Housing Price Cycles and Prepayment Rates of U.S. Mortgage Pools

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Abstract

Empirical mortgage prepayment models generally have trouble explaining differences in mortgage prepayment speeds among pools with similar interest rates on the underlying mortgages. In this paper, we model some of the sources of termination heterogeneity across mortgage pools, particularly the role of regional variations in housing prices in generating atypical prepayment speeds. Using a sample of Freddie Mac mortgage pools from 1991-1998, we find evidence that differences in house price dynamics across regions are an important source of between-pool heterogeneity. This finding is then shown to be robust to alternative ways of parameterizing pool heterogeneity in mortgage termination models.

1 Introduction

Empirical mortgage prepayment models generally have trouble explaining differences in mortgage prepayment speeds among pools with similar interest rates on the underlying mortgages. A common failing of existing models is that predicted prepayment levels for seasoned mortgages often over/underestimate the degree to which existing pools are "burned-out" from prior periods of interest rate driven refinancing, owing to inadequate controls for transaction cost heterogeneity between and within the mortgage pools. In this paper, we model some of the sources of termination heterogeneity across mortgage pools, particularly the role of regional variations in housing prices in generating atypical prepayment speeds. In compiling this evidence on the importance of housing price differences in explaining between-pool heterogeneity, we show that the results are robust to alternative ways of parameterizing the effects of heterogeneity within mortgage pools.

A growing literature recognizes the importance of understanding the role of house prices in mortgage terminations. Differences across mortgage holders in propensities to prepay can arise either from the characteristics of the individual mortgage holders or from the characteristics of the regional housing and labor markets in which they participate. Modeling the regional component of prepayment risk is more important than modeling the idiosyncratic component of prepayment risk because diversification can more easily reduce the idiosyncratic risk (Archer and Ling, 1997; Archer, Ling, and McGill, 1996). The geographic, housing market dimension of mortgage termination is stressed in recent research concerning the determinants of mortgage default (Kau et al., 1992, 1995; Deng et al., 1998). In addition to increasing defaults, weak housing prices have been shown to decrease refinancing and mobility-related mortgage terminations.[1]

[1] Early contributions to the study of heterogeneity in prepayment rates of mortgage pools, such as that of Becketti and Morris (1990), used the location of the operations of the originator-servicer as a proxy for the geographic location of the collateral and documented substantial variation in prepayment speeds by state from 1982 to 1988. Evidence from the early 1990s also has corroborated the importance of geographic factors to prepayments and identified housing price developments as the primary geographic factor. As noted by Monsen (1992) and demonstrated formally by Caplin et al. (1993), home prices declined in much of the Northeast over the 1990-92 period, and the reduction in collateral depressed prepayment activity there relative to other states. Caplin et al. (1993) attribute this depressed level of prepayment in the Northeast to lower refinancing activity, but their data does not allow them to actually distinguish between prepayments related to refinancing and prepayments related to home purchases. Using loan-level data on refinancings, Peristiani et al. (1996, 1997) were able to document a large effect of low home equity on the propensity to refinance, but they were not able to address the issue of how

In Mattey and Wallace (1998), we investigated terminations by type (refinancing, default, and mobility) for fifteen California counties from 1992 through 1996. We found that the path of house prices was important for each of these types of terminations: weak collateral values held down refinancing and mobility, while boosting defaults. The effect of housing prices on refinancing was most economically significant, both because the magnitude of the effect was large and because the effects of housing prices on default and mobility were partly offsetting.

In this paper we extend the Mattey and Wallace (1998) line of analysis to include empirical evidence from housing markets throughout the United States and focus on the sources of termination heterogeneity across individual mortgage pools. The broader geographic variation in the pool-level data allows us to examine the extent to which the California experience was atypical, particularly whether many other states have had weak enough housing markets to hold down refinancing rates as much as we found in the California sample. We consider the effects of house price evolution in the context of two quite different specifications for mortgage terminations: an empirical hazard model and a rational prepayment model. We find that house prices are a statistically significant omitted factor in both of these representations of typical prepayment models. Also, we find that the empirical hazard model, augmented to include house prices, is better able to explain mortgage terminations in pools with loans concentrated in states such as California that experienced large housing price declines in the early 1990s. We also find that the California experience was relatively atypical in this sample period. Hawaii is the only other state for which housing market conditions clearly showed through to prepayment patterns.

2 Mortgage Termination Model Specification

The approaches used in the literature to specify empirical prepayment models have differed according to data availability and purposes of the studies. We are interested in the class of model best-suited to pool-level data, not individual loan-level data. Also, we seek mortgage termination model specifications that can be easily integrated into algorithms for valuing passthrough mortgage-backed securities (MBS).

MBS valuation algorithms are of two basic types, backward-solving option-pricing models and forward-solving Monte Carlo simulations. In both approaches to valuation, the theoretical value of the MBS can be

much regional economic conditions affect the propensity to prepay for other reasons, such as home purchases. Stein (1995), Archer, Ling, and McGill (1996), and Mayer and Genesove (1997) also emphasize housing prices as a determinant of household mobility.

written as the expected present discounted value of the cash flows to be received between the present and the termination date of the mortgages, where the discount factors are stochastic functions that depend on the evolution of interest rates and on the price of interest rate risk. In forward-solving Monte Carlo techniques (e.g., Patruno, 1994; Chan and Russell, 1997), the cash flows depend on current (and potentially past) interest rates, but there is no explicit dependence of the cash flows on what these interest rate realizations imply about the likely future course of interest rates. In backward-solving option-pricing models with rational prepayments (Dunn and McConnell, 1981; Timmis, 1985; Stanton, 1995, 1996), the functions defining cash flows explicitly incorporate the dependence of optimal refinancing decisions on expectations about future interest rates. In other words, rational models incorporate the option value-of-waiting into the measures of refinancing incentives.

Solving for the optimal option exercise rule can be computationally burdensome, particularly if the model incorporates multiple stochastic state variables. Accordingly, our empirical implementation of the rational model follows Dunn and McConnell (1981) and Stanton (1995, 1996) in assuming that a single interest rate factor, the current riskless rate r_t, summarizes all movements in the entire term structure of interest rates. Realizations of this interest-rate process can trigger refinancing; other sources of mortgage termination are assumed to arrive exogenously at a mean rate of λ.

The Stanton-type rational prepayment model can be written as:

$$\pi_{it} = \lambda + \rho I(r_t \leq r^*_{it}) + v_{it} \tag{1}$$

where the hazard function governing termination for loan i in period t takes on the value λ if $r_t > r^*_{it}$ and the value $\lambda + \rho$ if $r_t \leq r^*_{it}$. Here, π_{it} is the predicted termination rate for mortgage i at time t, λ is the mean Poisson arrival rate of exogenous termination, ρ governs the frequency with which refinancing decisions are made, I is an indicator variable for whether the spot interest rate, r_t, has fallen below the critical level, r^*_{it}, at which refinancing becomes optimal, and v_{it} is the error term. The critical interest rate r^*_{it} depends on the expected future evolution of interest rates and the level of transactions costs faced by this individual. Following Stanton (1996), we proceed as if neither ρ nor λ differ across mortgage holders. Thus, this rational model incorporates heterogeneity in termination predictions only through the effects of transactions costs differences on the critical interest rates, r^*_{it}.

For application to pool-level data we aggregate the model across individuals. In the pool-level context, predicted refinancing rates for the kth mortgage pool, π_{kt}, are largely determined by the decision-frequency parameter ρ and the proportion of surviving individual loans in pool k with transactions costs low enough for refinancing to be optimal at time t. We denote this proportion by $F_{kt}(r_t \le r^*_{kt})$. Accordingly, the rational pool-level single-factor prepayment model can be written as:

$$\pi_{kt} = \lambda + \rho F_{kt}(r_t \le r^*_{kt}) + v_{kt}. \qquad (2)$$

Following Stanton (1995), we assume that the initial distributions of transactions costs across individuals within the *kth* pool are given by a Beta probability distribution with parameters α and β, so that the mean transactions cost at mortgage origination is $\alpha/(\alpha+\beta)$ of the mortgage balance. Over time, the distribution of transactions costs across surviving mortgages within the pool evolves, and this evolution depends on whether prepayments have been triggered by exercise of the refinancing option or the realization of an exogenous termination. On average, realizations of exogenous terminations do not alter the location or shape of distribution of transactions costs across holders of surviving mortgages. However, only those mortgage holders with sufficiently low transactions costs exercise refinancing, so when a pool experiences an interest rate environment in which exercise of the refinancing option is optimal, there is an increase in the mean of the distribution of transactions costs across holders of surviving mortgages. Thus, Stanton's model has an explicit behavioral structure for the phenomenon of "burnout", which is the tendency of a mortgage pool to exhibit less responsiveness to refinancing incentives if it previously experienced such refinancing incentives.[2]

Prior to Stanton's application of this rational model to data, empirical mortgage termination models used only loosely motivated measures of the refinancing incentives (Green and Shoven, 1986; Schwartz and Torous, 1989). At best, these measures can be interpreted as simplified approximations to Stanton's explicitly optimization-based measures of refinancing incentives. These earlier-vintage empirical prepayment models also used ad hoc parameterizations for the burnout phenomenon. That said, even with only four unknown parameters ($\alpha, \beta, \rho, \lambda$), estimation of the Stanton-style rational model is computationally burdensome, and the addition of more explanatory factors to the model would add to the computational burden. In contrast, non-optimization-based models generally can be scaled up to handle a relatively large number of explanatory variables.

