Risk-Based Pricing and the Enhancement of Mortgage Credit Availability among Underserved and Higher Credit-Risk Populations

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ABSTRACT

This paper estimates an option-based hazard model of the competing risks of FHA mortgage termination. Results indicate that the elevated default risks of loans originated among lower credit quality and minority borrowers are more than offset by the damped prepayment speeds of those loans, so as to result in markedly lower loan termination probabilities among underserved borrower groups. Those damped termination risks translate into sizable reductions in risk premia to investors in simulated lower credit-quality mortgage pools. Empirical findings suggest that such pooling and risk-based pricing of FHA-insured mortgages could serve to substantially reduce housing finance costs among underserved borrowers, so as to advance both their homeownership opportunities and related federal housing policy objectives.

(*JEL* G21, J78, R20)

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1. INTRODUCTION

In the wake of persistent housing disparities, ongoing research and policy debate have sought insights and methodologies necessary to boost mortgage and homeownership access among underserved, minority, and higher credit-risk populations.[1] Indeed, the Clinton and Bush Administrations have made homeownership access the cornerstone of domestic housing policy.[2] Research accordingly has sought to identify the determinants of ongoing disparities in mortgage origination and homeownership attainment among targeted and non-targeted groups, (see, for example, Gabriel and Rosenthal [2005], Painter, Gabriel and Myers [2001], Rosenthal [2002], Goetzman and Spiegel [2002], Coulson [1999], and Deng, Quigley and Van Order [1996]). On the mortgage side, studies largely have focused on the role of borrower credit risk and credit constraint in the analysis of mortgage origination and performance (see, for example, Ambrose and Sanders [2005], Ambrose, Capone and Deng [2001], Bradley, Gabriel and Wohar [1995], Ondrich, Ross and Yinger [2000], Berkovec, Canner, Gabriel, and Hannan [1998], Ambrose, Buttimer and Capone [1997], Avery, Bostic, Calem and Canner [1996], Goering and Wienk

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[1] The U.S. homeownership rate rose markedly over the past decade to nearly 69 percent by the first quarter of 2004. However, a sizable gap remains between white and minority homeownership rates. In the first quarter of 2004, roughly three-fourths of white households owned their own home while less than one-half of African American and Hispanic households were owner-occupiers.
[2] In 1994, President Clinton asked HUD Secretary Henry Cisneros to "lead a dramatic effort to increase homeownership in our nation over the next six years." Clinton further requested that the HUD program "include strategies to ensure that families currently underrepresented among homeownership—particularly minority families, young families, and low-income families—can partake of the American Dream." That letter can be found at http://www.pragueinstitute.org/housing_us.htm. Further, on June 18, 2002, President George W. Bush wrote "The goal is everybody that wants to own a home has got a shot at doing so. The problem is we have what we call a homeownership gap in America. Three-quarters of Anglos own their homes, and less than 50 percent of African Americans and Hispanics own homes. That ownership gap signals that something might be wrong in the land of plenty. And we need to do something about it." See http//www. whitehouse.gov/news/releases/2002/06/20020618-1.htm.

[1996], Munnell, Tootell, Browne and McEneaney [1996], Canner, Passmore and Smith [1994], Gabriel and Rosenthal [1991]).

While prior research has provided substantial evidence of elevated default risk among lower-income, minority, and less credit-worthy borrowers [see, for example, Avery, Bostic, Calem and Canner (1996), Deng, Quigley and Van Order (1996), Berkovec, Canner, Gabriel and Hannon (1998), and Pennington-Cross and Nichols (2000)], recent studies also suggest offsets to those risks via the slower prepayment speeds of targeted borrower groups [see, for example, Kelly (1995),Van Order and Zorn (2002) and Archer, Ling, and McGill (2002)].[3] In certain circumstances, the damped prepayment speeds of loans originated among targeted groups could serve to appreciably reduce total loan termination probabilities and result in more favorable risk-based pricing of those loans. The enhanced efficiency of loan pricing also could result in improved distributional outcomes, serving to facilitate homeownership attainment among lower-income, minority, and underserved homebuyers.

Recent studies of the micro-foundations of mortgage loan performance suffer from numerous limitations, however, in the assessment of prepayment and default risks. Most prior analyses fail to include contemporaneous valuation of the mortgage put and call options over the life of the mortgage; further, many analyses have focused on prediction of mortgage default without consideration of prepayment risk and vice-versa (see, for example, Gabriel and Rosenthal [1991], Hakim (1992), Kelly (1995), Avery et al [1996], Caplin, Freeman and Tracy [1997], Berkovec et al [1998] LaCour-Little (1999) and Pennington-Cross and Nichols [2000]). Recent papers (see, for example, Archer, Ling and McGill [1996, 2002], Deng, Quigley and Van Order [1996, 2000], Cotterman [2001], Van Order and Zorn [2002], Deng and Quigley [2002]) often do

[3] As discussed in Deng, Quigley, and Van Order [2000]), analyses of loan termination and pricing should account for the joint and competing nature of borrower prepayment and default option exercise.

not include important information on borrower creditworthiness (credit scores) and are further circumscribed by the limited availability of other borrower, loan, and locational information important to prediction of loan performance, including indicators of borrower wealth and other common underwriting controls. Indeed, Peristiani et al (1997) and LaCour-Little (1999) demonstrate the importance of controls for borrower credit worthiness in analysis and prediction of mortgage prepayments.[4] Other recent studies provide new insights on mortgage terminations as derive from call, mobility, and default behavior [see, for example, Archer and Ling (1997), Pavlov (2000), and Clapp, Goldberg, Harding, and LaCour-Little (2001)].[5] Those studies, however, are subject to many of the same data limitations described above and further fail to distinguish loan pricing implications among underserved and like borrower groups.

This study applies a competing risk framework to model the micro-foundations of FHA-insured mortgage performance.[6] The FHA data are well suited to analyses of loan default, given the inclusion in the program of large numbers of relatively higher credit risk borrowers. The data further enable an assessment of whether those same higher credit risk and underserved borrowers prepay their mortgages more slowly, due perhaps to problems of access to mortgage finance, difficulties in loan qualification, limited borrower knowledge of mortgage refinance opportunities, or reduced residential mobility. To the extent the prepayment risks of mortgages originated among lower-income, lower credit-quality, and minority borrowers are relatively damped, they should be reflected in the pricing of those loans. In certain circumstances, the efficient risk-based pricing of loans should serve to enhance mortgage and housing affordability

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4 Results of LaCour-Little (1999) indicate that borrower characteristics primarily affect mortgage prepayment risk in the region where the prepayment option is at-the-money. When the prepayment option is substantially in- or out-of-the-money, borrower and loan characteristics appear to be largely irrelevant.

5 Specifically, the Clapp et al study suggests aggregation bias in combining the refinance and mobility-based mortgage termination decisions into a single refinance term.

6 Von Furstenberg (1970) used loan-to-value ratio as the only risk characteristic of the mortgage loan to study the risk structures and the cross subsidy of the FHA program.

among targeted underserved populations.

This analysis employs an option-based hazard model to simultaneously assess the competing risks of FHA-insured mortgage default and prepayment. The empirical model is motivated by option theory and employs well-specified contemporaneous proxies for the intrinsic values of mortgage put and call options in the default and prepayment equations. Given the availability of high quality micro data, the empirical specification also controls for borrower credit worthiness (credit scores) and a large number of common underwriting variables among the approximately 30 contemporaneous and time-invariant indicators of borrower, loan, and locational risk.

Results of the analysis strongly support the predictions of option theory in explaining the exercise of default and prepayment options among FHA-insured mortgage borrowers. The estimates confirm that the intrinsic values of the call and put option variables are positive and highly significant in the exercise of the prepayment and default options, respectively. Results further suggest that a higher probability of negative equity (a proxy for the intrinsic value of the put option) reduces the risk of mortgage prepayment.

Research findings further point to the importance of other borrower, loan, and market characteristics in the estimation of mortgage default and prepayment risks. As would be expected, higher credit score borrowers are less likely to exercise the default option, whereas lower credit score borrowers are less likely to prepay. In that regard, the 5-year cumulative probability of prepayment is about 13 percentage points higher among borrowers with scores in excess of 680 than among those with scores below 620. The 5-year cumulative prepayment probabilities of Black and Hispanic borrowers are about 14 and 8 percentage points lower than those of white borrowers, respectively.

Overall, results indicate the appropriateness of the competing risk specification and illustrate the importance of slower prepayment speeds among higher credit risk and underserved borrowers. As is evidenced below, the substantially elevated default probabilities of higher credit risk FHA borrowers are more than offset by their damped prepayment propensities, resulting in significantly lower loan termination probabilities overall. Indeed, the estimated cumulative probability of mortgage termination at five years post-origination among high default risk FHA borrowers (39 percent) is about 23 percent lower than that of low-default risk FHA borrowers (48 percent).

Monte Carlo methods are then utilized to simulate the term structure of interest rates and to compute the mortgage pricing implications of the FHA-insured loan performance results. In the simulation, we adopt an Affine Term Structure Model as proposed by Dai and Singleton [2000]. In the case of a mean weighted average coupon of 8.25 percent and a 10-year seasoned pool, we compute a negative risk premium of 44 basis points for the high default/slow prepayment speed pool. In all cases, the simulated stratification of mortgage pools results in a potentially sizable reduction in risk premia to investors in high default/low prepayment risk mortgages. Empirical findings suggest that such risk-based pooling and pricing of FHA-insured mortgages could serve to substantially reduce the housing finance costs of underserved borrowers, so as to advance both their homeownership opportunities and related federal housing policy objectives.

The plan of the paper is as follows. Section 2 presents the loan performance model and estimation strategy. Section 3 describes the FHA database whereas section 4 discusses estimation and performance simulation results. Section 5 assesses the mortgage pricing implications of the performance results. Conclusions and implications for mortgage pricing are discussed in section 6.

