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Collateral Damage: Refinancing Constraints and Regional Recessions

In the current structure of the U.S. residential mortgage market, a decrease in property values may make it very difficult for homeowners to refinance their mortgages to take advantage of declining interest rates. In this paper, we show that this form of collateral constraint has greatly reduced refinancing in states with depressed property markets. We outline the interaction between regional recessions and refinancing constraints.

WHEN ADVERSE ECONOMIC SHOCKS cause property values in a region to decrease, the damage to the collateral makes it difficult or impossible for some homeowners to obtain new mortgages. In the recent period, this has meant that homeowners in economically depressed regions have been unable to refinance their mortgages to take advantage of declining interest rates. This inability to refinance has further economic impacts on the region through lowering the wealth and the discretionary income of local homeowners, thereby deepening the regional recession.

While the possible link between regional declines in property values and refinancing activity has been understood for some time (for example, Monsen 1992), the subject has received very little empirical attention. We provide the first quantitative assessment of the impact of constraints arising from regional property market dynamics on refinancing activity. To accomplish this, we use a new data set on more than thirty-five thousand individual mortgages. The sample consists of all mortgages serviced by Chemical Bank with originations between June 1989 and May 1992.

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There are two key features that make this data so valuable for the question of collateral constraints. First, the time period involves a significant and rapid decline in long-term interest rates so that many households had a financial incentive to refinance their mortgages. Second, over the same time period, there was a great deal of regional variation in the performance of the residential housing market, with decreases in property values in some regions and increases in other regions, giving rise to regional variations in the ability to qualify to refinance the mortgage.

Our analysis of this data confirms both the qualitative and the quantitative importance of property market behavior in determining differences in refinance rates across states. In particular, we estimate that in our sample of states with weak property markets the rate of refinancing was reduced by 50 percent relative to the rate in the remaining states in our sample.

The remainder of the paper is structured as follows. In section 2 we outline the process of qualifying to refinance a mortgage, and indicate why our sample period presents an ideal opportunity for testing the importance of these constraints. Section 3 outlines our database of 30-year fixed-rate mortgages, explains our statistical methodology, and connects our work to the existing literature on mortgage refinancing. Section 4 presents the model estimates and quantifies the impact of the constraints on refinancing. Section 5 outlines some of the linkages between regional economic performance and refinancing constraints. Section 6 concludes.

1. THE REFINANCE APPLICATION PROCESS

The U.S. residential mortgage market for 1–4 family dwellings totals 3.9 trillion dollars.[1] Much of the mortgage debt is in the form of thirty-year mortgages with the interest rate fixed for the life of the contract. These mortgages can be prepaid without penalty at any time, and this becomes worthwhile for most households if there is a large enough decline in mortgage interest rates. The simplest view of refinancing is to see it as a decision to pay the fixed costs involved in taking out a new mortgage in order to benefit from a reduction in the interest rate [see Richard and Roll (1989) for an overview of the theory of refinancing]. The benefits of refinancing are the reductions in monthly interest payments in the future. The present value of the interest savings depends critically on the homeowner's expected future tenure in the house. The costs of refinancing include the transactions costs involved in obtaining a new mortgage. These involve time costs, loan application fees, legal fees, and any up front points for the new mortgage. An industry standard is that the transactions costs average from 1–3 percent of the value of the mortgage (excluding any up front points paid to the lender).[2]

1. *Federal Reserve Bulletin*, vol. 79, June 1993, Table 1.54, p. A37.

2. See Appendix Table A3 for a detailed listing of these costs for the NY/NJ/CT area. Up-front points paid on a refinance mortgage are more expensive than points paid on a mortgage for a home purchase. The latter are deductible from the homeowner's federal income tax while the former are not deductible. Lenders also offer no point refinance mortgages that charge on average a premium of ³⁄₈ths of a point in the rate.

But the fact that a given mortgage holder has an incentive to refinance does not mean that they will be able to refinance. There is one important hurdle for the household to cross: it must be able to qualify for a new mortgage. It is here that property market conditions enter the picture, since a decrease in house prices may make the household unable to get a new mortgage. To see how this may happen, we briefly outline the various steps involved in the process of refinancing a mortgage [see Caplin, Freeman, and Tracy (1993) for a more detailed description of the mortgage market].

Consider a household that applies for a mortgage in the high-quality A-credit market (this is by far the largest and cheapest segment of the mortgage market). In the A-credit market, the lender applies three basic screens in its underwriting process: credit tests, debt/income tests, and loan-to-value (LTV) tests. If the loan application fails any of these three screens, the application is likely to be rejected by the lender. This screening process and the method of calculating the ratios is standardized across all major lenders dealing in A-credit mortgage lending. The degree of standardization reflects the role of the secondary market for mortgages.

In the credit test, the applicant's credit records are pulled and reviewed according to several criteria. Applicants judged as having an adequate credit record are then given a debt/income test. The test comprises two ratios which are called the "front-end" and the "back-end" debt ratios. The front-end ratio is calculated as the borrowers' monthly principal, interest, taxes and insurance (PITI) divided by the monthly pretax income. The back-end ratio is the PITI plus any recurring monthly obligations (debt or lease payments) divided by the monthly pretax income. Applications with front and/or back-end ratios above the set limits (that is 28/36) are generally rejected.

Applications passing both the credit test and the debt/income test are put through one final screen.[3] The lender hires an appraiser to value the property. The lender uses the appraised value to calculate the loan-to-value ratio (LTV). A loan application with an LTV below 80 percent is routinely accepted. Applications passing the earlier two screens and with an LTV in the 80–90 percent region will generally be asked by the lender to reduce the LTV to 80 percent by making a higher down payment, or to apply for private mortgage insurance (PMI). PMI companies typically charge a 25 basis point rate premium and one point up front for every five-percentage-point increase in the LTV above 80 percent. The PMI policy typically insures the lender on the first 25 percent of the loan amount.

In regions suffering from adverse economic conditions, the ability to refinance will likely be constrained by declining property values. As LTV's increase into the 80–90 percent region, the costs of refinancing increase due to the need for PMI. As LTV's increase past 90 percent, homeowners may be completely rationed out of the

3. Borrowers that fail the credit and/or the debt/income screen may reapply for a refinance with a lender that deals with below A-credit paper. These institutions charge a premium over the A-credit lenders in the form of up-front points. Loans with B-level credit generally will pay 5–7 points as compared to 2–3 points for A-level credit.

