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Abstract

After a mortgage is originated the borrower promises to make scheduled payments to repay the loan. These payments are sent to the loan servicer, who may be the original lender or some other firm. This firm collects the promised payments and distributes the cash flow (payments) to the appropriate investor/lender.

A large data set (loan-level) of securitized subprime mortgages is used to examine if individual servicers are associated with systematic differences in mortgage performance (termination). While accounting for unobserved heterogeneity in a competing risk (default and prepay) proportional hazard framework, individual servicers are associated with substantial and economically meaningful impacts on loan termination.

Loan Servicer Heterogeneity and the Termination of Subprime Mortgages

1 Introduction

In the days of old before the S&L crisis and mortgage securitization, a borrower needed to only identify a lender for a loan to purchase a home. Typically this lending institution was locally based and the decision to make the loan was made on the basis of traditional underwriting standards: debt-to-income ratios, loan-to-value ratios, employment history, and location. The same institution that originated the loan would also collect the promised payments. Thus, part of the decision to apply for a loan from a particular institution could depend on the reputation of that lender as a debt collector or, in the parlance of the mortgage market, the "quality of the servicing of outstanding mortgages or loans." In fact, the bulk of borrower/lender interactions take place during the servicing of a loan and not at origination.

Today, mortgage lending has been "atomized" so that different institutions may be responsible for each stage of the lending process (Jacobides, 2001). For example, the origination of a loan may be handled by a bank, a mortgage corporation, a financial institution, or a mortgage broker, among others. Often these subprime loans are packaged with other similar loans, and Wall Street firms create securities that investors may purchase that are backed by the expected cash flows from the mortgages. These investors are then able to sell and trade securities based on a group of loans without having to deal directly with the borrower or the property purchased with the loan. A Special Purpose Vehicle (SPV) can also be used as a trust to hold the loans for the investors. The SPV does none of the actual work of collecting the payments or even distributing them to the investors. This is the work done by the servicer.

The servicer enters into a contract with the trustees and is typically paid 25 basis points to service prime mortgages and 50 basis points to service subprime mortgages (Office of the Comptroller of the Currency, 2003). In the subprime market, the high delinquency rates and less automation in servicing tend to make servicing more intensive. It has been estimated that the cost of servicing in the subprime market can be four times higher than that in the prime market (Kogler, 1997). The servicer is responsible for payment collection, cash management, escrow administration, and investor reporting, among other things. Another type of servicer, called a "special servicer," is used to deal with delinquent borrowers by managing foreclosures and using loss-mitigation techniques if the borrower defaults.

The servicer is the primary entity that the borrower interacts with after the origination of a mortgage. It is in this capacity that the servicer has the ability to affect the performance of a mortgage as well as the perception that a borrower has of the lender. In fact, according to Fitch Ratings, even when a pool of mortgages has similar characteristics the servicer can affect the loss severity by as much as 30% (Fitch, 2003). In addition, Baku and Smith (1998) showed that the quality of servicing in the nonprofit sector can have substantial effects on the performance of loans.

The primary research question asked in this paper is whether and how much the servicer matters to the performance (default and prepayment) of subprime loans after controlling for individual loan characteristics and prevailing economic conditions. A competing risks model that incorporates unobserved heterogeneity on a sample of over 56,000 30- and 15-year fixed-rate subprime loans is used.

2 Background on Subprime Servicers

Since subprime loans default and prepay at elevated levels, the subprime market provides an excellent segment of the mortgage market to examine how servicers affect mortgage performance. In addition, there has been substantial controversy and legal action over the behavior of subprime servicers. Despite the fact that most attention is paid to predation during the origination of subprime loans, there is also compelling evidence of predatory behavior by at least some subprime servicers. The types of predation include: forced insurance, abuse of escrow accounts, improper fees, and improper foreclosure proceedings. Although the most notorious cases involve Fairbanks Capital Corporation (Fairbanks), other well known and large servicers such as GMAC Mortgage Corporation and Ocwen Federal Bank have also been party to law suits and settlements with regulators. For example, Fairbanks entered into an out of court settlement with the Federal Trade Commission and the U.S. Department of Housing and Urban Development (HUD) on November 12 2003 in which it agreed, without admitting any wrongdoing, to create a $40 million fund to aid those harmed by their servicing practices. The agreement also states that Fairbanks will fulfill its obligations by accurately accounting for the arrival of funds and crediting the accounts in timely fashion, not forcing insurance on mortgages, answering the help line, responding to borrower requests and concerns, among others. Eggert (2004) provides an extensive discussion of the servicing practices of Fairbanks, discusses various methods of predation in servicing, and provides a nice summary of the legal history of subprime servicing. Despite legal and regulatory problems, Fairbanks is still a top 10 servicer of subprime loans. After being downgraded by Fitch, Moody's, and S&P in 2003, the 2004

Fairbanks' rating was upgraded after improved controls; and in July 2004 the company changed its name to Select Portfolio Servicing, Inc.

This history implicitly indicates that servicers have a lot of control over mortgage outcomes. For example, when a loan becomes delinquent, does the servicer immediately call the borrower and ask if there is a problem at work or home? Or does the servicer make no contact with the delinquent borrower and simply send a letter at 60 days delinquent saying the whole loan is due today and that foreclosure proceedings will be initiated (an acceleration letter)? If this heterogeneity in servicing practice is widespread, as indicated by Fitch (2003) and Baku and Smith (1998), we should expect to observe substantially different rates of mortgage terminations among different servicers. As a result, the experience of the borrower and the expected cash flows of investors could be different depending on who is servicing the loan.

2.1 *Market Consolidation*

In many respects the history of subprime servicing parallels the history of subprime lending overall. The origination and servicing segments of subprime lending have experienced substantial consolidation from 1995 through 2003. For example, as shown in Table 1, the market share of subprime servicers has grown from just over 16 percent in 1995 to over 84 percent in 2004. Over the same time period, the top 25 originators' market share also rose from 77 to over 93 percent. In addition, securitization rates rose from 28 to over 58 percent over the same time period. This market wide consolidation has been associated with the transformation of subprime lending from niche products provided by independent financing companies to an important segment of the mortgage market conducted by large, well-known financial institutions. For example, the top 25 subprime servicers include household names such as CitiFinancial, Ameriquest Mortgage, Countrywide Financial, Chase Home Finance, Washington Mutual, Wells Fargo Home Mortgage, and others (Inside Mortgage Finance, 2005).

3 Data

The data are leased from LoanPerformance (LP, formerly MIC). LP collects data from pools of non-agency, publicly placed securitized loans. Static information about individual loans is collected, such as documentation type, origination balance, purchase price, and servicer, as well as monthly updated information on loan status. The database contains information on over 1,000 pools of subprime loans, representing over 3,500,000 individual loans. Therefore, the LP data is unlikely to represent the whole subprime mortgage market, but instead represents only the securitized portion of the market. For example, Chomsisengphet and Pennington-Cross (2006) show that subprime foreclosure rates reported by the Mortgage Bankers Association of America (MBAA) are typically much higher than those calculated using the LP data. While the MBAA does not claim that their rates reflect the whole subprime market, the data may show the different characteristics of subprime loans that are held in portfolio versus those that are securitized.