Given these competing considerations, we estimate both a Stanton-style rational model and an exponential hazard model that uses non-optimization-based measures of refinancing incentives and burnout. In

[2]We use Stanton's (1995) discrete approximation to the evolution of these transactions costs distributions.

this exponential hazard model the logarithm of the hazard rate can be written as

$$log[\pi_{kt}] = \beta_0 + X_{kt}\beta + \varepsilon_{kt} \tag{3}$$

where β_0 is a constant that determines the location of the baseline hazard, which gives the probability of termination (from all sources considered jointly) when the vector of covariates X_{kt} are equal to their sample means. The unpredictable component of terminations is subsumed in an error term, ε_{kt}. We implement a time-varying covariate version of the model. With time-varying covariates, the current period realizations of X_{kt} determine the current period hazard rate π_{kt} , and the entire historical path of the covariates affects the probability of surviving long enough to be at risk of prepayment during that period.

Empirical studies have shown that average prepayment rates tend to be lowest at the beginning of the mortgage term and tend to increase during an initial "seasoning" period that lasts for a few years.[3] Such a ramp-up during the initial seasoning period can be incorporated into a parametric baseline hazard that varies with τ, an index of the age of the loans in the pool that increments by one with time t. Alternatively, in our favored specification we proxy for this seasoning effect by letting the first covariate, X_{1kt}, be a piecewise linear function of loan age τ.[4] We choose the kink in this piecewise-linear seasoning variable to be at loan age month thirty, which is the month at which the widely-referenced "PSA Schedule" also kinks. Accordingly, this representation of the age-related component of prepayment speeds can incorporate the "PSA Schedule" values for the baseline hazard as a special case.

In addition to the seasoning variable, the covariates X_{2kt} and X_{3kt} are measures of the burnout phenomenon and refinancing incentive, respectively. Our "burnout" measure is the Schwartz and Torous (1989) specification; that is, we use the (one-month lagged) logarithm of the ratio of the actual pool factor to the scheduled balance of the pool (in the absence of prepayments) as a measure of the cumulative degree of

[3] The theory of mortgage choice provides theoretical support for the notion that conventional fixed-rate mortgages should appear to have an increasing hazard over an initial range. Borrowers who know that they are likely to have a brief tenure in a mortage (e.g., because they plan to move) are more likely to select adjustable rate loans with initial rates lower than prevailing fixed rates. The effect of this selection bias on the baseline hazard diminishes with loan age.

[4] More specifically, our measure of SEASONING is the logarithm of the PSA schedule, which increases linearly from zero to a single-month mortality (SMM) of about 5 basis points (6 percent per annum) in month thirty and remains constant thereafter. If $\beta_0 = 0$ and $\beta_1 = 1$, then the baseline hazard of this exponential model is the PSA schedule.

previous prepayment. For the refinancing incentive variable, we use the spread between the weighted-average coupon (WAC) mortgage rate of the pool and the (lagged) primary mortgage rate for newly issued mortgages. To isolate circumstances when this spread likely is sufficiently wide to overcome the transactions costs associated with refinancing, our explanatory variable takes on the value of the spread only for spreads in excess of 1 percentage point and is zero otherwise.

These two models–the rational model given by equation (2) and the exponential hazard model given by (3) with only the three above-defined covariates X_{1kt}, X_{2kt}, and X_{3kt}–are not well-suited to explaining heterogeneity of prepayment rates across mortgage pools. Under this version of the Stanton rational model, all pools with a common month of origination and underlying mortgage rate (WAC) have common predicted values for prepayments.[5] Under this parsimonious version of the exponential hazard model, pools with a common month of origination and underlying mortgage rate (WAC) have differing predicted values for prepayments only if they have differing cumulative prepayment histories and the coefficient (β_2) on the related burnout measure is nonzero.

Recent theoretical contributions to the mortgage valuation literature and empirical research on loan-level mortgage terminations suggest that regional housing market conditions likely are particularly important to understanding why mortgage prepayment patterns differ across mortgage pools. As previously noted, the geographic, housing price dimension of mortgage termination has been stressed in recent research concerning the determinants of mortgage default, and housing prices also have been shown to be correlated with both refinancing-related and mobility-related terminations.

Wall Street models of mortgage backed security (MBS) prepayment, such as those described by Patruno (1994) and Hayre and Rajan (1995), include submodels for separate pieces of aggregate prepayment activity, including default (π^D_{kt}), refinancing (π^R_{kt}), and mobility-related (π^M_{kt}) mortgage terminations. Such modeling of variations across pools in determinants of these separate pieces of aggregate prepayment activity can be important because mortgage values are sensitive to the source of the prepayments. However, unlike Deng et. al. (1998) and others who have estimated loan-level models for separate types of prepayment, most modelers of MBS pool prepayments must work with data in which all

[5] Although the Stanton (1995) model we implement here does not have any structure for explaining differences in prepayment rates among pools with common WAC and month of loan origination, Stanton (1996) does extend the model to allow one of the parameters in the Beta distribution for transactions costs to differ across mortgage pools.

three of these sources of terminations–defaults, refinancings, and home sales–appear as an aggregate rate of mortgage termination:

$$\pi_{kt} = \pi^M_{kt} + \pi^D_{kt} + \pi^R_{kt}. \tag{4}$$

In this paper, we seek to expand on our earlier (Mattey and Wallace (1998)) evidence that the single-factor rational model, equation (2) is mis-specified in omitting house prices h_{kt} as an explanatory variable, owing to the unmodeled sensitivity of defaults, refinancing and mobility-related terminations (home purchases) to housing prices. Also, we seek to show that the basic exponential hazard model (with the three covariates defined above) also is mis-specified because of such omissions. Our main alternative hypothesis is that declines in home prices tend to increase defaults $(\partial\pi^D_{kt}/-\partial h_{kt}) > 0$, decrease terminations related to home purchases $(\partial\pi^M_{kt}/-\partial h_{kt}) < 0$, and decrease refinancing $(\partial\pi^R_{kt}/-\partial h_{kt}) < 0$. Also, we expect that the effect of house prices on home purchases is larger than the offsetting effect of house prices on defaults $(|\partial\pi^M_{kt}/-\partial h_{kt})| > |\partial\pi^D_{kt}/-\partial h_{kt}|)$, so that the sum of expected defaults and mobility-related terminations tends to decrease as housing prices fall $(\partial[\pi^M_{kt}+\pi^D_{kt}]\ /-\partial h_{kt}) > 0$. This latter implication runs counter to the implications of the two-factor rational model of default and refinancing (e.g., Kau et al., 1992; Kau and Keenan, 1995) that provides the motivation for the recent empirical studies by Deng (1997) and Deng, Quigley, and Van Order (1998).

Generally, the two-factor rational model assumes that mobility-related terminations do not depend on home prices (i.e., $(\partial\pi^M_{kt}/\partial h_{ikt}) = 0)$) and implies that refinancing is reduced by declines in housing prices (i.e., $(\partial\pi^R_{kt}/-\partial h_{kt}) < 0$) only to the extent that the competing risk of defaulting has increased. In the two-factor model, the competing risk effect is relatively large when interest rates are low enough to otherwise trigger refinancing (i.e., $(\partial\pi^R_{kt}/-\partial h_{kt}) \approx -(\partial\pi^D_{kt}/-\partial h_{kt}))$, but the competing risk effect is negligible at higher interest rates (i.e., $(\partial\pi^R_{kt}/-\partial h_{kt})$ $\approx 0)$. However, the empirical evidence of Peristiani et. al. (1996, 1997) and Mattey and Wallace (1998) suggests that the effect of home price changes on refinancing is larger in absolute value than the effect on defaults. Accordingly, we expect that the aggregate rate of terminations, π_{kt}, tends to decrease as housing prices fall $(\partial\pi_{kt}/-\partial h_{kt}) < 0$. This is likely to lead to a negative correlation between measures of the extent to which housing prices have declined and the residuals from estimates of the models that omit house prices.

We develop evidence on the statistical significance of the omission of house price variables for total terminations by examining the residuals from estimates of the single-factor rational model $\hat{v}_{kt}$ and the residuals from estimates of the basic exponential hazard model (with the three covariates defined above) $\hat{\varepsilon}_{kt}$. Then, we further explore the evidence from the estimates of the exponential hazard model under the assumption that its specification of the refinancing incentive as a spread in excess of 1 percentage point has successfully delineated a switching-regime model. This idea follows Kau and Springer (1992), who use a switching-regime model to identify the separate parameters governing subtypes of prepayment behavior with pool-level data, even though only the aggregate rate of mortgage termination actually is observable with such data. More specifically, note that our basic exponential hazard model can be interpreted as assuming that the baseline hazard (with seasoning and burnout effects) represents the sum of predicted terminations from mobility and defaults:

$$E\left[\pi_{kt}^{M}+\pi_{kt}^{D}\right]=\exp^{\beta_0+X_{1kt}\beta_1+X_{2kt}\beta_2} \tag{5}$$

and the remaining contribution to total predicted terminations represents terminations from refinancing:

$$E\left[\pi_{kt}^{R}\right]=\exp^{\beta_0+X_{1kt}\beta_1+X_{2kt}\beta_2}[\exp^{X_{3kt}\beta_3}-1] \tag{6}$$

Because the refinancing incentive variable X_{3kt} equals zero when the interest rate spread is negative or narrow (less than 1 percentage point), the predicted rate of refinancing is zero in such cases.

