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HOUSING PRICE CYCLES AND PREPAYMENT RATES OF U.S. MORTGAGE POOL

By

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

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Abstract

Proper valuation of mortgage-backed securities hinges on the ability to model mortgage termination risk. 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. Our other recent work has demonstrated that the path of house prices was quite important for explaining variations in mortgage termination rates across California counties in recent years; weak collateral values in some counties held down refinancing and mobility, while boosting defaults. The effect of housing prices on refinancing was larger than the other effects, so, on balance, overall mortgage terminations were depressed in markets with weak housing prices. Here, we extend this line of analysis to include empirical evidence from housing markets throughout the United States, explaining prepayment rates for individual Freddie Mac mortgage pools. We find that housing prices are statistically significant in two empirical prepayment model specifications, an exponential hazard model and a rational prepayment model. Looking at the fit of these models for pools with geographic concentrations in particular states, we again find that, on balance, weak housing prices were a deterrent to mortgage termination in California. In our 1991-98 sample period, housing price effects were not as important in other U.S. states.

1 Introduction

Proper valuation of mortgage-backed securities hinges on the ability to model mortgage termination risk. 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.

A growing literature recognizes the importance of understanding the role of house prices in mortgage terminations. Differences across mortgageholders 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, Ling, and McGill, 1997).

Most theoretical and empirical prepayment models (e.g., Dunn and McConnell, 1981; Schwartz and Torous, 1989; 1993; Stanton, 1995, 1996) consider the mortgage-refinancing termination in isolation from explicit determinants of default and household mobility. The value of exercising the option often is modeled as depending on the evolution of one stochastic factor, a spot interest rate. Such single-factor rational prepayment models sometimes include a Poisson arrival rate λ for terminations, but this arrival rate is assumed to be exogenous with respect to the interest rate process. Although, in principle, the conditional mean of the Poisson process could be generalized to vary over time and to depend on exogenous observables that determine default and mobility (Dunn and McConnell (1981), Kau et. al. (1992)), this is difficult to implement, in practice. Accordingly, while researchers such as Archer and Ling (1993) have been able to integrate optimal call and empirical models of prepayment, they have done so only in a comparative static

sense. That is, they have compared MBS values for different configurations of time-invariant transactions costs and Poisson arrival rates.

Another ambitious strand of the literature has extended the assumption of optimizing behavior to the default dimension. The work of Kau and his co-authors (Kau et al., 1992; 1994), summarized in Kau and Keenan (1995), introduces a geographic dimension by emphasizing the evolution of house values as a determinant of default. In these models, default is a competing risk to other sources of termination, such as refinancing. However, empirical models of default (Quigley and Van Order, 1995) or of the competing risks of prepayment and default (Deng et al., 1996; Quigley, et al., 1994) generally do not completely impose the theoretical constraints of rational option valuation on the specifications.

In addition to default effects, geographic factors have been shown to be correlated with both interest-related and non-interest-related terminations. For example, for mortgage pools, Becketti and Morris (1990) use the location of the operations of the originator-servicer as a proxy for the geographic location of the collateral and document 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. 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 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.

In Matthey and Wallace (1998), we investigate terminations by type (refinancing, default, and mobility) for fifteen California counties from 1992 through 1996. We find 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 largely offsetting. Also, we found that an error-correction model similar to those employed in Abraham and Hendershott (1996) and Capozza, Mack, and Mayer (1997) worked well for describing the evolution of housing prices, and this facilitated prediction of the future path of housing prices and termination probabilities. In this error-correction model, a simple representation of housing fundamental values, based largely on net migration flows to an area, seemed to be adequate, consistent with the Blanchard and Katz (1992) emphasis on migration as an equilibrating mechanism across regional housing and labor markets.

In this paper we extend the Matthey and Wallace (1998) line of analysis to include empirical evidence from housing markets throughout the United States and focus on the prepayment rates for 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.

2 Approaches to Modeling Mortgage Terminations

2.1 The Rational Valuation Paradigm

Much of the academic mortgage valuation literature models mortgage terminations as a function of optimal call policies (see Dunn and McConnell, 1981; Brennan and Schwartz, 1985) or optimal call policies with transaction costs (See Stanton, 1995, 1996; Timmis, 1985; Schwartz and Torous, 1989; 1993). In addition, most of the early models consider the mortgage-refinancing termination option in isolation from optimizing over default, with interest rates as a sole stochastic factor determining the value of this refinancing option.

For example, in the one-factor model framework of Stanton (1996), which is a generalization of Dunn and McConnell (1981), termination predictions can be written as:

$$(1) \quad \pi_{it} = \lambda + \rho I(r_t \leq r_{it}^*) + v_{it}$$

In this particular model, 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 $r_t \leq r_{it}^*$, where r_t is the risk free rate and r_{it}^* is a time- and state-dependent threshold value where the call is optimally exercised. Here, π_{it} is the predicted termination rate for mortgage i at time t , and λ is the mean Poisson arrival rate of exogenous termination. 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 parameter ρ governs the frequency with which refinancing decisions are made. The critical interest rate r_{it}^* depends on the expected future evolution of interest rates,

the parameters (ρ, λ) , and the level of transactions costs faced by this individual.

Stanton's (1996) approach to modeling mortgage terminations at the more aggregate level of a mortgage pool is to assume that the function which specifies how individual mortgage holders react to evolving interest rates, at a given transactions cost, is common across mortgage pools, but the distributions of transactions costs themselves differ across pools. In particular, the distributions of transactions costs across individuals within the k th pool are assumed to be given by a Beta probability distribution with parameters α and β_k , so that the mean transactions cost is $\alpha/(\alpha + \beta_k)$ of the outstanding mortgage balance. Overlaid on this is an additional "decision-frequency" impediment to refinancing; with probability $(1 - \rho)$, the decision to refinance is not even considered, and with probability ρ the optimal exercise rule is followed. Since neither ρ nor λ differ across pools in Stanton (1996), this model incorporates heterogeneity in termination predictions only through differences in the critical interest rates, r_{kt}^* .

Let $F_{kt}(r_t \leq r_{kt}^*)$ denote the proportion of surviving individual loans in pool k with transactions costs low enough for refinancing to be optimal at time t . Then, the pool-level single-factor prepayment model can be written as a discrete hazard of the form:

$$(2) \quad \pi_{kt} = \lambda + \rho F_{kt}(r_t \leq r_{kt}^*) + v_{kt}$$

In this paper, we are interested in the problem of valuing mortgage pools which are collateralized by houses in known geographic locations, which we will index by a 51-dimensional vector reflecting the original proportion of loans by state (j) in pool k , $w_k = (w_{1k}, w_{2k}, \dots, w_{jk}, \dots, w_{51k})$. (The District of Columbia is treated as a 51st state.) Irrespective of this geographic distribution, the value V_{kt} to a lender at time t of the mortgages in pool k can be written as the expected present discounted value of the cash flows to be

received, $X_{k,t+\tau}$, between the present and the termination date of the mortgages, T . If time is discretized, this present value can be written as :

$$V_{kt} = E_t \sum_{\tau=0}^{T-t} \beta_{k,[t,t+\tau]} X_{k,t+\tau} .$$

The discount factors $\beta_{k,[t,t+\tau]}$ should be treated as stochastic functions which depend on the evolution of interest rates and on the price of interest rate risk. If the Poisson process governing additional terminations is independent of the interest rates, then the present value relation may be written in the one-factor model context as:

$$(3) \quad V_{kt} = \sum_{\tau=0}^{T-t} [\lambda X_{k,t+\tau}^p E_t \beta_{k,[t,t+\tau]} + (1 - \lambda) X_{k,t+\tau}^p \rho E_t \beta_{k,[t,t+\tau]} F(r_{t+\tau} \leq r_{k,t+\tau}^*) \\ + (1 - \lambda) X_{k,t+\tau}^s (1 - \rho) E_t \beta_{k,[t,t+\tau]} F(r_{t+\tau} \leq r_{k,t+\tau}^*) \\ + (1 - \lambda) X_{k,t+\tau}^s \rho E_t \beta_{k,[t,t+\tau]} (1 - F(r_{t+\tau} \leq r_{k,t+\tau}^*))]$$

Here, X^p denotes the cash flow upon prepayment and X^s denote the cash flow for a scheduled payment, amounts which we assume are known in advance¹. The first line of equation (3) shows two reasons for cash flows at the prepayment level, X^p : an exogenous prepayment or an interest-rate related prepayment. The second and third lines show two reasons for cash flows remaining at the scheduled level, X^s , when no exogenous prepayment was triggered: failure to exercise an optimal call or failure of the interest rate to be in the exercise region.

Researchers such as Dunn and McConnell (1981) and Stanton (1996) consider the continuous-time

¹We abstract from the possibility of partial prepayments.

counterpart to this valuation problem with a particular assumption about how the term structure of interest rates evolves and use methods for solving partial differential equations to solve for V_{kt} . In this solution method, the critical interest rates $r_{k,t+\tau}^*$ that define the optimal exercise regions for prepayment are “calculated” at least implicitly.

A similar valuation paradigm also motivates MBS pricing practice in the capital markets. It is common to estimate MBS passthrough valuations by Monte Carlo integration of the expected present discounted value of cash flows. As in the rational valuation paradigm, predicted cash flows are discounted according to a shifted Treasury spot curve, with discount factors and prepayment cash flows both linked to realizations of interest rates, as in equation (3) above. However, empirical valuation models often do not impose theoretical constraints of optimizing theory on the empirical specification of the relationship between interest rates and termination behavior. Rather, simplified empirical proxies tend to be used for the refinancing incentives, with Monte Carlo simulations used to capture the covariation between the evolution of the discount factors and the interest-related prepayment responses.

2.2 Empirical Prepayment Models

The approach to specifying an empirical prepayment model has tended to differ somewhat across researchers, depending on whether the available data is at the more aggregative level of mortgage pools or disaggregative level of individual loans. At the pool level, proportional hazard models for total terminations have been popular. For example, both Green and Shoven (1986) and Schwartz and Torous (1989)

specify that the hazard function is

$$(4) \quad \pi_{kt} = \pi_{0\tau_{kt}} \exp^{X_{kt}\beta}$$

where $\pi_{0\tau_{kt}}$ is a baseline hazard which gives the probability of termination (from all sources considered jointly) when the covariates X_{kt} are zero (equal to their sample means). The $\exp^{X_{kt}\beta}$ term is an exponential proportionality factor that captures the dependence of the hazard on these covariates. Here, τ indexes the age of the loans in the pool, which increments by one with time t . Note that under such a proportional hazard specification, the log hazard can be written as the sum of the log baseline and a linear term:

$$(5) \quad \log[\pi_{kt}] = \log[\pi_{0\tau_{kt}}] + X_{kt}\beta$$

Much of the empirical literature on individual loan prepayments also has used exponential proportional hazard specifications. In some cases, the availability of data on whether the source of termination is a default has allowed researchers to specify separate hazards for defaults and for other types of terminations. For example, Deng (1997) and Deng, Quigley, and Van Order (1998), estimate log hazard models of the form:

$$(6) \quad \log[\pi_{kt}^d] = \log[\pi_{0\tau_{kt}}^d] + X_{kt}^d\beta^d$$

$$(7) \quad \log[\pi_{kt}^o] = \log[\pi_{0\tau_{kt}}^o] + X_{kt}^o\beta^o$$

where the superscripts d and o denote the separate sources of terminations.