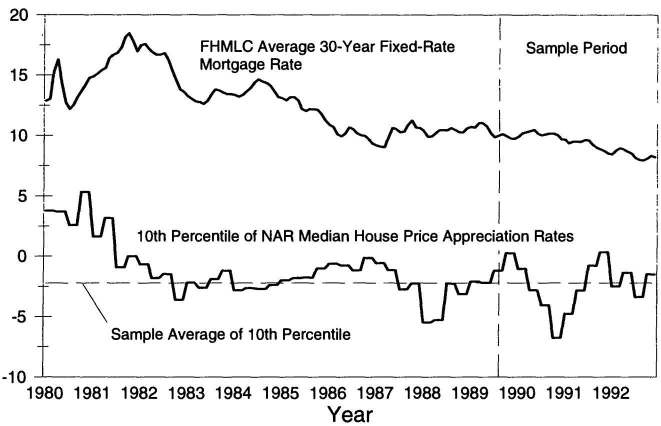

FIG. 1. Mortgage Interest Rates and Property Market Performance

refinance market. In addition to increasing LTVs, adverse regional shocks can also constrain mortgage refinancing by depressing incomes and/or damaging credit profiles, thereby making it more difficult for homeowners to pass the credit and/or debt/income screens.

The impact of collateral constraints on mortgage refinancing will be most easily estimated during a period of both declining interest rates and weak property values in some housing markets. Figure 1 plots the average mortgage interest rate for FHMLC thirty-year fixed rate loans over the period 1980–1992. In addition, we plot the bottom tenth percentile of SMSA annual housing-price appreciation rates as measured by the National Association of Realtors. The period from 1989 to 1992 exhibits both declining interest rates and weak property markets in the bottom tail of the distribution of SMSA house price appreciation rates. We will focus on this period in our empirical work.

2. EMPIRICAL SPECIFICATION

In this section, we discuss the basic characteristics of the data we use in our analysis. Measuring the incentive to prepay facing a mortgage holder involves several issues which we discuss in light of our data. Incentives to prepay can be constrained by deteriorating equity positions in housing markets suffering from declining prices. We discuss how we capture this housing market effect through disaggregating our overall sample into four subsamples. Finally, we discuss why we estimate the model using a hazard function methodology.

An important point to stress is that having access to individual mortgage data greatly enhances our ability to study the refinance decision. The empirical literature on refinancing is based almost entirely on models estimated using pool data derived from the secondary market.[4] The *Bond Buyer,* a subsidiary of International Thomson Publishing Corporation, holds the distribution rights for all data on GNMA, FHLMC, and FNMA mortgage pools. Their pool data contains a pool identifier, the original pool balance, the current prepayment factor, the pass-through rate, the issue date, the latest loan maturity date, the original and current weighted average maturity (WAM), the original and current weighted average coupon (WAC), and lender information. No appraisal information is available, making it impossible to compute a weighted average LTV for the pool. Prepayment models are estimated using the percent of the pool which has prepaid at any point in time. It is clear that the high quality and level of detail in our data give us a significant informational advantage for estimating the impact of refinancing constraints.

2.1 Data Description

We focus our empirical analysis on fully documented (no NIVs or NAVs) thirty-year fixed-rate conventional conforming mortgages for 1–4 family dwellings (excluding Coops).[5] The sample consists of all mortgages serviced by Chemical Bank with originations between June 1989 and May 1992. The sample includes mortgages whose servicing was purchased by Chemical Bank, and excludes mortgages whose servicing was sold by the bank. This results in a total of 35,865 mortgages involving a total of 630,183 monthly observations. Mortgage servicing involves collecting the monthly principal and interest payments from the borrower, and remitting this to the investors in the pool in return for a fee. Mortgage servicing data is very accurate as a result of its use for billing.

For each mortgage, we observe the following information: the origination date, balance, and interest rate on the mortgage; and the location and original appraised value of the property. When a mortgage prepays, we do not observe in our data if the house was sold or the mortgage was refinanced. We use the original appraised value and original loan balance to calculate the original loan-to-value ratio (LTV_0). For each month the mortgage is in the sample, we calculate the current loan balance using the loan amortization and any partial prepayments. The resulting sample is quite consistent throughout the period of study. Appendix Table A1 presents summary statistics for our sample disaggregated into six month intervals. The average LTV_0 remained roughly unchanged at 73–75 percent, while the average loan size remained in the $95,000 range.

The prepayment experience within the Chemical Bank portfolio mirrors the refinancing observed in the overall market. Figure 2 shows the similarity of the prepayment pattern between our sample and the Mortgage Bankers Association (MBA) overall mortgage refinance index (base period: 3/16/90 = 100). This establishes

4. Exceptions are Green and Shoven (1986) and Schwartz and Torous (1993). See also Hayre, Lauterbach, and Mohebbi (1989), Schorin (1992), Archer, Ling, and McGill (1995), and Peristiani et al. (1996).

5. Conventional mortgages exclude government-insured FHA and VA mortgages.

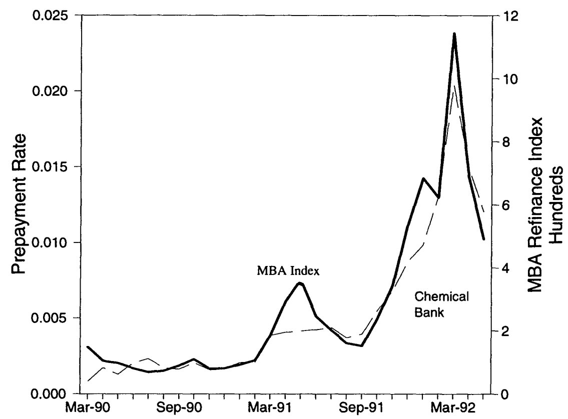

FIG. 2. Comparison of MBA Refinance Index to Chemical Bank Sample Prepayments

that the prepayment cycle in our data is driven by refinancing not home sales. We also expect that our qualitative findings will quite easily generalize to the broader market for A-credit mortgage refinancing.

2.2 *Empirical Model*

The aim of our empirical model is to quantify the determinants of the decision to fully prepay a mortgage.[6] The homeowners' decision to refinance a mortgage involves weighing the benefits versus the costs. As discussed in section 1, the costs of refinancing a mortgage are roughly proportional to the size of the loan. The appropriate formulation for the incentive to refinance, then, is a function of the origination rate relative to the current rate. If the costs of refinancing were primarily fixed in nature, then the incentive would be best measured as a function of the difference in rates.

Following Richard and Roll (1989), we use the Principal/Value (PV) ratio as our basis for measuring the incentive to refinance. The PV_t is defined to be the mortgage principal outstanding at time t divided by the present value of the current mortgage payments using the "current rate" at time t.

$$PV_t = \frac{r_t}{r_0}\left[\frac{1 - (1 + r_0)^{t-360}}{1 - (1 + r_t)^{t-360}}\right].$$

If the current rate, r_t, is the same as the origination rate on the mortgage, r_0, then $PV_t = 1$. If r_t is below the origination rate, then $PV_t < 1$ and there is a positive incentive to refinance.