For the estimation, we use data on loans originated from 2000 through 2005 and followed thorough the end of 2005. The data set is limited to 30- and 15-year fixed-rate loans for owner-occupied single-family properties (first-lien purchase or refinance) from the LP database. This will help to reduce unobserved heterogeneity associated with product type. We include only those loans with an identifiable servicer. In addition, in an attempt to reduce any erroneous information and include only substantial servicers, we include only the top 20 servicers (by number of loans in the sample). Therefore, these results may not apply to the whole market. In addition, the performance of each loan is followed for up to six years. After eliminating loans with missing data, a sample of over 56,000 loans is used in the analysis.

Table 2 provides some selected characteristics of the loans at origination. Because the average FICO (Fair Isaac's consumer credit score) is 661, these loans typically look like the A- segment of the market in terms of credit scores and reflect the higher credit scores of borrowers who use fixed rates in the subprime market (Chomsisengphet and Pennington-Cross, 2006). The average loan provides just over a 20 percent down payment, almost one half of the loans have a prepayment penalty, and over 40 percent provided low or no documentation. As should be expected, the loans that defaulted tended to provide a smaller down payment and the borrower had a lower credit score at origination.

The estimation follows each of the loans through time to determine in which month the loan defaults or prepays. In addition, many of the loans are seasoned before they become part of a security. Loans are only included in the sample if they were seasoned less than two years before entering the security. Therefore, the observations are both left and right censored. The data are arranged as a panel with each loan defining the cross section and time being defined by each month the loan is observed. Loans are observed until termination or right censoring after six years or in December 2005, whichever is first.

Table 3 provides the summary statistics on the variables used to explain the probability of prepayment or default in each month that the loan is alive. In addition, the sample is broken down into large servicers and small servicers. Large or big servicers are those identified by Inside B&C Lending as one of the top 25 B&C at some point between 2000 and 2004. All other servicers included in the data are identified as small servicers. Over 43,000 loans are serviced by large or big servicers and over 13,000 loans by small servicers. Eight servicers are included for both the large and small servicer samples.[1]

In general the loan characteristics are very similar for both small and large servicers. For example, the FICO credit scores, *FICO*, are only nine points apart and the Loan-To-Value ratio in the current month, *CLTV*, are almost identical on average. Other loan characteristics such as the existence of a prepayment penalty in force for the current month, *PPEN*; low or no documentation, *LNDOC*, are all very similar. Therefore, at least in terms of observed mortgage characteristics, there does not seem to be much if any difference between loans serviced by the largest servicers versus the rest of the industry.

4 Motivations to Terminate a Mortgage

Despite the fact that the borrower is technically in default when a single payment is missed or any other provision of the mortgage is violated, it is common practice for lenders not to pursue the property or even enter into other loss-mitigating strategies for short-term delinquencies.

The academic literature on mortgage termination has used many different definitions of default, ranging from “90-days delinquent” to “the end of foreclosure proceedings” or “Real Estate Owned (REO) property”. In this paper, default is defined as any month that the loan becomes REO property or when foreclosure proceedings are initiated. This definition delineates when the lender/investor has actively taken or attempted to take possession of the property. Once the loan is declared to be in default, the loan is considered terminated.[2] The study of the final disposition of property in REO or in foreclosure is left to further research. The definition of a prepaid loan is when the balance becomes zero and in the prior month the loans was either current or delinquent. Prepayments, then, are motivated by many different factors including interest rates, mobility, severe loan delinquency, and improving credit history.

4.1 Motivations to Default

Households primarily default (REO or enter foreclosure) on a mortgage when the value of the mortgage is larger than the value of the property. To measure whether it is "in the money" to default on the loan and put the mortgage back to the lender/investor, the current loan-to-value ratio, *CLTV*, is used. *CLTV* is created using the stated outstanding balance of the loan at the beginning of the month, as indicated in the servicer records, and the updated house value using the metropolitan area repeat sales price index as reported by the Office of Federal Housing Enterprise Oversight (OFHEO). It is expected that low or negative equity will make it more likely that the loan will default. However, it is not expected that loans will automatically default when in negative equity. For example, there can be substantial transaction costs, which could vary by borrower, property, or even servicer, that could affect the prescription of and reaction to a negative equity position. The measure of negative equity is also only a proxy because individual house prices will grow at varied rates. Due to this measurement error previous studies have constructed a variable (e.g., Deng et. al., 2000; Pennington-Cross, 2003) that explicitly includes individual property appreciation dispersion. Unfortunately, the information at the metropolitan area level is not provided to the general public. However, these studies did not observe the monthly outstanding balance on the loan and used only the amortization schedule to update the outstanding balance in each month. Because of the high rate of delinquency (Danis and Pennington-Cross, 2005) of subprime loans this approach would lead to an overestimate of the equity in the home. The measure of CLTV used in this paper corrects for this problem by using the actual outstanding loan balance in each month instead of the amortization schedule. However, since the property level appreciation rates are only proxied for by the metropolitan area appreciation rate, it will be important for the empirical estimation to allow for unobserved heterogeneity in the termination of the loans.

The use of *CLTV* to measure whether it is "in the money" to default on the loan and put the mortgage back to the lender/investor provides only a static point of view. The optimal time to default is best seen in a dynamic and forward looking context because payments are made sequentially through time. For example, it may be in the money to default on a particular day, but this value could become larger or smaller in the future depending on future equity payments and house price appreciation patterns. As a result it may be optimal to delay putting the mortgage even if the property is currently in a negative equity position (Kau and Kim, 1994). Therefore, there is value in the option to default and this value is larger when there is more variability in price appreciation patterns. Therefore, we would expect that the variance of house prices, *VARHPI*, measured as the standard deviation in the monthly growth rate of the OFHEO house price index[3] in the prior two years, would be negatively associated with the probability of default.

Households may also have a difficult time making payments when there is stress in the labor market. To proxy for labor market conditions the metropolitan area unemployment rate, *UNEMP*, as collected from the Bureau of Labor and Statistics (BLS) is lagged one month. Again, this is only a crude proxy for when the borrower actually does become unemployed. However, we should expect higher unemployment rates to be associated with higher probabilities of default.

Elevated probabilities of default could also be associated with the characteristics of the loan itself. For example, Quercia et al. (2005) found that prepayment penalties, *PPEN*, were associated with higher probabilities of default. One potential explanation of this result is that, in some cases, defaulting may be a more attractive option than prepaying the loan when delinquent, because the relative cost of prepaying is higher due to the penalty.

The ability of the borrower to meet prior financial obligations may also provide a good indication of their ability to meet future financial obligations. Therefore, it is expected that loans with higher consumer credit scores, *FICO*, at origination will be less likely to default in the future.

