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THE PERFORMANCE OF LOW INCOME AND MINORITY MORTGAGES

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ABSTRACT

This paper analyzes the performance of low income and minority mortgages (LIMMs) from a large sample of fixed rate conventional conforming mortgages. We test the extent to which exercise of prepayment and default options differ across groups. In particular, we test the extent to which options embedded in LIMMs are exercised more or less "ruthlessly." We find that low-income borrowers are less likely to prepay when it is optimal, while Black and Hispanic borrowers prepay more slowly than other borrowers, regardless of whether the option is in or out of the money. We also find that after controlling for equity, credit history and some other variables, LIMMs default slightly more frequently and have about the same loss severity as other loans. Application of simple price models and rules of thumb suggest that for a downward sloping yield curve, the positive effect of differences in prepayment speed on price approximately cancels out the effect of the higher incidence of default.

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I INTRODUCTION

The purpose of this paper is to analyze the performance of mortgages made to Low-Income and Minority (LIMM) mortgage borrowers with respect to default and prepayment, and to analyze the implications of these differences for mortgage pricing. Using loan-level data on over 1.2 million conventional conforming mortgages[4], we find that prepayment speeds are significantly smaller for Black and Hispanic borrowers. The prepayment speeds are higher regardless of whether the exercise of the prepayment option is optimal (whether or not current rates are smaller than the coupon rate on the loan), but they are slower for low-income borrowers when the option is "in the money."

Berkovec et al (1994) and Van Order and Zorn (2000) examined the incidence of default by minority groups. Both found that default is higher, and thus performance is worse, among such borrowers. However, differences in prepayment speeds are an important factor in performance, and they must be included in any complete performance analysis. Default is a relatively rare event, occurring in approximately 0.6% of our sample; in contrast, over 92% of the mortgages in our sample prepaid during the period of observation. Slower exercise of prepayment options therefore could more than compensate for a greater frequency of default.

We find that, absent any controls for borrower or loan characteristics, LIMM borrowers are more likely to default and less likely to prepay than the rest of our sample. These differences are robust to adding simple controls for credit-related and geographic variables. We exploit our large amount of loan-level data by analyzing the performance of "pseudo-pools" of loans matched by age, date of origination, credit quality, coupon, loan amount, and loan-to-value ratio. This approach allows us to control for complex path-dependent effects such as burnout (see Hall (2000)), where mortgages that survive repeated exposure to declines in interest rates prepay more slowly, and seasoning (see Richard and Roll (1989)), where older mortgages are observed to prepay quickly relative to newer mortgages. We find that differences in prepayment speeds are large and robust to such controls.

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[4] Conventional" refers to loans that are not insured by the government. "Conforming" refers to loans that are eligible for purchase by Fannie Mae and Freddie Mac; this mainly has to do with loan size (a maximum that is indexed to house prices) and credit quality.

We extend the literature on the relationship between low-income and minority borrowers and the mortgage markets. It has long been recognized that low income and minority households face multiple barriers to homeownership. Examples of such barriers include challenges to maintaining good credit and accumulating wealth, which Barakova *et al.* (2003) and others have identified as keys to attaining homeownership. Lacour-Little (1999) offers a good survey of the literature on discrimination in primary lending, which is another barrier often cited for these borrowers. Our results show that differences between LIMMs and other mortgages survive beyond the moment of tenure and mortgage choice and affect mortgage performance.

Deng and Gabriel (2006) analyzed the behavior and pricing of LIMMs with FHA loan data, controlling for both prepayment and default, and Goldberg and Harding (2003) analyzed low and moderate-income mortgage terminations with a sample of mortgages subsidized by a state housing finance authority. Both found a tendency for LIMM type loans to prepay more slowly than other loans, and Deng and Gabriel explored some pricing implications. We extend this analysis to a sample of 30 year fixed rate conventional conforming mortgages, which represents a much larger and more heterogeneous market.

The issue of prepayment differences between LIMMs and other mortgages, and the implications for pricing, has been raised in Chinloy and Megbolugbe (1994). Their argument was based on the notion that low income and minority borrowers are less mobile and less liquid than other borrowers, and as a result they prepay less and are therefore less costly to lenders. However, that does not imply that LIMMs have a less valuable prepayment option. For example, lower mobility means that such borrowers have a longer time period over which they may exercise these options, which increases the options' value for the borrower and will tend to make mortgage rates higher. The key question is whether the options are exercised more ruthlessly, i.e., when the prepayment option is "in the money" in the sense of the rate on the loan being greater than the current market rate. We find that LIMM borrowers generally refinance more both when the prepayment option is in the money and when it is at or out of the money. This leads to small and somewhat ambiguous pricing implications.[5]

It is difficult to disentangle explanations for the slower prepayment speeds that we document. Peristiani *et al.* (1997) find that deterioration in credit and home equity impedes refinancing. Green and LaCour-Little (1999) show that a large fraction of households who fail to prepay when their option is in the money might be constrained by declining collateral values. Another explanation is a lower degree of mobility for such households, which would be consistent with the results in Goldberg and Harding (2003). Finally, low-income households may take out additional mortgages more frequently, and high loan to value ratios (including all mortgage debt) may prevent refinancing, as discussed in Lacour-Little (2004). We find credit history is an also an important predictor of prepayment.

In Section Two, we discuss our estimation strategy. Section Three provides our results. Section Four discusses the implications of our results for pricing LIMMs, while Section Five concludes.

II ESTIMATION STRATEGY

It is by now well established that prepayment and default behavior can be viewed as exercising options.[6] Both prepayment and default are "American" options, meaning they can be exercised before maturity, but the options are costly to exercise and are not exercised in the way that, say, corporate bond options are exercised[7]. This is clearly true for default because exercising the default option involves significant costs to borrowers (e.g., worse credit history and diminished access to future credit, as well as moving costs). It is also true for prepayment; for instance, most

[5] This result is different from earlier drafts on this paper where in the raw data minority borrowers prepaid more slowly when the option was in the money but about the same otherwise. In revising this paper we have recreated and extended the sample. We do find some difference in the direction of the results of the previous paper for the pre 2000 period, but considerable smaller in magnitude. The results that we get for conditional estimates are very similar to our previous results.

[6] See Findley and Capozza,(1977) and Dunn and McConnell,(1981) for early discussions, and Hendershott and Van Order (1987) Kau *et al*.(1995) for additional analysis.

[7] See Deng *et al*. (2000) and Kau and Keenan (1995) for somewhat different versions.

mortgages are not assumable (the lender has the right to demand payment if the house is sold), so they are usually prepaid when the house is sold.

We follow other papers, such as Deng *et al.*, (2000) and Van Order and Zorn (2000) in modeling option exercise in a proportional hazard framework, using variables that affect the probability that an option is the money and other variables that capture the likelihood of "trigger events" that affect the probability of exercising the option.