6. We view this as a zero/one event; that is, we do not model the decision to partially prepay a mortgage.

The mortgage prepayment option is similar to an implied call option. Consequently, option-pricing models are a common starting point for building empirical models of the refinance decision. The option effect suggests that in periods of high interest rate volatility there is an incentive to delaying refinancing. In an attempt to control for this option effect, we fit a GARCH(1,1) model for the conditional variance of the monthly time series of average mortgage interest rates.[7] We use the predicted conditional variance as our measure of volatility. Controlling for *PV*, we find no additional explanatory power associated with our measure of interest rate volatility. As a consequence, we drop the variable from the analysis.

An immediate issue we must confront is that we never observe the rate at which a homeowner is able to refinance. This is a result of the interest rate heterogeneity that exists in our sample. For a typical quarter in our sample, the inner quartile range (the difference between the 75th and the 25th percentiles) in origination rates is one hundred basis points. This dispersion reflects more than just regional rate differences. Looking at an analysis of variance, we find that regressing the origination rate on a set of dummy variables for time (measured quarterly) and state explains only 21 percent of the total variance in rates.

We estimate the model using a variety of assumptions regarding the current rate. The qualitative results are similar across definitions. For the results we present in this paper, we use the following approach to estimate the current rate. Using the month in which a mortgage is booked, we calculate the spread between the origination rate on the mortgage and the national average rate as reported by GNMA, $\Delta = r_0 - r_{g0}$. We then assume that for this mortgage the current rate t periods after it is booked is the GNMA rate for that period plus that mortgage's initial spread, $r_t = r_{gt} + \Delta$. This definition of the current rate initializes each mortgage to have a *PV* equal to one in the month it was booked.

A second issue in defining the current rate involves the lags in processing a mortgage refinance application. If a homeowner responds to an incentive to refinance in period t (based on r_t), the actual refinance will not show up in the data until the loan closes in period $t + 2$ or $t + 3$. For this reason, we assume a two-month processing lag when constructing the current rate. Our findings are robust to the choice of a lag of two or three months.

Unlike a standard call option, mortgages that are "out of the money" may still prepay due to a home sale. This raises a final specification issue of how to treat mortgages that are out of the money, that is, those mortgages with $PV_t > 1$. While we will still see in our data prepayments of mortgages with $PV_t > 1$ due to home sales, we would not expect to see any significant number of refinances. Since we want *PV* to capture the pure incentive to refinance, we decided to truncate PV_t at one, hereafter denoted as PV_t (≤ 1). That is, once r_t is greater that r_0, further increases in r_t have no additional disincentive effects.

PV_t does an excellent job of tracking prepayments in our sample. Figure 3 plots the sample prepayment experience and the average PV_t. As the average PV_t in the

7. See Engle (1982) and Bollerslev (1986) for detailed discussions of GARCH models.

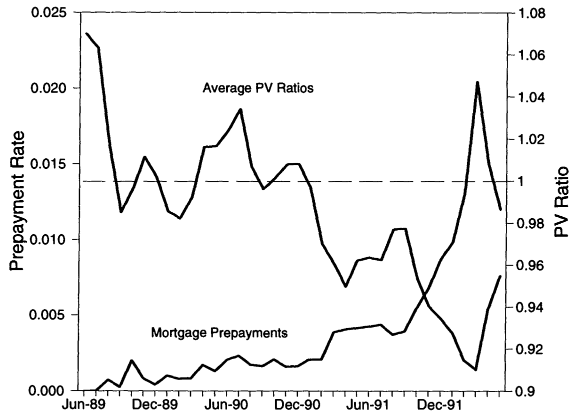

FIG. 3. PV Ratios and Mortgage Prepayment Rates

sample moves below one due to a drop in general rates, prepayments accelerate. In section 3, we will demonstrate that this strong correlation survives in a multivariate analysis where we control for a mortgage's age, LTV_0, and original loan size.

A final key issue in the empirical model is how to formulate the collateral constraints. As we discussed in section 1, loans with high LTV_ts will be more costly to refinance. In our data we observe the LTV_0 based on the original appraisal value and original loan balance. LTV_t depends on the current loan balance and the current appraisal value of the property. We observe the current loan balance in our data. To determine a mortgage's LTV_t we would need an appraisal index, that is, an index that would predict the change in appraisal values in a particular housing market over time. No such appraisal index exists. The difficulty with using one of the many existing house price indices as a substitute is that they all suffer from a variety of different biases.[8] We feel that much more work needs to be done to produce an index suitable for determining current LTVs.

Lacking a reliable measure for LTV_ts, we split our data into four subsamples each meant to capture a varying degree of collateral constraint. The subsamples are defined by the LTV_0 and location. We divide the sample into LTV_0 "constrained" and LTV_0 "unconstrained" mortgages based on whether the LTV_0 is above or less than or equal to 80 percent. The rationale for using 80 percent as the line of demarcation is based on the PMI requirement. A loan with an LTV_0 above 80 percent pays a premium for PMI insurance. If the homeowner has any additional free capital at closing, then the total financing costs could have been lowered by buying down the LTV_0 to 80 percent, thereby avoiding the cost of PMI. Evidence for this argument can be seen in Figure 4 in the bunching of LTV_0s in our sample at 80 percent.[9] This suggests that borrowers taking our mortgages with LTV_0s above 80 percent generally

8. See Haurin and Hendershott (1991) for a summary of the various indices and their problems.

9. The high LTV loans listed in Figure 4 all have PMI insurance and have been sold by Chemical Bank onto the secondary market.

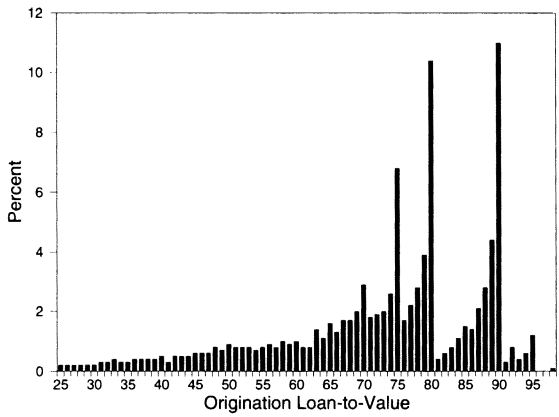

FIG. 4. Frequency Distribution of Initial LTV Ratios

are financially constrained at the time of closing. These financial constraints may be expected to persist into the future limiting the borrowers' ability to finance a refinance.