When the applicant for a loan provides limited or no documentation, *LNDOC*, of income or down payment source, this may indicate additional risks associated with income flows in the future. Therefore, it is possible that providing low or no documentation will be associated with elevated default probabilities.

Lastly, lenders will often allow loans to season before trying to package it into a security to prove that the loan was properly underwritten and had sufficient compensating factors. Therefore, seasoning may indicate other unobserved problems with the loan. We include *SEASON*, a dummy variable indicating the loan has been seasoned one year or longer, and expect that it will be associated with a higher probability of default.

4.2 Motivations to Prepay

One financial incentive to prepay a fixed rate loan is to refinance to take advantage of lower interest rates. To measure the extent that it is in the money to refinance, the present discounted cost of all future payments on the current mortgage are compared with the present discounted cost of future payments on a new mortgage at prevailing rates.

The monthly payments for each borrower *j* can be calculated for fixed rate mortgages using the original balance (*O*), the term of the mortgage (*TM*), and the interest rate on the mortgage (*i*).

$$P_j = i_j * O\left[\frac{\left(1+i_j\right)^{TM}}{\left(1+i_j\right)^{TM}-1}\right]. \tag{1}$$

These constant payments are discounted by *d*, the 10-year constant maturity Treasury rate, in each month (*m*) until the mortgage is fully paid in *TM* months.

$$PDC_{jc} = \sum_{m=0}^{TM} \frac{P_j}{(1+d_j)^m} \ . \tag{2}$$

In each time period PDC_{jc} is calculated as long as the loan exists. For the refinanced loan the same calculations are used to estimate the present discounted cost, PDC_{jr}, while using the outstanding balance as the original balance, the remaining term as the term of the loan (*TM*), and the prevailing interest rate. The call option is thus defined as

$$REFI_{jt} = \left[\frac{(PDC_{jc} - PDC_{jr})}{PDC_{jc}}\right] . \tag{3}$$

The variable $REFI_{jt}$ is defined as the percentage reduction in the present values of future payments that borrower *j* will gain in time period *t* if the mortgage is refinanced. The choice of the correct refinancing interest rate is complicated by the use of risk-based pricing in the subprime market. Therefore, to hold credit quality constant the interest rate on the refinanced mortgage is defined as the market prime rate, as collected from the Freddie Mac Primary Mortgage Market Survey (PMMS) in that month, increased by the percent spread between the contract rate on the existing loan at origination and the PMMS rate at origination.

Again, this measure of interest rate--driven prepayments provides a static look at the extent that it is in the money to refinance. Similar to default, the variance of interest rates can make the value of the option to refinance larger. It may be worth delaying the refinance because interest rates may drop even more in the future. Therefore, interest rate variance, *VARINT*, measured by the standard deviation in the one-year constant maturity U.S. Treasury bill yield over the prior 15 months, should be negatively associated with the probability of prepaying.

While the amount of equity has been found to be a strong predictor of default, it can also make it easier to refinance a loan. For example, if a loan has substantial positive equity, even those borrowers with low credit scores should be able to refinance with a subprime lender because the equity compensates for the risk that the borrower might not be able to make future payments. In contrast, for loans with low or negative equity, it can become more difficult to find financing, even in the subprime market (Alexander et al., 2002). Therefore, it is expected that loans with high *CLTV* are less likely to prepay.

Locations with higher unemployment rates are more likely to be associated with individual borrower unemployment spells. The impact of unemployment on prepayment can be either negative or positive. Being unemployed should make it more difficult to refinance and thus lower the probability of prepaying. However, prepaying a loan can be one way of terminating a loan that is delinquent and often can be a cheaper method than going through foreclosure and defaulting on a loan. Empirical research, not surprisingly, has found mixed results. Using subprime loans, Quercia et al. (2005) find that state unemployment rates are associated with a higher probability of prepayment, while Deng et al. (2000) find state unemployment rates to be associated with higher and lower probabilities of prepaying, depending on location for prime loans.

Over 40 percent of the loan-months have a prepayment penalty, *PPEN*, in effect. Since these penalties make it more expensive to refinance the loan, the probability of prepaying should be lower. In addition, the ability of the borrower to meet prior financial obligations, measured by their consumer credit, *FICO* score, may be associated with an increase or decrease in prepayment probabilities. While the reasoning for any relationship is unclear, Pennington-Cross (2003) found that high-interest-rate loans with high credit scores were more likely to prepay.

5 A Competing Risks Model

As previously noted, a loan can terminate through default or prepayment – two options that compete with each other to be the first observed event. In addition, there may be unobserved characteristics that could influence the termination of the loans. To control for unobserved heterogeneity, the model estimates what fraction of the loans in the sample belong to discrete unobserved types or groups.

This section reviews a competing risk proportional hazard model that was introduced in the study of unemployment duration (McCall, 1996).[4] Prior empirical work in the termination of mortgages has also used this same approach (e.g., Ambrose and LaCour-Little, 2001; Deng, Quigley, and Van Order, 2000; Alexander et al., 2002; Pennington-Cross, 2003).

Random variables indicating the time to default, T_d, and the time to prepayment, T_p, have a continuous probability distribution, $f(t_w)$, where t_w is a realization of T_w(w=p,d; p=*prepay*, d=*default*). The joint survivor function for loan j is then $S_j(t_p,t_d)=\pi(T_p>t_p, T_d>t_d \mid x_{tj})$ and is conditioned on exogenous variables, x_{tj}, including the baseline (loan age) hazard function. The shortest mortgage duration is observed duration, $T_j=\min(T_p,T_d,T_c)$. The survivor function is defined as follows

$$S_j\left(t_p,t_d\right)=\exp\left(-\theta_p\sum_{t=0}^{t_p}\exp\left(\beta_p^{'}x_{jt}\right)-\theta_d\sum_{t=0}^{t_d}\exp\left(\beta_d^{'}x_{jt}\right)\right)\ . \qquad (4)$$

