Autonomous and Financial Mortgage Prepayment

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***Abstract*. Using individual data from Freddie Mac's portfolio of conventional mortgages, this paper estimates prepayment probabilities as a function of characteristics pertaining to the borrower, the loan, regional, and economic variables. Distinction is made between induced and autonomous prepayments. Based on the curvature of the underlying termination pattern, nonparametric methods are derived to estimate the prepayment probabilities and to predict a mortgage life under various scenarios. The findings point to a response asymmetry with respect to the level and trend of interest rates. Non-interest effects reveal the significance of the borrower's characteristics, property age and regional mobility rates on mortgage termination.**

Introduction

For many years, prepayment and default options embedded in mortgage contracts were shown to affect the value of mortgages and mortgage-backed securities substantially. The default motive is generally based upon equity considerations. The prepayment risk is a function of the interest rate as well as macroeconomic, demographic and geographical variables. Of course, one cannot fully predict exact prepayment behavior, but a current line of research proposes to separate total prepayment into two parts, the first being interest rate related, that is, an *induced* prepayment resulting from an individual optimal refinancing strategy, and a second component caused by pure individual *autonomous* reasons. As the understanding of induced prepayment increases, the greater gains in the understanding of mortgage pricing seem to lie in the study of the autonomous prepayments.[1]

The current research can be summarized into two broad categories. First, are the prepayment estimation models that rely almost exclusively on the term structure of interest rates by focusing on the differential between market and contracted rates. As Peters, Pinkus and Askin (1984) write, these models necessarily imply that only the refinancing part of prepayment matters. This means that the chosen methodology overlooks prepayments motivated purely by individual reasons, such as house sales caused by job transfers, the desire to upgrade the quality of housing, and other macroeconomic, demographic and geographic variables.

The models in the second category analyze prepayment using conditional probabilities which, as the name indicates, attempt to estimate the conditional prepayment rate as the proportion of principals outstanding at the beginning of a particular year that prepay

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Date Revised—September 1994; Accepted—December 1994.

during that year. Until recently, most of these models were estimated using a standard linear regression, which could cause inference problems.[1]

The direction taken in this paper is to explore the nature of this relationship and find the sensitivity of the prepayment probabilities to the factors outlined above. We first review the literature on prepayment in part two of this study. In part three we discuss the borrower's strategy, and the determinants of the prepayment decision. In the fourth, we describe the data set and its limitations. In part five, we use a basic life table method to estimate the baseline prepayment risk and justify the use of a distribution-free approach within the context of a maximum partial likelihood technique. The results are discussed in part six. In the same section, we provide an example to show how the model can be applied in practice. In the paper's conclusion, we summarize the results.

The Prepayment Literature

Recent work on mortgage prepayment includes the work of Peters et al. (1984) who examine the prepayment experience on a nationwide rich sample of conventional mortgages. Approximately half a million mortgages are classified into 921 cohorts and used in a least squares model. The conditional prepayment rate is regressed on several variables: refinancing costs, percent change in difference between the contract and market rate, mean of household earnings in the cohort, a borrower's age, the size of the property per dependents, regional migration, and percentage growth in GNP. Though these variables are all significant, the authors find that the refinancing costs have the dominant impact on prepayment.

The application of a proportional hazard model to mortgage termination is originally due to Green and Shoven (1986). By accounting for possible censorship in the data (mortgages that do not prepay during the sample period), their model constituted a significant improvement over traditional estimation techniques. The explanatory power of their study rests on a single independent variable they describe as a "lockin," defined as the difference between the face and market values of the mortgage divided by the initial principal amount. In order to account for property appreciation over time, they adjust the initial principal amount by the regional housing price index. Although they obtain extremely significant estimates for the "lockin" variable, their model was limited to interest-related mortgage prepayment. As a result, terminations due to factors such as regional mobility and family size or the need to upgrade the quality of housing could not be accounted for in their study.

Quigley (1987) elaborates on the work of Green and Shoven by including household mobility factors. He shows that mobility (and therefore prepayment) is positively correlated with household size and education and negatively correlated with borrower's age, and the present value of his mortgage premium (or lockin). However, the sign of the coefficient of the borrower's income is found unstable over time.[2] Most importantly, Quigley pointed to the significance of the assumption underlying the proportional hazard model.

Schwartz and Torous (1989) apply a log-logistic hazard on aggregated GNMA mortgage pools and argue that the prepayment experience is consistent with the log-logistic function. Their prepayment estimates are subsequently integrated in a valuation model for mortgage-backed securities.