We estimate prepayment and default probabilities with models of the form:

$$h(t) = \exp(Bx(t)) \qquad (1)$$

where *h(t)* is the instantaneous probability of the borrower prepaying or defaulting conditional on having survived (neither prepaying nor defaulting) until time *t*, *x* is a vector of explanatory variables, and B a vector of coefficients. The multiplicative nature of the model means if, as is the case in most of our analysis, the *x*'s are categorical variables, then letting B_k be the coefficient of x_k, exp(B_k (l)) gives a multiplier for the effect of variable x_k being in category 1, relative to a baseline case. We use the estimated multipliers to adjust existing pricing models or rules of thumb to estimate cost differences across groups for both options.

Because of the jointness of the options, default and prepayment should be modeled and estimated jointly (see Deng *et al.*, (2000) for a discussion). We control for the jointness of these options in two stages. We divide our sample of observations by the extent to which prepayment is rational, i.e. the extent to which the prepayment option is "in the money." [8] We estimate the default hazards separately depending on the "moneyness" of the prepayment option, with controls for initial loan to value ratio, credit history and other variables, as well as controls for race and income groups, in order to see if LIMMs default differently. We also estimate determinants of loss severity rates, conditional on default. In the second stage, we estimate our prepayment models, including the fitted probability of default from the first stage as a covariate.

[8] See footnote #12 for a description of the method used.

We group our observations into quarters and assume that the hazard rates are constant within quarters. Let *h(T)* be the continuous time hazard rate within quarter *T* and *H(T)* be the probability of the hazard happening at some time during *T*. *S(T)*, the probability of surviving throughout the quarter conditional on having survived until the beginning of the quarter is

$$S(T) = 1 - H(T) = \exp(-h(T)\Delta T) \qquad (2)$$

where ΔT is the length of the period. That is, the survival rate declines exponentially at a rate equal to the instantaneous hazard rate during the period. Letting $\Delta T=1$ and taking logs twice we have the complementary log-log model[9]:

$$\log(-\log(1 - H(T)) = \log(h(T)) = Bx(T) \qquad (3)$$

This formulation has the advantage that the estimates are not affected by size of the interval (e.g., weeks vs. quarters). We use this equation to obtain estimates of the *B*s.

We estimate both unconditional and conditional models. The unconditional models are hazard models that have race/ethnicity and income variables as the main *x*'s, with controls for time in the form of baseline hazards that are fixed effects for loan age. The conditional models add thousands of interactive fixed effects by creating the pseudo pools of mortgages.

For each calendar quarter of mortgage exposure we create fixed effects by forming "pseudo-pools," which are formed by dividing loans into relatively homogeneous groupings based on observed characteristics such as contract rate (50 basis point buckets), LTV (4 buckets), credit history measured by "FICO"[10] score (4 buckets) and loan amount (3 buckets). For each origination quarter this results in on the order of 200 pseudo-pools. Each of these pseudo pools is then given a fixed-effect for each quarter it is alive (up to 51 quarters). With 20 origination quarters this amounts to a total of over 200,000 fixed effects, which because our data have well

[9] See Agresti (1990) and Prentice and Gloecker (1978) for discussions of complimentary log-log models.
[10] This is a generic credit score developed by Fair Isaac Corporation, which has become widely used by lenders.

over one million loans and millions of loan-quarters, still leaves a large number of degrees of freedom.

This is a very simple but also rather complete representation, which allows us to isolate the effects of race, income, etc. within pools, holding effects at the pool level constant and allowing for extremely complicated interactions among the other explanatory variables; in particular the procedure handles the "burnout" and other age related heterogeneity problems discussed above.

An analogy to typical panel data analysis is useful in understanding the conditional models. We can divide x into characteristics that vary within a group and those that vary only across groups. For the purposes of this study we are interested in estimating within group variation in behavior. To accomplish this we partition x as follows. Let

$$y \equiv \log(-\log(1-H(T)) = Bx \qquad (4)$$

If we let y^{ij} be the value of *y* for the ith borrower in the jth pseudo pool, we can partition the right hand side into two parts, so that

$$y^{ij} = B_1 x_1^{ij} + B_2 x_2^{j} \qquad (5)$$

where x_1^{ij} is a vector of the individual characteristics of the ith individual in the jth pseudo pool, such as borrower income and race/ethnicity, and x_2^{j} includes characteristics common to all borrowers in the jth pseudo pool, including initial loan-to-value ratio, date of origination, loan age, and other characteristics.

We are interested in estimates of $B_{1.}$ Following the analogy with panel data analysis, this can be accomplished by including group level fixed effects to capture the effects of x_2^{j}. Alternatively, this can be accomplished through the subtraction of group level means. Subtracting pseudo pool means from both sides, we can rewrite (5) as

$$y^{ij} - \overline{y^{j}} = (x_1^{ij} - \overline{x_1^{j}})B_1 + (x_2^{j} - \overline{x_2^{j}})B_2 \qquad (6)$$

where $\overline{y^{j}}$ is the average level of *y* in the loan's pseudo pool in the quarter in question and $\overline{x_1^{j}}$ and $\overline{x_2^{j}}$ are the mean levels of x_1^{ij} and x_2^{j} in the jth pseudo pool.

Because, by construction, $x_2^{j} = \overline{x_2^{j}}$ we have

$$y^{ij} - \overline{y^{j}} = (x_1^{ij} - \overline{x_x^{j}})B_1 \qquad (7)$$

which we can rewrite as

$$y^{ij} = (x_1^{ij} - \overline{x_x^{j}})B_1 + \overline{y^{j}} \qquad (8)$$

We estimate equation (8) using maximum likelihood.[11] We do not produce estimates of B_2. The creation of the pseudo pools allows us to control for their effects without estimating thousands of parameters.

We estimate the effect of differences in prepayment behavior on pricing by using Yieldbook ©, a proprietary pricing model developed by Citigroup, and use rules of thumb to translate differences in default and severity into pricing. Finally, to understand the net effect of LIMM status on loan performance, we compare the pricing implications of differences in prepayment and default performance.

III DATA

[11] Pseudo pools with no prepayments or defaults are excluded from the analysis because there is no within group variation to explain. Mathematically, this results in values of log(0) for $\overline{y^{j}}$. We use a SAS program for estimation of log-log models.

Our data consist of all 30 year fixed rate mortgages originated from 1993-1997 and purchased by Freddie Mac for which key data are not missing or obviously inaccurate. The full data set contains about 2.7 million loans. There were sharp mortgage rate declines in 1993, 1995 and 1998, so our data are rich in prepayment experience. The default modeling suffers from excessively good times in the 1990s and relatively small levels of default. However, the California economy performed rather poorly in the early part of the period and provides us with some significant default data. The performance of all loans was followed through the third quarter of 2005.