The Wall Street models of pool-level MBS prepayment activity of Patruno (1994) and Hayre and Rajan (1995) also include submodels for separate pieces of aggregate prepayment activity, including default,

refinancing, and home sales due to household relocation. 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, most modelers of MBS pool prepayments must work with data in which all three of these sources of terminations—defaults, refinancings, and home sales—appear as an aggregate rate of mortgage termination. With pool-level data that does not distinguish defaults from relocations or refinancings, switching-regime models offer a promising means of identifying the separate parameters governing types of prepayment behavior (Kau and Springer (1992)).

2.3 Our Hypotheses and Empirical Specifications

Although the bulk of empirical research on mortgage pool valuation is based on one-factor models with interest rates as the underlying stochastic process, other theoretical and empirical work has introduced a geographic dimension into mortgage valuation models by emphasizing the evolution of house values as a determinant of default. For example, in the largely theoretical work of Kau and his co-authors (Kau et al., 1992; 1994), summarized in Kau and Keenan (1995), default is a competing risk to other sources of termination, such as refinancing and home sales. Generalizing the above, we have

$$(8) \quad \pi_{kt} = \lambda^M + F_D(h_{ikt} \leq h_{kt}^*) + \rho F_R(r_t \leq r_{kt}^*) + v_{kt}$$

Here, as before, F_R is a distribution function for the proportion of mortgage holders for whom the spot interest rate has fallen below the critical level, r_{kt}^* , at which refinancing becomes optimal. Similarly, F_D is a distribution function for the proportion of mortgage holders for whom the house price, h_{ikt} , has fallen below the critical level, h_{kt}^* , at which default becomes optimal. In this case of a two-factor model, λ^M is the

exogenous termination probability due to the home sales/relocation behavior of homeowners who have not defaulted. Deng (1997) and Deng, Quigley, and Van Order (1998) estimate empirical models motivated by this rational prepayment and default specification, taking into account that both critical values, r_{kt}^* and h_{kt}^* , depend on both the interest rate and house price state variables. That is, there are critical regions (in interest rates and house prices), not critical values (in two separate single factors), determining the exercise regions.

In this paper, we seek to expand on our earlier (Mattey and Wallace (1998)) evidence that the single-factor model, equation (2), is mis-specified in omitting house prices as an explanatory variable, but a rational competing risk model of the form of equation (8) has limited usefulness as a way to integrate housing prices into MBS pool valuation models, owing to the unmodeled sensitivity of refinancing and home purchases to housing prices (even when default is so far out of the money that it ceases to be a competing risk). The rational competing risk approach emphasizes that declines in home prices have a first-order effect of increasing defaults, $(\delta F_D(\cdot)/ - \delta h_{ikt}) > 0$, and a second-order effect of reducing other types of terminations, $(\delta(\lambda^M + F_R(\cdot))/ - \delta h_{ikt}) = (\delta(F_R(\cdot))/ - \delta h_{ikt}) < 0$, through reducing refinancings (i.e., $(\delta\lambda^M / \delta h_{ikt}) = 0$). We also adopt the assumption that reductions in housing prices tend to increase defaults. But, our main alternative hypothesis is that terminations related to home purchases tend to decrease as housing prices fall $((\delta\lambda^M / - \delta h_{ikt}) < 0)$ and that this latter effect of house prices on home purchases is larger than the offsetting effect of house prices on defaults $(|\delta\lambda^M / - \delta h_{ikt}| > |\delta F_D(\cdot)/ - \delta h_{ikt}|)$. Also, we seek to admit the possibility that the decline in refinancings when home prices fall $(\delta(F_R(\cdot))/ - \delta h_{ikt}) < 0$ arises even when there is no quantitatively significant increase in the

competing risk of default.

Some of the extant literature is supportive of these alternative hypotheses². For example, in Matthey and Wallace (1998), we found evidence supportive of these hypotheses by investigating 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. Also, we found that the effects of housing prices on mobility were larger than the effects on defaults, so that the mobility effect dominated in their sum, which appears as an “exogenous termination probability” in the single-factor valuation model, equations (2) and (3). In this paper, we extend the Matthey and Wallace (1998) line of analysis to include empirical evidence from housing markets throughout the United States and focus on the prepayment rates for individual mortgage pools.

We consider the single-factor model, equation (2), as misspecified in omitting house prices as an explanatory variable. To evaluate whether the usefulness of the competing risks generalization is limited by its failure to model the sensitivity of home purchases and refinancing to housing prices (even when default is

²Substantial evidence suggests that geographic housing market factors significantly affect refinancing and mobility-related terminations, in addition to defaults. For example, for mortgage pools, Becketti and Morris (1990) use the location of the operations of the originator-servicer as a proxy for the geographic location of the collateral and document substantial variation in overall prepayment speeds by state from 1982 to 1988. Evidence from the early 1990s also has corroborated the importance of geographic factors to prepayments. 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 much regional economic conditions affect the propensity to prepay for other reasons, such as home purchases. Separately, using another dataset, Engelhardt (1998) shows that house prices have had a strong effect on household mobility within metropolitan areas.

so far out of the money that it ceases to be a competing risk), we estimate an empirical prepayment model that nests null and alternative hypotheses as differing combinations of parameter values in an exponential hazard model.

3 Prepayments on Freddie Mac Mortgage Pools

Our empirical analysis focuses on prepayment characteristics of Freddie Mac passthrough residential mortgage-backed securities (MBS). 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) MBS 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 primarily backed by newly-issued, standard 30-year fixed-rate mortgage loans³. 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.

³Specifically, we subset to pools with a Pool Type of "30 yr Gold PC", an original weighted average loan age of two months or less, and an original weighted average remaining maturity of 350 months or more.

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 dataset 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 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 month⁴. 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

⁴In 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 principal balances remaining in each of the pools at those times are used as weights.

observation period.

Figure 1 illustrates how much of the variation in the combined time-series, cross-section of prepayment rates is associated with the time-dimension and how much is associated with the cross-sectional dimension. Averaging across the full sample of pools with loans outstanding at each month, the upper panel of figure 1 shows that SMMs ranged from near zero at the beginning of the time period to a peak of 3.8 percent in December, 1993. In the majority of these 90 months, the average prepayment rate was quite near 1 percent. Average prepayment rates by pool, shown in the bottom panel, ranged from zero for some pools to 8.2 percent per month. However, about 21,500 of the pools experienced average prepayment rates of less than 2 percent per month.

Much of the pool-specific variation in average prepayment rates is associated with the vintage of origination, given that this also is highly correlated with the WACs of the pools. As shown in the upper panel of figure 2, the 1991 vintage reference pool (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. These 1991 pools and the 1992 8.5s and 1992 8.0s experienced large refinancing waves in 1993 and 1994, when primary mortgage rates were relatively low. The pools originated in 1993 and early 1994, shown in the middle panel, generally carry the lowest coupons of the pools in the sample; except for a little bit of action in the 1993 7.5s in late 1993, 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.

In specifying an empirical hazard model, we account for the effects of differing refinancing incentives

(primarily driven by differing WACs) and a few other factors. Our first purpose is to represent those empirical models that do a reasonable job of predicting overall prepayments, averaged across pools of similar WAC and age, but do not incorporate a housing price channel for explaining the heterogeneity of prepayment rates within these WAC/loan age classes. The univariate distributions of prepayment rates by age of loan and by the spread between the WAC and the primary mortgage rate are summarized in figure 3⁵. As shown in the upper panel of figure 3, the prepayment rate has averaged less than 1 percent per month for spreads below 50 basis points, and below this threshold there is not much sensitivity of the prepayment rate to the exact level of the spread. Somewhere above 50 basis points the effect of the spread on prepayments appears to begin to increase sharply, with a clear bivariate correlation between spreads and prepayments for spreads above 100 basis points.

As shown in the lower panel of figure 3, average prepayment rates are lowest at the beginning of the mortgage term and tend to increase during an initial “seasoning” period. Empirical prepayment models usually are parameterized in such a way that a ramp-up during the initial seasoning period can be incorporated into a baseline hazard⁶. Here, we use an exponential proportional hazard model of the form of equation (4), with a baseline hazard that can incorporate the “PSA Schedule” of seasoning as a special

⁵In figure 3 and elsewhere in this paper, we define the spread as the WAC less a three-month lag of the primary mortgage rate, to account for the built-in lags between the contractual decision to prepay and the appearance of prepayments in the reported factor data.

⁶The 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 mortgage (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 as the horizon lengthens.

case⁷:

$$(9) \quad \pi_{0\tau_{kt}} = \exp^{\beta_0 + \beta_1 \text{Log}(PSA_{\tau_{kt}})}$$

We use four time-varying covariates to scale this baseline hazard up and down. To measure the refinancing incentive, we use the spread between the WAC on the pool and the (lagged) primary mortgage rate, as in our discussion of figure 3 above. 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. We also include a “burnout” measure in the model, following 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 previous prepayment. Various researchers have argued that some such burnout measure should be included in empirical prepayment models as a way to control for changes in the distribution of “transactions costs” across pool survivors. Other things equal, loans held by pool members with the lowest transactions costs will be terminated first, increasing over time the average level of transactions costs among survivors; see, for example, the Stanton (1995) rational prepayment model. If this transactions cost related selection process is at work, then prepayments will tend to be lower for those pools that have experienced a lot of prior prepayments.

Last, we include two variables that are a function of house prices. Both measure the probability that

⁷The PSA schedule increases linearly from zero to an 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 in this exponential model is the PSA schedule. For our purposes of assessing mortgage valuation models, a parsimonious parameterization of the baseline such as this is preferred to semi-parametric estimation, which runs more of a danger of overfitting and can be difficult to extrapolate beyond the observed distribution of loan ages.

house prices have fallen sufficiently since loan origination to render the current loan-to-value ratio greater than unity. We allow the coefficients on this variable to differ, depending on whether or not refinancing incentives are dormant. More specifically, we again use a 1 percentage point spread to demarcate a switch point between the presence and absence of a refinancing incentive.