Using also a log-logistic hazard model similar to Schwartz and Torous (1989), Giliberto and Thibodeau (1989) make an important contribution by analyzing individual data and including borrower-specific variables. The authors provide a theoretical framework to analyze a borrower's decision. They show that a borrower's wealth depends on the gain from exercising the prepayment option. In particular, they find that the interest-rate volatility slows down prepayment because a borrower's wealth depends on the value of continuing to hold the prepayment option. Their data, however, is limited to borrowers who prepay but do not move.

Cunningham and Capone (1990) compare the termination experience of ARM vs. FRM between 1982 and 1985, a period marked by volatile interest rates and house prices. Their results support the option-based notions that the dominant factors are the current equity net of moving costs for the default option, and the equity variables in case of prepayment.

This paper is based on the spirit of the study by Peters et al. (1984) and Giliberto and Thibodeau (1989). It uses similar data but also accounts for the aging effect in a mortgage. Its contribution to the literature can be summarized as follows:

- We allow for both the *level* and the *trend* of mortgage rates to influence a borrower prepayment decision.
- In addition to the difference between a mortgage book and market values, we explicitly account for mortgage refinancing costs, and their impact in reducing prepayment.
- We do not impose, a priori, a specific pattern for prepayment. Based on the underlying hazard, we justify the use of a nonparametric approach that allows many prepayment forms. We also test the model goodness of fit and the proportional hazard assumptions.
- We model autonomous prepayment using borrower characteristics from a large sample of individual mortgages. Our prepayment data is regionally diversified and not restricted to borrowers who have not moved.

The Determinants of Prepayment

The Borrower's Strategy

In determining whether or not to move, homeowners assess the value of their existing contract by comparing the difference between their contract rate and the prevailing market rates. Borrowers also weigh in other personal factors, such as job relocations, size of the household relative to their existing home, or divorces. But in addition to assessing the magnitude of this difference, homeowners also look at the *level* of the contract rate and compare that with what mortgage rates have been recently. This is important because homeowners tend to delay their action to move if current market rates are relatively higher than they have been in the recent past. We model the evolution of the interest rate by constructing two variables that would motivate a borrower to prepay immediately or delay action. Our basic assumption is that borrowers do not act the same way when interest rates are rising as opposed to when they have been in decline. That is, borrowers take positions on the future course of interest rates when making a prepayment decision. Therefore, the previous trend of interest rates may influence prepayment.[3]

In addition, we note that a homeowner's decision to refinance depends not on the interest-rate differential as such, but on the current monthly payment stream compared with an alternative evaluated at the market rate. The larger the mortgage present value differential, the more the incentive to prepay. For a given month, we choose the national average of fixed conventional mortgage rates as a proxy to the corresponding market rate.

Any refinancing decision must take into account the concomitant refinancing costs. These include discount points, closing costs, escrow, application and origination fees, title searches, legal fees, and taxes. As the refinancing costs rise, one would expect homeowners to move less frequently. A rational homeowner would prepay only if the potential savings from a new mortgage at a lower rate exceed the costs of refinancing. Since no *induced* prepayment will take place unless the present value differential is positive, homeowners would *delay* prepayment when market rates are too high compared with their locked-in contract rate. We model the interest-rate effect using the *Lockin* variable which has been employed frequently in previous studies. The *Lockin* is defined as the difference between a mortgage book and market values, net of refinancing costs.

Homeowner, Loan and Regional Characteristics

It is our belief that an important part of observed prepayments is not interest rate related but depends primarily on individual factors that are difficult to predict, much less observe. We posit that homeowners' moving habits depend on their income and family size. For example, a high income could influence prepayment rates in two opposite directions. On the one hand, a high income and wealth may reflect social and income stability which suggests a lower probability of moving. On the other hand, an increase in income encourages a homeowner to upgrade the quality of his/her housing, thereby making a "move" more likely. Unfortunately, the data is limited to the borrower's information at the time of mortgage origination. Updates on a borrower's future well-being are unavailable. Data on income at the time of the mortgage origination is available in our sample. To capture any family size effects on prepayment, we include a measure of the borrower's number of dependents.[4] An increase in the number of dependents increases the need to move to a larger property, and raises the prepayment risk.

We also test the significance of the property age on prepayment. This variable may reflect housing preferences of a certain risk category of borrowers. To account for changes in borrowers' mobility over time, we introduce a variable measuring annual mobility rates by state at the time of prepayment. Implicitly, this variable captures the gain from moving as borrowers change their residence seeking better jobs, housing location, etc.

Finally, to model any prepayment variation across regions, we include two dummy variables that capture any residual prepayment effect unaccounted for in the preceding variables. Examples include the effects of divorces which often lead to the sale of a dwelling, or price appreciation which gives the borrower the possibility to cash equity out of the property and refinance the mortgage.