The N loans are indexed by j, time is indexed by t and measured in months, and the outcomes in each month include prepay, default, and continue (indexed by p, d, or c). The baseline hazard function is parameterized by loan age and age squared. The exogenous variables can be time constant or time varying. θ_p and θ_d are the unobserved prepay and default heterogeneity parameters. They can correlate with each other, but are assumed to be jointly independent of x_{jt}. Two groups or types of loans are identified with frequency or mass of m_1 and m_2.[5] θ_p and θ_d proportionally shift the hazards for the four types of loans (θ_{p1}, θ_{p2}, θ_{d1}, θ_{d2}), 1 and 2 index the mass or frequency of each group. The hazard probabilities of prepay, $A_{pj}(t)$, default $A_{dj}(t)$, or continuing $A_{cj}(t)$ in time period t are defined as

$$
\begin{aligned}
&A_{pj}(t \mid \theta_p, \theta_d) = S_j(t,t \mid \theta_p, \theta_d) - S_j(t+1,t \mid \theta_p, \theta_d) \\
&-.5\left(S_j(t,t \mid \theta_p,\theta_d) + S_j(t+1,t+1 \mid \theta_p,\theta_d) - S_j(t,t+1 \mid \theta_p,\theta_d) - S_j(t+1,t \mid \theta_p,\theta_d)\right) \\
&A_{dj}(t \mid \theta_p, \theta_d) = S_j(t,t \mid \theta_p, \theta_d) - S_j(t,t+1 \mid \theta_p, \theta_d) \\
&-.5\left(S_j(t,t \mid \theta_p,\theta_d) + S_j(t+1,t+1 \mid \theta_p,\theta_d) - S_j(t,t+1 \mid \theta_p,\theta_d) - S_j(t+1,t \mid \theta_p,\theta_d)\right) \\
&A_{cj}(t \mid \theta_p, \theta_d) = S_j(t,t \mid \theta_p, \theta_d)\ .
\end{aligned} \tag{5}
$$

For prepay and default hazards, the term multiplied by 1/2 adjusts the duration because months are a discrete measure of time, not continuous. The unconditional probability can be expressed by

$$F_z(t) = m_1 A_z(t \mid \theta_{p1}, \theta_{d1}) + m_2 A_z(t \mid \theta_{p2}, \theta_{d2}), \quad z = p, d, c\ . \tag{6}$$

The sum of the m_1 and m_2 must equal 1 ($m_1 + m_2 = 1$). In the estimation m_1 is normalized to one and m_2 is estimated as any nonnegative number. The log of likelihood of the proportional competing risks model is as follows

$$\sum_{j=1}^{N} \delta_{pj} \log(F_p(T_j)) + \delta_{dj} \log(F_d(T_j)) + \delta_{cj} \log(F_c(T_j)). \tag{7}$$

δ_{zj}, $z=p, d, c$ indicate reason for the termination of the j^{th} loan (prepayment, default, or right censoring).

The conditional probability of borrower j prepaying the mortgage in period t is therefore

$$\pi(T_w = t \mid x_{jt}, \theta_w, T > t-1) = 1 - \exp(-\exp(x_{jt}\beta_w)\theta_w)\ . \tag{8}$$

6 Results

The results of the competing risks proportional hazard model are presented in the appendix. Two different samples are used and four different model specifications are estimated. Tables A1 and A2 present the results for the large or big servicer sample and tables A3 and A4 present the results for the small servicer sample. For each sample, four model specifications are shown. Models 2 and 4 include servicer specific dummy variables and Models 3 and 4 include unobserved heterogeneity. Most variables are largely significant and of the expected sign.

Because it is difficult to interpret the coefficients directly, elasticity estimates are provided in Table 4 and a series of figures illustrate the results for a few key variables. The reported elasticity is the percent change in the predicted termination (default or prepay) probability in response to a one-standard-deviation increase in continuous variables from their mean or an increase from 0 to 1 for dummy variables. Elasticities are reported for the large servicer sample and the small servicer sample. All reported elasticities include servicer-specific fixed effects and unobserved heterogeneity as estimated in Model 4. Test of interactions of servicers with key variables such as *CLTV* and *REFI* were largely insignificant or could not converge. Therefore, the results focus on the impact of fixed effects of servicers on the probability of terminating the loans.

6.1 Servicer

Even after controlling for observed and unobserved loan and market characteristics, servicers are associated with very large increases and decreases in the probability of defaulting and prepaying. For the large servicers, the impact on the probability of default ranges from -61 percent to +73 percent, relative to servicers 1, 3 and 8.[6] The impact is also large on the probability of prepaying and ranges from +60 percent to +555 percent, relative to servicer 1. For the smaller servicers, the impacts are again very large. For example, servicer 5 has a 54 percent higher probability of default on an identical loan than servicer 1-4, and 8. For prepayment, the fixed effects vary from -8 percent to -65 percent.

In addition, it is reasonable to expect servicer impacts to vary through time due to the dynamic nature of the industry. We test to see if such a time-varying effect exists by adding to Model 4 interactions of servicer dummies and the calendar years in which the servicer is actively servicing loans. For a given servicer, only the years in which a reasonable number of loan terminations occur (50 defaults/prepays or more) are used in the test and therefore the reference years will be different for each servicer. Table 5 reports the elasticity (percentage change in predicted termination) for the large servicers. Elasticities are cumulative so that they indicate the total (not marginal) effects of a given servicer in a given year. The results indicate that for most large servicers the effect on loan termination can vary through time. For example, servicers 2 and 4 experienced more defaults in 2004 and 2005 while servicer 5 had fewer defaults in 2005 than earlier years. Servicers 2 and 5 also had fewer prepaid loans in the more recent years. However, the direction and general impact of the servicer fixed effects are fairly similar (for example, the fixed effects do not change sign). In addition, not all servicer effects change through time. The effect of servicer 7 on loan terminations, for example, is largely constant from 2000 to 2005.

6.2 Other Covariates

As shown in Figure 1 and consistent with prior literature, borrowers with higher credit scores are less likely to default. In fact, a one-standard-deviation increase in the *FICO* score decreases the probability of default by approximately 36 to 61 percent. The responsiveness to credit scores is much higher for loans serviced by big servicers. In addition, better or higher credit scores at origination are associated with lower probabilities of prepaying. However, the proportional impact is much smaller and ranging from -10 to 8 percent. Figure 1 also shows that the average loan using a big servicer tends to default less often than the average loan using a small servicer.

As shown in Figure 2 and consistent with prior literature, the impact of current equity in the home on mortgage terminations meets prior expectation. For example, a one-standard-deviation increase in *CLTV* increases the probability of default by approximately 66 percent and decreases the probability of prepaying by approximately 9 percent. Therefore, current equity has a strong impact on the termination of subprime loans. In addition, the impact is almost identical for both servicer types.

The impact of unemployment rates, *UNEMP*, is unclear from the results. Depending on the sample and specification, the impact of unemployment rates can be insignificant or positive or negative. Therefore, there does not seem to be any strong link between prepay or default probabilities and metropolitan area unemployment rates.

As anticipated, loans with prepay penalties in effect, *PPEN*, prepay 17 to 45 percent less. The impact of the penalties tends to be larger for the loans serviced by the small servicers. The impact of prepay penalties on the probability of default is mixed (positive and only marginally significant for loans serviced by small servicers and insignificant for those serviced by large servicers). These findings differ from Quercia et al. (2005), who found a positive relationship between prepayment penalties and default probabilities. Consistent with the option theories the volatility of interest rates (house prices) is associated with a lower probability of prepaying (defaulting) for both the small and big servicer samples.