To develop evidence on the sensitivity of refinancing to house prices and the sensitivity of the sum of mobility and defaults to house prices, we also estimate a version of the exponential hazard model with two additional explanatory variables (X_{4kt} and X_{5kt}) that are a particular (increasing) function of house price declines and interact with the refinancing incentive switch point. The X_{4kt} variable assumes nonzero values related to house prices only if the spread is negative or narrow, and X_{4kt} is zero otherwise, whereas the X_{5kt} assumes nonzero values related to house prices only when the spread exceeds 1 percentage point. Therefore, this extended model preserves the switching-regime decomposition as follows:

$$E\left[\pi_{kt}^{M}+\pi_{kt}^{D}\right]=\exp^{\beta_0+X_{1kt}\beta_1+X_{2kt}\beta_2+X_{4kt}\beta_4} \tag{7}$$

and

$$E\left[\pi_{kt}^{R}\right]=\exp^{\beta_0+X_{1kt}\beta_1+X_{2kt}\beta_2+X_{4kt}\beta_4}\ [\exp^{X_{3kt}\beta_3+X_{5kt}\beta_5}-1] \tag{8}$$

This decomposition is useful because it allows us to interpret the sign of the estimate of the coefficient (β_4) on X_{4kt} as the estimated sign of $(\partial[\pi_{kt}^{M}+\pi_{kt}^{D}]\,/-\partial h_{kt})$ and the estimated sign of $(\partial\pi_{kt}^{R}\,/-\partial h_{kt})$ is further determined by the sign of the estimate of the coefficient (β_5) on X_{5kt}.

3 Prepayments in Freddie Mac Mortgage Pools

Our empirical analysis focuses on the prepayment characteristics of a broad class of Freddie Mac passthrough residential mortgage-backed securities. Freddie Mac is one of the two largest issuers of MBS pools, along with Fannie Mae. The universe of data for this study consists of all Gold Participation Certificate (Gold PC) pools issued by Freddie Mac between January, 1991 and December, 1994. The underlying mortgages in Gold PCs primarily are first lien residential mortgage loans secured by one-to-four family dwellings. Among the Gold PCs, we focus on those pools backed by newly-issued, standard 30-year fixed-rate mortgage loans.[6] As shown in table 1, there are 27,878 MBS pools which meet our initial sample selection criteria.

On average, there are about 40 mortgage loans backing each Gold PC. Thus, our data on 27,878 mortgage pools pertains to prepayment histories on about 1.1 million underlying mortgage loans. We observe the prepayment histories of these pools from the month of issuance through June, 1998. Accordingly, the prepayment history of the earliest-issued pools are observed for 90 months,and the latest-issued pools are tracked for 42 months.

In the primary market where mortgage loans are originated, interest rates were relatively variable over the four year period during which these pools were issued. Interest rates on conventional mortgages evolved in somewhat of a U-shaped pattern; the peak was in 1991, at the beginning of the period, and primary mortgage rates declined to a trough in late 1993 before moving up sharply again during 1994. This variability is reflected in the distribution of mortgage coupon rates on the pools, which we summarize in table 1 by year of issuance and passthrough coupon.

The passthrough coupon rates on Freddie Mac Gold PCs have changed relatively infrequently and in discrete, fifty basis point steps. It is convenient to summarize the aggregate properties of this data set at the level of "reference pools", which are groupings of pools according to common year of issuance and passthrough coupon. At the beginning of the sample period, the 1991 vintage, 9.0 coupon reference pool group of 4,127 pools consisted of 148,962 underlying loans. The weighted average coupons (WACs) on the underlying loans tend to run about 50 basis points above the passthrough coupon rates, and for the 1991 9.0s, the original WAC was 9.6 percent. The WACs of the reference pools drifted down to 8-1/2 percent during 1992 and continued falling to a low of

[6] Specifically, we subset to pools with a Pool Type of 30 year Gold Participation Certificates, an original weighted average loan age of two months or less, and an original weighted average remaining maturity of 350 months or more.

about 7-1/2 percent at the beginning of 1994, before picking back up to 8-1/2 percent by the end of that year.

The full sample average prepayment rate on these MBS from pool inception to June, 1998 was 1.09 percent per month.[7] Given that, on average, the prepayment history of the pools was followed for about 60 months, this means that about 48 percent of the loans in the pools were prepaid over the course of the observation period.

3.1 Estimation of the Rational Model

One of the primary potential advantages of a Stanton-type rational model is that the predicted prepayments from the rational model actually obey the *optimal* exercise rule for the refinancing option. As discussed above, the model implies that the overall prepayment probability for the kth pool is a function of the interest rate at which refinancing becomes optimal, r^*_{kt}; the frequency of refinancing decisionmaking among borrowers in the pool, ρ; a hazard function accounting for the likelihood of exogenous prepayment, λ; and a beta distribution of transaction costs with shape and location governed by the parameters α and β. To implement this model, we also must specify the dynamic process for interest rates and provide a numerical solution algorithm for calculating the optimal exercise rule for the refinancing option.

For these model implementation details, we follow Stanton (1995) in most respects. We assume that the nominal interest rate process is a one-factor Cox, Ingersoll, and Ross (1985) (CIR) process, and we calibrate the CIR interest rate process to the parameter values from Pearson and Sun (1989).[8] We calculate the optimal exercise strategy

[7] In computing pool-level single month mortality (SMM) conditional prepayment rates, we follow the Bartlett (1994, p. 205) formula for estimating terminations, given data on pool factors, time to maturity, and coupon interest rates. In computing weighted average SMMs across pools or time periods, the beginning-of-period unpaid balances remaining in each of the pools at those times are used as weights.

[8] The CIR model is a long run model of nominal interest rates in which the instantaneous risk-free interest rate r_t satifies the differential equation

$$dr_t = \kappa(\mu - r_t)dt + \sigma\sqrt{r_t}dz_t$$

In principle given the long run general equilibrium nature of the model, fitted model parameters should be unaffected by the sample period used for estimation. We use the Pearson and Sun (1989)

$$\kappa = 0.29368,$$
$$\sigma = 0.11425$$
$$q = -.12165$$

for the options using standard numerical methods to value interest rate contingent claims written on coupon bonds.[9]

For an individual borrower, the optimal refinancing decision depends on the position of the current interest rate r_t relative to a critical interest rate r^*_{it} that depends on the expected future evolution of interest rates and the level of transactions costs faced by the individual. For each mortgage pool (k), the individual transactions costs at pool origination are assumed to be drawn from a beta distribution with shape and location parameters α and β. Over time the distribution of transactions costs across remaining mortgage holders evolves, depending on the unknown parameters $(\alpha, \beta, \rho, \lambda)$ and also on the realized sequence of interest rates up to that time, which we denote as an information set Ψ_t. We solve the model for the proportion of surviving individual loans at time t in pool k with transactions costs low enough for refinancing to be optimal, $F_{kt}(r_t \leq r^*_{kt};\, \Psi_t; \alpha, \beta, \rho, \lambda)$, by discretely approximating the evolution of the transactions cost distribution; see Stanton (1995) equations (19)-(25) for details on the updating rule for F_{kt}.

We estimate the unknown parameters $(\alpha, \beta, \rho, \lambda)$ of the rational model using observations on pool prepayment rates π_{kt} at the monthly frequency of time t, using equation (2) as the basis for our econometric estimation strategy:[10]

$$\pi_{kt} = \lambda + \rho F_{kt}(r_t \leq r^*_{kt}; \Psi_t; \alpha, \beta, \rho, \lambda) + v_{kt}. \tag{9}$$

Following Stanton (1995), we estimate the model by minimizing an objective function that is the sum of squared average prediction errors. Specifically, averaging across the N pools, the average prediction error at the t^{th} month is $\bar{v}_t = 1/N \sum_{k=1}^{N} v_{kt}(\alpha, \beta, \rho, \lambda)$, and the objective function

assuming that the long-run mean interest rate is $\mu = 0.04935$.

To derive a monthly sequence of risk-free interest rates r_t, we match the implications of the model for 10-year yields to actual monthly observations on 10-year Treasury yields and then back out the short-run riskless rate implied by the CIR model. Pool-level mortgage prepayments are assumed to respond to these monthly changes in interest rates with a three-month lag. This lag reflects the built-in delays between the time of mortgage refinancing loan applications and realizations of prepayments in MBS passthrough cash flows.

[9] We use finite difference approximations to backwardly solve the value function subject to appropriate boundary conditions. The solutions were found by the Crank-Nicholson algorithm.

