnitude of the coefficient for rate spread interacting with Hispanic borrowers, the interaction of neighborhood racial composition with Hispanic borrowers is not significant either.

We simulated the cumulative probabilities of prepayment by key borrower and loan characteristics after five-years' seasoning, relative to a baseline group. The result is presented in Table 10. For our baseline group, we use characteristics that might comprise a typical non-CRA portfolio: origination credit score above 660 and LTV below 85%. The baseline profile is set to a white, male, non-first time homebuyer in a predominantly white neighborhood, in a state other than North Carolina, California or Oklahoma (to isolate the impact of these predominant markets). The values of other time invariant variables, loan amount and income, are set at sample means. The time varying variable, spread between current market rate and market rate at origination, is set at the sample mean in each period. We did not simulate the effect of larger loan amounts because the data set we used did not include larger loans typical of non-CRA portfolios, and forecasting on outliers can lead to inaccuracies. The relative prepayment predictions are specific to the interest rate environment that prevailed over the period studied. [16]

Relative to the baseline group, the largest reduction in prepayment likelihood results from changing the LTV to above 85%. The combined effect of raising the LTV and dropping the origination FICO score to below 660 is an 81% reduction in likelihood of prepayment by year 5, in the prevailing interest rate context. These two variables represent credit risk factors that might pose barriers to refinancing at market rates. We adjusted borrower characteristics relative to the baseline, and found the following changes in likelihood of year-5 prepayment: African-American borrower reduced the likelihood by 40%, Hispanic borrower by almost one-quarter, and first-time homebuyer had a negligible effect. Changing the baseline borrower's gender to female increased the prepay probability by 11%. Neighborhood and locational factors were also adjusted. A loan similar in all respects to the baseline, except that it is made on a property located in a neighborhood where 50% or more of the residents are black reduced the predicted year-5 prepayment by 17%.

V. Using Data from the CAP Panel to Examine Prepayment Behavior

The CCC also conducted a longitudinal study of a panel of borrowers in the CAP program. We drew an original sample of households for 3,745 loans from the CAP portfolio to undertake a series of annual surveys. We finished administering the wave-1 survey in 2003; as of 2006 we were in the fourth wave of data collection. Most respondents of the wave-1 survey

[16] We did not use simulated interest rate since forecasting term structure is highly technical. Therefore, our predictions didn't simulate the effects of varying two basic option value drivers (rate spread and loan amount) on relative prepayment likelihood.

completed the survey at 12 to 24 months from loan origination (average 17 months). We collected information on household roster, employment history, educational attainment, household income, debt, emergency assets, medical insurance, neighborhood quality, and other household characteristics for the panel. This study used the data collected from the first wave.

Because these interviews provide us with more detailed information about borrower attitudes, wealth and assets, family status, employment information, and other data, the survey is a rich potential source of insight into the measurable outcomes of the CAP demonstration project.

To further explore prepayment behavior, we ran the original Cox PHM on the CAP panel and added some variables available only on panel participants, namely, education level, employment status, availability of medical insurance, number of dependents, level of emergency assets, and marital/partner status. Of particular interest is that changes in these variables from interview to interview should have an impact on prepayment behavior.

The panel also enables us to distinguish those who paid off their loan because they moved and those who paid off because they refinanced. Some 30% of the panel participants prepaid because they moved, so mobility has a significant impact on overall prepayment performance. Table 9 provides descriptive statistics on the 3,736[17] panel participants in this analysis.

Table 9 presents the results of the Cox PHM model run on the panel borrowers, treating *moving* and *paying off but not moving* ("refinance") as different events of termination.

Several important variables increase the risk of both moving and refinancing, but not always at the same magnitude. Rate spread and loan amount, for example, are significant and positive for both but increase the risk for refinance by substantially more than for moving. This is not surprising, as the decision to refinance is a more economically driven, and rate spread and loan amount both factor in to option value. The positive effect on mobility is largely because as the rate spread increases, the household can afford an increasingly more expensive house and the appeal of moving increases.

Indicators of household financial condition factor in equally or more strongly for moving than for refinancing. High CLTV (or low equity) has a strong and equally depressing effect on both choices. Lower credit score is almost as much of a constraint to move as to refinance.