We also divide the sample into locationally "constrained" mortgages originated in states with weak property markets and "unconstrained" mortgages originated in states with relatively stable property markets. We use two criteria to determine if a state should be allocated to the location constrained or unconstrained samples. We rank states by their average percent change in the SMSA median house prices from 1990 to 1992, and by their ratio of high LTV_0 to low LTV_0 prepayment rates.[10] The rationale for the second criteria is that if collateral constraints are binding in a particular market, then we expect that they will affect the high LTV_0 loans disproportionately.[11] The data suggest that the location constrained set of states consists of Connecticut, Florida, Massachusetts, New Jersey, New York, and Rhode Island. The average percentage change in median house prices for the location-constrained states is 1.6 percent as compared to 6.5 percent for the location-unconstrained states. Similarly, the average ratio of high LTV_0/low LTV_0 prepayment rates for the location-constrained states is 0.3 as compared to 0.8 for the location-unconstrained states.

The resulting four subsamples consist of (1) unconstrained low LTV_0 non-CT, FL, MA, NJ, NY, and RI mortgages; (2) LTV_0 constrained mortgages with LTV_0s above 80 percent originated outside of CT, FL, MA, NJ, NY, and RI; (3) locationally constrained mortgages with LTV_0s less than or equal to 80 percent originated in CT, FL, MA, NJ, NY, and RI; and (4) locationally and LTV_0-constrained mortgages with

10. We use changes in median house price indices since we have this data for 128 SAs. The correlation with changes in repeat-sale price indices for a sample of 42 SAs is 0.82.

11. The correlation (p-value) between the ratio of prepayments of high/low LTV_0 mortgages and overall prepayment rates is 0.13 (0.39), while the correlation with the percentage change in median house prices is 0.72 (0.00).

LTV_0 above 80 percent originated in these same states. The concentration of the Chemical Bank portfolio in the Northeast ensures a reasonable size for our locationally constrained subsamples. Appendix Table A2 gives summary statistics for each subsample.

The impact of LTV_0 and property market conditions on prepayments can be clearly seen in the simple tabulation of sample prepayment rates given in Table 1. The overall sample prepayment rate is 10 percent. Moving from high to low LTV_0 mortgages increases the observed prepayment rate by 3.4 percent. Moving from weak to stable property markets (as defined above) increases the observed prepayment rate by 6.6 percent. There is a strong interaction between LTV_0 and property markets indicated by the table. Moving from high to low LTV_0 mortgages increases prepayments by 1.7 percent in stable property markets (less than the average of 3.4 percent) and by 4.9 percent in weak property markets (more than the average of 3.4 percent). Similarly, moving from weak to stable property markets increases prepayments by 5.5 percent for low LTV_0 mortgages (less than the average of 6.6 percent) and by 8.8 percent for high LTV_0 mortgages (more than the average of 6.6 percent). The next section extends the analysis to a multivariate setting.

2.3 *Econometric Specification*

We model the conditional probability that a mortgage prepays in a particular month using a hazard function. This is a natural choice for several reasons. The hazard rate measures the probability of prepayment in a month given that a mortgage has not prepaid in a prior month. This is exactly the conditional probability we are interested in estimating. Hazard models also allow us to incorporate time-varying covariates such as PV_t (≤ 1) in a natural way. This is clearly critical to relating current prepayments to current incentives in the market. Finally, hazard models can handle censoring of spell durations. Many mortgages in our sample have not prepaid by the end of the sample period. Their duration time until prepayment is censored. Hazard models allow us to keep these mortgages in the sample, and to use the information on their current duration to help in estimating the effect of observed heterogeneity in mortgages on prepayment probabilities.

TABLE 1

SAMPLE PREPAYMENT RATES

	Stable Housing Market[a]	Weak Housing Market[b]	
Low LTV[c]	13.05	7.51	10.93
High LTV[d]	11.37	2.59	7.55
	12.63	6.06	10.03

NOTES: Sample size of 35,865 mortgages.

[a]Non-CT, FL, MA, NJ, NY and RI.
[b]CT, FL, MA, NJ, NY and RI.
[c]$LTV_0 \leq 0.8$.
[d]$LTV_0 > 0.8$.

We use the proportional hazard specification developed in Flinn and Heckman (1983).

$$h(t|X, \theta) = \exp(\gamma_0 + X_t\beta + \sum_{k=1}^{K} \gamma_k(t^{\lambda_k} - 1)/\lambda_k + c\theta)$$

where

t = current duration of mortgage,
X = vector of exogenous variables,
θ = mortgage-specific unobserved heterogeneity,
c = factor loading on unobserved heterogeneity.

One advantage of this specific functional form for the empirical hazard is that it embeds many different forms of duration dependence as special cases. For example, this hazard specification can be specialized to the Weibull, Gompertz, and the Quadratic hazards. This flexibility facilitates the selection of an appropriate parametric form for the duration dependence. Testing between these hazard formulations can be carried out using standard likelihood ratio tests. In addition, we can easily incorporate unobserved heterogeneity into the estimation using the Heckman and Singer (1984) methodology.

The first topic of investigation is exploring the fit for various specifications of the "baseline" hazard. This baseline captures the pure "seasoning" effect for a typical mortgage in our sample, that is, the effect of the age of the mortgage on prepayment rates holding all other observed factors constant. In a proportional hazard framework, the covariates measuring the observed heterogeneity among mortgages in our sample affect prepayment rates by proportionally shifting this baseline prepayment rate.

The Weibull baseline hazard results if $\lambda_k = 0$ for all k and $\gamma_k = 0$ for $k \geq 2$. The Gompertz baseline corresponds to $\lambda_1 = 1$, $\lambda_k = \gamma_k = 0$ for $k \geq 2$. When we estimate γ_1 for the unconstrained sample we get a value of -0.13 with an associated standard error of 0.09.[12] The data for the unconstrained sample of mortgages, then, do not reject the Weibull specification. Further, we can not reject the Weibull formulation in any of our three samples of constrained mortgages. We also estimated a Quadratic baseline and found no significance evidence of curvature in the rate of seasoning. Table 2 summarizes our findings for each group of mortgages. The data do indicate that the rate of seasoning increases as the degree of constraints facing homeowners is relaxed. Figure 5 compares these differential seasoning patterns.[13]

12. We thank James Heckman for providing us with the CTM software that we use to estimate the hazard specifications.

13. We used the Heckman and Singer methodology for controlling for unobserved heterogeneity. In each subsample, the data rejected even two points of support for the unobserved heterogeneity distribution.