[10] Stanton (1995), Table 1, shows parameter estimates of .6073 and .0345, respectively, for ρ^c and λ^c parameters which are continuous-time Poisson arrival rates expressed at annual rates. We present results in terms of the monthly discrete time counterparts, which are related to these by $\rho = (1 - \exp^{-\rho^c/12})$ and $\lambda = (1 - \exp^{-\lambda^c/12})$.

is the sum of the squares of these average residuals, $\Omega_T = 1/T \sum_{t=1}^{T} \bar{v}_t^2$. We use the adaptive simulated annealing algorithm of Ingber (forthcoming) to find the values of the parameters that minimize this objective function.

Using the full sample of 27,878 pools, the objective function would involve more than 1-1/2 million pool-by-month observations. To lower computational burdens, we apply the rational model estimation procedure to a subset consisting of 2,575 pools. These pools are stratified across the nine reference pool groups, and within each reference pool group we select all pools with weighted-average coupon exactly fifty basis points above the passthrough coupon rate.

Estimation results are shown in the first row of table 2. All coefficients are estimated relatively precisely, and hypotheses that they are statistically indistinguishable from zero can be sharply rejected. The estimate of $\hat{\lambda} = .007$ implies that the monthly rate of (exogenous) default and mobility-related terminations is about 70 basis points, consistent with the findings of Stanton (1995) and other studies, which typically show $\hat{\lambda}$ in the 50 to 100 basis point range. The estimates of ($\hat{\alpha} = 2.295$, $\hat{\beta} = 4.692$) imply an initial mean transactions cost of about one-third the mortgage balance, which is very substantial but somewhat lower than the forty percent mean found by Stanton (1995) for his sample of 1000 GNMA pools. Our estimate of $\hat{\rho} = .113$ implies that if interest rates suddenly drop and make it optimal for a group of mortgageholders to refinance, only about 11 percent of those mortgageholders actually will refinance in that initial month. Absent additional changes in economic conditions, refinancing will continue in subsequent months, with a mean elapsed time until lack of impediment to rational exercise of about 9 months. Stanton (1995) found an even longer average delay to rational refinancing.

3.2 Estimation of the basic exponential hazard model

We estimate the time-varying covariate exponential hazard model using the method of maximum likelihood.[11] The maximum likelihood method allows us to control for the important feature that most pools have not fully prepaid prior to the end of the observation period. Using the full

[11]The log-likelihood function for this problem is the sum of log-likelihoods for individual observations, with each observation contributuing a survivor function to the likelihood. Observations that experience terminations during the sample period also contribute the probability density, evaluated at the point of termination, to the likelihood function. In constructing the survivor function, we handle appropriately the fact that the covariates are time varying. That is, we accumulate the integrated hazards applicable to each time period in the sample.

sample, the likelihood function would involve about 67 million loan-by-month observations.[12] For tractability, we present estimates computed from a random sample of 1,000 pools per model estimation, which still covers more than 2 million loan-by-month observations per estimation.

The estimated coefficients of the basic exponential hazard model are shown in second row of table 2. All coefficients are estimated relatively precisely and are statistically distinguishable from zero. Also, the estimated coefficients have the anticipated signs. The estimated coefficient on the Log(PSA) schedule is positive, reflecting the initial range of increasing hazards as loans season. Pools tend to burnout; they experience higher prepayments if they have not experienced a lot of cumulative prior prepayments, as measured by the lagged factor to balance ratio. Last, an increase in the refinancing incentive as measured by the spread between the WAC and the current mortgage rate tends to have a large positive effect on terminations.

3.3 Evidence of Mis-specification from the Residuals

To check for evidence that these models are mis-specified in omitting housing prices as a determinant of mortgage prepayments, we first need to devise time-series measures of housing market conditions for each mortgage pool. Our data set contains information on the geographic distribution across U.S. states of the underlying loans in each pool at the time of pool origination. We use this distribution to define the weights used in constructing pool-specific housing price series from published housing price indices for the fifty states (and the District of Columbia).

We expect the relationship between house price changes and mortgage pool prepayments to be highly non-linear, even after controlling for the factors included in the rational model and the basic exponential hazard model. Models of default introduce such a non-linearity by emphasizing that a necessary (but perhaps not sufficient) condition for optimal default is that housing prices must decline enough for the current mortgage loan-to-housing-value ratio to exceed unity. Thus, for mortgage loans originated with an eighty percent loan-to-value ratio,

[12] Because we know the original count of loans in the Freddie Mac pools, we are able to construct dichotomous dependent variables for each pool that represent the number of loans fully prepaid in each month. This calculation is made recursively by rounding to the nearest integer the estimated number of prepaid loans, where the latter is computed by multiplying the actual prepayment rate (SMM) by the number of loans remaining in the pool at the beginning of the period. Although such a computation abstracts from partial prepayments, these discretized dependent variables appear to well-approximate the actual continuous prepayment history, which includes partial prepayments.

the probability of default increases much faster with additional declines in house prices as the cumulative declines in house prices since loan origination approach twenty percent. However, this sensitivity to house prices is not symmetric; default rates do not tend to drop faster with additional house price increases as the cumulative change in house prices since loan origination reaches twenty percent. Similar non-linearities may be present for the other types of prepayment, because the eighty percent loan-to-value threshold for mortgage insurance also affects the sensitivity of refinancing and mobility-related mortgage prepayments to house prices.

Given these considerations, we follow Deng, Quigley, and Van Order (1998, appendix A) in transforming our information on house prices into a measure of the probability that the current loan to value ratio exceeds unity. Basically, this consists of rolling forward the denominator of the initial loan to value ratio of the loans in the pool by the sequence of observed changes in a house price index for their geographic area and extrapolating the numerator by the scheduled decline in the principal balance of the loan. Such an estimate of the central tendency of the current loan to value ratio is converted to a probability by assuming that the distribution of logarithmic changes in house prices is normally distributed. The variance of this normal distribution is estimated from the moments of the underlying individual home price data from which the aggregate home price indices are constructed.[13]

In constructing this variable, we assume that all pools have the same initial loan-to-value ratio of 80 percent.[14] Thus, in the first month after

[13] We use the Office of Federal Housing Enterprise Oversight (OFHEO) quarterly repeat sales home price indices by state as the data source. These are interpolated by a spline to the monthly frequency. We then compute a price index for each pool, using the original distribution across states of amounts of principal outstanding to construct a weighted average of the state-level price indices. For the probability calculation, we also compute pool-specific house price volatility indices using the pool-specific weighted average of the state level volatilities published by OFHEO.

[14] Our dataset does not contain any information on initial loan-to-value ratios by pool. the prospectus on Freddie Mac Gold PCs indicates that initial loan-to-value ratios cannot exceed 80 percent unless satisfactory mortgage insurance of one form or another is obtained; because such insurance is costly, most of the mortgage securtizied by Freddie Mac have met the requirement of having an initial LTV less than 80 percent, historically. For example, Deng, Quigley and Van Order (1998) report that about 15,000 of the roughly 22,000 loans they study (originated between 1976 and 1983 and purchased by Freddie Mac) had initial LTVs less than 80 percent, with the remainder primarily in the 80 percent to 90 percent range. Owing to our lack of information on initial LTVs by pool, our analysis likely is biased toward finding against the ability of pool-specific house price indices to explain pool-level prepayments. The fact that we do find some effect of house prices despite the data limitation, suggests that our results would be even stronger if we had data on initial

loan origination, it would take a 20 percent decline in home prices to eliminate the homeowner's equity. Accordingly, at the beginning of a loan's age profile, the probability measure basically is zero. The probability measure increases a bit in the first two years of the loan for almost all pools, and thereafter it's evolution is strongly affected by the direction and rate of change in the home price index for the pool.

For most of the months during which we observe pools' prepayment histories, the $Prob(LTV(HP_t) > 1)$ measure is below 1-1/2 percent. Only about one-quarter of the pool-month observations have a $Prob(LTV(HP_t) > 1)$ value that exceeds 3-1/2 percent. However, a small portion (about one-tenth) of our observations experience realizations of this covariate above 8 percent. Looking at the distribution of $Prob(LTV(HP_t) > 1)$ by pool, 653 of the 27,878 pools experience realizations of this variable above 20 percent at some point in their observed prepayment history. All of these 653 pools with high measured probability of negative equity (sharp declines in house prices) have at least 75 percent of their loans in either California or Hawaii. California experienced a sharp decline in home prices beginning in 1990 and extending through 1996, and the highest proportions of estimated negative equity are concentrated in 1995 and 1996 in pools that were originated in 1991.

To check for potential mis-specification, we compute the rational model and basic exponential hazard model predictions of prepayment probabilities π_{kt} for all 27,878 pools in our data set for each month in which the pool factor history is observed. Then, we compute the residuals for the logarithms of these hazards, $\log(\pi_{kt}) - \log(\hat{\pi}_{kt})$. In the case of the rational model, this log hazard residual is $\log(1+(\hat{v}_{kt}/\hat{\pi}_{kt}))$, whereas for the exponential model the residual is just $\hat{\varepsilon}_{kt}$ .We display the slope coefficient results of OLS regressions of these prediction errors on an intercept and the (transformed) housing price measures in the rightmost column of table 2. As shown there, each of the models' residuals are negatively correlated with $Prob(LTV(HP_t) > 1)$. This indicates that the overall rate of mortgage terminations tends to be depressed for those mortgage pools in housing markets experiencing particularly large declines in housing prices.