6.3 *Unobserved Heterogeneity*

One of the advantages of the estimation approach used is the ability to estimate and hence control for unobserved heterogeneity through a semi-parametric approach, which does not assume a specific functional form. In all specifications and samples the heterogeneity parameters are all significant at the 5 or 1 percent level. Figures 3 and 4 illustrate the proportional impact of the parameters on the estimated probabilities of termination. Figures 3 and 4 show that for one group of loans, regardless of the servicer, there is a relatively low probability of default regardless of the value of the FICO score or any other covariate. Another group of loans have a much higher probability of defaulting for all values of *FICO* and a greater absolute sensitivity to changes in the FICO scores.[7] In addition, the distribution of loans into groups is fairly similar for each sample. For the large servicer sample, a little over one-half of the loans are associated with the fast termination groups while for the small servicer sample a little under one-half of the loans are associated with the fast termination group.

7 Conclusion

The servicer plays a key role in the mortgage market. In fact, the servicer is the primary and sometimes only point of contact for the borrower after origination. This paper asks the simple question of whether different servicers are associated with different probabilities of default and prepayment of securitized subprime loans after controlling for all observed loan, housing, and labor market conditions.

Using a competing risk model of mortgage duration that allows for unobserved heterogeneity, the results find strong evidence that servicers are associated with large changes in the probability of a loan going into default or prepayment. In addition the magnitude of the impact can be substantial. For example, for eight large subprime servicers, the proportional impact on the probability of default, relative to the reference large servicers, varies from 60 to 555 percent. Large servicers affect the probability of prepayment to a lesser but still substantial degree, ranging from 9 to 318 percent. For eight smaller subprime servicers, the heterogeneity is also economically significant, but the proportional impacts are usually under 100 percent.

These results indicate that, when valuing a pool of subprime mortgages, it is potentially more important to consider who is servicing the loans than the loan or pool characteristics. The experience of borrowers in the subprime market will vary depending on who is servicing the loan. Therefore, when selecting a lender, subprime borrowers should do additional homework, beyond looking at the lender, to determine who will end up servicing the loan.

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Table 1: Top 25 Subprime Servicers

Year	Market Share	Volume
1995	16.2%	$47,098.3
1996	31.7%	$89,847.9
1997	45.4%	$144,749.0
1998	55.6%	$191,332.2
1999	63.9%	$244,404.6
2000	67.2%	$279,559.7
2001	68.3%	$326,926.0
2002	73.7%	$423,082.3
2003	77.8%	$543,944.6
2004	84.8%	$825,300.1

Source: The 2005 Mortgage Market Statistical Annual Volume 1, Top 25 B&C Servicers

Table 2: Selected Characteristics at Origination

Characteristics	All originations	Defaulted loans	Prepaid loans
FICO score	660.86	596.73	655.62
Loan-to-value ratio	78.03	80.66	78.22
Prepayment penalties	47.4%	65.2%	52.9%
Low or no documentation	42.0%	32.7%	45.3%

Table 3: Descriptive Statistics of Estimation Samples

Variable	Big servicer sample		Small servicer sample	
	Mean	Std. Dev.	Mean	Std. Dev.
FICO	671.33	75.15	679.92	60.84
LNDOC	0.39	0.49	0.55	0.50
SEASON	0.01	0.11	0.02	0.14
CLTV	67.38	16.76	70.68	14.73
REFI	0.04	0.06	0.09	0.06
UNEMP	5.33	1.51	5.51	1.65
VARINT	0.47	0.24	0.51	0.25
VARHPI	0.34	0.23	0.30	0.21
PPEN	0.44	0.50	0.30	0.46
servicer 1	0.32	0.47	0.05	0.23
servicer 2	0.32	0.47	0.23	0.42
servicer 3	0.01	0.11	0.10	0.30
servicer 4	0.06	0.24	0.03	0.16
servicer 5	0.09	0.28	0.04	0.20
servicer 6	0.03	0.18	0.38	0.48
servicer 7	0.06	0.24	0.10	0.29
servicer 8	0.10	0.30	0.07	0.26
Number of loans	43,340		13,130	

Table 4: Standardized Elasticities

	Big Servicer Sample		Small Servicer Sample	
Variable	Default	Prepay	Default	Prepay
FICO	-61.07%	-10.61%	-36.15%	8.39%
LNDOC	37.86%	-7.34%	88.48%	6.06%
SEASON	73.15%	33.72%	181.81%	22.40%
CLTV	65.89%	-9.12%	65.80%	-8.48%
REFI	13.73%	14.09%	38.88%	10.49%
UNEMP	-5.62%	1.65%	-12.73%	-1.64%
VARINT	8.52%	-8.24%	25.02%	-6.16%
VARHPI	-8.77%	23.41%	-7.37%	9.69%
PPEN	-11.72%	-17.15%	2.31%	-45.44%
servicer 1	--	--	--	--
servicer 2	60.09%	8.96%	--	-65.04%
servicer 3	--	318.02%	--	-8.30%
servicer 4	391.86%	89.60%	--	-33.69%
servicer 5	555.81%	96.02%	54.10%	-43.93%
servicer 6	438.36%	48.19%	105.98%	-33.93%
servicer 7	274.68%	46.54%	31.00%	-33.00%
servicer 8	--	133.85%	--	-24.24%

Note: Elasticity is estimated as percentage changes in predicted probabilities in response to a one standard deviation change in the variable of interest. For dummy variables, elasticity is the percentage change in probability as the variable goes from zero to one. Servicer 1-8 represents eight different servicers for the big and small servicer samples.

Table 5: Elasticity of Time-varying Servicer Effects, Big Servicer Sample

Variable	Default (%)	Prepay (%)
servicer 1	--	--
servicer 2	11.1	31.1*
servicer 2*2004	46.7*	9.4*
servicer 2*2005	107.4*	0.3*
servicer 3	--	311.9*
servicer 4	275.7*	92.8*
servicer 4*2004	450.1*	107.3
servicer 4*2005	518.5*	87.6
servicer 5	644.0*	132.7*
servicer 5*2004	637.0	99.2*
servicer 5*2005	335.4*	78.1*
servicer 6	286.9*	26.1*
servicer 6*2002	624.6*	66.5*
servicer 6*2003	366.8	67.2*
servicer 7	267.6*	53.3*
servicer 7*2001	259.6	46.0
servicer 7*2002	218.4	42.1
servicer 7*2003	212.2	37.4
servicer 8	--	137.3*

Notes: Elasticity is percentage change in predicted probability as the variable goes from 0 to 1. For example, servicer#*year indicates the estimated percent change in the probability in that year. Servicer interactions are added to Model 4 (with unobserved heterogeneity). * indicates statistical significance at 5% level or lower and are marked by the dark shading.