[17] The panel includes 3,736 members, of which 1,667 (45%) were still active, 541 moved and prepaid, 1,342 refinanced without moving, and 186 entered foreclosure or were returned to originating lender for non-performance ("defaults"). In the model, defaults were treated as censored.

Lower-income borrowers are less likely to do either, but the income effect is much more powerful on moving than on refinance. We learn from the panel variables that borrowers with more liquid assets are also more likely to prepay for both reasons, and that the effect is greater on moving. Panel members lacking health insurance were 30% (1-0.72) less likely to move, but this condition had no impact on refinances.

Of special interest is the fact that while African-American panel members were 43% (1-0.57) less likely to refinance, they were 66% (1-0.34) *less likely to move* than white borrowers. The relatively lower mobility rate for African Americans contributes to their lower overall rate of prepayment. At the same time, it raises another set of questions. At this time we are not able to test whether discrimination, either experienced or expected, was a cause in not obtaining a new home or a mortgage to purchase a new home.

The previously identified propensity for borrowers under age 35 to prepay seems entirely due to mobility; these borrowers are more than twice as likely to move as the comparison group (over 50), but this age category is insignificant for refinance risk.

The only opposing effect from the variables we tested was number of dependents: Households with two or more dependents were less likely to move but slightly more likely to refinance. The latter may be because households with dependents face tighter budgets or are more likely to cash out equity to pay for education or home expansion improvements. We do not believe this factor is particularly over- or under-represented in the affordable mortgage market, but it is possible that among lower-income households, having a large number of dependents may be a constraint on moving.

Insignificant variables for prepayment risk are female borrower, Hispanic borrower, and whether the borrower is partnered or not. Surprisingly, whether the borrower or co-borrower is unemployed at the time of the survey turns out to be insignificant. It could be because current employment status as a stock variable has limited impact on the time until prepayment, which is a flow variable.

VI. Conclusion

Previously, we discussed the important implications of prepayment speeds on the value of mortgages. Using a unique portfolio of affordable mortgages, we illustrate the slower prepayment behavior of affordable mortgages, a fact that has been previously documented in

academia. Our prepayment modeling using the CAP dataset contributes to our existing understanding of this area:

- Because the CAP portfolio concentrates on low-income and minority homeowners, it allows for more detailed study of the different prepayment behaviors of those households.
- We tested effects, such as costs of mortgage insurance because of high CLTV, neighborhood characteristics, and interaction terms, like responsiveness to option value by race group and by neighborhood characteristics. These may play a particular role in prepayment by borrowers in the affordable segment, many of whom must contend with lower liquidity, limited financial awareness, and possible discrimination.
- The additional panel data provides new insights into the factors that drive prepayment and mobility among affordable mortgage borrowers.

Our analysis adds to the evidence that affordable mortgages prepay more slowly than conventional mortgages, particularly in times of interest rate and prepayment volatility, when investors are most concerned about the risk of early prepayments. Our research suggests that value should be attributed to affordable mortgages, and we plan future studies to better understand the pricing implications of this finding.

Using the database and panel variables, we identify several characteristics prevalent among affordable mortgages that act to dampen prepayment speeds. These include factors that have been recognized to limit the option value, in particular, low loan balance. But they also include a number of borrower-specific constraints, particularly low levels of equity, as well as credit score, income and liquid assets, and racial and ethnic attributes of both borrowers and neighborhoods.

In addition to noting the dampened sensitivity to interest rates and refinance option value, we find that reduced mobility is an important factor in prepayments. Many of the factors that limit refinancing are also associated with reduced mobility in the CAP portfolio, though option value has less effect while financial constraints have a greater limiting effect. Lacking health insurance or having more dependents also acts to reduce mobility.

Finally, even after uncovering these factors, we note the continued statistical significance of race on both economic- and mobility-driven prepayments. Minority borrowers, particularly

African-American borrowers, are less likely to prepay than their white counterparts and even more particularly when living in neighborhoods with higher concentrations of African-American residents. The fact that African-American borrowers were about one-third as likely to move contributes to their slower overall prepayment rates. Though we have speculated about discrimination and media effects as possible explanations, this is an intriguing area for future exploration.