3.4 Estimation of the augmented exponential hazard model

We also have estimated a version of the exponential hazard model augmented to include two additional explanatory variables (X_{4kt} and X_{5kt}) that are a particular (increasing) function of house price declines and

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LTVs.

interact with the refinancing incentive switch point (table 3, first row). The X_{4kt} variable equals $Prob(LTV(HP_t) > 1)$ only if the spread is narrow or negative, and X_{4kt} is zero otherwise, whereas X_{5kt} equals $Prob(LTV(HP_t) > 1)$ only when the spread exceeds 1 percentage point and X_{5kt} is zero otherwise. The estimated coefficients on the intercept, seasoning and refinancing incentive variables are not very sensitive to whether or not the housing-price-related explanatory variables also are included in the model. Although the estimated coefficient on the burnout variable is moderately sensitive to whether or not the housing-price-related explanatory variables also are included in the exponential hazard model, this variable does not contribute much to the predictive power of the model; thus, changes in the estimated coefficient on burnout have a relatively small impact on the overall fit of the model.

The estimated coefficients $\hat{\beta}_4$and $\hat{\beta}_5$ on the final two housing-price-related variables are negative and statistically distinguishable from zero. The result ($\hat{\beta}_4 < 0$) that falling house prices tend to depress overall prepayments when refinancing incentives are negligible is consistent with the alternative hypothesis we described above: the sum of default and mobility-related terminations tends to decrease as housing prices fall. Apparently, this is because mobility-related terminations drop in weak housing markets $((\partial[\pi^M_{kt}/-\partial h_{ikt}) < 0))$, and this latter effect of house prices on home purchases is larger than the offsetting effect of house prices on defaults $(|\partial\pi^M_{kt}/-\partial h_{kt})| > |\partial\pi^D_{kt}/-\partial h_{kt}|)$. The result $(|\hat{\beta}_5| > |\hat{\beta}_4|)$ that weak house prices have an even larger depressing effect on overall terminations when refinancing incentives are active than when they are inactive suggests that weak housing prices affect refinancing through much more than just increasing the risk of default.

3.5 Model Adequacy and Robustness of Results

Figure 1 shows a comparison of the time-series average actual SMMs to the aggregated predictions of the three models we have estimated. The upper panel plots the results for the full data set of 27,878 pools and the lower panel plots the results for the 653 weak housing market pools comprised primarily of mortgages from California and Hawaii. Several features of these plots are notable. First, using the full data set, all three models meet the minimal requirement of being able to predict elevated, spiking prepayments in declining interest-rate environments, such as that experienced in 1993. Second, all three models display shortcomings in some historical episodes. The exponential models generally underpredicted prepayments in the high prepayment period of late 1992 and 1993 and then overpredicted prepayments throughout the quieter remainder of the mid-1990s, until there were unpredictably large spikes in prepayments in early 1996 and early 1998. The rational model over-predicted prepayments in the refinancing waves of 1993 and early 1996. Last, in the time-series dimension, the aggregated fit of the exponential hazard model is relatively insensitive to whether or not the house price variables are included in the model.

For the weak housing market subsample shown in the lower panel of Figure 1, the two models that omit house prices–the rational model and basic exponential hazard model–significantly overpredict prepayments in the low interest rate environments of late 1993 and early 1996. These are periods with particularly large cumulative declines in housing prices in California and Hawaii relative to 1991, when most of these weak housing price pools were originated. Thus, the results displayed in this figure suggest that the negative correlation between housing prices and the prediction errors of the models that omit housing prices is largest when housing prices are low and interest rates are low. Also, there is some evidence that the suppression of refinancing and mobility-related terminations in the mid-1990s led to "reverse burnout" in early 1998, when interest rates fell again but housing prices had recovered. For the pools shown in the lower panel, the version of the exponential model augmented to include house prices is able to capture both the subsumed prepayments in the mid-1990s and the acceleration of prepayments in early 1998. This ability of the model to improve the fit for these weak housing price pools likely is part of the reason why the housing price variables are statistically significant in the augmented exponential hazard model (table 3, first row).

The finding that the house price variables are statistically significant in the augmented exponential hazard model is robust. Various authors have suggested alternative measures of seasoning, burnout, and refinancing incentives for empirical prepayment models, and the use of such alternative measures does not change this result on house prices. For example, the use of a quadratic function of age instead of the log(PSA) schedule for the seasoning effect produces little change in the estimated size and standard errors of the coefficients on the house price, burnout, and refinancing incentive variables (table 3, row 2), partly because the implied fits of the quadratic and the log (PSA) seasoning variables are very similar over the first sixty months of loan age. Second, although various authors have advocated using a burnout measure that accumulates the "in-the-moneyness" of the prepayment option, instead of the Schwartz and Torous (1989) log factor to balance ratio we use to measure burnout, the use of such an alternative burnout measure does not change our main results. Specifically, Schwartz and Torous (1993) propose accumulating the values of the interest rate spread variable for those periods when the spread exceeds the refinancing incentive threshold. When we use as a burnout measure the accumulated values of the spread when the spread exceeds one percentage point, the house price variables remain statistically significant, and the coefficients on other explanatory variables also are little-changed (table 3, row 3). Last, some authors have argued that the ratio of outstanding mortgage coupon to current primary market mortgage rates is a better measure of refinancing incentives than the spread between these interest rates. Our result that weakness in housing prices tends to depress refinancing and mobility-related prepayments is robust to the use of the ratio form of the refinancing incentive variable (table 3, row 4).

Although the diagnostics we have applied suggest that the rational model and basic exponential hazard model are adequate for investigating the additional explanatory power of house price variables for prepayments, we also recognize that these models have some additional shortcomings. To further review model performance, we also display the fits of the models and actual prepayment histories by selected reference pool groups (Figure 2). Much of the pool-specific variation in average prepayment rates is associated with the vintage of origination and WACs of the pools, which are clustered by reference pool group. The 1991 vintage reference pool group (with 9.0 percent passthrough coupon and 9.6 percent original WAC) experienced the highest rates of prepayment throughout all of the sample except early 1998. The 1992 8.0s also experienced large refinancing waves in 1993 and 1994, when primary mortgage rates were relatively low. The 1993 7.0s (lower panel) and other pools originated in 1993, generally carry the lowest coupons of the pools in the sample; these pools generally experienced prepayment rates of less than 1 percent per month until early 1998. Pools originated in late 1994 generally bear WACs of 8-1/2 percent or above and experienced a mild bout of refinancing in early 1996 and a larger spike of prepayments in early 1998 (not shown). Fitting the wide variety of prepayment patterns across reference pool groups with a single set of parameter estimates is a major challenge for the models.

Neither type of model (rational or exponential hazard) is able to fit the variety of prepayment patterns well with a single set of parameter estimates. As shown by the fits of the various models by selected reference pool aggregates also shown in Figure 2, the rational model captured the basic features of actual prepayments for the relatively high coupon 1991 9.0s and 1992 8.0s, but the rational model shows too much interest rate sensitivity for the low coupon 1993 7.0s. In contrast, the exponential models fit the low coupon 1993 7.0s pattern well, but the exponential models notably underpredict the late 1993 prepayment spike in the 1992

8.0s and notably overpredict the late 1993 prepayment spike in the 1991 9.0s.

Although this paper is not the place to attempt to fully refine these prepayment models, we will note a few directions for future research. The exponential hazard model clearly could benefit from some improvement in its specification of refinancing incentives. One indication of this comes from a plot of the average actual and fitted values of prepayments by discrete (10 basis point wide) classes of the interest rate spread variable (Figure 3, upper panel). Except for a slight underprediction of prepayments in the range of 50 to 100 basis points of spread, the basic exponential model fits well for ranges of the spread below 200 basis points. But, the model substantially overpredicts prepayments at very wide spreads that exceed 200 basis points. In contrast, the rational model fits the actual data by class of spread for a wider range of spreads.

The basic exponential model fits the seasoning profile in the data well (Figure 3, lower panel), but the rational model clearly could benefit from some improvement in its specification of how prepayment probabilities vary as loans age. In this regard, the mis-specification of the rational model occurs primarily in the first two years after mortgage origination, during which predicted prepayments on individual pools remain at or above the background (default and mobility) hazard rate of $\hat{\lambda} = .007$, and average actual prepayments fall short of the predicted values.

4 Conclusions

As we have shown, a common failing of existing models of mortgage termination is that predicted prepayment levels for seasoned mortgages often over/underestimate the degree to which existing pools are "burned-out" from prior periods of interest rate driven refinancing, owing to inadequate controls for transaction cost heterogeneity between and within the mortgage pools. A particular focus of our work has been to determine the degree to which regional variations in housing prices generate atypical prepayment speeds. Our findings indicate that mortgage termination models that do not include housing prices as a state variable are mis-specified.

