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A Dynamic Look at Subprime Loan Performance

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Abstract: This paper examines the implications of delinquency on the performance of subprime mortgages. Specifically, we examine whether delinquency has any predictive power of the future performance of a mortgage. Using a sample of subprime mortgages from the Loanperformance database on securitized private-label pool collateral, we utilize a two-step estimation procedure to control for the endogeneity of delinquency in an estimation of default and prepayment probabilities. We find strong support for the "distressed prepayment" theory that very delinquent loans are more likely to prepay than to default and that the rate of increase of prepayment is substantially larger as delinquency intensity increases. Delinquency predominately leads to termination of a loan through prepayment while negative equity leads to termination through default.

JEL Classifications: G21, C25
Keywords: Mortgages, Subprime, Delinquency

Introduction

Mortgage performance is typically studied in terms of the probability or frequency of default and prepayment. However, this static characterization does not consider the behavior of a loan before it terminates. Before termination a loan can be current or delinquent. The delinquency could last for only a short period of time or for a very long time. Understanding the dynamic link between delinquency and loan termination is important for several reasons. For example, the delinquency behavior of loans can impact the payment streams of securities with underlying mortgage collateral. In addition, regulators, lenders, and other secondary market participants will benefit from understanding the risk of termination associated with delinquent mortgages.

The high risk nature of subprime mortgages provides an ideal market segment to study the dynamic nature of mortgage performance because these loans tend to be default and terminate at elevated rates (Alexander et al. 2002, Pennington-Cross 2003, Capozza and Thomson 2005, and Cowan and Cowan 2004). In addition, subprime lending tends to be concentrated in low-income and minority areas and areas with worse economic conditions. Subprime borrowers also tend to have worse credit characteristics, are less knowledgeable about the mortgage process, and are less satisfied with their mortgage. In general, these are characteristics that have overall been found to be consistent with a segment of the market that has trouble meeting all of its financial commitments (Pennington-Cross 2002, Courchane, Surette, and Zorn 2004, and Calem, Gillen, and Wachter 2004).

This paper examines the implications of delinquency on the performance of subprime mortgages. Specifically, we examine whether delinquency has any predictive power of the future performance of a mortgage. In addition, while it seems obvious on first inspection that delinquency naturally leads to default, we also test to see if delinquency increases or decreases the probability of a loan terminating through prepayment. We find evidence suggesting that when a loan is delinquent over a long period of time, prepayments dominate defaults as the primary terminating resolution.

Motivation and Literature Review

We examine the history of a loan until it defaults, which we define as entering foreclosure proceedings or become real estate owned by the lender, or until the loan is terminated through prepayment.[1] Figure 1 provides a conceptual overview of the dynamic relationship between delinquency and the final outcome or termination of the loan. In each month that a loan is "alive" or still active it can either be current or delinquent.[2] Loans can terminate at any time, but can only default after being delinquent. But, delinquency can lead to any other state (current, default or prepayment). In addition, prepaid loans can be delinquent or current in the prior month.

As a result, delinquency plays an important part in the path that a loan takes to termination. Since a loan must necessarily be delinquent prior to default it may seem obvious that delinquent loans must be more likely to default. Mitigating factors can retard the transition from delinquency to default, the most important of which is prepayment of the mortgage. A rational borrower may attempt to avoid the costs of foreclosure, which can be substantial and include legal fees and a negative credit report. A negative credit report can impact the cost of credit in the future. One method to avoid these costs is to sell the property and thus prepay the mortgage. Likewise, lenders also have incentives to avoid foreclosure costs through workout arrangements with delinquent borrowers. Many of these workouts, such as "short refinances," result in prepayment of the mortgage.[3] An important element to consider is that default and prepayment are competing risks. Increases in the probability of prepayment must necessarily lead to decreases in either the probability of continuing the mortgage and/or the probability of default.