VII. Additional Tables

Table 1 ***Selected Characteristics of Sample and Total Population of CAP loans***

	Sample of 20,970 loans	Missing data	Total Population
Origination Year			
1998	13.6%	10.3%	13.3%
1999	10.6%	10.8%	10.6%
2000	19.9%	20.0%	19.9%
2001	25.1%	17.1%	24.5%
2002	14.4%	20.2%	14.8%
2003 & 2004	16.4%	21.7%	16.8%
Race/Ethnicity			
Black	18.9%	15.4%	18.7%
Hispanic	20.8%	12.9%	20.2%
White	52.7%	50.6%	52.5%
Other	7.6%	21.1%	8.6%
State			
NC	25.9%	29.6%	26.2%
CA	17.1%	7.4%	16.3%
OK	9.1%	0.7%	8.5%
OH	8.0%	4.9%	7.8%
SC	4.5%	5.5%	4.6%
IL	4.3%	4.3%	4.3%
FL	3.0%	4.7%	3.2%
All Others (41)	28.1%	42.9%	29.1%
Credit Score @ Origination			
No score	2.4%	10.0%	3.0%
≤620	18.4%	12.8%	18.0%
≤660	22.6%	21.2%	22.5%
≤720	31.9%	29.%	31.7%
>720	24.7%	27.0%	24.8%

Breakdown of 20,970 loans presented and 1,799 loans with missing data.

Table 2 ***Descriptive Statistics-Original Sample and By 12.2005 Status***

CAP Loan and Borrower Characteristics by Loan Status

		Loan Status as of December 2005		
Variable	Original	Active	Prepaid	Defaulted
Borrower Characteristics:				
Credit Score – mean (std. dev.)	676.5 (61.0)	672.8 (62.7)	683.7 (57.6)	626.2 (56.3)
No Credit Score/Missing (%)	2.4%	2.8%	1.9%	4.7%
Credit score<=620 (%)	18.4%	19.8%	15.1%	45.0%
Credit score 621-660 (%)	22.6%	23.7%	21.3%	26.2%
Female Borrower (%)	41.3%	44.8%	37.9%	45.1%
African American Borrower (%)	18.9%	25.3%	11.8%	38.5%
Hispanic Borrower (%)	20.8%	13.8%	28.1%	7.6%
Borrower Age – mean (%)	34.6	35.0	34.3	33.8
Borrower Age<=35 (%)	60.7%	61.0%	60.4%	61.0%
Borrower Age 36-50 (%)	29.4%	28.6%	30.1%	29.2%
First-time-home-buyer (%)	38.5%	37.1%	38.4%	55.8%
Annual Income – mean (std. dev.)	$32,010 (11,562)	$30,172 (10,572)	$34,055 (12,114)	$26,831 (9,912)
Loan Characteristics				
Loan Amount – mean (std. dev.)	86,145 (38,652)	77,027 (32,502)	95,818 (41,875)	66,521 (25,324)
Interest Rate – mean (std. dev.)	7.46 (.90)	7.15 (.83)	7.69 (.86)	8.10 (0.89)
Initial Rate Spread – mean	0.48	0.43	0.52	0.63
Original Loan-to-Value – mean (std. dev.)	94.7 (10.2)	94.6 (12.0)	94.6 (8.7)	96.7(4.6)
Original LTV<=60% (%)	1.8%	2.5%	1.3%	0.0%
Original LTV 85%-95% (%)	15.9%	14.0%	18.2%	8.8%
Original LTV >95% (%)	74.8%	75.4%	73.2%	87.1%
Neighborhood Characteristics				
Very High (>50%) African American (%)	13.4%	17.3%	8.8%	29.2%
High (31-50%) African American (%)	9.3%	10.1%	8.4%	12.2%
Very Low Income (<=50% AMI) (%)	4.9%	5.3%	4.5%	5.4%
Low income (51-80% AMI) (%)	28.9%	30.0%	27.6%	34.3%
North Carolina (%)	25.9%	31.7%	20.9%	22.9%
Oklahoma (%)	9.2%	13.6%	5.1%	9.9%
California (%)	17.1%	4.4%	29.6%	1.9%
Number of loans	20,970	9,499	10,640	831
% of total		45.3%	50.7%	4.0%

Note: Means are above; standard deviations are in parentheses. All loans were originated between 1998 and 2004. Values are reported as of the time of loan origination.