Figure 1:

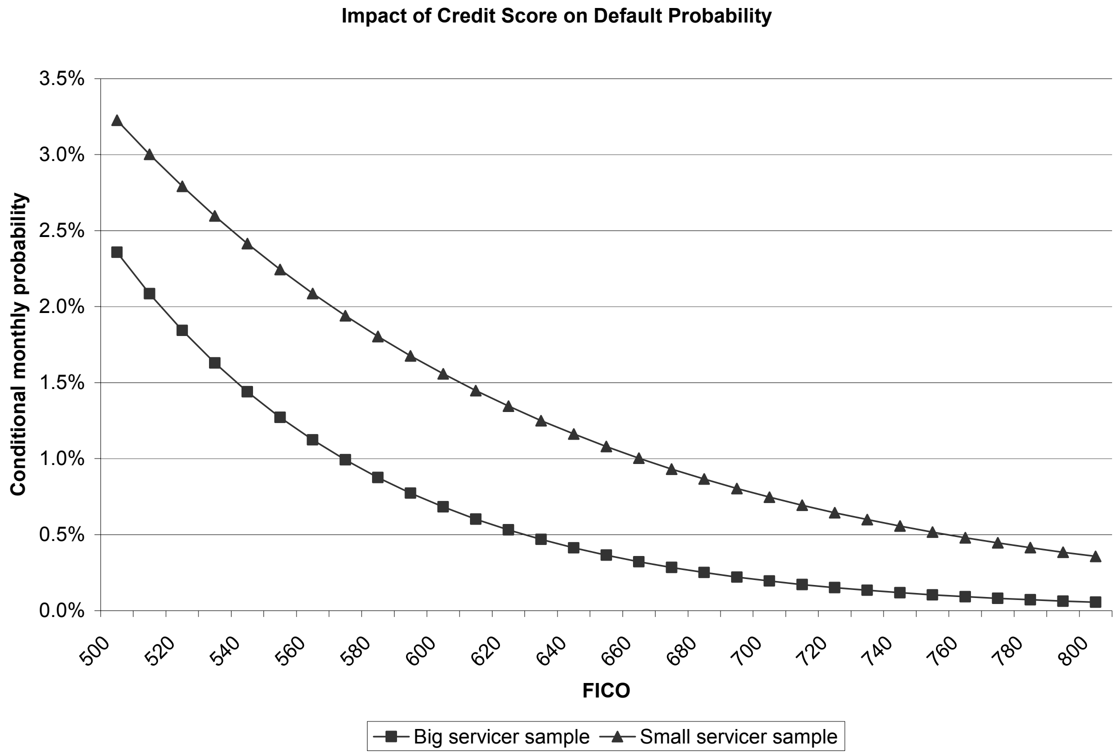


Figure 2:

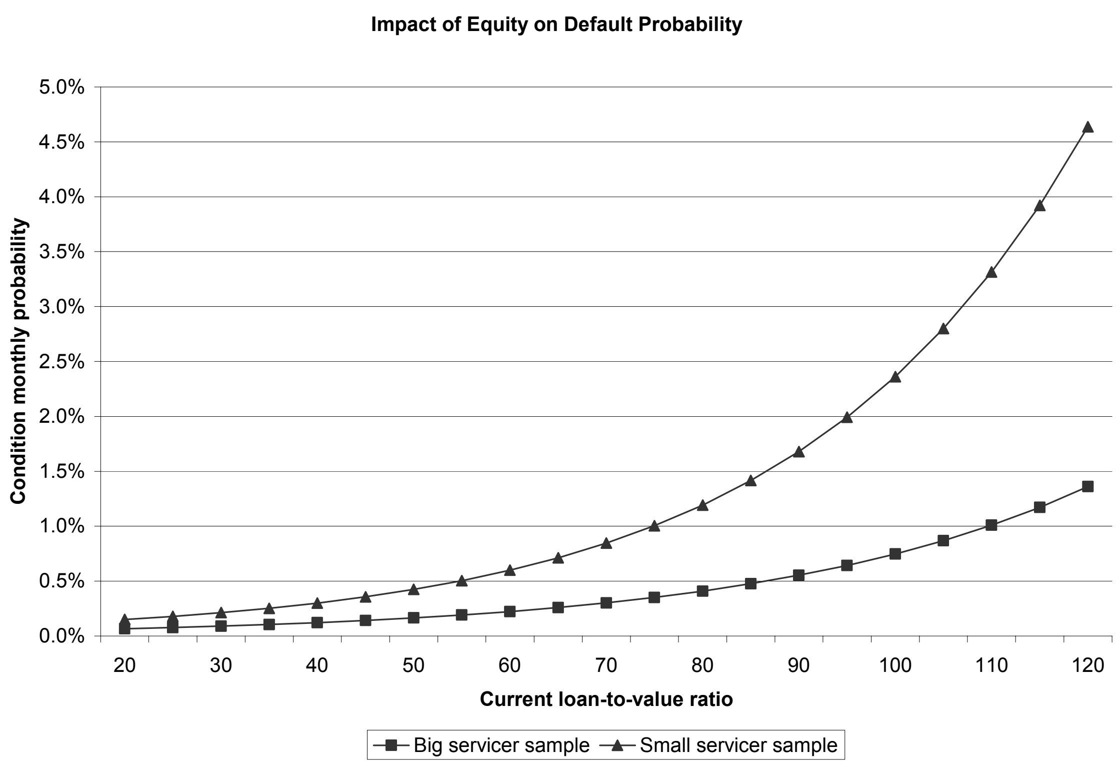


Figure 3:

