Neighborhood Effects in Mortgage Default Risk

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Preface

This study examines the effect of neighborhood characteristics on the default of FHA mortgages. The analysis includes both neighborhood characteristics and characteristics of the individual loan and borrower, so that the effects of the neighborhood can be distinguished from those of the individual loan. In particular, the analysis seeks to distinguish the effects of neighborhood race, ethnicity, and income from the effects of the of the individual borrower's status. Research on the effects of neighborhood characteristics on default has been somewhat limited in the past, and this study's contribution to the literature is the inclusion of credit history data. The analysis finds that lower tract income and higher tract black composition are associated with higher rates of default, whereas individual borrower race or income are unrelated to default.

The study then goes on to examine possible causes for these findings, including whether higher defaults reflect more limited access to mortgage finance (as measured by refinance probability) or a response to previous defaults in the neighborhood. The findings regarding access to refinancing are not definitive. FHA refinancing probabilities seem to be higher in minority tracts and are a least equal to low-income tracts. Refinancing through other non-FHA sources of refinance funds, including conventional, is statistically less in predominantly Hispanic and lower-income tracts for holders of FHA mortgages. The effects of neighborhood race and income on default are reduced when lagged defaults and prepayments and neighborhood house price change are included in the analysis. Although the higher default rate in lower-income tracts remains significant, the higher default rate in minority tracts becomes insignificant, suggesting that lower house price appreciation is an important factor in the higher default rates observed in minority neighborhoods.

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SUMMARY

The primary purpose of this paper is to investigate the effect of neighborhood characteristics, especially mean income and racial or ethnic composition, on the default of individual FHA-insured loans. En route we also present estimated default effects of individual income and race or ethnicity. We attempt not only to estimate neighborhood default effects, but also to understand what might lie behind these effects. We first ask whether neighborhood default effects might be traceable to differential access to funds for refinancing mortgages. To this end, we examine effects of race, ethnicity, and income at both the individual and tract level on two kinds of individual prepayment activity: (a) prepayment for the purpose of obtaining FHA refinancing, and (b) prepayment for all other reasons, one of which may be to obtain conventional refinancing. Attention then turns to two other explanations that might underlie the effect of neighborhood characteristics on individual default behavior: neighborhood default activity that might lead to abandoned structures, or undesirable instability associated with turnover of homeowners in the neighborhood. The methods used and conclusions drawn from the study may be conveniently organized around four research questions that are used to guide the analysis.

1. Once one controls for a variety of borrower- and loan-related factors, including time-varying characteristics, in an appropriate econometric model of default, do neighborhood effects seemingly related to income or race persist?

We answer this question in the first portion of the study via a statistical analysis of individual default behavior in which both individual and tract (neighborhood) effects are permitted. The analysis is based on samples of FHA-insured loans[1] that were endorsed in 1992 or 1994, or for which applications were submitted in one of these years, and for which the subject property was contained within 22 selected MSAs. In contrast with the data used in many previous studies, the

[1] Streamline refinances are excluded because the applications for such loans lack critical information, such as loan-to-value ratios.

data files used here contain information on individual race, ethnicity, income, and a summary credit measure, the FICO score. Moreover, this study utilizes a hazard model that offers two principal advantages over the probit and logit models that have more typically been used in related studies: first, the ability of the hazard approach to take proper account of time-varying characteristics and, second, the ability of the hazard approach to accommodate the censoring that occurs when the observation window closes while a loan remains active.

We find that decreases in tract income and, less clearly, increases in representation of blacks within the tract, are associated with higher default probabilities of individual loans, and this relationship holds even when one controls for the race, ethnicity, and credit history of the borrower in an appropriate hazard model of default behavior. We also observe that although neighborhood impacts remain, their importance is dramatically affected by introducing critical controls for characteristics of individual loans, borrowers, and the economic environment.

2. Do neighborhood characteristics, such as race and income, have effects on default that are separate and distinct from the effects of these same characteristics at the individual level?

Estimates of the default hazard shows that while greater tract representation of blacks is probably associated with higher individual default probabilities, individual race effects --- black or Hispanic --- are absent. Hispanic representation at the tract level does not seem to matter in default behavior. Although tract income does seem to affect default behavior, individual income has no statistically significant impact.

3. Is there evidence that differences in default probabilities reflect differences in the probability of refinancing?

To assess this possibility, the study combines the evidence from the default hazard with a parallel set of estimated prepayment hazards utilizing the same set of individual FHA-insured mortgages. If differential access to funds for refinancing were the culprit in generating higher default rates in more heavily black neighborhoods, we might expect to find that either FHA refinancing probabilities or other prepayment probabilities would be lower for blacks. Instead the estimated prepayment hazard models reveal that FHA refinancing probabilities, as well as other prepayment probabilities (which include conventional refinancing activities) tend to be higher, if anything, among loans in tracts with heavier minority (black or Hispanic) representation. Among these neighborhood effects, only the effect of tract-level Hispanic representation for other prepayment is statistically significant at conventional levels.

We do find that individual Hispanic ethnicity is associated with lower FHA refinancing probabilities, and individual blacks and Hispanics have lower probabilities of other types of prepayment, which may or may not be the result of discrimination in refinancing against individual borrowers on the basis of race or ethnicity. Yet there are no corresponding default effects traceable to the race of individuals.

Tract income is positively related to the probability of prepayment (other than for FHA refinancing) but has no significant effect on the FHA refinancing probability; as noted tract income is negatively related to default probabilities of individual loans.[2] The sign pattern is consistent with, but surely does not prove, that higher tract income supports lower default probabilities partially through greater access to conventional refinancing. Clearly, other explanations for this sign pattern are also possible.

We emphasize that this assessment of the role of differential access to funds is, by design, very narrow. It is restricted to effects arising among holders of FHA mortgages; conventional mortgage holders are excluded. The evidence is also entirely indirect. We do not account in any way for possible differences in the rate at which groups actually apply for refinancing from either FHA or conventional sources.

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[2] It is less easy to assess the role of individual income within the context of default and refinancing, mainly because the estimation also uses income indirectly as part of the front-end ratio. Evaluating income effects under the assumption that the front-end ratio is to be held fixed, we find that individual income has no significant effect on default but has positive impacts on probabilities of FHA refinancing and other prepayment.

4. Do neighborhood differences in default probabilities arise because of earlier defaults and, if so, what is the mechanism?

Next we entertain the possibility that neighborhood race (or income) effects on individual default behavior are traceable to (a) past defaults within these same neighborhoods, which may lead to abandoned structures and declining neighborhood amenities, or (b) past turnover of homeownership within these same neighborhoods, which may be associated with undesirable neighborhood instability. Under either scenario, lagged neighborhood default activity and (under the second alternative) neighborhood prepayment activity, may directly affect individual default behavior, or effects may occur indirectly via changes in neighborhood house prices. To investigate these ways in which neighborhood default effects might arise, we turn to additional statistical analysis that is restricted to the Chicago MSA.

We first utilize quarterly data from tract aggregates --- dubbed "supertracts" --- within the Chicago MSA from 1994 to mid-1999 to explore the aggregate relationship between house prices, on the one hand, and previous defaults and prepayments, on the other. Regression analysis with these aggregate data generally appears to show that lagged defaults lead to lower neighborhood house price growth. It is unclear whether the reason is that defaults lead to abandoned structures and neighborhood deterioration, whether defaults are one component of undesirable instability in homeownership, or whether some other default-related impact is at work. The regression estimates of the effects of current and lagged prepayment rates tend to be more irregular, sometimes suggesting positive effects on house price growth --- findings which are inconsistent with the turnover-leads-to-default theory --- but sometimes suggesting negative impacts.

These results should be interpreted with caution for several reasons. First, the statistical results are fragile, with estimated impacts varying with whether fixed effects are permitted, with the number of origination years over which the default and prepayment rates are calculated, with the number of lagged values of house prices included as explanatory variables, and with the number of lags of default and prepayment rates that are included in the regression. In addition, other specifications sometimes show that one quarter leads in default rates and prepayment rates are sometimes statistically significant, suggesting that such rates may proxy the effects of other influences on house prices.

To see whether lagged default and prepayment rates in the neighborhood might exert a direct effect on individual default probabilities, in addition to any indirect effects that occur via reductions in house prices, we reestimate default hazards for individual loans in the Chicago MSA. The estimation sample is composed of all 1994 Chicago MSA applications or originations for homes located in one of the supertracts that contain the requisite data. The new hazard specification augments the original specification by including a direct measure of supertract house price growth (measured in various ways), as well as lagged values of the supertract default and prepayment rates.

The results are mixed. The impact of supertract-level house price growth is often not significantly different from zero at conventional levels, though its effect is always of the anticipated sign. Lagged neighborhood defaults generally seem to have a positive impact on the probability of default of an individual loan, but lagged neighborhood prepayment rates are generally of mixed signs, casting substantial doubt on the role of prepayment activity (at least as measured here) as having a direct effect on default behavior.

It is noteworthy that introducing direct measures of neighborhood house price growth and lagged default and prepayment rates changes other estimated default effects. In particular, the estimated default impacts of supertract income and of supertract black representation are substantially reduced. While the effect of supertract income remains statistically significant, the neighborhood race effect is now far from statistical significance. Again caution is urged in interpreting these findings, in part because there is some evidence that lagged neighborhood default rates proxy other omitted variables that affect current individual default probabilities.

To conclude, the findings from the reestimated hazard models reinforce the idea that lagged neighborhood defaults may induce later individual defaults, and that the local price effects induced by lagged defaults (and other factors) may affect individual default probabilities as well. These default effects may arise because defaults result in vacant properties, leading to neighborhood decay, or because defaults are one component of undesirable turnover in neighborhood homeownership. In either case, a temporary rise in local default rates may tend to persist. There is no support here for a role of lagged prepayments as a trigger that induces defaults directly, and there is an uncertain role for prepayments affecting house prices. Although inconsistencies, anomalies, and serious data limitations (including the narrowness and nonrandomness of the Chicago MSA data) make these conclusions highly tentative, it appears that this wider and more precise set of neighborhood controls may reduce the remaining estimated impact of neighborhood racial composition on individual default behavior.

SECTION 1

INTRODUCTION

1.1 Motivation and Background

This paper examines the existence and nature of the effect of neighborhood characteristics, particularly income and race or ethnicity, on the default of FHA loans. Such a study is motivated by several considerations. First, there is a continuing public policy interest in the fortunes of minority and low-income residents in general, and thus neighborhood effects tied to race and income are of special concern. Second, neighborhood effects related to race and income may be indicative of other problems, such as inability of low-income or minority borrowers to obtain funds for refinancing their homes; and such problems may (or may not) call for policy changes. Third, the existence of neighborhood effects implies that samples of loans drawn from specific, narrowly defined geographic areas will tend to covary in their default behavior, even after controlling for individual characteristics of loans and borrowers. The assessment of riskiness of loan portfolios should presumably recognize this covariance, which implies greater variance in outcomes for loan portfolios that are not distributed randomly with respect to geography.

Several existing studies deal in some way with the effects of neighborhood racial composition and neighborhood income on default. Given that these studies differ substantially in data sources, the types of information available, and the statistical methods that are employed, there is no unanimity in findings. For example, using data on loans purchased by Freddie Mac to estimate a proportional hazard model, but lacking data on borrower race, Van Order and Zorn (1995),[1] find that both borrower income and tract income help explain default behavior, but the effect of neighborhood income is stronger and more stable. Tract racial composition (share of households that are black) also appears to affect default probabilities. In contrast, in a logit estimation procedure using FHA data that include borrower race information, Schnare and

[1] Van Order, Robert, and Zorn, Peter. "Income, Location, and Default: Some Implications for Community Lending," July 1995.

Gabriel (1994)[2] find no consistent statistically significant impacts on default of either income or race at either the borrower or tract level. Berkovec, et al (1994),[3] also use FHA data, but they find that tract income is associated with reduced default probabilities, black representation within the tract is "not strongly and consistently" associated with default, and increasing Hispanic representation is associated with lower default probabilities. Although not focusing on neighborhood race and income *per se,* Calem and Wachter (1999)[4] examine the effect of neighborhood housing market conditions, among other factors, on long-term delinquency of home purchase loans that were originated in Philadelphia from 1988 through 1994 as part of an affordable home loan program. They find evidence that increases in housing market activity are associated with a lower probability of delinquency, and more expensive homes relative to the neighborhood tend to have higher delinquency rates.[5]

This paper attempts to improve upon and extend these existing studies. In contrast to the work of Van Order and Zorn (1995) and Van Order, Westin, and Zorn (1993),[6] which rely on race measured at the area (census tract or zip code) level, this study uses a data set that has information on borrower's race as well. This detail will permit us to take a more refined look at the factors that may lie behind differences in default across neighborhoods. In particular and of

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[2] Schnare, Ann, and Gabriel, Stuart A. "The Role of FHA in the Provision of Credit to Minorities," ICF Incorporated, April 1994.

[3] Berkovec, James A., Canner, Glenn B., Gabriel, Stuart A., and Hannan, Timothy H. "Race, Redlining, and Residential Mortgage Loan Performance," *Journal of Real Estate Finance and Economics,* 9: 263-294 (1994).

[4] Calem, Paul S., and Wachter, Susan M., "Community Reinvestment and Credit Risk: Evidence from an Affordable-Home-Loan-Program," *Real Estate Economics,* V27, Number 1: 105-134 (1999).

[5] An NTIC study ("The Devil's in the Details," National Training and Information Center, October 1997) examines neighborhood effects of FHA loans, but the statistical analysis is generally informal. As required by Congress, the Federal Reserve Board is studying default of CRA loans in neighborhoods. See "The Performance and Profitability of CRA-Related Lending," Report by the Board of Governors of the Federal Reserve System, submitted to the Congress pursuant to section 713 of the Gramm-Leach-Bliley Act of 1999, July 17, 2000.

[6] Van Order, Robert, Westin, Ann-Margret, and Zorn, Peter. "Effects of the Racial Composition of Neighborhoods on Default and Implications for Racial Discrimination in Mortgage Markets," March 1993.

special importance, we will be better able to tell whether factors like race affect default at the neighborhood level (through, say, correlation with unobserved rates of house price growth) or only at the individual level (because, say, race is correlated with the unobserved occurrence of trigger events, like unemployment). In addition, our findings will be more directly applicable to FHA policy questions since we will be using data on FHA-insured loans rather than the conventional loans used in the latter set of studies.

In contrast to studies by Schnare and Gabriel (1994), Berkovec, et al (1996)[7], and Berkovec, et al, (1994), all of which are based on FHA-insured loans, we will see whether interarea differences in default rates remain even after using more appropriate estimation techniques and controlling for events that occur after loan origination (*e.g.,* changes in principal balance). In our view, the empirical work in the latter studies offers unconvincing evidence of area effects because the estimation technique (a logit on whether a default has occurred since origination) cannot account properly for post-origination changes in the housing or economic environment, which in many cases may be substantial. Indeed, as revealed by the list of explanatory variables used in these studies,[8] there is no attempt to recognize this source of variation across areas, thus leaving open the possibility that interarea differences (or lack thereof) represent nothing more than spurious correlations of area-level measures with post-origination economic events.[9]

Finally, unlike almost all of these other studies, this study will be able to exploit a database containing credit history information on most borrowers.[10] This capability will enable us to

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[7] Berkovec, James A., Canner, Glenn B., Gabriel, Stuart A., and Hannan, Timothy H. "Mortgage Discrimination and FHA Loan Performance," *Cityscape* Volume 2, Number 1, February 1996.

[8] Berkovec, et al (1994) justify considering only factors known at origination by arguing that they are looking for discrimination in the lending decicion. Of course, some characteristics, such as the current, scheduled principal balance on a fixed-rate loan, are time- varying, but the time path is known in advance.

[9] Van Order, Westin, and Zorn (1993) recognize post-origination differences across loans by introducing a variable representing the probability of negative equity over an eight-year horizon, but the variable is not entered into the hazard model as a time-varying covariate. Again, there is no attempt to build in the appropriate dynamics.

[10] Calem and Wachter (1999) have credit scores on about 56 percent of the sample; they impute credit scores for the remainder.

isolate more clearly the effects of neighborhood by permitting us to control for a factor --- differences in past credit performance --- that is often alleged to lie behind area or individual differentials in default behavior. (See, for example, Van Order and Zorn (1995).)

The availability of additional data is in a sense a mixed blessing. Because we will have the luxury of more detailed data, we shall be forced to turn elsewhere for explanations in the event that area or individual differences related to race or income persist. That is, when one attempts to estimate area or individual effects of race or income on default using a database that lacks information on potentially important factors, one can reasonably wonder whether the estimated effects are attributable in total or in part to omitted variable bias. For example, in attempting to estimate the effects of race at the neighborhood level by using a database that lacks individual race information, one must contend with the possibility that findings are seriously distorted by omitted variable bias. Moreover, even if race at both the neighborhood and individual level is recognized in estimation, findings can be strongly affected by the omission of potentially important data on, for example, credit history.[11] Because this study includes credit history information in the default analysis, there is at least some hope that we have effectively dealt with this potentially important source of variation, and thus it will be more difficult to claim that remaining race or income effects at the individual or area level are due to correlations with missing credit history data. Although one could reasonably argue that there are other omitted variables, as well as a host of other potential econometric problems (some of which are discussed below), we shall turn elsewhere for explanations. We consider three possibilities, and we attempt to explore each in some detail.

One explanation revolves around the possibility that racial impacts on default are traceable to difficulty in refinancing loans when it would be advisable to do so, *i.e.*, when there is a sufficiently large reduction in mortgage rates. Such an explanation is suggested by the possibility of racial disparities in the probability of obtaining refinancing loans --- "redlining" when operating at the neighborhood level, or simple race discrimination when operating at the

[11] For this reason, Berkovec, et al (1994) attempt to assess the size of the bias in estimated race effects attributable to the omission of credit history data. Unfortunately, there appears to be an error in their derivation.

level of the individual borrower.[12] In this regard, note that Schnare and Gabriel (1994) find that individual blacks have lower loan acceptance probabilities than do whites in both the conventional and FHA sectors.[13] They do not, however, find a consistent pattern of effects of neighborhood racial composition on the probability of loan acceptance. Schill and Wachter (1993)[14] study the accept/reject decision for conventional loans in Philadelphia and Boston and find little evidence of redlining once controls for neighborhood risk are included in the analysis.[15] (They do report significant individual race effects, and they note that these could be traceable to the omission of individual borrower characteristics, such as credit scores and LTV.)

If redlining in obtaining refinancing is the culprit in generating higher default probabilities, one might expect to find that racial composition of the neighborhood enters the probability of default as well as the probability of refinancing. If discrimination in refinancing at the individual level generates higher default probabilities, one might expect to find that individual race influences both the probability of default and the probability of refinancing. Naturally, other less insidious explanations — *e.g.,* lack of information or unwillingness to pursue refinancing — could account for the same pattern.[16] Hence, we shall more realistically be able only to reinforce or cast doubt on these explanations, rather than deduce the single correct explanation.

A second explanation for interarea differences in default propensities (assuming they exist) is

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[12] Noneconomic discrimination in obtaining home purchase loans is expected to result in lower default probabilities (on the margin) for affected individuals or groups. See, for example, Berkovec, et al (1994). Here we focus instead on possible discrimination in obtaining refinancing.

[13] It is unclear whether the paucity of relevant data on individual borrowers is playing an important role in generating these findings.

[14] Schill, Michael H., and Wachter, Susan M., "A Tale of Two Cities: Racial and Ethnic Geographic Disparities in Home Mortgage Lending in Boston and Philadephia," *Journal of Housing Research,* Volume 4, Issue 2: 245-275 (1993).

[15] The evidence for conventional mortgage refinance applications reported in Schill and Wachter is more ambiguous: Boston, but not Philadelphia, shows differences in acceptance probabilities based on the racial composition of the tract even when neighborhood risk characteristics are included in the analysis.

[16] One might question the importance of refinancing difficulties in generating higher default probabilities. This question is considered at greater length below.

that higher levels of default within the neighborhood, set off by any reason, result in abandoned structures[17] that tend to make the neighborhood less desirable, which in turn propagates additional defaults in the future. The abandoned structures could act as a trigger for default, causing borrowers to default on homes that were ripe for default in any case. Alternatively, declines in house prices may act as a mediating factor. That is, abandoned structures may adversely affect house price appreciation in the area, thus increasing the probability of default in the area. Such an effect should be apparent in house price information at the neighborhood level. This explanation, of course, begs the question of what sets off the initial increases in defaults in certain neighborhoods, and why these are correlated with racial composition or neighborhood income. It does, however, provide a reason for defaults to continue at a high level for some time following a neighborhood shock in the default rate, perhaps even for a very long time.

A third possible explanation is that instability in the form of higher turnover of homeowners, as reflected in default or in simple changes of residence, makes minority or low income neighborhoods less desirable.[18] Again, higher turnover may act as a trigger event that brings on default directly. Alternatively, local house price changes may act as a mediating factor; that is, higher turnover may result in locally decreasing demand for housing which reduces local house prices, leading to default. This explanation again begs the question of what sets off the initial increases in turnover in certain neighborhoods, and why these are correlated with racial composition or neighborhood income.

1.2. Specific Aims

The latter considerations suggest the following specific questions that the study will attempt to

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[17] On this point, see the aforementioned study by NTIC (1997).

[18] Note in this regard that while high-income families may be more likely to make long-distance moves, low-income families are more likely to move at all. For example, the March 2000 Current Population Survey shows that about 28 percent of families with annual incomes less than $10,000 have moved in the previous year. This percentage declines across income classes, reaching 11 percent for families with annual incomes exceeding $90,000.

answer; the remainder of the paper is organized around these questions.

Once one controls for a variety of borrower- and loan-related factors, including time-varying characteristics, in an appropriate econometric model of default, do neighborhood effects seemingly related to income or race persist? There may, for example, be differences across neighborhoods in house price growth and in the rates at which loans amortize (due to diffences in note rates and mortgage terms), and these differences may give rise to differences in default behavior even when controlling for conditions at loan origination, such as LTV. Spurious correlations between these factors and other neighborhood characteristics, such as race or income, may make it appear that differences in race and income, rather than these primary factors, are at work. If so, statistically correcting for differences in these primary factors may eliminate the appearance of neighborhood effects based on these spurious correlations. Naturally, our ability to introduce a comprehensive set of relevant time-varying characteristics will be circumscribed by the available data; in particular, we lack data on house price growth at the neighborhood level,[19] and thus we rely on MSA-wide house prices for a major portion of the study.

Do neighborhood characteristics, such as race and income, have effects on default that are separate and distinct from the effects of these same characteristics at the individual level? That is, are previous findings of neighborhood impacts truly traceable to the neighborhood, or are they instead proxying individual effects that cannot be measured in databases that are often used.

Is there evidence that differences in default probabilities reflect differences in the

[19] There is only a small literature on house price change at the neighborhood level in general and in lower-priced neighborhoods in particular. Exceptions are Pollakowski, et al, and Newburger, et al, who indicate that rates of house price appreciation may not be lower in the lower-valued portions of the market. (See Pollakowski, Henry O., Stegman, Michael A., and Rohe, William, "Rates of Return on Housing of Low- and Moderate-Income Owners," *AREUA Journal,* 19 (3), 417-425, and Newburger, Harriet, Pollakowski, Henry, Stegman, Michael A., and Rohe, William, "House price Appreciation in Neighborhoods with Modestly-Valued Properties," (undated).)

probability of refinancing? As noted, one possibility, prompted by earlier studies suggesting that blacks suffer discrimination in loan qualification, is that neighborhoods or individuals differ in default propensities because of differential access to refinancing alternatives. If so, we expect to find that default probabilities are positively related to factors related to (unrealized) refinancing probabilities and, second, that there are neighborhood or individual race effects in refinancing probabilities, conditional on the measurable incentives to prepay.

Finally, do neighborhood differences in default probabilities arise because of earlier defaults and, if so, what is the mechanism? That is, does an increase in the default rate at one point in time lead to higher default rates at later times? If so, are the default-inducing effects of earlier defaults transmitted through reductions in neighborhood house price growth or through some other mechanism?

1.3. A Roadmap for the Remainder of the Paper

The exercise begins in Section 2 with a brief discussion of data sources and some tables that illustrate some of the interesting features of the data. Next is a discussion of statistical models of default and prepayment, as well as the formulation of variables that attempt to match the theoretical constructs. We then move to a presentation of statistical estimates that rely on both relatively standard default-related factors measured at the time of origination, but also on default-related factors that change over the course of loan duration. To provide a benchmark that may permit comparisons to existing studies, the analysis initially excludes information on individual race and credit history, as well as neighborhood characteristics. We then add, in sequence, neighborhood characteristics, individual race, and finally a summary credit score, assessing at each stage the remaining estimated impact of neighborhood characteristics. This work permits us to assess the roles of neighborhood and individual characteristics, as well as the possibility that difficulties in refinancing lie at the heart of neighborhood differences in default rates.

In Section 3, we begin a second strand of the analysis that asks more directly whether neighborhoods differ in identifiable ways that would logically lead to differences in default rates.

In particular, there we examine questions of whether default behavior seems to spawn subsequent default behavior, either by leaving vacant structures or because default is one component of undesirable turnover of ownership. The analysis turns first to an analysis of house price changes at the neighborhood level in the Chicago MSA and investigates the possibility that past default behavior and turnover of homeownership in general affect house price growth. We then apply the findings from this analysis to reestimate default models for the Chicago MSA.

Section 4 offers some tentative conclusions.

SECTION 2

ESTIMATION OF NEIGHBORHOOD EFFECTS IN LOAN-LEVEL DATA

2.1. Data Sources and Key Definitions

The primary data used in this study are samples of FHA-insured loans[20] that were endorsed in 1992 or 1994, or for which applications were submitted in one of these years, and for which the subject property was contained within the 22 MSAs listed in Table 1 below. The choice of these particular MSAs was dictated by several factors. First, each of these MSAs contained sufficient numbers of defaults to support statistical analysis. Second, these MSAs contain a substantial portion of FHA business. Third, many of these MSAs contain substantial populations of blacks and Hispanics, but there is also significant variation in minority representation, thus supporting explorations along race/ethnic lines.

Table 1 provides some key characteristics of the 22 MSAs. The first four columns are based on data from all 1992 and 1994 FHA-insured purchase money loans. The first column shows the number of FHA defaults (defined more precisely below) in these data; there are at least a few hundred defaults (as of April 1996) in each of the 22 MSAs. The second third and fourth columns give the number of black, Hispanic, and total FHA-insured loans. In each case there are at least several hundred loans to at least one of the two minority groups. The next two columns, which are based on the 1990 Census of the Population, show the percentages of the MSA population that were black or Hispanic, respectively, in 1990. Minority representation varies substantially across these MSAs, but in some cases exceeds 40 percent. The final two columns are produced from 1993 and 1994 HMDA data. The second column from the right shows the precentage of national FHA-insured loans arising in each of the 22 MSAs. In the aggregate, these 22 MSAs contain about 44 percent of FHA business in 1993-94. Finally, the last column

[20] Streamline refinances are excluded because the applications for such loans lack critical information, such as loan-to-value ratios.

on the right shows FHA originations as a percentage of total originations within each MSA. These percentages vary widely, but in many cases the FHA share of originations exceeds 25 percent.

The FHA data files contain a variety of loan and borrower characteristics measured at loan origination, as well as information on the status of the loan at the time that the files were constructed (*e.g.,* whether the loan had prepaid or had resulted in a claim) and dates of critical events in the life of the loan (*e.g.,* the date of default, if any). After stripping these loan files of all identifying information that could be used to link a loan to a specific individual, portions of the 1992 and 1994 application data were sent to Trans Union and Equifax to obtain credit scores for borrowers and coborrowers.

For purposes of this analysis, defaults were defined to include only those loans that (a) defaulted on or before April 30, 1996, and (b) for which a claim[21] was recorded as of April 30, 1998.[22] In particular, loans that entered default status but subsequently cured are not included under this definition of default. To maintain consistency with the timing requirements for defaults, loans were recorded as prepayments only if they prepaid on or before April 30, 1996. Prepayments were further subdivided into two categories: (a) those occurring en route to refinancing with FHA, and (b) the remainder of prepayments, which occur for unspecified reasons that could include conventional refinancing, changing residence, or simply paying off the mortgage.[23]

The statistical estimation (described below) follows each of the loans on a monthly basis until it defaults or prepays or, if neither of the latter actions occurs, until April 30, 1996. Given

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[21] Loans entering the assignment program are treated as defaults even though such loans technically remain active.

[22] We require that default occur at least two years prior to when our observation window closes (on April 30, 1998) so that sufficient time remains for all those who have defaulted to be observed in claim status by the close of the observation window. The concern with including defaults that occur later is that we may treat defaults inconsistently; that is, we may miss some defaults which, because of state foreclosure practices, are not recorded as claims by April 30, 1998.

[23] Inability to separate conventional refinances from other types of prepayment activity is a problem that weakens some of the statistical analyses in this paper.

that we are using 1992 and 1994 applications and originations, we follow loans for a maximum of 52 months, but most loans --- particularly the 1994 loans --- have a much smaller potential period of observability. Because defaults must also occur within at most 52 months, the defaults examined here would probably be considered "early" defaults. By way of comparison, Calem and Wachter (1999) use originations from 1998 through July 31, 1994, of which over 90 percent originated during or after 1990. Because they record delinquency as of November 15, 1994, potential duration in their study ranges from a few months up to a maximum of about 59 months for the 1990-1994 originations. Berkovec, et al (1994) examine loans that have had potential exposure of about 39 to 75 months.

Sampling from the universe of endorsed loans helped reduce the estimation burden to more manageable proportions.[24] Because defaults are relatively rare, they were oversampled. Because prepayment was relatively common, however, prepayment was not used explicitly to structure the sample. Among the 231,583 (non-streamline refinance) loans with 1992 application or endorsement dates, 9801 were defaults by our definition (and 221,782 were nondefaults). Of these, we selected a sample[25] consisting of 3,057 defaulted loans and 6,534 nondefaulted loans for inclusion in the statistical analysis. The set of nondefaulted loans contains 535 loans that refinanced through FHA and 836 that prepaid for other reasons. Among the 235,214 (non-streamline refinance) endorsements with 1994 application or endorsement dates, 5320 were defaults by our definition (and 229,894 were nondefaults). From these, we selected a sample consisting of 2,184 defaulted loans and 6,609 nondefaulted loans for inclusion in the statistical analysis. Of the nondefaulted loans, 402 refinanced with FHA and 264 prepaid for other reasons. Given the stratified nature of the sample, the statistical procedures employed weighting according to sample stratum (application year and default status) from which the loan was

[24] The hazard estimation procedure used below treats each month of loan activity as an observation, thus greatly expanding the effective sample size used in estimation and providing the impetus to subsample from the population of available loans.

[25] A moderate amount of data "cleaning" was performed prior to drawing the samples, and additional cleaning was performed afterwards, mainly to remove cases with doubtful values of relevant variables.

drawn.[26]

A problem that must be faced at the outset is how to define a neighborhood for the purposes of this analysis. One pragmatic approach is to follow area delimitations established by others, while admitting that these definitions may not be most appropriate for the task at hand. Here we follow this procedure, identifying the census tract as the neighborhood. Census tracts, which generally contain between 2,500 and 8,000 people and (when formed) are intended to be relatively homogeneous with regard to economic status, living conditions, and population characteristics, are small enough that they might plausibly be considered neighborhoods. Of course, there is no guarantee that they do indeed represent a correct geographical division from the housing market perspective, and it would be surprising if in fact tract boundaries perfectly coincided with those of local housing markets.