Table 3 .*Variable List With Expected Effects*

Variable	Prepayment	Default
Borrower Characteristics		
Missing/No Credit Score	-	+
Credit Score <620	-	+
Credit Score 620-660	-	+
Borrower household income (Log)	+	-
Female Borrower	-	+
African American	-	+
Hispanic	-	+
Age Less than 35	+	?
Age 35 to 50	+	?
First Time Home Buyer	?	?
Loan and Housing Market		
Original loan balance (Log)	+	+
Current loan-to-value ratio (CLTV)[1]	-	+
Rate spread (Indiv loan rate to current market rate) [2]	+	-
Neighborhood variables		
Very High (>50%) African American	-	+
High (30-50%) African American	-	+
Very low income (<50% AMI)	-	+
Low income (50-80% AMI)	-	+
North Carolina	?	?
Oklahoma	?	?
California	?	?

[1]Calculated for each month using the appreciation rate estimated from Fannie Mae market value data and assuming constant appreciation over the life of the loan.

[2]Calculated for each month as the interest rate at origination minus that month's mean Freddie Mac 30-year fixed-rate conforming loan rate.

Table 4 . ***Mortgage Terminations of CAP Portfolio***

Estimates for Mortgage Prepayment and Default – Cox Model, not competing risks

	Prepayment		Default	
Variable	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
Borrower Characteristics				
No Credit Score	0.00	1.00	1.52***	4.59***
Credit Score <620	-0.42***	0.66***	1.12***	3.08***
Credit Score 620-660	-0.13***	0.88***	0.72***	2.06***
Borrower household income (in log)	0.34***	1.40***	-0.67***	0.51***
Female	0.00	1.01	-0.18***	0.83***
African American	-0.57***	0.56***	-0.06	0.95
Hispanic	-0.13***	0.88***	-0.47***	0.62***
Age Less than 35	0.25***	1.29***	0.02	1.02
Age 35-50	0.02	1.02	-0.05	0.95
First Time Buyer	0.03	1.04	0.13*	1.14*
Loan Characteristics				
Original loan balance (in log)	0.72***	2.06***	0.29**	1.34**
Current LTV<60%	0.47***	1.60***	-0.83***	0.44***
Current LTV 85-95%	-0.32***	0.73***	0.93***	2.53***
Current LTV>95%	-1.05***	0.35***	1.27***	3.57***
Rate spread (Indiv loan rate to current market rate)	0.48***	1.61***	0.52***	1.69***
Neighborhood Variables				
Over 50% African American	-0.21***	0.81***	0.22*	1.24*
30 to 50% African American	-0.11***	0.90***	0.19	1.21
Very low income (<50% AMI)	-0.09*	0.92*	-0.15	0.86
Low income (50-80% AMI)	-0.04*	0.96*	0.06	1.06
North Carolina	-0.27***	0.76***	-0.95***	0.39***
Oklahoma	-0.24***	0.79***	-0.09	0.92
California	0.01	1.01	-1.96***	0.14***
Log Likelihood	6857.5***		1152.2***	

*Note: N=20,970. * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.*

Table 5 . ***Mortgage Terminations of CAP Portfolio***

Estimates for Mortgage Prepayment and Default – Cox Model, not competing risks (Same as 0 but with two components of interest rate spread)