Construction of the Covariates

We divide the covariates chosen for this study into three main categories: financial, borrower-specific and macroeconomic variables. A detail of their construction follows:

Financial:

$$LOCKIN\text{: } PMT \times [\Sigma_{t}{}^{\tau}{}_{=1}(1+m_t)^{-t} - \Sigma_{t}{}^{\tau}{}_{=1}(1+c)^{-t}] - RC\,,$$

where c and m_t represent the contract and market rates of interest, PMT the borrower's monthly payments, RC the refinancing costs, and τ the remaining life of the mortgage. The whole expression equals the difference between the present values of the mortgage at the market and the contract rate minus the refinancing costs.

UPTREND: A measure of the rise in mortgage rates. For a given month, we take the difference between the current national average mortgage rates and the last month that an upturn occurred in that rate. We let *UPTREND* be equal to that difference if the latter is positive, and 0 otherwise.

DOWNTREND: A measure of mortgage rates decline, defined similarly to *UPTREND* above. It is equal to the difference between the current national mortgage rates and the last downturn if that difference is negative, and 0 otherwise. In short, downtrend (uptrend) is the absolute difference between the peak (trough) and the current market interest rate.

LOANTOVAL: The ratio of the loan to the appraised value of the property at the time of purchase.

Borrower-specific:

DEPEND: The square-root of the household's number of dependents.

PROPTAGE: The age of the property in years at the time of purchase.

AGEBORRW: The age of the primary borrower in year.

INCOME: The logarithm of household total monthly income in dollars.

Macroeconomic:

MOBILITY: The logarithm of the annual mobility rates by state at the time of prepayment for mortgages which terminate during the study. For all other mortgages the mobility rates are calculated for the last year of the study.

CALIF, NORTCENT: Variable dummies that reflect the mortgage origination in California or the Northcentral region. If a mortgage originated in neither regions, by default it is part of the Northeastern region.

Data Description

Our data consists of a nationwide random sample of 6,248 mortgages from Freddie Mac's portfolio of conventional mortgages between 1973 and 1980. Data on borrower mobility is obtained from the Census of Housing published by the Census Bureau. All mortgages in the data set originated in or after January 1973 in three national regions:[5] California, Northcentral and the Northeast. The statistical inferences are conditional on the path of interest rates between 1973 and 1980. During this period declines of interest rates were few and short. This allowed few opportunities for borrowers to refinance. When confronted with sizable refinancing costs, borrowers had to make sure that they would stay in their current dwelling long enough to recoup the refinancing costs. When a relocation was anticipated, this left fewer opportunities for borrowers to take advantage of lower interest rates.

Each mortgage has an age representing the time elapsed from its origination to the date of our final observation (1980). Let t denote calendar time from the date of issue (or birth) of the mortgage to its termination. This termination can either fall within the time interval of the study, or occur after 1980. Data on mortgages prepaid after 1980 are termed "censored" in the sense that the observed termination date does not indicate prepayment. Correspondingly, mortgages prepaid during our eight-year time interval will be termed "failures". The estimation technique does not throw out the censored mortgage observations. The factors that led borrowers to not prepay during the eight years of the study are explicitly accounted for in the likelihood of prepayment.

Exhibit 1 lists the percentage breakdown of mortgage rates in the data set. It appears that about 60% of the mortgages have rates between 9% and 10%. Origination years are reported in Exhibit 1. About 56% of the mortgages in the data set originated between 1975 and 1978. Exhibit 1 also reports other sample statistics.

Estimation Methodology

The basic advantage of the Proportional Hazard Model (PHM) is its ability to separate the prepayment risk into two major elements: an aging affect, and a mortgage-specific component. It posits that at each point in time, there exists a baseline risk of termination which depends on the age of the mortgage alone. The mortgage-specific risk component will raise or reduce the baseline risk depending on the magnitude of the mortgage-specific variables, such as the interest rate, regional mobility rate or the household characteristics. The total risk (or hazard) of failure is a mixture of a baseline and mortgage-specific risks. For a mortgage i, described by a vector of characteristics X, the total hazard at time t can be written in the form:

$$h(t|X_i) = h_0(t) \exp\{X_i\beta\}, \tag{1}$$

where $X_i\beta = X_{i1}\beta_1 + \ldots + X_{ik}\beta_k$, X is a row vector of k covariates, β is a column vector of k covariate coefficients, and $h_0(t)$ is defined to be the baseline hazard, being the hazard function of a mortgage for which $\exp(X\beta)=1$. The baseline hazard is comparable to FHA/PSA experiences which estimate the conditional prepayment probability as a function of the mortgage age alone.