The FHA data were supplemented with monthly BLS data on unemployment rates at the MSA level, quarterly Freddie Mac data on house price indices at the MSA level, monthly data on Treasury rates, monthly data on conventional mortgage rates and points from the Freddie Mac Primary Mortgage Market Survey, and a variety of tract-level and MSA-level measures from Census files. Among the latter are counts of the populace by race or ethnicity, as well as area (MSA and tract) median incomes.

2.2. A Preliminary Look at the Data

Before undertaking a more detailed statistical analysis of the loan-level data from the 22 MSAs, it is of interest to give a brief overview of some relevant and interesting features of the data.

[26] The sample selection procedure was complicated by the fact that credit scores had been obtained only for loans for which applications were submitted in 1992 or 1994, not for cases that were endorsed in these years but for which applications were submitted in other years. We structured the sample for this analysis by selecting two different stratified samples, one composed of loans with credit scores and one composed of loans that had not been submitted for scoring. After preliminary statistical analysis that indicated that results for the full sample were very similar to those for the sample with scores, we proceeded to use the combined sample with appropriate weights. An additional complicating factor in calculating weights is that stratification was performed prior to the final determination of default status and was based on claim status as of an earlier date.

These will serve to illustrate some important empirical regularities that will be investigated more systematically in the statistical work to follow. This overview utilizes Tables 2 through 4, each of which is based on a large sample of approximately 600,000 purchase money loans drawn from the two application or origination years, 1992 and 1994. For these tables, default and prepayment rates are calculated over the pooled sample from both years.

Table 2 shows default rates by race[27] within census tracts classified by 1989 racial composition; in addition, the table gives the percentage of FHA loans by race falling in each tract classification. Note in this regard that within the universe of loans for these 22 MSAs, overall black and Hispanic default rates are virtually equal at 5.0 percent,[28] while that of others (the predominately white group composed of those who are neither black nor Hispanic) is much lower at about 2.3 percent. The table is split into three sections. The top section classifies tracts by the percentage of the population that is black; the middle section classifies tracts by the percentage of the population that is Hispanic; the bottom section classifies tracts by the percentage of the population that is of races other than black or Hispanic. Each section of the table gives default rates by race within each tract classification. In the first section of the table, we see, for example, that within tracts in which blacks make up no more than 10 percent of the population, the overall default rate is 2.51 percent, the black default rate is 3.79 percent, the Hispanic default rate is 4.31 percent, and the "other" (predominately white) default rate is 2.08 percent. Such tracts contain 69.03 percent of the FHA loans in this sample, 19.36 percent of the black loans, 71.05 percent of the Hispanic loans, and 79.81 percent of the "other" loans.

The first section shows that default rates, both overall and within race, tend generally to rise as the black percentage rises, though the pattern for default rates of Hispanics seems more irregular than the others. Note also that the vast majority of the loans (over 80 percent) fall into tracts in which no more than 20 percent of the population is black. The second section of the table shows a more confusing pattern. For most race/ethnic groups, default rates tend to rise with

[27] Here and in what follows we shall often use "race" as a shorthand for "race and ethnicity."

[28] Hispanic default rates over this interval have presumably been affected by the California recession and the concomitant decline in California house prices.

the percentage Hispanic but then to peak out and decline as Hispanic representation continues to rise. Finally, the bottom section of the table generally shows declines in default rates as population composition shifts to heavier representation of "other" (predominately white) persons.

Another interesting feature of these figures is revealed by making cross-race comparisons within each tract classification, *i.e.,* by looking across each row of the table. We see that while the default rate for "others" is always lower than that of blacks and Hispanics within each tract classification, the relationship between black and Hispanic default rates is irregular. The rate for Hispanics never exceeds that of blacks for any of the groups classified by tract percentage Hispanic; at the same time, the rate for Hispanics exceeds that of blacks for all but one of the groups classified by tract percentage black.

Table 3 is intended to show how default rates vary jointly by tract income and by borrower income. Each column of the table corresponds to an approximate decile of the difference between tract median income and MSA median income, as measured in the 1990 Census. Each row of the table corresponds to an approximate decile of the difference between borrower income and MSA median income for the corresponding application year. Each figure within the table gives the default rate for all loans within the relevant tract and borrower income decile. Thus, for example, the upper left-hand cell indicates that the default rate is 5.81 percent for loans in which tract income (less MSA income) is in the bottom decile and individual income (less MSA income) is in the bottom decile. Looking down each column of the table, we see patterns that are generally unclear; that is, there does not appear to be any strong systematic change in the default rate as one moves across borrower income categories within tract income categories. Looking across a row, however, seems to show that default rates decline as one moves towards higher tract income categories within a borrower income category.

Table 4 shows how default rates by race vary with the prepayment rate of the tract. Prepayments here include refinances with FHA as well as prepayments for unspecified purposes. All tracts are classified according to their prepayment rates in the full universe of (FHA-insured purchase money) loans. Next, the default rate is calculated for all loans within those tracts that fall into each class of prepayment rates. Each row in Table 4 corresponds to a different category of tract prepayment rates, and each of the first four columns gives the default rates for a race/ethnic group within the corresponding tracts; the last four columns show the percentage of loans by race falling into tracts within each prepayment class. We see, for example, that in tracts having no prepayments, 5.09 percent of all loans, 6.94 percent of black loans, 5.95 percent of Hispanic loans, and 2.72 percent of "other" (nonblack and nonHispanic) loans defaulted. Moreover, these tracts contained 4.92 percent of all loans, 9.66 percent of black loans, 6.8 percent of Hispanic loans, and 3.56 percent of "other" loans.

Table 4 indicates that default rates for "others" are always less than those of blacks and Hispanics. Hispanic default rates tend to be higher than those of blacks in tracts at the lower end of the prepayment rate categories, but the ordering is reversed at the upper end of the prepayment rate categories. Within each race/ethnic group and overall, default rates tend to be higher in tracts with lower prepayment rates. The latter apparent regularity --- higher prepayment rates accompanying lower default rates --- could be traceable to a common set of underlying factors that lead, on the one hand, to higher default rates and, on the other hand, to lower prepayment probabilities. The empirical work below may shed some light on this possibility.

2.3. Statistical Models and Methods

2.3.1. A Default Model

In this section we turn to statistical analysis designed to isolate the effects of neighborhood on the probability of default of individual loans. We begin by controlling for a variety of default-related factors related to the loan, the economic environment, and the borrower. Included are time-varying factors designed to pick up important changes that evolve over the lifetime of the loan, some of which are preprogrammed and thus known with relative certainty at the outset and others which are highly uncertain at loan origination.

The statistical model used to estimate the impact of default related factors is the proportional hazard model which, for a single risk (say, default), gives the conditional probability of default at each point in time given that a loan has survived to that point in time. The proportional hazard (in continuous time) is represented as

$$\lambda(t)=\lambda(0)\exp(x'(t)\beta) \qquad (1)$$

where $\lambda(t)$ is the hazard function (in continuous time), $\lambda(0)$ is the baseline hazard, $x(t)$ is the vector of observables at time t, and β is a vector of unknown parameters. For the empirical implementation here, time-varying data elements are assumed to remain constant over one month intervals.[29]

2.3.1.1 Possible Advantages and Disadvantages of the Empirical Approach

In the current context, there are two principal advantages of the hazard specification over simple dichotomous dependent variable models, such as probit and logit, that recognize only whether or not each loan defaulted over the observation interval. First, the logit and probit approaches cannot properly recognize time-varying characteristics, for such models either evaluate these time-varying characteristics at only a few "representative" points, or they attempt to parameterize the time series with a few parameters that will typically not capture all features of the time series. In contrast, the hazard approach allows arbitrary changes in time-varying characteristics for each period (months in this case) over the observation interval. The hazard approach thus offers more appropriate treatment of dynamic processes in particular. Second, the hazard approach easily accommodates the censoring that occurs when the observation window on a loan closes while the loan remains active, in which case we do not know when, if ever, the loan will default. This feature permits us to use all observations on each active loan in the sample, even if the potential observation window differs wildly from loan to loan.[30]

Although the hazard approach offers potential advantages over simple logit or probit, it does not solve all potential statistical problems in estimating models of default. In particular, some

[29] As noted, weighting is used to accommodate stratification.

[30] Despite the theoretical advantages of the hazard approach, we have sometimes found empirically that default predictions using a logit model are generally no worse than those using the hazard.

researchers have pointed out a number of possibly serious difficulties in applying standard single-equation methods to estimate default relationships, and these problems would not be solved by utilizing a hazard approach. Yezer, et al (1994)[31] and Rachlis and Yezer (1993)[32] discuss in particular the issues of simultaneous equations bias and sample selection bias. In the context of estimating default relationships, simultaneous equations bias may arise because borrowers select the terms of their loans with an eye towards what underwriters will accept, and underwriters in turn look to anticipated default probabilities for guidance on what terms to accept from each borrower. Sample selection bias may arise in estimating the default relationship because that relationship is observed only for those who receive loans, and the set of those receiving loans is dictated by anticipated default probabilities.

One might have different views of these critiques of the standard estimation framework. On the one hand, one could argue that this work is too pessimistic, both in general and in the context of estimating default models in particular. With regard to simultaneous equations bias in mortgage terms, it is reasonable to assume that borrowers choose mortgage terms with an eye towards what underwriters will approve, and the result will be that mortgage terms, such as LTV, will vary with borrower characteristics, like asset levels. Simultaneous equations bias arises under the assumption that the default index used by underwriters enters the equation that determines ultimate mortgage terms, while mortgage terms themselves enter the equation for the default index. More generally, the presence of unobservables in the default index that are correlated with mortgage terms will lead to simultaneous equations bias. Notice, however, that if mortgage terms are determined by factors that affect default and that are observed by the researcher, but mortgage terms are not determined by unobserved factors that enter the default index, then there is no simultaneous equations bias. For this reason, the observation that

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[31] Yezer, Anthony M.J., Phillips, Robert F., and Trost, Robert P., "Bias in Estimates of Discrimination and Default in Mortgage Lending: The Effects of Simultaneity and Self-Selection," *Journal of Real Estate Finance and Economics*, 9: 197-215 (1994).

[32] Rachlis, Mitchell B., and Yezer, Anthony M.J., " Serious Flaws in Statistical Tests for Discrimination in Mortgage Markets," *Journal of Housing Research*, Volume 4, Issue 2, 315-336 (1993).

mortgage terms vary with borrower characteristics does not in itself imply simultaneous equations bias in estimating default probabilities.

The potential sample selection problem is in some ways similar. The selection problem arises if applicants are selected to receive loans partly on the basis of default-related factors that are unobserved to the analyst.[33] Notice, however, that selection of borrowers strictly on the basis of variables that are observed to the analyst and are already included in the default model need not cause a sample selection problem. As with the potential problem of simultaneous equations bias, the importance of sample selection bias will presumably vary with the amount and quality of underwriting data available to the analyst. In particular, if the analyst has most of the information available to the underwriter and incorporates this information properly in estimating the default relationship, problems of simultaneous equations bias and sample selection bias may be less important.

On the other hand, one may take the view that these problems are likely to be serious, in part because there may be numerous factors available to underwriters but not to analysts using even the best of data bases. Even aside from the potential problems of sample selection bias and simultaneous equations bias, there may more generally be omitted variables correlated with the included explanatory variables, and the resulting omitted variable bias could be substantial. Moreover, there may be other problems as well. For example, the appropriate functional form for estimation is unknown; as discussed above, a simple dichotomous dependent variable estimation procedure, such as logit or probit, is highly unlikely to be correct. Many of the variables may be measured with error; heteroskedasticity may be present in the unobservables that enter the default index function; observations may not be independent but instead be correlated within areas; and the list goes on.

Our view is that the approach taken in this paper is likely to be better than in prior work in some important dimensions, but we clearly cannot reject the possibility that serious statistical problems remain. The inclusion of a credit score seems likely to compensate partially for the

[33] Sample selection, and possible bias as a result, could also arise at earlier stages of the loan selection and approval processes.

important omission of such data in most prior work, and the use of a hazard model is likely to do a better job of estimating dynamics than would the traditional logit or probit approach. Nonetheless, there are surely other omitted variables; we cannot be sure that the proportional hazard specification is correct; and so forth. Hence, while we hope to offer improvement, we cannot claim perfection.

2.3.1.2. A Motivation for the Structure of the Hazard Model

An option-based model of default provides a useful starting point for parameterization within this statistical framework, though we later deviate from this approach in several ways. Letting time t be measured relative to the date of mortgage origination and assuming that the prepayment option is costless to pursue, default occurs when V_t, the market value of the mortgage at time t, exceeds the sum of H_t, the value of the home at time t, and C_t, the costs of mortgage default at t (expressed as a fraction of house price). That is, default occurs when (in discrete time notation)

$$V_t > H_t(1+C_t)$$

or, in logarithmic terms,

$$\ln(V_t) > \ln(H_t) + \ln(1+C_t) \tag{2}$$

Ignoring uncertainty over interest rates, future prepayment possibilities, and the like, the current value of a fixed-rate mortgage may be expressed as the discounted value of future mortgage payments using the current market rate, or (with continuous discounting):

$$V_t = (M/r_t)[1 - \exp(-r_t(T-t))] \tag{3}$$

where M is the monthly mortgage payment, r_t is the current market rate at t, and T is the term of the loan.[34]

Optimal and costless refinancing of the loan (if available) will prevent the value of the loan from exceeding the principal balance at t, B_t, but the valuation equation above continues to hold for loans that remain active whether or not refinancing would be optimal. Because the principal balance B_t is the value of the loan evaluated using the note rate (presumably the market rate at loan origination), r_0, we may rewrite the valuation equation as

$$V_t = B_t(r_0/r_t)[(1-\exp(-r_t(T-t)))/((1-\exp(-r_0(T-t))] \tag{4}$$

or in logarithmic terms as

$$\ln(V_t) = \ln(B_t) + \ln(r_0/r_t) + \ln[(1-\exp(-r_t(T-t)))/((1-\exp(-r_0(T-t))] \tag{5}$$

For simplicity in estimation, we represent the final term in the latter equation as simply proportional to ln (T-t).

For ARMs, the mortgage rate and mortgage payment adjust to keep the current-rate-discounted value of remaining mortgage payments equal to the current principal balance, aside from lags and limits on the size of adjustment permitted. Thus, for ARMs, the latter valuation equation reduces to

[34] An implication of this and other option-based default models is that a reduction in interest rates after loan origination should lead to an increase in the market value of the loan and, absent refinancing possibilities, to an increase in the incentive to default. Not all would agree that, as a practical matter, such a reduction in interest rates is an important determinant of default behavior. Additional discussion of this point is offered below.

$$\ln(V_t) = \ln(B_t)$$

The components of the proportionate costs of default (C_t) are unclear, but possible proxies include income, age, and credit scores, to the extent that the latter reveal past willingness to engage in credit-damaging behavior. Elements of affordability, such as the front-end ratio, are entered into the hazard specification in ad hoc fashion. Trigger events — such as loss in income due to unemployment — are often alleged to greatly increase the probability that an "in-the-money" default option will be exercised; proxies for these events may also be entered into the specification in ad hoc fashion.

If refinancing is not freely available to holders of fixed rate mortgages, then default need not necessarily occur even when inequality (2) holds. In particular, even if refinancing is completely prohibited for whatever reason, the holder of a mortgage valued at more than the market value of the home would wish to sell rather than default as long as the market value of the home (net of sales expenses) exceeds the principal balance of the existing mortgage. The existence of additional (monetary or nonmonetary) costs of default would further reinforce the incentive to sell rather than default.

Although the possibility of selling the home may serve an important role in reducing default probabilities for borrowers facing difficulties in refinancing, it is surely possible to imagine cases in which difficulties in refinancing lead to defaults that would not otherwise occur. Consider, for example, a case in which the borrower wishes to take advantage of lower interest rates by refinancing his or her mortgage and but is prevented from doing so by reason of discrimination. Sales expenses may exceed the owner's equity (plus costs of default), and the owner may thus find it optimal to default. Perhaps more importantly, homeowners wishing to refinance, but unable to do so when they would otherwise qualify for refinancing, may later face a decline in home value that induces them to default. Had they been able to refinance earlier, they may have been willing to hold onto their home through the subsequent price decline; because they were unable to refinance earlier, however, they later face a situation in which they would no longer qualify for refinancing and default is optimal. Whether cases like these arise frequently enough to make default probabilities rise as a result of reduced refinancing opportunities is, of course, an empirical question.

2.3.2. A Prepayment Model

Because one purpose of the analysis is to examine a possible link between default behavior and refinancing probabilities, specification of the probability of refinancing is required as well. As noted, the FHA data used here permit FHA refinancing to be separated from other types of prepayment, and thus we specify and estimate two prepayment probabilities, one for each of the two observable types of prepayment activity.[35] We assume that each of the two conditional prepayment probabilities follows a proportional hazard model. That is, the form of each conditional prepayment probability is that given in Eq. (1) above.[36]

Prepayments can occur for a variety of purposes, all of which should be considered in developing a specification. Prepayment may occur, for example, because the borrower has found a job elsewhere and decides to change residence. The FHA data contain a few correlates of job-related geographic mobility, such as age of the borrower. One might also expect income to be positively related to the probability of long distance job-related changes of residence.

Prepayments may also occur because the borrower faces anticipated or unanticipated (positive or negative) changes in wealth or in the cost of homeownership. Unanticipated increases in cost seem especially likely when mortgage rates rise to holders of ARMs; this effect

[35] As noted above, it is unfortunate that we are unable to distinguish refinancing with conventional sources from other kinds of prepayment activity within the set of loans that prepay for purposes other than for FHA refinancing.

[36] A study by Deng, Quigley, and Van Order uses a minimum distance estimator to estimate a competing risks proportional hazard model of default and prepayment. See Deng, Yong-Heng, Quigley, John, and Van Order, Robert. "Mortgage Default and Low Downpayment Loans: The Costs of Public Subsidy," National Bureau of Economic Research, October 1994. Here we estimate separate proportional hazard models for each prepayment type and for default; there is no guarantee that the sum of the predicted probabilities does not exceed one. To accommodate the dependence of each choice on the characteristics of the other choices, variable lists are identical for all models. We do not, however, build in any covariance across unobservables in the three models. For estimating each model, the at-risk set in each month is all loans that have not yet defaulted or prepaid.

may be represented by $\ln(M_t / M_0)$, where M_t is the monthly mortgage payment at time t and M_0 is the mortgage payment at mortgage origination. Although we have no direct measures of post-origination changes in wealth, higher unemployment rates may be a weak proxy if higher unemployment rates result in higher unemployment probabilities for individual borrowers, and this change affects total wealth as perceived by the borrower.

Prepayments for the purpose of refinancing a loan --- FHA or otherwise --- might be expected to occur among holders of fixed-rate mortgages when mortgage rates decline. Under such conditions, the incentive to refinance is increasing in the size of the existing mortgage balance (B_t), the ratio of mortgage rates at origination to current mortgage rates (r_0 / r_t), and the length of the remaining loan term, T-t. Although holders of ARMs automatically benefit (with a lag) from declines in mortgage rates, there may still be incentives to refinance ARMs in order to lock in lower rates. If so, the incentive to refinance might be again expected to vary with the current mortgage balance, the ratio of mortgage rates at origination to current mortgage rates, and the length of remaining loan term. Even if rates do not decline after origination, however, a steeper yield curve may reveal higher anticipated rates in the future, which may lead holders of ARMs to refinance with a fixed-rate loan so as to lock in a currently lower rate.

In practice, prepayment for refinancing purposes can occur only when the borrower wishes to refinance and the borrower is found qualified to do so. Thus, we might expect prepayments to depend upon variables that affect the ability to obtain refinancing, but these variables would include many if not all of the same variables that are included in the default hazard. Moreover, because default probabilities may depend on refinancing incentives that remain unexercised, variables appearing in the prepayment hazards should appear in the default hazard as well. In addition, the choice between the two kinds of prepayment presumably depends on the characteristics of both choices. Thus, we arrive at empirical prepayment hazard models containing the same set of variables as those in the default hazard model.

2.4. Variable Definitions and Concepts

Table 5 lists variable names and provides brief definitions. The variables fall into five categories that are distinguished by the nature and source of information: first, "neighborhood controls," which characterize the tract or the MSA; second, "demographic and credit characteristics" (race, age, credit (FICO) score); third, "measures of financial resources and costs," consisting of income and asset information, as well as the (log of the) front-end ratio; fourth, "characteristics of the property, the mortgage, and the interest rate environment," including changes therein; and, fifth, a set of "miscellaneous variables" that include various functions of mortgage duration.

The first group of variables --- "neighborhood controls" --- will be a major source of interest, for this group contains the tract characteristics that may be reflected in default rates. All of the tract-level variables are obtained from the 1990 Census and represent a single point-in-time snapshot of the tract. The monthly MSA unemployment rate is produced by BLS.

The second group — "demographic and credit characteristics" --- includes only variables measured at the time of origination. Age and race are obtained from FHA files. The FICO score, which characterizes an individual's credit history, is obtained from either Equifax or Trans Union. More specifically, when an individual (borrower or coborrower) had more than one FICO score present, we arrived at a single "operational" score for that person by taking the minimum of the two credit bureau scores. When both the borrower and coborrrower had one or more FICO score readings, we averaged the operational scores for borrower and coborrower.[37]

The third group of variables --- "measures of financial resources and costs" — consists of FHA variables measured at the time of loan application. Note that the effect of assets, measured as assets after closing relative to the monthly mortgage payment, is entered as a spline — a series of linear segments (only two segments in this case) joined at the endpoints. The particular breakpoint for the spline was chosen with the aid of plots of log odds ratios,[38] plots of probabilities of default, and/or experimentation with alternative breakpoints.

The fourth group — "characteristics of the property, the mortgage, and the interest rate environment" — includes a variety of measures that arose in the discussion of default and

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[37] This procedure is fairly similar to that developed for a study of mortgage scoring.

[38] This exercise was performed in a different study using similar data. The spline was not reestimated for the two kinds of prepayment hazards.

prepayment models above. The log of the mortgage balance (lnbal) is calculated from the FHA data on the initial principal balance, the note rate, and the term of the loan.[39] Home values in each month (used in calculating lnhval) are obtained by updating the initial value of the home using post-origination MSA-level house price growth calculated from the quarterly Freddie Mac house price index series. Note that the difference between lnbal and lnhval is the (log of the) contemporaneous loan-to-value ratio; permitting these variables to enter the estimation equation separately allows the numerator and denominator of LTV to have separate effects. Market mortgage rates (for use in computing lintrat) are calculated using internal rates of return on 30-year conventional fixed-rate mortgages; the calculation scheme includes both the note rate and points and assumes that prepayment occurs at 10 years. The variable rtdiff is the slope of the yield curve, measured using monthly values of 30-year and 1-year constant maturity Treasuries. The variable logpirto is the (log of the) ratio of the current mortgage payment to the original mortgage payment (principal and interest); as such, the variable assumes the value zero for fixed-rate loans.

The relative house price variables merit additional explanation. The variable HPrelPW is the ratio of the sales price of the home relative to the reference home price in the area, as given by the PricewaterhouseCoopers median home price series.[40] When the Price-Waterhouse median price series is unavailable, we set HPrelPW to zero and instead measure relative house prices with the variable HPrelLL.[41] The latter construction measures the area reference house price by dividing the area FHA loan limit by 0.95. Because FHA loan limits are intended to be 95 percent of the area median house price, HPrelLL is effectively sales price divided by the area median house price. For those relatively rare loans in areas for which (a) the Price-Waterhouse series is

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[39] For ARMs, we calculate the current principal balance by annually updating the original note rate using the contemporaneous one-year constant maturity Treasury rate, recalculating mortgage payments accordingly, and calculating the implied mortgage balance in each month.

[40] The PricewaterhouseCoopers median home price series is briefly described in the *MMI Fund Analysis FY 1998,* an actuarial review by PricewaterhouseCoopers LLP.

[41] More precisely, HPrelPW is set to zero when HPrelLL is used to measure relative price, and HPrelLL is set to zero when HPrelPW is used to measure relative house price.

unavailable, and (b) the FHA loan limit is at the legislative maximum or minimum, and is thus constrained so that it may no longer accurately measure median area house prices, we set both HPrelPW and HPrelLL to zero; in such a case, we also set an indicator (LLmax or LLmin) to unity.

The fifth group --- "miscellaneous variables" --- includes a spline in mortgage duration at six months, as well as the square of duration. These controls attempt to capture unexplained changes associated with mortgage duration. An indicator for the applications or closings in 1994 permits a shift in the intercept for the more recent endorsements. Finally, MSA indicators are introduced to permit differences in intercepts across MSAs.[42]

The discussion of the parameter estimates below provides additional explanation and justification for individual variables.

Sample means by point-in-time status and by race are presented in Table 6. That is, for each loan in the estimation sample, each month is classified as one in which the loan remains active, enters default, or enters prepayment (of either kind); these are the "point-in-time status" classifications. Notice that each defaulted loan has only a single month classified as a point-in-time status of default, and each prepaid loan has a single prepaid point-in-time status; all other months are classified as active point-in-time status. The columns in Table 6 give the means of each variable for each race group calculated over all months falling in the appropriate point-in-time status.[43] For variables that do not change or are not re-measured after loan origination, the focus on point-in-time status is no better than a focus on ultimate loan status — default or prepayment. For variables that change over the course of loan duration, the focus on values in the month of prepayment or default could be more revealing.

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[42] Note that the inclusion of MSA dummies makes it unnecessary to deduct MSA means or other MSA-specific values from tract-level measures. That is, estimates (other than the intercept) would be unaffected by doing so. The presence of MSA dummies also removes the need to introduce additional indicators for areas that were impacted by the California recession.

[43] Note that the means for FICO scores (fico) appear low because the zeros (which replace missing values) are included in the calculation. The mean for the variable NOfico can be used to recover the mean for loans with nonmissing FICOs.

2.5. Statistical Estimates of Default and Prepayment Hazard Models

2.5.1. Estimates of Basic Hazard Models of Default and Prepayment

Panels A, B, and C of Table 7 present estimates of default and both prepayment hazard models; the estimated models use sample data from both 1992 and 1994 loans. The two kinds of prepayment hazards are distinguished as "FHA refinance" and as "other prepayment." As noted, the latter includes all kinds of prepayment activity other than refinancing through FHA. The specification used in these models excludes most neighborhood characteristics, the individual race indicators, and the credit scores. It does, however, include many time-varying characteristics, and these distinguish these models from many of the typical default and prepayment models relying solely on data measured at loan application or origination. A brief discussion will illustrate that most effects are as anticipated.

2.5.1.1. Default

Turning first to the default model in Panel A, neither increases in the MSA unemployment rate (unemprt) nor differences in the age of the borrower (borage) appear to matter in default behavior. Holding constant the remaining factors (including the log of the front-end ratio), the effects of individual income (loginc) cannot be statistically distinguished from zero.[44] Analogously, the effect of changing the front-end ratio cannot be statistically distinguished from zero. Additional assets after closing (RSVpmts) reduce the default rate until one has four monthly payments in reserve, after which there is essentially no marginal effect of additional asset holdings (the sum of the coefficients on RSVpmts and RSVpmt4 is approximately zero). Smaller principal balances (lnbal) are associated with lower default rates. Note that differences

[44] Notice that because the front-end ratio contains income in the denominator, the total effect of log income is the coefficient on loginc minus the coefficient on logfront. Because loginc and logfront are both included, however, the total effects of log income and of log monthly mortgage payments (the numerator of the front-end ratio) are unconstrained.

in principal balances after loan origination may result from different mortgage terms at origination, different note rates at origination, variation in ARM rates after origination, differences in seasoning, or differences in initial mortgage amounts. Notice also that the estimated impact of lnbal holds fixed contemporaneous house values (and the remaining explanatory variables), and thus increases in lnbal should be viewed as increases in the numerator of contemporaneous LTV. Higher contemporaneous house values, holding constant the contemporaneous principal balance (and thus reducing contemporaneous LTV), are associated with lower default rates, not surprisingly.[45] Default rates do not appear to be higher on condominiums.

The estimates show that by either measure (HPrelPW or HPrelLL) higher house prices relative to the area reference price are associated with lower probabilities of default. This finding may reflect differences in wealth of those buying relatively more expensive homes — beyond the effects captured by the other wealth-related measures. The relative house price variables may convey other information as well, however. Given that FHA-insured homes tend to be lower priced than conventionally insured homes, the more expensive FHA-insured homes in an area may be closer to the heart of the overall house price distribution than are less expensive FHA-insured homes. A thinner market for lower priced homes may increase time spent on the market, and the resulting rise in the implicit cost of selling may increase the likelihood of default.

Increases in the length of time remaining on the mortgage (lnhorizn), conditional on duration as reflected in the spline and quadratic in duration (t, t6, tt), and conditional on mortgage balance (lnbal), appear to increase default, but the effect is not measured very precisely. Given the remaining controls, this variable may be picking up in part the sorting induced by borrowers opting for mortgage terms of different lengths; more specifically those choosing mortgages with shorter terms are less likely to default. The failure to obtain precise estimates may in part reflect the paucity of short-term FHA mortgages.

The remaining substantive variables that measure movements in mortgage rates from the time

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[45] The fact that the coefficient estimates on lnbal and lnhval are nearly equal in magnitude and opposite in sign suggests that it may be appropriate to use (the log of) LTV in the default model, thus imposing the usual restriction. We did not conduct the appropriate test.

of origination (lnintrat and lnintarm), the slope of the yield curve (rtdiff and armrtd), and the post-origination change in mortgage payments for ARMs (logpirto) cannot be statistically distinguished from zero.

Increases in duration (t, tt, t6) lead to conditional default rates that rise rapidly with duration initially, but the rate of increase tapers off substantially at six months. The conditional default probability begins to decline at about 35 months, other things the same.[46] Finally, there does not appear to be a significant shift in the intercept in the more recent data (year94).

2.5.1.2. Prepayment Other Than FHA Refinancing

Turning briefly to the estimated effects in the model for other prepayments (*i.e.,* for all purposes other than for FHA refinancing) in Panel B, we see first that variation in the MSA unemployment rate (unemprt) does not appear to matter in this kind of prepayment behavior. Increases in the age of the borrower (borage), however, are associated with lower prepayment possibilities, perhaps a reflection of age-related reductions in geographic mobility in general. Holding constant the remaining factors (including the log of the front-end ratio), higher incomes (loginc) lead to higher prepayment probabilities.[47] It is unclear whether this income impact is associated with increased mobility of higher income borrowers, increased probabilities of qualifying for conventional refinancing, or some other source. Higher front-end ratios (logfront) also lead to higher prepayment probabilities, perhaps because those with additional financial burdens at the outset are more likely to find themselves too burdened to continue with home ownership in the event of any unanticipated shock to income. Under this interpretation, however, it is somewhat surprising that additional financial reserves after closing (RSVpmts) have no discernible effect

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[46] Note that other explanatory variables are held fixed when examining the estimated default effects of duration. For this reason, this estimated path of conditional default probabilities over loan duration may not be identical to the path of empirical conditional default probabilities when nothing else is held fixed.

[47] Again, because the front-end ratio contains income in the denominator, the total effect of log income (holding constant monthly payments) is the coefficient on loginc minus the coefficient on logfront; the result is again a positive, but much smaller, effect.

on prepayment probabilities.[48] Higher principal balances (lnbal) are associated with lower prepayment probabilities. One possible explanation for the latter finding is that the negative impact of higher contemporaneous principal balances (holding fixed contemporaneous home value) on the probability of qualifying for conventional refinancing swamps a positive impact of higher balances on the gains from conventional refinancing. Higher contemporaneous house values are associated with higher prepayment probabilities, again perhaps reflecting their impact on the probability of qualifying for refinancing, or perhaps reflecting increased wealth that induces borrowers to move up to higher priced homes. Prepayment probabilities appear to be somewhat higher on condominiums.