Table provides descriptive statistics for the major variables. We define income classes relative to the area median income, with low income as less than 80% of the area median. Of particular interest is the variable “In-the-moneyness,” which measures the extent to which the coupon rate on the loan is above or below the current market rate. Table 2 presents simple cross tabs. Part A gives prepayment rates (percent that ever prepaid during the sample period) by borrower race/ethnicity and income. Blacks and Hispanics prepay at a slower rate than Whites and other minorities, and low-income borrowers prepay more slowly than high-income borrowers. On the default side, Blacks and Hispanics have higher default rates than Whites. Low-income borrowers tend to default more, but the differences are not very large, and the relationship does not hold for all groups. For example, defaults by Hispanics and Other Minorities increase with income. These are, of course, crude statistics without basic controls. To address this concern, we now turn to estimates of various forms of hazard models.

IV DEFAULT MODELS

Panel A of Table 3 presents a basic hazard model of default. We approximate the extent to which the default option is in the money with an estimate of current loan to value (CTLV), and we control for the value of the prepayment option by separately estimating the model according to the degree to which prepayment is “in the money[12].” We estimate CLTV by using Freddie Mac’s Conventional Mortgage Home Price Index to control for home price appreciation at the state level. Our other explanatory variables are credit history, as measured by the FICO score at

[12] Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows:a<-0.035=Discount, -0.035<a<0.035=Current, 0.035<a<0.100=Cusp, 0.100<a<0.25=Premium, a>0.25=Super Premium.

origination, the ratio of borrower debt payments to income, loan amount, loan purpose, and loan age.

The model works very much as expected. Credit history and CLTV have strong effects on default. Coefficients do not vary much by in-the-moneyness. The exception is across current loan to value ratio, where the effect decreases as in-the-moneyness increases. Borrowers are less likely to default on low rate loans; the low rate means that the market value of the mortgage is below par, so that mark to market equity is higher than is given by our calculation of CLTV.

Multipliers relative to a baseline are presented in Panel B. A loan in the lowest FICO class is about four times as likely to default as one in the medium (680-720) class. Refinance loans and smaller original loan sizes are also associated with a higher frequency of default. Multipliers are fairly consistent for all categories of the prepayment option with the exception of super-premium mortgages, where prepayment is most valuable.

In Table 4, we show the results of adding minority status and income to the default model. Recall that absent controls, LIMM borrowers had much higher default rates, on the order of three times as high for Hispanic and four times as high for Black. In this model, with controls for borrower and loan characteristics, the effect of LIMM status is smaller. For instance the multiplier for "Black" (relative to the base case, "White") is 1.2 rather than four. Most of the minority status effect is eliminated with controls for other characteristics, and none of the coefficients on the other variables are affected much by adding minority and income.

To analyze default cost we need to model loss severity rates as well. Table 5 presents OLS results from regressing log of loss severity[13] divided by mortgage balance on the basic minority status and income variables. It suggests small differences by minority but bigger differences by income. Table 6 controls for LTV, FICO etc. and adds census tract variables. It suggests that the major explanatory factor is census tract income.

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[13] The loss used to compute severity is based on internal Freddie Mac calculations, which include collateral deficiency as well as lost interest, transaction costs, legal expenses and selling expenses.

Pricing

We do not have a well-developed pricing model for credit risk. However, from Freddie Mac history we can approximate a base line level of default to which we can apply our estimated multipliers. In this sample the median loan has an LTV just under 80%. Freddie Mac history suggests that loans like these have about a 1 to 2% chance of ever defaulting; this was higher in the early 90s during the recession and was smaller later, during the housing boom. Average loss severity rates on these have been about 30%. This suggests average losses of about 0.3 to 0.6% of loan balance, which, discounted to the present, implies an expected present value of about 0.25% to 0.5% of loan balance. This decline in value can be converted into an equivalent required increase in coupon rate on the mortgage.

In Section IV we make use of Yieldbook ©, a proprietary model developed by CitiGroup for pricing mortgages with prepayment risk. It has the property, which is also approximately true in the market for mortgage-backed securities, that a one basis point increase in coupon rate will lead to a 5 basis point increase in mortgage value and *vice versa*. Hence, we can divide the value decline by 5 to get an estimate of the required increase in coupon rate to compensate for the higher default cost. This implies an average annual charge of 5 to 10 basis points.

For loans to Blacks and Hispanics the overall unconditional multiplier estimate (including severity rates) is around 3, suggesting a range of cost of 15 to 30 bp and a difference from the baseline of 10 to 20 bp. The multipliers from the model that incorporates FICO and loan characteristics are much smaller for both groups, on the order of 1.5, consistent with a difference from the baseline of 5 to 10 bp. For low-income borrowers the unconditional multiplier, including severity rate differences, is about 2, which suggests a range of default costs of 10 to 20 bp with a differential of 5 to 10 bp[14]. Inclusion of other borrower and loan characteristics reduces both the multiplier and effect on price by one-quarter, consistent with a differential of 3 to 8 bp.

V PREPAYMENT MODELS

[14] A factor not included is capital costs. Riskier loans require more capital, which will increase costs.

The Unconditional Model. Panel B of Table 2 presents cross tabs for prepayment by income and minority status. It suggests that minority status is negatively associated with prepayment, with a similar effect associated with income. Table 7 presents results for estimates of complementary log-log models, controlling only for loan age. Results in the first column tell the same story as in Table 2; Black, Hispanic, and low-income borrowers tend to prepay at a slower rate.

The right hand column adds two neighborhood characteristics, the median income of households in the loan's census tract relative to the area median, and the minority (Black + Hispanic + Other minority) share of households in the census tract. Including these variables affects the race/ethnic coefficients, lowering them a bit. For instance, the coefficient for Black increases from -0.42 to -0.33, and the coefficient for low minority concentration (Min1 (0 to 10)) is .22, relative to high concentration (greater than 50%). Hence, the result that minorities tend to prepay less is partly explained by the racial composition of the neighborhood as well as the race of the borrower. The results for income are that there is virtually no change in the coefficient for individual income but a small effect of neighborhood income on prepayment.

Table 8 presents estimates of a hazard model for the probability of prepayment as a function of how far into the money the option is, as is given by the categories described in Table 1: discount, current, cusp, premium and super premium, where the latter is the furthest into the money and the first the furthest out of the money.[15] There are also controls for loan age and origination year, which are not shown. Premium loans prepay about three times as often as current loans, and super premium loans prepay four times as rapidly. Current loans have historically had prepayment speeds on the order of 10% (annual rates); so a super premium loan will tend to have a speed in excess of 40%.