Our approach leaves the baseline hazard unspecified and estimates the parameter vector β using a technique called partial likelihood. By using a nonparametric estimation technique we make no distributional assumption on the baseline hazard which enables us to derive more general results than other studies on mortgage termination.[6]

Exhibit 1

State of Origination	Frequency	Percent	State of Origination	Frequency	Percent
CA	4119	65.9	NH	2	.0
CT	15	.2	NJ	123	2.0
DC	75	1.2	NY	23	.4
DE	9	.1	OH	225	3.6
IA	31	.5	PA	50	.8
IL	149	2.4	PR	18	.3
IN	56	.9	RI	4	.1
MA	40	.6	SD	4	.1
MD	302	4.8	VA	513	8.2
ME	13	.2	VT	4	.1
MI	361	5.8	WI	66	1.1
MN	35	.6	WV	11	.2

Loan-to-Value Ratio	Frequency	Percent
<20%	11	.2
20%<.<30%	31	.5
30%<.<40%	71	1.1
40%<.<50%	158	2.5
50%<.<60%	335	5.4
60%<.<70%	600	9.6
70%<.<80%	2127	34.0
80%<.<90%	2775	44.4
90%<.<100%	140	2.2

Property Age (Years)	Frequency	Percent
0–9	2556	40.9
10–19	1377	22.0
20–29	1101	17.6
30–39	628	10.1
40–49	254	4.1
50–59	187	3.0
60–69	81	1.3
70–79	35	.6
80–89	21	.3
90+	8	.1

Borrower's Age (Years)	Frequency	Percent
<20	712	11.4
<30	3123	50.0
<40	1348	21.6
<50	728	11.7
<60	272	4.4
<70	54	.9
<80	7	.1

Estimation of the Baseline Hazard

As a first step to our study of the prepayment experience in the data set, we estimate the distribution of failure times in order to analyze the risk pattern of mortgage termination. This gives us a preliminary result on the prepayment risk in the absence of individual effects specific to the borrower, the loan, or the prevailing economic conditions. These factors will be captured later in a vector of covariates.

In Exhibits 2, 3 and 4, we plot the estimates of the prepayment rate by mortgage rate class. The graphs are equivalent to the hazard function that includes a single argument: the age of the mortgage per month. The hazard rate is defined as: *Total mortgages prepaying in month t/Total mortgages alive at the start of month t*. The shape of the hazard varies significantly from one interest-rate class to the other. Looking at the hazard for the mortgages with rates of 7.75%, we notice that the highest rate of 0.014 is attained at age forty-eight months or four years.

Since the prepayment rate is quoted per month, a rate of 0.014 is equivalent to 16.8% a year. The hazard at interest rate of 11% is substantially higher than the one at 7.75%.

Exhibit 2
Hazard Function Estimates

The maximum prepayment risk is attained in three years and reaches 4.2% per month (51% a year!). One would expect the prepayment risk to increase with the mortgage rate. A simple comparison between mortgages in the last two classes shows that the risk can be as much as three times higher.

The shape of the hazard function reveals important information about the pattern of prepayment. Mortgages wih a rate of 9% have more than one minimum. The risk pattern of mortgages falling in this category is problematic because it indicates that within this class, mortgages are not homogeneous, but belong to more than one group. This observation is also evident from the panels of Exhibit 5, which show the hazard by geographical region. Multimodality in the hazard is noted for all three regions.

The presence of a multimodal hazard indicates that the population may not be uniform in risk; that is to say, their prepayment patterns vary significantly with some mortgages achieving their highest prepayment risk at forty-five months and others around seventy-eight. In a parametric hazard model, such heterogeneity would warrant a special treatment when choosing a functional form for the baseline hazard. While one achieves a