Figure 4 displays average prepayment rates by discretized levels of the cumulative prepayment/burnout measure and the house price/LTV probability measure. Any transactions cost related selection process which might be at work does not show through clearly in the distribution of average prepayments by cumulative prepayment level. In the majority of months for which pool prepayments are observed, the factor to scheduled balance ratio is above 75 percent, so the log of this ratio is in the 0 to -.3 range. Over the range from 0 to -.5 on the logarithm of the factor to scheduled balance ratio, average prepayment rates actually increase and then plateau at about 2 percent per month (upper panel of figure 4). Although the seasoning process, which we capture in the loan age component of the baseline hazard, might account for some of this initial ramp-up in prepayment rates as cumulative prepayments increase, we realize from this peek at the data that burnout does not seem to be a feature that will explain a lot of the variance in prepayment among Freddie Mac pools. In fact, the upper panel of figure 4 demonstrates the potential for finding evidence of “reverse burnout”.

Average prepayments by the range of our housing-price-related variable are shown in the bottom panel of figure 4. We use a method similar to that described in Deng, Quigley, and Van Order (1998, appendix A) to construct this 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 constructed⁸.

In constructing this variable, we assume that all pools have the same initial loan-to-value ratio of 80 percent⁹. Thus, in the first month after 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, this $Prob(LTV(HP_t) > 1)$ measure is below 1-1/2 percent. Only about one-quarter of the pool-month observations have a

⁸We 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 a pool-specific weighted average of the state level volatilities published by OFHEO.

⁹Our 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 mortgages securitized 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 towards 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 likely would be even stronger if we had data on initial LTVs.

$Prob(LTV(HP_t) > 1)$ 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. The average prepayments by range of $Prob(LTV(HP_t) > 1)$ shown in the bottom panel of figure 4 show a slight tendency of prepayments to decrease at the highest levels of $Prob(LTV(HP_t) > 1)$.

We estimate the exponential hazard model by the method of maximum likelihood¹⁰. 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.

If we used the full sample, this likelihood function would involve about 67 million loan by month observations¹¹. For tractability, we present estimates computed from a random sample of 1,000 pools per

¹⁰The log-likelihood function for this problem is the sum of log-likelihoods for individual observations, with each observation contributing 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 have been time-varying. That is, we accumulate the integrated hazards applicable to each time period in the sample.

¹¹Because 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.

model estimation, which still covers more than 2 million loan by month observations per estimation.

The estimated coefficients in the exponential hazard models are shown in table 2. The first two rows show results using a random draw from all pools. The second model estimated from the full sample is our preferred exponential hazard model, as it contains the housing-price-related variables. Using the wide variety of pools present in the full sample, all coefficients are estimated relatively precisely and are statistically distinguishable from zero. Also, the coefficients on the elements of the baseline hazard and on the non-housing-price related covariates have the anticipated signs. As expected, the estimated coefficient on the Log(PSA) schedule is positive, reflecting the initial range of increasing hazards as loans season. Also, an increase in the spread between the WAC and the current mortgage rate tends to have a large positive effect on terminations. Last, pools tend to experience higher prepayments if they have not experienced a lot of cumulative prior prepayments, as measured by the lagged factor to balance ratio. The coefficients on these first four explanatory variables are not very sensitive to whether or not the housing-price-related explanatory variables also are included in the model.

When included in the full sample estimation, the coefficient estimates on the final two housing-price-related variables are negative and statistically distinguishable from zero. The result that falling house prices tend to depress overall prepayments when refinancing incentives are negligible (spread is less than 1 percentage point) is consistent with the alternative hypothesis we described above: terminations related to home purchases tend to decrease as housing prices fall ($(\delta\lambda^M / -\delta h_{ikt}) < 0$), and this latter effect of house prices on home purchases is larger than the offsetting effect of house prices on defaults ($(|\delta\lambda^M / -\delta h_{ikt}| > |\delta F_D(.) / -\delta h_{ikt}|)$). The result that weak house prices have an even larger depressing effect on overall

terminations when refinancing incentives are active (spread is greater than 1 percentage point) than when they are inactive suggests that weak housing prices affect refinancing through more than just increasing the risk of default.

The lower rows of table 2 show subsample model estimation results by reference pool group, using separate random draws of 1000 pools per estimation. Reviewing the pattern of changes in estimated coefficients across subsamples is useful both for judging the stability of the parameter estimates and also for highlighting which subsamples help achieve stronger identification in the full-sample results. The estimated coefficient on the spread variable is relatively stable across all subsample results except for the 1994 7.0s reference pool group, for which the coefficient is not estimable because there are no pools that experienced a spread greater than 1 percent in this case. Similarly, for the 1993 7.0s, there are not many pools with active refinancing incentives, so the coefficients on the spread and on $Prob[LTV(HP_t)] > 1$ when the spread exceeds 1 percent are very imprecisely estimated in this case. The coefficient on the burnout measure has the expected positive sign only for the older pools, which have experienced the most significant cumulative prepayments.

The signs of the estimated coefficients on the house price variables are very stable across reference pool sub-samples. In only one case (the 1994 8.5s) the estimated sign of the coefficient on $Prob[LTV(HP_t)] > 1$ when $Spread < 1$ switches to positive; in this case there is not much variation in the housing-price-related variable, and the standard error on the coefficient estimate is relatively large.

Aggregated fitted values of the hazard models estimated from the full sample are shown in figure 5,

along with the actual prepayment rates¹². As shown in the upper panel, the relatively simple exponential hazard model fits the time-series profile of the actual full-sample average prepayment rate relatively well¹³. Also, once the results have been averaged across pools, as shown here, there is very little difference between the fits of the models with and without the housing-price-related variables.

However, the housing-price-related variables are very important to explaining some aspects of the cross-sectional distribution of prepayment rates. To illustrate this, the lower panel of figure 5 displays the aggregate actual and predicted prepayment rates for those 653 pools that experienced realizations of $Prob(LTV(HP_t) > 1)$ greater than 20 percent at some point in their observed prepayment history. Most of these pools contain almost exclusively loans from California (and in some cases also Hawaii), as noted above. For these pools, the model without house price variables predicts a large spike in prepayments in early 1994, but actual prepayments came in at only about one-half of the predicted level. Similarly, the model without house price variables predicts another spike in prepayments in early 1996, but no such surge materialized. The predicted prepayment levels from the model that includes the house price effects captures the observed relative unresponsiveness of prepayments in these two historical periods.

¹²Figure 5 shows actual and fitted values using all pools in these groups, not just from the subset of 1000 pools used in the estimation process.

¹³Although the fit is far from perfect, our objective in this paper is to shed light on the effect of housing prices on prepayments, not to search for the best specification of interest-rate effects.

4 Estimating the Rational Prepayment Model

One of the primary potential advantages of a Stanton-type rational model over the exponential model specified in Section 3 is that the predicted prepayments from the rational model actually obey the *optimal* exercise rule for the refinancing option. Thus, the rational model accurately controls for the option value of delaying prepayment given expected interest rate dynamics and the magnitude of transactions costs. As discussed in Section 3, the overall prepayment probability is defined as a function of the interest rate at which refinancing becomes optimal, r_{it}^* ; the mean 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 . We estimate the rational model here to see whether the model's prediction errors are correlated with a housing price variable. A positive finding for this test would suggest that the model's parameters are structurally unstable and its solution for the optimal prepayment boundaries fail to incorporate an important state variable, housing prices.

To implement the model we follow Stanton (1995) and assume that the nominal interest rate process follows a one factor Cox, Ingersoll, and Ross (1985) process. The parameter values used for the model are those from Pearson and Sun (1989).¹⁴ Given the interest rate process, we can calculate the value of

¹⁴The CIR model is a long run model of nominal interest rates in which the instantaneous risk-free interest rate r_t satisfies 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)

$$\kappa = 0.29368,$$

the mortgage and the optimal exercise strategy for the options using standard methods to value interest rate contingent claims written on coupon bonds. We use finite difference approximations to backwardly solve the value function subject to appropriate boundary conditions.¹⁵ Following the logic of Section 3, equation 1, for a given mortgage coupon rate and interest rate, r_t , there is a critical transaction cost Q_t^* such that if $Q_i \leq Q_t^*$, the mortgage holder will optimally repay the mortgage. As discussed above, the individual transactions costs Q_i are assumed to be drawn from a beta distribution. If it is not optimal for the mortgage holder to repay, observed prepayment only arises for exogenous reasons, so that the prepayment hazard is defined only as a function of λ . If it is optimal to refinance, the mortgage holder will repay either for exogenous reasons or for interest rate reasons. For small time intervals, the hazard rate governing prepayment in the Stanton rational prepayment model equals

$$\begin{aligned} \lambda & \quad \text{if } r_t > r_{t^*} \quad (\text{equivalently, } Q_i > Q_t^*) \\ \lambda + \rho & \quad \text{if } r_t \leq r_{t^*} \quad (\text{equivalently, } Q_i \leq Q_t^*). \end{aligned}$$

We define the expected value of the proportion of a pool i prepaying in month t as

$$(10) \quad \varpi_{it}(\alpha, \beta, \rho, \lambda) = E[(\omega_{it} \mid \Psi_t; \alpha, \beta, \rho, \lambda)]$$

$$\begin{aligned} \sigma & = 0.11425 \\ q & = -.12165 \end{aligned}$$

assuming that the long-run mean interest rate is $\mu = 0.04935$. In future drafts of the paper we plan to use Ait-Sahalia (1996) estimates which were obtained from a more recent and longer time series of interest rates.

¹⁵We used the 10 year Treasury Note rate to derive the short-run riskless rate. The iterative valuation solution assumes that prepayment decisions exhibit three month lags in an effort to control for the institutional realities of mortgage prepayment and origination.

where ω_{it} is the proportion of pool i that is observed to prepay in month t and Ψ_t is the information set determined by the observed interest rate dynamics. For any month t , at the critical transaction cost level Q_t^* , the proportion of pool i with transaction costs less than or equal to Q_t^* is defined by P_t^* . The expected value of the proportion prepaying can then be written as

$$(11) \quad \varpi_{it}(\alpha, \beta, \rho, \lambda) = (1 - \exp^{-\lambda/12}) \times (1 - P_t^*) + (1 - \exp^{-(\lambda+\rho)/12}) \times P_t^*$$

where $(1 - \exp^{-\lambda/12})$ is the probability of exogenous prepayment in month t when it is not optimal to prepay for interest rate related reasons and $(1 - \exp^{-(\lambda+\rho)/12})$ is the probability of prepayment due to both exogenous and fixed cost factors when it is optimal to refinance for interest rate related reasons. We use Stanton's (1995) strategy to discretize the prepayment cost distribution into m different cost levels and then determine the critical transaction cost level over all m mortgage cost "types" using a grid of interest rate and time values to determine the optimal exercise strategy for each "type". This strategy allows us to calculate the proportion of pool i with transaction costs less than or equal to the critical value Q_t^* .