The effect of prepayment speeds on pricing depends on when prepayment speeds differ. If a group prepays relatively slowly when the option is in the money, the investment value of the mortgage increases, while slower prepayment when the option is out of the money decreases its

[15] Note that the multiplier for super-premium is set to 1, and the prepayment speed of all other "in the moneyness" categories are measured relative to it.

value to investors. Given the importance of the value of the option, we perform the rest of the estimation separately by the option value category.

Table 9 repeats the analysis of the first column of Table 7, with the estimation performed separately by option value category. The results differ for race and income. In Table 9 we see virtually the same difference for Black and Hispanic prepayment rates (and a small decline for other minority) whether the option is in or out of the money. The coefficient for "Black" implies that for premium loans Blacks are approximately exp(-0.-4518) or about 0.6 times as likely to prepay as Whites, regardless of option value. For the lowest income group, results depend on the option value. There is virtually no difference in prepayment speeds when the option is out of the money, while they are about 0.75 times as likely to prepay as those with incomes more than 120% of median (about half the loans in the sample) when the option is in the money. Table 10 shows the results of adding census tract variables. The relationship between prepayment speeds and low-income status is smaller, but otherwise the results are similar.

The Conditional Model. Here we control for loan to value ratio (LTV), credit history (FICO), loan amount (given our controls for LTV this is equivalent to controlling for property value) and other variables by forming pseudo pools as described above. Tables 11 and 12 report estimates of B_1 in equation (7). The new coefficients are, as before, for race/ethnicity and income by extent in and out of the money as in Tables 9 and 10, but now they are conditional effects, after controlling for the loan characteristics that define the pseudo-pools. Table 11 corresponds to Table 9. The controls have relatively little effect on the coefficients; the magnitude is slightly larger for the minority controls and somewhat smaller for the income controls Table 12 repeats Table 10. Here, the controls almost eliminate the income effects, but not the race/ethnicity effects.[16]

Stability over Time

Mortgage markets changed rapidly in the 1990s, particularly with respect to prepayments; it has become increasingly easy to refinance, and it may well be the case that it has become

[16] FICO has an important effect on prepayment. Low FICO borrowers have a multiplier less than one when the option is in the money, but a multiplier greater than one when it is out of the money. This makes low FICO borrowers relatively desirable prepayment wise. This is consistent with results in Deng and Gabriel, who find a relatively impact of this on pricing for new loans, but a big effect if the loans are seasoned.

increasingly easy for LIMM borrowers to get loans. Hence, it may be that the coefficients estimated above have changed over time. Because of the large size of our data set we can test this by re-estimating the models for different exposure (i.e., calendar rather than origination) years.

The first panel of Table 13 presents results from the unconditional model, re-estimated for each exposure year. It presents only the coefficients for Black and Hispanic and the lowest income group. Note that results for the Black and Hispanic coefficients have a similar pattern, in that they are both fairly stable over time, in spite of changes in overall refinance activity over these years. This is consistent with Black and Hispanic borrowers being slower to prepay, regardless of the financial incentives involved. There does appear to have been a decline (in the absolute value of) the effects in last two years of the sample. The magnitude of the coefficients on low-income borrower status dips during 1999 and 2000, years of relatively slow refinance activity. This is consistent with low-income borrowers being slowest to prepay for financial incentives. Panel B of Table 13 depicts the conditional results. Results are similar to the first panel, with coefficients on Black and Hispanic borrowers stable over time, and those on low-income borrowers becoming smaller in magnitude during periods of relatively low refinance activity.

Pricing

Unconditional Model. The estimates suggest that there are significant differences in degree of prepayment speeds across groups. In addition, the exercise of prepayment options appears to be somewhat less “ruthless” among low-income groups. During recent refinance booms prepayment speeds have often been in the range of 40% annual rates, so small relative differences in prepayment speeds can have large effects on the value to investors.

To evaluate the effect on value we applied YieldBook ©, a pricing model from CitiGroup (see Hayre and Rajan (1995) for a description). This model is widely available, but proprietary. It uses Monte Carlo techniques combined with empirical prepayment models to compute the value of a mortgage as the expected present value of mortgage cash flows. A disadvantage of using the model is that because it is proprietary we do not know the details (coefficients) of the model, and our ability to tweak the model is limited. However, the model has been widely used, and we have the ability to change some of its parameters, by multiples of the sort we estimate, so that we can compare changes in value due to changes in the propensity to exercise prepayment options.

In particular, the model can be broken down into an option-exercising part and a part that takes account of other factors. To the extent that we can identify these with our in-the-money and out-of -the money coefficients we can use the model to predict pricing and mortgage rate differences given the multipliers we estimate. This is, of course, imprecise as our prepayment model does not have the same functional form as the Citigroup model and it was estimated with an entirely different data set.

Black and Hispanic borrowers have slower prepayment speeds regardless of whether the option is in or out of the money. Consequently, we adjusted both the “turnover multiplier” and the “refinancing multiplier,” The turnover multiplier corresponds to prepayment in states of the world where refinancing motives other than “rational” prepayment, such as home sales, are the primary reason for prepayments, while the refinancing multiplier relates to states where it is financially beneficial to prepay. The effect of differences in the frequency of this kind of prepayment on prices is ambiguous, as prepayment when the option is in the money decreases the price that the investor is willing to pay, while prepayment when the option is out of the money should increase the price. A model is required to determine which effect dominates.

We analyze a current coupon 30 year fixed rate mortgage. The model requires inputting the yield curve and a measure of interest rate volatility. We do not adjust the model’s volatility numbers, but we do explore prices for different yield curves. Our base case uses the current flat yield curve. We asked the model to give us the difference between a base case price for the mortgage and the one adjusted for the new prepayment model. We then asked the model for the difference in mortgage coupon rate between the base case and the adjusted case assuming both are priced at par. We then chose scenarios with a sudden change to a downward sloping and the more typical upward sloping yield curves, and we considered the effects on yields spreads.

Our results are in Table 14. For the most common scenario, an upward sloping term structure, the required yield on mortgages held by black borrowers should be discounted by two basis points, while that for low-income borrower should be discounted by four basis points. The effect on yields for mortgages with Hispanic borrowers is less than a basis point. For downward sloping yield curves, where the anticipated financial benefits for the borrower are substantial, the effects are larger: a six basis point discount for Hispanic borrowers, nine for low-income borrowers, and fifteen for Black borrowers. In the current regime of a relatively flat yield curve, the net result is a required addition to yield of one basis point for low-income and Hispanic borrowers, and two basis points for Black borrowers. Results are not much affected by whether or not we use conditional or unconditional results.