The economic motives behind prepayments in the case of a seriously delinquent mortgage are distinct from the traditional motives for prepayment. Customary drivers of

[1] We also examine loans that do not terminate to account for all possible states.
[2] It should be noted that loans that are in foreclosure proceedings have not fully terminated. In fact, a portion of these loans will can be reinstated, prepaid, modified (extended term or other alterations to reduce the monthly payments), or other alternative outcomes. For examples in the literature that examine these issues see Ambrose and Capone1998, Lambrecht et al 2003, Ambrose and Capone 1996, Wang, Young, and Zhou 2002, Lawrence and Arshadi 1995, Phillips and Rosenblatt 1997,Weagley 1988, and Geppert and Karels 2001.

[3] In a short refinance, the lender forgives a portion of the debt and allows the borrower to refinance the existing delinquent mortgage into a new mortgage with a lower principal balance.

prepayments include drops in interest rates and trigger events such as job loss or divorce. In contrast, prepayments of delinquent mortgages can be viewed as "distressed prepayments" brought about by the desire by borrowers and/or lenders to avoid a default outcome. The current equity status of the property is a key determinant of whether a delinquent mortgage will prepay or will default. From the borrower's perspective, having a positive equity position makes the borrower more likely to attempt to preserve equity by selling the house rather then letting the property go into foreclosure. From the lender's perspective, the opposite is true in the case of a property with positive equity. If the borrower does not want to sell the house the least costly alternative may be to foreclose on the house, sell it, and use the proceeds to satisfy the debt. The net impact of current equity on defaults and prepayments is thus an open empirical question.

In addition, there is no reason to assume that the relationship between delinquency and default is linear. For example, Ambrose, Buttimer, and Capone (1997) identify three benefits to delinquency, namely free rent, income smoothing, and time to cure or the value of delay. Free rent is received during delinquency because the mortgage is not being paid in a timely fashion. A borrower can also not pay their mortgage in an attempt to maintain a standard of living beyond current income streams. This may make most sense for those with highly variable income sources or anticipated permanent increases income in the near future. Lastly, being delinquent is by its nature a period of delay. Delaying can be valuable because it can buy time to solve the problem. For example, house prices may rise dramatically or the liquidity problem may be solved through a change in job status, seasonal income streams, or improved credit availability. Kau and Kim (1994) provide a discussion of the value of delay and the role of house price volatility in the options theory framework.

There are significant costs borne by the borrower for being delinquent. Late fees accrue through time making it cost more in the long run to cure the loan. In addition, the delinquency is reported to the credit agencies which can have long term and dramatic impacts on a household. The cost of credit will increase, the availability of credit will decrease, and it may become more difficult to be hired at a new job due to credit and background checks. Likewise, there are significant costs to default that could make prepayment a more attractive option to delinquent borrowers. In summary, delinquency can lead to almost any outcome and it is an empirical question whether delinquency leads to more defaults, prepayments, or just more delinquency.

Delinquency

Before we can examine the influence of delinquency on the future performance of a mortgage we need to understand the forces that impact the probability of a loan being delinquent and the intensity of the delinquency. Empirical research over the last 30 years have included many of the same drivers. For example, Morton (1975) and Furstenberg (1974) found that the Loan to Value (LTV) ratio at origination as well as the income of the borrower play important roles in mortgage delinquency. Getter (2003) complemented these finding by using the 1998 Survey of Consumer Finances to show that borrowers use other non-housing financial assets to help make payments during unexpected periods of financial stress. Again, consistent with prior findings, Chinloy (1995) found that in the United Kingdom during the period 1983 through 1992 that LTV and income were the primary covariates associated with delinquency. Other research has also found that credit scores, contemporaneous economic conditions, and the incentive structure of the lender all can impact delinquency (Baku and Smith 1998, Calem and Wachter 1999, Ambrose and Capone 2000).[4]

Ambrose and Capone (1996 and 2000) have shown empirically that the behavior of a loan in the past can help to predict the behavior of a loan in the future. For example, they find that the length of the first serious delinquency (defined as time spent 90 or more days delinquent) reduces the probability of a second period of serious delinquency (90 days plus delinquent). In addition, if the loan enters serious delinquency for a second time it is less likely to be reinstated. These results provide empirical evidence that the current status of a mortgage is not independent of previous months.