Exhibit 3
Hazard Function Estimates

Mortgage Rate 9%

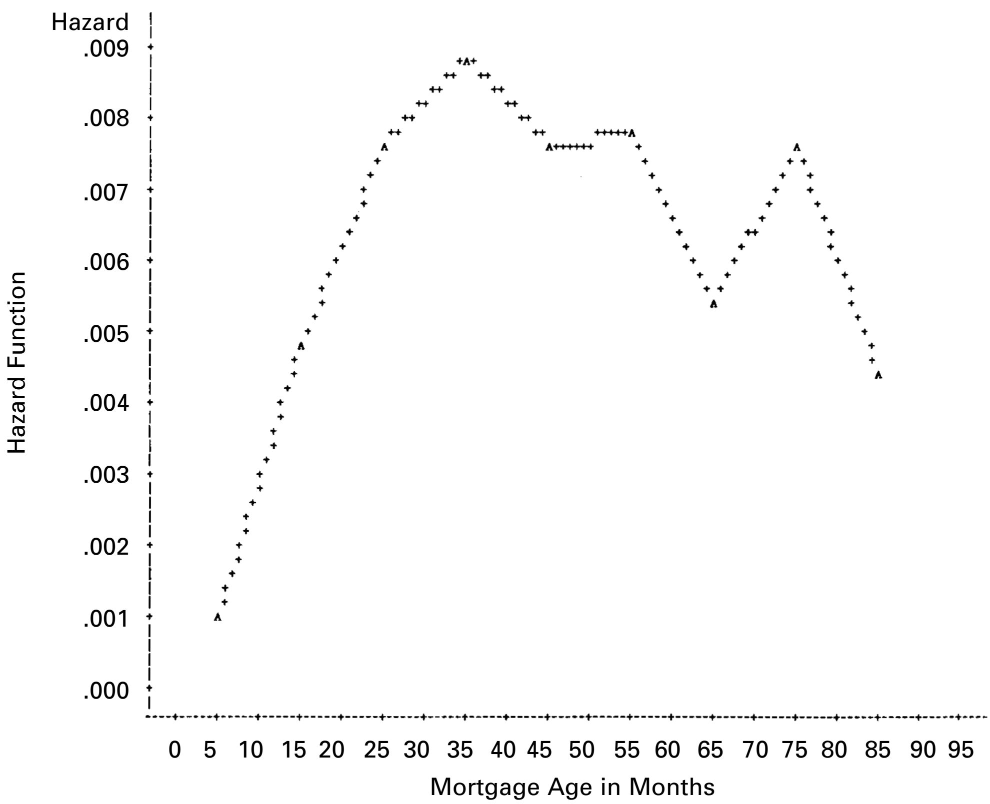
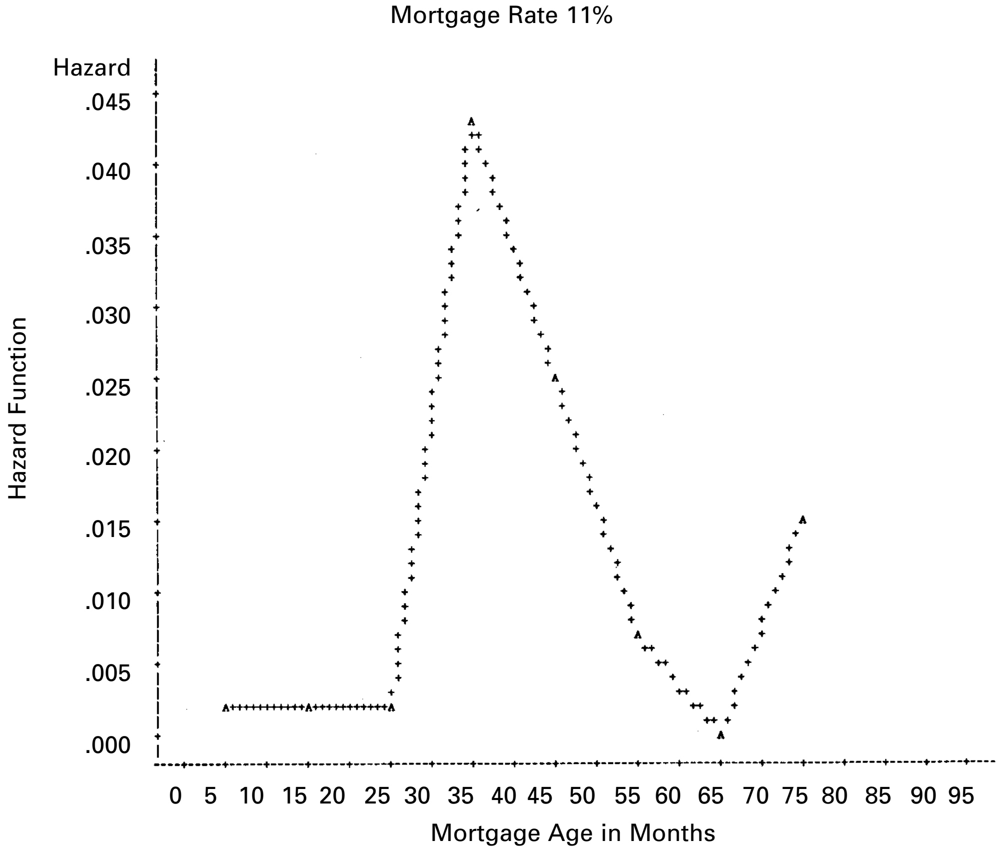