TABLE 2

MORTGAGE PREPAYMENT HAZARD ESTIMATES

Variable	Unconstrained[a] (1)	Only LTV Constrained[b] (2)	Only Location Constrained[c] (3)	Location and LTV Constrained[d] (4)
Constant	19.86	27.71	33,53	18.42
	(5.24)	(9.73)	(9.12)	(26.71)
Gamma	0.87	1.15	1.13	1.34
	(0.05)	(0.09)	(0.08)	(0.30)
Original LTV	−0.007	−0.03	−0.01	−0.10
	(0.002)	(0.01)	(0.002)	(0.03)
Loan Size	0.05	0.05	0.04	0.01
	(0.005)	(0.01)	(0.01)	(0.03)
PV_t	−42.54	−58.63	−78.65	−28.59
	(11.45)	(21.03)	(19.88)	(58.03)
PV_t^2	14.73	24.77	36.86	8.49
	(6.25)	(11.43)	(10.79)	(31.46)
-Log Likelihood	11,421	3,603	4,565	790

NOTES: Standard errors are given in parentheses.

[a]Non-CT, FL, MA, NJ, NY and RI and $LTV_0 \leq 0.8$.
[b]Non-CT, FL, MA, NJ, NY and RI and $LTV_0 > 0.8$.
[c]CT, FL, MA, NJ, NY and RI and $LTV_0 \leq 0.8$.
[d]CT, FL, MA, NJ, NY and RI and $LTV_0 > 0.8$.

3. EMPIRICAL FINDINGS AND COMPARISON TO THE LITERATURE

A basic question is to what extent the large reduction in prepayment rates in the constrained states is due to differences in the characteristics of the mortgages originated in those states. To answer this question, we used the model estimates to calculate the predicted monthly prepayment rates for each mortgage originated in a constrained state. We then calculated the predicted monthly prepayment rates for the same mortgages assuming that they were originated in an unconstrained state. We took the ratio of these predicted prepayment rates and averaged them over all the

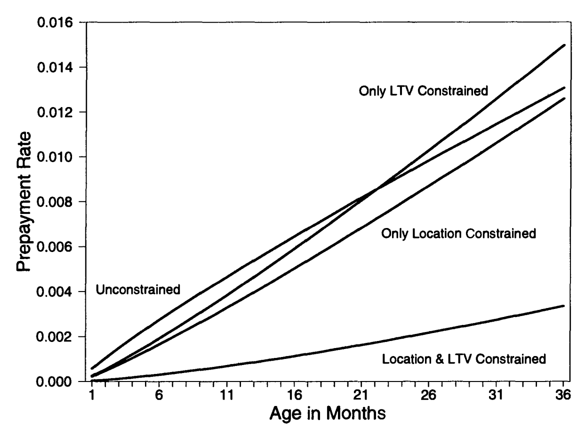

FIG. 5. Marginal Effects of Age on Prepayment Rates

mortgage months in the constrained samples. We find that nearly all of the reduction in prepayment speeds is attributable to differences in the coefficient estimates across the constrained and unconstrained models, rather than to differences in the characteristics of mortgages originated in the constrained and unconstrained states. At this basic level, then, the empirical findings suggest an important role for prepayment constraints in explaining prepayment behavior. To address further the empirical importance of prepayment constraints, we need to specify how they are manifested in our empirical model.

For each homeowner, we assume that there is a critical value for the PV_t (≤ 1) that will induce a refinance of the existing mortgage. That is, the individual's demand for refinancing is a step function with the step occurring at the critical PV_t (≤ 1) value. This critical value is determined by the individual's specific cost of refinancing, which we have no direct measures of in our data. We assume, though, that a distribution of refinance costs exist in a specific housing market. This distribution induces a smooth market demand for refinancing that is swept out as the PV_t (≤ 1) decreases. As we move from our unconstrained to our constrained samples, we assume that the constraints shift outward the distribution of refinance costs. As a consequence, we expect to see an inward shift in the demand for refinancing; that is, the level of prepayments for a given PV_t should be lower in the constrained samples.

The data strongly support this hypothesis. For the unconstrained sample of mortgages, we find a large effect of PV_t (≤ 1) on prepayment rates. Decreases in PV_t (≤ 1) below one are associated with a rapidly rising payoff rate. Holding other variables constant at their mean values, a decline in PV_t (≤ 1) from 1 to 0.8 results in a four percentage point increase in the monthly prepayment rate. This is illustrated in Figure 6 along with the incentive effects for the three constrained samples of mortgages. As we move from the unconstrained to the constrained samples, we find that

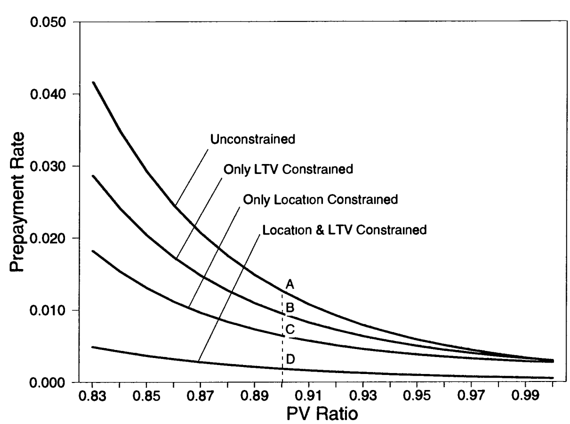

FIG. 6. Marginal Effects of PV on Prepayment Rates

the constraints significantly diminish the effect of a given PV_t (≤ 1) on the likelihood of prepayment. In our location- and LTV-constrained sample, decreases in PV_t (≤ 1) have only a *negligible* effect on the speed of prepayment.

The fact that the constraints significantly diminish the effect of PV_t (≤ 1) on prepayments is clear from Figure 6. The relative importance of the credit, income, and collateral constraints is more difficult to establish. Making this distinction is irrelevant for many policy recommendations. However, the results in Figure 6 are suggestive that the collateral constraint plays a primary role.

To see the importance of the collateral constraint in reducing prepayments consider a PV_t (≤ 1) of 0.9. The predicted total effect of the credit, income, and collateral constraints combined is a 1 percent reduction in the monthly prepayment rate as shown in Figure 6 by the movement from point A to point D. Recall from Figure 4 the bunching of LTVs at the 80 percent level indicating the advantages of avoiding PMI if financially feasible at the origination of the mortgage. This suggests that the impact of the income and credit constraints can be measured by comparing low LTV_0 to high LTV_0 mortgages in a stable property market. This effect is a reduction in the monthly prepayment rate of 0.3 percent as shown in Figure 6 by the movement from point A to point B. This decomposition implies that 70 percent of the reduction in the effect of PV_t (≤ 1) on prepayments is due to the collateral constraint.[14]

Two characteristics that are observed at the outset of the mortgage help to explain subsequent prepayment rates. Figures 7 and 8 illustrate the impact of changes in LTV_0 on the monthly prepayment hazard holding constant all other variables at their mean values. Within each sample, increases in LTV_0 are associated with slower prepayment rates. This effect is largest in magnitude for the constrained samples of mortgages. Figure 9 illustrates the impact of loan size on the monthly prepayment hazard holding constant all other variables at their mean values.[15] The data indicate that with the exception of the location- and LTV-constrained sample, higher initial loan balances are associated with faster prepayment rates.