This paper extends this literature by jointly estimating the probability of being delinquent with the intensity of delinquency measured by the cumulative delinquency rate. In addition, we estimate the impact of the predicted probability and predicted intensity of delinquency on the probability of default and prepayment in the second step

[4] Industry reports have also examined the delinquency of mortgages. For example, Gjaja and Wang (2004) examine transition matrices of subprime loans for a single servicer.

of the estimation.[5] This approach allows for the dynamic and non-linear nature of mortgage behavior to be observed and empirically tested.

Econometric Model

A mortgage's status is the result of joint decisions by the borrower and the lender. The current status – prepaid, defaulted, or continuing – is influenced by its cumulative payment history. Because a mortgage's current outcome is not independent of the previous monthly outcomes, we use a Heckman two-step procedure to control for the endogeneity. We specifically focus on the impact of past delinquency on the current outcome. In the first step, we estimate the intensity of delinquency, defined as the fraction of the observed life of the loan that it is delinquent. In the second step, we estimate a seemingly unrelated bivariate probit model of mortgage outcomes and include predicted intensity of delinquency and predicted delinquency probability from the first step.

In the first step of our model, we estimate a double-hurdle tobit model (Cragg's model) of the intensity of delinquency because the majority of mortgages have zero incidence of delinquency. The double-hurdle tobit model separately models the probability of having a delinquency and the intensity. Specifically, let the first hurdle be represented as

(1) $$d_i^* = z_i\alpha + \varepsilon_i$$

where d_i^* is an unobserved measure of the propensity of a mortgage *i* to be delinquent, z_i is a vector of borrower and loan characteristics, α is a vector of parameters to be estimated, and $\varepsilon_i \sim N(0,1)$. Define a dummy variable, d_i, as

(2) $$\begin{aligned} d_i &= 1 \text{ if } d_i^* > 0 \\ d_i &= 0 \text{ if } d_i^* \le 0 \end{aligned}.$$

The second hurdle is given by

(3) $$y_i = \max(x_i\beta + u_i, 0)$$

where y_i is the fraction of the observed life mortgage *i* that it is delinquent or the intensity of delinquency, x_i is a vector of borrower and loan characteristics, β is a vector

[5] Recall that default is defined as the beginning of foreclosure proceedings.

of parameters to be estimated, and $u_i \sim N(0, \sigma^2)$. It is important to note that ε and u are assumed independent. By this we mean that unobserved factors that cause a mortgage to be potentially delinquent are uncorrelated with the unobserved factors that determine the fraction of the observed life that the mortgage is actually delinquent.

The log-likelihood function is given by

$$(4) \qquad L_1 = \sum_0 \ln\left[1 - \Phi(z_i\alpha)\Phi\left(\frac{x_i\beta}{\sigma}\right)\right] + \sum_+ \ln\left[\Phi(z_i\alpha)\frac{1}{\sigma}\phi\left(\frac{y_i - x_i\beta}{\sigma}\right)\right]$$

where $\sum_0$ denotes the summation over observations with zero delinquency, $\sum_+$ denotes the summation over observations with a positive delinquency rate, Φ denotes the standard normal distribution function, and ϕ denotes the standard normal density function. The log-likelihood function is maximized by choosing the unknown parameters α, β, and σ.