2. LOAN PERFORMANCE ANALYSIS

Recent research on mortgage markets indicates that prepayment and default option exercise on the part of mortgage borrowers is behaviorally distinct, but not independent. For example, one cannot calculate accurately the economic value of the default option without considering simultaneously the financial incentive for prepayment (Deng, Quigley, and Van Order [2000]). Furthermore, risk preferences and other idiosyncratic differences may vary widely across borrowers. Appropriate modeling of prepayment and default risks is then crucial to the pricing of mortgages and to an understanding of the economic behavior of homeowners.

This analysis applies a proportional hazard framework to assess the competing risks of mortgage termination by prepayment and default.[7] The specification of the model is motivated by option theory, which predicts that well-informed mortgage borrowers in a perfectly competitive market will exercise the default or prepayment option in order to increase their wealth. Theory suggests that mortgage borrowers will exercise the default option when the market value of the mortgage equals or exceeds the market value of the collateral. Similarly, borrowers can increase their wealth by refinancing their loans when the market value of the mortgage exceeds the par value of the mortgage. However, these two options compete against each other. For example, when an individual decides to exercise the default option, she is making the decision to forego future exercise of the prepayment option. Kau et al [1992, 1995] have outlined the theoretical relationships among the options, and Schwartz and Torous [1993] have demonstrated their practical importance. Furthermore, empirical evidence shows that certain borrower characteristics that have strong association with one option may have the opposite

[7] Green and Shoven [1986] are among the first to apply the proportional hazard model to analyze mortgage prepayment risks.

association with the other option. For example, a lower-income borrower with a poor credit history may have higher default risks but lower refinance risks, due to those same credit problems and/or liquidity constraints that typically affect the ability to qualify for a new loan.

This paper follows Deng, Quigley, and Van Order [2000] in application of an option-based hazard model to simultaneously estimate the competing risks of mortgage loan default and prepayment. In this model, T_p and T_d are discrete random variables representing the duration of a mortgage prior to termination by the mortgage holder in the form of prepayment or default, respectively. Following the Cox model, the joint survivor function conditional on ξ_p, ξ_d, r, H, Y, and X can be expressed in the following form:[8]

$$\begin{aligned} & S\left(t_p, t_d \mid r, H, Y, X, \xi_p, \xi_d, \theta\right) \\ & = \exp\left\{ -\xi_p \sum_{k=1}^{t_p} \exp\left(\gamma_{pk} + \beta_{p_1}' g_{pk}\left(r, H, Y\right) + \beta_{p_2}' X\right) \right. \\ & \qquad \left. - \xi_d \sum_{k=1}^{t_d} \exp\left(\gamma_{dk} + \beta_{d_1}' g_{dk}\left(r, H, Y\right) + \beta_{d_2}' X\right) \right\}. \end{aligned} \qquad (1)$$

In this formulation $g_{jk}\left(r, H, Y\right),\ j = p, d$ are time-varying variables measuring the intrinsic values of the prepayment and default options. The relevant interest rates and property values are r and H, respectively, whereas Y is a vector of other variables that also are relevant to an empirical description of the market values of the default and prepayment options.

Following Deng, Quigley and Van Order [2000], the intrinsic value of exercising the "*Call Option*" for each individual FHA loan borrower is defined as:

$$Call\_Option_{i,k} = \frac{V_{i,m} - V_{i,r}^{*}}{V_{i,m}}, \qquad (2)$$

[8] The proportional hazard model introduced by Cox [1972] provides a framework for considering the contingent claims empirically and for measuring the effect of financial options on the behavior of mortgage holders.

where

$$V_{i,r}^{*} = \sum_{s=1}^{TM_i - k_i} \frac{P_i}{\left(1+r_i\right)^s},$$
$$V_{i,m} = \sum_{s=1}^{TM_i - k_i} \frac{P_i}{\left(1+m_{\tau_i + k_i}\right)^s}, \qquad (3)$$

r_i is mortgage note rate, TM_i is the mortgage term, k_i is the seasoning period of the mortgage after origination at time τ_i, $m_{\tau_i + k_i}$ is the market interest rate, and P_i is the monthly mortgage payment.

Typically, we cannot measure directly from the micro data the extent to which the default option is "in the money" without knowing the entire path of individual house values. We can, however, estimate the probability of negative equity as a trigger point for borrower exercise of the "put option" based on the initial loan-to-value ratio and the diffusion process of house prices. Specifically, the "*put option*" variable is defined as:

$$Put\_Option_{i,k} = \Phi\left(\frac{\left(\log V_{i,m} - \log M_{i,k}\right)}{\sqrt{\omega}}\right), \qquad (4)$$

where $\Phi(\cdot)$ is cumulative standard normal distribution function, ω is an estimated variance that follows a diffusion process, $V_{i,m}$ is defined previously, and the market value M_i of property i, purchased at a price of C_i at time τ_i and evaluated k_i periods thereafter is

$$M_{i,k} = C_i\left(\frac{I_{j,\tau_i + k_i}}{I_{j,\tau_i}}\right), \qquad (5)$$

where the term in parentheses follows a log normal distribution and I_{j,τ_i} is an index of house prices in metropolitan area j at time τ_i.

The vector X is comprised of other non-option-related variables, including both time-varying and time-invariant determinants of mortgage performance. Time-invariant variables include categorical measures of borrower credit score, borrower race/ethnicity, borrower housing expenditure-to-income ratio, borrower debt-to-income ratio, borrower gender and marital status, borrower age group, first-time homebuyer status, seller offer to buy down the mortgage rate, whether the mortgage is amortized in 30 years or less, whether the property is located in the central city, whether the property is located in a rural area, and whether the property is a new home. Other time-invariant controls include mortgage loan-to-value ratio at origination, log value of property appraisal value, number of dependents in borrower's household, log value of borrower liquid assets, and log value of household income. Also included among controls for mortgage performance are census tract level variables reflecting neighborhood racial/ethnic mix, proportion rental occupied stock, and ratio of census tract to MSA median income. The unemployment rate of the MSA is included as a time-varying control for local economic conditions.[9] Accordingly, our analysis draws upon the unusual richness of the FHA micro data to specify an empirical model that includes contemporaneous valuations of the mortgage default and prepayment options as well as a large number of other borrower, loan, and locational controls.

Unobserved error terms associated with the hazard functions for prepayment and default are denoted ξ_p and ξ_d, respectively. θ is a vector of parameters (*e.g.*, γ and β) of the hazard function. γ_{jk} are parameters of the baseline hazard function. The baseline may be estimated with a flexible form suggested by Han and Hausman [1990], such that:

$$\gamma_{jk} = \log\left[\int_{k-1}^{k} h_{0j}(s)\,ds\right], \quad j = p,d. \tag{6}$$

Alternatively, the form of the baseline may be imposed by employing mortgage industry

[9] Caplin et al (1997) estimate the interaction between regional recessions and refinancing constraints. In a similar manner, the contemporaneous unemployment term included in our model is intended to control for regional

performance benchmarks such as those reflected in the "PSA and SDA curves." [10]

The estimated competing risks of prepayment and default are then used to simulate the potential risks to FHA mortgage lending as derived from various borrower and loan characteristics, notably including loan-to-value and payment-to-income ratios as well as borrower liquid assets and credit scores. Further mortgage performance and pricing simulations are undertaken for simulated high- and low-credit risk borrower groups. As indicated below, total loan terminations from default and prepayment among higher credit risk borrowers are estimated to be substantially less than those of low credit risk borrowers, suggesting enhanced returns to investors in those loans when such prepayment options are "in the money".

3. DATA

The principal data utilized in this study consist of a large random sample of FHA-insured home purchase loans originated during the 1992-1996 period.[11, 12] All loans are fully amortizing,

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economic downturns that could make it difficult for homeowners to refinance. Such a downturn would similarly be expected to result in elevated mortgage defaults.

[10] The Public Securities Association (PSA) has defined a prepayment measurement standard that has been widely adopted by fixed-income securities analysts. This is a series of 360 monthly prepayment rates expressed as constant annual rates. The series begins at 0.2 percent in the first month and increases by 0.2 percent in each successive month until month 30, when the series levels out at 6 percent per year until maturity. (See Hayre [2001, pp. 24-25] for details.) The Bond Market Association has also developed a Standard Default Assumption (SDA) that is widely used as a benchmark to measure loan default experience. The SDA series begins at 0.02 percent annual constant rate in the first month and increases by 0.02 percent in each successive month until month 30, when the series levels out at 0.6 percent per year for the next 30 months. Then the series declines by 0.0095 percent each month from month 61 to month 120. At that point, the default rate remains level through maturity. (See Hayre [2001, pp. 168-169] for details.) Prepayments and defaults are often reported as simple linear multiples of the PSA and SDA schedules, respectively. When the PSA and SDA schedules are utilized as baselines for the prepayment and default functions, respectively, the factors of proportionality estimated from the hazard model can be expressed simply as a percentage of the PSA and SDA experiences.

[11] The final sample consists of 12,012 loans randomly drawn from the 120,342 endorsed loans applications from 1992, 1994, and 1996. Loan origination dates are concentrated in those three calendar years but also spread out into other years. The 120,342 loan database provided by Unicon Research is a stratified choice-based sample with weights that account for choice-based sampling from strata based on differential loan losses by race and loan status. For each of the application years, the weighted cumulative default rates for the loans comprising the sub-sample of 12,012 loans were found to be quite similar to those observed in the parent population. The individual loan files are

most with thirty-year terms. The individual loan records contain information on a large number of loan, borrower, and property-related characteristics and also indicate termination date of each loan and reason for termination.[13] Attached to the loan record files are borrower credit scores at time of loan application as well as measures of local housing market performance including house price appreciation and variance.[14] Further, using a census tract indicator for each property location, each loan record file is matched to neighborhood socioeconomic and housing market indicators from the 1990 Census of Population and Housing. Other neighborhood or metropolitan area level variables, including unemployment rates, also are appended to the record file. FHA data on the race of the borrower and census measures of neighborhood racial composition enable assessment of race-related effects associated with the performance of FHA-insured loans. The FHA data set encompasses nearly 300 different metropolitan areas, allowing for substantial variability in the structure of local lending markets.