To check how well our model fits the data, we compare predicted to actual prepayment rates for our portfolio of mortgages. For each mortgage, we use the model to predict the conditional probability the mortgage prepays for each month that the mortgage is in our sample. These predictions take into account the original LTV and original loan balance, the effect of seasoning, and the effect of changing incentives through variation in PV_t (≤ 1). For each month, we average the mortgage specific predicted hazard rates to arrive at a predicted prepayment rate for the portfolio. This

14. That is, this decomposition measures the effect of the collateral constraint by comparing high LTV_0 mortgages across stable and weak property markets, as shown in Figure 6 by the movement from point B to point D. It is unlikely that this effect measures some other unrelated long-term regional effect. Becketti and Morris (1990, p. 42, Table 15) report median prepayment rates by selected states for the period 1982–1988. The weighted average median prepayment rate in FL, NJ, NY, and MA was 3.56 percent while for IL, MO, OH, and PA it was 2.49 percent.

15. Our model does not incorporate the feature that prepayments may be a function of the history of incentives facing the borrower, known as "burnout" in the mortgage trade literature, because of the relatively short time period covered by our study.

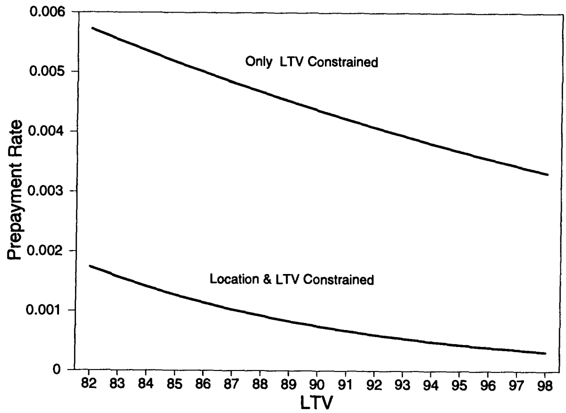

FIG. 7. Marginal Effects of Initial LTV Ratios on Prepayment Rates—High LTV Ratios

rate reflects the predicted percent of outstanding mortgages that will prepay in that month.

There are two types of goodness-of-fit measures that we are interested in examining. The first is how well the model fits the in-sample portfolio prepayment pattern. The second is how well the model fits an out-of-sample portfolio prepayment pattern. To address both issues, we withheld eleven months of data from the sample used in estimation. This allows us to evaluate the out-of-sample fit of the model for the period from June 1992 to April 1993. Figure 10 plots the actual and predicted portfolio prepayment rates. If we regress the in-sample actual monthly prepayment rate on the predicted monthly prepayment rate we end up with an R^2 of 91 percent. The out-of-sample R^2 is 68 percent.[16]

Two recent papers using different data and econometric methods find corroborating evidence of the importance of collateral constraints on mortgage refinancing. Archer, Ling, and McGill (1995) match the 1985 and 1987 national samples of the American Housing Survey. They select a subsample of nonmoving, owner-occupied houses with fixed-rate primary mortgages. They measure the incentive to refinance using the difference between the actual rate on the mortgage and the lowest Freddie Mac monthly commitment rate on thirty-year fixed-rate mortgages over their sample period. A current LTV is estimated using the book value of the mortgage divided by the owner's assessment of the current market value of the house. In addition, a current debt-to-income ratio is calculated using the household's current income and an estimate of the debt costs assuming the household refinanced into a new thirty-year fixed-rate mortgage at the rate specified above. No credit information is available. Refinances are identified separately from home sales. A logistic regression is esti-

16. The model overpredicts prepayments in the out-of-sample period. This likely reflects the burnout feature discussed earlier. That is, some of the mortgages in this period previously faced strong incentives to refinance and did not exercise the option. This indicates that these homeowners face higher "costs" of refinancing, and will be less likely to refinance in the future when faced with similar incentives.

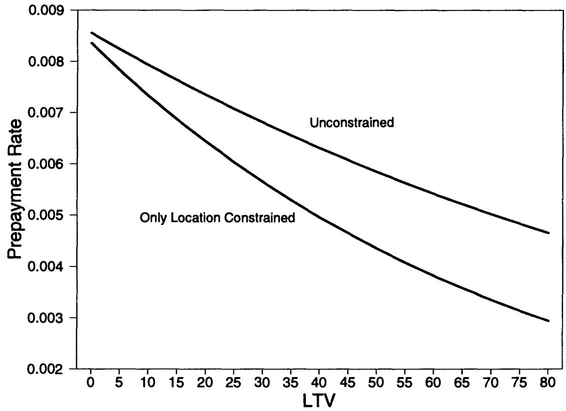

FIG. 8. Marginal Effects of Initial LTV Ratios on Prepayment Rates—Low LTV Ratios

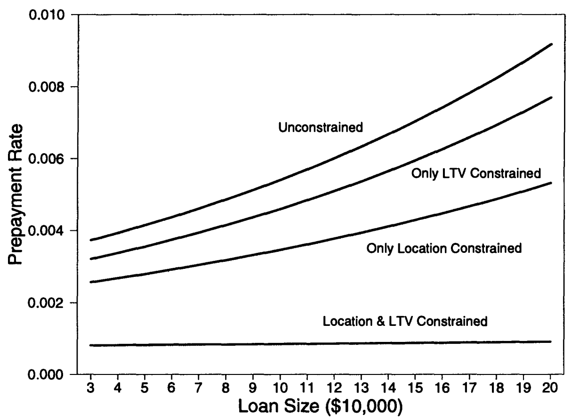

FIG. 9. Marginal Effects of Loan Size on Prepayment Rates

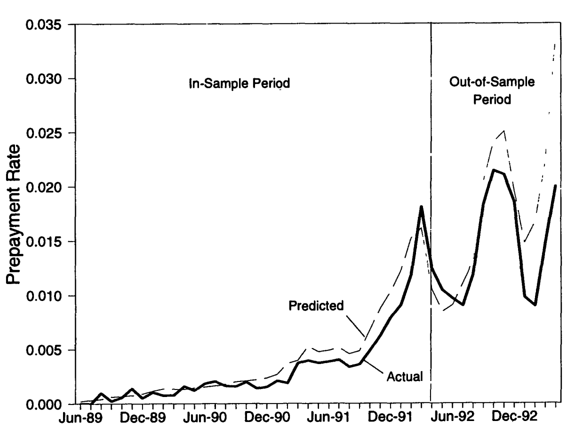

FIG. 10. Sample Prepayment Rates—Actual versus Estimated

mated. They find that when a household faces a binding collateral or debt constraint, the impact of the incentive to refinance is reduced by roughly 50 percent.