VI CONCLUSIONS

Our main results are that there is some tendency for the prepayment behavior of low income borrowers to be less "ruthless" than that of high income borrowers, Black and Hispanic borrowers prepay more slowly than Whites regardless of the value of their prepayment option, and the equations with the controls added are relatively stable over time. The pricing implications of LIMM prepayment performance is relatively small for upward sloping and flat yield curves, but for downward sloping yield curves it is almost large enough to offset the effect of higher expected default.

While our data set is both larger and more representative than other studies, which have exclusively analyzed subsidized loans, it is still limited to conventional conforming thirty year fixed rate mortgages. As selection across mortgage types is surely not a random decision, LIMM mortgage performance may differ for jumbo mortgages and other kinds of products, such as ARMs. Many of mortgage products outside the scope of this paper are designed to enhance affordability, making their relationship to historically underserved populations of particular interest. Within the range of conventional conforming loans, a very large part of the market, it appears to be the case that differences in prepayment behavior by LIMM borrowers are significant, but not very important in terms of cost and pricing.

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Table 1: Descriptive Statistics

Panel A

	Borrower Income By % of Area Median Income				
Borrower Race	**All**	***Inc1*** **(0-80%)**	**Inc2 (81-100%)**	**Inc3 (101-120%)**	**Inc4 (>120%)**
Black	3.20	4.51	3.20	2.87	2.64
Hispanic	2.93	4.44	3.39	2.85	2.04
Other minority	4.12	4.17	4.53	4.34	3.85
White	89.75	86.88	88.88	89.94	91.47
Total	100.00	100.00	100.00	100.00	100.00

Panel B

Borrower Income	***Borrower Race***				
(Percent of Area Median)	**All**	**Black**	**Hispanic**	**Other**	**White**
Inc1 (0-80%)	22.73	32.13	34.50	23.10	22.01
Inc2 (81-100%)	16.05	16.12	18.60	17.69	15.90
Inc3(101-120%)	15.39	13.84	15.00	16.28	15.43
Inc4 (>120%)	45.83	37.90	31.87	42.93	46.66
Total	100.00	100.00	100.00	100.00	100.00

Panel C

Property Location	***Borrower Race***					***Borrower Income as % of Area Median Income***			
% Minority in Census Tract	**All**	**Black**	**Hispanic**	**Other**	**White**	**Inc1 (0-80%)**	**Inc2 (81-100%)**	**Inc3 (101-120%)**	**Inc4 (>120%)**
Tract %Min1 (01-10%)	62.87	17.39	17.84	27.35	67.67	58.04	61.96	63.84	64.45
Tract %Min2 (11-30%)	25.97	26.25	31.20	33.23	25.45	27.30	26.11	25.39	25.89
Tract %Min3 (31-50%)	5.74	14.09	19.09	15.61	4.55	6.90	6.02	5.62	5.32
Tract %Min4 (>50%)	5.42	42.27	31.86	23.81	2.39	7.76	5.92	5.15	4.35
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Panel D

Property Location	*Borrower Race*					*Borrower Income as % of Area Median Income*			
Census Tract Median Income						Inc1	Inc2	Inc3	Inc4
(as percent of Area Median)	All	Black	Hispanic	Other	White	(0-80%)	(81-100%)	(101-120%)	(>120%)
Tract Med Inc1 (0-80%)	9.10	25.91	25.39	12.10	7.82	15.73	10.03	7.84	5.96
Tract Med Inc2 (81-100%)	22.89	23.92	27.66	23.93	22.66	31.46	26.77	23.56	17.14
Tract Med Inc3 (101-120%)	30.02	23.54	22.94	27.16	30.62	30.13	32.85	32.59	28.07
Tract Med Inc4 (>120%)	37.99	26.62	24.01	36.80	38.89	22.69	30.36	36.02	48.84
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Table 2: Cumulative Prepayment and Default Rates
By Borrower Race and Income

Panel A: Cumulative Default Rate

	Borrower Race				
Borrower Income	**Black**	**Hispanic**	**Other**	**White**	**Total**
Inc1 (0-80%)	2.80	1.35	0.75	0.83	0.94
Inc2 (81-100)	2.06	1.60	0.81	0.62	0.71
inc3(101-120)	2.01	1.63	0.93	0.52	0.62
inc4 (>120)	1.44	1.40	0.84	0.37	0.44
Total	2.05	1.45	0.83	0.54	0.63

Panel B: Cumulative Prepayment Rate

	Borrower Race				
Borrower Income	**Black**	**Hispanic**	**Other**	**White**	**Total**
Inc1 (0-80)	72.87	84.45	90.00	88.94	88.05
Inc2 (81-100)	79.81	88.13	92.82	92.04	91.56
inc3(101-120)	81.04	88.66	92.86	93.11	92.63
inc4 (>120)	84.04	89.45	93.53	94.37	93.97
Total	79.36	87.36	92.50	92.62	92.03

Table 3: Default Model

Panel A: Model

	By Prepayment "In the Moneyness"									
	Discount		**Current**		**Cusp**		**Premium**		**Super-Premium**	
Variable	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**	**Coeff**	**std error**	**coeff**	**std error**
CTLV	0.099	0.0049	0.0747	0.0043	0.0724	0.0035	0.0519	0.0023	0.1036	0.0064
Fico <620	2.4528	0.1125	2.6004	0.0981	2.5654	0.0843	2.5289	0.0595	1.5756	0.1235
Fico 620-679	1.9172	0.0931	1.7868	0.0884	2.0041	0.0752	1.9428	0.0554	1.2821	0.1132
Fico 680-720	0.9921	0.1051	1.0348	0.0978	1.0473	0.0863	1.1137	0.0631	0.6939	0.1314
Debt 0-30	-0.5917	0.0830	-0.6455	0.0749	-0.5102	0.0602	-0.4749	0.0413	-0.3229	0.0888
Debt 31-36	-0.1793	0.0836	-0.2674	0.0756	-0.2529	0.0614	-0.2446	0.0424	0.0044	0.0890
Loanamt <76k	0.6691	0.0891	0.6800	0.0805	0.6086	0.0649	0.4727	0.0461	0.4830	0.1130
Loanamt 76-125k	0.2878	0.0836	0.2444	0.0785	0.1741	0.0645	0.1093	0.0479	0.2053	0.1215
Purp=Purchase	-0.7595	0.0738	-0.7403	0.0667	-0.8069	0.0541	-0.6610	0.0364	-0.7494	0.0767
Num. Obs.	*6,625,793*		*4,845,736*		*5,854,388*		*7,280,606*		*881,590*	
Log Likelihood	*-7,819*		*-9,136*		*-15,559*		*-27,361*		*-5,610*	