Additionally, we find that weak housing prices have a larger depressing effect on overall terminations when refinancing incentives are active and than when they are not which suggests that housing prices affect terminations in ways other than simply increasing the risk of default. This result is robust to alterations in the specification of the termination models, however, because most Freddie Mac pools tend to be relatively well-diversified across geographic areas, and given that housing prices were increasing in most states during the 1991 to 1998 historical period we study, most Freddie Mac pools were not subject to the test of whether weak housing prices hold down aggregate prepayments. From the fit of the housing-price augmented exponential model relative to the one that omits these effects, we find that the model with housing price effects was much better able to explain low levels of mortgage terminations in pools with concentrations of loans in California.

Our investigation of the performance of rational and exponential models of mortgage termination indicates that neither class of model, when constrained to a single set of parameter estimates, is able to accurately fit the variety of prepayment patterns exhibited by Freddie Mac pools of different coupons and vintages. Furthermore, we find that the exponential model appears to need refinement of its specification for refinancing incentives whereas the rational model needs to refine its specification of how prepayment probabilities vary as loans age. Together these findings highlight the need for additional research on why large declines in house prices tend to hold down refinancing and home sales related mortgage terminations and what factors underlie transaction cost heterogeneity within and between mortgage pools.

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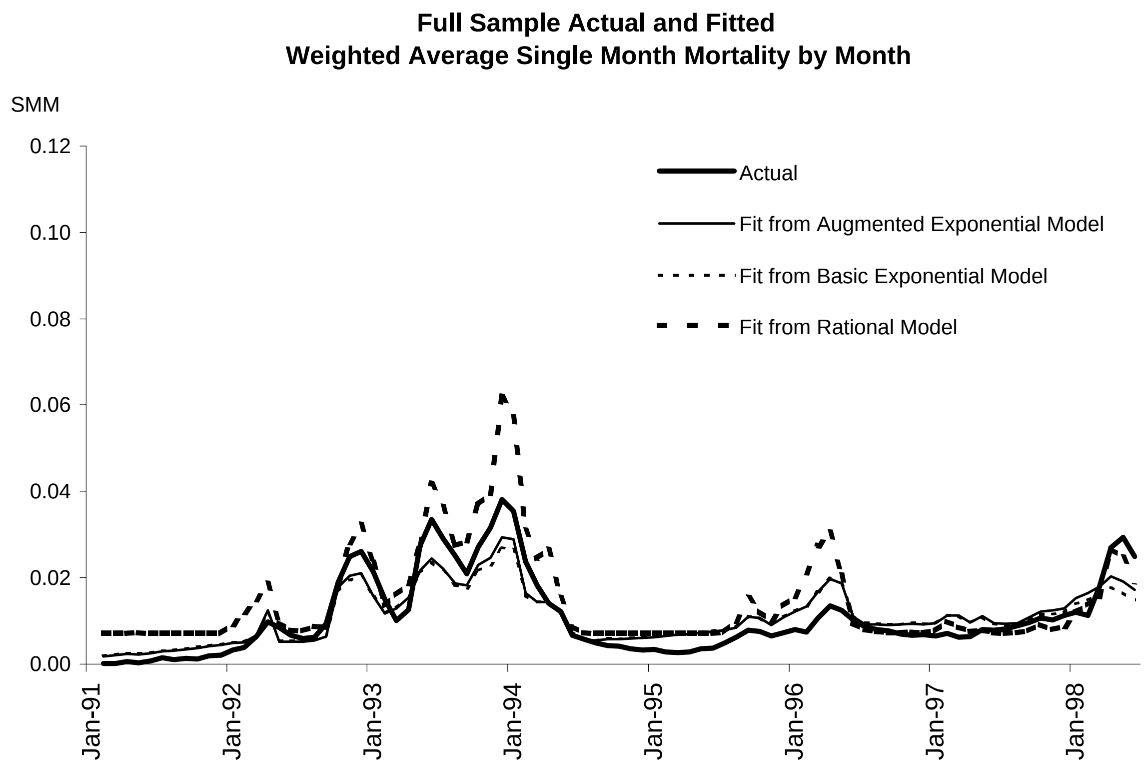
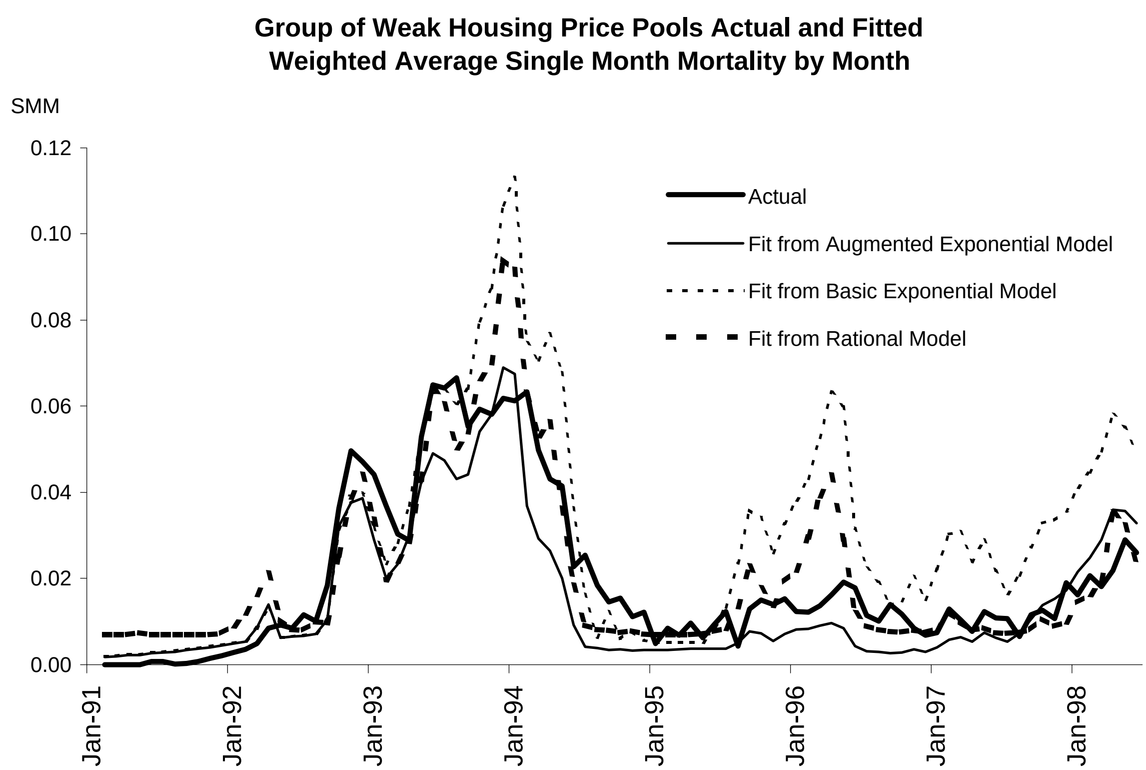
Figure 1



Full Sample Actual and Fitted
Weighted Average Single Month Mortality by Month
SMM
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Actual
Fit from Augmented Exponential Model
Fit from Basic Exponential Model
Fit from Rational Model
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98

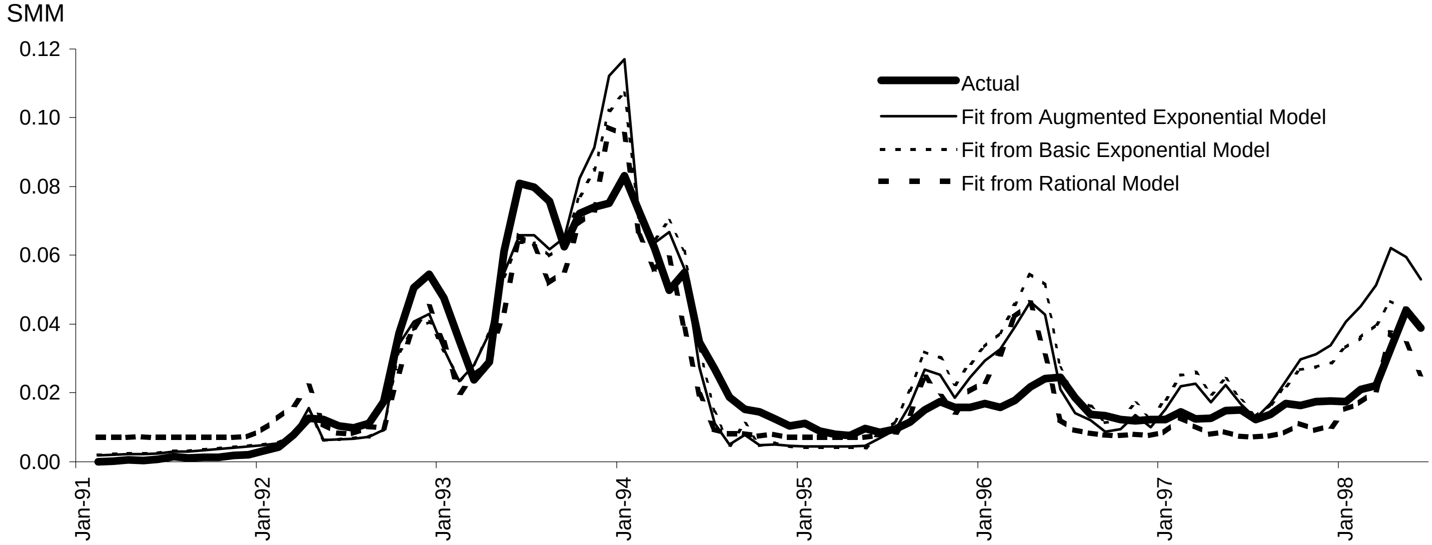


Group of Weak Housing Price Pools Actual and Fitted
Weighted Average Single Month Mortality by Month
SMM
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Actual
Fit from Augmented Exponential Model
Fit from Basic Exponential Model
Fit from Rational Model
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98