The estimates show that higher house prices relative to the area reference price generally matter little in prepayment behavior. Increases in the length of time remaining on the mortgage (lnhorizn) lead to higher prepayment probabilities, as would be expected given that gains to refinancing are higher when there is a longer time left over which to reap the benefits. Also not surprising is the effect of changes in mortgage rates. Reductions in mortgage rates after origination (increases in lnintrat) have a precisely measured positive effect on prepayment probabilities. It may also be the case that rate reductions induce some homeowners to move into more expensive homes. As anticipated, for holders of ARMs, the total effect is smaller (lintarm is negative, though imprecisely measured) but still positive (the sum of the coefficients on lnintrat and lnintarm).[49] Also as expected, larger increases in ARM mortgage payments after origination (logpirto) increase the probability of prepayment. A steeper yield curve (rtdiff) leads to higher prepayment probabilities, and that effect is stronger (though imprecisely measured) for holders of ARMs (armrtd).

The coefficients on the duration spline and quadratic (t, t6, tt) imply that conditional prepayment probabilities initially rise with duration, but the rate of growth tapers off at six months. Conditional probabilities eventually decline with duration (after about 38 months),

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[48] Part of the problem here may be incorrectly chosen breakpoints on the spline.

[49] We had no success in permitting ARM effects to differ depending on whether contemporaneous mortgage rates were higher or lower than those at mortgage origination.

other things the same. There appears to be a significant shift in the intercept in the more recent data (year94).

2.5.1.3. FHA Refinancing

Turning finally to the estimated effects in the model for FHA refinancing (Panel C), we see that variation in the MSA unemployment rate (unemprt) does not appear to matter in FHA refinancing. Increases in the age of the borrower (borage) reduce refinancing probabilities. Holding constant the remaining factors (including the log of the front-end ratio), higher incomes (loginc) lead to higher refinancing probabilities, but the total effect of income conditional on the mortgage payment (*i.e.*, the coefficient on loginc minus that on logfront) is slightly negative. One possibility is that while higher incomes increase the probability of qualifying for an FHA-insured loan, higher incomes also increase the probability of qualifying for a preferable conventional loan. Higher front-end ratios (logfront) lead to higher refinancing probabilities, perhaps because the demonstrated ability to contend successfully with greater financial burdens is a positive signal to lenders. Additional financial reserves after closing (RSVpmts) at first increase and later decrease FHA refinancing probabilities, which may again reflect the ability of wealthier borrowers to qualify for, and shift to, conventional loans.[50] Higher principal balances (lnbal) seem to be associated with higher FHA refinancing probabilities, as might be expected, but the effect is not statistically significant by conventional standards. There appears to be no statistically significant effect of greater contemporaneous house values, with perhaps the increased ability to qualify for preferable conventional loans dominating the increased ability to qualify for FHA loans. FHA refinancing probabilities appear to be unrelated to condominium ownership.

The estimates show that higher house prices relative to the area reference price generally reduce FHA refinancing probabilities; once again a shift to conventional refinancing is one possible logical explanation. Increases in the length of time remaining on the mortgage

[50] Here again breakpoints on the spline may be incorrect.

(lnhorizn) lead to higher refinancing probabilities, as expected. Again conforming to expectations, a reduction in mortgage rates after origination (increases in lnintrat) increases FHA refinancing probabilities. As anticipated, the latter effect is reduced for holders of ARMs (lintarm is negative), but the estimated differential is very small.[51] More sizable increases in ARM mortgage payments after origination (logpirto) increase the probability of FHA refinancing. Unexpectedly, a steeper yield curve (rtdiff) leads to lower FHA refinancing probabilities; that effect is more pronounced for holders of ARMs (armrtd). Shifts to conventional financing may again be part of the story.

The coefficients on the duration spline and quadratic (t, t6, tt) imply that conditional FHA refinancing probabilities rise with duration, but the rate of increase tapers off substantially at six months; conditional probabilities decline with duration after about 12 months, other things the same. There does not appear to be a significant shift in the intercept in the more recent data (year94).

2.5.2. Adding Neighborhood Characteristics to Default and Prepayment Models

In this section we modify the basic models introduced in the last section by adding neighborhood characteristics obtained from 1990 Census data: the fraction of the tract population that is black (trtblk), the fraction of the population that is Hispanic (trthisp), and the (log of the) median income of the tract (lnincmed). Panels A, B, and C of Table 8 show the hazard estimates obtained after this modification to the list of explanatory variables. According to the estimates in Panel A, loans in neighborhoods (tracts) with greater black representation have higher default probabilities, while representation of Hispanics appears to have no statistically significant impact. Increases in tract income appear to reduce the probability of default. Other coefficients appear to be only modestly affected by the inclusion of these tract characteristics.

A finding that the racial composition and income of the neighborhood matter in individual

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[51] As noted, we had no success in allowing ARM effects to depend on whether contemporaneous mortgage rates were higher or lower than rates at origination.

default behavior is consistent with the findings of Van Order and Zorn (1995) in the context of conventional loans. As noted there, tract income may appear to be more important than individual income because individual income at loan qualification may contain a substantial transitory component not present in the tract level measure.

Turning to prepayments for purposes other than FHA refinancing, the estimates in Panel B indicate that an increase in the percentage of the tract that is black is associated with reduced prepayment probabilities, while higher tract income may increase prepayment probabilities. Hispanic representation in the tract appears not to matter.

The estimates in Panel C show that tract characteristics have no statistically significant effect on FHA refinancing probabilities.

Although we do not think it especially enlightening to include additional tract characteristics that have no well-founded causal role in default or prepayment behavior, it is nonetheless of some interest to examine the effects of including some additional tract characteristics. Panels A, B, and C of Table 9 modify the last specification by adding more neighborhood characteristics measured in the 1990 Census: the tract proportion of owner-occupied units that are not mortgaged (misleadingly named propmort), the fraction of the population that did not move within the previous five years (*i.e.*, from 1985 to 1990) (misleadingly named propmove), and the fraction of owner- and renter-occupied units that are in one-unit structures (prop1unt). In Panel A we see that only propmove has an estimated effect that passes typical standards of statistical significance; it indicates that higher fractions of nonmovers are associated with lower default rates. Perhaps tracts with more stable populations are wealthier and therefore less likely to default, or perhaps additional turnover of homeowners itself generates more default activity. We shall return to this point later. The remaining coefficient estimates are largely unchanged when these additional tract characteristics are included.

Turning to prepayment for purposes other than FHA refinancing (Panel B), we see again that only propmove is statistically significant at conventional levels. Perhaps not surprisingly, higher proportions of nonmovers are associated with lower prepayment probabilities. The inclusion of the additional area measures reduces somewhat the estimated impact of trtblk and increases the estimated effect of tract income. There is little impact on most of the remaining estimates.

Panel C shows that among the additional neighborhood characteristics, only prop1unt is statistically significant at conventional levels. A larger share of one-unit structures is associated with higher FHA refinancing probabilities, a finding for which we have no ready explanation. Tract race and income characteristics remain statistically insignificant.

2.5.3. Adding Individual Characteristics to Default and Prepayment Models

Models in the last section control for those factors that might be available to researchers dealing with data on conventional mortgages. In this section we introduce important individual characteristics that are not often available to researchers. In particular, race information is not generally present in databases on conventional loans, and credit scores are typically not available for either conventional or FHA loans.

Panels A, B, and C of Table 10 add only the information on the race of the borrower — black and hisp. In Panel A (default) we see that, perhaps surprisingly, neither race effect on default is statistically significant at conventional levels; the impacts of tract racial composition and income remain, though the former is reduced somewhat in magnitude. According to this specification, race and income appear to operate at the tract level rather than the individual level.

Examining effects on prepayment other than for the purpose of FHA refinancing, Panel B of Table 10 shows, even more surprisingly, that adding individual race indicators changes the estimated tract black (trtblk) effects on prepayment from negative and significant to positive and insignificant. The effects of Hispanic representation in the tract and tract income increase in magnitude and become statistically significant. The individual race indicators themselves are highly significant and point to reduced prepayment activity for individual members of both groups.

Turning next to FHA refinancing, Panel C of Table 10 shows that adding individual race indicators leaves estimated tract race and income effects statistically insignificant. Of the two individual race impacts, only the negative Hispanic effect is statistically significant.

Next we introduce a measure of past credit performance, the FICO score. Panel A of Table 11 shows that the FICO score itself has a precisely measured negative impact on default probabilities. Individual race effects are absent by any reasonable standard of statistical significance, and the presence of the FICO reduces the estimated impact of trtblk, rendering it of questionable statistical significance. The latter change upon the introduction of the FICO readings suggests that one "explanation" that loans default more frequently in tracts that are more heavily black is that borrowers in these tracts have had, on average, poorer credit performance in the past.

One might question whether the latter finding constitutes an "explanation." That is, one might interpret the estimated FICO effect itself as saying that poor performance on credit in the past is associated with poor performance on paying off mortgages in the future. If differences across tracts in default behavior of individual loans are "explained" by the past credit performance of individual borrowers within those tracts, one might then ask why there are differences across tracts in the past credit performance of individual borrowers. We have no ready answer for this question, nor do we know why past credit performance is predictive of future credit performance.

Panel B of Table 11 introduces the FICO score in the prepayment (other than for FHA refinancing purposes) hazard. We see that higher FICO scores lead to higher prepayment probabilities, presumably in part because those with higher FICOs find it easier to qualify for conventional refinancing. In addition, we see that all other neighborhood effects and individual race effects remain largely unchanged. Individuals in more heavily Hispanic and higher income tracts still appear to have higher prepayment probabilities, while minority members themselves have significantly lower prepayment probabilities.

Panel C of Table 11 enters the FICO score in the FHA refinancing hazard. Higher FICO scores lead to higher prepayment probabilities. Again, higher FICO scores increase the probability of qualifying for refinancing, though presumably some of this enhanced ability to qualify permits borrowers to transfer to conventional loans, thus reducing the net impact on FHA refinancing probabilities. We see that all other neighborhood effects and individual race effects are little influenced by the introduction of FICO scores. Only the reduced FHA refinancing probability for individual Hispanics passes conventional statistical significance.

Before proceeding, it is worth noting that the default model presented in Panel A of Table 11 was explored in a few other dimensions. First, one of the salient features of the estimated default hazard is that individual race seems not to matter while the proportion of the tract that is black may matter. As in most data files, variables in the FHA data files are subject to error, and it would be shocking if race information were measured perfectly. Although we have no way of knowing the extent of error in race information, there is some possibility that tract racial composition is a better proxy for race of borrower than is the individual loan-level information. If so, there is some chance that individual race is important, but its effect is masked by measurement or reporting error. While there is no foolproof way to determine whether this possibility has been realized, we conducted one test that should provide a bit more information. The idea behind this test is as follows. Individual race information seems more likely to be in error when the reported race of the individual differs from that of the overwhelming majority of the population in the same tract; similarly, race information seems unlikely to be in error when the reported race is identical with that of the vast majority of the population within the same tract. Thus, we introduced two new interaction indicator variables for blacks and two for Hispanics. One of the black indicators was activated when reported race was black and the property was located in a tract that was at least 80 percent black; the other was activated when reported race was black and the property was located in a tract that was less than 10 percent black. Similarly, the two Hispanic indicators were activated (a) when reported race was Hispanic and tract representation was at least 80 percent Hispanic, and (b) when reported race was Hispanic and tract representation was less than 10 percent Hispanic. These additional four indicators, when used in the default model underlying Panel A of Table 11, yielded coefficients that could not be statistically distinguished from zero. Hence, on the basis of these tests, which are surely not definitive, we find no indication that measurement error lies behind the absence of individual race effects in the default model reported in Table 11.

We also explored in piecemeal fashion the possibility that race effects, at both the tract and individual level, differ across MSAs. Because our main focus is on default behavior, these explorations were again restricted to the default hazard. The ideal procedure would be to estimate a fully interactive model that would permit all effects to differ across MSAs. This rather cumbersome procedure was not attempted. Instead we ran separate estimation procedures in which one kind of tract or individual effect for a minority group was allowed to vary across MSAs while all remaining effects (other than the intercept) were constrained to be equal across MSAs. Thus, for example, one estimation procedure permitted trtblk to differ across MSAs while effects of trthsp, hisp, and black were constrained to be equal across MSAs. These experiments revealed no significant differences across MSAs in tract or individual race effects on default.[52]

Finally, earlier versions of the models were run with interactions between each individual and tract race variable, on the one hand, and duration, on the other hand. These experiments revealed no important changes in race impacts with loan duration.[53]

2.6. Interpretation and Conclusions

The evidence thus far permits answers to three questions raised at the beginning of the paper. First, once one controls for a variety of borrower- and loan-related factors in an appropriate econometric model of default, neighborhood effects related to income and, less clearly, to race do persist. In particular, even though some estimated neighborhood effects in earlier studies could be traceable to changes over time in house prices, principal balances, or unemployment rates that are inadequately accounted for in many studies, these controls do not completely remove the effects of tract income and (perhaps) tract racial composition on default probabilities of

[52] Using a single hazard that included both FHA refinancing and all other prepayments, we found that the individual black effect showed no significant differences across tracts, but trthsp effects differed in three MSAs, two MSAs had significantly different trtblk effects, and individual Hispanic effects differed in two MSAs.

[53] In earlier specifications, we also carried out some experiments to try to identify default effects flowing from neighboring tracts. After all, it is not clear that the census tract is the relevant neighborhood, and even if the tract appropriately delimits the neighborhood, characteristics of nearby neighborhoods may matter as well. We used the longitude and latitude of the centroid of each census tract in the Chicago MSA to calculate the distance between the centroids of each pair of tracts. Using a few different functions to weight characteristics of other tracts by distance from the own tract, we examined whether default probabilities at the loan level depend on the characteristics of not only one's own tract, but also the characteristics of other tracts. In limited experimentation, we were unable to find any impacts of neighboring tracts.

individual loans.

Although neighborhood impacts remain, their importance is dramatically affected by introducing controls for characteristics of individual loans, borrowers, and the economic environment. To illustrate this point, we provide estimated tract effects in the absence of all controls other than the duration-related variables, the year 1994 indicator, and the MSA indicators. Table 12 gives these estimates. Panel A contains the default model; Panels B and C provide the two prepayment models for completeness. Comparing Panel A of Table 12 with Panel A of Table 11, we see that the estimated default impact of trtblk falls substantially and becomes of marginal significance with the introduction of a host of controls (in Table 11), while the estimated impact of trthsp remains insignificant. The estimated effect of tract income falls in magnitude but remains significantly different from zero.

It is also interesting to note that the prepayment results in Panel B of Tables 11 and 12 show that the introduction of additional controls causes the estimated effect of trtblk to change signs, reduces the estimated effect of tract income, and increases the positive estimated impact of trthsp. A comparison of Panel C in Tables 11 and 12 reveals that with the introduction of additional controls, the FHA refinancing effects of tract racial composition remain insignificant, and the effect of tract income is rendered insignificant as well.

At the same time, we emphasize that our ability to account for time-varying explanatory variables is severely limited by data availability. Notice in particular that the contemporaneous house value lnhval is based, in part, on house price growth within the MSA. Tract level price change would, of course, be preferable but is not available in these data. This issue is revisited below.

The second question raised at the start of the paper was whether neighborhood characteristics, such as race and income, have effects on default that are separate and distinct from the effects of these same characteristics at the individual level. We find that greater tract representation of blacks is probably associated with higher default probabilities, but individual race effects --- black or Hispanic --- are absent. Hispanic representation at the tract level does not seem to matter in default behavior. Tract income does seem related to default behavior, while individual income has no discernible effect.

In this context, it is of interest to consider the arguments raised by Schill and Wachter (1993) in the context of discrimination in mortgage lending. They note that, given residential segregation of races and ethnicities, racial or ethnic discrimination at the level of the individual may have effects that are virtually identical to discrimination at the level of the neighborhood. Although it is true that residential segregation may make individual-level and neighborhood-level discrimination approximately equivalent in their effects, these two forms of discrimination are still empirically distinguishable as long as residential segregation is incomplete. That is, as long as races and ethnicities are not completely isolated (and as long as neighborhoods are properly identified), discrimination at the neighborhood level can be distinguished empirically from discrimination at the individual level. Partial but incomplete segregation makes the job more difficult in the same way that lack of orthogonality reduces the effective informational content of a given number of observations on other correlated explanatory variables, but empirical identification of separate effects is still possible in principle. In particular, incomplete segregation does not cause bias in estimated effects. In the case at hand, the fact of partial residential segregation does not introduce bias in distinguishing individual from neighborhood differences in default, but it does make the task more difficult.

The third question was whether there is evidence that differences in default probabilities reflect differences in the probability of refinancing, which may in turn be indicative of unequal access to refinancing funds. We find that default probabilities may be higher in tracts with heavier black representation, but even this differential is of questionable significance. If race-based redlining in refinancing were the culprit in generating higher default rates in more heavily black neighborhoods, we would expect to find that either FHA refinancing probabilities or other prepayment probabilities (to the extent they are indicative of conventional refinancing probabilities) would be lower for blacks. Instead we find that FHA refinancing probabilities, as well as other prepayment probabilities (which include conventional refinancing activities) tend to be higher, if anything, among loans in tracts with heavier minority (black or Hispanic) representation; only the Hispanic effect for other prepayment is statistically significant at conventional levels. The results here do not support the notion that race-based redlining or racial discrimination in refinancing lie behind race-related neighborhood differences in default probabilities,[54] but of course, these results should only be viewed as suggestive.[55]

We emphasize that this assessment of redlining pertains only to its potential role in explaining differential default behavior, and the evidence is essentially indirect. Moreover, this investigation is restricted to effects arising among holders of FHA mortgages; holders of conventional mortgages are excluded from the analysis. In addition, we do not account in any way for possible differences in the rate at which groups actually apply for refinancing. For these reasons, this discussion is not intended to comment on the possible existence of redlining in general.

We do find that individual Hispanic ethnicity is associated with lower FHA refinancing probabilities, and individual blacks and Hispanics have lower probabilities of other types of prepayment, which may or may not be the result of discrimination in refinancing against individual borrowers on the basis of race or ethnicity. Yet there are no corresponding default effects traceable to the race of individuals.

These findings suggest that we look elsewhere for possible explanations for the effect of tract income and tract racial (black) composition on default probabilities. We next consider some alternatives.

[54] Income-based "redlining" is a possibility, but of course there are other possible explanations for tract income effects on default and prepayment, including the potentially important role of missing variables. Note also that there appears to be no tract income impact on FHA refinancing probabilities; thus, any such refinancing impacts must apparently arise from conventional lending.

[55] One difficulty is that, for reasons given above, one might expect discrimination in refinancing to result in increased probabilities of prepayment for purposes of changing residence. This effect will tend to blur the impact of discrimination on other refinancing probabilities when, as here, data on other refinancing includes both refinancing (by other than FHA) and prepayments for other purposes. In addition, increased difficulty in refinancing in one sector (say, FHA) might also lead to increased refinancing activity in the other (say, non-FHA) sector as borrowers attempt to circumvent difficulties in (say, FHA) refinancing. However, because the increase in prepayment probabilities is derivative of the declining ability to refinance --- serving as one possible outcome for a borrower facing increased difficulties in refinancing --- as is the substitution of one avenue for refinancing for another, it seems very unlikely that difficulties in refinancing would yield increases in both FHA refinancing and in other prepayment probabilities.

SECTION 3

ALTERNATIVE EXPLANATIONS FOR DIFFERENCES IN DEFAULT PROBABILITIES ACROSS TRACTS

If differences in default probabilities of individual loans are related to differences across tracts in racial composition and income, holding constant a wide variety of observable characteristics of the loan, the property, and the borrower, what might lie behind such neighborhood effects? In this and the next section we consider a few explanations and present an empirical analysis that will provide some tentative answers. In particular, here we entertain the possibility that these neighborhood effects are traceable to (a) past default behavior within these same tracts that leads to abandoned structures and declining neighborhood amenities, or (b) past turnover of homeownership within these same tracts, resulting in undesirable neighborhood instability, or (c) transitions in racial or ethnic composition within these tracts. Under any of these possibilities, the effect on default of individual loans may operate through changes in local house prices, or the primary event may act as a "trigger" event, increasing the probability of default among homes for which the default option is already "in-the-money." Indeed, if one result is an adverse change in local house prices, then it may make sense for resident homeowners to treat the primary event as a trigger, for the primary event then forecasts adverse house price changes that will reinforce current default incentives. Notice in this regard that if a decline (or slower growth) in neighborhood house prices is the vehicle by which default probabilities are affected, such tract-level differences in house price growth would not be revealed in the work presented in the last section. Calculations of contemporaneous home values there relied on MSA-wide house price growth; as noted earlier, corresponding tract level data are unavailable directly from standard sources.

Consider then the first of the explanations offered above. As noted earlier, an NTIC study has suggested that default activity results in vacant structures; the consequent neighborhood decay may in turn lead to other defaults. The presence of abandoned structures could act as a trigger for default, causing borrowers to default on homes that were ripe for default in any case.

Alternatively, or in addition, declines in local home prices could act as a mediating event. That is, defaults spawn vacant structures, and the consequent deterioration of the neighborhood adversely affects home prices in the area, leading in turn to more defaults. As noted earlier, this explanation begs the question of what sets off the initial increase in defaults in certain neighborhoods, and why the frequency of these events is correlated with tract racial composition or neighborhood income. It does, however, provide a rationale for defaults to continue for a time following a shock in the neighborhood default rate.

Two other explanations are motivated by a somewhat different view of the effects of tract racial composition on default and prepayment. The results in Panel B of Table 12 indicate that borrowers in more heavily minority tracts may have higher probabilities of prepayment (other than FHA refinancing). Although we have no way of knowing the precise components of this prepayment activity, changes of residence are surely one part, perhaps an important part. We also have seen that default probabilities may be higher in tracts with heavier black representation. Noting that high default probabilities and high prepayment probabilities seem to go hand in hand, one possible explanation is that neighborhood instability in the form of more rapid turnover of homeowners, as reflected in the departure of homeowners following default or in simple changes of residence (a component of prepayment), makes minority neighborhoods less desirable.[56] Higher turnover may act as a trigger event that brings on default, or local house price changes may act as a mediating factor. This explanation is somewhat unsatisfying because it offers no reason for the initial increase in turnover in certain neighborhoods, and in particular, it does not indicate why higher turnover is correlated with racial composition of the neighborhood.

A possibly more satisfying explanation is that higher default and prepayment probabilities in more heavily minority neighborhoods reflect movements out of neighborhoods in transition. That is, as minority representation rises, homeowners may leave in greater numbers via both avenues of departure, default and prepayment (which again is assumed to represent primarily changes of residence). Increasing minority representation may act as a trigger event for either

[56] The estimated impacts of propmove in Panels A and B of Table 9 above are consistent with this story as well.

default or change of residence, and declines in home prices may ensue, further reinforcing default behavior. According to this explanation, we should find that changes in neighborhood racial composition affect prepayment (read change of residence) and default probabilities. Unfortunately, data on changing racial composition of the tract for the appropriate time period are unavailable.[57] It may be possible to extract useful information from the racial composition of FHA endorsements, though we have not yet attempted to do so. For now, this alternative explanation remains an essentially unexplored idea. One could argue that the neighborhoods-in-transition-lead-to-default explanation is subsumed — somewhat poorly to be sure — under the high-turnover-leads-to-default explanation. That is, under the high-turnover-leads-to-default explanation, as well as under the neighborhoods-in-transition-lead-to-default explanation, we expect to find lagged defaults and prepayments associated with higher current default rates.[58] A safer and more conservative view, however, is that more convincing evidence on the neighborhoods-in-transition theory must await additional empirical work.

To provide a preliminary exploration of the first two possibilities, we begin by examining the relationship between aggregate data on house prices, on the one hand, and previous defaults and prepayments, on the other. That is, we first explore explanations for neighborhood default effects under the assumption that changes in house prices may act as a mediating force. Under the defaults-lead-to-neighborhood-deterioration theory, we expect to find default activity resulting in lower neighborhood house prices, but with a lag long enough to allow exit of the defaulted homeowner and possible deterioration of the property. Presumably, the lag effects would endure as long as the property remains vacant or in a state of disrepair. Under the high-

[57] Calvin Bradford suggests comparing the fraction of minority homeowners in a census tract in 1990 with the fraction of home purchase loans to the same minority group in the succeeding years of HMDA data for the same census tract. See Bradford, Calvin, et al, "Crisis in Deja Vu: A Profile of the Racial Patterns in Home Purchase Lending in the Baltimore Market," The Public Justice Center, May 2000.

[58] One could argue that under the latter explanation, defaults and prepayments may operate without a lag as well since contemporaneous default or prepayment may be indicative of current neighborhood transition activity. Under the high-turnover theory, however, the response to default must presumably lag because it is the exit of the owner, which likely follows the default action, that generates the subsequent responses. Given the lags with which individuals respond to stimuli, however, it seems imprudent to try to distinguish between these explanations based on observed lag lengths.

turnover-leads-to-default theory, we expect to find defaults resulting in lower neighborhood house prices, but again with a lag long enough for the defaulting homeowner to exit the residence. Under this theory, however, changes of residence (one form of prepayment) should operate almost immediately, though the full impact may be delayed because of informational lags or lags in buyers' responses. Notice, moreover, that the existence of home price responses to current and lagged prepayment activity could in principle be used to distinguish the two theories, since only one of the two theories implies such responses.

3.1. Estimation of Tract-Level Models for House Prices in the Chicago MSA

3.1.1. Aggregate Models and Data

Our study of house prices and default activity utilizes data from the Chicago MSA only. Although this particular choice of MSA is arbitrary, and we cannot be certain that findings would apply to other MSAs, the choice of Chicago is dictated in part by its large number of FHA endorsements over the observation period. Data on all Chicago MSA endorsements[59] of FHA-insured loans were provided for the years 1986 through mid-1999. The data were aggregated by quarter of origination within neighborhoods, as defined below. For each quarterly aggregate, we calculated the average house price, as well as the average income, assets, and other characteristics of the borrowers for these same loans. Data on defaults were also aggregated on a quarterly basis within each neighborhood, but in this case the aggregation was over all defaults on originations that had occurred over the previous six years; average values for various borrower and mortgage characteristics were calculated for these same loans.

Although it would be preferable to use tract boundaries to define neighborhoods for the purposes of this study, changes in tract definitions over time made this procedure infeasible. We chose instead to aggregate all tracts that had split off from a single tract. The resulting

[59] As with the data used in estimating the hazard models above, the sample was restricted to loans that were not streamline refinances.

aggregates, which we denote "supertracts," were used as neighborhoods for the purposes of this portion of the study.[60]

The statistical model followed for this exercise is a linear regression utilizing time series of cross sections, where a calendar quarter is the time series unit of observation and the supertract is the cross sectional unit of observation. Given the requirements for data construction and the requirements for lag variables, observations used in the (log of the) house price regression ran from 1994 through mid-1999. The dependent variable is the log of the average sales price for all FHA-insured homes that originated within each calendar quarter in each supertract. The explanatory variables are listed in Table 13. Discussion is required on what is included, as well as what is excluded, from this regression.

Notice first that the house prices are averaged over only those homes that were financed with FHA-insured mortgages. The limitation to FHA-insured loans — which in any case was dictated by the available data — implies much smaller sample sizes than would be obtained if conventionally financed homes were included as well. This limitation does, however, serve an important purpose in focusing on the particular segment of the market in which our interest lies -- - FHA-insured loans. It is possible that prices in different segments of the housing market move at different rates; if so, we wish to follow the segment that most closely matches that served by FHA. Because our sample is so limited, however, quarterly samples of homes sold within supertracts are sometimes very small; for this reason, we include only observations with sales price averages based on at least ten homes.[61]

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[60] The alternative of using 6-digit zip codes as neighborhoods was judged inferior, given the presumed lack of homogeneity of the population within zip codes. Because the number of tracts in the Chicago MSA varies over time, it is difficult to give a precise estimate of the numbers of tracts that are collapsed to arrive at supertracts. To give some indication, we note that for the first quarter of 1992, our data contain approximately 1600 tracts that are collapsed to about 1200 supertracts.

[61] We additionally require that default and prepayment rates be based on at least 20 loans. The requirement that the appropriate lags be available also limits the number of usable observations. More specifically, there are approximately 14,000 quarterly observations on Chicago supertracts with at least one home sale. The sample declines to about 8500 when appropriate lags are required. The sample further declines to about 2800 when we require that price averages be based on 10 sales and default and prepayment rates be based on 20 loans.

Notice next that the identities of homes sold change from quarter to quarter; in particular, these are not prices for repeat sales. Moreover, the list of explanatory variables contains no direct measures of house quality, again a necessary consequence of the data at our disposal. For this reason we are unable to hold house quality fixed in any direct fashion while the samples of homes sold change over time. To help overcome this problem, though surely in crude fashion, we include (in a manner to be explained) the average incomes and assets of the homebuyers as a way of controlling for house quality. The hope is that the latter controls, together with the fact that we are working within supertracts, serve to standardize adequately for house quality; of course, these precautions may be inadequate.

One of the main ingredients in our linear regression is (the log of) average house prices in the same supertract four quarters earlier. The use of house prices four quarters ago, rather than, say, in the previous quarter, helps correct for possible seasonality in prices and also helps to make the distinction between the two house price readings (current and lagged four quarters) more likely to reflect true house price changes, as opposed to simple measurement error or sampling error. That is, the signal-to-noise ratio should be higher when using a longer lag in house prices.

The remaining explanatory variables attempt to explain the new level of average sales price (*i.e.*, as given by the dependent variable) within the supertract, given the observed average price four quarters earlier. Many of these variables are expressed as differences in the current quarter relative to their values four quarters ago. These include the difference in rates on 30-year fixed rate mortgages (FRM30), the unemployment rate in the MSA (unemmsa), the (log of) average income of the homebuyers (loginc), the (log of) assets of homebuyers having positive assets,[62] the fraction of homebuyers recorded as having no assets (ass0rt), and the (log of the) house price index at the MSA level (loghindx). The percentage change in the number of homes sold, comparing the current quarter to that four quarters ago, is included in anticipation of the possibility that increases in FHA-insured home sales may be associated with changes in the FHA share of sales at different places along a fixed house price distribution, rather than shifts in the house price distribution itself. Additional controls include characteristics of the supertract

[62] Assets are measured prior to closing; assets after closing were deemed to be more error-ridden.

obtained from the 1990 census:[63] the unemployment rate in the supertract (tractune), the percentage of the supertract population that is black (blkpct) or Hispanic (hsppct), and supertract median income (medinc). A trend term (the number of the quarter, amtg, relative to an arbitrary time in the past) allows for unexplained growth.

The final entry in the list of explanatory variables is a set of lags in the quarterly default rates (defrt) and prepayment rates[64] (preprt) for the supertract.[65] Once again, the nature of the data prevents us from including homes with conventional financing in the calculations of default and prepayment rates, but the hope is that this restriction is not fatal in that either (a) the default and prepayment rates on FHA-insured loans are good proxies for the corresponding rates on all loans, or (b) that behavior within the segment of the market at issue here is better represented by rates on FHA-insured loans. The fact that our rate calculations are restricted to cover loans made in the previous six years[66] is also a potential defect, though we assume that these default and prepayment rates are adequate proxies for rates on the full range of FHA-insured loans.