Exhibit 4
Hazard Function Estimates

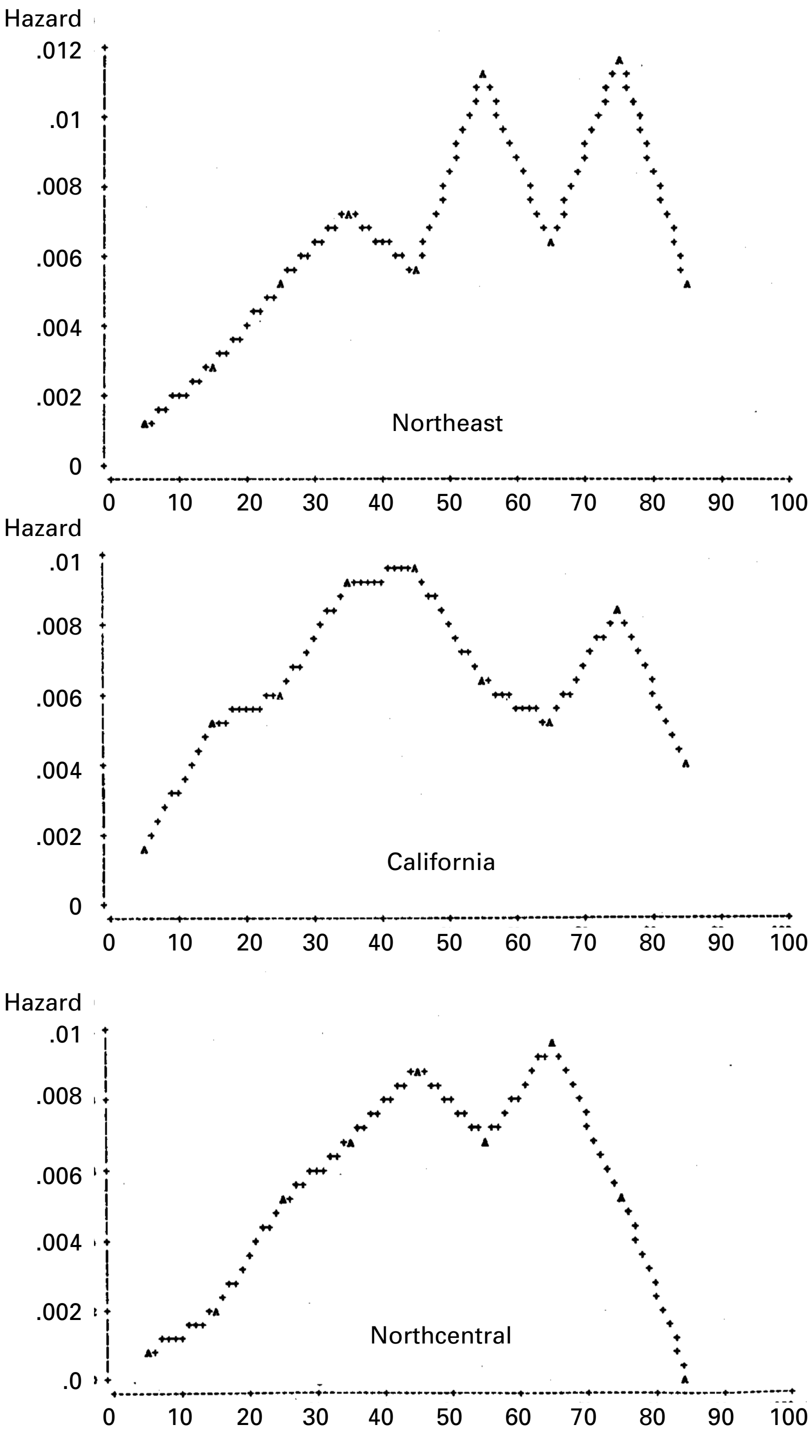


better fit by using a correct distribution, the prepayment pattern may not belong to a particular class of distributions and therefore, it would be inappropriate to impose, a priori, a prepayment structure on the model.[7] This would produce inconsistent parameter estimates if the wrong distribution is chosen. Based on these results, it appears that the most likely hazard function for prepayment in our data set would be a multimodal inverted U-shaped curve. While such patterns could be generated by a mixture of hazard functions, it would impose an exogenous heterogeneity on the model rather than allowing the data to determine its shape. Therefore, we deemed it more appropriate to leave the baseline hazard unspecified, and chose to apply a distribution-free technique. Consequently, the inferences we shall make would not depend upon a specific lifetime distribution.

A Distribution-Free, Partial Likelihood Estimation

The basic advantage of the proportional hazard model as described by (1), is that the baseline hazard needs not to be specified for the estimation of the regression coefficients.