	Prepayment		Default	
Variable	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
Borrower Characteristics				
Missing/No Credit Score	-0.01	.993	1.52***	4.55***
Credit Score <620	-0.42***	0.66***	1.12***	3.07***
Credit Score 620-660	-0.13***	0.88***	0.72***	2.05***
Income (Log)	0.34***	1.40***	-0.68***	0.51***
Female	0.00	1.01	-0.18***	0.83***
African American	-0.57***	0.56***	-0.05	0.95
Hispanic	-0.13***	0.88***	-0.47***	0.62***
Age Less than 35	0.25***	1.29***	0.02	1.02
Age 35-50	0.02	1.02	-0.05	0.95
First Time Buyer	0.04*	1.04*	0.13*	1.14*
Loan Characteristics				
Original loan balance (Log)	0.73***	2.07***	0.30**	1.36**
Current LTV<60%	0.47***	1.60***	-0.83***	0.44***
Current LTV 85-95%	-0.32***	0.72***	0.93***	2.52***
Current LTV>95%	-1.06***	0.35***	1.27***	3.55***
Loan rate spread (Indiv loan rate to original market rate)	**0.49*** **	**1.64*** **	**0.55*** **	**1.73*** **
Market rate spread (orig mkt rate to curr mkt rate)	**0.47*** **	**1.60*** **	**0.50*** **	**1.65*** **
Neighborhood Variables				
Over 50% African American	-0.21***	0.81***	0.22*	1.25*
30 to 50% African American	-0.11***	0.90***	0.20	1.21
Very low income (<50% AMI)	-0.09*	0.91*	-0.15	0.86
Low income (50-80% AMI)	-0.04*	0.96*	0.05	1.06
North Carolina	-0.27***	0.77***	-0.95***	0.39***
Oklahoma	-0.23***	0.80***	-0.07	0.93
California	0.01	1.01	-1.97***	0.14***
Log Likelihood	6864.4***		1152.5***	

*Note: N=20,970. * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.*

Table 6 . ***Mortgage Terminations of CAP Portfolio***

Estimates for Mortgage Prepayment and Default – MNL Model, competing risks

	Prepayment		Default	
Variable	P-value	Coeff	P-value	Coeff
Borrower Characteristics				
No credit score	0.11	-0.09	0.00	1.36***
Credit Score <620	0.00	-0.29***	0.00	1.17***
Credit Score 620-660	0.00	-0.08***	0.00	0.70***
Annual Household income (Log)	0.00	0.36***	0.00	-0.45***
Female	0.26	-0.02	0.13	-0.14
African American	0.00	-0.52***	0.50	-0.09
Hispanic	0.00	-0.17***	0.00	-1.00***
Other race/ethnicity	0.01	-0.10***	0.77	0.05
Age Less than 35	0.00	0.26***	0.28	-0.15
Age 35-50	0.23	0.04	0.08	-0.27*
First Time Buyer	0.00	-0.09***	0.59	-0.05
Loan and Housing Market				
Original loan balance (in log)	0.00	0.51***	0.82	0.03
Market Rate spread (orig mkt rate to curr mkt rate)	0.00	0.53***	0.00	0.72***
Current LTV<60%	0.00	0.28***	0.03	-0.49**
Current LTV 85-95%	0.00	-0.33***	0.56	0.06
Current LTV>95%	0.00	-0.86***	0.12	0.26
Neighborhood variable				
Over 50% African American neighborhood	0.00	-0.20***	0.34	0.14
30 to 50% African American neighborhood	0.00	-0.12***	0.51	0.11
Very low income (<50% AMI)	0.01	-0.15***	0.98	-0.01
Low income (50-80% AMI)	0.01	-0.06**	0.53	0.06
North Carolina	0.00	-0.32***	0.00	-0.84***
Oklahoma	0.00	-0.40***	0.44	0.11
California	0.00	0.55***	0.00	-1.31***
Log Likelihood		-52599.645***		

Note: N=20,970. * *significant at 0.1 level,* ** *significant at 0.05 level, and* *** *significant at 0.01 level.*

Table 7 . *Mortgage Terminations of CAP Portfolio*

Estimates for Mortgage Prepayment – Logit model with Interaction Terms, not competing risks