The predicted value of intensity can be calculated using the estimated parameters $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\sigma}$. The predicted value is given by

$$(5) \qquad y_i^* = \begin{cases} \hat{y}_i \text{ if } \hat{y}_i > 0 \\ 0 \text{ if } \hat{y}_i \leq 0 \end{cases},$$

where

$$(6) \qquad \hat{y}_i = \Phi(z_i\hat{\alpha})\Phi\left(\frac{x_i\hat{\beta}}{\hat{\sigma}}\right) * \left[x_i\hat{\beta} + \frac{\hat{\sigma}\phi\left(\frac{x_i\hat{\beta}}{\hat{\sigma}}\right)}{1 - \Phi\left(\frac{x_i\hat{\beta}}{\hat{\sigma}}\right)}\right].$$

Intuitively, $\hat{y}$ equals the probability of delinquency multiplied by the expected value of the delinquency ratio conditional on the delinquency ratio being greater than zero.

The second stage of the estimation utilizes the predicted value of the intensity of delinquency in a seemingly unrelated bivariate probit model of the mortgage outcome. Specifically, we jointly model the probability of default and the probability of prepayment of a mortgage.[6] The model specification is given by

[6] The probability of the third possible outcome, a mortgage continuing, equals one minus the probability of default minus the probability of prepayment.

$$\pi_i^{*d} = w_i^d \delta^d + \varepsilon_i^d, \qquad \pi_i^d = 1 \text{ if } \pi_i^{*d} > 0, 0 \text{ otherwise} \tag{7}$$
$$\pi_i^{*p} = w_i^p \delta^p + \varepsilon_i^p \qquad \pi_i^p = 1 \text{ if } \pi_i^{*p} > 0, 0 \text{ otherwise}$$

and

$$\begin{aligned} &E[\varepsilon_i^d] = E[\varepsilon_i^p] = 0 \\ &Var[\varepsilon_i^d] = Var[\varepsilon_i^p] = 1. \\ &Cov[\varepsilon_i^d, \varepsilon_i^p] = \rho \end{aligned} \tag{8}$$

Equation (7) models the probability of default and prepayment of mortgage *i* (π_i^{*d} and π_i^{*p}, respectively) as a function of loan and borrower characteristics, w_i, including the predicted intensity of delinquency, and unknown parameters δ. The error terms ε_i have a correlation coefficient equal to ρ.

The log-likelihood function for the seemingly unrelated bivariate probit is given by

$$L_2 = \sum_i \ln \Phi_2 \left[(2\pi_i^d - 1) w_i^d \delta^d, (2\pi_i^p - 1) w_i^p \delta^p, \rho \right] \tag{9}$$

where Φ_2 denotes the standard bivariate normal cumulative density function.[7] The function is maximized by choosing the parameters δ^d, δ^d, and ρ.

Following Murphy and Topel (1985), we correct the variance-covariance matrix of the bivariate probit model to account for the fact that estimated variables are included as regressors. We utilize the procedure outlined in Hardin (2002) to accomplish the correction in Stata.[8] The standard errors exhibit very little change as a result of the correction.

Data

We drew a sample of loans to use in the estimation from a dataset consisting of the performance history of the underlying collateral of pools of private-label subprime

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[7] As indicates in William Greene's book Econometric Analysis, Fourth Edition (Prentice –Hall, Inc. Upper Saddle River, New Jersey) multivariate probit allows the error terms to be correlated and thus relaxes the independence assumption of the multinomial logit. The assumption of a normal error term instead of logistic is also consistent with the first stage error assumptions. In addition, in a J-dimensional problem J-1 probabilities must be considered. Therefore, in our case with a 3 dimensional problem 2 probabilities must be considered.

[8] In calculating cross-partial matrices (i.e., $E\left\{\left(\frac{\partial L_2}{\partial \theta_2}\right)\left(\frac{\partial L_2}{\partial \theta_1^T}\right)\right\}$, and $E\left\{\left(\frac{\partial L_2}{\partial \theta_2^T}\right)\left(\frac{\partial L_1}{\partial \theta_1^T}\right)\right\}$, where θ_1 and θ_1 are vectors of all estimated parameters), we account for the inclusion of the predicted intensity of delinquency variable, Dq, only.

securitizations available from Loanperformance (LP). Only loans that are 30 year fixed rate for home purchase in metropolitan areas are included. The LP database contains information on the loan at origination, including property location, LTV, credit score (FICO), documentation and prepayment penalty status. The database also contains pool-level information including the provider of the data to LP. In addition, monthly information on the age and the status of the loan (current, defaulted, prepaid, or delinquent) is available.