Panel B: Multipliers

Variable	**Discount**	**Current**	**Cusp**	**Premium**	***Super*** **Premium**
CTLV	1.10	1.08	1.08	1.05	1.11
Fico <620	11.62	13.47	13.01	12.54	4.83
Fico 620-679	6.80	5.97	7.42	6.98	3.60
Fico 680-720	2.70	2.81	2.85	3.05	2.00
Debt 0-30	0.55	0.52	0.60	0.62	0.72
Debt 31-36	0.84	0.77	0.78	0.78	1.00
Loanamt <76k	1.95	1.97	1.84	1.60	1.62
Loanamt 76-125k	1.33	1.28	1.19	1.12	1.23
Purp=Purchase	0.47	0.48	0.45	0.52	0.47

Table 4: Default Model with Borrower Race and Income

Panel A: Model

	By Prepayment "In the Moneyness"									
	Discount		**Current**		**Cusp**		**Premium**		***Super-Premium***	
Variable	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**	**Coeff**	**std error**	**coeff**	**std error**
CTLV	0.0986	0.0050	0.0738	0.0044	0.0720	0.0036	0.0526	0.0023	0.1056	0.0065
Fico <620	2.4536	0.1154	2.5826	0.1003	2.5221	0.0865	2.4697	0.0605	1.5824	0.1252
Fico 620-679	1.9437	0.0951	1.7801	0.0900	2.0019	0.0766	1.9107	0.05600	1.3034	0.1139
Fico 680-720	1.0145	0.1070	1.0400	0.0992	1.0487	0.0877	1.0958	0.0636	0.7045	0.1320
Debt 0-30	-0.5009	0.0871	-0.5108	0.0784	-0.4019	0.0631	-0.3810	0.0431	-0.2473	0.0919
Debt 31-36	-0.1325	0.0849	-0.2354	0.0772	-0.2025	0.0624	-0.2159	0.0432	0.0421	0.0900
Loanamt <76k	0.5197	0.1048	0.4775	0.0944	0.4054	0.0762	0.2790	0.0537	0.2331	0.1274
Loanamt 76-125k	0.2501	0.0901	0.1308	0.0845	0.0718	0.069	0.0142	0.0508	0.0610	0.12700
Purp=Purchase	-0.7690	0.0749	-0.7259	0.0676	-0.8076	0.0548	-0.6627	0.0369	-0.7432	0.0775
Black	0.2112	0.1328	0.3312	0.1141	0.4339	0.08600	0.3683	0.0551	-0.1673	0.1155
Hispanic	0.3111	0.1466	0.4899	0.1227	0.5810	0.0938	0.3212	0.0686	-0.2423	0.1623
Other minority	0.5149	0.1325	0.4638	0.1268	0.4170	0.1075	0.3548	0.0782	-0.3863	0.2293
Inc1 (0-80)	0.4454	0.0984	0.5219	0.0925	0.4345	0.0733	0.4003	0.0499	0.4053	0.1033
Inc2 (81-100)	0.0695	0.1067	0.4515	0.0941	0.2732	0.0760	0.2381	0.0534	0.2121	0.1162
Inc3(101-120)	0.0953	0.1037	0.3907	0.0935	0.1111	0.0794	0.1272	0.0558	0.1867	0.1205
Num. Obs.	*6,625,793*		*4,845,736*		5,854,388		*7,280,606*		*881,590*	
Log Likelihood	*-7,819.77*		*-9,136.81*		*-15,559.43*		*-27,361.50*		*-5,610.07*	

Panel B: Multipliers

Variable	Discount	Current	Cusp	Premium	*Super* Premium
Black	1.24	1.39	1.54	1.45	0.85
Hispanic	1.36	1.63	1.79	1.38	0.78
Other minority	1.67	1.59	1.52	1.43	0.68
Inc1 (0-80)	1.56	1.69	1.54	1.49	1.50
Inc2 (81-100)	1.07	1.57	1.31	1.27	1.24
Inc3(101-120)	1.10	1.48	1.12	1.14	1.21

* Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows: a<-0.035=Discount, -0.035<a<0.035=Current, 0.035<a<0.100=Cusp, 0.100<a<0.25=Premium, a>0.25=Super Premium.

Table 5: Loss Severity by Borrower Race/Income

Variable	Coefficient	Std Err
Black	0.0201	0.0053
Hispanic	0.0127	0.0052
Other	-0.0199	0.0071
Inc1	0.0873	0.0038
Inc2	0.0426	0.0043
Inc3	0.0208	0.0044
Num. Obs	*22,038*	
R-Squared	*0.0279*	

Table 6: Loss Severity by Race/Income/Tract Variables

Includes controls for LTV, Orig Amt, # Units, Fico, State

Variable	Coefficient	Std Err
Black	-0.0024	0.0054
Hispanic	0.0018	0.0053
Other	-0.0236	0.0070
Inc1	0.0218	0.0042
Inc2	0.0026	0.0043
Inc3	-0.0032	0.0042
Tract %Min1 (<10%)	-0.0298	0.0068
Tract %Min 2 (11-30%)	-0.0357	0.0068
Tract %Min 3 (31-50%)	-0.0442	0.0080
Tract Med Inc1 (0-80%)	0.0584	0.0057
Tract Med Inc2 (80-100%)	0.0012	0.0044
Trct MedInc3 (101-120%)	-0.0240	0.0045
Num. Obs	*22,038*	
R-Squared	*0.1763*	

Table 7: Basic Prepayment Results

	Without Census Tract Characteristics		**With Census Tract Characteristics**	
Variable	**coeff**	**std error**	**coeff**	**std error**
Black	-0.4288	0.0057	-0.3308	0.0060
Hispanic	-0.2146	0.0056	-0.1263	0.0059
Other	-0.0390	0.0047	0.0304	0.0048
Inc1 (0-80)	-0.1798	0.0024	-0.1737	0.0025
Inc2 (81-100)	-0.0828	0.0027	-0.0804	0.0027
Inc3(101-120)	-0.0423	0.0027	-0.0417	0.0027
Tract %Min1 (01-10)			0.2244	0.0050
Tract %Min2 (11-30)			0.1582	0.0050
Tract %Min3 (31-50)			0.1111	0.0059

Trct Med Inc1 (0-80%)			0.0115	0.0038
Trct Med Inc2 (81-100%)			-0.0123	0.0025
Trct med Inc3 (101-120%)			0.0020	0.0023
Num Obs	*26,651,811*		*26,651,811*	
Log Likelihood	*-4,585,535*		*-4,584,022*	

Table 8: Simple Prepayment Model

Variable	coeff	std error	multiplier
Discount	-1.3852	0.0055	0.25
Current	-1.0293	0.0050	0.36
Cusp	-0.5409	0.0043	0.58
Premium	0.1491	0.0035	1.16
Num Obs	*26,651,811*		
Log Likelihood	*-4,442,810*		

* Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows:a<-0.035=Discount, -0.035<a<0.035=Current, 0.035<a<0.100=Cusp, 0.100<a<0.25=Premium, a>0.25=Super Premium.