Peristiani et al. (1996) use a large micro data set on mortgages provided by the Mortgage Research Group. The sample is limited to properties financed with a thirty-year fixed-rate mortgages in five states.[17] Properties that sold are removed from the sample. Current LTVs are estimated using county-based repeat-sale price indices and the initial LTV of the mortgage. In addition, credit information is available based on credit reports on each household. The incentive to refinance is measured both in dollar and percent amounts to check for sensitivity of the model estimates.[18] Logit models are estimated on whether a mortgage refinances over the observed time period (which varies by mortgage). To control for different exposure times across mortgages in the sample, the exposure time is entered as an independent variable. They find that both poor credit and lack of estimated current house equity significantly diminish the likelihood of refinancing, and these two factors interact with each other to further diminish the sensitivity of the refinance decision to the incentive measures.

4. INTERACTIONS BETWEEN THE REGIONAL RECESSION AND REFINANCING CONSTRAINTS

Our results suggest that the regional recession of the late 1980s and early 1990s cost residents of depressed areas dearly in terms of increased interest costs on their mortgages. From 1987 to 1991 roughly 2.4 trillion dollars of fixed-rate mortgages have been originated. Department of Housing and Urban Development (HUD) (1993) data indicate that our locationally constrained states have accounted for roughly 19 percent of the total originations, or roughly 460 billion dollars. During this period, refinancing accounted for approximately 25 percent of total originations.[19] Making the conservative assumption that the collateral constraints did not depress home sales and using the model's estimate of a 50 percent reduction in prepayment rates, refinances would account for 14 percent of total originations in our constrained states. We conclude that somewhere in the order of 65 billion dollars worth of residential mortgages did not refinance that would have done so had the property market not collapsed.

One direct effect of this lack of refinancing activity is to redistribute wealth away from the areas in which the constraints are relatively more binding to the rest of the country. Homeowners in the constrained states end up paying higher interest rates on their mortgage debt than would otherwise be the case. The beneficiaries of these

17. Specifically, they look at Orange County in NY; Essex, Bergen, and Monmouth Counties in NJ; Citrus, Clay, Escambia, Hernando, Manatee, and Marion Counties in FL; Cook County in IL; and Los Angeles, Ventura, and Riverside Counties in CA.

18. For mortgages that refinance, the incentive is measured using the average of the distribution of rates on A-credit mortgages at the time of refinance. For mortgages that do not refinance, the incentive is measured assuming that they could have received the 75th percentile of the distribution of average rates over the time period (where the lowest average rate is the 100th percentile). This choice closely matches the experience of the households that do refinance in their data.

19. See Lekkas (1993).

higher interest payments are the owners of the securities backed by the mortgages. Since the market for mortgage-backed securities is a national market, the higher interest rate in the constrained states represents a redistribution of wealth toward the unconstrained states. An interesting question for future research concerns the feedback effect of this wealth effect on local income and expenditure.

Another interesting question is the extent of the feedback effect on the local property market. Among those who wish to refinance but are constrained from doing so, there may be many who are experiencing economic hardship. Indeed, this widespread hardship may be one of the underlying reasons for the property market collapse. These individuals are at risk of going delinquent on their mortgage. The advantage of being able to refinance is that it may reduce monthly payments enough to allow the individual to avoid delinquency.[20] There is, therefore, an interesting interaction between prepayment and delinquency. The presence of a significant stock of houses in the process of being "worked out" by lenders does further damage to property values in an area, and may contribute to the depth of the real estate slump itself.

A final issue that may be of value in future research concerns the interaction between regional constraints on refinancing and attempts at the federal level to stimulate the economy through monetary policy. The constraints on refinancing imply that reductions in interest rates will have more of an expansionary effect in regions that have robust property markets. The refinancing constraints make it hard for the monetary authorities to get liquidity to those regions of the economy that need it the most.

5. CONCLUDING REMARKS

In the current structure of the U.S. residential mortgage market, a decrease in property values may make it very difficult for individuals to refinance their mortgages to take advantage of declining interest rates. In this paper, we show just how quantitatively important this effect has been in the recent period.

By confirming the importance of collateral constraints in the residential housing market, our work contributes to the growing literature on the interaction between fluctuations in the net worth position of borrowers and economic activity, as surveyed by Gertler and Hubbard (1989). The work that they survey focuses on cases in which borrower net worth constrains the level of investment due to asymmetric information. For example, in the model of Bernanke and Gertler (1989) the larger the borrowers' stake in the projects the easier it is to trust them to select only good projects, and to put sufficient effort into these projects. Similarly, Hubbard and Kashyap (1992) have argued that reductions in agricultural land values reduced farmers' collateral so much that real investment in agriculture was significantly reduced.

In contract, incentive problems are all but irrelevant to the issue of whether or not

20. Lenders will occasionally "modify" the interest rate on a loan they hold in portfolio to allow borrowers who can demonstrate severe temporary hardship a chance to avoid delinquency.

an individual should be allowed to refinance an existing thirty-year mortgage. In the case of refinancing a mortgage, the real investment project has already been undertaken. Viewed in this light, the presence of a collateral constraint on refinancing should be seen as an issue of contract design. Why does the mortgage contract not contain a clause stipulating that during the term of the loan the rate could be reduced to a market rate for a set fee, thereby insuring homeowners against decreasing property values? This is a subtle question, and is related to other issues of optimal contract design in the housing finance market, which is a subject of current research.

APPENDIX TABLE 1

SUMMARY STATISTICS: BY SIX-MONTH INTERVALS

	Time Period					
Variable	6/89–12/89	1/90–6/90	7/90–12/90	1/91–6/91	7/91–12/91	1/92–6/92
Number of Mortgages	7,132	5,687	5,723	4,601	7,933	4,789
Original Interest Rate	10.14	10.30	10.13	9.65	9.22	8.61
	(0.58)	(0.54)	(0.41)	(0.38)	(0.50)	(0.38)
Original LTV	74.64	73.58	72.73	72.99	73.77	72.74
	(14.80)	(14.59)	(14.40)	(14.27)	(14.14)	(14.04)
Loan Size	97,434	96,734	95,140	96,868	97,922	96,774
	(41,016)	(40,281)	(40,839)	(41,230)	(41,464)	(41,286)

NOTES: Sample consists of Chemical Bank thirty-year fixed rate conventional comforming mortgages. Standard deviations in parentheses.