The appropriate lag structure for defaults and prepayments is unknown. As noted above, under the defaults-lead-to-neighborhood-deterioration theory, lags in default must be long enough to result in vacant properties, and effects would presumably last until the vacant properties were rehabilitated. Note that we have no way of knowing when, if ever, the defaults

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[63] Population weighted averages were used to convert tract-level variables to values at the supertract level.

[64] This analysis included all prepayments in the calculated prepayment rate, though in principle FHA refinances should have been excluded. Because FHA refinances were only about 12 percent of all prepayments in these Chicago MSA data, it is unclear how much difference such a restriction would have made. Again, the fact that other prepayments contain refinances through conventional sources is a general disadvantage for the purposes of this analysis.

[65] As with the FHA data used in the loan-level study above, the times of default and prepayment are recorded in the FHA database.

[66] The reason that defaults are limited to those occurring among the previous six years of originations is that there are severely limited numbers of quarterly observations, a problem that is exacerbated by the presumption that default and prepayment effects operate with a lag. Increasing the range of originations covered by the default and prepayment rates reduces the number of quarters that may be used in the house price regression.

in our samples result in vacant structures. For this reason, we include various lags of the default rate, but we are unsure about the appropriate lag length. Similarly, the high-turnover-leads-to-default theory can justify lags in the effects of default and prepayment, but again the appropriate lag structure is unclear. As indicated above, however, it seems logical that, because change of ownership is likely to be more immediate in a prepayment (assumed here to represent a change of residence) than in a default, shorter lag lengths might be anticipated for prepayments. For this reason, we include the current value of the prepayment rate, but not the current default rate, in the regressions to explain house prices.

3.1.2. Estimation Results

Panels A, B, and C of Table 14 provide estimates of various specifications of the regression model, estimated with quarterly supertract observations from 1994 through mid-1999, to explain house prices within the supertracts.[67] Specifications differ only in the number of included lags of the prepayment and default rates. Most coefficient estimates tend to be qualitatively similar in all specifications. Many effects are in the expected direction; in particular, higher incomes and asset levels among homebuyers, and higher rates of MSA-wide house price growth, are associated with larger increases in sales prices over the four-quarter interval. Contrary to expectations, however, higher mortgage rates and higher MSA unemployment rates are associated with higher sales prices as well. Notice also that supertracts marked by higher 1990 unemployment rates and higher 1990 percentages of black residents have lower house prices, other things the same. The influence of supertract income (which always has an estimated negative impact) and the percentage of the population that is Hispanic (which always has a positive impact) often cannot be statistically distinguished from zero.

It is noteworthy that the house price regressions seem to show that house prices tend to be

[67] Serial correlation in the residuals is a concern, but we made no attempts to correct for this potential problem. Time series for individual supertracts need not be complete and may have holes, making attempts to estimate and correct for serial correlation more difficult. In addition, we acknowledge the possibility of a simultaneous equations problem in estimating this aggregate relationship.

lower, other things the same, in supertracts with heavier black representation. Hence, attempting to take the explanation back one step further raises a new question: why house prices appear to lag in black neighborhoods, other things the same, even after controlling for sales prices four quarters earlier, lagged default and prepayment behavior, and a variety of other factors.

The lagged effects of the supertract default rate indicate that higher default activity does appear to lead to lower house prices. Many of the individual lags are statistically significant, and the sum of the lag effects is statistically significant as well.[68] A one percentage point increase in the default rate[69] is estimated to lead in the long run to a 14 percent reduction in house prices (Panel A). Although a response in house prices of this magnitude may seem large, it is not necessarily unreasonably large. A one percentage point increase in the default rate is, after all, a sizable increase, and thus a related reduction in house prices of 14 percent might be a reasonable point estimate within the range of the data. (The estimated long run impact of a one percentage point increase in the default rate is estimated to be even larger in Panels B and C — a 17 percent reduction in house prices.)

Although these estimates offer some support for the hypothesis that increases in default rates adversely affect house prices in later periods, these results should be interpreted with caution. The fact that the first quarterly lag effect is always the strongest seems to cast some doubt on the possibility that the default rate is really picking up abandoned structures or changes in homeownership.[70] Additional caveats are offered below.

Current and lagged effects of prepayment rates generally have positive estimated effects, and

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[68] The F-tests on the sum of effects are as follows: in Panel A, $F(1,2751) = 18.51$, significant at better than 0.0001; in Panel B, $F(1,2747) = 20.26$, significant at better than 0.001; in Panel C, $F(1,2743) = 15.18$, significant at 0.0001.

[69] The impact is estimated as the sum of the coefficients on the lagged default rates divided by one minus the coefficient on the four quarter lag in log house price.

[70] Rapid responses may, however, be consistent with default rates proxying changes in racial composition of the neighborhood.

the sum of the coefficients on the current and lagged values is positive and significant as well.[71] Assuming that the prepayments here represent changes of ownership, these findings are inconsistent with the turnover-leads-to-default theory discussed above. Since these prepayments contain both refinancing and changes of residence, however, it may of course be that the refinancing component is dominant and is masking the change-of-residence component on which the empirical specification is based.

It should also be noted that these statistical results are fragile. Estimated impacts vary with the number of origination years over which the default and prepayment rates are calculated, the number of lagged values of (the log of the) house price included as explanatory variables, and the number of lags of default and prepayment rates that are included in the regression.

Because these regression specifications clearly omit numerous important factors, many of which could easily be correlated with the included variables, we have reestimated one of the models as a fixed effects model. This model permits each supertract to have a supertract-specific effect that may be correlated with any or all of the included explanatory variables. Estimates of the fixed effects model are presented in Table 15. Focusing on the effects of default and prepayment rates, we again see that lagged default effects are estimated to be negative, and the sum of the effects is also statistically significant.[72] The implied long run impact of a one percentage point increase in the default rate is a 2 percent reduction in house prices, a much smaller estimate than those found in any of the panels of Table 14. Prepayment effects now look very different that they did in Table 14. Individual coefficients now tend to be negative, and the sum of the coefficients is now negative and statistically significant as well.[73] The implied long run impact of a one-percentage point increase in the prepayment rate is to reduce house prices by 0.3 percent.

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[71] The F-tests on the sum of the coefficients are: in Panel A, $F(1,2571) = 8.89$, significant at a level of 0.0029; in Panel B, $F(1,2747) = 14.32$, significant at 0.0002; in Panel C, $F(1,2743) = 22.43$, significant at better than 0.0001.

[72] The F-test on the sum is $F(1,2368) = 3.45$, significant at the 0.0635 level.

[73] The F-test on the sum is $F(1,2368)=2.77$, significant at the 0.0961 level.

These fixed effect models are also fragile, however. In particular, both the default and the prepayment effects depend heavily on the lag structure; reestimating the fixed effect model with four lags or eight lags, rather than six, yields sums of coefficients that are no longer statistically significant.

Although the fragility of the estimated models raises questions about which, if any, estimated effects are to be believed, there are at least hints that lagged defaults in particular have an adverse effect on subsequent house price growth. It is unclear, of course, whether the reason is that defaults lead to abandoned structures, or whether defaults are one component of undesirable instability in homeownership, or whether some other default-related impact is at work. Effects of lagged prepayment rates are on even less certain standing.

To provide some additional information on whether the lagged default effects are truly capturing the effects of abandoned structures or turnover of homeownership, we performed another experiment. In particular, although one interpretation of these findings is that defaults lead to subsequent weakness in house prices, it is also possible that some other force is leading to both additional defaults and the subsequent effects on house prices. To explore this possibility further, we reran two of the house price regressions with one and two quarter leads of the default rate and prepayment rate. If the role of default rates in the price regressions arises solely because past defaults lead to abandoned structures or turnover of homeownership, which in turn adversely affects house prices, then we would expect to find that future default rates do not affect current house prices. That is, it is reasonable to believe that abandonment of the structure or turnover of ownership does not precede the default date. Similarly, future prepayment rates are not expected to affect current prices if they are picking up changes in homeownership.

Panels A and B of Table 16 give the findings using two of the previous regression specifications, one of them the fixed effects model. Looking first at Panel A, we see that default rates one quarter ahead have an estimated effect on current house prices that borders on statistical significance. One interpretation of this finding is that future default rates, and probably past default rates as well, are proxying the effects of other influences on house prices. That is, while some of the lag effect of default rates on house prices may operate through abandonments and the like, other portions of this impact may reflect the presence of other forces that work to increase defaults and simultaneously lower house price growth. Similarly, the two quarter lead in prepayment rates has a statistically significant estimated impact on house prices, suggesting that prepayment rates and house prices are picking up common factors leading both to increase.[74]

The fixed effects model in Panel B again presents a different story. Now neither of the leads in the default rate has a statistically significant effect. The one quarter lead in the prepayment rate has an impact of marginal statistical significance, but in contrast with the Panel A results, now the prepayment effect is negative. Once again, the conflict between the standard regression and the fixed effects model makes any conclusions hazardous.

Although the results in this section do not lead to complete resolution of whether lagged defaults have a true structural impact on current house prices, and results for lagged prepayment rates are even more uncertain, we proceed with our explorations by applying the results in this section to reestimate default and prepayment hazards for the Chicago MSA. Recall in this regard that the house price index used to approximate house price growth in the context of the hazard models discussed earlier was an MSA-level measure. The estimation in this section, however, is performed at the level of the supertract. If the data and the estimates in this section are valid, it should be possible to apply the supertract-level estimates of house prices to the data used in the hazard estimation procedure. In addition, by including lagged neighborhood default and prepayment rates directly in the default hazard for individual loans, we may see whether these rates affect individual defaults directly rather than, or in addition to, indirectly via changes in house prices. Naturally, this extension is available for the Chicago MSA only.

3.2. Revisiting Hazard Models of Default for the Chicago MSA

We now return to hazard estimation. The estimation sample is composed of all 1994 Chicago MSA applications or originations for homes located in one of the supertracts that contained the

[74] One might even argue that the latter spurious correlation dominates the true structural effect, yielding the "incorrect" sign (under the turnover theory) on lagged prepayment rates in the house price regressions.

requisite data.[75] There can be no claim that the resulting estimation sample is representative of even the Chicago MSA. To ensure that this sample is comparable to that used in the earlier hazard estimation or, even if it is not, to provide a benchmark for later comparisons, we first estimate a default hazard model using a specification presented earlier for the full set of 22 MSAs. The estimates for the Chicago MSA are contained in Table 17. Comparing these estimates to those in Panel A of Table 11 above indicates that the estimates are indeed similar, though of course, not identical.

Further explorations rely on some additional variables. Recall that Eq. (2) above was used to justify the inclusion of the log of house value in the hazard model. Although our hazard estimates for the sample drawn from 22 MSAs relied on house price indices measured at the MSA level, the results in the previous section suggest that those estimates are not in fact appropriate because there is variation in house price growth at the supertract level. We may express the log of current house price as

$$\ln(H_t) = \ln(H_0) + \ln(P_t / P_0)$$

where P_t / P_0 is the ratio of neighborhood house prices at time t to those at time 0. In the hazard estimation discussed in Section 2, we used MSA-level data to estimate this ratio. In this section we simply include an estimate of the log of the house price ratio $\ln(P_t / P_0)$ at the supertract level, or its predicted value,[76] in the default hazard specification. At the same time, we include lagged values of the supertract default rate and prepayment rate, thus testing directly for trigger effects on default behavior. That is, if default probabilities respond directly to previous

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[75] Data on individual Chicago MSA loans from 1992 cannot be used because the necessary variables derived from the Chicago house price regressions are not available until 1994.

[76] In practice we simply include a term that contains the new estimate of the log of the (supertract) house price ratio relative to (*i.e.*, minus) estimated MSA-wide house price growth. Now the term lnhval represents (the log of the) current house value under the assumption that house prices increase solely in accordance with MSA-wide house price growth.

default or prepayment behavior with or without intervening reductions in house prices, we should find that lagged defaults and prepayments in the neighborhood have a positive effect on the default probability of individual loans.[77]

Panels A, B, and C of Table 18 show the hazard estimates for three alternative specifications. Specifications differ in the way in which supertract house price levels are used to form the new estimates of house price growth.[78] One method, yielding the specification presented in Panel A, bases the log of the house price ratio, pric2CHG, on the observed averages of sales prices in the supertract, *i.e.*, on the dependent variable in the regression analysis presented in the last section. Other methods use average house prices predicted from one of the regression specifications in the last section; these methods offer the potential advantage of removing some of the noise in average house prices. Panel B of Table 18 uses house prices predicted using the house price regression given in Panel B of Table 14, yielding a log house price ratio denoted by pred6; Panel C of Table 18 uses the predicted values from the regression in Table 15, yielding a log house price ratio denoted by pred6x.

The results in Table 18 show that the impact of supertract-level house price growth is not significantly different from zero at conventional levels in two of the three panels, though its effect is always of the anticipated sign. Estimated house price growth effects tend to be larger when the predicted house price figures, rather than the raw averages, are used, but even then the estimated impact falls short of statistical significance in Panel B and is of somewhat marginal significance in Panel C.

Turning to lagged default rates, note first that in Table 18 the variable defx denotes the default rate lagged x quarters. The only statistically significant effect of lagged defaults is that

[77] Notice that the new variables are measured quarterly, whereas the hazard model is based on monthly observations. In practice, the quarterly variables were simply applied to each month of the appropriate quarter.

[78] As in the earlier hazard models, local house price changes are assumed to affect default via the current value of the home and to operate without a lag.

from four quarters earlier (def4), but the sum of the effects is also significant as well.[79] Although all lags have a positive impact on the probability of default for an individual loan, the peak impact generally occurs at lag four, which seems a plausible lag for the change of ownership or vacancy associated with a default.

Turning next to prepayment rates in Table 18, note first that the current rate is the variable preprt, and prepayment rates lagged x quarters are denoted by prepx. Lagged prepayment rates are of mixed signs, and the sum of the effects is never statistically significant, casting substantial doubt on the role of prepayment activity (at least as measured here) as a default trigger.

Notice finally that in all three specifications the effect of supertract income and the effect of the fraction of the supertract that is black are substantially reduced relative to their values in Table 17. While the effect of supertract income remains statistically significant, the race effect is now far from statistical significance. Apparently, the introduction of supertract price growth, lagged default rates, and lagged prepayment rates serve to reduce the estimated impact of tract characteristics.[80]

There is again a question of whether these impacts of lagged defaults truly reflect their role as a default trigger, or whether lagged default rates proxy other omitted variables that affect both current individual default probabilities and lagged aggregate default rates. Performing a test like that employed above in the context of the house price regressions, we add one and two quarter leads of default and prepayment rates to one of the hazard specifications. The findings are in Table 19. The two leads of the default rate are denoted def1F and def2F, and the two leads of the prepayment rate are denoted prep1F and prep2F. The one-quarter lead in the supertract default rate (as well as in the supertract prepayment rate) appears to have a statistically significant effect on the current individual default probability, again suggesting that part of what is picked up in the effect of the lagged default rate is something other than its role as a trigger for individual

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[79] The Chi-square tests on the sum of effects (each with one degree of freedom) are as follows: in Panel A, Chi-square = 6.02, significant at 0.0142; in Panel B, Chi-square = 5.83, significant at 0.0157; in Panel C, Chi-square = 5.61, significant at 0.0178.

[80] Recall that tract racial composition enters the house price regressions, suggesting an additional source of effect of tract-level racial composition on individual default behavior.

default behavior.

To conclude, the findings from the reestimated hazard models reinforce the idea that lagged defaults may act as a trigger for later defaults, and that the price effects induced by lagged defaults (and other factors) may affect default probabilities as well. These default effects may arise because defaults result in vacant properties, leading to neighborhood decay, or because defaults are one component of undesirable turnover in neighborhood homeownership. There is no support here for a role of lagged prepayments as a trigger that induces defaults directly, and there is an uncertain role for prepayments affecting house prices. The inconsistencies and anomalies in the various specifications, data limitations, and the powerful estimated effect of future defaults, however, make these conclusions highly uncertain.

Hence, we can provide only a very tentative answer to the last question raised at the beginning of the paper. Although the evidence from the Chicago MSA is not conclusive in itself (and is of uncertain applicability to other MSAs), it appears that a portion of the default effects of neighborhood racial composition in particular may be traceable to temporary, but perhaps long lasting, responses to higher past default rates that happen to occur in more heavily black neighborhoods.

SECTION 4

CONCLUSIONS

The empirical findings in this study permit at least qualified answers to the questions raised at the outset. First, evidence from the default hazard models estimated over individual FHA-insured loans in the 22 target MSAs suggests that once one controls for a variety of borrower- and loan-related factors, including time-varying characteristics, in an appropriate econometric model of default, some neighborhood effects do persist. We find that decreases in tract income, and (less clearly) increases in representation of blacks within the tract, are associated with higher default probabilities of individual loans, and this relationship holds even when one controls for the race, ethnicity, and credit history of the borrower. Interestingly, we also observe that although neighborhood impacts remain, their importance is dramatically affected by introducing controls for characteristics of individual loans, borrowers, and the economic environment.

Second, estimation of the default hazard for individual loans also suggests that neighborhood characteristics, such as racial composition and mean income, have effects on default that are separate and distinct from the effects of these same characteristics at the individual level. Although we find that greater tract representation of blacks is probably associated with higher default probabilities, individual race effects --- black or Hispanic --- are absent. Hispanic representation at the tract level does not seem to matter in default behavior. Although tract income does seem to affect default behavior, individual income has no statistically significant impact.

Third, we find little evidence that race or income differences in the probability of default are traceable to differences in the probability of refinancing, which may in turn reflect differential access to funds. In particular, if default rates are higher in more heavily black neighborhoods, and if this differential reflects differential borrowing opportunities, we might expect to find that either FHA refinancing probabilities or other prepayment probabilities would be lower for blacks. Instead we find that FHA refinancing probabilities, as well as other prepayment probabilities (which include conventional refinancing activities) tend to be higher, if anything, among loans in tracts with heavier minority (black or Hispanic) representation. Among these neighborhood effects on FHA refinancing and other prepayment, only the effect of tract-level Hispanic representation on other prepayment is statistically significant at conventional levels.

We do find that individual Hispanic ethnicity is associated with lower FHA refinancing probabilities, and individual blacks and Hispanics have lower probabilities of other types of prepayment, which may or may not be the result of discrimination in refinancing against individual borrowers on the basis of race or ethnicity. Yet there are no corresponding default effects traceable to the race of individuals. Again, we find no evidence of a link between differential default activity, on the one had, and differential prepayment activity on the other, which would reveal a potential role for discrimination in access to refinancing in generating default behavior.

Tract income is positively related to the probability of prepayment (other than for FHA refinancing) but has no significant effect on the FHA refinancing probability; as noted, tract income is negatively related to default probabilities of individual loans.[81] The sign pattern is consistent with, but surely does not prove, the proposition that higher tract income helps support lower default probabilities partially through greater access to conventional refinancing. There are clearly other possible explanations for this sign pattern.

We emphasize that these assessments of the possible role of differential access to funds are very limited. Not only is this analysis restricted to effects arising among holders of FHA mortgages, completely ignoring holders of conventional mortgages, but in addition the evidence is entirely indirect. We do not account in any way for possible differences in the rate at which individuals or groups actually apply for refinancing from FHA or conventional sources.

Finally, we have used data from the Chicago MSA to examine some other possible ways in which neighborhood differences in default probabilities might arise. House price regressions for

[81] It is less easy to assess the role of individual income within the context of default and refinancing, mainly because the estimation procedure also uses income indirectly as part of the front-end ratio. Evaluating income effects under the assumption that the front-end ratio is to be held fixed, we find that individual income has no significant effect on default but has positive impacts on probabilities of FHA refinancing and other prepayment.

tract aggregates generally appear to show that lagged neighborhood defaults lead to lower house price growth in the neighborhood; effects of neighborhood prepayment rates on house price growth are more uncertain. It is unclear, however, whether the default effects arise because defaults lead to abandoned structures and neighborhood deterioration, whether defaults are one component of undesirable instability in homeownership, or whether some other default-related impact is at work. Moreover, these results should be interpreted with caution. Additional analysis reveals that estimated effects are sensitive to specification, and there is indirect evidence that neighborhood defaults may proxy other omitted factors affecting local house prices.

Reestimation of default hazard models for individual loans in the Chicago MSA leads to additional insight. Even after controlling for house price growth at a more local level, lagged values of the neighborhood default rate generally seem to have a positive impact on the probability of default of an individual loan, but lagged prepayment rates are generally of mixed signs, again casting substantial doubt on the role of prepayment activity (at least as measured here) as a default trigger. Again caution is urged in interpreting these findings, in part because there is some evidence that lagged default rates proxy other omitted variables that affect both current individual default probabilities and lagged aggregate default rates.

It is noteworthy that introducing direct measures of neighborhood house price growth and lagged default and prepayment rates changes other estimated default effects on individual loans. In particular, the estimated effects of neighborhood income and of the fraction of the neighborhood that is black are substantially reduced. While the effect of neighborhood income remains statistically significant, the race effect is now far from statistical significance.

To conclude, the findings from the Chicago MSA data reinforce the idea that neighborhood defaults may act directly as a trigger for later defaults, and that the neighborhood price effects induced by lagged defaults (and other factors) affect individual default probabilities as well. These default effects may arise because defaults result in vacant properties, leading to neighborhood decay, or because defaults are one component of undesirable turnover in neighborhood homeownership. In either case, the result is that temporary increases in default activity may tend to persist. There is no support here for a role of lagged neighborhood prepayments as a direct influence on default, and there is an uncertain role for prepayments affecting house prices. Although various inconsistencies, anomalies, and serious data limitations (including the nonrandomness and lack of generality of the Chicago MSA data) render these conclusions highly tentative, it appears that controlling for a wider and more precise array of neighborhood characteristics may reduce the extent to which individual differences in default behavior are attributed to differences in neighborhood racial composition.

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TABLE 1

Miscellaneous Statistics on the Selected MSAs

MSA	Number of FHA Defaults [1]	FHA Loan Counts [1]			Population Percentages [2]		% of National FHA Loans [3]	FHA Loans as % of Total Loans [3]
		Black	Hispanic	Total	Black	Hispanic		
ATLANTA, GA MSA	750	9226	744	32938	25.09	1.97	2.75	23.1
BALTIMORE, MD PMSA	601	3468	184	21694	25.69	1.27	2.06	30.11
CHICAGO, IL PMSA	1293	9490	11619	48137	19.01	11.36	4.16	20.03
DALLAS, TX PMSA	611	2491	2921	22711	15.47	13.98	2.08	24.83
DENVER, CO PMSA	-	1081	2955	28989	5.69	13	2.88	30.86
DETROIT, MI PMSA	454	3883	164	21240	21.99	1.97	1.93	15.62
FORT LAUDERDALE, FL P	368	2451	1749	10977	14.87	8.64	0.97	18.13
FORT WORTH-ARLINGTON, TX PMSA	417	977	1240	12315	10.39	11.12	1.14	29.3
HOUSTON, TX PMSA	377	1532	2242	11687	18.04	21.33	1.04	13.03
LOS ANGELES-LONP	1834	2025	11277	19734	10.55	37.81	1.99	13.95
MEMPHIS, TN-AR-MS MSA	291	4407	53	13913	40.59	0.81	1.23	41.96
MIAMI, FL PMSA	489	3226	7777	13361	19.08	49.22	1.09	21.4
MINNEAPOLIS-ST PAUL, MN-WI MSA	371	451	235	35670	3.48	1.49	3.54	32.62
NORFOLK-VIRGINIA BEACH-NEWPORT	389	2902	181	12823	28.05	2.26	1.11	25.55
ORLANDO, FL MSA	425	1147	1484	10919	11.69	8.22	1.03	24.85
PHILADELPHIA, PA-NJ PMSA	583	3726	801	21478	18.75	3.56	2.13	18.69
PHOENIX-MESA, AZ MSA	685	556	4655	27802	3.32	16.96	2.85	28.7
RIVERSIDE-SAN BERNARDINO, CA PMSA	2968	1458	12663	30351	6.53	26.5	2.85	41.86
SACRAMENTO, CA PMSA	403	620	1163	9050	7.13	10.76	1.06	27.58
ST. LOUIS, MO-IL MSA	374	2562	165	15691	16.96	1.06	1.62	21.41
TAMPA-ST PETERSBURG-CLEARWATER	296	713	731	9727	8.77	6.73	0.96	14.65
WASHINGTON, DC-MD-VA-WV, PMSA	913	10255	2305	35590	25.03	5.4	3.38	22.98

1 Source: FHA data from 1992 and 1994 applications and originations

2 Source: 1990 Census of Population

3 Source: 1993 and 1994 HMDA data

TABLE 2

Default Rates by Race/Ethnicity Within Tracts Classified by Racial Composition of Population [1]

Tract % Black	Default Rate in Tract				Percentage of Loans in Tract Category			
	All	Black	Hispanic	Other	All	Black	Hispanic	Other
≤10	2.51	3.79	4.31	2.08	69.03	19.36	71.05	79.81
>10, ≤20	4.11	4.54	6.93	3.19	12.55	14.27	14.94	11.63
>20, ≤40	4.00	4.62	5.47	3.03	7.84	18.11	8.46	5.38
>40, ≤60	4.97	4.90	8.05	3.60	3.53	13.05	3.17	1.46
>60, ≤80	5.99	6.12	8.91	4.35	2.67	11.60	1.66	0.87
> 80	5.91	6.10	3.92	5.07	4.38	23.61	0.72	0.85

Tract % Hispanic	Default Rate in Tract				Percentage of Loans in Tract Category			
	All	Black	Hispanic	Other	All	Black	Hispanic	Other
≤10	2.34	4.67	2.64	1.80	70.11	80.06	17.77	79.56
>10, ≤20	4.30	5.56	4.76	3.87	13.38	11.14	20.14	12.37
>20, ≤40	5.90	6.38	6.38	5.29	9.93	6.74	28.95	6.40
>40, ≤60	5.87	10.12	5.81	4.72	3.25	1.54	14.59	1.11
>60, ≤80	5.41	13.22	5.24	4.61	2.22	0.45	11.79	0.48
> 80	3.71	10.53	3.66	3.30	1.10	0.07	6.76	0.08

Tract % Other	Default Rate in Tract				Percentage of Loans in Tract Category			
	All	Black	Hispanic	Other	All	Black	Hispanic	Other
≤10	6.20	6.40	6.09	5.51	7.54	27.86	15.34	1.21
>10, ≤20	5.13	5.85	4.84	4.43	5.16	12.42	13.39	1.68
>20, ≤40	5.06	4.87	5.85	4.39	8.35	15.96	19.71	4.10
>40, ≤60	4.45	4.84	5.52	3.90	18.55	21.21	28.47	15.73
>60, ≤80	2.72	3.42	3.33	2.55	21.00	13.94	14.73	23.98
> 80	1.53	2.54	2.29	1.47	39.40	8.61	8.36	53.30

[1] Source: FHA data on 1992 and 1994 applications and originations in 22 MSAs. Defaults are restricted to those resulting in claims. See text for additional details.

TABLE 3

Default Rates for Loans Classified by Deciles of Borrower Income Relative to MSA Income and Deciles of Tract Income Relative to MSA Income [1]

Difference Between Borrower Income and MSA Income	Difference Between 1990 Tract Income and MSA Income									
	≤-12600	>-12600 ≤-8400	>-8400 ≤-5500	>-5500 ≤-2900	>-2900 ≤-600	>-600 ≤2000	>2000 ≤4700	>4700 ≤8100	>8100 ≤12800	>12800
≤ -23700	5.81	4.84	4.05	2.92	3.35	2.81	2.45	1.81	1.36	1.56
>-23700 ≤-18600	5.76	4.16	3.17	3.32	2.86	2.83	2.63	1.83	2.23	1.25
>-18600 ≤-14600	4.64	3.41	3.60	2.84	3.00	2.66	3.47	2.91	2.27	1.19
>14600 ≤-10900	5.28	4.41	3.85	3.47	3.66	2.93	3.31	2.43	2.36	1.59
>-10900 ≤-7200	5.06	4.79	3.29	3.48	3.48	2.91	3.02	2.10	1.97	1.44
>-7200 ≤-3300	4.96	4.05	3.45	3.34	2.99	2.71	3.01	2.35	2.31	2.18
>-3300 ≤1300	6.34	4.09	3.78	3.11	3.09	3.02	3.38	3.23	2.65	1.75
>1300 ≤7000	5.80	4.81	3.59	4.16	2.74	2.93	3.59	2.66	2.87	2.18
>7000 ≤16000	6.26	4.23	4.09	3.29	3.17	3.31	3.03	2.41	2.63	1.84
>16000	4.48	4.09	2.54	3.44	2.46	2.66	2.81	2.82	2.25	1.48

[1] Source: FHA data on 1992 and 1994 applications and originations in 22 MSAs. Defaults are restricted to those resulting in claims. See text for additional details.

TABLE 4

Default Rates by Race/Ethnicity Within Tracts Classified by Prepayment Rates, and Percentage Distribution of Loans Across Tracts [1]

Prepayment Rate	Default Rates				Percentage of Loans in Tract Prepayment Rate Category			
	All	Black	Hispanic	Other	All	Black	Hispanic	Other
0	5.09	6.94	5.95	3.72	4.92	9.66	6.80	3.56
>0, ≤5	4.72	5.54	5.87	3.82	5.80	12.43	6.91	4.20
>5, ≤8	4.33	5.08	6.17	3.48	9.26	14.61	11.54	7.69
>8, ≤10	4.10	5.46	5.74	3.19	8.59	11.21	11.10	7.53
>10, ≤12	4.27	4.99	5.86	3.56	9.64	11.04	13.77	8.51
>12, ≤14	3.65	4.53	6.46	2.83	9.97	9.04	11.38	9.87
>14, ≤17	3.44	4.17	5.25	2.89	12.34	12.13	13.26	12.20
>17, ≤20	2.77	4.59	4.64	2.20	10.70	9.00	8.06	11.60
>20, ≤23	2.13	5.39	3.25	1.59	7.69	4.32	7.17	8.50
>23, ≤30	1.73	3.89	2.86	1.49	10.50	4.08	5.82	12.78
>30	1.11	2.18	1.88	1.03	10.58	2.47	4.19	13.57

[1] Source: FHA data on 1992 and 1994 applications and originations in 22 MSAs. Defaults are restricted to those resulting in claims. See text for additional details.