	Interaction of Race/Ethn & LTV		Additional Race/Ethn Interaction Variables	
Variable	**P-value**	**Coefficient**	**P-value**	**Coefficient**
Borrower Characteristics				
No credit score	0.11	-0.09	0.13	-0.09
Credit Score <620	0.00	-0.29***	0.00	-0.29***
Credit Score 620-660	0.00	-0.08***	0.00	-0.08***
Income (Log)	0.00	0.35***	0.00	0.35***
Female	0.29	-0.02	0.11	-0.04
African American	0.00	-0.55***	0.03	-0.26**
Hispanic	0.00	-0.16***	0.07	-0.08*
Other race/ethnicity	0.01	-0.10***	0.01	-0.10***
Age Less than 35	0.00	0.26***	0.00	0.25***
Age 35-50	0.25	0.04	0.36	0.04
First Time Buyer	0.00	-0.09***	0.00	-0.09***
Loan Characteristics				
Original loan balance (in Log)	0.00	0.51***	0.00	0.51***
Market rate spread (orig mkt rate to curr mkt rate)	0.00	0.53***	0.00	0.57***
Current LTV<60%	0.00	0.25***	0.00	0.28***
Current LTV 85-95%	0.00	-0.32***	0.00	-0.32***
Current LTV>95%	0.00	-0.88***	0.00	-0.85***
Neighborhood Characteristics				
Over 50% African American	0.00	-0.19***	0.60	-0.05
30 to 50% African American	0.00	-0.12***	0.01	-0.20***
Very low income (<50% AMI)	0.00	-0.16***	0.00	-0.15***
Low income (50-80% AMI)	0.01	-0.06***	0.01	-0.06***
North Carolina	0.00	-0.31***	0.00	-0.33***
Oklahoma	0.00	-0.40***	0.00	-0.41***
California	0.00	0.55***	0.00	0.55***
Interaction Variables *('AA' = 'African American')*				
AA[1] * CLTV < 60%	0.01	0.27***	[18]	
AA * CLTV 85%–95%	0.24	-0.09		
AA * CLTV >95%	0.31	0.17		
AA * Female			0.11	0.10
AA * market rate spread			0.00	-0.22***
Hispanic * market rate spread			0.01	-0.07***
Neighborhood > 50% AA * market rate spread			0.40	-0.04
Neigbhorhood 30-50% AA * market rate spread			0.03	0.10**
AA * neighborhood > 50% AA			0.02	-0.21**
AA * neighborhood 30% - 50% AA			0.02	-0.22**
Hispanic * neighborhood > 50% AA			0.58	-0.06
Hispanic * neighborhood 30-50% AA			0.75	-0.03
Age < 35 * AA			0.49	0.07
Age 35-50 * AA			0.66	0.05
Log Likelihood	-48715.662***		-48695.763***	

[18] All the 3 interaction terms AA[1] * CLTV < 60%, AA * CLTV 85%–95%, AA * CLTV >95% are dropped here because of collinearity.

*Note: N=20,970. * significant at 0.1 level, **significant at 0.05 level, and *** significant at 0.01 level.*

Table 8 . *Descriptive Statistics*

CAP Panel Loan and Borrower Characteristics by Loan Status
(*similar to Table 2 but pertains to panel only)*