APPENDIX TABLE 2

SUMMARY STATISTICS: BY LOCATION/*LTV* SUBSAMPLES

	Unconstrained[a]	Only LTV Constrained[b]	Only Location Constrained[c]	Location and LTV Constrained[d]
Variable	(1)	(2)	(3)	(4)
Number of Mortgages	16,260	5,436	9,981	4,188
Number of Mortgage Months	283,283	99,952	164,949	81,999
Original Interest Rate	9.85	9.95	9.99	10.51
	(0.51)	(0.56)	(0.68)	(0.81)
Original LTV	68.36	89.31	66.56	88.66
	(12.11)	(3.41)	(13.59)	(2.77)
Loan Size	88,289	93,959	102,585	118,600
	(40,566)	(37,121)	(41,207)	(35,713)
$PV_t(\leq 1)$	0.96	0.96	0.96	0.96
	(0.04)	(0.04)	(0.04)	(0.04)
Prepayment Rate	13.05	11.37	7.51	2.59

NOTES: Counts or sample means are listed with sample standard deviations given in parentheses.

[a]Non-CT, FL, MA, NJ, NY and RI and $LTV_0 \leq 0.8$.

[b]Non-CT, FL, MA, NJ, NY and RI and $LTV_0 > 0.8$.

[c]CT, FL, MA, NJ, NY and RI/$LTV_0 \leq 0.8$.

[d]CT, FL, MA, NJ, NY and RI/$LTV_0 > 0.8$.

APPENDIX TABLE 3

ESTIMATED CLOSING COSTS AND *PMI* COSTS

Closing Costs:

Area	Closing Costs	Title Insurance	Origination Fee (2 points)	Total (percent of loan)
Connecticut	1,482	550	3,100	5,132 (3.31)
New Jersey	1,457	1,068	3,100	5,625 (3.63)
New York	2,619	1,112	3,100	6,831 (4.41)
New York City	4,169	1,112	3,100	8,381 (5.41)

PMI Costs:

	Loan-to-Value		
25 bps in rate	80–85%	85–90%	90–95%
Points	1.90	2.55	3.80

NOTES: Dollar costs based on a non Co-op loan of $155,000. Closing costs include fees for attorney, appraisal, credit report, recording, lien search, UCC-1 filing, documentation preparation, mortgage tax and fifteen days interim interest. Source is Chemical Bank closing cost estimates prepared for *RESPA* purposes.

LITERATURE CITED

Archer, Wayne, David C. Ling, and Gary A. McGill. "The Effect of Income and Collateral Constraints on Residential Mortgage Terminations." *Regional Science and Urban Economics* 26 (June 1995), 235–61.

Azfar, Omar, "Restricting the Choice Set in the Modeling of Contracts." Mimeo. Columbia University, 1993.

Becketti, Sean, and Charles S. Morris. *The Prepayment Experience of FNMA Mortgage-backed Securities*. In *Monograph Series in Finance and Economics*. New York: New York University Salomon Center, 1990.

Bernanke, Ben S., and Mark Gertler, "Agency Costs, Net Worth, and Business Fluctuations." *American Economic Review* 79 (March 1989), 14–31.

Bollerslev, Tim. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31 (1986), 307–27.

Caplin, Andrew, Charles Freeman, and Joseph Tracy. "Collateral Damage: How Refinancing Constraints Exacerbate Regional Recessions." Working paper no. 4531. National Bureau of Economic Research, August 1993.

Department of Housing and Urban Development. "Survey of Mortgage Lending Activity." Estimate Dollar Volume of 1-to-4 Family Mortgage Originations, by State, 1981–1992, March 1993.

———. *Survey of Mortgage Lending*. Washington: U.S. Government Printing Office, 1994.

Engle, Robert F. "Autoregressive Conditional Heteroskedasticity with Estimates of the Variants of U.K. Inflation." *Econometrica* 50 (July 1982), 987–1007.

Fabozzi, Frank, J., and Franco Modigliani. *Mortgage and Mortgage-Backed Securities Markets*. Boston: Harvard Business School Press, 1992.

Flinn, Chris, and James Heckman. "The Likelihood Function for a Multistate-Multiepisode Model in 'Models for the Analysis of Labor Dynamics'." In *Advances in Econometrics*, edited by R. Bassman and G. Rhodes. Greenwich, Conn.: JAI Press, 1983.

Gertler, Mark, and Glenn Hubbard. "Financial Factors in Business Fluctuations." In *Financial Market Volatility: Causes, Consequences, and Policy Recommendations,* 33–71. Kansas City: Federal Reserve Bank of Kansas City, 1989.

Green, Jerry, and John B. Shoven. "The Effects of Interest Rates on Mortgage Prepayments." *Journal of Money, Credit, and Banking* 18 (February 1986), 41–59.

Haurin, Donald R., and Patric H. Hendershott. "House Price Indexes: Issues and Results." *AREUEA* 19, no. 3 (1991), 259–69.

Hayre, Lakhbir S., Kenneth Lauterbach, and Cyrus Mohebbi. "Prepayment Models and Methodologies." In *Advances and Innovations in Bond and Mortgage Markets,* edited by Frank J. Fabozzi, 329–49. Chicago: Probus Publishing, 1989.

Heckman, James, and Burt Singer. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica* 52 (1984), 271–320.

Hubbard, Glen, and Anil K. Kashyap. "Internal Net Worth and the Investment Process: An Application to U.S. Agriculture." *Journal of Political Economy* 100 (June 1992), 506–34.

Lekkas, Vassilis. "Comparing Refinance Booms." *Secondary Mortgage Markets* 10 (Winter 1993), 15–18.

Monsen, Gordon. "The New Thinking on Mortgage Prepayments." *Mortgage Banking* (October 1992), 51–56.

Mortgage Bankers Association. *Weekly Survey,* 1994.

Peristiani, S., Bennett P., G. Monson, R. Peach, and J. Raiff. "Effects of Household Creditworthiness on Mortgage Refinancings." Working paper, Federal Reserve Bank of New York, June 1996.

Richard, Scott F., and Richard Roll. "Prepayments on Fixed-Rate Mortgage-backed Securities." *The Journal of Portfolio Management* (Spring 1989), 73–82.

Schorin, Charles N. "Modeling and Projecting MBS Prepayments." In *Handbook of Mortgage Backed Securities,* edited by Frank J. Fabozzi, pp. 221–62. Chicago: Probus Publishing, 1992.

Schwartz, Eduardo S., and Walter N. Torour. "Mortgage Prepayment and Default Decisions: A Poisson Regression Approach." *Journal of the American Real Estate and Urban Economics Association* 21 (Winter 1993), 431–49.