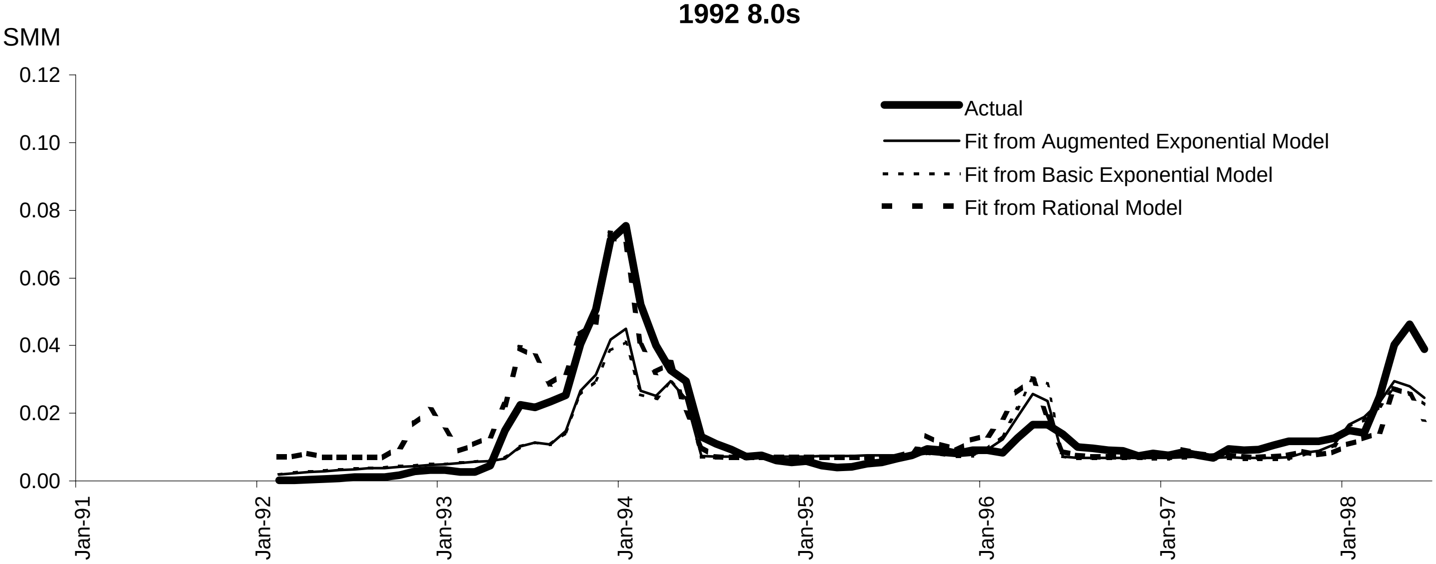
Figure 2

Reference Pool Aggregates of Actual and Fitted Weighted Average Single Month Mortality by Month

1991 9.0s



1992 8.0s



1993 7.0s

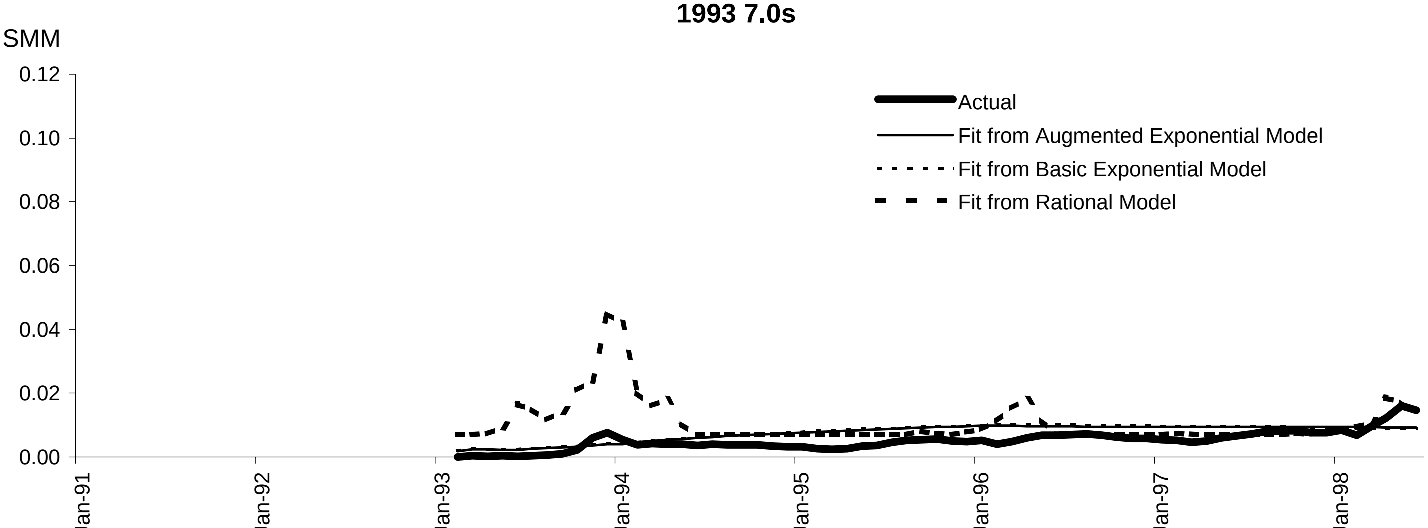
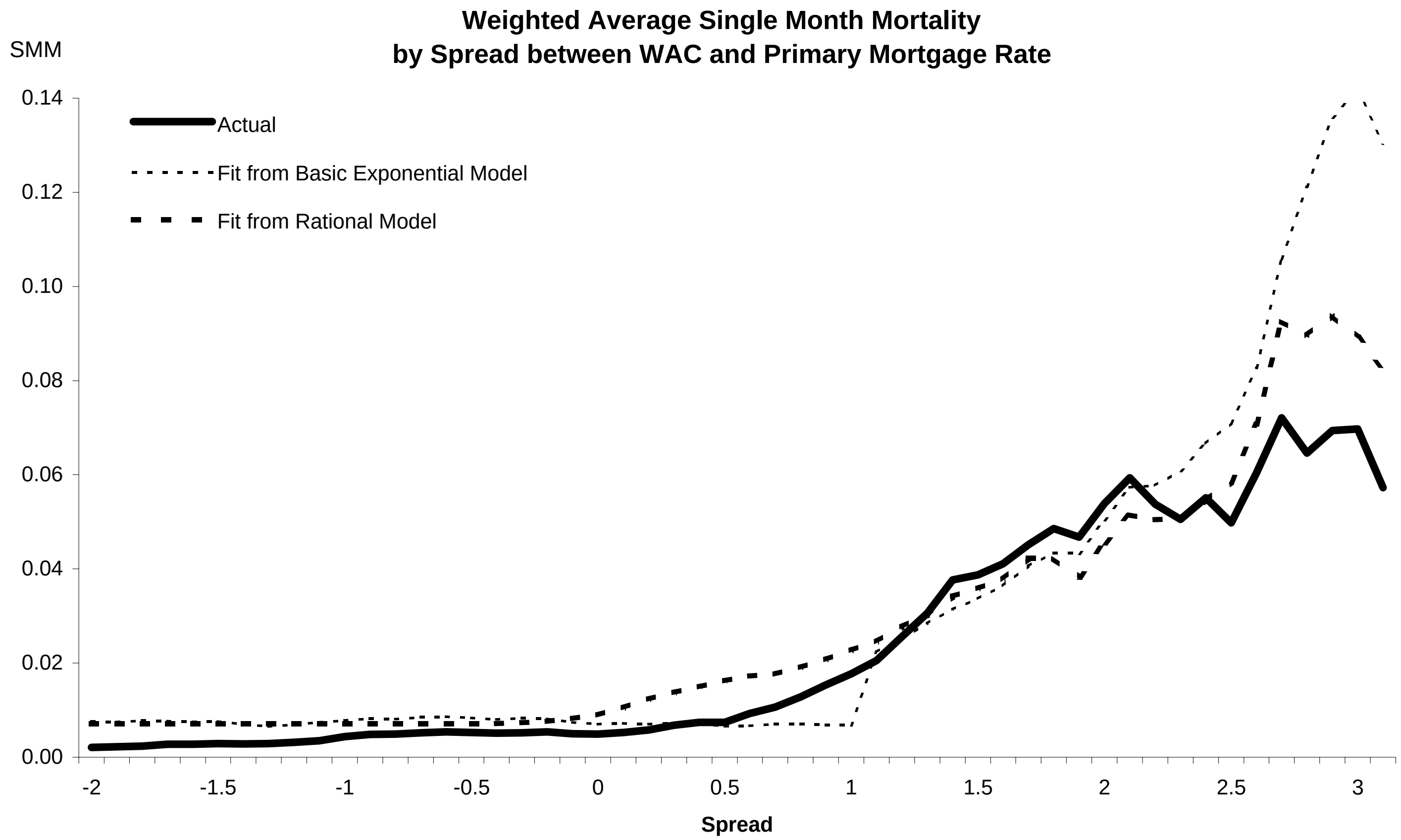