Table 5

Names and Definitions of Explanatory Variables in Hazard Models

VARIABLE DESCRIPTION	**CATEGORY** (Note: Indicator variables are denoted by (I).)	**NAME**
Neighborhood Controls:		
Pct of tract population that is black (1990)		trtblk
Pct of tract population that is Hispanic (1990)		trthsp
Log of median tract income (1990)		lntrtinc
Proportion of tract pop that has not moved in previous 5 yrs (1990)		propmove
Proportion of owner- and renter-occupied tract units that are in 1-unit structures (1990)		prop1unt
Proportion of tract owner-occupied units that are not mortgaged (1990)		propmort
MSA unemployment rate in month		unemprt
Demographic and Credit Characteristics:		
Age of borrower at loan origination		borage
Borrower is black		black
Borrower is Hispanic		hisp
Credit score of borrower/coborrower		fico
No credit score available	(I)	NOfico
Measures of Financial Resources and Costs:		
Assets after closing/mortgage payment (spline)	Any amount	RSVpmts
	Amount by which exceeds 4	RSVpmt4
Log of monthly income		loginc
Log of front-end ratio		logfront
Characteristics of the Property, Mortgage, and Interest Rate Environment:		
Log of contemporaneous principal balance		lnbal
Log of contemporaneous home value		lnhval
Structure is condominium	(I)	condo

Log of contemporaneous number of months remaining on mortgage		lnhorizn
Log of (average market mortgage rate at origination/ average contemporaneous mortgage rate in market)		lnintrat
Interaction of ARM and lnintrat		lnintarm
Contemporaneous slope of yield curve (30-year Treasury rate minus 1-year Treasury rate)		rtdiff
Interaction of ARM and rtdiff		armrtd
Log of (contemporaneous mortgage payment / mortgage payment at origination) (ARMs only)		logpirto
House price at origination relative to area median price	Price/PriceWaterhouse median price	HPrelPW
	Price/ (loan limit/0.95)	HPrelLL
	Loan limit at cont. max (I)	LLmax
	Loan limit at cont. min (I)	LLmin
Miscellaneous:		
Current loan duration (months)	Any duration	t
	Number of months over 6	t6
	Square of duration	tt
Indicator for 1994 data	(I)	year94
Indicators for MSA number xxxx	(I)	_xxxx

TABLE 6

Mean Values of Selected Variables by End-of-Month Loan Status and Race/Ethnic Group

Variable	Default Status				Prepaid Status				Active Status			
Name	Overall	Black	Hispanic	Other	Overall	Black	Hispanic	Other	Overall	Black	Hispanic	Other
fico	563.3237	517.546	531.3871	593.048	644.8634	591.375	604.6959	654.2828	612.8194	563.7572	571.7496	629.984
NOfico	0.122166	0.1676673	0.1808532	0.0821802	0.0671478	0.0962609	0.1051689	0.0605028	0.0983175	0.1326983	0.1497544	0.0824457
trtblk	0.1994733	0.5154667	0.1241437	0.1089135	0.0950278	0.4048896	0.0929111	0.0625218	0.1305864	0.4464355	0.0971643	0.0706079
trthsp	0.153834	0.0846606	0.3461589	0.1055191	0.0841837	0.0646171	0.3147629	0.0645854	0.0934299	0.0560783	0.324967	0.061915
lntrtinc	10.48111	10.4142	10.39826	10.53857	10.62879	10.59715	10.48131	10.64599	10.57815	10.49332	10.44391	10.61855
black	0.2145321	1.000	0.000	0.000	0.0879923	1.000	0.000	0.000	0.1508884	1.000	0.000	0.000
hisp	0.2193722	0.000	1.000	0.000	0.0783268	0.000	1.000	0.000	0.1231529	0.000	1.000	0.000
propmort	0.2425927	0.2484056	0.2360014	0.2429441	0.2288371	0.2252768	0.2460777	0.2275931	0.2391734	0.251617	0.254627	0.2339654
propmove	0.4792932	0.5331035	0.4488608	0.4706939	0.4977744	0.5375671	0.4721541	0.4959815	0.499065	0.5380554	0.4803959	0.494128
prop1unt	0.7507315	0.7018938	0.7374865	0.7743722	0.7662992	0.7594423	0.6614377	0.776875	0.7609197	0.7359396	0.6870627	0.778641
unemprt	6.313282	5.678401	7.592085	6.058322	5.224471	5.396006	6.587691	5.078288	5.431748	5.498113	6.683049	5.205681
borage	34.31741	36.54051	33.22879	33.89679	32.79724	35.57628	34.1538	32.37647	34.19936	36.94962	34.81703	33.52295
loginc	8.019488	7.91715	8.121863	8.0186	8.162541	8.17405	8.183968	8.159314	8.05417	7.987623	8.062778	8.066541
RSVpmts	3.367813	2.560361	2.449902	4.029519	4.839978	3.609328	6.461393	4.817532	5.538293	4.427113	3.95646	6.037594
RSVpmt4	2.28349	1.626159	1.510269	2.832234	3.253919	2.249385	4.831716	3.211706	3.938221	3.041021	2.565426	4.357584
logfront	3.163884	3.157039	3.210901	3.148258	3.116001	3.096172	3.179609	3.112118	3.095494	3.088985	3.176866	3.083042
lnbal	11.2578	11.12996	11.42023	11.24329	11.32341	11.30494	11.4046	11.31773	11.22342	11.12569	11.31273	11.22858
lnhval	6.733842	6.623682	6.858699	6.727205	6.871773	6.841648	6.928683	6.869606	6.7367	6.633335	6.800641	6.747336
condo	0.0424561	0.0376864	0.0368583	0.0464329	0.0328597	0.030086	0.0393438	0.0325432	0.0319074	0.0229608	0.0180841	0.036112
HPrelPW	0.6052922	0.4808557	0.6041398	0.6528963	0.8444154	0.6608871	0.7597914	0.8717368	0.7059866	0.5169799	0.6761928	0.7503254
HPrelLL	0.0712591	0.0712772	0.0320601	0.0864425	0.0691031	0.0656334	0.0419774	0.0720178	0.092408	0.0969903	0.0566595	0.09752
LLmin	0.0003494	0.000	0.000	0.0006172	0.0001888	0.000	0.000	0.0002265	0.0001263	0.000	0.000	0.000174
LLmax	0.0668594	0.1592698	0.0261868	0.0476002	0.0617599	0.1772385	0.0203447	0.0534626	0.0669693	0.1383501	0.0379168	0.0570615
lnhorizn	5.818491	5.823867	5.815722	5.817527	5.808204	5.819868	5.802382	5.80752	5.816068	5.816642	5.820358	5.815221
lnintrat	0.0577242	0.0537858	0.0570123	0.0594926	0.1270162	0.138457	0.1184452	0.126614	0.042423	0.0438787	0.0398357	0.0425593
lnintarm	0.0190127	0.0158861	0.0233713	0.0185086	0.0310709	0.0304695	0.035705	0.030699	0.0123306	0.0088783	0.0128778	0.0129554
rtdiff	1.58764	1.632229	1.474498	1.614587	1.722017	1.600892	1.619014	1.744479	1.818112	1.792077	1.749314	1.835194
armrtd	0.4521101	0.3796361	0.5221443	0.4524359	0.3661999	0.2657277	0.3516836	0.3781683	0.488818	0.3410472	0.5220335	0.513897
logpirto	0.0098488	0.0066086	0.0148259	0.009148	0.0100432	0.0051043	0.0066069	0.0108873	0.0060197	0.0043356	0.0062306	0.0063339
t	21.76047	20.1924	23.26604	21.77129	21.21137	20.0776	21.67519	21.28746	18.17757	17.87788	17.40954	18.37015
tt	600.6776	529.8595	683.753	595.322	567.6386	502.9862	593.1457	572.066	474.6648	462.7469	441.524	482.7639
t6	15.85329	14.32212	17.36842	15.84641	15.240	14.0776	15.67519	15.3218	12.65859	12.37202	11.91755	12.84386
year94	0.3388553	0.3734689	0.3596202	0.3176911	0.3456452	0.457483	0.3605624	0.3324396	0.3719942	0.3959791	0.4419223	0.3551463

TABLE 7

Panel A

Parameter Estimates for Monthly Hazard Model of Claim Default in 22 MSA's - Basic Specification

Residual df	= 500119	No. of obs	= 500164
Pearson X2	= 829557.5	Deviance	= 7607.832
Dispersion	= 1.65872	Dispersion	= 0.015212

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
unemprt	0.0591019	0.084556	0.699	0.485	-0.1066248	0.2248286
borage	0.0057668	0.0048542	1.188	0.235	-0.0037473	0.0152809
loginc	-0.3472763	0.4399647	-0.789	0.430	-1.209591	0.5150386
RSVpmts	-0.2010156	0.0318036	-6.321	0.000	-0.2633494	-0.1386817
RSVpmt4	0.2008899	0.0332461	6.043	0.000	0.1357287	0.2660512
logfront	0.1050169	0.4470464	0.235	0.814	-0.7711779	0.9812118
lnbal	2.991059	0.7690857	3.889	0.000	1.483679	4.498439
lnhval	-2.987206	0.6413611	-4.658	0.000	-4.244251	-1.730162
condo	-0.0894179	0.2410381	-0.371	0.711	-0.561844	0.3830081
HPrelPW	-0.8370439	0.4879447	-1.715	0.086	-1.793398	0.1193101
HPrelLL	-1.648433	0.9688609	-1.701	0.089	-3.547366	0.250499
LLmin	1.711547	3.133114	0.546	0.585	-4.429244	7.852338
LLmax	1.145631	4.830778	0.237	0.813	-8.322519	10.61378
lnhorizn	1.226456	0.7753039	1.582	0.114	-0.2931115	2.746024
lnintrat	0.998226	0.5644252	1.769	0.077	-0.1080271	2.104479
lnintarm	0.647745	0.9226518	0.702	0.483	-1.160619	2.456109
rtdiff	-0.1774459	0.1202293	-1.476	0.140	-0.413091	0.0581991
armrtd	-0.0522602	0.0724147	-0.722	0.470	-0.1941904	0.0896699
logpirto	1.038163	1.379803	0.752	0.452	-1.6662	3.742526
t	0.3989617	0.0937257	4.257	0.000	0.2152627	0.5826607
tt	-0.0008864	0.000405	-2.189	0.029	-0.0016802	-0.0000927
t6	-0.3370648	0.1018896	-3.308	0.001	-0.5367648	-0.1373648
year94	-0.0334582	0.215392	-0.155	0.877	-0.4556188	0.3887025
_0520	0.0024459	0.3453959	0.007	0.994	-0.6745175	0.6794094
_0720	-0.0781617	0.2511145	-0.311	0.756	-0.5703371	0.4140137
_1920	-0.0251676	0.4014873	-0.063	0.950	-0.8120683	0.7617331
_2080	-0.6891227	0.4478024	-1.539	0.124	-1.566799	0.188554
_2160	-0.4470473	0.3212612	-1.392	0.164	-1.076708	0.182613
_2680	0.1988248	0.612647	0.325	0.746	-1.001941	1.399591
_2800	-0.0391844	0.6019227	-0.065	0.948	-1.218931	1.140562
_3360	0.0871688	0.4424015	0.197	0.844	-0.7799222	0.9542599
_4480	0.6057817	0.375706	1.612	0.107	-0.1305884	1.342152
_4920	-0.309283	0.5582927	-0.554	0.580	-1.403517	0.7849506
_5000	-0.2059751	0.4311955	-0.478	0.633	-1.051103	0.6391525
_5120	-0.8076248	0.3875145	-2.084	0.037	-1.567139	-0.0481102
_5960	0.6456242	0.6035294	1.070	0.285	-0.5372717	1.82852
_6160	-0.3807969	0.2467219	-1.543	0.123	-0.8643628	0.1027691
_6200	0.1674239	0.3905795	0.429	0.668	-0.5980979	0.9329458
_6780	0.7192805	0.3612321	1.991	0.046	0.0112786	1.427282
_6920	0.1658701	0.3690825	0.449	0.653	-0.5575183	0.8892585
_7040	-0.1306939	0.3874357	-0.337	0.736	-0.8900538	0.6286661
_8280	0.2265586	0.6333231	0.358	0.721	-1.014732	1.467849
_8840	-1.791066	4.817153	-0.372	0.710	-11.23251	7.650381
_5720	0.238133	0.5731152	0.416	0.678	-0.8851522	1.361418
_cons	-27.03373	6.133782	-4.407	0.000	-39.05573	-15.01174

TABLE 7

Panel B

Parameter Estimates for Monthly Hazard Model of Other Prepayment in 22 MSA's - Basic Specification

Residual df	= 500119	No. of obs	= 500164
Pearson X2	= 493875.1	Deviance	= 17426.4
Dispersion	= 0.9875151	Dispersion	= 0.0348445

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
unemprt	0.0668958	0.0588976	1.136	0.256	-0.0485414	0.1823329
borage	-0.0173877	0.0032867	-5.290	0.000	-0.0238295	-0.0109458
loginc	2.478168	0.2670787	9.279	0.000	1.954704	3.001633
RSVpmts	-0.0082649	0.0173072	-0.478	0.633	-0.0421864	0.0256566
RSVpmt4	0.0094911	0.0179684	0.528	0.597	-0.0257264	0.0447085
logfront	2.135046	0.276365	7.725	0.000	1.593381	2.676712
lnbal	-2.922382	0.3211064	-9.101	0.000	-3.551738	-2.293025
lnhval	1.803017	0.1835367	9.824	0.000	1.443292	2.162742
condo	0.6041536	0.1295713	4.663	0.000	0.3501985	0.8581087
HPrelPW	-0.2557808	0.245624	-1.041	0.298	-0.7371949	0.2256334
HPrelLL	0.1723889	0.5207684	0.331	0.741	-0.8482984	1.193076
LLmin	3.085268	1.472609	2.095	0.036	0.199008	5.971529
LLmax	16.09562	1316.788	0.012	0.990	-2564.761	2596.953
lnhorizn	0.3881909	0.217431	1.785	0.074	-0.0379661	0.8143479
lnintrat	3.389289	0.388565	8.723	0.000	2.627716	4.150863
lnintarm	-0.0248933	0.61789	-0.040	0.968	-1.235935	1.186149
rtdiff	0.3368494	0.0774945	4.347	0.000	0.184963	0.4887358
armrtd	0.0192972	0.0481464	0.401	0.689	-0.075068	0.1136625
logpirto	4.662443	0.7313326	6.375	0.000	3.229058	6.095829
t	0.3521314	0.0752242	4.681	0.000	0.2046947	0.4995682
tt	-0.0022749	0.0002585	-8.800	0.000	-0.0027816	-0.0017683
t6	-0.1786418	0.0808715	-2.209	0.027	-0.337147	-0.0201367
year94	0.7066045	0.1323708	5.338	0.000	0.4471624	0.9660466
_0520	-0.0161987	0.1953336	-0.083	0.934	-0.3990455	0.366648
_0720	-0.8266647	0.1677865	-4.927	0.000	-1.15552	-0.4978092
_1920	-0.6699195	0.2592315	-2.584	0.010	-1.178004	-0.1618352
_2080	0.9623034	0.1876866	5.127	0.000	0.5944445	1.330162
_2160	0.3108937	0.1607676	1.934	0.053	-0.004205	0.6259924
_2680	-0.3885312	0.3743639	-1.038	0.299	-1.122271	0.3452085
_2800	-0.4439075	0.3723317	-1.192	0.233	-1.173664	0.2858491
_3360	-0.5248851	0.307207	-1.709	0.088	-1.127	0.0772297
_4480	-1.802461	0.3317254	-5.434	0.000	-2.452631	-1.152291
_4920	-0.294156	0.350093	-0.840	0.401	-0.9803257	0.3920138
_5000	-0.1627202	0.2573653	-0.632	0.527	-0.6671469	0.3417065
_5120	0.250804	0.2001145	1.253	0.210	-0.1414132	0.6430213
_5960	-1.225847	0.4756483	-2.577	0.010	-2.158101	-0.2935938
_6160	-1.028119	0.1751396	-5.870	0.000	-1.371387	-0.6848522
_6200	0.374684	0.2306672	1.624	0.104	-0.0774154	0.8267834
_6780	-1.210758	0.2879851	-4.204	0.000	-1.775198	-0.6463174
_6920	-1.415932	0.4423364	-3.201	0.001	-2.282896	-0.5489691
_7040	0.3159483	0.2085973	1.515	0.130	-0.0928949	0.7247914
_8280	-0.1695786	0.3992472	-0.425	0.671	-0.9520887	0.6129316
_8840	-16.80702	1316.788	-0.013	0.990	-2597.664	2564.05
_5720	-0.5155479	0.3581432	-1.440	0.150	-1.217496	0.1863997
_cons	-18.15404	2.736595	-6.634	0.000	-23.51766	-12.79041

TABLE 7

Panel C

Parameter Estimates for Monthly Hazard Model of FHA Refinance in 22 MSA's
Basic Specification

Residual df	= 500120	No. of obs	= 500164
Pearson X2	= 434302.6	Deviance	= 13410.18
Dispersion	= 0.8683967	Dispersion	= 0.0268139

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
unemprt	-0.0342175	0.060086	-0.569	0.569	-0.1519839	0.0835489
borage	-0.0230464	0.0038051	-6.057	0.000	-0.0305043	-0.0155885
loginc	2.454291	0.3052535	8.040	0.000	1.856005	3.052576
RSVpmts	0.0644371	0.0188207	3.424	0.001	0.0275493	0.1013249
RSVpmt4	-0.0757678	0.0205115	-3.694	0.000	-0.1159696	-0.0355661
logfront	2.513634	0.3177161	7.912	0.000	1.890922	3.136346
lnbal	0.8608488	0.5793587	1.486	0.137	-0.2746734	1.996371
lnhval	-0.2857844	0.4849965	-0.589	0.556	-1.23636	0.6647912
condo	-18.51211	1370.631	-0.014	0.989	-2704.899	2667.875
HPrelPW	-0.5120917	0.2923435	-1.752	0.080	-1.085074	0.060891
HPrelLL	-1.39259	0.7104657	-1.960	0.050	-2.785077	-0.0001028
LLmin	-17.99153	19850.55	-0.001	0.999	-38924.35	38888.36
LLmax	-0.3861037	0.3364012	-1.148	0.251	-1.045438	0.2732305
lnhorizn	1.92765	0.5258373	3.666	0.000	0.8970277	2.958272
lnintrat	17.10791	0.5190253	32.962	0.000	16.09064	18.12518
lnintarm	-0.0896142	0.7158161	-0.125	0.900	-1.492588	1.31336
rtdiff	-0.2181235	0.0943226	-2.313	0.021	-0.4029925	-0.0332545
armrtd	-0.3930938	0.0812368	-4.839	0.000	-0.552315	-0.2338727
logpirto	7.97494	1.330458	5.994	0.000	5.36729	10.58259
t	1.683653	0.4316599	3.900	0.000	0.8376149	2.529691
tt	-0.0015143	0.0003294	-4.597	0.000	-0.0021599	-0.0008686
t6	-1.648419	0.4335787	-3.802	0.000	-2.498218	-0.7986207
year94	-0.2202653	0.1770716	-1.244	0.214	-0.5673192	0.1267887
_0520	0.8269978	0.2408697	3.433	0.001	0.3549019	1.299094
_0720	0.8252058	0.1562278	5.282	0.000	0.519005	1.131407
_1920	0.4476243	0.3029898	1.477	0.140	-0.1462247	1.041473
_2080	1.461472	0.2411811	6.060	0.000	0.9887654	1.934178
_2160	1.426478	0.2119547	6.730	0.000	1.011055	1.841902
_2680	1.395507	0.5174497	2.697	0.007	0.3813245	2.40969
_2800	0.6094245	0.5361327	1.137	0.256	-0.4413764	1.660225
_3360	0.0599508	0.4180594	0.143	0.886	-0.7594305	0.8793321
_4480	-0.4595536	0.2729454	-1.684	0.092	-0.9945168	0.0754097
_4920	0.4691452	0.5323324	0.881	0.378	-0.5742071	1.512498
_5000	0.3907105	0.3339195	1.170	0.242	-0.2637597	1.045181
_5120	1.266735	0.2331055	5.434	0.000	0.8098566	1.723613
_5960	1.778734	0.5262526	3.380	0.001	0.7472981	2.81017
_6160	0.0015494	0.1849172	0.008	0.993	-0.3608816	0.3639805
_6200	1.361421	0.2857059	4.765	0.000	0.8014473	1.921394
_6780	0.5104079	0.2545547	2.005	0.045	0.0114899	1.009326
_6920	0.7494432	0.2368532	3.164	0.002	0.2852195	1.213667
_7040	2.015531	0.2483118	8.117	0.000	1.528849	2.502213
_8280	1.677538	0.5555154	3.020	0.003	0.5887477	2.766328
_8840			(dropped)			
_5720	-0.7838115	0.6643511	-1.180	0.238	-2.085916	0.5182928
_cons	-63.45219	5.263871	-12.054	0.000	-73.76919	-53.13519

TABLE 8

Panel A

Parameter Estimates for Monthly Hazard Model of Claim Default in 22 MSA's - Basic Specification Plus Tract Characteristics

Residual df	= 500066	No. of obs	= 500114
Pearson X2	= 659011.8	Deviance	= 7577.071
Dispersion	= 1.31785	Dispersion	= 0.0151521

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.7620121	0.2058525	3.702	0.000	0.3585486	1.165476
trthsp	-0.3111604	0.3696578	-0.842	0.400	-1.035676	0.4133557
lntrtinc	-0.4437449	0.1970811	-2.252	0.024	-0.8300167	-0.0574731
unemprt	0.0566993	0.0846374	0.670	0.503	-0.1091869	0.2225856
borage	0.0021166	0.0049518	0.427	0.669	-0.0075889	0.011822
loginc	-0.2516583	0.4461181	-0.564	0.573	-1.126034	0.622717
RSVpmts	-0.190307	0.031956	-5.955	0.000	-0.2529396	-0.1276744
RSVpmt4	0.1906135	0.0334077	5.706	0.000	0.1251356	0.2560914
logfront	0.1994779	0.453413	0.440	0.660	-0.6891952	1.088151
lnbal	2.979072	0.7725116	3.856	0.000	1.464977	4.493167
lnhval	-2.720874	0.6406225	-4.247	0.000	-3.976471	-1.465277
condo	0.1003394	0.2443416	0.411	0.681	-0.3785614	0.5792401
HPrelPW	-0.8441095	0.4928076	-1.713	0.087	-1.809995	0.1217758
HPrelLL	-1.619279	0.9754065	-1.660	0.097	-3.53104	0.292483
LLmin	1.724142	3.13297	0.550	0.582	-4.416365	7.86465
LLmax	0.9024074	4.830786	0.187	0.852	-8.565759	10.37057
lnhorizn	1.225626	0.7756132	1.580	0.114	-0.2945481	2.7458
lnintrat	0.925822	0.5642974	1.641	0.101	-0.1801807	2.031825
lnintarm	0.6520115	0.9213931	0.708	0.479	-1.153886	2.457909
rtdiff	-0.1798489	0.1200912	-1.498	0.134	-0.4152234	0.0555256
armrtd	-0.0496185	0.0724622	-0.685	0.494	-0.1916418	0.0924048
logpirto	1.074016	1.379414	0.779	0.436	-1.629586	3.777618
t	0.3996183	0.0937328	4.263	0.000	0.2159054	0.5833312
tt	-0.0009	0.000405	-2.222	0.026	-0.0016938	-0.0001061
t6	-0.3375401	0.1019162	-3.312	0.001	-0.5372922	-0.1377881
year94	-0.0305336	0.2157412	-0.142	0.887	-0.4533786	0.3923113
_0520	0.024216	0.3475015	0.070	0.944	-0.6568745	0.7053065
_0720	-0.0661708	0.2535324	-0.261	0.794	-0.5630852	0.4307435
_1920	0.2048058	0.4079087	0.502	0.616	-0.5946806	1.004292
_2080	-0.5313581	0.4512848	-1.177	0.239	-1.41586	0.3531439
_2160	-0.3463012	0.3290489	-1.052	0.293	-0.9912252	0.2986228
_2680	0.3224784	0.6196011	0.520	0.603	-0.8919175	1.536874
_2800	0.1769283	0.6069835	0.291	0.771	-1.012738	1.366594
_3360	0.3566091	0.448507	0.795	0.427	-0.5224485	1.235667
_4480	0.5983702	0.3871258	1.546	0.122	-0.1603825	1.357123
_4920	-0.3887871	0.5548243	-0.701	0.483	-1.476223	0.6986485
_5000	-0.0341584	0.4467758	-0.076	0.939	-0.9098228	0.8415061
_5120	-0.6006082	0.3945792	-1.522	0.128	-1.373969	0.1727527
_5960	0.7415785	0.6105955	1.215	0.225	-0.4551667	1.938324
_6160	-0.3151732	0.2510519	-1.255	0.209	-0.8072258	0.1768794
_6200	0.4074404	0.3994946	1.020	0.308	-0.3755546	1.190435
_6780	0.8521025	0.3668303	2.323	0.020	0.1331282	1.571077
_6920	0.2027549	0.3724434	0.544	0.586	-0.5272207	0.9327305
_7040	0.0082232	0.3933601	0.021	0.983	-0.7627485	0.7791949
_8280	0.3618834	0.6406521	0.565	0.572	-0.8937716	1.617538
_8840	-1.590138	4.81672	-0.330	0.741	-11.03074	7.850459
_5720	0.1999895	0.5755103	0.347	0.728	-0.9279899	1.327969
_cons	-25.12767	6.409818	-3.920	0.000	-37.69068	-12.56466

TABLE 8

Panel B

Parameter Estimates for Monthly Hazard Model of Other Prepayment in 22 MSA's - Basic Specification Plus Tract Characteristics

Residual df	= 500066	No. of obs	= 500114
Pearson X2	= 492987.3	Deviance	= 17411.82
Dispersion	= 0.9858445	Dispersion	= 0.034819

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	-0.4138964	0.1820647	-2.273	0.023	-0.7707367	-0.0570561
trthsp	0.1757122	0.2979508	0.590	0.555	-0.4082607	0.7596851
lntrtinc	0.2499639	0.1391734	1.796	0.072	-0.0228109	0.5227386
unemprt	0.0672464	0.0588951	1.142	0.254	-0.0481859	0.1826788
borage	-0.0162593	0.0033068	-4.917	0.000	-0.0227404	-0.0097782
loginc	2.395738	0.2702406	8.865	0.000	1.866076	2.9254
RSVpmts	-0.0117905	0.0173458	-0.680	0.497	-0.0457876	0.0222065
RSVpmt4	0.0128373	0.0180024	0.713	0.476	-0.0224468	0.0481214
logfront	2.048771	0.2793414	7.334	0.000	1.501272	2.59627
lnbal	-2.96348	0.3220489	-9.202	0.000	-3.594685	-2.332276
lnhval	1.753478	0.1878946	9.332	0.000	1.385212	2.121745
condo	0.543377	0.1310362	4.147	0.000	0.2865507	0.8002032
HPrelPW	-0.2272082	0.2461823	-0.923	0.356	-0.7097166	0.2553002
HPrelLL	0.1631629	0.5250104	0.311	0.756	-0.8658387	1.192164
LLmin	3.172462	1.473998	2.152	0.031	0.2834781	6.061446
LLmax	16.3069	1316.2	0.012	0.990	-2563.398	2596.012
lnhorizn	0.3898347	0.2183245	1.786	0.074	-0.0380736	0.8177429
lnintrat	3.415267	0.3889817	8.780	0.000	2.652877	4.177658
lnintarm	-0.0246468	0.6181625	-0.040	0.968	-1.236223	1.186929
rtdiff	0.3379316	0.0775307	4.359	0.000	0.1859743	0.4898889
armrtd	0.011172	0.048277	0.231	0.817	-0.0834492	0.1057932
logpirto	4.569307	0.732035	6.242	0.000	3.134544	6.004069
t	0.3521016	0.0752279	4.680	0.000	0.2046577	0.4995455
tt	-0.002266	0.0002586	-8.764	0.000	-0.0027728	-0.0017592
t6	-0.178953	0.0808699	-2.213	0.027	-0.3374551	-0.0204509
year94	0.7131483	0.1323171	5.390	0.000	0.4538114	0.9724851
_0520	-0.0229498	0.1973417	-0.116	0.907	-0.4097325	0.3638328
_0720	-0.8101609	0.1707165	-4.746	0.000	-1.144759	-0.4755627
_1920	-0.7481186	0.2601593	-2.876	0.004	-1.258021	-0.2382157
_2080	0.8962606	0.1894484	4.731	0.000	0.5249487	1.267573
_2160	0.2677569	0.1643374	1.629	0.103	-0.0543385	0.5898523
_2680	-0.3987123	0.37667	-1.059	0.290	-1.136972	0.3395474
_2800	-0.4919556	0.3748892	-1.312	0.189	-1.226725	0.2428137
_3360	-0.6278544	0.3083917	-2.036	0.042	-1.232291	-0.0234178
_4480	-1.764603	0.3365357	-5.243	0.000	-2.4242	-1.105005
_4920	-0.2651726	0.356772	-0.743	0.457	-0.9644328	0.4340877
_5000	-0.2606788	0.2832172	-0.920	0.357	-0.8157743	0.2944166
_5120	0.1781809	0.2043212	0.872	0.383	-0.2222814	0.5786431
_5960	-1.223957	0.4792636	-2.554	0.011	-2.163297	-0.284618
_6160	-1.041359	0.1783789	-5.838	0.000	-1.390975	-0.6917425
_6200	0.2874933	0.2331778	1.233	0.218	-0.1695268	0.7445135
_6780	-1.225404	0.2895587	-4.232	0.000	-1.792929	-0.6578794
_6920	-1.390322	0.4428527	-3.139	0.002	-2.258297	-0.5223463
_7040	0.2558975	0.2131501	1.201	0.230	-0.161869	0.673664
_8280	-0.1847408	0.405301	-0.456	0.649	-0.9791162	0.6096345
_8840	-16.97399	1316.2	-0.013	0.990	-2596.679	2562.731
_5720	-0.464894	0.3625833	-1.282	0.200	-1.175544	0.2457563
_cons	-19.07672	3.019734	-6.317	0.000	-24.99529	-13.15815

TABLE 8

Panel C

Parameter Estimates for Monthly Hazard Model of FHA Refinance in 22 MSA's - Basic Specification Plus Tract Characteristics

Residual df = 500067	No. of obs = 500114
Pearson X = 433618.1	Deviance = 13407.07
Dispersion = 0.8671199	Dispersion = 0.0268105

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.1779254	0.1802455	0.987	0.324	-0.1753493	0.5312
trthsp	-0.3159586	0.3486165	-0.906	0.365	-0.9992343	0.3673171
lntrtinc	0.0112024	0.1414763	0.079	0.937	-0.266086	0.2884908
unemprt	-0.0330327	0.0601346	-0.549	0.583	-0.1508943	0.084829
borage	-0.0234852	0.0038364	-6.122	0.000	-0.0310044	-0.0159659
loginc	2.438951	0.3059689	7.971	0.000	1.839263	3.038639
RSVpmts	0.0643427	0.0188435	3.415	0.001	0.0274102	0.1012752
RSVpmt4	-0.0757558	0.0205364	-3.689	0.000	-0.1160065	-0.0355051
logfront	2.505438	0.3182439	7.873	0.000	1.881691	3.129185
lnbal	0.8957403	0.5799894	1.544	0.122	-0.241018	2.032499
lnhval	-0.2834753	0.4857147	-0.584	0.559	-1.235459	0.668508
condo	-18.50873	1370.078	-0.014	0.989	-2703.812	2666.794
HPrelPW	-0.5268451	0.2923317	-1.802	0.072	-1.099805	0.0461144
HPrelLL	-1.400175	0.7098028	-1.973	0.049	-2.791363	-0.0089874
LLmin	-18.02228	19852.35	-0.001	0.999	-38927.9	38891.86
LLmax	-0.4581442	0.3417762	-1.340	0.180	-1.128013	0.2117249
lnhorizn	1.908209	0.5261166	3.627	0.000	0.8770391	2.939378
lnintrat	17.08589	0.5194907	32.890	0.000	16.0677	18.10407
lnintarm	-0.0611242	0.7159474	-0.085	0.932	-1.464355	1.342107
rtdiff	-0.2165957	0.0943069	-2.297	0.022	-0.4014339	-0.0317575
armrtd	-0.3949698	0.0812735	-4.860	0.000	-0.5542629	-0.2356766
logpirto	7.951175	1.330011	5.978	0.000	5.344402	10.55795
t	1.68377	0.4316587	3.901	0.000	0.8377343	2.529805
tt	-0.0015215	0.0003295	-4.617	0.000	-0.0021673	-0.0008756
t6	-1.648009	0.433578	-3.801	0.000	-2.497806	-0.7982119
year94	-0.2206277	0.1770576	-1.246	0.213	-0.5676542	0.1263988
_0520	0.7871002	0.242838	3.241	0.001	0.3111464	1.263054
_0720	0.7788515	0.1609062	4.840	0.000	0.4634811	1.094222
_1920	0.4551303	0.3035082	1.500	0.134	-0.1397348	1.049995
_2080	1.474616	0.2420612	6.092	0.000	1.000184	1.949047
_2160	1.406431	0.2163548	6.501	0.000	0.9823838	1.830479
_2680	1.387829	0.5174664	2.682	0.007	0.3736136	2.402045
_2800	0.6024871	0.5369776	1.122	0.262	-0.4499697	1.654944
_3360	0.0731339	0.4188214	0.175	0.861	-0.747741	0.8940087
_4480	-0.4093511	0.2818569	-1.452	0.146	-0.9617804	0.1430783
_4920	0.4176672	0.5331677	0.783	0.433	-0.6273222	1.462657
_5000	0.5150557	0.3558665	1.447	0.148	-0.1824297	1.212541
_5120	1.253383	0.2372624	5.283	0.000	0.7883571	1.718409
_5960	1.772741	0.5272797	3.362	0.001	0.7392917	2.80619
_6160	-0.0300593	0.1890393	-0.159	0.874	-0.4005696	0.3404509
_6200	1.386291	0.2869033	4.832	0.000	0.8239708	1.948611
_6780	0.5524505	0.2572091	2.148	0.032	0.04833	1.056571
_6920	0.7444858	0.2380438	3.128	0.002	0.2779286	1.211043
_7040	1.99395	0.2518965	7.916	0.000	1.500242	2.487659
_8280	1.67352	0.557283	3.003	0.003	0.5812658	2.765775
_8840			(dropped)			
_5720	-0.8360466	0.6651757	-1.257	0.209	-2.139767	0.4676738
_cons	-63.68369	5.409528	-11.773	0.000	-74.28617	-53.08121