Exhibit 5


Hazard
.012
.01
.008
.006
.004
.002
0
0 10 20 30 40 50 60 70 80 90 100
Northeast
Hazard
.01
.008
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.004
.002
0
0 10 20 30 40 50 60 70 80 90 100
California
Hazard
.01
.008
.006
.004
.002
.0
0 10 20 30 40 50 60 70 80 90 100
Northcentral

Detail of the estimation procedure and derivation of the likelihood function are found in Kiefer (1985). The sample likelihood function over all mortgages $i=1, \ldots$, n can be written as:

$$L(\beta) = \Pi_i^n \, [\exp(X_i\beta) \,/\, \Sigma_{k\epsilon ri} \exp(X_k\beta)] \,, \tag{2}$$

where R_i is the set of mortgages at risk of prepayment at age t_i. The maximization of the likelihood is done by a Newton-Raphson Algorithm.

Empirical Results

The model parameter estimates are reported in Exhibit 6. At first sight, it appears that while the coefficients of the components of optimal prepayment are statistically significant (high *chi*-squares), they have little economic significance, and hence play a small role in affecting the prepayment probability.

For example, the coefficient of the covariate *Lockin* is negative, indicating that a higher net present value differential reduces the mortgage age,[8] and induces homeowners to prepay. Although the value of this coefficient is small, it expresses the impact of a one-dollar change in the present value differential on the prepayment rate per month. Naturally, such a minute change should have little bearing on the homeowner's decision to prepay. However, the effect of the *Lockin* variable is magnified by the costs of refinancing a new loan that are accounted for in computing the present value differential. Some of the previous studies did not account explicitly for the refinancing costs and their delay effect on prepayment.

The contribution of the interest-rate trend covariates to the prepayment hazard is both strong and significant. The estimated coefficients measure the impact of a one percent increase (or decline) in mortgage rates. The sign of the parameters suggests that borrowers prepay when rates are falling and delay prepayment when rates are rising. This confirms our previous intuition that a period of falling mortgage rates is generally coupled with high prepayment. In comparing the absolute values of the coefficient of the trend variables, we note an important *asymmetry* in borrower's response. Overall, homeowners are less responsive when rates are rising than when they are declining.

The impact of the borrower's specific variables is also important. People with high prepayment risk tend to be mature and own an older property. This is not surprising since 50% of the homeowners in the sample are between the ages of twenty and thirty. Why should new properties possess a smaller prepayment risk may be difficult to interpret. We suspect that the sign of the estimated coefficient reflects a borrower's latent attributes. The effect of the family size indicates that an increase in the number of dependents reduces the mortgage age, and hence raises the prepayment risk, as borrowers try to replace their existing property with a larger one. This supports the result of Quigley (1989). The effect of a mortgage loan-to-value ratio is marginally significant but with the right sign. Our findings indicate that an increase in financial leverage increases prepayment as the benefit of refinancing is magnified.[9] Unfortunately, household income is statistically insignificant. As expected, the coefficient of the state mobility rates has the right sign with a strong impact on mortgage termination.

Finally, with respect to the regional variables, both dummies are significant. Their effects indicate that, after accounting for all the variables in the model (including

Exhibit 6
Nonparametric Proportional Hazard Procedure

Total Mortgages	Prepaid	Alive	Percent Censored
6208	1078	5130	82.64

Testing Global Null Hypothesis: *BETA*=0

Criterion	Without Covariates	With Covariates	Model *Chi*-Square
−2 LOG L	17108.226	14196.723	2911.503 with 11 DF (p=.0001)

Dependent Variable: Mortgage Age

Analysis of Maximum Likelihood Estimates

Variable	DF	Parameter Estimate	Standard Error	Wald *Chi*-Square	Pr> *Chi*-Square
Financial					
LOCKIN	1	−14.779777	.27649	2857	.0001
UPTREND	1	.505714	.06556	59.50308	.0001
DOWNTREND	1	−1.258893	.11276	124.65339	.0001
LOANTOVAL	1	−.386177	.20727	3.47120	.0624
Borrower-specific					
INCOME	1	.000005447	.0000337	.02610	.8717
DEPEND	1	−.124091	.04432	7.84009	.0051
AGEBORRW	1	−.392739	.12020	10.67656	.0011
PROPTAGE	1	−.009048	.00263	11.87090	.0006
Macroeconomic					
MOBILITY	1	−.832889	.16000	27.09769	.0001
CALIF	1	.162970	.08692	3.51515	.0608
NORTCENT	1	−.302944	.11326	7.15462	.0075

mobility), any residual prepayment is attributed to special features in that region. For the valuation of mortgage-backed securities the important implication is that regionally diversified mortgage pools are likely to include less prepayment risk than nondiversified ones.

Overall, the effects of non-interest prepayment are found strong and significant. This supports the argument that reliance on the interest-rate differential alone overlooks important causes of prepayment. Our findings indicate that autonomous prepayment plays a substantial part in the total prepayment function.