The FHA-insured data are well-suited to analyses of loan performance, given the inclusion in the program of large numbers of relatively high credit-risk borrowers. During the 1992-1996 period of loan origination evaluated herein, the FHA lending guidelines were not as strict than those of conventional lenders, particularly as regards downpayment requirements and the acceptable ratios of housing expense-to-income and total debt expense-to-income.

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observed on a monthly basis from month of origination through that of termination, maturation, or through the end of 2000 for active loans.

[12] Clarke and Courchane (2005) examine the effect of sample design on estimation and inference for disparate treatment in binary logistic models used to assess for fair lending. Although our analysis does not focus, per se, on efficiency of estimation of the disparate treatment fair lending parameter, the authors do suggest the appropriateness of a stratified choice based sampling methodology as was utilized in the current study.

[13] As defined for this analysis, default outcomes include both lender foreclosure and situations where the borrower conveys title of the property in lieu of foreclosure. Loan prepayment is defined as pay-off prior to completion of the amortization period.

[14] MSA level house price index and variance are provided by Unicon Research Corporation. Borrower credit score information is provided by Equifax and Trans Union. If the data provides both Equifax and Trans Union scores for an individual borrower, we take the average of the two scores. Numerous recent papers (see, for example, Avery et al [1996]) point to the importance of controls for borrower credit score in micro-analyses of mortgage default likelihoods.

Approximately 61 percent of the loans in the sample had loan-to-value ratios exceeding 95%.[15] Similarly, the debt obligation ratios of the FHA borrowers in the sample exceeded those of conventional conforming mortgages, averaging about 35% for the ratio of total debt payments-to-income and about 23% for the ratio of housing debt payments-to-income. First-time homebuyers and moderate-income borrowers comprised a large portion of the sample, and minorities were well represented as well.

Table 1 displays the means and variances of the time-invariant covariates, whereas Table 2 provides the same for time-varying covariates at origination and termination. As is evidenced in Table 1, some two-thirds of FHA borrowers were first-time buyers; the average mortgage loan-to-value ratio among sampled loans was 94 percent. As would be expected, the majority of sampled loans were to married borrowers, aged 25-35, with housing expense-to-income ratios of 20-38%, debt-to-income ratios of 20-41%, and credit scores in the range of 620-740. As would be expected (Table 2), among prepaid loans, the computed mean of the intrinsic value of the call option at termination substantially exceeded that at time of loan origination. Owing to equity build-up over the loan period, the intrinsic value of the put option at the time of loan origination (probability of negative equity) substantially exceeded that at time of loan termination.

[15] In an analysis of GSE-conforming loan yield spreads, Ambrose, LaCour-Little and Sanders (2004) argue that the LTV, mortgage amount, and mortgage contract rate are jointly determined. Hence they introduce a two-stage methodology to estimate a fitted value for LTV. However, the current analysis does not estimate a relationship between loan rates and LTV and instead focuses on FHA loan termination risk. Further, to avoid potential problems of multicollinearity, we choose to include only the LTV as a regressor in the loan termination equations. Also, during the 1992-1996 period of loan origination, the underwriting of FHA-insured loans did not allow for variance in mortgage contract rates based upon borrower choice of LTV. Accordingly, the Ambrose et al (2004) two-stage least squares procedure is less pertinent to the analysis undertaken herein.

4. EMPIRICAL RESULTS

Our competing risks analysis is based on a stratified choice-based sample of FHA loan data provided by HUD. A weighting variable is used in the maximum likelihood estimation (MLE) procedure to correct the possible sample selection bias. That weight addresses the stratified choice-based sampling of mortgage files across race and loan status cells. More specifically, the weight is defined as the inverse of probability that the loan observation is being selected from a cell where it was sampled.[16] The competing risks of default and prepayment are estimated jointly.

Table 3 presents three variants of the competing risks model of FHA loan termination. Each model contains separate flexible baseline functions for default and prepayment that follow Han and Hausman [1990].[17] Model 1 does not control directly for the values of the call and put options in the estimating equations. Further, that model excludes controls for mortgage borrower credit scores. Accordingly, the specification of Model 1 approximates that of many prior micro-data analyses of FHA mortgage default and provides a benchmark for the competing risks specifications discussed below.[18] Further, Model 1 also includes the SMSA unemployment rate as a time-varying proxy for local economic conditions. The time-varying covariates include the SMSA level unemployment rate. Model 2 extends Model 1 by including the contemporaneous values of both the call and put options in both risk equations. Model 3 extends Model 2 by including the borrower's credit score information. In addition, the intrinsic values of the put and

[16] Here we assume that the sampling mechanism is independent of error distribution of the competing risks of FHA loan prepayment and default risks.

[17] We also estimate these models using 100% SDA and PSA curves as our baselines for loan default and prepayment, respectively. The estimated parameters are robust to alternative specifications of baseline hazards functions.

[18] For a recent micro-based analysis of the FHA default experience, see Cotterman (2001).

call options are interacted with borrower credit scores.[19] All specifications also include a rich set of time-constant controls for borrower, loan, and locational determinants of exercise of the default and prepayment options. Overall, the competing risks models are well-specified and control for approximately 30 different characteristics of the loan, the borrower, and the census tract or area in which the property is located.

As evidenced in Model 1, estimation results indicate that increases in local unemployment rates negatively affect the exercise of the prepayment option but positively affect the exercise of the default option. These results are highly significant across model specifications and are consistent with previous studies based on agency conforming loan data (see for example Deng, Quigley, and Van Order [2000]).

The estimates from Model 1 suggest that the initial loan-to-value ratio is negatively associated with prepayment risk and positively associated with default risk.[20] The estimated LTV coefficients are statistically significant across all model specifications. Higher levels of LTV may reflect in part borrower difficulties in loan re-qualification that diminish the exercise of the prepayment option. Model 1 also reports that prepayment likelihoods vary positively with mortgage expense burdens. An increase in the ratio of housing expense-to-income from less than 20% to 20-38% and to 38% or greater results in statistically significant increases in the likelihood of mortgage prepayment. However, results of the competing risk specifications (models 2 and 3) suggest that borrowers with housing expense-to-income ratios in the 20-38% range are most likely to prepay, whereas those with ratios below 20% or in excess of 38% are less likely to prepay. In contrast, borrower total debt-to–income burdens do not figure

[19] Ambrose, Capone and Deng [2001] found that the estimation of mortgage prepayment and default risks is also sensitive to housing cycle effects. However, the data utilized in our span pertain only to the expansionary period subsequent to the early-1990s downturn. As such, we were not able to test for market-cycle effects in our analysis.

significantly in the exercise of prepayment options. In the competing risk model, neither the front- or back-end mortgage obligation ratio is significant in the exercise of the default option.[21,22]

Model 1 indicates that prepayment likelihoods are elevated among loans subject to interest rate "buy-downs". The estimated coefficient associated with that variable is insignificant in the default equation. In contrast, exercise of the prepayment option is significantly damped among first-time borrowers and single-female borrowers. Compared to married couples, single male borrowers are of significantly higher default risk. As would be expected, shorter-term mortgage loans are characterized by significantly lower prepayment and default risks. Borrowers with a larger number of dependents are significantly less likely to exercise the prepayment option but significantly more likely to exercise the default option. Borrowers with greater liquid assets (and hence fewer liquidity constraints) are less likely to exercise the default option; however, borrower liquid assets do not significantly affect exercise of the prepayment option. Younger and higher income borrowers are more likely to prepay; however, those factors are not statistically significant in the exercise of the default option. Having accounted for borrower and loan characteristics, findings indicate that census tract level controls are not significant to the exercise of the mortgage options.[23] Further, estimation findings are largely robust to the

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[20] In many prior studies, the ratio of the size of loan to the market value of the property at the time of loan origination is particularly important in predicting default probability, with higher LTVs associated with higher likelihoods of default. See, for example, Berkovec, Canner, Gabriel, and Hannon [1998].

[21] The two "obligation ratios" of housing expense-to-income and total debt payment-to-income are presented as a series of dummy variables indicating specific ranges of these ratios. This approach was adopted because the cut-off values are relevant to FHA loan underwriting guidelines. Therefore we allow for these nonlinearities in our estimation procedure.

[22] Earlier micro-data analyses of default likelihood indicate the importance of increases in the front-end ratio to exercise of the default option. As suggested, those results are not robust to the competing risk specification of mortgage default and prepayment.

[23] Estimation of Table 3 inclusive of census tract controls is contained in Appendix A, Table A1.

exclusion of those controls. Research findings also indicate little systematic variations in loan termination propensities across central city, suburban, or rural areas.

The competing risks model also tests for variation in the exercise of default and prepayment options across borrower race and ethnicity. As evidenced in Model 1, Asian borrowers do not appear to be statistically different from white borrowers in their exercise of either the mortgage put or call options. In marked contrast, both Hispanic and black borrowers are characterized by statistically damped prepayment likelihoods. The damped exercise of the prepayment option among Hispanic and black borrowers — in cases where the call option is "in the money" — serves to enhance returns to investors in FHA-insured mortgages.[24] In contrast to earlier studies, results of the estimation of the competing risks model do not indicate the presence of statistically elevated default risks among black and Hispanic borrowers.[25]

Model 2 extends Model 1 through the introduction of the option-related time-varying covariates into both the prepayment and default equations. The call and put option controls are similar to those used by Deng, Quigley, and Van Order [1996]. Note, however, that the FHA data utilized herein enables a much richer specification of the competing risks than has been previously estimated using conventional loan data (see, for example, Deng, Quigley and Van Order [1996, 2000], and Van Order and Zorn [2002]). The estimates confirm that the call option value is positive and highly significant in the exercise of the prepayment option; similarly, the value of the put option (probability of negative equity) also is positive and highly significant in

[24] Kelly [1995] also found substantial difference between blacks and whites in prepayment behavior among VA mortgage borrowers. Chinloy and Megbolugbe [1994] and Kelly [1995] hypothesized that racial difference in prepayment risk might offset the higher credit risk associated with minority borrowers. But neither study was built upon a competing risks analysis of mortgage default and prepayment, nor did these earlier studies include crucial borrowers' credit worthiness information such as credit score and other time-varying controls.