Table 9: Basic Results by Exercise Category

Panel A: Coefficients

	By Prepayment "In the Moneyness"									
	Discount		**Current**		**Cusp**		**Premium**		**Super-Premium**	
Variable	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**	**Coeff**	**std error**	**coeff**	**std error**
Black	-0.4372	0.0249	-0.4100	0.0215	-0.4418	0.0150	-0.4518	0.0078	-0.5418	0.0134
Hispanic	-0.3365	0.0243	-0.3235	0.0214	-0.2439	0.0142	-0.2549	0.0076	-0.2055	0.0145
Other	-0.2907	0.0188	-0.1763	0.0163	0.0341	0.0104	0.0420	0.0062	0.0272	0.0153
Inc1 (0-80%)	0.0136	0.0087	-0.0185	0.0080	-0.2354	0.0057	-0.3273	0.0033	-0.3011	0.0076
Inc2 (81-100%)	-0.0387	0.0098	-0.0516	0.0090	-0.1294	0.0062	-0.1345	0.0036	-0.0989	0.0090
Inc3(101-120%)	-0.0527	0.0099	-0.0335	0.0091	-0.0696	0.0062	-0.0615	0.0036	-0.0551	0.0095
Pr. (Default)	-2.1029	9.3728	7.6298	7.2134	-135.4310	4.9796	-284.1700	2.6855	-157.6580	3.5105
Num Obs	*6,625,793*		*4,845,736*		*5,854,388*		*7,280,606*		*881,590*	
Log Likelihood	*-464,054*		*-498,759*		*-917,410*		*-2,129,178*		*-316,626*	

Panel B: Multipliers

Variable	**Discount**	**Current**	**Cusp**	**Premium**	*Super* **Premium**
Black	0.65	0.66	0.64	0.64	0.58
Hispanic	0.71	0.72	0.78	0.77	0.81
Other minority	0.75	0.84	1.03	1.04	1.03
Inc1 (0-80%)	1.01	0.98	0.79	0.72	0.74
Inc2 (81-100%)	0.96	0.95	0.88	0.87	0.91
Inc3(101-120%)	0.95	0.97	0.93	0.94	0.95

* Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows: $a<-0.035$=Discount, $-0.035<a<0.035$=Current, $0.035<a<0.100$=Cusp, $0.100<a<0.25$=Premium, $a>0.25$=Super Premium.

Table 10 Basic Results by Exercise Category with Tract Variables

	By Prepayment "In the Moneyness"									
	Discount		**Current**		*Cusp*		***Premium***		***Super-Premium***	
Variable	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**	**Coeff**	**std error**	**coeff**	**std error**
Black	-0.4019	0.0259	-0.3391	0.0222	-0.3711	0.0156	-0.3501	0.0082	-0.4522	0.0146
Hispanic	-0.2848	0.0251	-0.2645	0.0221	-0.1783	0.0147	-0.1542	0.0079	0.1186	0.0153
Other	-0.2389	0.0195	-0.1195	0.0169	0.0840	0.0108	0.1066	0.0065	0.0748	0.0158
Inc1 (0-80)	0.0077	0.0090	-0.0235	0.0083	-0.2193	0.0059	-0.2929	0.0033	-0.2607	0.0077
Inc2 (81-100)	-0.0401	0.0099	-0.0536	0.0091	-0.1188	0.0063	-0.1159	0.0036	-0.0776	0.0090
.Inc3(101-120)	-0.0527	0.0099	-0.0342	0.0091	-0.0628	0.0062	-0.0505	0.0037	-0.0425	0.0095
Tract %Min1 (01-10)	0.2149	0.0197	0.2189	0.0176	0.1764	0.0120	0.1902	0.0068	0.1149	0.0138
Tract %Min2 (11-30)	0.2151	0.0198	0.1971	0.0176	0.1350	0.0121	0.1202	0.0068	0.0895	0.0139
Tract %Min3 (31-50)	0.1405	0.0228	0.1377	0.0204	0.0974	0.0140	0.0894	0.0080	0.0664	0.0164
Tract Med Inc1 (0-80%)	0.1220	0.0143	0.1148	0.0128	-0.0256	0.0089	-0.1844	0.0051	-0.2553	0.0112
Tract Med Inc2 (81-100%)	0.0152	0.0092	0.0060	0.0085	-0.0699	0.0059	-0.1297	0.0034	-0.1533	0.0083
Tract Med Inc3 (101-120%)	-0.0375	0.0082	-0.0108	0.0075	-0.0441	0.0052	-0.0450	0.0031	-0.0753	0.0080
Pr. (Default)	-0.6758	9.4154	8.3043	7.2388	-127.2440	4.9813	-268.8530	2.6875	-149.3330	3.4834
Num Obs	*6,625,793*		4,845,736		*5,854,388*		*7,280,606*		*881,590*	
Log Likelihood	*-463,949*		*-498,654*		*-917,163*		*-2,126,870*		*-316,157*	

* Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows:a<-0.035=Discount, -0.035<a<0.035=Current, 0.035<a<0.100=Cusp, 0.100<a<0.25=Premium, a>0.25=Super Premium.

Table 11 Pseudo-Pools, Effect of Race and Income Variables

Panel A: Coefficients

	By Prepayment "In the Moneyness"							
	Discount		**Current**		**Cusp**		**Premium**	
Variable	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**
Black	-0.5731	0.0929	-0.3843	0.0918	-0.4969	0.0890	-0.6498	0.1206
Hispanic	-0.4089	0.0752	-0.3167	0.0775	-0.4428	0.0733	-0.3480	0.0904
Other	-0.2820	0.0488	-0.2127	0.0487	0.1350	0.0367	-0.0576	0.0562
Inc1 (0-80)	-0.1129	0.0256	0.0270	0.0291	-0.1162	0.0271	-0.1521	0.0382
Inc2 (81-100)	-0.1228	0.0250	-0.0473	0.0281	-0.0333	0.0242	-0.0032	0.0320
Inc3(101-120)	-0.1032	0.0248	-0.0100	0.0271	0.0248	0.0224	0.0554	0.0303
Pr. (Default)	-859.005	249.8324	-673.063	179.0979	-269.904	236.8483	383.8331	241.3582
Num Obs	*1,275,635*		*643,017*		*458,007*		*98,469*	
Log Likelihood	*-76,265*		*-59,269*		*-65,539*		*-27,271*	

Panel B: Multipliers

Variable	**Discount**	**Current**	**Cusp**	**Premium**
Black	0.56	0.68	0.61	0.52
Hispanic	0.66	0.73	0.64	0.71
Other Minority	0.75	0.81	1.14	0.94
Inc1 (0-80)	0.89	1.03	0.89	0.86
Inc2 (81-100)	0.88	0.95	0.97	1.00
Inc3(101-120)	0.90	0.99	1.03	1.06

* Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows:a<-0.035=Discount, -0.035<a<0.035=Current, 0.035<a<0.100=Cusp, 0.100<a<0.25=Premium, a>0.25=Super Premium.