A cross-section of 22,799 loans from the time period January 1996 through May 2003 was selected from the LP database. For each loan, we randomly selected a month from the performance history and computed the intensity of delinquency up to that point in time. This is the fraction of the observed life of the loan that is delinquent. For example, 0 indicates that the loan has never been delinquent, 0.5 indicates that the loan has been delinquent one-half of the time, and 1 indicates that the loan has always been delinquent.

External data from a number of sources was matched to the sample. We used the metropolitan area repeat sales House Price Index from the Office of Federal Housing Enterprise Oversight and the balance of the loan to calculate a current loan-to-value ratio. We matched the contemporaneous metropolitan area unemployment rate from the Bureau of Labor and Statistics to the loan. We also computed the change in the prevailing prime interest rate from the date of loan origination to the current date using Freddie Mac's Primary Mortgage Market Survey as a measure of the change in interest rates affecting the refinancing incentive. A more detailed description of the variables used in the estimation is in Table 1. Summary statistics for the data used in the estimation are in Table 2.

Identification was achieved in the model using a theory-based specification approach. The double hurdle model and the bivariate probit model include a common set of covariates such as age of the loan and FICO that were chosen based on their theoretical relationship. One variable, a low documentation binary, is included in the double hurdle model of cumulative delinquency but is not included in the bivariate model of default and prepayment. Low documentation loans are typically used by borrowers with lumpy income streams such as small business owners. Because of the uneven income streams of these borrowers, we would expect to see higher rates of missed payments. However, we would not expect to see differing levels of loan termination based on uneven income streams. Two variables, the change in interest rates and a prepayment penalty binary, are included in the bivariate probit model only.[9] Interest rate changes are theorized to affect the prepayments through the refinance incentive and to affect defaults through the option theory of mortgages.

Results

The results from the first step of the estimation, the double hurdle tobit model, are in Table 3. The first column reports the results from estimation of the first hurdle (the α vector in equation (1)), the probability of delinquency, and the second column reports the results from estimation of the second hurdle (the β vector in equation (3)), the intensity of delinquency. The results from the second step of the estimation, the seemingly unrelated bivariate probit model, are in Table 4 (the δ^d and δ^p vectors in equation (7)).

Because many of the independent variables enter into both the first and second stages of the estimation, interpretation of the coefficients is not straightforward. For instance, FICO affects the predicted cumulative delinquency frequency by affecting the probability of delinquency as well the level of delinquency conditional on being delinquent. The predicted intensity of delinquency and the predicted probability of delinquency then affect the probability of default and the probability of prepayment in the seemingly unrelated bivariate probit model. In the second step, then, FICO has an indirect effect on the probability of default and prepayment through its impact on predicted delinquency probability and intensity of delinquency, and a direct effect through inclusion of a FICO variable. Figure 2 graphically represents this relationship and the mechanism by which FICO ultimately affects default and prepayment probabilities. In order to interpret the coefficients, we graph in Figures 3 through 7 the estimated probability of default and prepayment over the range of observed values for each of the continuous independent variables, holding all other variables at their means. For the discrete independent variables, we calculate in Table 7 the percentage change in

[9] The prepayment penalty indicator variable is included in the prepay specification only.

the estimated probabilities as the variable moves from 0 to 1. We discuss each of these relationships below.

The past delinquency behavior of a loan is strongly positively related to the probability of default and prepayment as shown in Figure 3. This is the direct effect of the intensity of delinquency, and does not incorporate the indirect effects of variables that caused the delinquency to change in the first place. As one would expect, as a loan increases in the intensity of delinquency, the probability that the loan defaults increases. There is a peak in defaults at 6.3% when the intensity is 0.72 and a slight decline thereafter. Somewhat surprising is the magnitude of the impact of past delinquency behavior on prepayments. At an intensity of delinquency of 0.72, the probability of prepayment is 26.3%. This is a strong indicator of distressed prepayments.