An Example

The primary purpose of the econometric model is to provide a forecasting tool to predict conventional mortgage termination. This would enable lenders to achieve a better understanding of mortgage behavior and price more accurately the securities backed by these assets. In the example below, we deal with the expression in (4).

Consider two new homeowners. *A* is a homeowner with a loan of $100,000 and a fixed mortgage rate equal to 11%. If the prevailing market rate is 9%, his *Lockin* variable[10] would be 16.36%. For homeowner *B*, let the mortgage coupon equals the current market rate (i.e., *Lockin*=0). The predicted relative risk is computed by forming point estimates of the hazard functions. The model predicts a risk ratio:

$$\begin{aligned} \rho(X_1, X_2) &= (h_1/h_2) \\ &= \exp\{(X_1 - X_2)\beta\} \\ &= e^{2.42} \\ &= 11.22\,. \end{aligned} \tag{7}$$

Therefore, mortgage one is approximately eleven times riskier than mortgage two. That is, the prepayment rate for mortgage one is eleven times larger than for mortgage two.

Conclusion

Using a nationwide random sample of 6,248 mortgages, this study distinguished between a mortgage theoretical and effective lives and showed how prepayment varied with a set of characteristics pertaining to the loan, the borrower, regional, and economic variables. An important part of this study was to identify two different motives underlying a borrower decision to terminate a mortgage prematurely. Precisely, a distinction was made between financial and autonomous prepayments, despite the fact that the borrower's true motives may be difficult to discern, particularly when mortgage termination has multiple causes.

Preliminary estimates of the baseline prepayment risk showed that mortgage termination varied with the contract rate and region. More detailed analysis indicated that the prepayment pattern was multimodal with more than one risk group of borrowers within each region. Consequently, a nonparametric approach was adopted in order not to impose a particular distribution pattern on the data.

Subsequent analysis of specific mortgage variables showed that borrowers speculate on the future course of interest rates and exhibit an asymmetry in their response to the evolution of interest rates. Precisely, borrowers were found more responsive when rates are falling than when they are rising. The results of testing the effect of the loan-to-value ratio indicate that prepayment risk increases with the degree of financial leverage which would augment the benefit from refinancing.

Regional and borrower variables suggest that prepayment is positively correlated with the borrower's age, propensity to have more dependents, the property age, and regional mobility rates. Overall, these variables reflect the impact of social and demographic effects that may explain why rational borrowers freely choose to prepay during adverse economic conditions, when, for example, the prevailing market rate of interest exceeds their mortgage rate.

Finally, the regional dummies showed that prepayment varied by region even after all the preceding variables were accounted for. The implication for mortgage securitization is that regionally diversified pools are less risky than nondiversified ones.

Notes

[1]Hakim (1992a,b) provides a closer focus on autonomous prepayment.
[2]For the proportional hazard model, Quigley found that family income increased prepayment in 1979 and 1980 but reduced it in 1981. For the non-proportional hazard model, family income reduced prepayment in 1979 and 1981 but increased it in 1981. However, only 1980 was statistically significant.
[3]Some of the Wall Street literature includes interest trend measures. For example, Chen and Ling (1989) use the yield curve to proxy interest expectations.
[4]It is not the number of dependents that matters; rather, it is a measure of the borrower's propensity to have more dependents in the future. We capture this effect using a nonlinear (square-root) transformation of the actual number of dependents. We wish to thank an anonymous referee for bringing this point to our attention.
[5]The regional classification is as follows: **Northeast**: New York, New Jersey, Pennsylvania, Delaware, Maryland, Washington, D.C., Virginia, West Virginia, Puerto Rico, Maine, New Hampshire, Vermont, Massachussets, Rhode Island, Connecticut, the Virgin Islands. **Northcentral**: Ohio, Indiana, Illinois, Michigan, Wisconsin, Minnesota, Iowa, North Dakota, South Dakota. **California**: California.
[6]Giliberto and Thibodeau (1989) and Schwartz and Torous (1989) assume a log-logistic hazard distribution. Cunningham and Capone (1990), on the other hand, do not use a hazard model but assume a logistic prepayment distribution.
[7]Insights to this problem are provided in Moffitt (1985).
[8]A reduction in the mortgage age implies an increase in the prepayment hazard.
[9]The impact of the LTV ratio is capturing some of the effect of property appreciation on prepayment. For example, an increase in the property value will, ceteris paribus, reduce the LTV ratio and the benefit of refinancing the existing outstanding mortgage. However, an increase in property appreciation also increases the likelihood that property owner borrowers will borrow against their accumulated equity or trade it up for a better dwelling. We wish to thank one of the reviewers for pointing out to us the significance of property appreciation on prepayment.
[10]For simplicity, assume that the refinancing costs are zero.

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Financial support from The Office of Thrift Supervision, Washington, D.C., is acknowledged.