The model prediction error is then defined as

$$(12) \quad \zeta_{it}(\alpha, \beta, \rho, \lambda) = \omega_{it} - \varpi_{it}(\alpha, \beta, \rho, \lambda).$$

The model thus generates a moment condition for every t^{th} month of data defined as $\bar{\zeta}_{it}(\alpha, \beta, \rho, \lambda) = 1/N \sum_{i=1}^N \zeta_{it}(\alpha, \beta, \rho, \lambda)$, the simple mean of the t^{th} period prediction error across N pools. We obtain consistent estimates of the parameters by minimizing a quadratic form defined by

$$(13) \quad \Omega_T(\alpha, \beta, \rho, \lambda) = \bar{\zeta}_{it}(\alpha, \beta, \rho, \lambda)^\top \bar{\zeta}_{it}(\alpha, \beta, \rho, \lambda).$$

We apply this estimation procedure to nine samples, each of which corresponds to a reference pool group as identified in figure 2. That is, we allow the estimates of the parameters $(\alpha, \beta, \rho, \lambda)$ to differ according to the vintage and passthrough coupon of the pools. For tractability, a sample of pools from each reference pool group is used in this stage of the estimation. Specifically, we use only the pools with weighted-average-coupons exactly fifty basis points above the passthrough coupon rate. We report the coefficient estimates and their estimated standard errors in table 3.

From the perspective of predicting pool-level prepayment rates the estimation results are quite reasonable. Also, the estimated values of the specific parameters are in most cases broadly consistent with the estimates calculated by Stanton (1995, 1996), which were derived from a quite different dataset and a different period for the estimation

The α and β coefficient estimates define the reference pool-specific beta distributions of transaction costs as a percentage of principal. The mean of each beta distribution is $\mu_Q = \alpha/(\alpha + \beta)$. Stanton found mean transactions costs of about 40% of the remaining principal balance in his sample of about 1000 GNMA pools, all of which carried a WAC of 9.5 percent and were followed over 1983 to 1989. In our results, the estimated mean transactions cost ranges from a high of nearly 40% for the 1994 8.5s to a low of about 23% for the 1993 7.0s¹⁶.

¹⁶The calculated standard errors suggest that the coefficients are very imprecisely estimated. In some cases this is to be expected; for example, one would not expect the transactions cost distribution parameters to be well-identified in those samples with low passthrough coupons and hence no predicted interest-rate related refinancing. However, the estimated standard errors also might be misleading, owing to their dependence on numeric derivative calculations in a context where we have discretely approximated the interest rate and time grid. In searching for a global minimum of the objective function, we have avoided this problem of inaccuracy in numeric derivatives by using an adaptive simulated annealing optimization algorithm (Ingber, 1995). In future drafts of the paper, we intend to explore the effects on calculated standard errors of increasing the grid fineness and of using alternative simulation-based methods for computing the standard errors.

The parameter ρ controls the likelihood of prepaying when exercising the refinancing option is optimal but impeded by additional costs associated with search; the average time between search for a refinancing opportunity is $(1/\rho)$. Higher values of ρ indicate that these search costs are lower and more people prepay when it is optimal to do so. For most of the high-coupon reference pool groups, we find estimated ρ s in excess of one, which are higher than the ρ values of about 0.6 estimated by Stanton. For our low-coupon reference pool groups, the estimated ρ s tend to be smaller, but in these cases the estimated values of ρ have little or no effect on the predicted prepayment rates.

Most of the estimates for λ , the likelihood of exogenous prepayment due to such factors as job relocation or house sales, are in the range of 6 to 10 percent per annum. These exogenous prepayment rates are a bit higher than those found by Stanton (1995, 1996).

In figure 6, we compare the actual prepayment experience for several of the reference pools to the estimated prepayment rates obtained from the rational and exponential empirical models. We select the 1991 9.0s, the 1992 8.0s, and the 1993 7.0s to provide results over a range of vintage and coupon. The figures show that both the rational and the exponential hazard models generate remarkably similar predictions. For the 1991 9.0s, both models overpredict the actual levels of prepayment observed in the low interest rate environments of 1994 and 1996. However, for the high-coupon 1991 9.0s, the rational model outperforms the exponential model in the low interest rate environment of early 1998.

For the 1992 8.0s, the rational model outperforms the exponential model during the 1993/1994 interest rate decreases, and then both it and the exponential model over-estimate the prepayment levels in the 1996 downturn and underpredict the effect of the 1998 downturn in rates. Finally, the 1993 7.0s appear to have

been out-of-the-money for all recent interest rate movements. The rational model overpredicts the initial prepayment levels relative to the actual and does not capture the reverse burnout observed in the early 1998 period. The exponential model predicts a long slow increase in prepayments which does not burnout until the early 1998; the exponential model does not track the observed prepayment levels as well as the rational model.

Because the rational model is a function of only one state variable, the short-run riskless interest rate, we must pose the test of whether the time- and place-varying house price variables are important determinants of prepayments as a test for misspecification. That is, we proceed under the null hypothesis that house prices have no effect and then consider whether the prediction errors from the rational Stanton-type model are correlated with house price variables. To implement this test, we calculate the expected prepayment rates and implied prediction errors for all 27,878 pools, not just those pools used in the first estimation stage, which lie on the discrete grid of WACs fifty basis points above the passthrough coupons. We then run a regression of the calculated monthly pool-level prediction errors on an intercept and our time-varying house price variable $Prob(LTV(HP_t) > 1)$.

In this regression of the residuals on the house price variable, we obtain a negative and statistically significant parameter estimate (-.008266 coefficient; .00097 standard error) for the house price variable. The sign of this coefficient implies that for those pools and dates when house prices have fallen alot since mortgage origination, actual prepayments tend to be smaller than predicted prepayments. Thus, house prices appear to be an important omitted factor. One interpretation of this result is that the level of house prices relative to loan amount is a determinant of the level of transaction costs faced upon refinancing.

When house prices are high, borrowers can easily refinance into mortgages that carry lower coupons, but when house prices fall, the loss in equity leads to higher costs of refinancing due to newly required mortgage insurance or to the need for a cash infusion to avoid such a need for mortgage insurance. Another interpretation of this result is that exogenous prepayments are held down in weak housing price markets by the lack of trade-up equity for home sales.

In figure 7 we further consider this result by plotting a comparison of the actual SMMs with the exponential predictions with and without the house price variable and the rational model predictions. The upper panel of the table plots the results for the full sample and the lower panel plots the results for the sample of 653 weak housing market pools comprised primarily of mortgages from California and Hawaii. As shown, in the overall sample the fitted rational and exponential SMMs slightly overpredict the actual SMMs in the early part of 1991 and 1992 and the low interest rate environment of early 1996. The exponential model underpredicts the low interest environment of late 1994 and both the rational and exponential models miss the reverse burnout exhibited in March 1998 when house prices were strong across the country.

In the weak housing market subsample, the exponential model without housing prices and the rational model significantly overpredict the SMMs in the low interest rate environments of 1994 and 1996. This is the same period in which housing prices in California and Hawaii continued to experience a sustained period of decreases. For these weak housing market pools, the exponential model with house prices better predicts the relatively low level of observed prepayments in 1994 and 1996.

Thus, Figure 7 suggests that the negative correlation between the rational model prediction errors and

the house price variable is largest when house prices are lowest and interest rates are low. Also, there is some evidence that this leads to reverse burnout in subsequent periods when interest rates again are low but housing prices have recovered.

Note that the sign of the correlation between overall prepayments and house prices is the opposite of that which would exist in a model where the only direct effect of house prices on prepayments is through defaults. Also, given the relatively low frequency of default, even in the weakest housing markets, it is unlikely that this pattern of results would arise from complicated competing risk effects. Instead, the results suggest that the housing price channel affects prepayment levels through transaction costs that are associated with mortgage repayment. These transaction costs could be associated with mortgage insurance costs, qualification impediments, or possibly higher coupons associated with higher loan-to-value mortgages and they would impede prepayment when house prices are high and would accelerate prepayment when house prices are low.

5 Conclusion

Proper valuation of mortgage-backed securities hinges on the ability to model mortgage termination risk. In this paper, we examined the extent to which regional variations in housing prices generated atypical prepayment speeds in Freddie Mac mortgage pools. Some of the recent literature emphasizes the possibility that large declines in house prices will tend to hold down refinancing and home sale related mortgage terminations, more than offsetting the increased terminations that come from increased defaults. We found that 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. However, there was a large decline in California house prices during this period. Overall, we found that housing price effects are statistically significant in two forms of empirical prepayment models. Looking at the fit of an exponential hazard model that includes house price effects relative to one that omits these effects, we found that the model with housing price effects was much better able to explain low levels of mortgage termination in pools with concentrations of loans in California. Also, we found that the residuals from a rational prepayment model that does not incorporate house prices were correlated in the anticipated way with house prices. These findings highlight the need for additional research on why large declines in house prices tend to hold down refinancing and home sale related mortgage terminations.

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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 Exponential Hazard Models
of Mortgage Termination in Freddie Mac MBS Pools

Year Issued	Passthrough Coupon	<i>Estimated Coefficient on</i>					
		Constant	Log(PSA)	Spread when Spread \geq 1	Log Factor to Balance	<i>Prob[LTV(HP_t)] > 1) when</i> Spread<1 Spread \geq 1	
All	All	-1.822 (.074)	.505 (.013)	1.131 (.008)	.755 (.015)		
All	All	-1.629 (.083)	.539 (.014)	1.244 (.010)	.447 (.017)	-3.846 (.513)	-12.980 (.408)
1991	9.0	3.369 (.166)	1.264 (.026)	.764 (.012)	.796 (.013)	-1.295 (.425)	-9.246 (.257)
1992	8.5	-2.155 (.164)	.419 (.025)	1.190 (.016)	.392 (.024)	-1.737 (.483)	-13.980 (.447)
1992	8.0	-1.001 (.149)	.609 (.024)	1.280 (.017)	.433 (.029)	-4.965 (.482)	-13.607 (.590)
1993	7.5	-4.429 (.105)	.065 (.016)	1.281 (.035)	-1.019 (.051)	-15.339 (.730)	-27.729 (4.088)
1993	7.0	-3.476 (.117)	.327 (.019)	1.021 (1.147)	-1.977 (.080)	-9.641 (.731)	-264.225 (432.475)
1994	7.0	-1.945 (.136)	.615 (.022)	n.a.	-2.484 (.105)	-9.506 (1.219)	n.a.
1994	7.5	-.564 (.157)	.789 (.026)	.921 (.085)	-2.372 (.073)	-13.142 (7.328)	-.564 (.157)
1994	8.0	.813 (.175)	.979 (.028)	1.017 (.023)	-.401 (.054)	-22.42 (2.067)	-27.49 (1.935)
1994	8.5	-1.866 (.147)	.547 (.023)	1.069 (.016)	-.343 (.040)	7.988 (2.171)	-40.630 (1.745)

Sources: Maximum likelihood estimation of exponential hazard models by the authors.

Notes: The data used in estimating each of the models was for a 1000 pool random subset of the group identified by year issued and passthrough coupon. 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.