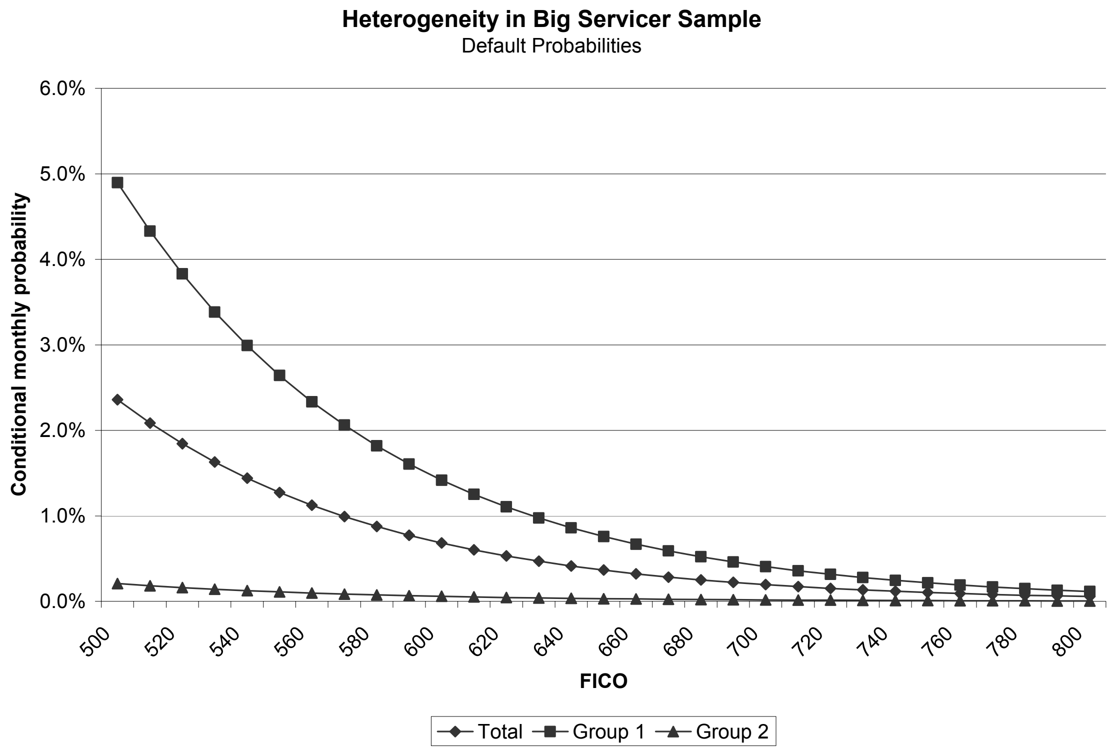
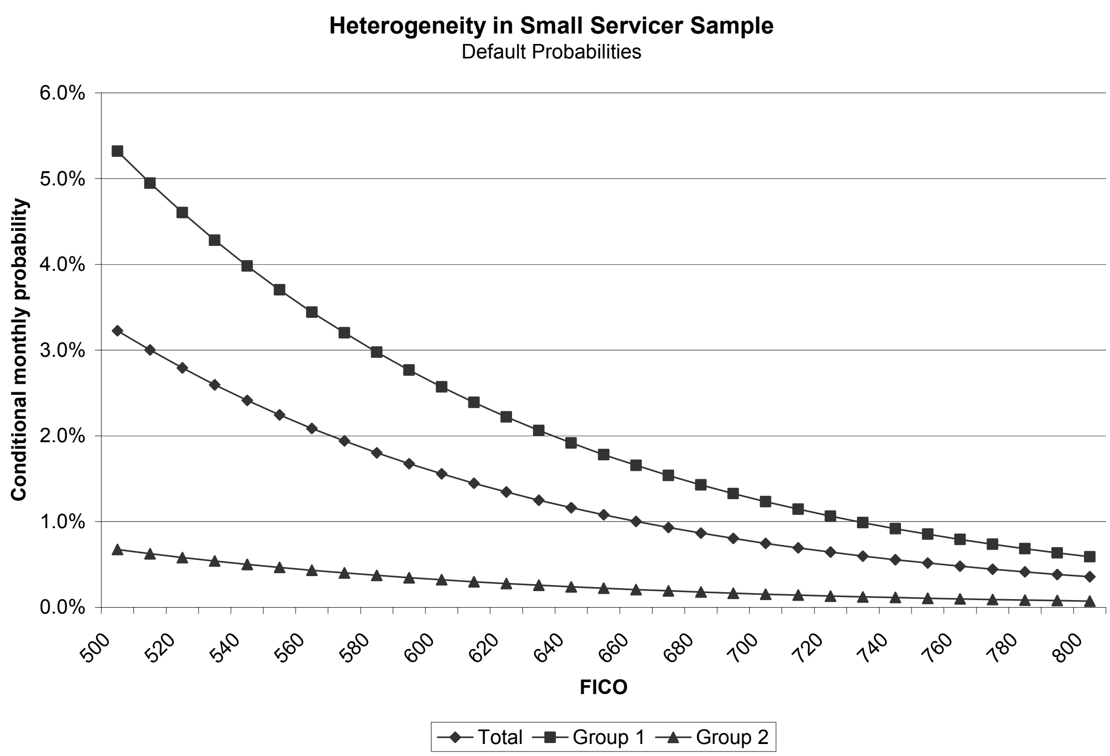


Figure 4:



End Notes

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[1] It is a coincidence that the same number of servicers is included in both samples.
[2] This also has the added appeal of removing the special servicer phase of servicing from the data set.
[3] The OFHEO house price index is only available in quarterly frequency, so we use linear interpolation to create monthly index.
[4] The author thanks Brian McCall for providing a copy of the Fortran code he developed to conduct the estimation. Also see Appendix B of McCall (1996) for more details on the likelihood function.
[5] While the likelihood function is more general and allows N groups to be estimated, attempts to estimate three or more groups did not converge because mass point estimates approached zero for at least one group.
[6] Servicer 1 is the excluded servicer for both samples. However, some servicers did not have enough observed defaults to include a reliable estimate of the servicer fixed effect on the probability of default. Therefore, servicers 3 and 8 for the big servicer sample and servicers 2, 3, 4, and 8 in the small servicer sample are part of the reference group.
[7] However, this sensitivity is identical in terms of proportional shifts within each sample.

Appendix:

Table A1: Big Servicer Sample, Default Coefficient Estimates

Parameter	Without unobserved heterogeneity				With unobserved heterogeneity			
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats
FICO	-0.91	-35.66	-0.75	-26.65	-1.17	-35.12	-0.95	-26.86
LNDOC	0.37	8.25	0.28	6.11	0.48	9.19	0.32	5.92
SEASON	0.63	5.14	0.30	2.31	0.99	6.24	0.55	3.30
CLTV	0.53	19.00	0.42	14.31	0.66	20.43	0.51	14.83
REFI	0.14	6.61	0.08	3.08	0.20	8.26	0.13	4.65
UNEMP	-0.03	-1.04	-0.05	-2.24	-0.03	-1.06	-0.06	-2.12
VARINT	0.11	5.68	0.10	4.70	0.11	5.46	0.08	3.75
VARHPI	-0.10	-3.65	-0.13	-4.54	-0.07	-2.29	-0.09	-2.99
PPEN	0.16	3.71	0.00	0.06	0.12	2.40	-0.12	-2.32
servicer 1	--	--	--	--	--	--	--	--
servicer 2	--	--	0.68	5.48	--	--	0.47	3.58
servicer 3	--	--	--	--	--	--	--	--
servicer 4	--	--	1.45	11.27	--	--	1.60	11.35
servicer 5	--	--	1.62	12.64	--	--	1.89	13.69
servicer 6	--	--	1.49	11.35	--	--	1.70	11.88
servicer 7	--	--	1.21	9.23	--	--	1.33	9.37
servicer 8	--	--	--	--	--	--	--	--
age	0.11	17.15	0.11	16.93	0.19	21.94	0.18	22.36
age2	-0.15	-12.81	-0.16	-13.12	-0.19	-13.72	-0.19	-13.72
location1	3.3E-04	11.29	1.6E-04	7.50	3.3E-04	9.29	1.7E-04	6.85
location2	--	--	--	--	1.3E-05	4.63	6.8E-06	4.43

Notes: For the estimation the continuous variables are normalized (*(x-mean)/stdev*). The *age2* parameter is scaled by 1/100.