TABLE 9

Panel A

Parameter Estimates for Monthly Hazard Model of Claim Default in 22 MSA's - Basic Specification Plus More Detailed Tract Characteristics

Residual df	= 499623	No. of obs	= 499674
Pearson X2	= 625370	Deviance	= 7569.43
Dispersion	= 1.251684	Dispersion	= 0.0151503

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.8417292	0.2320262	3.628	0.000	0.3869663	1.296492
trthsp	-0.2243842	0.3856411	-0.582	0.561	-0.9802268	0.5314584
lntrtinc	-0.658503	0.251712	-2.616	0.009	-1.15185	-0.1651565
propmort	-0.2824701	0.4387301	-0.644	0.520	-1.142365	0.5774252
propmove	-0.9469927	0.4733983	-2.000	0.045	-1.874836	-0.0191491
prop1unt	0.3941863	0.273072	1.444	0.149	-0.141025	0.9293976
unemprt	0.0559956	0.0846478	0.662	0.508	-0.1099111	0.2219023
borage	0.0026953	0.0049494	0.545	0.586	-0.0070054	0.012396
loginc	-0.251805	0.4486391	-0.561	0.575	-1.131122	0.6275115
RSVpmts	-0.1894783	0.0320296	-5.916	0.000	-0.2522552	-0.1267015
RSVpmt4	0.189619	0.0334801	5.664	0.000	0.1239992	0.2552388
logfront	0.2031084	0.4560037	0.445	0.656	-0.6906423	1.096859
lnbal	2.956205	0.7738257	3.820	0.000	1.439534	4.472875
lnhval	-2.632727	0.6409025	-4.108	0.000	-3.888873	-1.376582
condo	0.1226864	0.2485975	0.494	0.622	-0.3645557	0.6099285
HPrelPW	-0.8899662	0.4923762	-1.807	0.071	-1.855006	0.0750735
HPrelLL	-1.739693	0.9773885	-1.780	0.075	-3.655339	0.1759535
LLmin	1.764333	3.132392	0.563	0.573	-4.375043	7.903709
LLmax	0.8244035	4.830009	0.171	0.864	-8.642241	10.29105
lnhorizn	1.22417	0.7763164	1.577	0.115	-0.2973826	2.745722
lnintrat	0.9163092	0.5645021	1.623	0.105	-0.1900945	2.022713
lnintarm	0.6332772	0.9213763	0.687	0.492	-1.172587	2.439142
rtdiff	-0.1707538	0.1201399	-1.421	0.155	-0.4062236	0.0647161
armrtd	-0.0534397	0.072479	-0.737	0.461	-0.195496	0.0886166
logpirto	1.018639	1.380368	0.738	0.461	-1.686833	3.724111
t	0.4003432	0.0937435	4.271	0.000	0.2166093	0.584077
tt	-0.0008921	0.000405	-2.203	0.028	-0.0016859	-0.0000984
t6	-0.3379941	0.1019201	-3.316	0.001	-0.5377538	-0.1382343
year94	-0.0255428	0.2154761	-0.119	0.906	-0.4478681	0.3967825
_0520	-0.1330363	0.353063	-0.377	0.706	-0.825027	0.5589544
_0720	-0.1138729	0.2553264	-0.446	0.656	-0.6143035	0.3865577
_1920	0.0627852	0.4123652	0.152	0.879	-0.7454357	0.8710061
_2080	-0.6940926	0.4568896	-1.519	0.129	-1.58958	0.2013946
_2160	-0.3778821	0.3354225	-1.127	0.260	-1.035298	0.279534
_2680	0.2366357	0.6208306	0.381	0.703	-0.9801699	1.453441
_2800	0.048343	0.6106507	0.079	0.937	-1.14851	1.245196
_3360	0.1970994	0.4537347	0.434	0.664	-0.6922043	1.086403
_4480	0.3865769	0.3954307	0.978	0.328	-0.388453	1.161607
_4920	-0.5090243	0.5577886	-0.913	0.361	-1.60227	0.5842213
_5000	-0.2336557	0.4552221	-0.513	0.608	-1.125875	0.6585632
_5120	-0.6416311	0.3978924	-1.613	0.107	-1.421486	0.1382236
_5960	0.5876067	0.6138404	0.957	0.338	-0.6154984	1.790712
_6160	-0.2555528	0.2550862	-1.002	0.316	-0.7555125	0.244407
_6200	0.1957274	0.4098826	0.478	0.633	-0.6076278	0.9990826
_6780	0.5847	0.3809359	1.535	0.125	-0.1619208	1.331321
_6920	-0.0450331	0.3842624	-0.117	0.907	-0.7981737	0.7081074
_7040	0.0260415	0.3946237	0.066	0.947	-0.7474067	0.7994897
_8280	0.2914544	0.6406428	0.455	0.649	-0.9641825	1.547091
_8840	-1.666988	4.815855	-0.346	0.729	-11.10589	7.771914
_5720	0.0694308	0.5782957	0.120	0.904	-1.064008	1.20287
_cons	-22.88198	6.622061	-3.455	0.001	-35.86098	-9.902981

TABLE 9

Panel B

Parameter Estimates for Monthly Hazard Model of Other Prepayment in 22 MSA's - Basic Specification Plus More Detailed Tract Characteristics

Residual df	= 499623	No. of obs	= 499674
Pearson X2	= 489300.1	Deviance	= 17369.37
Dispersion	= 0.9793387	Dispersion	= 0.0347649

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	-0.3418401	0.1911876	-1.788	0.074	-0.716561	0.0328808
trthsp	0.1641164	0.3019692	0.543	0.587	-0.4277323	0.7559652
lntrtinc	0.3971578	0.1636283	2.427	0.015	0.0764524	0.7178633
propmort	0.3220089	0.2660129	1.211	0.226	-0.1993669	0.8433847
propmove	-0.5498077	0.2875003	-1.912	0.056	-1.113298	0.0136825
prop1unt	-0.1516227	0.1613939	-0.939	0.347	-0.467949	0.1647036
unemprt	0.0602665	0.0589533	1.022	0.307	-0.0552798	0.1758129
borage	-0.0163528	0.0033216	-4.923	0.000	-0.0228631	-0.0098425
loginc	2.30334	0.27644	8.332	0.000	1.761527	2.845152
RSVpmts	-0.0116063	0.0173842	-0.668	0.504	-0.0456788	0.0224662
RSVpmt4	0.0125812	0.0180381	0.697	0.486	-0.0227728	0.0479351
logfront	1.946187	0.2857772	6.810	0.000	1.386074	2.5063
lnbal	-2.868696	0.3251895	-8.822	0.000	-3.506056	-2.231337
lnhval	1.759425	0.18667	9.425	0.000	1.393558	2.125291
condo	0.4872666	0.1344912	3.623	0.000	0.2236686	0.7508645
HPrelPW	-0.2494	0.2461354	-1.013	0.311	-0.7318165	0.2330165
HPrelLL	0.0896925	0.5263099	0.170	0.865	-0.9418559	1.121241
LLmin	3.189574	1.474422	2.163	0.031	0.2997596	6.079389
LLmax	16.32127	1315.838	0.012	0.990	-2562.674	2595.316
lnhorizn	0.3544684	0.2190667	1.618	0.106	-0.0748944	0.7838312
lnintrat	3.424147	0.3891796	8.798	0.000	2.661369	4.186925
lnintarm	-0.0128468	0.6193952	-0.021	0.983	-1.226839	1.201146
rtdiff	0.3452485	0.0776365	4.447	0.000	0.1930838	0.4974132
armrtd	0.0045969	0.0484861	0.095	0.924	-0.0904341	0.099628
logpirto	4.410572	0.7346276	6.004	0.000	2.970728	5.850415
t	0.3528594	0.0752485	4.689	0.000	0.2053751	0.5003437
tt	-0.0022413	0.0002585	-8.670	0.000	-0.0027479	-0.0017346
t6	-0.1807603	0.0808849	-2.235	0.025	-0.3392917	-0.0222289
year94	0.7125535	0.1324346	5.380	0.000	0.4529864	0.9721206
_0520	-0.0373952	0.2009812	-0.186	0.852	-0.4313111	0.3565206
_0720	-0.8059623	0.1718714	-4.689	0.000	-1.142824	-0.4691007
_1920	-0.7641438	0.2631604	-2.904	0.004	-1.279929	-0.2483589
_2080	0.9078922	0.1936462	4.688	0.000	0.5283527	1.287432
_2160	0.3317782	0.1674479	1.981	0.048	0.0035863	0.6599701
_2680	-0.373158	0.3785292	-0.986	0.324	-1.115062	0.3687456
_2800	-0.4841951	0.3769559	-1.284	0.199	-1.223015	0.254625
_3360	-0.6178351	0.3113398	-1.984	0.047	-1.22805	-0.0076202
_4480	-1.737509	0.3383849	-5.135	0.000	-2.400731	-1.074287
_4920	-0.2607971	0.3589779	-0.726	0.468	-0.9643809	0.4427868
_5000	-0.2272356	0.2869425	-0.792	0.428	-0.7896326	0.3351614
_5120	0.1772744	0.2066803	0.858	0.391	-0.2278115	0.5823603
_5960	-1.202397	0.4811437	-2.499	0.012	-2.145422	-0.2593731
_6160	-0.998741	0.1798666	-5.553	0.000	-1.351273	-0.6462089
_6200	0.2685634	0.2399925	1.119	0.263	-0.2018133	0.73894
_6780	-1.227844	0.2957823	-4.151	0.000	-1.807566	-0.6481211
_6920	-1.388832	0.4457837	-3.115	0.002	-2.262552	-0.5151116
_7040	0.2766099	0.2140917	1.292	0.196	-0.1430022	0.6962219
_8280	-0.1420395	0.4071158	-0.349	0.727	-0.9399718	0.6558928
_8840	-17.06416	1315.838	-0.013	0.990	-2596.059	2561.931
_5720	-0.4427421	0.3643699	-1.215	0.224	-1.156894	0.2714098
_cons	-20.12045	3.14758	-6.392	0.000	-26.28959	-13.9513

TABLE 9

Panel C

Parameter Estimates for Monthly Hazard Model of FHA Refinance in 22 MSA's - Basic Specification Plus More Detailed Tract Characteristics

Residual df	= 499624	No. of obs	= 499674
Pearson X2	= 443833.4	Deviance	= 13392.38
Dispersion	= 0.8883349	Dispersion	= 0.0268049

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.1753126	0.187339	0.936	0.349	-0.191865	0.5424902
trthsp	-0.2679471	0.3504349	-0.765	0.445	-0.9547868	0.4188927
lntrtinc	-0.2212225	0.1771316	-1.249	0.212	-0.568394	0.1259491
propmort	0.0552142	0.2983632	0.185	0.853	-0.529567	0.6399954
propmove	0.0243026	0.3041881	0.080	0.936	-0.5718951	0.6205003
prop1unt	0.6173082	0.188844	3.269	0.001	0.2471808	0.9874355
unemprt	-0.0293425	0.0601491	-0.488	0.626	-0.1472326	0.0885475
borage	-0.0230126	0.003841	-5.991	0.000	-0.030541	-0.0154843
loginc	2.553864	0.3057849	8.352	0.000	1.954536	3.153191
RSVpmts	0.0681351	0.0188517	3.614	0.000	0.0311864	0.1050838
RSVpmt4	-0.0793528	0.0205178	-3.868	0.000	-0.119567	-0.0391387
logfront	2.623254	0.3182511	8.243	0.000	1.999494	3.247015
lnbal	0.8087711	0.5805017	1.393	0.164	-0.3289914	1.946534
lnhval	-0.2773648	0.4844183	-0.573	0.567	-1.226807	0.6720776
condo	-18.39379	1370.526	-0.013	0.989	-2704.575	2667.787
HPrelPW	-0.4825179	0.2967719	-1.626	0.104	-1.06418	0.0991442
HPrelLL	-1.357097	0.7176555	-1.891	0.059	-2.763676	0.0494821
LLmin	-17.99197	20038.57	-0.001	0.999	-39292.86	39256.88
LLmax	-0.4303748	0.3481791	-1.236	0.216	-1.112793	0.2520437
lnhorizn	1.96616	0.5264226	3.735	0.000	0.934391	2.99793
lnintrat	17.07531	0.519452	32.872	0.000	16.0572	18.09342
lnintarm	-0.1360532	0.7157139	-0.190	0.849	-1.538827	1.26672
rtdiff	-0.2154421	0.0943232	-2.284	0.022	-0.4003122	-0.0305719
armrtd	-0.387369	0.0811973	-4.771	0.000	-0.5465128	-0.2282253
logpirto	8.017487	1.330688	6.025	0.000	5.409387	10.62559
t	1.68325	0.4315526	3.900	0.000	0.837422	2.529077
tt	-0.0015414	0.0003297	-4.676	0.000	-0.0021876	-0.0008953
t6	-1.64595	0.4334736	-3.797	0.000	-2.495542	-0.7963572
year94	-0.2174146	0.1770172	-1.228	0.219	-0.564362	0.1295328
_0520	0.6936342	0.2480679	2.796	0.005	0.20743	1.179838
_0720	0.7155753	0.1618994	4.420	0.000	0.3982583	1.032892
_1920	0.3609579	0.30932	1.167	0.243	-0.2452981	0.9672139
_2080	1.390273	0.2486193	5.592	0.000	0.9029884	1.877558
_2160	1.283652	0.2199356	5.836	0.000	0.8525858	1.714717
_2680	1.370878	0.523243	2.620	0.009	0.3453405	2.396415
_2800	0.5341656	0.5404228	0.988	0.323	-0.5250436	1.593375
_3360	-0.016969	0.4235183	-0.040	0.968	-0.8470496	0.8131117
_4480	-0.5017584	0.2867328	-1.750	0.080	-1.063744	0.0602275
_4920	0.359664	0.5363248	0.671	0.502	-0.6915133	1.410841
_5000	0.4222484	0.360256	1.172	0.241	-0.2838404	1.128337
_5120	1.201586	0.2399834	5.007	0.000	0.7312272	1.671945
_5960	1.663333	0.5336148	3.117	0.002	0.6174672	2.709199
_6160	-0.11353	0.1904788	-0.596	0.551	-0.4868615	0.2598015
_6200	1.312242	0.2952215	4.445	0.000	0.7336183	1.890865
_6780	0.4300238	0.2652481	1.621	0.105	-0.089853	0.9499005
_6920	0.6442895	0.2436781	2.644	0.008	0.1666892	1.12189
_7040	1.909352	0.2541476	7.513	0.000	1.411232	2.407472
_8280	1.574099	0.5616462	2.803	0.005	0.4732924	2.674905
_8840			(dropped)			
_5720	-0.9168939	0.67007	-1.368	0.171	-2.230207	0.3964192
_cons	-62.44931	5.520568	-11.312	0.000	-73.26943	-51.6292

TABLE 10

Panel A

Parameter Estimates for Monthly Hazard Model of Claim Default in 22 MSA's - Basic Specification Plus Tract Characteristics and Race/Ethnicity of Borrower

Residual df	= 500064		No. of obs	= 500114
Pearson X2	= 650272.1		Deviance	= 7575.075
Dispersion	= 1.300378		Dispersion	= 0.0151482

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.5955557	0.243765	2.443	0.015	0.117785	1.073326
trthsp	-0.271588	0.3987784	-0.681	0.496	-1.053179	0.5100033
lntrtinc	-0.4671757	0.1979362	-2.360	0.018	-0.8551236	-0.0792278
black	0.1896849	0.1478877	1.283	0.200	-0.1001696	0.4795394
hisp	-0.0381071	0.1423371	-0.268	0.789	-0.3170827	0.2408684
unemprt	0.0569734	0.084632	0.673	0.501	-0.1089022	0.222849
borage	0.0017497	0.0049662	0.352	0.725	-0.0079839	0.0114832
loginc	-0.2379341	0.4461293	-0.533	0.594	-1.112331	0.6364632
RSVpmts	-0.1902868	0.0320071	-5.945	0.000	-0.2530196	-0.1275539
RSVpmt4	0.1905835	0.0334743	5.693	0.000	0.1249751	0.2561919
logfront	0.216413	0.4536393	0.477	0.633	-0.6727036	1.10553
lnbal	2.972926	0.7742163	3.840	0.000	1.45549	4.490362
lnhval	-2.709952	0.6426071	-4.217	0.000	-3.969439	-1.450466
condo	0.0913267	0.2459428	0.371	0.710	-0.3907124	0.5733658
HPrelPW	-0.8546971	0.4935022	-1.732	0.083	-1.821944	0.1125493
HPrelLL	-1.615782	0.9772055	-1.653	0.098	-3.531069	0.2995059
LLmin	1.821016	3.133741	0.581	0.561	-4.321004	7.963035
LLmax	0.955838	4.830897	0.198	0.843	-8.512547	10.42422
lnhorizn	1.220845	0.7753753	1.575	0.115	-0.2988628	2.740553
lnintrat	0.91694	0.5643182	1.625	0.104	-0.1891034	2.022983
lnintarm	0.6540723	0.9211372	0.710	0.478	-1.151323	2.459468
rtdiff	-0.1783983	0.1200939	-1.485	0.137	-0.4137781	0.0569815
armrtd	-0.0471334	0.0724807	-0.650	0.516	-0.189193	0.0949262
logpirto	1.093852	1.379453	0.793	0.428	-1.609827	3.79753
t	0.3999858	0.0937371	4.267	0.000	0.2162644	0.5837072
tt	-0.0009012	0.0004051	-2.225	0.026	-0.0016951	-0.0001073
t6	-0.3377113	0.1019235	-3.313	0.001	-0.5374777	-0.137945
year94	-0.0324385	0.2158246	-0.150	0.881	-0.4554468	0.3905699
_0520	0.0212374	0.347807	0.061	0.951	-0.6604519	0.7029267
_0720	-0.0517167	0.2543022	-0.203	0.839	-0.5501398	0.4467064
_1920	0.2249939	0.4086517	0.551	0.582	-0.5759487	1.025937
_2080	-0.5068536	0.4525264	-1.120	0.263	-1.393789	0.3800818
_2160	-0.3327873	0.330346	-1.007	0.314	-0.9802536	0.314679
_2680	0.301645	0.6212023	0.486	0.627	-0.9158893	1.519179
_2800	0.1847465	0.6078403	0.304	0.761	-1.006599	1.376092
_3360	0.3734532	0.4489584	0.832	0.406	-0.5064892	1.253396
_4480	0.6254592	0.3878219	1.613	0.107	-0.1346579	1.385576
_4920	-0.4127382	0.5545711	-0.744	0.457	-1.499677	0.6742011
_5000	-0.0278808	0.4467982	-0.062	0.950	-0.9035893	0.8478276
_5120	-0.574388	0.3958061	-1.451	0.147	-1.350154	0.2013777
_5960	0.7569511	0.6117988	1.237	0.216	-0.4421524	1.956055
_6160	-0.3102372	0.2515999	-1.233	0.218	-0.803364	0.1828897
_6200	0.4346705	0.4008558	1.084	0.278	-0.3509925	1.220333
_6780	0.8733491	0.3672407	2.378	0.017	0.1535706	1.593128
_6920	0.2058472	0.3732388	0.552	0.581	-0.5256874	0.9373818
_7040	0.014858	0.3937021	0.038	0.970	-0.756784	0.7865
_8280	0.3659893	0.6415666	0.570	0.568	-0.8914581	1.623437
_8840	-1.651233	4.816698	-0.343	0.732	-11.09179	7.789321
_5720	0.2007969	0.5763436	0.348	0.728	-0.9288158	1.33041
_cons	-25.02706	6.417012	-3.900	0.000	-37.60417	-12.44995

TABLE 10

Panel B

Parameter Estimates for Monthly Hazard Model of Other Prepayment in 22 MSA's - Basic Specification Plus Tract Characteristics and Race/Ethnicity of Borrower

Residual df	= 500064	No. of obs	= 500114
Pearson X2	= 480794.8	Deviance	= 17359.42
Dispersion	= 0.9614665	Dispersion	= 0.0347144

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.2374829	0.2094331	1.134	0.257	-0.1729984	0.6479642
trthsp	0.7458497	0.3250017	2.295	0.022	0.1088581	1.382841
lntrtinc	0.3036913	0.1379485	2.201	0.028	0.0333172	0.5740654
black	-0.7636718	0.1341875	-5.691	0.000	-1.026674	-0.5006691
hisp	-0.5486226	0.1249237	-4.392	0.000	-0.7934684	-0.3037767
unemprt	0.0671718	0.0588646	1.141	0.254	-0.0482007	0.1825444
borage	-0.0146116	0.0032984	-4.430	0.000	-0.0210763	-0.0081469
loginc	2.34982	0.2697495	8.711	0.000	1.82112	2.878519
RSVpmts	-0.0163978	0.0173691	-0.944	0.345	-0.0504405	0.017645
RSVpmt4	0.0172626	0.0180292	0.957	0.338	-0.018074	0.0525992
logfront	2.023438	0.2786598	7.261	0.000	1.477275	2.569601
lnbal	-2.874489	0.3213474	-8.945	0.000	-3.504319	-2.24466
lnhval	1.704817	0.1936154	8.805	0.000	1.325338	2.084297
condo	0.4986071	0.1311629	3.801	0.000	0.2415325	0.7556817
HPrelPW	-0.2300744	0.2444708	-0.941	0.347	-0.7092283	0.2490795
HPrelLL	0.1102491	0.5251745	0.210	0.834	-0.919074	1.139572
LLmin	2.911749	1.474847	1.974	0.048	0.0211025	5.802396
LLmax	16.14687	1317.37	0.012	0.990	-2565.851	2598.144
lnhorizn	0.4059724	0.2183264	1.859	0.063	-0.0219395	0.8338844
lnintrat	3.429235	0.3892863	8.809	0.000	2.666248	4.192222
lnintarm	-0.0557232	0.6182527	-0.090	0.928	-1.267476	1.15603
rtdiff	0.3340583	0.077528	4.309	0.000	0.1821063	0.4860103
armrtd	0.0048162	0.0482886	0.100	0.921	-0.0898277	0.0994601
logpirto	4.553604	0.7332197	6.210	0.000	3.11652	5.990688
t	0.3522864	0.0752323	4.683	0.000	0.2048339	0.4997389
tt	-0.0022611	0.0002584	-8.750	0.000	-0.0027677	-0.0017546
t6	-0.1794138	0.0808675	-2.219	0.027	-0.3379113	-0.0209164
year94	0.7304665	0.1323359	5.520	0.000	0.4710929	0.9898401
_0520	-0.0566677	0.1970241	-0.288	0.774	-0.4428279	0.3294925
_0720	-0.8951301	0.1710224	-5.234	0.000	-1.230328	-0.5599324
_1920	-0.8235096	0.2603886	-3.163	0.002	-1.333862	-0.3131572
_2080	0.7870606	0.1895005	4.153	0.000	0.4156464	1.158475
_2160	0.2043439	0.1631845	1.252	0.210	-0.1154919	0.5241796
_2680	-0.3507803	0.3771644	-0.930	0.352	-1.090009	0.3884485
_2800	-0.5406417	0.3761632	-1.437	0.151	-1.277908	0.1966246
_3360	-0.6836164	0.3081603	-2.218	0.027	-1.2876	-0.0796333
_4480	-1.803446	0.3364591	-5.360	0.000	-2.462893	-1.143998
_4920	-0.2903188	0.3585861	-0.810	0.418	-0.9931346	0.412497
_5000	-0.3329724	0.2842679	-1.171	0.241	-0.8901273	0.2241824
_5120	0.0973529	0.2043302	0.476	0.634	-0.3031269	0.4978327
_5960	-1.274122	0.4795217	-2.657	0.008	-2.213967	-0.3342762
_6160	-1.094876	0.1785931	-6.131	0.000	-1.444913	-0.7448403
_6200	0.194886	0.233328	0.835	0.404	-0.2624285	0.6522005
_6780	-1.266727	0.289755	-4.372	0.000	-1.834636	-0.6988178
_6920	-1.490569	0.4432014	-3.363	0.001	-2.359228	-0.6219102
_7040	0.1972339	0.2128775	0.927	0.354	-0.2199984	0.6144663
_8280	-0.2212028	0.4070037	-0.543	0.587	-1.018915	0.5765097
_8840	-16.86284	1317.37	-0.013	0.990	-2598.86	2565.135
_5720	-0.5317838	0.3643002	-1.460	0.144	-1.245799	0.1822315
_cons	-19.9292	3.00344	-6.635	0.000	-25.81583	-14.04256

TABLE 10

Panel C

Parameter Estimates for Monthly Hazard Model of FHA Refinance in 22 MSA's - Basic Specification Plus Tract Characteristics and Race/Ethnicity of Borrower

Residual df	= 500065	No. of obs	= 500114
Pearson X2	= 421479.9	Deviance	= 13388.48
Dispersion	= 0.8428502	Dispersion	= 0.0267735

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.2398149	0.2052965	1.168	0.243	-0.1625588	0.6421886
trthsp	0.2709845	0.3736948	0.725	0.468	-0.4614439	1.003413
lntrtinc	0.0281573	0.1418439	0.199	0.843	-0.2498516	0.3061663
black	-0.0684499	0.1107585	-0.618	0.537	-0.2855326	0.1486327
hisp	-0.5380828	0.1303006	-4.130	0.000	-0.7934672	-0.2826983
unemprt	-0.0299483	0.0601468	-0.498	0.619	-0.1478339	0.0879373
borage	-0.0233136	0.0038542	-6.049	0.000	-0.0308676	-0.0157595
loginc	2.424832	0.3054209	7.939	0.000	1.826218	3.023446
RSVpmts	0.0613372	0.0188685	3.251	0.001	0.0243557	0.0983188
RSVpmt4	-0.0730546	0.0205664	-3.552	0.000	-0.113364	-0.0327451
logfront	2.505006	0.3177205	7.884	0.000	1.882285	3.127726
lnbal	1.009377	0.5873929	1.718	0.086	-0.141892	2.160646
lnhval	-0.3646197	0.4937714	-0.738	0.460	-1.332394	0.6031545
condo	-18.55467	1368.454	-0.014	0.989	-2700.675	2663.565
HPrelPW	-0.5517105	0.2934265	-1.880	0.060	-1.126816	0.0233949
HPrelLL	-1.396364	0.7109336	-1.964	0.050	-2.789768	-0.0029593
LLmin	-18.10051	19729.97	-0.001	0.999	-38688.12	38651.92
LLmax	-0.5374196	0.3431633	-1.566	0.117	-1.210007	0.1351681
lnhorizn	1.906158	0.5261183	3.623	0.000	0.874985	2.937331
lnintrat	17.04473	0.518867	32.850	0.000	16.02777	18.06169
lnintarm	0.0034833	0.7164741	0.005	0.996	-1.40078	1.407747
rtdiff	-0.2185087	0.0943132	-2.317	0.021	-0.4033592	-0.0336582
armrtd	-0.3994383	0.0813488	-4.910	0.000	-0.558879	-0.2399975
logpirto	7.930677	1.329951	5.963	0.000	5.324021	10.53733
t	1.684493	0.43169	3.902	0.000	0.8383964	2.53059
tt	-0.00154	0.0003297	-4.670	0.000	-0.0021863	-0.0008937
t6	-1.647443	0.4336112	-3.799	0.000	-2.497305	-0.7975805
year94	-0.2165548	0.1771212	-1.223	0.221	-0.563706	0.1305963
_0520	0.7479188	0.2428061	3.080	0.002	0.2720276	1.22381
_0720	0.7110855	0.1615109	4.403	0.000	0.3945298	1.027641
_1920	0.397672	0.3043642	1.307	0.191	-0.1988708	0.9942148
_2080	1.411776	0.2432869	5.803	0.000	0.9349421	1.888609
_2160	1.350505	0.216592	6.235	0.000	0.9259928	1.775018
_2680	1.334881	0.5164564	2.585	0.010	0.3226448	2.347117
_2800	0.5270759	0.5382504	0.979	0.327	-0.5278756	1.582027
_3360	0.0369309	0.4192358	0.088	0.930	-0.7847562	0.858618
_4480	-0.4197089	0.2829142	-1.484	0.138	-0.9742105	0.1347927
_4920	0.3451971	0.5340361	0.646	0.518	-0.7014944	1.391889
_5000	0.4665935	0.3574499	1.305	0.192	-0.2339955	1.167182
_5120	1.201887	0.2379517	5.051	0.000	0.7355107	1.668264
_5960	1.703393	0.5278744	3.227	0.001	0.6687783	2.738008
_6160	-0.0952356	0.1892531	-0.503	0.615	-0.4661649	0.2756938
_6200	1.318433	0.2882286	4.574	0.000	0.7535153	1.88335
_6780	0.4878517	0.2575658	1.894	0.058	-0.016968	0.9926715
_6920	0.6370845	0.2395469	2.660	0.008	0.1675813	1.106588
_7040	1.950756	0.2524322	7.728	0.000	1.455998	2.445514
_8280	1.588438	0.55903	2.841	0.004	0.4927594	2.684117
_8840			(dropped)			
_5720	-0.9177455	0.6656882	-1.379	0.168	-2.22247	0.3869795
_cons	-64.41133	5.430633	-11.861	0.000	-75.05518	-53.76749

TABLE 11

Panel A

Parameter Estimates for Monthly Hazard Model of Claim Default in 22 MSA's -
Basic Specification Plus Tract Characteristics, Race/Ethnicity of Borrower, and FICO Score

Residual df	= 500062	No. of obs	= 500114
Pearson X2	= 650641.2	Deviance	= 7434.683
Dispersion	= 1.301121	Dispersion	= 0.0148675