TABLE 3
Estimated Coefficients of Rational Models
of Mortgage Termination in Freddie Mac MBS Pools

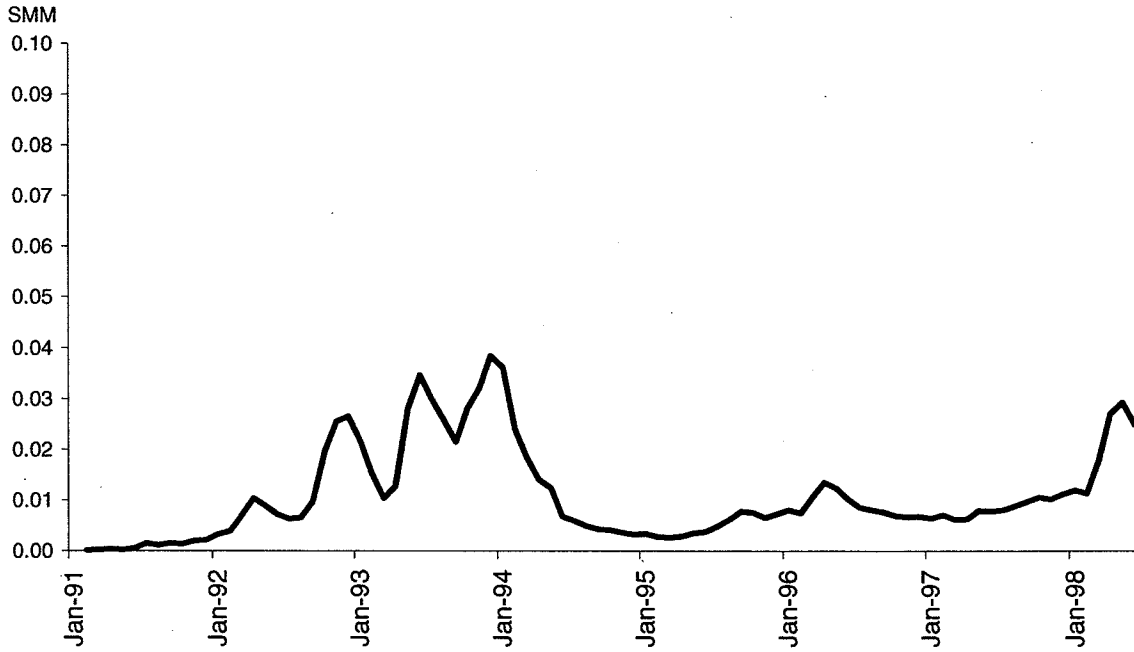
Year Issued	Passthrough Coupon	<i>Estimated Coefficient</i>				Number of Pools
		$\hat{\alpha}$	$\hat{\beta}$	$\hat{\rho}$	$\hat{\lambda}$	
1991	9.0	1.638 (1.08)	3.634 (2.03)	1.542 (.54)	.0863 (.06)	679
1992	8.5	5.950 (6.11)	9.401 (8.74)	1.247 (.79)	.1285 (.11)	319
1992	8.0	5.034 (2.98)	9.818 (6.67)	1.406 (1.31)	.0938 (.07)	734
1993	7.5	4.129 (9.89)	6.937 (1.99)	.976 (4.14)	.0792 (.15)	181
1993	7.0	2.939 (73.69)	9.816 (122.55)	.057 (.00)	.0631 (4.48)	309
1994	7.0	2.633 (57.65)	6.809 (79.91)	.092 (.00)	.0672 (3.98)	175
1994	7.5	4.699 (23.44)	9.607 (33.48)	.452 (5.34)	.0709 (.36)	69
1994	8.0	5.272 (9.48)	9.938 (1.36)	1.241 (5.59)	.0864 (.25)	80
1994	8.5	6.290 (20.71)	9.449 (26.17)	.841 (4.01)	.1160 (.50)	29

Source: Non-linear least squares estimation of rational prepayment models by the authors.

Notes: The data used in estimating each of the models was for pools issued in the year shown and with loan coupon exactly fifty basis points above the given passthrough coupon rate; the number of pools in each such sample is indicated in the rightmost column. The dependent variables are pool by month observations on the proportion of remaining pool value prepaid (SMM), and the non-linear predictors of these prepayment rates are from the rational prepayment model described in the text. The observations span the date range from the latest month of pool inception until the month when an observation on terminations first becomes right-censored, which is no later than June, 1998. Estimated standard errors are shown in parentheses.

Figure 1

**Full Sample Weighted Average Single Month Mortality
by Month**



**Weighted Average Single Month Mortality
by Pool**

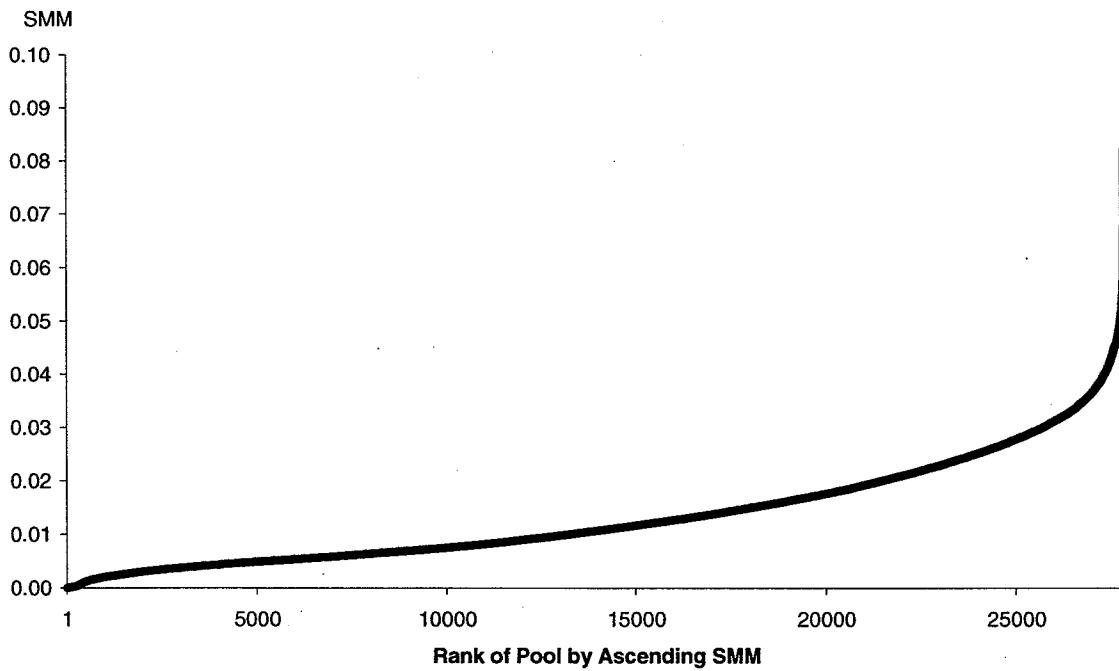


Figure 2
Reference Pool Aggregates of
Weighted Average Single Month Mortality by Month