[25] This result stands in contrast to earlier results indicating statistically elevated default probabilities among black borrowers (see, for example, Berkovec, Canner, Gabriel, and Hannon [1998]). As well appreciated, however, the FHA data utilized herein derives from a more recent period. Further, earlier results did not derive from a competing

the exercise of the default option. In other words, declines in mortgage interest rates that bring the call option "into-the-money" will lead to a high volume of prepayment activities, as is observed in the data in the sharp upward movement in mortgage prepayment activity in both 1993 and 1998. On the other hand, when the probability of negative equity becomes imminent, the incidence of default increases dramatically. These findings strongly support the predictions of option theory in explaining the exercise of default and prepayment options on the part of mortgage borrowers.

Model 2 further suggests that a higher probability of negative equity significantly reduces the risk of mortgage prepayment. Such an outcome is indeed plausible, in that households with poor equity positions may be less willing to exercise the refinance option owing to equity values that may be insufficient to refinance the remaining loan balance. On the other hand, the value of the call option exerts a significant positive influence on default propensities. This may be explained by the fact that when market rates drop, the value of call option increases, as does the market value of the mortgage. Relative to the market value of the outstanding balance of the loan, the underlying collateral (the house) is less valuable to the borrower so as to encourage borrower exercise of the default option. These findings are consistent with Deng, Quigley, and Van Order [2000]. For the most part, the remaining estimated coefficients of Model 2 are robust to the inclusion of the call and put option values.

Model 3 extends Model 2 through the introduction of borrower credit scores into both the default and prepayment equations. The credit scores are entered in a nonlinear fashion consistent with cut-off values commonly used in loan underwriting. As evidenced in Model 3, the credit score terms are statistically significant in the default equation. As would be expected, relative to

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risks model of mortgage default and prepayment replete with credit score information and other time-varying controls.

the excluded highly credit qualified borrowers (credit score > 740), lower score borrowers are more likely to exercise the default option. On average, the default propensity of the middle qualified group (credit score in the 620-680 range) is almost twice as high as the more highly qualified group (score in the 680-740 range), whereas the default risks associated with the least qualified group (credit score below 620) are about 2.3 times higher than the group with score between 680-740.[26]

The credit score variables also are interacted with the time-varying estimates of the call and put options. As evidenced in Model 3 results, the interactive credit score and call option terms are positive and highly significant in the loan prepayment equation. Further, the estimated coefficients indicate more ruthless exercise of the call option among the most credit worthy borrowers.[27] Among borrowers with credit scores in excess of 740, for example, the influence of the call option value on prepayment propensities is about one-third higher than that of borrowers with credit scores below 620. The estimated interactions between credit scores and the value of the call option also underscore the relatively damped prepayment propensities of less credit worthy borrowers, even as that prepayment is "in the money". Similarly, the estimated coefficients on the interactive put option and credit score terms are positive and highly significant, suggesting a U-shaped relation with elevated propensities to default among both relatively low and high credit score borrowers. The estimated coefficients of the interactive put option and credit score variables also are negative and highly significant in the loan prepayment equation.

[26] The default likelihood of the middle qualified group (credit score in the 620-680 range) relative to that of the more highly qualified group (score in the 680-740 range) is 1.405/0.756=1.9, whereas the default risks associated with the least qualified group (credit score below 620) relative to the group with a score between 680-740 is 1.757/0.756=2.3.

[27] These findings are consistent with Bennett et al [2001].

Table 4 reports on the *unadjusted* cumulative probability of prepayment and default by various covariates and at the end of post-origination years one, three, and five. The unadjusted probabilities derive from the full sample of FHA loans. Overall, the data indicate very substantial upward movement in prepayment probabilities over the five years subsequent to mortgage origination; default propensities similarly are shown to move up perceptibly over that period. The top panel reports on the cumulative probabilities of prepayment and default by borrower race. The data indicate elevated default probabilities as well as damped prepayment probabilities among black and Latino borrowers relative to white or Asian borrowers. As would be expected, the data also indicate substantially higher prepayment probabilities and similarly damped default probabilities among those borrowers with liquid assets in excess of median levels. Among other borrower and loan characteristics, elevated prepayment propensities are observed among loans with LTVs below 95 percent and housing expense-to-income ratios of 20-38 percent, and among repeat buyers. Those same borrower and loan categories are associated with relatively damped five-year cumulative default probabilities.

Table 5 simulates the cumulative probabilities of prepayment and default by those borrower and loan characteristics identified in Table 4. As in Table 4, those probabilities are computed for one, three, and five years post loan origination. The simulations are based on a ten percent random sample of loans originated in June 1992. The baseline borrower is assumed to be a white household purchasing an existing suburban home with a 30-year fixed rate mortgage. The values of the other time-invariant control variables are set at their sample means, whereas time-varying covariates are set at their sample mean in each period.[28] Those covariates that are the focus of model simulation are specified in the table.[29]

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[28] Among time-invariant controls, for example, the simulation assumes two dependents per household. Further, the average loan-to-value ratio is set equal to 94 percent, whereas the log values of property value, household liquid

As would be expected, the 5-year cumulative probability of prepayment rises substantially with borrower credit worthiness (as reflected in borrower credit scores). That probability is 31 percent higher among borrowers with scores in excess of 680 than among those with scores below 620 ([42.43%-29.46%]/42.43% = 31%). Among white borrowers, for example, the 5-year cumulative probability of prepayment of 39.93% is about 1-1/2 times the 26.19% rate estimated for similarly credit worthy blacks. Indeed, computation of cumulative prepayment rates by race and credit worthiness illustrates the strikingly lower prepayment propensities of black borrowers, relative to their white, Latino, and Asian counterparts. Likewise, cumulative default rates among black borrowers are estimated to be substantially in excess of those for other racial groups. At 7.2%, the 5-year cumulative default rate of highly credit worthy black borrowers is 43 percent higher ([7.22%-4.15%]/7.22% = 43%) than that of similarly qualified white borrowers.

We also simulated the cumulative probability of prepayment and default by initial loan-to-value ratios. As would be expected, higher levels of credit risk serve both to elevate default likelihoods and to damp prepayment propensities. For example, as shown in Table 5, at 5 years post loan origination, borrowers with high LTVs (LTVs ≥ 95%) are characterized by slightly higher default risk than borrowers with lower LTVs. Also evident, however, are the substantially lower prepayment propensities of those high LTV borrowers; at 5 years post loan origination, the prepayment likelihoods of high LTV borrowers were 10 percent below those of lower LTV loans. A similar outcome is evidenced, for example, in the simulation of default and prepayment propensities among more or less credit worthy borrowers. At 5 years post loan origination, borrowers with lower credit scores (credit scores < 620) are characterized by 3.8

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assets, and family income are set to 11.13, 8.54, and 8.00, respectively. These simulations further assume that the borrowers are married, first-time buyers and that the loan interest rate is not subject to buy-down.

times the default risk (10.98/2.86= 3.84) of borrowers with higher credit scores. Those same lower credit score borrowers are characterized by damped prepayment risk relative to their higher credit score counterparts.[30]

The bottom rows of Table 5 provide simulations of default and prepayment propensities among more fully specified high- and low- credit risk borrowers. The precise specification of those borrower profiles is reported in Appendix A, Table A2. In general, high credit risk borrowers are first-time buyers with subprime quality credit (credit scores less than 620) and lower levels of liquid assets. With some limited nuance, lower credit risk borrowers are the opposite.

As is evidenced in Table 5, loan performance behavior differs markedly over these borrower risk profiles. For example, by end of year 5 post loan origination, the simulated prepayment propensity of the lower credit risk borrower is about 18 percentage points higher than that of the higher credit risk borrower. However, lower credit risk borrowers are characterized by a 5-year cumulative default propensity that is about 9 percentage points lower than that of their higher credit risk counterparts. On net, results provide clear evidence of elevated total loan termination probabilities among the lower credit risk group.

The right-hand columns of Table 5 provide an assessment of total termination risks of FHA-insured mortgage loans. Those risks are defined as the sum of the default and prepayment

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[29] In our simulation, we choose to hold the baseline prepayment and default risks constant at 10 years post loan origination. This is similar to the flat tail assumption used in computing the standard industry PSA prepayment benchmark.

[30] Other simulations suggest that by the end of year five post-origination, younger borrowers (age of household head is less than 25 years old) are characterized by 1.4 times the prepayment risks (46.98%/33.66%=1.4) of older households (age of household head greater than 45 years old). While the simulated risks of loan default similarly move up over the five-year period post origination, the differences between age groups is slight. Findings further suggest that the cumulative 5-year risk of prepayment is relatively higher among married couples (41%) than single females (38%). In marked contrast, the 5-year cumulative probability of default among single males is about 1.4 times (4.71%/3.45%=1.4) that of single females. We further find little quantitative variation in the cumulative probabilities of default across first-time buyer status. Results of these analyses are available from the authors upon request.

propensities at the end of years 1, 3, and 5. Total loan terminations (from all sources) are relevant to the profitability of investment in FHA-insured mortgages. Typically, those loans not only are FHA-insured, but if pooled and sold also often are backed by a Ginnie Mae guarantee of timely repayment of principal and interest in the event of borrower default. Accordingly, from the perspective of the FHA-backed and Ginnie Mae insured loan investor, a loan termination via default is equivalent to that which derives from prepayment. Clearly, when the call option is "in the money", borrower groups with lower total loan termination risks may provide opportunities for elevated investor returns, relative to returns on mortgages originated among groups with higher total termination propensities.