Table A2: Big Servicer Sample, Prepay Coefficient Estimates

Parameter	Without unobserved heterogeneity				With unobserved heterogeneity			
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats
FICO	-0.07	-8.10	-0.07	-6.63	-0.15	-12.91	-0.12	-8.80
LNDOC	0.02	1.14	-0.05	-3.06	0.05	2.21	-0.08	-3.41
SEASON	0.34	5.97	0.17	2.99	0.53	7.38	0.30	4.20
CLTV	-0.01	-1.14	-0.07	-7.67	-0.01	-0.48	-0.10	-8.35
REFI	0.16	33.62	0.12	21.18	0.18	29.91	0.14	18.84
UNEMP	0.03	3.24	0.02	2.75	0.02	1.92	0.02	1.68
VARINT	-0.05	-6.06	-0.07	-7.87	-0.06	-6.57	-0.09	-9.54
VARHPI	0.21	26.48	0.20	24.66	0.23	23.35	0.22	21.74
PPEN	-0.08	-4.65	-0.12	-6.24	-0.13	-5.82	-0.20	-8.02
servicer 1	--	--	--	--	--	--	--	--
servicer 2	--	--	0.12	4.11	--	--	0.09	2.49
servicer 3	--	--	1.17	22.79	--	--	1.56	20.64
servicer 4	--	--	0.46	12.60	--	--	0.67	13.32
servicer 5	--	--	0.43	11.68	--	--	0.71	14.74
servicer 6	--	--	0.16	3.49	--	--	0.41	6.98
servicer 7	--	--	0.21	5.08	--	--	0.40	7.68
servicer 8	--	--	0.74	18.48	--	--	0.90	17.38
age	0.10	42.02	0.11	42.68	0.14	40.70	0.14	43.49
age2	-0.19	-35.31	-0.19	-36.12	-0.18	-28.66	-0.19	-29.35
location1	7.0E-03	35.52	5.8E-03	30.04	1.2E-02	28.30	8.5E-03	24.68
location2	--	--	--	--	1.4E-03	12.58	9.6E-04	12.80
Support points								
mass point 1	1.00	--	1.00	--	1.00	--	1.00	--
mass point 2	--	--	--	--	1.41	19.83	1.18	22.76
Number of loans	43,340		43,340		43,340		43,340	
Log likelihood	-88,523		-87,959		-88,248		-87,629	

Notes: For the estimation the continuous variables are normalized (*(x-mean)/stdev*). The *age2* parameter is scaled by 1/100.

Table A3: Small Servicer Sample, Default Coefficient Estimates

Parameter	Without unobserved heterogeneity				With unobserved heterogeneity			
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats
FICO	-0.49	-14.37	-0.44	-10.61	-0.52	-14.43	-0.45	-10.41
LNDOC	0.65	9.55	0.61	8.76	0.68	9.38	0.64	8.52
SEASON	0.81	5.57	0.84	5.75	1.03	6.60	1.05	6.53
CLTV	0.50	10.84	0.48	10.38	0.54	11.41	0.51	10.67
REFI	0.28	9.25	0.33	10.87	0.29	9.38	0.33	10.70
UNEMP	-0.08	-1.96	-0.09	-2.20	-0.12	-2.95	-0.14	-3.24
VARINT	0.14	4.32	0.23	6.47	0.13	4.20	0.22	6.33
VARHPI	-0.09	-1.95	-0.09	-2.05	-0.07	-1.66	-0.08	-1.71
PPEN	0.21	3.15	0.15	2.08	0.11	1.48	0.02	0.29
servicer 1	--	--	--	--	--	--	--	--
servicer 2	--	--	--	--	--	--	--	--
servicer 3	--	--	--	--	--	--	--	--
servicer 4	--	--	--	--	--	--	--	--
servicer 5	--	--	0.43	2.96	--	--	0.44	2.79
servicer 6	--	--	0.75	7.41	--	--	0.73	6.98
servicer 7	--	--	0.28	1.91	--	--	0.27	1.81
servicer 8	--	--	--	--	--	--	--	--
age	0.16	14.60	0.16	14.40	0.24	15.48	0.23	15.48
age2	-0.26	-11.95	-0.26	-11.77	-0.33	-13.76	-0.31	-13.28
location1	3.6E-04	7.12	2.3E-04	6.28	3.5E-04	6.09	2.4E-04	5.71
location2	--	--	--	--	4.3E-05	3.02	3.0E-05	3.04

Notes: For the estimation the continuous variables are normalized (*(x-mean)/stdev*). The *age2* parameter is scaled by 1/100.

Table A4: Small Servicer Sample, Prepay Coefficient Estimates

Parameter	Without unobserved heterogeneity				With unobserved heterogeneity			
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats	Coeff.	T-stats
FICO	0.10	8.20	0.09	6.64	0.11	6.40	0.09	4.43
LNDOC	0.12	4.80	0.06	2.47	0.12	3.50	0.06	1.81
SEASON	0.04	0.55	0.06	0.83	0.29	2.78	0.22	2.11
CLTV	-0.06	-5.11	-0.09	-7.38	-0.06	-3.49	-0.10	-5.43
REFI	0.15	21.39	0.12	14.36	0.15	16.32	0.11	10.62
UNEMP	0.04	3.88	0.02	1.97	0.00	-0.16	-0.02	-1.13
VARINT	-0.03	-2.28	-0.05	-4.09	-0.05	-3.11	-0.07	-4.59
VARHPI	0.08	6.81	0.09	7.22	0.09	5.95	0.10	6.27
PPEN	-0.45	-15.74	-0.46	-15.37	-0.66	-16.14	-0.65	-15.39
servicer 1	--	--	--	--	--	--	--	--
servicer 2	--	--	-1.08	-13.96	--	--	-1.12	-12.32
servicer 3	--	--	-0.03	-0.51	--	--	-0.09	-1.24
servicer 4	--	--	-0.30	-3.90	--	--	-0.44	-4.07
servicer 5	--	--	-0.51	-6.57	--	--	-0.62	-5.88
servicer 6	--	--	-0.38	-8.34	--	--	-0.45	-6.84
servicer 7	--	--	-0.41	-7.60	--	--	-0.43	-5.60
servicer 8	--	--	-0.50	-8.46	--	--	-0.30	-3.57
age	0.09	23.69	0.07	19.69	0.18	33.97	0.16	30.41
age2	-0.15	-19.70	-0.13	-16.37	-0.19	-19.02	-0.17	-16.45
location1	1.4E-02	24.12	2.4E-02	16.83	1.5E-02	19.44	2.6E-02	13.09
location2	--	--	--	--	7.8E-04	10.54	1.5E-03	9.12
Support points								
mass point 1	1.00	--	1.00	--	1.00	--	1.00	--
mass point 2	--	--	--	--	0.84	27.49	0.82	26.36
Number of loans	13,130		13,130		13,130		13,130	
Log likelihood	-37,652		-37,452		-37,334		-37,183	

Notes: For the estimation the continuous variables are normalized (*(x-mean)/stdev*). The *age2* parameter is scaled by 1/100.