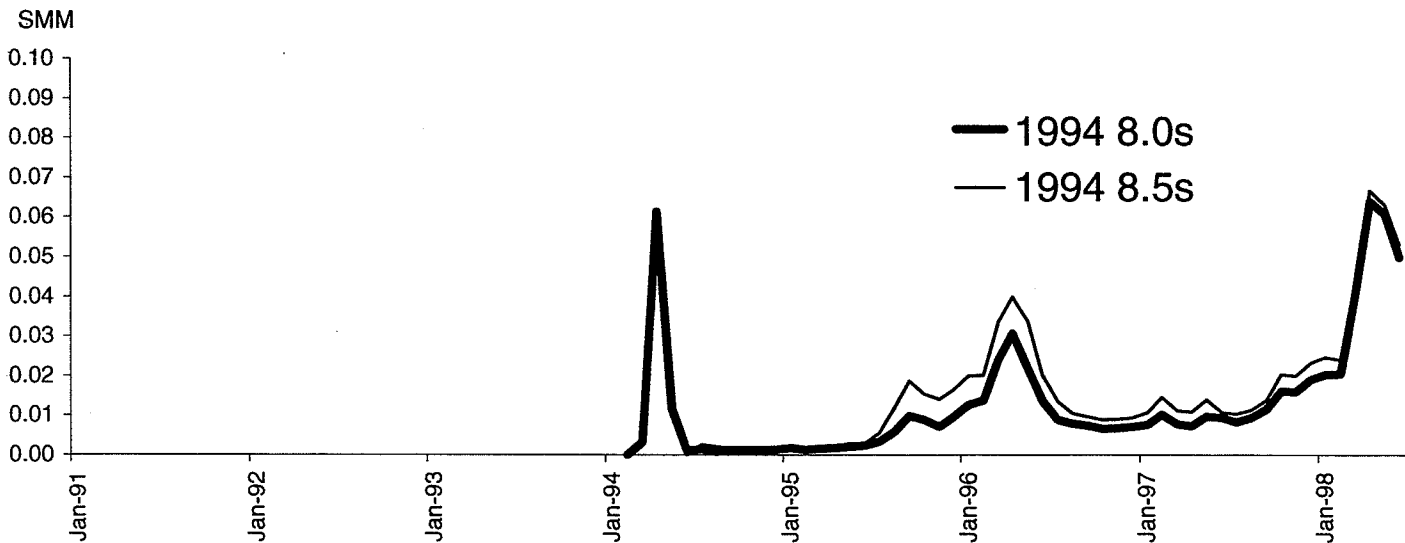
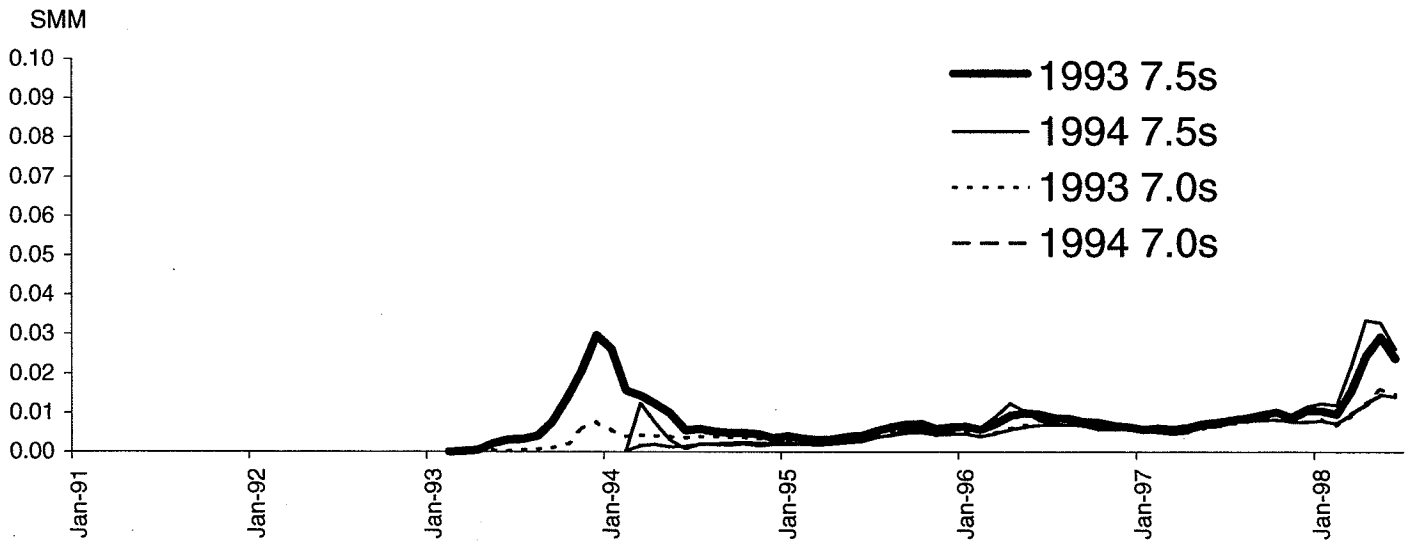
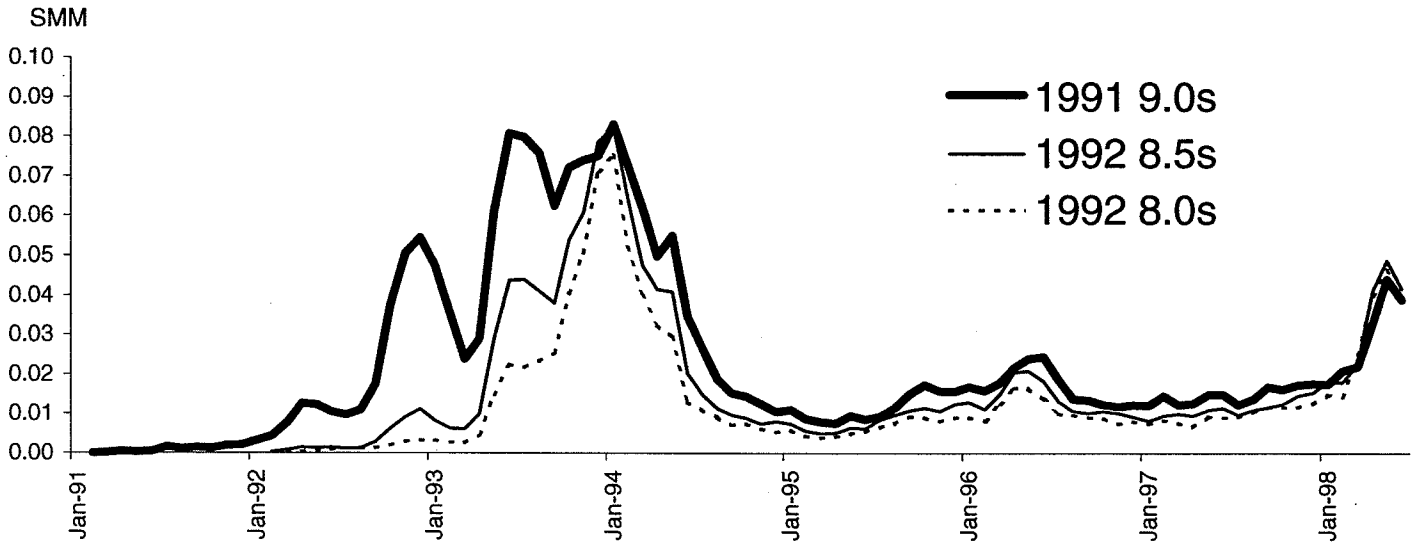
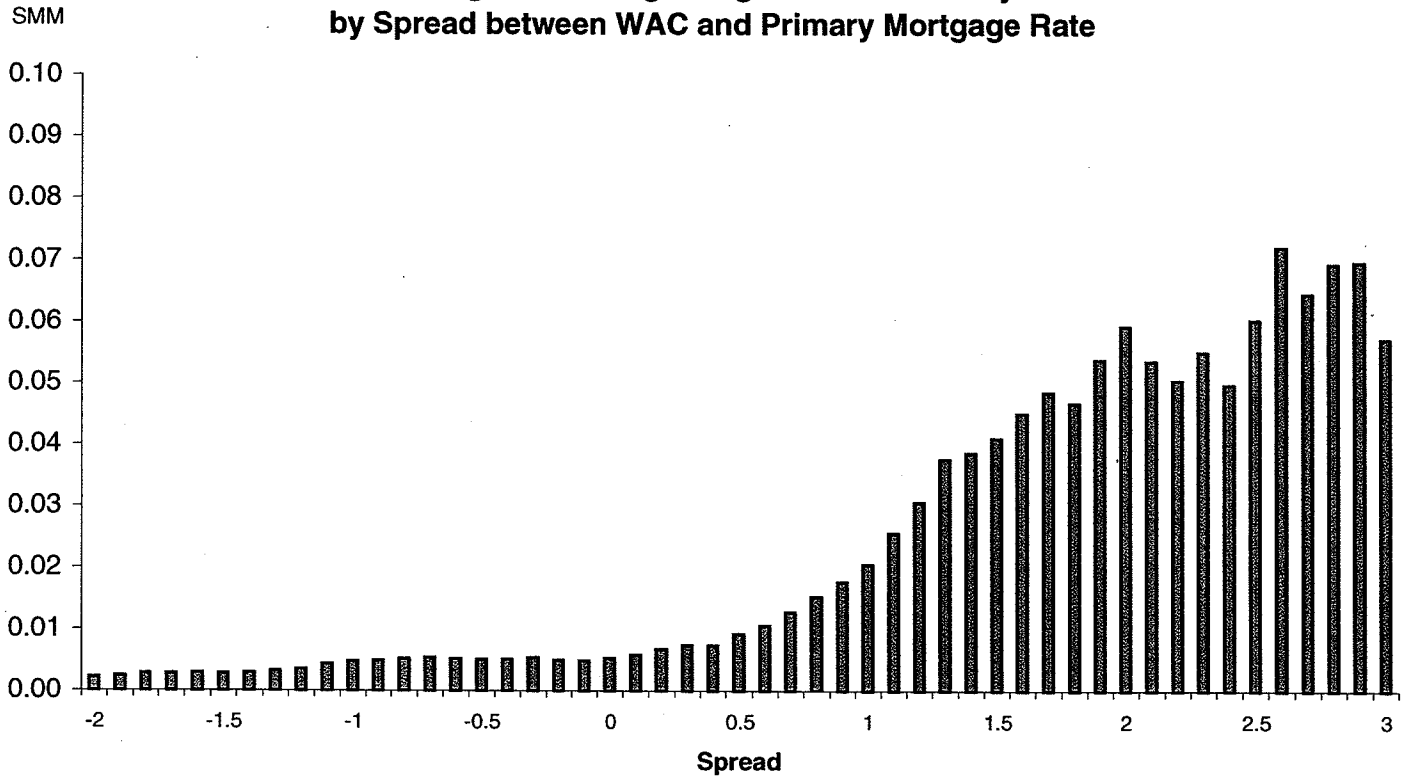