As is evident in Table 5, total loan termination risk is substantially elevated among lower credit risk borrowers. In that regard, total termination risk among low credit risk borrowers is about 23 percent ([47.91%-39.01%]/39.01% = 23%) in excess of that of high credit risk borrowers. As is further apparent, the substantially elevated default probabilities among the high credit risk group are more than offset by the damped prepayment propensities, resulting in significantly lower loan termination propensities overall. Indeed, among high credit risk borrowers, loan termination probabilities via prepayment at the end of year 5 post origination are about 2.3 times that of loan termination propensities from default, while for low credit risk borrowers, prepayment probabilities at the end of year 5 post origination are about 17.5 times that of default probabilities. In a declining interest rate environment, loans originated among high credit risk borrowers may provide elevated returns to the investor, given their substantially depressed overall termination propensities.

5. IMPLICATIONS FOR LOAN PRICING

To assess the mortgage pricing implications of the loan performance results, we simulate the difference in market value of high credit risk versus low credit risk mortgage pools. In the simulation, we adopt an Affine Term Structure Model (ATSM) as proposed by Dai and Singleton [2000].[31]

In our application, we simulate short rates over a thirty-year period with 3.6 million equally divided intervals. We then randomly sample 2,000 monthly interest rate paths over the thirty-year period. These 2,000 randomly sampled interest rate paths are applied to the prepayment and default functions reported by Model 3 in Table III to compute the monthly prepayment and default risks associated with hypothetical one million dollar mortgage pools. We compare two hypothetical mortgage pools characterized by different credit risks. The borrowers contained in the high credit risk pool are defined by the following risk characteristics: credit score less than 620, housing expense-to-income ratio greater than 38 percent, first-time home buyer, limited liquid assets. Borrowers in the low credit risk pool are defined by the following risk characteristics: credit score greater than 680, housing expense-to-income ratio less than 38 percent, repeat home buyer, higher levels of liquid asset. The LTVs for both groups are set as 95 percent.[32] Finally, the prepayment and default risk-adjusted mortgage amortization cash flows are discounted to the present using the individual interest rate paths.

Table 6 reports the simulated risk premia measured in basis points. We compute the basis point spread using an approach similar to the OAS computation. In other words, we employ a Newton-Raphson optimization routine to compute the basis point spread between the high credit

[31] Our simulation is based upon equation (23) of Dai and Singleton [2000], using the parameters reported in Dai and Singleton [2000] Table II, Column 2. Appendix B reports the average path of simulated interest rates over ten and thirty years, respectively, using these equations and parameters.

risk/low prepayment and low credit risk/high prepayment pools that make the risk premium between those pools go to zero. More specifically, the optimal BSP spread is computed through a Newton-Raphson iteration routine such that

$$BSP^{i+1} = BSP^{i} - \left(H\right)^{-1} S\left(BSP^{i}\right), \tag{7}$$

$$S = \sum_{t=1}^{T}\left(\frac{CF_{HighRisk,t}}{\left(1+r_t+\left(BSP/10,000\right)\right)^{t}} - \frac{CF_{LowRisk,t}}{\left(1+r_t\right)^{t}}\right), \tag{8}$$

$$\begin{aligned} H &= \frac{\partial S\left(BSP\right)}{\partial BSP} \\ &= -\sum_{t=1}^{T}\frac{t}{10,000}\times\frac{CF_{HighRisk,t}}{\left(1+r_t+\left(BSP/10,000\right)\right)^{t+1}}, \end{aligned} \tag{9}$$

where $CF_{HighRisk}$ and $CF_{LowRisk}$ are risk adjusted mortgage amortization cash flows computed from high and low credit risk pools, respectively, and S and H are score and Hessian information matrices, respectively.

Results of the Dai-Singleton simulated term structure indicate a negative risk premium associated with the high credit risk/low prepayment speed pools throughout, owing to the markedly lower prepayment probabilities associated with the underserved borrower group. As would be expected, the estimated magnitude of the negative risk premia increases with the seasoning of the pool and the weighted average coupon rate. Indeed, prepayment probabilities move up with increases in the WAC relative to it's historic norm, suggesting a more negative risk premia for the slower prepayment borrower group. In the case of a long-term mean weighted average coupon rate of 8.25 percent, we compute a negative risk premium of approximately 21 basis points for a 5-year seasoned pool. The negative risk premia increases to

[32] A precise specification of the hypothetical pools of high credit risks vs. low credit risk borrowers is reported in Appendix A, Table A2.

44 basis points in the case of a 10-year seasoned pool.[33] In all cases, the simulated stratification of mortgage pools results in a potentially sizable reduction in risk premia to investors in high default/low prepayment risk mortgages, in turn suggesting a like reduction in mortgage interest rates to those relatively higher credit risk and low prepayment borrowers.[34]

6. SUMMARY AND CONCLUSION

This paper applies micro-data from the FHA to estimate an option-based hazard model of the competing risks of mortgage default and prepayment. The empirical model is motivated by option theory and includes proxies for mortgage put and call options, borrower credit worthiness, lending market concentration, and numerous other contemporaneous and time-invariant borrower, loan, and locational controls. The estimated competing risks of prepayment and default are then used to simulate the performance of FHA-insured mortgages originated among low- and high credit risk borrowers. Further simulation enables estimation of the mortgage pricing implications of the loan performance results.

Results of the analysis strongly support the predictions of option theory in explaining the exercise of default and prepayment options among FHA mortgage borrowers. The estimates confirm that the call option value is positive and highly significant in the exercise of the prepayment option; similarly, the value of the put option (probability of negative equity) also is

[33] We have also tested two alternative specifications of high/low credit risk pools. For example, we have set LTV to be 95% for the high credit risk pool and 80% for the low credit risk pool; alternatively we assumed that high credit risk borrowers live in neighborhoods where house value appreciate at 3% annually, while low credit risk borrowers live in a neighborhoods where house value appreciate at 7% annually. In both cases, results are robust as those reported in Table 6.

[34] Other factors could contribute to a reduction in the pricing of mortgage pools comprised largely of low-income and minority borrowers. For example, investment in such pools could be valuable to financial institutions seeking to fulfill community lending obligations under the Community Reinvestment Act. As such, the pricing of such pools could reflect their regulatory value in addition to anticipated performance differentials.

positive and highly significant in the exercise of the default option. Results further suggest that a higher probability of negative equity reduces the risk of mortgage prepayment. Such an outcome is indeed plausible, in that households with poor equity positions may be less willing to exercise the refinance option owing to equity values that may be insufficient to refinance the remaining loan balance.

Results further point to the importance of other borrower, loan, and market characteristics in the estimation of mortgage termination risks. Among FHA borrowers, the initial loan-to-value ratio is negatively associated with prepayment propensity and positively associated with default propensity. As would be expected, higher credit score borrowers are less likely to exercise the default option, whereas lower credit score borrowers are less likely to prepay. In that regard, the 5-year cumulative probability of prepayment is 31 percent higher among borrowers with scores in excess of 680 than among those with scores below 620. Relative to white borrowers, estimates suggest that black and Hispanic borrowers are statistically less likely to prepay. Indeed, computation of cumulative prepayment rates by race and credit worthiness illustrates the strikingly lower prepayment propensities of black borrowers, relative to their white, Latino, and Asian counterparts.

Overall, results indicate the appropriateness of the competing risk specification and indicate the importance of slower prepayment speeds among higher risk FHA-insured borrowers. As is evidenced, the substantially elevated default probabilities of higher credit risk borrowers are more than offset by their damped prepayment propensities, resulting in significantly lower loan termination propensities overall. Indeed, among high credit risk borrowers, at 5 years post loan origination, loan termination probabilities via prepayment are about 2.3 times that of loan default, while for low credit risk borrowers, prepayment probabilities at the end of year 5 post origination are about 17.5 times that of loan default. For the investor in FHA-insured mortgage pools, the estimated 5-year cumulative probability of mortgage termination among high default risk and minority borrowers is only about four-fifths that of low-default risk and non-minority borrowers, respectively.

Simulation methods are then utilized to compute the mortgage pricing implications of the loan performance results. In the case of a mean weighted average coupon of 8.25 percent and a 5-year seasoned pool, we compute a negative risk premium of 21 basis points in the case of a high default/slow prepayment speed pool. The estimated negative risk premium increases to 44 basis points in the case of a 10-year seasoned pool. In all cases, the simulated stratification of mortgage pools results in a potentially sizable reduction in risk premia to investors in high default/low prepayment risk mortgages. Empirical findings suggest that such pooling and risk-based pricing of FHA-insured mortgages could serve to substantially reduce the housing finance costs of underserved borrowers, so as to advance both their homeownership opportunities and related federal housing policy objectives.