Figure 3


Weighted Average Single Month Mortality
by Spread between WAC and Primary Mortgage Rate
SMM
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Actual
Fit from Basic Exponential Model
Fit from Rational Model
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2
2.5
3
Spread

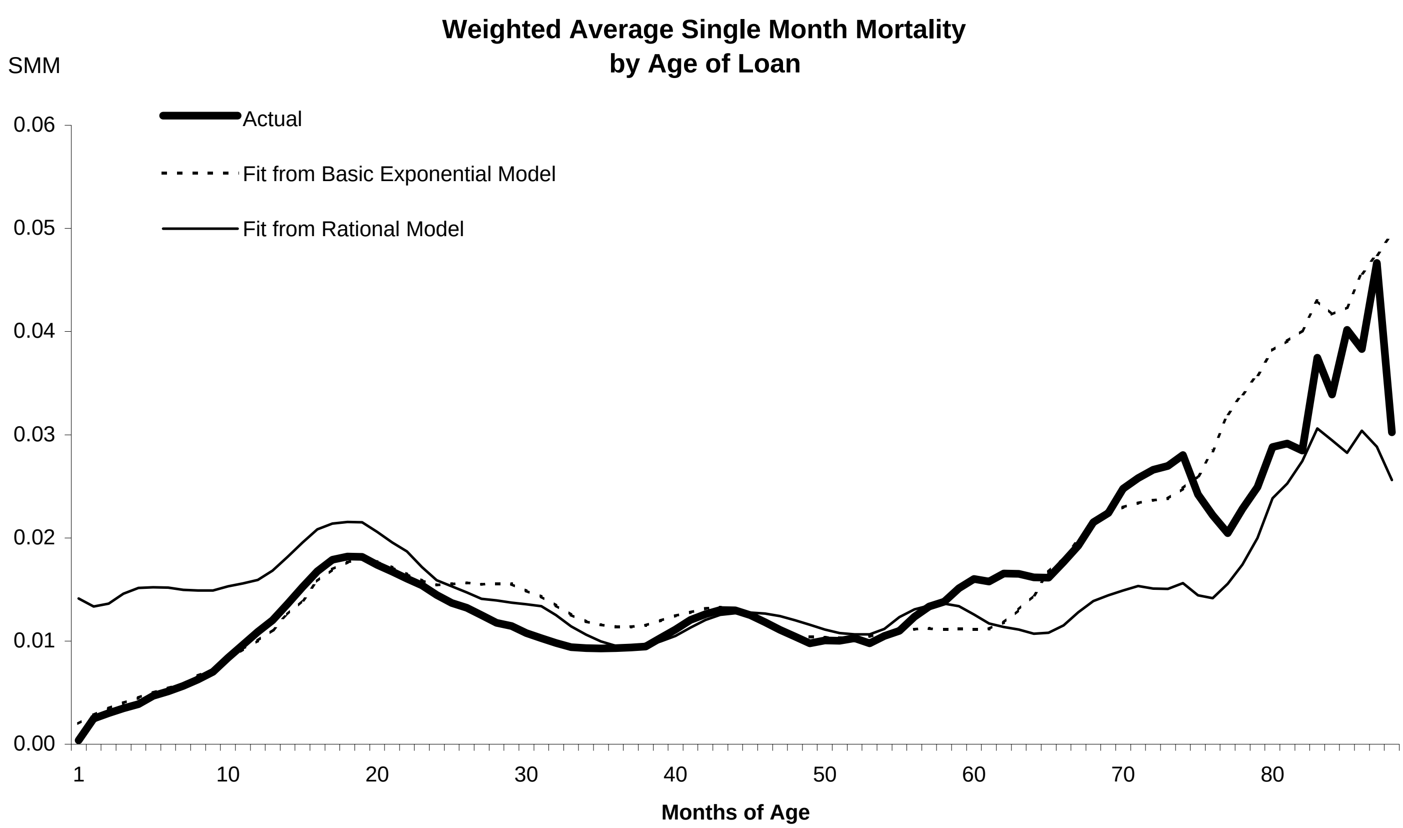

Weighted Average Single Month Mortality
by Age of Loan
SMM
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Actual
Fit from Basic Exponential Model
Fit from Rational Model
1
10
20
30
40
50
60
70
80
Months of Age

TABLE 1
Basic Characteristics of Freddie Mac Pools of Newly Issued Conventional Mortgages

Year Issued	Passthrough Coupon	Weighted Average Original Coupon	Number of Pools	Number of Loans	Weighted Average Single Month Mortality
1991	9.0	9.60	4,127	148,962	.0259
1992	8.5	8.92	2,760	62,824	.0203
1992	8.0	8.53	4,827	123,328	.0155
1993	7.5	7.96	3,620	125,644	.0090
1993	7.0	7.50	5,433	234,709	.0055
1994	7.0	7.45	2,647	182,530	.0052
1994	7.5	7.97	1,603	82,068	.0073
1994	8.0	8.52	1,715	93,836	.0119
1994	8.5	8.92	1,146	67,910	.0155
Full Sample			27,878	1,121,811	.0109

Sources: Authors calculations of aggregates from pool-level data.
Notes: Weighted average single-month mortalities are computed using monthly observations from pool inception to June, 1998 using the beginning-of-month outstanding balances of each pool as a weight.

TABLE 2

Estimated Coefficients of Rational and Basic Exponential Hazard Models of Mortgage Termination in Freddie Mac MBS Pools

———Rational Prepayment Model———				
			Refinancing Decision	——Memorandum——
Intercept	*Transactions Costs*		*Frequency*	OLS Slope Estimate of
$\hat{\lambda}$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\rho}$	Residual on $Prob[LTV(HP_t)] > 1)$
.007	2.295	4.692	.113	-3.565
(.001)	(.19)	(.43)	(.014)	(.061)

———Exponential Hazard Model———				
	Seasoning	*Burnout*	*Refinancing Incentive*	
		Log Factor	Spread when	——Memorandum——
Intercept	$Log(PSA)$	*to Balance*	$Spread \geq 1$	OLS Slope Estimate of
$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	Residual on $Prob[LTV(HP_t)] > 1)$
-1.822	.505	.755	1.131	-8.377
(.074)	(.013)	(.015)	(.008)	(.059)

Sources: Estimation by the authors.
Notes: (1) The exponential hazard model was estimated by the method of maximum likelihood using a 1000 pool random subset of all pools. The dependent variables are loan by month observations on whether a loan has prepaid, spanning the date of pool inception to June, 1998. The rational prepayment model was estimated by non-linear least squares using data from those 2575 pools with weighted-average coupons exactly 50 basis points above their passthrough coupon. Both subsamples span the full range of passthrough coupons and years of issuance shown in table 1. Estimated standard errors of the coefficients are shown in parentheses. The final column shows the estimated slope coefficients on the house price probability variable in regressions using as dependent variables the residuals of each model for the log hazards, computed from observations on all 27,878 pools.

TABLE 3
Estimated Coefficients of Exponential Hazard Models
of Mortgage Termination in Freddie Mac MBS Pools
using Alternative Measures of Seasoning, Burnout, and Refinancing Incentive

		Seasoning		*Burnout*		*Refinancing Incentive*		*House Price Variables*	
		Quadratic Age Terms		Log Factor	Cumulative	Spread when	Ratio form	$Prob[LTV(HP_t)] > 1)$ *when*	
Intercept	Log(PSA)	τ	τ^2	to Balance	of Spread≥1	Spread≥1	of Spread	Spread<1	Spread≥ 1
-1.629	.539			.447		1.244		-3.846	-12.980
(.083)	(.014)			(.017)		(.010)		(.513)	(.408)
-5.626		.054	-.0006	.328		1.273		-5.128	-14.822
(.019)		(.001)	(.0000)	(.024)		(.011)		(.521)	(.408)
-2.077	.477				-.034	1.241		-3.150	-9.570
(.079)	(.013)				(.001)	(.010)		(.510)	(.424)
-9.788	.616			.566			8.620	-7.651	-8.177
(.117)	(.014)			(.018)			(.069)	(.514)	(.377)

Sources: Estimation by the authors.
Notes: (1) The exponential hazard models were estimated by the method of maximum likelihood using a 1000 pool random subset of all pools. The dependent variables are loan by month observations on whether a loan has prepaid, spanning the date of pool inception to June, 1998. Estimated standard errors of the coefficients are shown in parentheses.