Figure 3

**Weighted Average Single Month Mortality
by Spread between WAC and Primary Mortgage Rate**



**Weighted Average Single Month Mortality
by Age of Loan**

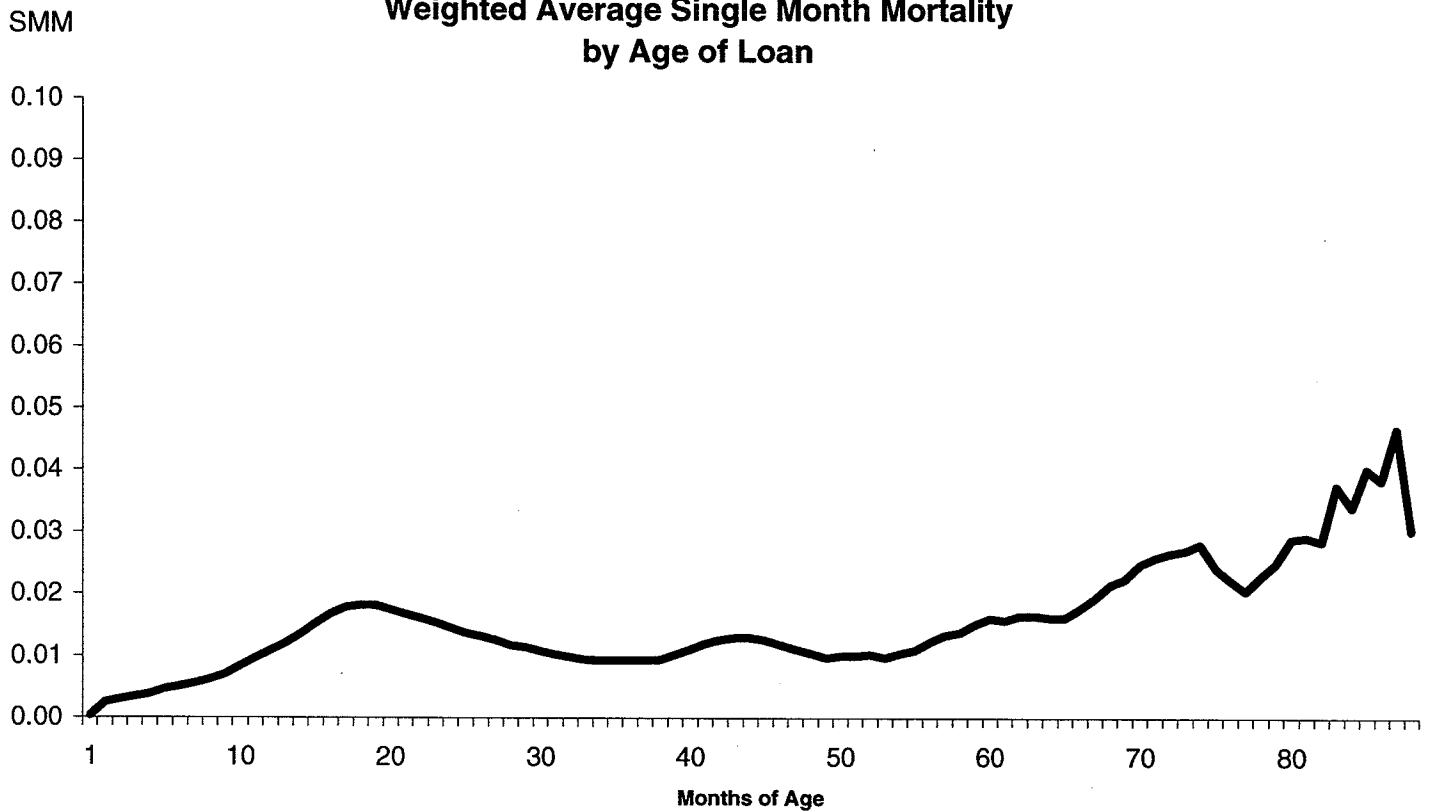


Figure 4

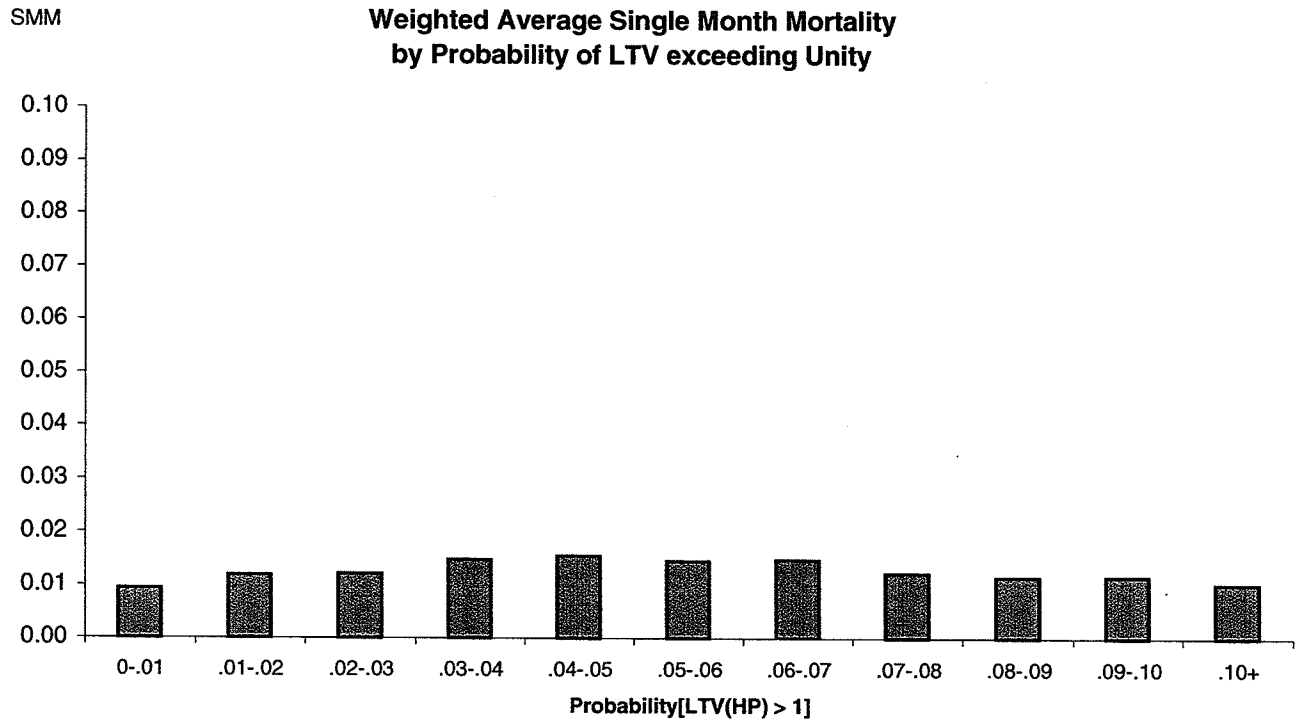
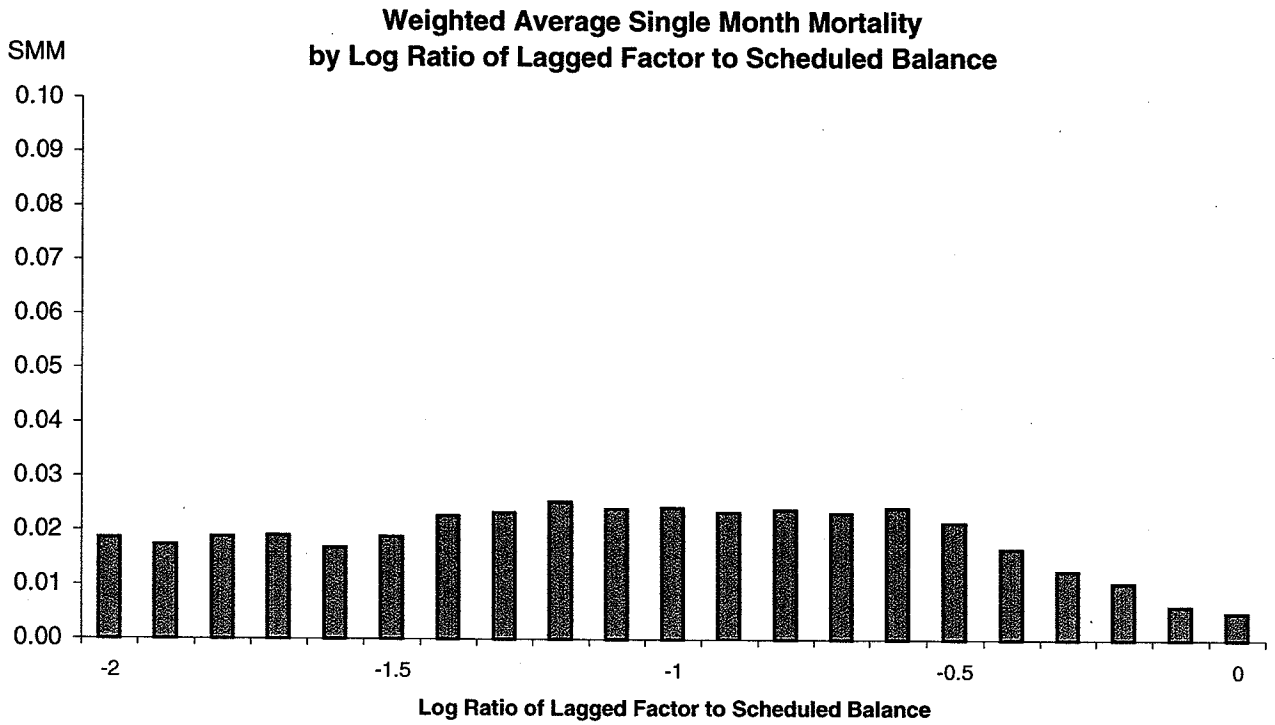
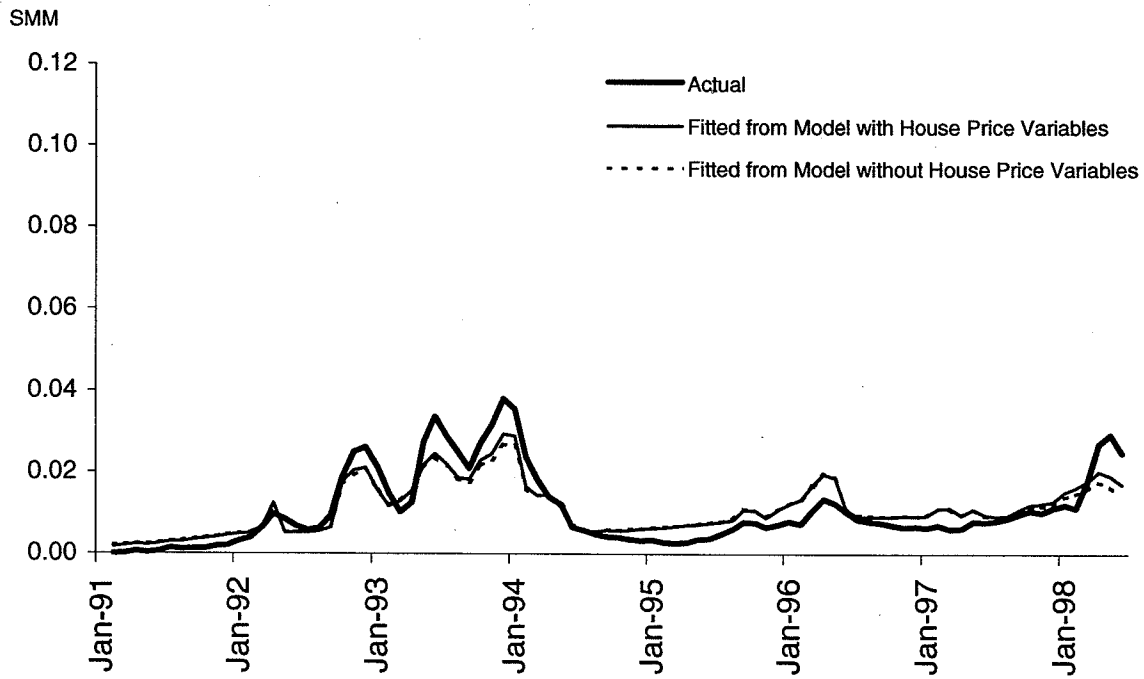