	N=3,736	Loan Status as of December 2005			
Variable	Original	Active	Moved	Refinanced	Defaulted
Borrower Characteristics					
Credit Score – mean (std. dev.)	675.0 (60.2)	671.3 (61.7)	685.1 (57.0)	681.5 (56.8)	627.5 (56.2)
No Credit Score/Missing (%)	4.8%	4.6%	2.6%	4.8%	11.8%
Credit score<=620 (%)	17.3%	18.9%	12.2%	14.2%	40.9%
Credit score 621-660 (%)	23.3%	24.7%	20.5%	22.6%	25.3%
Female Borrower (%)	45.0%	49.5%	39.2%	40.5%	53.8%
African American Borrower (%)	19.1%	23.9%	7.8%	14.3%	43.5%
Hispanic Borrower (%)	14.7%	13.9%	13.5%	17.8%	3.8%
Borrower Age – mean (%)	33.7	34.4	30.3	34.3	33.8
Borrower Age<=35 (%)	61.5%	58.2%	78.0%	59.6%	55.9%
Borrower Age 36-50 (%)	29.5%	32.0%	17.0%	30.8%	33.9%
First-time-home-buyer (%)	54.3%	58.2%	56.2%	49.3%	50.0%
Annual Income – mean (std. dev.)	32,202 (11,920)	30,351 (11,004)	34,428 (11,209)	34,078 (12,572)	28,782 (13,535)
Loan Characteristics					
Loan Amount – mean (std. dev.)	80,709 (35,693)	75,732 (31,898)	85,161 (35,566)	86,727 (39,361)	68,949 (30,846)
Interest Rate – mean (std. dev.)	7.64 (1.00)	7.33 (0.93)	7.77 (1.00)	7.89 (0.95)	8.34 (0.97)
Initial Rate Spread–mean (std dev)	0.62 (0.66)	0.50 (0.63)	0.63 (0.67)	0.73 (0.66)	0.94 (0.59)
Original LTV – mean (std. dev.)	95.6 (8.3)	95.4 (9.5)	96.2 (6.9)	95.5 (7.6)	97.0 (3.6)
Panel Variables					
Householder Employed	92.3%	91.6%	95.6%	92.7%	87.1%
Householder No Medical Insurance	13.2%	13.9%	8.5%	12.7%	24.7%
Number of Dependent >2	44.8%	44.2%	34.4%	48.6%	54.3%
Emergency Assets (>=2 months)	52.4%	49.9%	61.6%	54.5%	33.3%
Married or Partnered	56.7%	53.4%	62.1%	59.8%	49.5%
Number of loans	3736	1667	541	1342	186
% of total		44.6%	14.5%	35.9%	5.0%

Note: Means are above; standard deviations are in parentheses. All loans were originated between 1998 and 2004. Values are reported as of the time of loan origination. Note: 3,743 owners participated in Wave-1 survey. After removing ARMS and loans with missing data, the total is 3,736 (If income at origination is missing then we used income data collected though Wave-1 survey).

Table 9 . *Mortgage Terminations of CAP Panel*

Estimates for Competing Risks of Mortgage Prepayment and Default –
(Similar to Table 5 with additional variables but pertains to panel only)

	Prepaid & Moved		Prepaid but did not move (Refinanced)	
Variables	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
Borrower Characteristics				
Missing/No Credit Score	-0.51*	0.60*	-0.06	0.94
Credit Score <620	-0.40***	0.67***	-0.523***	0.59***
Credit Score 620-660	-0.24**	0.79**	-0.212***	0.81***
Female	-0.05	0.96	-0.01	0.91
African American	-1.07***	0.34***	-0.57***	0.57***
Hispanic	-0.12	0.89	-0.02	0.98
Age Less than 35	0.76***	2.14***	-0.11	0.90
Age 35-50	0.00	1.00	-0.12	0.89
Income (Log)	0.65***	1.92***	0.27***	1.32***
Loan Characteristics				
Original loan amt (Log)	0.39***	1.48***	0.77***	2.16***
Current LTV	-2.13***	0.12***	-2.32***	0.10***
Rate Spread	0.40***	1.49***	0.63***	1.88***
Panel Variables				
Employed	0.11	1.11	0.05	1.05
No Medical Insurance (⌖)	-0.32**	0.72**	-0.09	0.91
2 or more Dependents	-0.32***	0.72***	0.17***	1.18***
Emergency Assets (>=2 Months)	0.31***	1.36***	0.16***	1.17***
Partnered	0.07	1.07	-0.05	0.95
Likelihood Ratio	339.3 ***		614.2 ***	

significant at 0.1 level; ** significant at 0.05 level; * significant at the .01 level.*
The choices are: move or prepay but not move. Defaulted loans are treated as "censored".
⌖ householder had no medical insurance

Table 10 . ***Relative Prepayment Probabilities Forecast***

At the end of year 5	Relative Prepay Probabilities (%)
Base group: Non CRA Borrower	0
CRA Borrower:	
Credit Score<660 and CLTV >85%	-81.42
African American	-39.85
Hispanic	-23.92
First Time Home Buyer	-2.30
Female	11.47
Over 50% African American neighborhood	-17.33
30 to 50% African American neighborhood	1.55
North Carolina	-0.45
California	68.54
Oklahoma	-27.51

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