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
fico	-0.0093664	0.0007866	-11.907	0.000	-0.0109082	-0.0078246
NOfico	-6.039591	0.5281089	-11.436	0.000	-7.074666	-5.004517
trtblk	0.4438229	0.2423336	1.831	0.067	-0.0311422	0.918788
trthsp	-0.2611412	0.3982575	-0.656	0.512	-1.041712	0.5194291
lntrtinc	-0.4836739	0.1985074	-2.437	0.015	-0.8727414	-0.0946065
unemprt	0.0577455	0.0848629	0.680	0.496	-0.1085827	0.2240738
black	-0.0036598	0.146678	-0.025	0.980	-0.2911435	0.2838239
hisp	-0.1106789	0.1425163	-0.777	0.437	-0.3900057	0.1686478
borage	0.0049081	0.0050206	0.978	0.328	-0.0049321	0.0147484
loginc	-0.2192924	0.4467723	-0.491	0.624	-1.09495	0.6563652
RSVpmts	-0.1499388	0.0321112	-4.669	0.000	-0.2128756	-0.087002
RSVpmt4	0.1510139	0.0336482	4.488	0.000	0.0850647	0.2169632
logfront	0.3133854	0.4547425	0.689	0.491	-0.5778935	1.204664
lnbal	2.999894	0.7799195	3.846	0.000	1.47128	4.528508
lnhval	-2.717988	0.6445697	-4.217	0.000	-3.981321	-1.454654
condo	0.0872096	0.2464577	0.354	0.723	-0.3958386	0.5702578
HPrelPW	-0.7829595	0.4939199	-1.585	0.113	-1.751025	0.1851057
HPrelLL	-1.542308	0.9858488	-1.564	0.118	-3.474536	0.3899202
LLmin	1.850002	3.135374	0.590	0.555	-4.295218	7.995221
LLmax	0.8260135	4.830061	0.171	0.864	-8.640732	10.29276
lnhorizn	1.125933	0.7756762	1.452	0.147	-0.3943647	2.64623
lnintrat	0.8616751	0.5796384	1.487	0.137	-0.2743953	1.997745
lnintarm	0.6694889	0.9158931	0.731	0.465	-1.125628	2.464606
rtdiff	-0.1621532	0.1249481	-1.298	0.194	-0.4070469	0.0827406
armrtd	-0.0509729	0.0726861	-0.701	0.483	-0.1934351	0.0914893
logpirto	1.037376	1.380409	0.751	0.452	-1.668176	3.742927
t	0.4015552	0.0939577	4.274	0.000	0.2174014	0.585709
tt	-0.0009346	0.0004047	-2.309	0.021	-0.0017279	-0.0001413
t6	-0.3361084	0.1020529	-3.293	0.001	-0.5361283	-0.1360884
year94	-0.1110722	0.2303603	-0.482	0.630	-0.5625701	0.3404257
_0520	0.0150285	0.3499372	0.043	0.966	-0.6708358	0.7008928
_0720	-0.0058125	0.2544555	-0.023	0.982	-0.5045362	0.4929111
_1920	0.3277827	0.4090263	0.801	0.423	-0.473894	1.129459
_2080	-0.3838246	0.4524784	-0.848	0.396	-1.270666	0.5030168
_2160	-0.3348094	0.3329866	-1.005	0.315	-0.9874512	0.3178323
_2680	0.3163191	0.6260984	0.505	0.613	-0.9108111	1.543449
_2800	0.3041969	0.6090437	0.499	0.617	-0.8895068	1.497901
_3360	0.3639054	0.4497783	0.809	0.418	-0.5176438	1.245455
_4480	0.7310723	0.3898225	1.875	0.061	-0.0329657	1.49511
_4920	-0.3550503	0.5589514	-0.635	0.525	-1.450575	0.7404743
_5000	0.0467941	0.4459714	0.105	0.916	-0.8272938	0.9208821
_5120	-0.4544982	0.3960139	-1.148	0.251	-1.230671	0.3216748
_5960	0.6794434	0.6161609	1.103	0.270	-0.5282098	1.887097
_6160	-0.3155553	0.2526275	-1.249	0.212	-0.810696	0.1795854
_6200	0.6296479	0.4035708	1.560	0.119	-0.1613364	1.420632
_6780	0.9767619	0.3672452	2.660	0.008	0.2569745	1.696549
_6920	0.4396953	0.3747168	1.173	0.241	-0.2947361	1.174127
_7040	0.0560153	0.3945806	0.142	0.887	-0.7173485	0.829379
_8280	0.3786382	0.6524971	0.580	0.562	-0.9002326	1.657509
_8840	-1.349826	4.814802	-0.280	0.779	-10.78666	8.087012
_5720	0.3125274	0.5752203	0.543	0.587	-0.8148836	1.439938
_cons	-19.08584	6.425608	-2.970	0.003	-31.6798	-6.491875

TABLE 11

Panel B

Parameter Estimates for Monthly Hazard Model of Other Prepayment in 22 MSA's - Basic Specification Plus Tract Characteristics, Race/Ethnicity of Borrower, and FICO Score

Residual df	= 500062	No. of obs	= 500114
Pearson X2	= 481859.1	Deviance	= 17313.6
Dispersion	= 0.9635988	Dispersion	= 0.0346229

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
fico	0.0034788	0.0005237	6.643	0.000	0.0024525	0.0045052
NOfico	2.452235	0.3766707	6.510	0.000	1.713974	3.190496
trtblk	0.2991414	0.2110535	1.417	0.156	-0.1145159	0.7127986
trthsp	0.7525682	0.3243081	2.321	0.020	0.116936	1.388201
lntrtinc	0.2848318	0.1374184	2.073	0.038	0.0154967	0.5541669
unemprt	0.0644469	0.0589381	1.093	0.274	-0.0510695	0.1799634
black	-0.6868089	0.1359292	-5.053	0.000	-0.9532252	-0.4203925
hisp	-0.5046386	0.1253913	-4.025	0.000	-0.7504011	-0.2588762
borage	-0.0150722	0.0032921	-4.578	0.000	-0.0215245	-0.0086198
loginc	2.364927	0.271524	8.710	0.000	1.83275	2.897104
RSVpmts	-0.0350405	0.017621	-1.989	0.047	-0.0695771	-0.0005039
RSVpmt4	0.035511	0.0182794	1.943	0.052	-0.000316	0.071338
logfront	2.001866	0.2806217	7.134	0.000	1.451857	2.551874
lnbal	-2.810864	0.3233836	-8.692	0.000	-3.444684	-2.177044
lnhval	1.678834	0.197468	8.502	0.000	1.291804	2.065865
condo	0.4713743	0.1313046	3.590	0.000	0.214022	0.7287266
HPrelPW	-0.2933825	0.2461113	-1.192	0.233	-0.7757519	0.1889868
HPrelLL	0.0762983	0.529948	0.144	0.886	-0.9623807	1.114977
LLmin	2.843813	1.475897	1.927	0.054	-0.0488917	5.736518
LLmax	16.03377	1318.824	0.012	0.990	-2568.813	2600.881
lnhorizn	0.4494441	0.2189168	2.053	0.040	0.020375	0.8785132
lnintrat	3.485342	0.3937893	8.851	0.000	2.713529	4.257154
lnintarm	-0.0260295	0.6183337	-0.042	0.966	-1.237941	1.185882
rtdiff	0.3108356	0.0795305	3.908	0.000	0.1549587	0.4667125
armrtd	0.006174	0.048325	0.128	0.898	-0.0885413	0.1008893
logpirto	4.60217	0.7334979	6.274	0.000	3.164541	6.0398
t	0.3494272	0.0752532	4.643	0.000	0.2019337	0.4969207
tt	-0.0022529	0.0002583	-8.724	0.000	-0.0027591	-0.0017468
t6	-0.1785113	0.0808335	-2.208	0.027	-0.336942	-0.0200806
year94	0.7225418	0.1378865	5.240	0.000	0.4522891	0.9927944
_0520	-0.0126223	0.1974268	-0.064	0.949	-0.3995717	0.374327
_0720	-0.9129647	0.1711639	-5.334	0.000	-1.24844	-0.5774896
_1920	-0.8131204	0.261007	-3.115	0.002	-1.324685	-0.301556
_2080	0.7735709	0.1903842	4.063	0.000	0.4004247	1.146717
_2160	0.211496	0.1635606	1.293	0.196	-0.109077	0.5320689
_2680	-0.3527683	0.3783412	-0.932	0.351	-1.094303	0.3887669
_2800	-0.5637531	0.378345	-1.490	0.136	-1.305296	0.1777893
_3360	-0.616245	0.3088433	-1.995	0.046	-1.221567	-0.0109233
_4480	-1.850855	0.3368988	-5.494	0.000	-2.511164	-1.190545
_4920	-0.3058779	0.3601454	-0.849	0.396	-1.01175	0.399994
_5000	-0.344445	0.2840031	-1.213	0.225	-0.9010808	0.2121909
_5120	0.0719278	0.204936	0.351	0.726	-0.3297393	0.4735949
_5960	-1.296823	0.4819568	-2.691	0.007	-2.241441	-0.352205
_6160	-1.089923	0.1785534	-6.104	0.000	-1.439881	-0.7399648
_6200	0.1755668	0.2338048	0.751	0.453	-0.2826821	0.6338158
_6780	-1.30038	0.2899423	-4.485	0.000	-1.868657	-0.7321038
_6920	-1.563557	0.4433314	-3.527	0.000	-2.43247	-0.6946429
_7040	0.2370426	0.2136332	1.110	0.267	-0.1816707	0.6557559
_8280	-0.211525	0.4084704	-0.518	0.605	-1.012112	0.5890622
_8840	-16.85192	1318.824	-0.013	0.990	-2601.699	2567.995
_5720	-0.58105	0.3668755	-1.584	0.113	-1.300113	0.1380127
_cons	-22.79246	3.049917	-7.473	0.000	-28.77019	-16.81473

TABLE 11

Panel C

Parameter Estimates for Monthly Hazard Model of FHA Refinance in 22 MSA's - Basic Specification Plus Tract Characteristics, Race/Ethnicity of Borrower, and FICO Score

Residual df	= 500063	No. of obs	= 500114
Pearson X2	= 428595.1	Deviance	= 13382.39
Dispersion	= 0.8570822	Dispersion	= 0.0267614

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
fico	0.0011496	0.0005237	2.195	0.028	0.0001231	0.0021761
NOfico	0.6304651	0.3883335	1.624	0.104	-0.1306547	1.391585
trtblk	0.2500806	0.2054654	1.217	0.224	-0.1526243	0.6527855
trthsp	0.2946126	0.3740229	0.788	0.431	-0.4384589	1.027684
lntrtinc	0.0291703	0.1416515	0.206	0.837	-0.2484617	0.3068022
unemprt	-0.0271489	0.0601874	-0.451	0.652	-0.145114	0.0908163
black	-0.0303591	0.1120751	-0.271	0.786	-0.2500222	0.1893041
hisp	-0.5242221	0.1304756	-4.018	0.000	-0.7799496	-0.2684945
borage	-0.0232442	0.0038494	-6.038	0.000	-0.0307888	-0.0156996
loginc	2.438111	0.3059654	7.969	0.000	1.83843	3.037792
RSVpmts	0.0547877	0.0191018	2.868	0.004	0.0173488	0.0922265
RSVpmt4	-0.0667029	0.0207772	-3.210	0.001	-0.1074254	-0.0259804
logfront	2.509406	0.3182843	7.884	0.000	1.88558	3.133232
lnbal	0.9827744	0.5897598	1.666	0.096	-0.1731336	2.138682
lnhval	-0.3423566	0.4961017	-0.690	0.490	-1.314698	0.6299849
condo	-18.57097	1367.189	-0.014	0.989	-2698.213	2661.071
HPrelPW	-0.5729159	0.2941518	-1.948	0.051	-1.149443	0.003611
HPrelLL	-1.439625	0.7111122	-2.024	0.043	-2.83338	-0.0458711
LLmin	-18.13981	19564.32	-0.001	0.999	-38363.51	38327.23
LLmax	-0.5626698	0.3436377	-1.637	0.102	-1.236187	0.1108477
lnhorizn	1.927572	0.5265017	3.661	0.000	0.8956479	2.959496
lnintrat	17.04264	0.5199396	32.778	0.000	16.02358	18.06171
lnintarm	0.0398024	0.7176877	0.055	0.956	-1.36684	1.446444
rtdiff	-0.2133046	0.0948829	-2.248	0.025	-0.3992717	-0.0273375
armrtd	-0.4006534	0.0814249	-4.921	0.000	-0.5602433	-0.2410634
logpirto	7.901943	1.330476	5.939	0.000	5.294258	10.50963
t	1.682951	0.4314709	3.900	0.000	0.8372837	2.528619
tt	-0.0015414	0.0003305	-4.664	0.000	-0.0021892	-0.0008937
t6	-1.645206	0.4333976	-3.796	0.000	-2.49465	-0.7957622
year94	-0.1942334	0.1777304	-1.093	0.274	-0.5425785	0.1541118
_0520	0.7634083	0.243105	3.140	0.002	0.2869313	1.239885
_0720	0.7148972	0.16194	4.415	0.000	0.3975006	1.032294
_1920	0.4054092	0.3047349	1.330	0.183	-0.1918602	1.002679
_2080	1.413806	0.2437695	5.800	0.000	0.9360266	1.891586
_2160	1.359884	0.2169684	6.268	0.000	0.9346332	1.785134
_2680	1.353797	0.5157155	2.625	0.009	0.3430129	2.364581
_2800	0.5359077	0.5378464	0.996	0.319	-0.5182519	1.590067
_3360	0.0733927	0.4197162	0.175	0.861	-0.749236	0.8960214
_4480	-0.4441263	0.2833776	-1.567	0.117	-0.9995361	0.1112836
_4920	0.3635464	0.5340425	0.681	0.496	-0.6831576	1.41025
_5000	0.4656795	0.3582149	1.300	0.194	-0.2364089	1.167768
_5120	1.196487	0.2384238	5.018	0.000	0.7291851	1.663789
_5960	1.72478	0.5280768	3.266	0.001	0.6897688	2.759792
_6160	-0.0896149	0.1893225	-0.473	0.636	-0.4606802	0.2814504
_6200	1.321194	0.2887967	4.575	0.000	0.7551625	1.887225
_6780	0.472351	0.2576489	1.833	0.067	-0.0326315	0.9773335
_6920	0.6051587	0.2399874	2.522	0.012	0.1347921	1.075525
_7040	1.961621	0.2528367	7.758	0.000	1.46607	2.457171
_8280	1.617666	0.559278	2.892	0.004	0.5215014	2.713831
_8840			(dropped)			
_5720	-0.9120996	0.6658038	-1.370	0.171	-2.217051	0.3928518
_cons	-65.31051	5.45418	-11.974	0.000	-76.00051	-54.62051

TABLE 12

Panel A

Parameter Estimates for Monthly Hazard Model of Claim Default in 22 MSA's - Tract Characteristics Plus Duration, Year, and MSA Indicators

Residual df	= 500085	No. of obs	= 500114
Pearson X2	= 489652.8	Deviance	= 7680.458
Dispersion	= 0.9791391	Dispersion	= 0.0153583

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	0.9180811	0.202655	4.530	0.000	0.5208846	1.315277
trthsp	-0.1386288	0.365008	-0.380	0.704	-0.8540315	0.5767738
lntrtinc	-0.6234497	0.1802162	-3.459	0.001	-0.976667	-0.2702325
t	0.4311828	0.0925656	4.658	0.000	0.2497575	0.6126081
tt	-0.0007938	0.0003857	-2.058	0.040	-0.0015499	-0.0000378
t6	-0.3704001	0.100671	-3.679	0.000	-0.5677117	-0.1730885
year94	0.1847877	0.1090435	1.695	0.090	-0.0289337	0.398509
_0520	-0.3602348	0.2713947	-1.327	0.184	-0.8921586	0.171689
_0720	0.0146645	0.2388196	0.061	0.951	-0.4534133	0.4827423
_1920	-0.1888958	0.2834174	-0.666	0.505	-0.7443837	0.3665921
_2080	-1.098055	0.3754197	-2.925	0.003	-1.833864	-0.3622461
_2160	-0.3521706	0.2678623	-1.315	0.189	-0.8771712	0.1728299
_2680	-0.0046219	0.3433989	-0.013	0.989	-0.6776713	0.6684275
_2800	-0.1418488	0.4024561	-0.352	0.724	-0.9306484	0.6469507
_3360	0.1037819	0.3283942	0.316	0.752	-0.539859	0.7474228
_4480	1.345964	0.2056845	6.544	0.000	0.9428303	1.749099
_4920	-0.7063882	0.3540994	-1.995	0.046	-1.40041	-0.0123662
_5000	-0.0164581	0.3814562	-0.043	0.966	-0.7640985	0.7311822
_5120	-0.9002294	0.2871132	-3.135	0.002	-1.462961	-0.3374979
_5960	0.3933426	0.3005091	1.309	0.191	-0.1956444	0.9823297
_6160	-0.0014475	0.2322325	-0.006	0.995	-0.4566148	0.4537198
_6200	-0.0470049	0.2509865	-0.187	0.851	-0.5389295	0.4449196
_6780	1.44256	0.1871251	7.709	0.000	1.075802	1.809319
_6920	0.5825189	0.3346366	1.741	0.082	-0.0733567	1.238395
_7040	-0.3079015	0.2998868	-1.027	0.305	-0.8956689	0.2798659
_8280	-0.0878459	0.337871	-0.260	0.795	-0.750061	0.5743691
_8840	0.1089989	0.2273964	0.479	0.632	-0.3366899	0.5546878
_5720	-0.1224637	0.3394723	-0.361	0.718	-0.7878172	0.5428898
_cons	-3.52626	2.017719	-1.748	0.081	-7.480916	0.4283965

TABLE 12

Panel B

Parameter Estimates for Monthly Hazard Model of Other Prepayment in 22 MSA's - Tract Characteristics Plus Duration, Year, and MSA Indicators

Residual df	= 500085	No. of obs	= 500114
Pearson X2	= 523673.8	Deviance	= 17865.79
Dispersion	= 1.04717	Dispersion	= 0.0357255

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	-0.6478197	0.1761797	-3.677	0.000	-0.9931255	-0.3025139
trthsp	0.1392481	0.2924752	0.476	0.634	-0.4339928	0.712489
lntrtinc	0.658798	0.1321731	4.984	0.000	0.3997435	0.9178526
t	0.4950145	0.0765442	6.467	0.000	0.3449906	0.6450384
tt	-0.0007767	0.0002311	-3.361	0.001	-0.0012296	-0.0003238
t6	-0.4120987	0.0811485	-5.078	0.000	-0.5711467	-0.2530506
year94	0.1572061	0.0732921	2.145	0.032	0.0135563	0.3008559
_0520	-0.5817029	0.1432058	-4.062	0.000	-0.8623812	-0.3010247
_0720	-1.063479	0.1642752	-6.474	0.000	-1.385452	-0.7415052
_1920	-1.333231	0.1948386	-6.843	0.000	-1.715107	-0.9513544
_2080	0.462878	0.0984959	4.699	0.000	0.2698297	0.6559263
_2160	-0.0426046	0.1236096	-0.345	0.730	-0.284875	0.1996657
_2680	-0.4516201	0.1917453	-2.355	0.019	-0.827434	-0.0758062
_2800	-0.7008556	0.2257831	-3.104	0.002	-1.143382	-0.2583289
_3360	-1.276109	0.2562045	-4.981	0.000	-1.778261	-0.7739572
_4480	-1.51474	0.2647636	-5.721	0.000	-2.033667	-0.9958129
_4920	-0.5178016	0.1758555	-2.944	0.003	-0.862472	-0.1731312
_5000	-0.3997876	0.235676	-1.696	0.090	-0.8617041	0.0621289
_5120	-0.432196	0.1081468	-3.996	0.000	-0.6441598	-0.2202321
_5960	-1.576747	0.346545	-4.550	0.000	-2.255963	-0.8975312
_6160	-1.257878	0.1717124	-7.325	0.000	-1.594428	-0.9213281
_6200	-0.4864342	0.1292449	-3.764	0.000	-0.7397495	-0.2331189
_6780	-1.255032	0.2004573	-6.261	0.000	-1.647921	-0.8621426
_6920	-1.661895	0.4318653	-3.848	0.000	-2.508335	-0.8154542
_7040	-0.421887	0.1466748	-2.876	0.004	-0.7093643	-0.1344096
_8280	-0.5540287	0.2019504	-2.743	0.006	-0.9498443	-0.1582131
_8840	-0.7651056	0.1397157	-5.476	0.000	-1.038943	-0.4912678
_5720	-0.5534437	0.2031061	-2.725	0.006	-0.9515243	-0.1553632
_cons	-16.09036	1.500194	-10.726	0.000	-19.03068	-13.15003

TABLE 12

Panel C

Parameter Estimates for Monthly Hazard Model of FHA Refinance in 22 MSA's - Tract Characteristics Plus Duration, Year, and MSA Indicators

Residual df	= 500085	No. of obs	= 500114
Pearson X2	= 539307.8	Deviance	= 16113.03
Dispersion	= 1.078432	Dispersion	= 0.0322206

Bernoulli distribution, cloglog link

	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
trtblk	-0.1256242	0.1740538	-0.722	0.470	-0.4667634	0.2155149
trthsp	-0.0795101	0.3401618	-0.234	0.815	-0.746215	0.5871948
lntrtinc	0.6413137	0.1367345	4.690	0.000	0.3733189	0.9093084
t	2.765458	0.467544	5.915	0.000	1.849088	3.681827
tt	-0.0022547	0.0003371	-6.688	0.000	-0.0029154	-0.001594
t6	-2.698894	0.469115	-5.753	0.000	-3.618342	-1.779445
year94	0.2627704	0.0626833	4.192	0.000	0.1399133	0.3856274
_0520	0.1554179	0.1711321	0.908	0.364	-0.1799949	0.4908307
_0720	0.6714588	0.1477767	4.544	0.000	0.3818218	0.9610957
_1920	-0.3181148	0.2066294	-1.540	0.124	-0.723101	0.0868715
_2080	0.6366888	0.1469566	4.332	0.000	0.3486593	0.9247184
_2160	0.4349011	0.1641654	2.649	0.008	0.1131427	0.7566594
_2680	0.2966132	0.2201455	1.347	0.178	-0.134864	0.7280904
_2800	-0.4888771	0.3140368	-1.557	0.120	-1.104378	0.1266237
_3360	-0.9264244	0.3541535	-2.616	0.009	-1.620552	-0.2322963
_4480	0.3896063	0.1935067	2.013	0.044	0.0103401	0.7688725
_4920	-0.8626715	0.3155194	-2.734	0.006	-1.481078	-0.244265
_5000	-0.2148872	0.3194681	-0.673	0.501	-0.8410331	0.4112587
_5120	0.6024621	0.1357437	4.438	0.000	0.3364094	0.8685149
_5960	0.5447473	0.2194952	2.482	0.013	0.1145446	0.9749499
_6160	-0.0885852	0.1794124	-0.494	0.621	-0.440227	0.2630566
_6200	0.272757	0.1612719	1.691	0.091	-0.04333	0.5888441
_6780	0.7796764	0.1555473	5.012	0.000	0.4748093	1.084544
_6920	0.7430452	0.2187513	3.397	0.001	0.3143006	1.17179
_7040	0.899531	0.1534082	5.864	0.000	0.5988564	1.200206
_8280	0.0039265	0.2553567	0.015	0.988	-0.4965634	0.5044163
_8840	0.2612099	0.154689	1.689	0.091	-0.0419749	0.5643948
_5720	-1.55259	0.5073134	-3.060	0.002	-2.546906	-0.5582744
_cons	-29.48169	3.168101	-9.306	0.000	-35.69105	-23.27232

Table 13

Names and Definitions of Explanatory Variables in Regression Models

VARIABLE DESCRIPTION	NAME
Neighborhood Controls:	
Pct of tract population that is black (1990)	blkpct
Pct of tract population that is Hispanic (1990)	hsppct
Median tract income (1990)	medinc
Contemporaneous Chicago MSA unemployment rate	unemmsa unemsa
Tract unemployment rate (1990)	tractune
Characteristics of Borrowers in Quarter:	
Log of average income of borrowers	loginc
Log of average assets among borrowers having positive assets	logass
Fraction of borrowers with no assets	ass0rt
Market Characteristics:	
Contemporaneous market rate on 30-year fixed-rate mortgages	FRM30
Log of contemporaneous house price index in Chicago MSA	loghindx lghind
Quarterly tract default rate (%) on homes originated in previous six years With lag of x quarters	defrt ldefx
Quarterly tract prepayment rate (%) on homes originated in previous six years With lag of x quarters	preprt lprepx
Log of average price of homes sold in tract for the quarter	logpric2 logpr2
Miscellaneous:	
Proportional change from last quarter in home sales in tract	sampchg
Time trend (number of quarters since arbitrary date in past)	amtq

NOTE: The abbreviation "S4" appearing before or after a variable name denotes the difference between the current value of the variable and the value 4 quarters earlier. The abbreviation "Lx," where x is an integer, appearing before or after a variable name denotes a lag of x quarters.

TABLE 14

Panel A

Least Squares Regression Estimates - Log of House Prices in Chicago MSA - Four Lags of Default and Prepayment Rates

Number of obs	= 2774
F(22, 2751)	= 382.61
Prob > F	= 0
R-squared	= 0.7537
Adj R-squared	= 0.7517
Root MSE	= .10714

Source	SS	df	MS
Model	96.621537	22	4.39188804
Residual	31.5778532	2751	0.011478682
Total	128.19939	2773	0.046231298

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sampchg	-0.0014323	0.0016161	-0.886	0.376	-0.0046011	0.0017365
logpric2						
L4	0.734203	0.0116399	63.076	0.000	0.7113792	0.7570268
defrt						
L1	-0.0171955	0.0046457	-3.701	0.000	-0.0263049	-0.008086
L2	-0.0051137	0.0047073	-1.086	0.277	-0.014344	0.0041165
L3	-0.0107336	0.0044494	-2.412	0.016	-0.019458	-0.0020091
L4	-0.0044706	0.0045165	-0.990	0.322	-0.0133268	0.0043856
preprt						
--	0.0028565	0.0013986	2.042	0.041	0.0001141	0.005599
L1	0.0015129	0.0011428	1.324	0.186	-0.0007279	0.0037537
L2	-0.0003772	0.0011783	-0.320	0.749	-0.0026875	0.0019332
L3	0.0014639	0.001172	1.249	0.212	-0.0008341	0.003762
L4	0.0000442	0.0012153	0.036	0.971	-0.0023387	0.0024271
FRM30						
S4	0.0061169	0.0031378	1.949	0.051	-0.0000359	0.0122696
unemmsa						
S4	0.0342218	0.0056302	6.078	0.000	0.023182	0.0452616
tractune	-0.2917828	0.1135503	-2.570	0.010	-0.5144353	-0.0691303
amtq	0.0037612	0.0007008	5.367	0.000	0.002387	0.0051355
loginc						
S4	0.1207035	0.0106253	11.360	0.000	0.0998692	0.1415379
logass						
S4	0.0151886	0.0040053	3.792	0.000	0.0073348	0.0230423
ass0rt						
S4	-0.1379532	0.0145478	-9.483	0.000	-0.1664788	-0.1094275
loghindx						
S4	1.93764	0.4623898	4.190	0.000	1.030973	2.844306
blkpct	-0.0690825	0.0143621	-4.810	0.000	-0.097244	-0.040921
hsppct	0.0285718	0.0192403	1.485	0.138	-0.0091551	0.0662986
medinc	-0.0160881	0.0147011	-1.094	0.274	-0.0449144	0.0127382
_cons	2.518672	0.1529202	16.470	0.000	2.218822	2.818522

TABLE 14

Panel B

Least Squares Regression Estimates - Log of House Prices in Chicago MSA - Six Lags of Default and Prepayment Rates

Source	SS	df	MS
Model	96.749563	26	3.72113704
Residual	31.4498272	2747	0.01144879
Total	128.19939	2773	0.046231298

Number of obs	= 2774
F(26, 2747)	= 325.02
Prob > F	= 0
R-squared	= 0.7547
Adj R-squared	= 0.7524
Root MSE	= .107

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sampchg	-0.0010381	0.001626	-0.638	0.523	-0.0042264	0.0021501
logpric2						
L4	0.7303189	0.0116842	62.505	0.000	0.7074081	0.7532297
defrt						
L1	-0.016402	0.0046471	-3.530	0.000	-0.0255142	-0.0072899
L2	-0.004111	0.0047218	-0.871	0.384	-0.0133697	0.0051476
L3	-0.0098683	0.0044578	-2.214	0.027	-0.0186092	-0.0011273
L4	-0.0037149	0.0045167	-0.822	0.411	-0.0125713	0.0051416
L5	-0.0039091	0.0046035	-0.849	0.396	-0.0129357	0.0051176
L6	-0.0084956	0.0046295	-1.835	0.067	-0.0175732	0.000582
preprt						
--	0.0027141	0.0013985	1.941	0.052	-0.0000281	0.0054563
L1	0.0014545	0.0011514	1.263	0.207	-0.0008033	0.0037122
L2	-0.0001002	0.0011896	-0.084	0.933	-0.0024329	0.0022324
L3	0.0010178	0.0011987	0.849	0.396	-0.0013326	0.0033682
L4	-0.0008517	0.0012637	-0.674	0.500	-0.0033295	0.0016261
L5	0.0016325	0.0010792	1.513	0.130	-0.0004835	0.0037486
L6	0.0018848	0.0010589	1.780	0.075	-0.0001915	0.003961
FRM30						
S4	0.0091466	0.0034109	2.682	0.007	0.0024583	0.0158348
unemmsa						
S4	0.0368844	0.0058012	6.358	0.000	0.0255092	0.0482597
tractune	-0.2696	0.113751	-2.370	0.018	-0.4926461	-0.0465538
amtq	0.0046636	0.0007708	6.051	0.000	0.0031523	0.0061749
loginc						
S4	0.1214331	0.0106234	11.431	0.000	0.1006023	0.1422638
logass						
S4	0.0150363	0.0040128	3.747	0.000	0.0071678	0.0229048
ass0rt						
S4	-0.1274365	0.0150543	-8.465	0.000	-0.1569553	-0.0979177
loghindx						
S4	2.177436	0.4771148	4.564	0.000	1.241896	3.112976
blkpct	-0.0630873	0.014475	-4.358	0.000	-0.0914703	-0.0347044
hsppct	0.0275816	0.0192983	1.429	0.153	-0.010259	0.0654222
medinc	-0.0225406	0.0148196	-1.521	0.128	-0.0515993	0.006518
_cons	2.425001	0.1586043	15.290	0.000	2.114005	2.735996

TABLE 14

Panel C

Least Squares Regression Estimates - Log of House Prices in Chicago MSA - Eight Lags of Default and Prepayment Rates

Source	SS	df	MS
Model	96.8761583	30	3.22920528
Residual	31.3232318	2743	0.011419334
Total	128.19939	2773	0.046231298

Number of obs	= 2774
F(30, 2743)	= 282.78
Prob > F	= 0
R-squared	= 0.7557
Adj R-squared	= 0.753
Root MSE	= .10686