Figure 5

**Full Sample Actual and Fitted
Weighted Average Single Month Mortality by Month**



**Group of Weak Housing Price Pools Actual and Fitted
Weighted Average Single Month Mortality by Month**

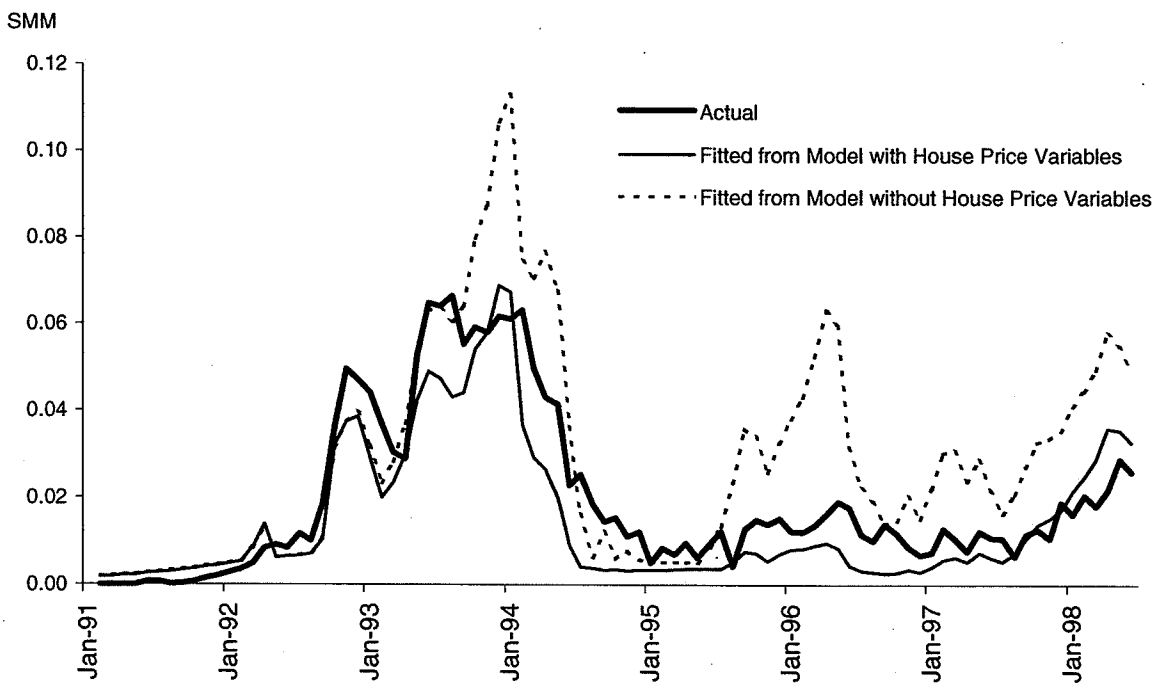
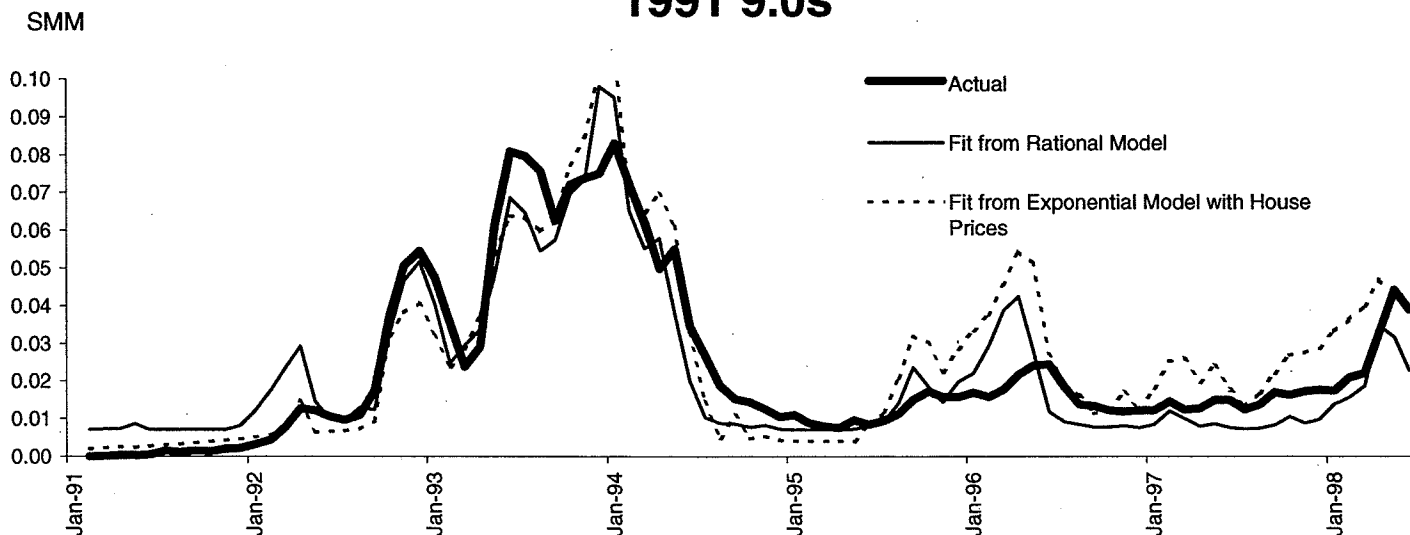
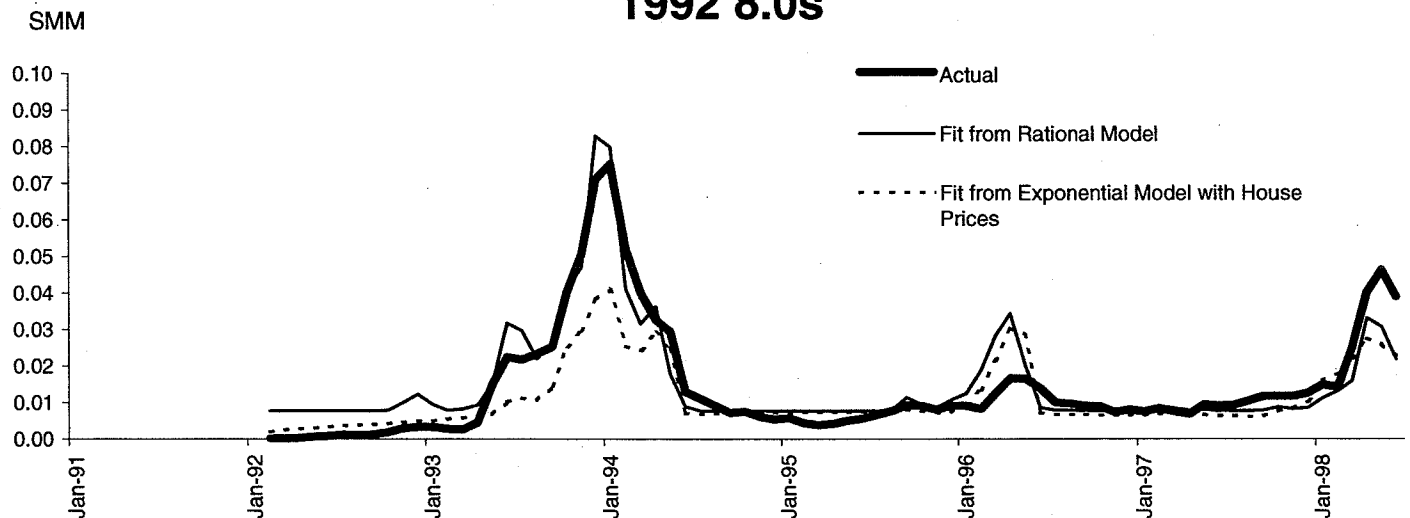


Figure 6
Actual and Predicted Reference Pool Aggregates of
Weighted Average Single Month Mortality by Month

1991 9.0s



1992 8.0s



1993 7.0s

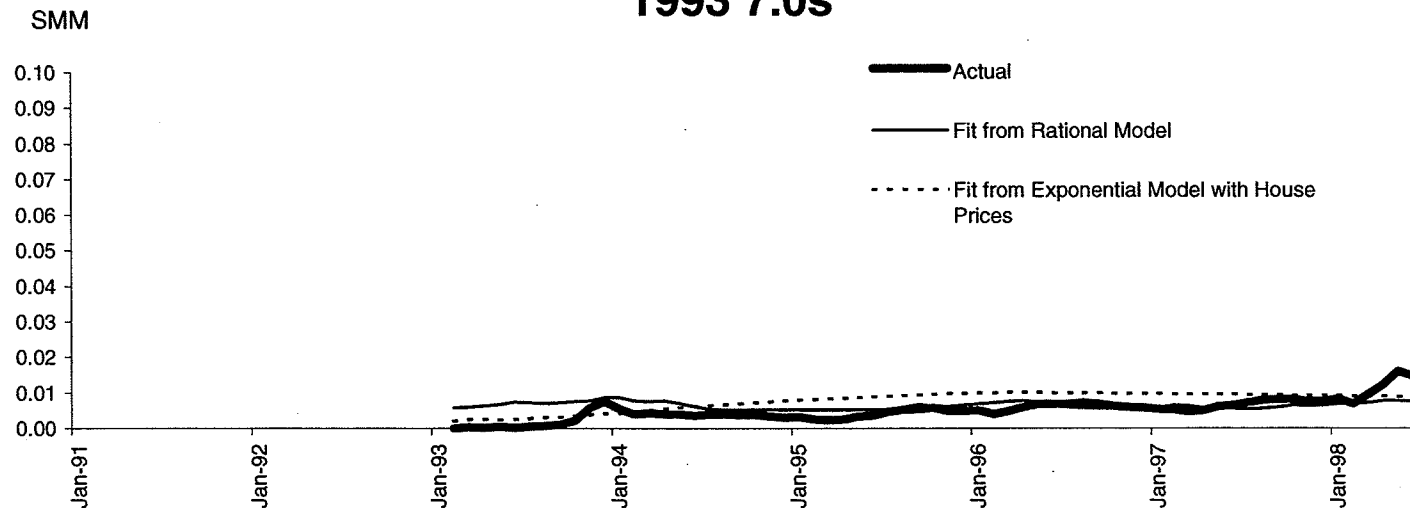
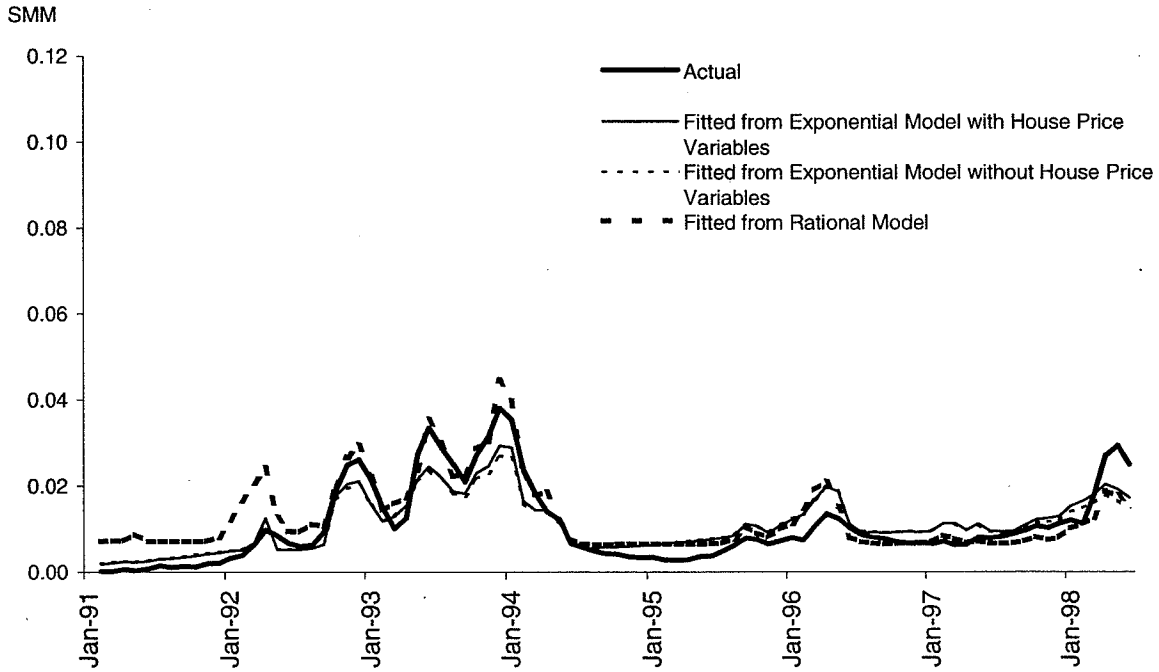


Figure 7

**Full Sample Actual and Fitted
Weighted Average Single Month Mortality by Month**



**Group of Weak Housing Price Pools Actual and Fitted
Weighted Average Single Month Mortality by Month**