There were not enough observations to conduct analysis of super-premium mortgages.

Table 12 Psuedo-Pools, Effect of Race and Income Variables with Tract Variables

	By Prepayment "In the Moneyness"							
	Discount		**Current**		**Cusp**		**Premium**	
Variable	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**	**coeff**	**std error**
Black	-0.4800	0.0945	-0.301	0.0933	-0.4221	0.0901	-0.5246	0.1219
Hispanic	-0.3311	0.0766	-0.2458	0.0789	-0.3729	0.0742	-0.2092	0.0922
Other	-0.2107	0.0501	-0.1423	0.0501	0.1955	0.0382	0.0432	0.0579
Inc1 (0-80)	-0.1070	0.0258	0.0264	0.0293	-0.0972	0.0274	-0.1201	0.0385
Inc2 (81-100)	-0.1158	0.0251	-0.0482	0.0282	-0.0199	0.0243	0.0116	0.0321
inc3(101-120)	-0.0986	0.0248	-0.0114	0.0271	0.0328	0.0225	0.0605	0.0303
Tract %Min1 (01-10)	0.2946	0.0543	0.2954	0.0560	0.2361	0.0502	0.3007	0.0710
Tract %Min2 (11-30)	0.2984	0.0542	0.2601	0.0559	0.1295	0.0504	0.1356	0.0714
Tract %Min3 (31-50)	0.1830	0.0618	0.1892	0.0635	0.1318	0.0575	0.0500	0.0834
Tract Med Inc1 (0-80%)	0.0867	0.0379	0.1404	0.0412	0.0229	0.0363	-0.0576	0.0526
Tract Med Inc2 (81-100%)	-0.0365	0.0236	0.0005	0.0257	-0.0672	0.0223	-0.1330	0.0310
Tract Med Inc3 (101-120%)	-0.0775	0.0201	-0.0152	0.0214	-0.0272	0.0186	0.0192	0.0249
Pr. (Default)	-674.931	251.8433	-555.2500	181.1550	-145.616	238.3777	471.8293	242.6732
Num. Obs	*1,275,635*		*643,017*		*458,007*		*98,469*	
Log Likelihood	*-76,236*		*-59,250*		*-65,506*		*-27,218*	

* Let a=1-current coupon rate/coupon rate on mortgage. We define prepayment option value as follows:a<-0.035=Discount, -0.035<a<0.035=Current, 0.035<a<0.100=Cusp, 0.100<a<0.25=Premium, a>0.25=Super Premium.

There were not enough observations to conduct analysis of super-premium mortgages.

Table 13: Stability Over Time

Panel A: Unconditional Model

Year	All Mortgages				Premium Mortgages			
	Black	Hispanic	Inc1 (0-80%)	Inc2 (81-100%)	Black	Hispanic	Inc1 (0-80%)	Inc2 (81-100%)
1994	-0.6053	-0.5135	-0.1114	-0.1295	-22.0448	0.5307	-1.1617	-0.2824
1995	-0.5592	-0.4834	-0.2952	-0.1575	-0.8167	-0.6771	-0.6818	-0.3193
1996	-0.4878	-0.4289	-0.1215	-0.0744	-0.7183	-0.6281	-0.3919	-0.1704
1997	-0.4517	-0.3162	-0.1122	-0.0910	-0.7252	-0.4572	-0.3755	-0.1842
1998	-0.5399	-0.3634	-0.2962	-0.1116	-0.6924	-0.4862	-0.4171	-0.1615
1999	-0.3118	-0.1319	-0.1330	-0.0536	-0.4383	-0.2150	-0.2916	-0.1154
2000	-0.3037	-0.1660	0.0747	-0.0022	-0.4274	-0.1762	-0.0831	-0.0466
2001	-0.5049	-0.1437	-0.1544	-0.0654	-0.6396	-0.2388	-0.2665	-0.1157
2002	-0.5277	-0.1805	-0.3204	-0.1430	-0.6287	-0.2844	-0.4192	-0.1877
2003	-0.5599	-0.2211	-0.3603	-0.1535	-0.5131	-0.2290	-0.3819	-0.1665
2004	-0.2288	0.0249	-0.2159	-0.1078	-0.2336	-0.0147	-0.1945	-0.1102
2005	-0.0707	0.1295	-0.1538	-0.0931	-0.0322	0.0704	-0.1427	-0.1228

Panel B: Estimation with Psuedo-Pools

Year	All Mortgages				Premium Mortgages			
	Black	Hispanic	Inc1 (0-80%)	Inc2 (81-100%)	Black	Hispanic	Inc1 (0-80%)	Inc2 (81-100%)
1995	-0.5483	-0.6180	-0.2104	-0.2047	-0.9153	-1.0005	-0.2124	-0.0460
1996	-0.5453	-0.3296	-0.1637	-0.1255	0.1494	0.4674	0.5390	0.8080
1997	-0.5061	-0.3749	0.0200	-0.0490	-0.7699	-0.4010	0.1500	0.1736
1998	-0.5563	-0.4494	-0.0612	0.0182	-0.5776	-0.4752	-0.0571	0.0402
1999	-0.4676	-0.2593	-0.0167	-0.0223	-0.4968	0.1634	0.0297	0.0320
2000	-0.4264	-0.3434	-0.0192	-0.0415				
2001	-0.5771	-0.3141	-0.0432	-0.0416	-0.6320	-0.3493	-0.0568	-0.0235
2002	-0.6666	-0.2941	-0.1143	-0.0173	-0.7147	-0.3309	-0.1284	-0.0221
2003	-0.4948	-0.2793	-0.1204	-0.0143	-0.4948	-0.2793	-0.1204	-0.0143
2004	-0.5848	-0.3697	-0.0733	-0.0254	-0.5848	-0.3697	-0.0733	-0.0254

Coefficients for premium mortgages in 2000 and all mortgages in 2005 omitted due to insufficient number of observations.

Table 14 Effect of Prepayment Speeds on Required Yield Spread

In Basis Points

	Yield Curve Slope		
Borrower Type	**Flat**	**Up**	**Down**
Black	2	-2	-15
Hispanic	1	0	-6
<80% Area Median Income	1	-4	-9

Table 14 shows the premium (positive numbers) or discount (negative numbers) in basis points required for an LIMM of the appropriate type to sell at par. Values were calculated by adjusting the prepayment model in Yieldbook ©.