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sampchg	-0.0009049	0.0016251	-0.557	0.578	-0.0040915	0.0022818
logpric2						
L4	0.7260969	0.0117832	61.621	0.000	0.7029919	0.7492018
defrt						
L1	-0.0158533	0.004645	-3.413	0.001	-0.0249613	-0.0067454
L2	-0.0038696	0.004732	-0.818	0.414	-0.0131482	0.005409
L3	-0.0095382	0.0044628	-2.137	0.033	-0.0182889	-0.0007874
L4	-0.0039396	0.0045232	-0.871	0.384	-0.0128089	0.0049297
L5	-0.0037373	0.0046102	-0.811	0.418	-0.0127771	0.0053025
L6	-0.0077205	0.0046321	-1.667	0.096	-0.0168033	0.0013622
L7	-0.0023676	0.0046466	-0.510	0.610	-0.0114788	0.0067436
L8	0.0017248	0.0045531	0.379	0.705	-0.007203	0.0106525
preprt						
--	0.0030655	0.0014016	2.187	0.029	0.0003172	0.0058139
L1	0.0018415	0.0011561	1.593	0.111	-0.0004255	0.0041085
L2	0.0004885	0.0012018	0.406	0.684	-0.0018681	0.0028451
L3	0.0007493	0.0012018	0.623	0.533	-0.0016072	0.0031058
L4	-0.0011263	0.0012715	-0.886	0.376	-0.0036195	0.0013668
L5	0.0009321	0.0011007	0.847	0.397	-0.0012261	0.0030902
L6	0.0008491	0.0011124	0.763	0.445	-0.0013321	0.0030302
L7	0.0027901	0.0010318	2.704	0.007	0.0007669	0.0048133
L8	0.0011024	0.001034	1.066	0.286	-0.0009252	0.00313
FRM30						
S4	0.0134926	0.0036631	3.683	0.000	0.00631	0.0206752
unemmsa						
S4	0.0342333	0.0061659	5.552	0.000	0.0221429	0.0463236
tractune	-0.2630858	0.1144026	-2.300	0.022	-0.4874097	-0.0387619
amtq	0.005906	0.0008731	6.764	0.000	0.0041939	0.007618
loginc						
S4	0.1225708	0.0106173	11.544	0.000	0.101752	0.1433895
logass						
S4	0.0148685	0.0040115	3.707	0.000	0.0070027	0.0227343
ass0rt						
S4	-0.1247682	0.0150741	-8.277	0.000	-0.154326	-0.0952104
loghindx						
S4	1.911989	0.5054475	3.783	0.000	0.9208932	2.903086
blkpct	-0.0575322	0.0145971	-3.941	0.000	-0.0861545	-0.0289098
hsppct	0.0314775	0.0194037	1.622	0.105	-0.0065698	0.0695248
medinc	-0.0276772	0.0149082	-1.857	0.063	-0.0569095	0.0015552
_cons	2.294887	0.1636719	14.021	0.000	1.973954	2.61582

Table 15

Regression with Fixed Effects - Log of House Prices in Chicago MSA

Fixed-effects (within) regression				Number of obs = 2774
Group variable (i) : panel				Number of groups = 384
R-sq:	within =	0.3497	Obs per group:	min = 1
	between =	0.2316		avg = 7.2
	overall =	0.1454		max = 15
				F(22,2368) = 57.89
	corr(u_i, Xb) =	0.1361		Prob > F = 0.0000

	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
sampchg	-0.0013523	0.001352	-1	0.317	-0.0040035	0.001299
l4logpr2	0.022028	0.0186485	1.181	0.238	-0.0145412	0.0585971
ldef1	-0.0124811	0.003953	-3.157	0.002	-0.0202327	-0.0047295
ldef2	0.001335	0.0039433	0.339	0.735	-0.0063977	0.0090677
ldef3	-0.0035567	0.0039063	-0.911	0.363	-0.0112168	0.0041033
ldef4	-0.0007159	0.0038416	-0.186	0.852	-0.0082491	0.0068174
ldef5	-0.0030421	0.0038454	-0.791	0.429	-0.0105828	0.0044987
ldef6	-0.0027076	0.0038791	-0.698	0.485	-0.0103145	0.0048992
preprt	0.0010586	0.0011463	0.923	0.356	-0.0011893	0.0033065
lprep1	-0.0015861	0.0009317	-1.702	0.089	-0.0034131	0.0002409
lprep2	-0.0008535	0.0009367	-0.911	0.362	-0.0026904	0.0009834
lprep3	0.0003708	0.0009489	0.391	0.696	-0.0014899	0.0022315
lprep4	-0.0010335	0.0010016	-1.032	0.302	-0.0029976	0.0009306
lprep5	-0.0002009	0.0008576	-0.234	0.815	-0.0018826	0.0014808
lprep6	-0.0009648	0.0008468	-1.139	0.255	-0.0026254	0.0006958
s4FRM30	0.0037277	0.0026273	1.419	0.156	-0.0014243	0.0088797
s4unemsa	0.0152075	0.0046802	3.249	0.001	0.0060298	0.0243853
tractune	(dropped)					
amtq	0.0097528	0.0006322	15.426	0.00	0.008513	0.0109926
s4loginc	0.0504035	0.0085366	5.904	0.00	0.0336635	0.0671435
s4logass	0.0037088	0.0032229	1.151	0.25	-0.0026112	0.0100289
s4ass0rt	-0.0696236	0.0119896	-5.807	0.00	-0.0931347	-0.0461124
s4lghind	1.131011	0.3657636	3.092	0.002	0.4137609	1.848261
blkpct	(dropped)					
hsppct	(dropped)					
medinc	(dropped)					
_cons	9.821508	0.2110921	46.527	0.00	9.407563	10.23545

sigma_u	0.21533433
sigma_e	0.07814989
rho	0.88361589 (fraction of variance due to u_i)

F test that all u_i=0: F(383,2368) = 7.26 Prob > F = 0.0000

TABLE 16

Panel A

Least Squares Regression Estimates - Log of House Prices in Chicago MSA - Six Lags and Two Leads of Default and Prepayment Rates

Source	SS	df	MS
Model	87.6194505	30	2.92064835
Residual	28.6547913	2487	0.01152183
Total	116.274242	2517	0.046195567

Number of obs	= 2518
F(30, 2487)	= 253.49
Prob > F	= 0
R-squared	= 0.7536
Adj R-squared	= 0.7506
Root MSE	= .10734

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sampchg	-0.0000483	0.001667	-0.029	0.977	-0.0033171	0.0032206
defrt						
F1	-0.0076274	0.0049799	-1.532	0.126	-0.0173926	0.0021378
F2	-0.0041968	0.0051219	-0.819	0.413	-0.0142404	0.0058468
preprt						
F1	0.0026368	0.0017911	1.472	0.141	-0.0008753	0.0061489
F2	0.0044635	0.001811	2.465	0.014	0.0009123	0.0080147
logpric2						
L4	0.727116	0.0123212	59.014	0.000	0.7029552	0.7512768
defrt						
L1	-0.015237	0.0049685	-3.067	0.002	-0.0249799	-0.0054942
L2	-0.0057928	0.0049461	-1.171	0.242	-0.0154916	0.003906
L3	-0.0090551	0.0047455	-1.908	0.056	-0.0183607	0.0002504
L4	-0.0020521	0.0047895	-0.428	0.668	-0.011444	0.0073398
L5	-0.0038078	0.0048383	-0.787	0.431	-0.0132954	0.0056797
L6	-0.0087513	0.0050772	-1.724	0.085	-0.0187073	0.0012048
preprt						
--	0.0011374	0.0015071	0.755	0.451	-0.0018179	0.0040926
L1	0.0008651	0.0012194	0.709	0.478	-0.001526	0.0032563
L2	-0.0000593	0.0012388	-0.048	0.962	-0.0024885	0.0023699
L3	0.000637	0.0012396	0.514	0.607	-0.0017937	0.0030677
L4	-0.0007083	0.0013117	-0.540	0.589	-0.0032804	0.0018639
L5	0.0012643	0.0011418	1.107	0.268	-0.0009747	0.0035033
L6	0.0014317	0.0011204	1.278	0.201	-0.0007653	0.0036287
FRM30						
S4	0.0110963	0.0036199	3.065	0.002	0.003998	0.0181945
unemmsa						
S4	0.0345645	0.0063111	5.477	0.000	0.0221889	0.04694
tractune	-0.2979213	0.1204337	-2.474	0.013	-0.5340819	-0.0617607
amtq	0.0038984	0.0011602	3.360	0.001	0.0016233	0.0061734
loginc						
S4	0.110214	0.0109309	10.083	0.000	0.0887795	0.1316486
logass						
S4	0.0156316	0.0042147	3.709	0.000	0.0073669	0.0238963
ass0rt						
S4	-0.1299464	0.0155353	-8.365	0.000	-0.1604099	-0.0994829
loghindx						
S4	2.120461	0.5541851	3.826	0.000	1.033749	3.207172
blkpct	-0.0640244	0.0154206	-4.152	0.000	-0.0942628	-0.0337859
hsppct	0.0163849	0.0205309	0.798	0.425	-0.0238745	0.0566443
medinc	-0.0361314	0.0159762	-2.262	0.024	-0.0674594	-0.0048035
_cons	2.584455	0.2099371	12.311	0.000	2.172785	2.996125

TABLE 16

Panel B

Regression with Fixed Effects - Log of House Prices in Chicago MSA - Six Lags and Two Leads of Default and Prepayment Rates

Fixed-effects (within) regression
Group variable (i) : panel

Number of obs = 2518
Number of groups = 371

R-sq: within = 0.3269
between = 0.1266
overall = 0.0925

Obs per group: min = 1
avg = 6.8
max = 14

F(26,2121) = 39.61
Prob > F = 0.0000

corr(u_i, Xb) = 0.0631

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
sampchg	-0.000609	0.0013779	-0.442	0.659	-0.0033112	0.0020933
def1F	0.002537	0.0043347	0.585	0.558	-0.0059637	0.0110376
def2F	0.0012608	0.0042839	0.294	0.769	-0.0071403	0.0096618
prep1F	-0.0007084	0.0003953	-1.792	0.073	-0.0014836	0.0000667
prep2F	0.0000366	0.0003766	0.097	0.922	-0.0007018	0.0007751
l4logpr2	0.0114898	0.0195048	0.589	0.556	-0.0267607	0.0497402
ldef1	-0.0118713	0.0041764	-2.842	0.005	-0.0200616	-0.0036811
ldef2	0.0007424	0.0042196	0.176	0.860	-0.0075326	0.0090174
ldef3	-0.0055336	0.0041807	-1.324	0.186	-0.0137323	0.0026651
ldef4	-0.0029845	0.0041104	-0.726	0.468	-0.0110454	0.0050764
ldef5	-0.0024917	0.0040653	-0.613	0.540	-0.010464	0.0054807
ldef6	-0.0023825	0.0042019	-0.567	0.571	-0.0106227	0.0058578
preprt	0.0000216	0.0012325	0.018	0.986	-0.0023954	0.0024386
lprep1	-0.0019993	0.0009814	-2.037	0.042	-0.0039238	-0.0000748
lprep2	-0.000567	0.0009661	-0.587	0.557	-0.0024616	0.0013275
lprep3	0.0003776	0.0009738	0.388	0.698	-0.0015321	0.0022872
lprep4	-0.0011001	0.0010288	-1.069	0.285	-0.0031176	0.0009175
lprep5	-0.0008128	0.0009076	-0.896	0.371	-0.0025926	0.000967
lprep6	-0.0013662	0.0008992	-1.519	0.129	-0.0031297	0.0003973
s4FRM30	0.0019906	0.0027784	0.716	0.474	-0.003458	0.0074393
s4unemsa	0.0140845	0.0049528	2.844	0.005	0.0043716	0.0237974
amtq	0.0087795	0.0009434	9.307	0.000	0.0069295	0.0106295
s4loginc	0.0418364	0.0087124	4.802	0.000	0.0247506	0.0589222
s4logass	0.004432	0.0033861	1.309	0.191	-0.0022084	0.0110724
s4ass0rt	-0.062275	0.0123702	-5.034	0.000	-0.086534	-0.038016
s4lghind	0.607343	0.4279347	1.419	0.156	-0.2318724	1.446558
_cons	10.11136	0.2462527	41.061	0.000	9.628435	10.59428

sigma_u	0.22246933	
sigma_e	0.07744164	
rho	0.89192236	(fraction of variance due to u_i)

F test that all u_i=0: F(370,2121) = 7.22 Prob > F = 0.0000

TABLE 17

Parameter Estimates for Claim Default Hazard in Selected Portions of Chicago MSA - Basic Specification Plus Tract Characteristics, FICO Score, and Individual Race/Ethnicity

Residual df	= 342902	No. of obs	= 342929
Pearson X2	= 393628.9	Deviance	= 5091.674
Dispersion	= 1.147934	Dispersion	= 0.0148488

Bernoulli distribution, cloglog link

Default	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
black	0.2826148	0.173531	1.629	0.103	-0.0574996	0.6227293
hisp	-0.4907002	0.1855105	-2.645	0.008	-0.8542941	-0.1271063
fico	-0.0113165	0.0013451	-8.413	0.000	-0.0139528	-0.0086803
NOfico	-6.802543	0.8350468	-8.146	0.000	-8.439205	-5.165882
trtblk	0.4460382	0.2573407	1.733	0.083	-0.0583402	0.9504167
trthsp	-0.2484711	0.5050061	-0.492	0.623	-1.238265	0.7413227
lntrtinc	-1.213294	0.3303348	-3.673	0.000	-1.860738	-0.5658497
unemprt	-0.2765826	0.1934618	-1.430	0.153	-0.6557607	0.1025955
borage	0.0008147	0.0059178	0.138	0.890	-0.0107839	0.0124134
loginc	0.0549189	0.6551159	0.084	0.933	-1.229085	1.338923
RSVpmts	-0.1527707	0.0413401	-3.695	0.000	-0.2337959	-0.0717455
RSVpmt4	0.1550327	0.0439569	3.527	0.000	0.0688787	0.2411868
logfront	0.3318877	0.6764462	0.491	0.624	-0.9939225	1.657698
lnbal	3.191184	1.2905	2.473	0.013	0.6618517	5.720517
lnhval	-2.968659	1.11062	-2.673	0.008	-5.145434	-0.7918842
condo	-0.1182407	0.2629411	-0.450	0.653	-0.6335957	0.3971143
HPrelPW	-0.9778401	0.7607872	-1.285	0.199	-2.468955	0.5132754
lnhorizn	0.302945	0.8375947	0.362	0.718	-1.338711	1.9446
lnintrat	0.9592056	0.7583262	1.265	0.206	-0.5270864	2.445498
lnintarm	0.5271444	0.8765586	0.601	0.548	-1.190879	2.245168
rtdiff	-0.1040687	0.2295108	-0.453	0.650	-0.5539017	0.3457642
armrtd	0.2812895	0.1300295	2.163	0.031	0.0264363	0.5361427
logpirto	1.829201	2.390261	0.765	0.444	-2.855624	6.514026
t	0.3611917	0.0851565	4.242	0.000	0.194288	0.5280954
tt	-0.0062449	0.0026093	-2.393	0.017	-0.0113589	-0.0011308
t6	-0.163966	0.1167636	-1.404	0.160	-0.3928185	0.0648865
_cons	-6.28501	8.891653	-0.707	0.480	-23.71233	11.14231

TABLE 18

Panel A

Parameter Estimates for Claim Default Hazard in Selected Portions of Chicago MSA - Includes Log of Actual Price Ratio

Residual df	= 342888	No. of obs	= 342929
Pearson X2	= 370331.7	Deviance	= 5070.996
Dispersion	= 1.080037	Dispersion	= 0.0147891

Bernoulli distribution, cloglog link

Default	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
preprt	-0.0280012	0.045188	-0.620	0.535	-0.1165681	0.0605656
pric2CHG	-0.1509369	0.2847924	-0.530	0.596	-0.7091198	0.4072461
def1	0.0449572	0.0792709	0.567	0.571	-0.1104109	0.2003254
def2	0.0150595	0.0871864	0.173	0.863	-0.1558227	0.1859418
def3	0.0550287	0.085002	0.647	0.517	-0.1115721	0.2216295
def4	0.1704715	0.0776148	2.196	0.028	0.0183493	0.3225937
def5	0.0518766	0.082532	0.629	0.530	-0.1098832	0.2136364
def6	0.0859414	0.0802594	1.071	0.284	-0.0713641	0.2432468
prep1	0.024969	0.0109088	2.289	0.022	0.0035882	0.0463499
prep2	-0.0285131	0.013795	-2.067	0.039	-0.0555508	-0.0014755
prep3	0.0132167	0.012007	1.101	0.271	-0.0103166	0.0367501
prep4	-0.0209668	0.0110268	-1.901	0.057	-0.0425789	0.0006453
prep5	0.0169164	0.0087514	1.933	0.053	-0.000236	0.0340688
prep6	-0.0056804	0.0061335	-0.926	0.354	-0.0177019	0.0063412
fico	-0.0112585	0.0013453	-8.369	0.000	-0.0138953	-0.0086217
NOfico	-6.768811	0.8351323	-8.105	0.000	-8.405641	-5.131982
trtblk	0.2915076	0.2690528	1.083	0.279	-0.2358262	0.8188414
trthsp	-0.152017	0.5101638	-0.298	0.766	-1.15192	0.8478857
lntrtinc	-1.023778	0.3675803	-2.785	0.005	-1.744222	-0.3033338
unemprt	-0.3343941	0.2018011	-1.657	0.098	-0.7299171	0.0611289
black	0.2711551	0.1744211	1.555	0.120	-0.0707039	0.6130141
hisp	-0.4747344	0.1861688	-2.550	0.011	-0.8396185	-0.1098504
borage	0.0006431	0.0059143	0.109	0.913	-0.0109487	0.0122349
loginc	0.0221019	0.6618512	0.033	0.973	-1.275103	1.319306
RSVpmts	-0.1516113	0.0413611	-3.666	0.000	-0.2326776	-0.0705449
RSVpmt4	0.1541268	0.0439473	3.507	0.000	0.0679916	0.240262
logfront	0.2984019	0.6832655	0.437	0.662	-1.040774	1.637578
lnbal	3.295214	1.295924	2.543	0.011	0.7552498	5.835179
lnhval	-2.959917	1.116137	-2.652	0.008	-5.147506	-0.7723287
condo	-0.0911494	0.2629732	-0.347	0.729	-0.6065674	0.4242686
HPrelPW	-1.036767	0.7542111	-1.375	0.169	-2.514994	0.4414592
lnhorizn	0.2824004	0.8385405	0.337	0.736	-1.361109	1.92591
lnintrat	0.8165244	0.7902101	1.033	0.301	-0.7322589	2.365308
lnintarm	0.476671	0.8894992	0.536	0.592	-1.266715	2.220057
rtdiff	-0.0668674	0.2456762	-0.272	0.785	-0.548384	0.4146491
armrtd	0.2759079	0.1311175	2.104	0.035	0.0189223	0.5328935
logpirto	1.347691	2.40374	0.561	0.575	-3.363552	6.058934
t	0.3520034	0.085914	4.097	0.000	0.183615	0.5203918
tt	-0.0055358	0.0026505	-2.089	0.037	-0.0107307	-0.000341
t6	-0.1747328	0.1173041	-1.490	0.136	-0.4046445	0.055179
_cons	-8.635458	9.142896	-0.944	0.345	-26.55521	9.284288

TABLE 18

Panel B

Parameter Estimates for Claim Default Hazard in Selected Portions of Chicago MSA - Includes Log of Predicted Price Ratio Based on Table 14, Panel B

Residual df	= 342888	No. of obs	= 342929
Pearson X2	= 370459	Deviance	= 5069.828
Dispersion	= 1.080408	Dispersion	= 0.0147857

Bernoulli distribution, cloglog link

Default	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
preprt	-0.0271884	0.0451484	-0.602	0.547	-0.1156775	0.0613008
pred6	-0.3276386	0.2965398	-1.105	0.269	-0.9088459	0.2535688
def1	0.0425815	0.0795521	0.535	0.592	-0.1133377	0.1985006
def2	0.0148743	0.0872063	0.171	0.865	-0.156047	0.1857955
def3	0.0534413	0.0849246	0.629	0.529	-0.1130078	0.2198903
def4	0.1681508	0.0771904	2.178	0.029	0.0168604	0.3194412
def5	0.049977	0.082515	0.606	0.545	-0.1117493	0.2117033
def6	0.0876074	0.0798883	1.097	0.273	-0.0689707	0.2441855
prep1	0.0249591	0.0109001	2.290	0.022	0.0035954	0.0463229
prep2	-0.0282097	0.0137847	-2.046	0.041	-0.0552272	-0.0011921
prep3	0.0132935	0.0120011	1.108	0.268	-0.0102283	0.0368153
prep4	-0.0211418	0.0110286	-1.917	0.055	-0.0427575	0.0004739
prep5	0.0169582	0.008751	1.938	0.053	-0.0001935	0.0341098
prep6	-0.005567	0.0061242	-0.909	0.363	-0.0175702	0.0064362
fico	-0.011214	0.001345	-8.338	0.000	-0.0138501	-0.0085779
NOfico	-6.742986	0.8348864	-8.077	0.000	-8.379334	-5.106639
trtblk	0.2915567	0.2692657	1.083	0.279	-0.2361944	0.8193078
trthsp	-0.1586797	0.5103044	-0.311	0.756	-1.158858	0.8414986
lntrtinc	-1.036776	0.3682575	-2.815	0.005	-1.758548	-0.3150049
unemprt	-0.3353601	0.2018717	-1.661	0.097	-0.7310214	0.0603013
black	0.2779035	0.1743607	1.594	0.111	-0.0638373	0.6196443
hisp	-0.4740369	0.1859376	-2.549	0.011	-0.8384678	-0.1096059
borage	0.0008361	0.0059107	0.141	0.888	-0.0107486	0.0124208
loginc	0.0179909	0.6615952	0.027	0.978	-1.278712	1.314694
RSVpmts	-0.1514426	0.041362	-3.661	0.000	-0.2325106	-0.0703746
RSVpmt4	0.1539423	0.0439439	3.503	0.000	0.0678138	0.2400708
logfront	0.2989561	0.682982	0.438	0.662	-1.039664	1.637576
lnbal	3.287849	1.294975	2.539	0.011	0.7497445	5.825953
lnhval	-2.959369	1.116093	-2.652	0.008	-5.146872	-0.7718668
condo	-0.0988837	0.2631095	-0.376	0.707	-0.6145689	0.4168015
HPrelPW	-1.012307	0.7533262	-1.344	0.179	-2.488799	0.4641852
lnhorizn	0.3053165	0.8383952	0.364	0.716	-1.337908	1.948541
lnintrat	0.7933567	0.7904775	1.004	0.316	-0.7559507	2.342664
lnintarm	0.4781322	0.8896723	0.537	0.591	-1.265593	2.221858
rtdiff	-0.0665009	0.2457649	-0.271	0.787	-0.5481913	0.4151895
armrtd	0.2758067	0.1310376	2.105	0.035	0.0189776	0.5326358
logpirto	1.319811	2.402457	0.549	0.583	-3.388917	6.02854
t	0.3531328	0.0859165	4.110	0.000	0.1847395	0.5215261
tt	-0.0054887	0.0026487	-2.072	0.038	-0.0106801	-0.0002974
t6	-0.1758824	0.1172896	-1.500	0.134	-0.4057658	0.054001
_cons	-8.396947	9.119659	-0.921	0.357	-26.27115	9.477257

TABLE 18

Panel C

Parameter Estimates for Claim Default Hazard in Selected Portions of Chicago MSA - Includes Log of Predicted Price Ratio Based on Table 15

Residual df	= 342888	No. of obs	= 342929
Pearson X2	= 369995.9	Deviance	= 5068.475
Dispersion	= 1.079058	Dispersion	= 0.0147817

Bernoulli distribution, cloglog link

Default	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
preprt	-0.0279961	0.0450729	-0.621	0.535	-0.1163374	0.0603452
pred6x	-1.323275	0.7977266	-1.659	0.097	-2.886791	0.2402402
def1	0.032199	0.0799036	0.403	0.687	-0.1244092	0.1888071
def2	0.0214006	0.0873499	0.245	0.806	-0.1498021	0.1926034
def3	0.0535351	0.0848456	0.631	0.528	-0.1127592	0.2198293
def4	0.1689439	0.0771588	2.190	0.029	0.0177155	0.3201723
def5	0.0505674	0.0823224	0.614	0.539	-0.1107815	0.2119163
def6	0.083046	0.0801168	1.037	0.300	-0.07398	0.240072
prep1	0.0245775	0.0109043	2.254	0.024	0.0032055	0.0459495
prep2	-0.0282523	0.0137854	-2.049	0.040	-0.0552711	-0.0012334
prep3	0.0134407	0.0120004	1.120	0.263	-0.0100797	0.036961
prep4	-0.0210508	0.0110328	-1.908	0.056	-0.0426747	0.0005731
prep5	0.0170718	0.0087407	1.953	0.051	-0.0000597	0.0342032
prep6	-0.0055502	0.0061252	-0.906	0.365	-0.0175554	0.006455
fico	-0.0112263	0.0013454	-8.344	0.000	-0.0138633	-0.0085892
NOfico	-6.748764	0.8352453	-8.080	0.000	-8.385815	-5.111713
trtblk	0.2883112	0.268797	1.073	0.283	-0.2385211	0.8151436
trthsp	-0.1593026	0.5097495	-0.313	0.755	-1.158393	0.839788
lntrtinc	-1.028762	0.367683	-2.798	0.005	-1.749407	-0.3081165
unemprt	-0.3329492	0.2020061	-1.648	0.099	-0.7288739	0.0629755
black	0.2770379	0.1742185	1.590	0.112	-0.0644241	0.6184999
hisp	-0.4741594	0.1857367	-2.553	0.011	-0.8381967	-0.1101222
borage	0.0008819	0.0059077	0.149	0.881	-0.0106969	0.0124607
loginc	0.0178718	0.6623874	0.027	0.978	-1.280384	1.316127
RSVpmts	-0.1506425	0.0413739	-3.641	0.000	-0.2317339	-0.0695512
RSVpmt4	0.1530703	0.0439606	3.482	0.000	0.0669091	0.2392315
logfront	0.2984965	0.6837411	0.437	0.662	-1.041611	1.638604
lnbal	3.280163	1.293589	2.536	0.011	0.744775	5.815551
lnhval	-2.958588	1.11592	-2.651	0.008	-5.145751	-0.7714249
condo	-0.0953837	0.263058	-0.363	0.717	-0.6109678	0.4202004
HPrelPW	-1.015733	0.7493673	-1.355	0.175	-2.484466	0.453
lnhorizn	0.2994916	0.8386599	0.357	0.721	-1.344252	1.943235
lnintrat	0.7018414	0.792449	0.886	0.376	-0.8513302	2.255013
lnintarm	0.4945457	0.8893003	0.556	0.578	-1.248451	2.237542
rtdiff	-0.0697031	0.2455035	-0.284	0.776	-0.550881	0.4114749
armrtd	0.2768564	0.131135	2.111	0.035	0.0198365	0.5338762
logpirto	1.352143	2.400423	0.563	0.573	-3.352599	6.056886
t	0.3577989	0.0859867	4.161	0.000	0.189268	0.5263297
tt	-0.0055126	0.0026471	-2.082	0.037	-0.0107008	-0.0003243
t6	-0.1748069	0.1173	-1.490	0.136	-0.4047106	0.0550969
_cons	-7.372121	9.143053	-0.806	0.420	-25.29218	10.54793

TABLE 19

Parameter Estimates for Claim Default Hazard in Selected Portions of Chicago MSA - Includes Log of Predicted Price Ratio Based on Table 15 and Leads of Default and Prepayment Rates

Residual df	= 342884	No. of obs	= 342929
Pearson X2	= 350586.5	Deviance	= 5034.586
Dispersion	= 1.022464	Dispersion	= 0.0146831

Bernoulli distribution, cloglog link

Default	Coef.	Std. Err.	Z-Statistic	P>|z|	[95% Conf.	Interval]
preprt	-0.034211	0.0452764	-0.756	0.450	-0.1229511	0.0545291
def1F	0.3505703	0.0614938	5.701	0.000	0.2300447	0.4710958
def2F	0.0848829	0.0735338	1.154	0.248	-0.0592406	0.2290064
prep1F	0.0258278	0.0126249	2.046	0.041	0.0010833	0.0505722
prep2F	-0.0169338	0.0126848	-1.335	0.182	-0.0417957	0.007928
pred6x	-1.343646	0.7942414	-1.692	0.091	-2.900331	0.2130384
def1	0.0337537	0.0797934	0.423	0.672	-0.1226386	0.1901459
def2	-0.0183876	0.0853615	-0.215	0.829	-0.185693	0.1489179
def3	0.0289821	0.0823799	0.352	0.725	-0.1324795	0.1904437
def4	0.1603503	0.0788165	2.034	0.042	0.0058728	0.3148278
def5	0.0259895	0.0844079	0.308	0.758	-0.1394468	0.1914259
def6	0.0606053	0.079958	0.758	0.448	-0.0961094	0.21732
prep1	0.0241166	0.0144309	1.671	0.095	-0.0041674	0.0524007
prep2	-0.0394668	0.0151166	-2.611	0.009	-0.0690949	-0.0098387
prep3	0.0136393	0.0123289	1.106	0.269	-0.0105249	0.0378034
prep4	-0.0151692	0.0112688	-1.346	0.178	-0.0372557	0.0069172
prep5	0.0173591	0.0088246	1.967	0.049	0.0000633	0.0346549
prep6	-0.0086045	0.0070099	-1.227	0.220	-0.0223435	0.0051346
fico	-0.0112368	0.0013474	-8.339	0.000	-0.0138777	-0.0085959
NOfico	-6.75536	0.8364628	-8.076	0.000	-8.394797	-5.115923
trtblk	0.1131345	0.2747742	0.412	0.681	-0.425413	0.651682
trthsp	-0.0825145	0.5088564	-0.162	0.871	-1.079855	0.9148257
lntrtinc	-0.7667646	0.3724601	-2.059	0.040	-1.496773	-0.0367562
unemprt	-0.3546606	0.2053536	-1.727	0.084	-0.7571464	0.0478252
black	0.2740908	0.1741123	1.574	0.115	-0.0671631	0.6153447
hisp	-0.4547265	0.1851393	-2.456	0.014	-0.8175929	-0.0918601
borage	0.000192	0.0058932	0.033	0.974	-0.0113584	0.0117424
loginc	0.0681852	0.663088	0.103	0.918	-1.231443	1.367814
RSVpmts	-0.1515717	0.0414004	-3.661	0.000	-0.2327149	-0.0704285
RSVpmt4	0.1539475	0.0440264	3.497	0.000	0.0676574	0.2402375
logfront	0.3630442	0.6843497	0.530	0.596	-0.9782565	1.704345
lnbal	3.310785	1.286734	2.573	0.010	0.7888326	5.832738
lnhval	-3.017199	1.1136	-2.709	0.007	-5.199815	-0.8345821
condo	-0.0692377	0.2630333	-0.263	0.792	-0.5847734	0.446298
HPrelPW	-1.039382	0.7527322	-1.381	0.167	-2.51471	0.4359462
lnhorizn	0.2917416	0.8372696	0.348	0.728	-1.349277	1.93276
lnintrat	0.6591212	0.7999359	0.824	0.410	-0.9087244	2.226967
lnintarm	0.3815263	0.9008083	0.424	0.672	-1.384026	2.147078
rtdiff	-0.0236818	0.2512162	-0.094	0.925	-0.5160566	0.4686929
armrtd	0.2715232	0.1317549	2.061	0.039	0.0132883	0.529758
logpirto	1.148191	2.407605	0.477	0.633	-3.570629	5.86701
t	0.3439647	0.0862838	3.986	0.000	0.1748516	0.5130779
tt	-0.0050796	0.0026391	-1.925	0.054	-0.0102521	0.000093
t6	-0.1716964	0.1171615	-1.465	0.143	-0.4013287	0.0579359
_cons	-10.58673	9.163138	-1.155	0.248	-28.54615	7.372693