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TABLE 1

MEANS AND VARIANCES OF TIME-CONSTANT VARIABLES

Variables	Means (Variances)	Variables	Means (Variances)
Credit Scores < 620 (categorical variable)	0.1874 (0.158)	Mortgage Term < 30 Years (categorical variable)	0.0380 (0.038)
Credit Scores 620~680 (categorical variable)	0.3098 (0.224)	Central City Location (categorical variable)	0.4405 (0.262)
Credit Scores 680~740 (categorical variable)	0.3161 (0.228)	Rural (categorical variable)	0.0662 (0.064)
Black (categorical variable)	0.1240 (0.117)	First Time Home Buyer (categorical variable)	0.6711 (0.244)
Asian (categorical variable)	0.0168 (0.019)	New House (categorical variable)	0.0789 (0.077)
Hispanic (categorical variable)	0.1214 (0.130)	Unmarried Co-borrower (categorical variable)	0.1114 (0.103)
Others (categorical variable)	0.0205 (0.023)	Single Male (categorical variable)	0.1936 (0.162)
Loan-to-Value Ratio	0.9383 (0.034)	Single Female (categorical variable)	0.2022 (0.168)
Housing Exp. to Income Ratio 20~38% (categorical variable)	0.6447 (0.254)	Number of Dependents	0.7692 (1.288)
Housing Exp. to Income Ratio > 38% (categorical variable)	0.0103 (0.011)	Log Value of Liquid Assets	8.4707 (4.966)
Debt to Income Ratio 20~41% (categorical variable)	0.8041 (0.187)	Borrower Age < 25 (categorical variable)	0.1101 (0.101)
Debt to Income Ratio 41~53% (categorical variable)	0.1577 (0.137)	Borrower Age 25~35 (categorical variable)	0.4977 (0.267)
Debt to Income Ratio > 53% (categorical variable)	0.0084 (0.009)	Borrower Age 35~45 (categorical variable)	0.2614 (0.204)
Buydown (categorical variable)	0.0242 (0.025)	Log Value of Household Income	8.0379 (2.340)
Log of Property Appraisal Value	11.2102 (4.423)		
Number of Observations		12,021	

Note: Variances are in parentheses.

TABLE 2

MEANS AND VARIANCES OF TIME-VARYING VARIABLES AT ORIGINATION AND TERMINATION

Variables	At Origination				At Termination	
	All Loans	Prepaid	Defaulted	Other*	Prepaid	Defaulted
Fraction of Contract Value (Call Option)	-0.0120 (0.007)	0.0001 (0.007)	-0.0022 (0.005)	-0.0265 (0.008)	0.0750 (0.007)	0.0352 (0.005)
Probability of Negative Equity (Put Option)	0.0111 (0.003)	0.0084 (0.002)	0.0113 (0.005)	0.0140 (0.004)	0.0169 (0.004)	0.0531 (0.0166)
SMSA Unemployment Rate (percent)	5.6901 (7.498)	5.7902 (5.526)	4.2433 (12.690)	5.8291 (8.333)	4.2383 (4.120)	3.4211 (8.283)
Number of Observations	12,021	5,730	913	5,378	5,730	913

Note: Variances are in parentheses.

*Other includes those outstanding at the end of the observation period.

TABLE 3

MAXIMUM LIKELIHOOD ESTIMATES FOR COMPETING RISKS OF FHA MORTGAGE PREPAYMENT AND DEFAULT

	Model 1		Model 2		Model 3	
	Prepay	Default	Prepay	Default	Prepay	Default
Fraction of Contract Value (Call Option)			4.932 (27.26)	2.203 (3.55)		
Probability of Negative Equity (Put Option)			-2.11 (9.64)	2.178 (6.7)		
Interaction of Call Option Credit Scores < 620					4.539 (10.67)	2.183 (1.99)
Interaction of Call Option Credit Scores 620~680					4.215 (13.36)	1.528 (1.57)
Interaction of Call Option Credit Scores 680~740					5.378 (18.19)	1.67 (1.38)
Interaction of Call Option Credit Scores >740					5.83 (15.94)	2.705 (1.42)
Interaction of Put Option Credit Scores < 620					-4.047 (6.71)	2.89 (3.95)
Interaction of Put Option Credit Scores 620~680					-2.648 (5.6)	1.845 (3.22)
Interaction of Put Option Credit Scores 680~740					-1.956 (5.24)	2.662 (5.15)
Interaction of Put Option Credit Scores >740					-1.529 (4.28)	3.068 (4.2)
Credit Scores < 620 (dummy)					-0.042 (0.65)	1.757 (5.78)
Credit Scores 620~680 (dummy)					0.005 (0.1)	1.405 (4.83)
Credit Scores 680~740 (dummy)					-0.019 (0.4)	0.756 (2.53)
Black (dummy)	-0.458 (9.66)	0.78 (6.50)	-0.527 (10.98)	0.768 (6.42)	-0.496 (10.19)	0.496 (4.05)
Asian (dummy)	-0.07 (0.75)	-0.061 (0.15)	0.003 (0.03)	-0.188 (0.43)	0.011 (0.11)	-0.249 (0.52)
Hispanic (dummy)	-0.235 (5.10)	0.386 (2.93)	-0.296 (6.34)	0.304 (2.29)	-0.284 (6.07)	0.19 (1.43)
Others (dummy)	-0.243 (2.46)	0.24 (0.78)	-0.369 (3.69)	0.145 (0.48)	-0.338 (3.36)	-0.02 (0.07)

TABLE 3–*Continued*.

	Model 1		Model 2		Model 3	
	Prepay	Default	Prepay	Default	Prepay	Default
SMSA Unemployment Rate (percent)	-0.129 (17.33)	0.08 (4.37)	-0.117 (15.05)	0.045 (2.19)	-0.117 (15)	0.048 (2.3)
Loan-to-Value Ratio	-1.402 (7.32)	0.767 (0.90)	-0.993 (5.24)	0.341 (0.40)	-1.002 (5.26)	0.205 (0.24)
Housing Exp. to Income 20~38% (dummy)	0.223 (5.63)	0.338 (2.15)	0.11 (2.73)	0.174 (1.07)	0.108 (2.67)	0.207 (1.24)
Housing Exp. to Income > 38% (dummy)	0.312 (2.18)	0.247 (0.45)	0.097 (0.65)	0.018 (0.03)	0.084 (0.56)	0.19 (0.34)
Debt to Income Ratio 20~41% (dummy)	0.11 (1.44)	-0.288 (0.86)	0 0.00	-0.293 (0.86)	0.012 (0.15)	-0.426 (1.25)
Debt to Income Ratio 41~53% (dummy)	0.219 (2.64)	-0.06 (0.17)	0.075 (0.90)	-0.061 (0.17)	0.099 (1.17)	-0.269 (0.75)
Debt to Income Ratio > 53% (dummy)	0.275 (1.69)	-0.467 (0.66)	0.01 (0.06)	-0.527 (0.74)	0.039 (0.24)	-0.75 (1.05)
Buydown (dummy)	0.236 (3.11)	0.138 (0.46)	0.142 (1.85)	0.058 (0.19)	0.141 (1.85)	0.1 (0.32)
Log Value of Property Appraisal Value	-0.094 (1.58)	-0.076 (0.37)	0.173 (2.79)	0.168 (0.78)	0.163 (2.64)	0.177 (0.80)
Mortgage Term < 30 Year (dummy)	-0.29 (4.25)	-1.219 (2.71)	-0.025 (0.36)	-1.014 (2.24)	-0.034 (0.49)	-0.975 (2.12)
Central City Location (dummy)	0.037 (1.39)	-0.158 (1.61)	0.04 (1.52)	-0.164 (1.68)	0.04 (1.51)	-0.152 (1.53)
Rural (dummy)	0.041 (0.75)	-0.271 (1.22)	0.048 (0.86)	-0.325 (1.48)	0.05 (0.90)	-0.286 (1.28)
First Time Home Buyer (dummy)	-0.184 (6.53)	0.135 (1.24)	-0.197 (7.00)	0.127 (1.17)	-0.189 (6.70)	0.069 (0.64)
New House (dummy)	-0.137 (2.86)	-0.08 (0.42)	-0.03 (0.62)	-0.045 (0.23)	-0.029 (0.60)	-0.035 (0.18)
Unmarried Co-borrower (dummy)	-0.008 (0.18)	-0.085 (0.48)	-0.012 (0.28)	-0.095 (0.53)	-0.016 (0.36)	-0.076 (0.43)
Single Male (dummy)	0.019 (0.51)	0.295 (2.33)	-0.01 (0.26)	0.308 (2.43)	-0.007 (0.18)	0.266 (2.09)
Single Female (dummy)	-0.087 (2.19)	-0.214 (1.47)	-0.107 (2.71)	-0.19 (1.30)	-0.108 (2.72)	-0.225 (1.51)
Number of Dependents	-0.07 (5.30)	0.125 (3.05)	-0.084 (6.31)	0.111 (2.74)	-0.077 (5.78)	0.068 (1.60)

TABLE 3–*Continued*.

	Model 1		Model 2		Model 3	
	Prepay	Default	Prepay	Default	Prepay	Default
Log Value of Liquid Assets	0.005 (0.61)	-0.084 (2.78)	0.016 (1.82)	-0.089 (2.91)	0.012 (1.41)	-0.066 (2.04)
Borrower Age < 25 (dummy)	0.418 (7.53)	0.19 (1.04)	0.441 (7.91)	0.257 (1.41)	0.444 (7.94)	0.147 (0.80)
Borrower Age 25~35 (dummy)	0.245 (5.71)	-0.211 (1.42)	0.281 (6.47)	-0.149 (1.00)	0.282 (6.48)	-0.206 (1.37)
Borrower Age 35~45 (dummy)	0.055 (1.19)	-0.174 (1.08)	0.069 (1.48)	-0.11 (0.68)	0.069 (1.46)	-0.153 (0.94)
Log Value of Household Income	0.58 (8.91)	-0.128 (0.53)	0.206 (3.04)	-0.425 (1.66)	0.222 (3.27)	-0.53 (2.02)
Log Likelihood	-35,721		-35,296		-35,206	

Note: T-ratios are in parentheses. All models are estimated by ML approach. Prepayment and default functions are considered as correlated competing risks and they are estimated jointly. Flexible baseline functions (following Han and Hausman [1990]) for prepayment and default are estimated simultaneously with the competing risks hazard functions.

TABLE 4

UNADJUSTED CUMULATIVE PROBABILITY OF PREPAYMENT AND DEFAULT BY VARIOUS COVARIATES AT THE END OF ONE-, THREE-, AND FIVE-YEAR

	Prepayment			Default		
	End of Year1	End of Year 3	End of Year5	End of Year1	End of Year 3	End of Year5
By Borrower Race						
White	2.33%	22.77%	39.65%	0.46%	2.21%	3.30%
Black	1.39%	14.12%	24.78%	1.03%	5.77%	8.77%
Hispanic	1.65%	16.35%	30.52%	1.15%	5.84%	7.92%
By Liquid Asset						
Liquid Asset ≥ Median	2.37%	23.59%	40.28%	0.48%	2.32%	3.48%
Liquid Asset < Median	2.00%	18.43%	33.33%	0.74%	3.82%	5.51%
By LTV						
LTV < 95%	2.68%	21.61%	37.75%	0.59%	2.76%	4.01%
LTV ≥ 95%	1.87%	20.61%	36.18%	0.63%	3.27%	4.81%
By Buyers' Type						
Repeat Buyer	3.26%	24.74%	41.18%	0.56%	2.56%	3.83%
First Time Buyer	1.65%	19.16%	34.64%	0.64%	3.33%	4.83%
By Housing Expense Ratio						
20% < HEI ≤ 38%	2.11%	20.81%	36.89%	0.69%	3.51%	5.13%
Otherwise	2.31%	21.35%	36.61%	0.46%	2.28%	3.37%
By Credit Score						
Credit Score ≥ 680	2.51%	23.36%	40.02%	0.22%	1.33%	2.34%
Credit Score < 620	1.66%	17.99%	31.38%	1.36%	6.39%	8.67%
By Risk Type						
Low Credit Risk	3.73%	27.57%	44.38%	0.25%	1.26%	2.43%
High Credit Risk	1.14%	15.59%	27.72%	1.63%	6.55%	8.04%

Note: Unadjusted probabilities are calculated based on cleaned full sample.

TABLE 5

PREDICTED CUMULATIVE PROBABILITY OF PREPAYMENT AND DEFAULT RISKS BY VARIOUS COVARIATES AT THE END OF ONE-, THREE-, AND FIVE-YEAR

	Prepayment			Default			Total Termination		
	End of Year1	End of Year3	End of Year 5	End of Year1	End of Year 3	End of Year5	End of Year1	End of Year 3	End of Year5
By Borrower Race									
White	2.25%	18.69%	39.93%	0.65%	2.71%	4.15%	2.91%	21.40%	44.08%
Black	1.37%	11.71%	26.19%	1.07%	4.58%	7.22%	2.45%	16.28%	33.40%
Hispanic	1.70%	14.36%	31.67%	0.79%	3.35%	5.23%	2.49%	17.71%	36.90%
By Liquid Asset									
Liquid Asset ≥ Median	2.11%	17.64%	38.01%	0.67%	2.78%	4.28%	2.78%	20.42%	42.29%
Liquid Asset < Median	2.09%	17.43%	37.58%	0.71%	2.97%	4.57%	2.80%	20.40%	42.15%
By LTV									
LTV < 95%	2.29%	18.99%	40.43%	0.68%	2.86%	4.42%	2.97%	21.85%	44.85%
LTV ≥ 95%	2.04%	17.02%	36.83%	0.70%	2.92%	4.50%	2.73%	19.94%	41.34%
By Buyers' Type									
Repeat Buyer	2.37%	19.55%	41.43%	0.71%	2.92%	4.43%	3.08%	22.47%	45.86%
First Time Buyer	1.96%	16.46%	35.79%	0.66%	2.84%	4.47%	2.63%	19.30%	40.26%
By Housing Exp/Inc Ratio									
20%<HEI≤38%	2.18%	18.09%	38.77%	0.74%	3.05%	4.62%	2.92%	21.13%	43.39%
Otherwise	1.96%	16.46%	35.83%	0.61%	2.60%	4.09%	2.57%	19.06%	39.92%
By Credit Score									
Credit Score ≥ 680	2.51%	20.22%	42.43%	0.46%	1.88%	2.86%	2.97%	22.10%	45.29%
Credit Score < 620	1.44%	12.95%	29.46%	1.73%	7.14%	10.98%	3.17%	20.09%	40.44%
By Risk Type									
Low Credit Risk	2.75%	21.93%	45.32%	0.43%	1.72%	2.59%	3.17%	23.65%	47.91%
High Credit Risk	1.33%	11.95%	27.35%	1.83%	7.55%	11.66%	3.15%	19.50%	39.01%

Note: The calculation of probability for each risk group is based on 10% random sample of the mortgage pools originated in June 1992. For each group, probabilities are evaluated at the mean value of each covariate (time-varying means are calculated for time-varying covariates) except for those specified in each risk category such that

a) Liquid asset is evaluated at 75% and 25% quartiles of the sample for higher and lower liquid asset groups, respectively.
b) LTV is set to 97% , and 85% for high LTV category, and low LTV category, respectively.
c) Weighted average of borrowers with credit score between 680 and 740, and credit score above 740 is used to define high credit score group; and weighted average of borrowers with credit below 620 is used to define low credit score group.
d) The low credit risk group consists of borrowers with liquid asset above sample median, repeat-buyer, housing expense to income ratio between 20% and 38%, and credit score above 680.

e) The high credit risk group consists of borrowers with liquid asset below sample median, first-time buyer, housing expense to income ratio greater than 38% , and credit score under 620.
f) We set LTV at 95% for both high credit risk group and low credit risk group.
g) The cumulative probabilities of total termination at the end of year 1, 3, and 5 are the sum of predicted cumulative prepayment and default rates at the end of year 1, 3, and 5, respectively.

TABLE 6

MEAN BASIS POINT SPREAD SIMULATED FROM MORTGAGE POOLS WITH HIGH CREDIT RISK/LOW PREPAYMENT VS. LOW CREDIT RISK/HIGH PREPAYMENT BORROWERS AT DIFFERENT WEIGHTED AVERAGE COUPON RATES

	WAC 7.25	WAC 8.25	WAC 9.25
3-Year Seasoned Pool	-10 bsp (452)	-14 bsp (291)	-15 bsp (194)
5-Year Seasoned Pool	-15 (813)	-21 (521)	-27 (411)
10-Year Seasoned Pool	-23 (5,930)	-44 (3,964)	-65 (2,577)

Note: T-ratios are in parentheses. The simulated market values are computed based on model 3 in Table 3 together with a term structure with a long term mean parameter of 8.27 percent, volatility parameter of 1.5 percent, used by Dai and Singleton and the other parameters reported in Dai and Singleton [2000] Table II, Column 2, page 1964. A detailed specification of high credit risk and low credit risk mortgage pools is reported in Appendix A, Table A2.

APPENDIX A: TABLE A1

MAXIMUM LIKELIHOOD ESTIMATES FOR COMPETING RISKS OF FHA MORTGAGE PREPAYMENT AND DEFAULT WITH CENSUS TRACT CONTROLS

	Model 1		Model 2		Model 3	
	Prepay	Default	Prepay	Default	Prepay	Default
Fraction of Contract Value (Call Option)			4.939 (27.30)	2.218 (3.56)		
Probability of Negative Equity (Put Option)			-2.117 (9.66)	2.19 (6.70)		
Interaction of Call Option Credit Scores < 620					4.545 (10.68)	2.221 (2.01)
Interaction of Call Option Credit Scores 620~680					4.221 (13.38)	1.517 (1.54)
Interaction of Call Option Credit Scores 680~740					5.386 (18.23)	1.661 (1.37)
Interaction of Call Option Credit Scores >740					5.832 (15.95)	2.875 (1.50)
Interaction of Put Option Credit Scores < 620					-4.05 (6.70)	2.917 (4.05)
Interaction of Put Option Credit Scores 620~680					-2.653 (5.60)	1.842 (3.22)
Interaction of Put Option Credit Scores 680~740					-1.957 (5.23)	2.638 (5.12)
Interaction of Put Option Credit Scores >740					-1.545 (4.33)	3.157 (4.24)
Credit Scores < 620 (dummy)					-0.04 (0.63)	1.771 (5.78)
Credit Scores 620~680 (dummy)					0.006 (0.12)	1.418 (4.83)
Credit Scores 680~740 (dummy)					-0.019 (0.40)	0.773 (2.57)
Black (dummy)	-0.459 (9.67)	0.784 (6.46)	-0.528 (11.00)	0.773 (6.39)	-0.497 (10.20)	0.501 (4.05)
Asian (dummy)	-0.071 (0.77)	-0.057 (0.14)	0.001 (0.01)	-0.171 (0.39)	0.009 (0.09)	-0.221 (0.46)
Hispanic (dummy)	-0.236 (5.11)	0.385 (2.91)	-0.297 (6.36)	0.306 (2.29)	-0.285 (6.08)	0.193 (1.45)
Others (dummy)	-0.246 (2.49)	0.238 (0.77)	-0.372 (3.71)	0.143 (0.47)	-0.341 (3.39)	-0.023 (0.08)

TABLE A1–*Continued.*

	Model 1		Model 2		Model 3	
	Prepay	Default	Prepay	Default	Prepay	Default
SMSA Unemployment Rate (percent)	-0.128 (17.27)	0.08 (4.38)	-0.116 (14.97)	0.045 (2.19)	-0.116 (14.92)	0.048 (2.30)
Loan-to-Value Ratio	-1.401 (7.29)	0.806 (0.94)	-0.989 (5.18)	0.369 (0.43)	-0.998 (5.21)	0.243 (0.28)
Housing Exp. to Income 20~38% (dummy)	0.223 (5.62)	0.334 (2.12)	0.109 (2.68)	0.169 (1.04)	0.107 (2.64)	0.2 (1.20)
Housing Exp. to Income > 38% (dummy)	0.314 (2.19)	0.232 (0.42)	0.097 (0.65)	-0.002 0.00	0.085 (0.57)	0.171 (0.30)
Debt to Income Ratio 20~41% (dummy)	0.114 (1.49)	-0.293 (0.87)	0.006 (0.07)	-0.298 (0.87)	0.017 (0.22)	-0.427 (1.25)
Debt to Income Ratio 41~53% (dummy)	0.223 (2.68)	-0.068 (0.19)	0.08 (0.95)	-0.069 (0.19)	0.103 (1.22)	-0.27 (0.76)
Debt to Income Ratio > 53% (dummy)	0.285 (1.75)	-0.456 (0.64)	0.022 (0.14)	-0.52 (0.72)	0.051 (0.31)	-0.74 (1.03)
Buydown (dummy)	0.237 (3.10)	0.135 (0.45)	0.142 (1.84)	0.055 (0.18)	0.141 (1.84)	0.095 (0.31)
Log Value of Property Appraisal Value	-0.09 (1.50)	-0.065 (0.31)	0.18 (2.91)	0.181 (0.83)	0.17 (2.75)	0.193 (0.86)
Mortgage Term < 30 Year (dummy)	-0.289 (4.23)	-1.21 (2.67)	-0.023 (0.33)	-1.003 (2.20)	-0.032 (0.46)	-0.962 (2.07)
Central City Location (dummy)	0.033 (1.19)	-0.146 (1.41)	0.037 (1.30)	-0.152 (1.46)	0.036 (1.29)	-0.134 (1.27)
Rural (dummy)	0.032 (0.58)	-0.221 (0.99)	0.037 (0.65)	-0.266 (1.20)	0.039 (0.69)	-0.218 (0.96)
First Time Home Buyer (dummy)	-0.185 (6.57)	0.137 (1.24)	-0.198 (7.03)	0.129 (1.18)	-0.19 (6.74)	0.07 (0.64)
New House (dummy)	-0.138 (2.89)	-0.084 (0.44)	-0.03 (0.63)	-0.05 (0.26)	-0.029 (0.61)	-0.039 (0.20)
Unmarried Co-borrower (dummy)	-0.008 (0.19)	-0.084 (0.46)	-0.012 (0.28)	-0.094 (0.53)	-0.016 (0.37)	-0.075 (0.41)
Single Male (dummy)	0.018 (0.50)	0.303 (2.37)	-0.009 (0.25)	0.315 (2.48)	-0.006 (0.17)	0.276 (2.15)
Single Female (dummy)	-0.088 (2.21)	-0.208 (1.41)	-0.108 (2.71)	-0.184 (1.25)	-0.108 (2.72)	-0.218 (1.46)
Number of Dependents	-0.07 (5.29)	0.125 (3.03)	-0.084 (6.28)	0.111 (2.75)	-0.077 (5.76)	0.068 (1.61)

TABLE A1–*Continued*.

	Model 1		Model 2		Model 3	
	Prepay	Default	Prepay	Default	Prepay	Default
Log Value of Liquid Assets	0.005 (0.58)	-0.085 (2.79)	0.015 (1.78)	-0.089 (2.91)	0.012 (1.39)	-0.066 (2.03)
Borrower Age < 25 (dummy)	0.42 (7.56)	0.199 (1.08)	0.443 (7.93)	0.266 (1.45)	0.445 (7.96)	0.156 (0.84)
Borrower Age 25~35 (dummy)	0.245 (5.68)	-0.205 (1.37)	0.28 (6.44)	-0.139 (0.93)	0.281 (6.44)	-0.198 (1.31)
Borrower Age 35~45 (dummy)	0.056 (1.19)	-0.172 (1.06)	0.069 (1.46)	-0.109 (0.67)	0.068 (1.45)	-0.154 (0.94)
Log Value of Household Income	0.58 (8.89)	-0.127 (0.52)	0.204 (3.01)	-0.429 (1.66)	0.221 (3.24)	-0.537 (2.03)
Percentage of Black in Census Tract Population	0.048 (0.65)	-0.008 (0.03)	0.034 (0.45)	-0.015 (0.05)	0.03 (0.40)	0.005 (0.02)
Percentage of Asian in Census Tract Population	-0.406 (1.21)	1.267 (1.32)	-0.476 (1.37)	1.389 (1.42)	-0.433 (1.24)	1.297 (1.27)
Percentage of Hispanic in Census Tract Population	0.076 (0.80)	0.013 (0.03)	0.083 (0.89)	0.025 (0.07)	0.082 (0.88)	0.033 (0.09)
Percentage of Others in Census Tract Population	1.081 (1.12)	-5.42 (0.77)	1.21 (1.19)	-5.679 (0.85)	1.212 (1.22)	-6.312 (0.90)
Census Tract to MSA Median Income Ratio	-0.058 (1.00)	-0.158 (0.69)	-0.081 (1.38)	-0.131 (0.57)	-0.08 (1.35)	-0.163 (0.70)
Census Tract Rental Ratio	-0.059 (0.65)	-0.073 (0.22)	-0.065 (0.71)	-0.057 (0.17)	-0.062 (0.68)	-0.111 (0.34)
Log Likelihood	-35,717		-35,290		-35,200	

Note: T-ratios are in parentheses. All models are estimated by ML approach. Prepayment and default functions are considered as correlated competing risks and they are estimated jointly. Flexible baseline functions (following Han and Hausman [1990]) for prepayment and default are estimated simultaneously with the competing risks hazard functions.

TABLE A2

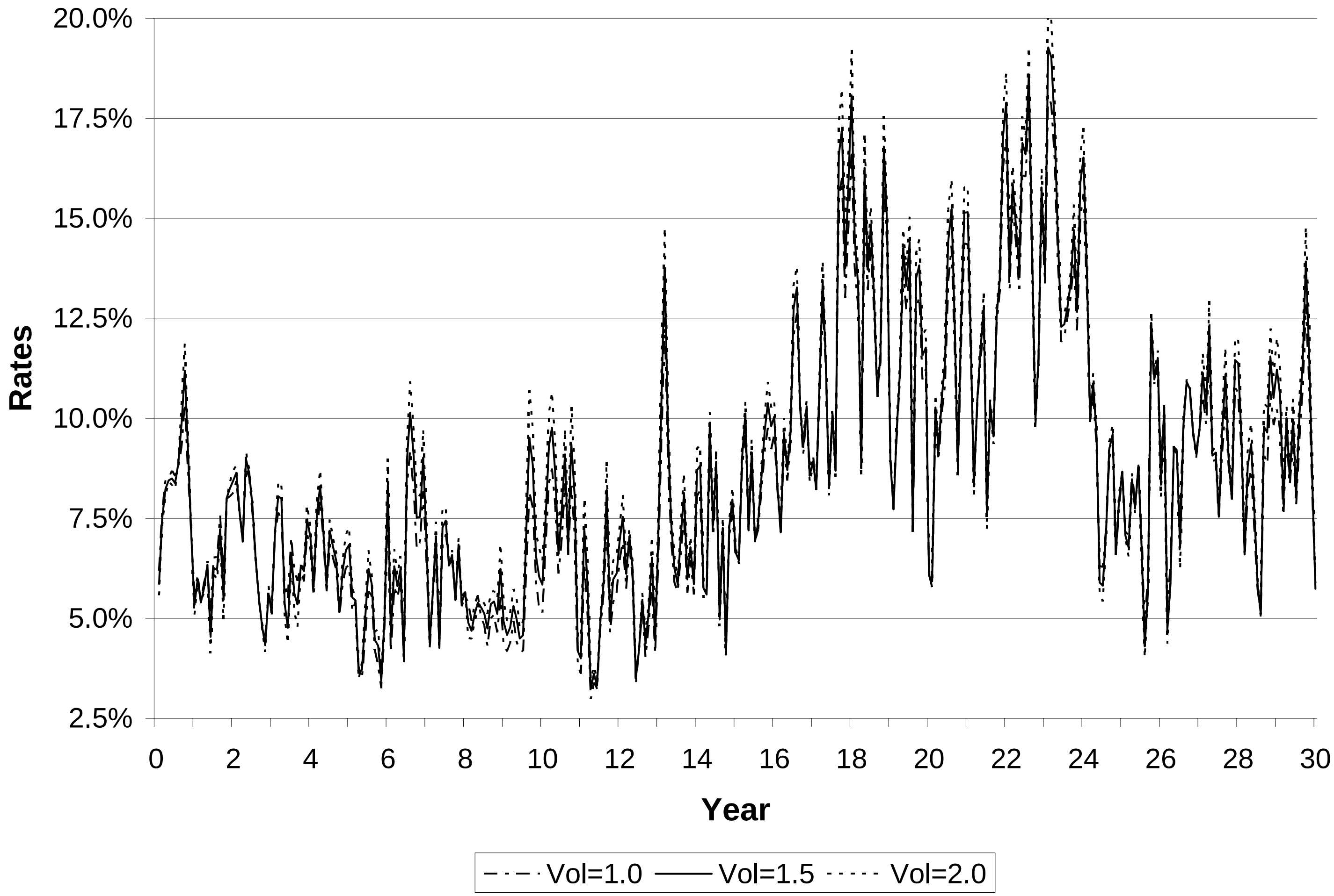
HYPOTHETICAL MORTGAGE POOLS OF HIGH CREDIT RISKS VS. LOW CREDIT RISKS IN SIMULATION

	High Credit Risks	Low Credit Risks
Credit Scores < 620	1	0
Credit Scores 680~740	0	1
SMSA Unemployment Rate (percent)	4.0	4.0
Loan-to-Value Ratio	0.95	0.95
Housing Exp. to Income 20~38% (dummy)	0	1
Housing Exp. to Income > 38% (dummy)	1	0
First Time Home Buyer	1	0
Log Value of Liquid Assets	8.17	9.16

Note: The values of all other covariates utilized in the simulation are identical across the high credit risk and low credit risk groups. Those values derived from the computed sample means reported in Table 1.

APPENDIX B: FIGURE B1

SIMULATED INTEREST RATES (ATSM) OVER 30-YEAR PERIOD



Note: The figure shows average of 2,000 monthly interest rate paths over thirty year period simulated from Dai and Singleton [2000], equation (23) using parameters reported in Table II, Column 2 of Dai and Singleton. Interest rate paths are simulated for three volatility assumptions.