One important finding of this paper is that delinquency in the subprime market tends to lead to prepayments more than defaults. Prepayments increase faster than defaults as the intensity of delinquency increases. The odds ratio for default and prepayment are 3.82 for default and 5.89 for prepayment as intensity of delinquency increases from 2 percent and 72 percent. As a result, while prepayments are almost always more likely, they are even more prevalent when a loan has been delinquent most of its observed life. Prepayments are 2.93 times more likely when we should see very few defaults (intensity of delinquency = 0.02) and prepayments are 4.16 times more likely when distressed prepayments are very likely (intensity of delinquency = 0.72). These results provide evidence that distressed prepayments are rapidly rising, and even more than defaults, in response to extended periods of delinquency.

Figures 4a and 4b reflect the marginal effects of LTV at origination and current LTV on our first and second stage estimates. The two graphs are practically mirror images of each other. While the origination LTV results reflect the impact of subprime underwriting requirements that higher LTV loans must have compensating factors, the marginal effects of current LTV support the ruthless default theory of borrower behavior. As current LTV crosses the threshold of 100, the probability of default increases exponentially. At an LTV of 100, the probability of default is 6.8%, and this figure rises to 25.9% as LTV climbs to 120.[10] When current LTV is in excess of 100, the value of the property is less than the mortgage outstanding, leading to a ruthless default on the mortgage in an option theoretic framework. We also find that prepayments are negatively related to the current LTV. This is consistent with the limited options that a borrower in a severe negative equity options would have.

Further evidence of distressed prepayments is found in Tables 5a and 5b. Delinquent borrowers with positive equity in their property, evidenced by low current LTV, prepay with greater probability than delinquent borrowers without equity. This appears to be a rational response for borrowers who are weighing selling their property and preserving equity versus borrowers without equity to protect. Delinquent borrowers with positive equity rarely default whereas delinquent borrowers without equity default with much higher probability. This suggests that, although lenders have incentives to foreclose on properties with positive equity, borrowers are prepaying in advance of having that happen.[11]

Credit scores play an important role in determining the probabilities of prepayment and default both directly and indirectly. Figure 5 shows the effects of FICO on the probability of delinquency and the intensity of delinquency. Borrowers with low credit scores are delinquent with probability 25%, and these loans are predicted to be delinquent nearly 20% of their lifetime. On the other hand, borrowers with credit scores of 750 are delinquent with probability 3% and these loans will spend just 0.65% of their lives in delinquency. The combined indirect and direct impact of FICO on default and prepayment is shown in Figure 6. At levels of FICO below 570, the probability of default is greater than the probability of prepayment. As expected, defaults decrease with FICO, indicating that performance on past financial obligations is a good predictor of current performance. We also find that prepayments increase with credit score. This may be an indication that borrowers with high credit scores are able to cure into prime mortgages.

Table 6 reflects the percentage change in our four estimates of interest as each of the continuous independent variables are increased by one standard deviation, holding all other variables at their means. Specifically, the impacts on the probability of

[10] The impact of an increase in current LTV by one standard deviation elasticity on the probability of default is 316%. See Table 5.
[11] Lenders also can allow short sales (sales price < outstanding balance) to avoid the costs of foreclosure.

delinquency, the intensity of delinquency, the probability of default, and the probability of prepayment are shown. Rising credit scores decrease the probability of delinquency and the intensity of delinquency. An increase in FICO by one standard deviation decreases the probability of default by nearly one-half, while the probability of prepayment increases by nearly one-quarter.

We find, as expected, that the probability of prepayment is negatively related to the change in interest rates over the life of the loan. Figure 7 reports the changes in our variables of interest as interest rates change. Prepayment and, to a lesser extent, default probabilities decline as interest rates rise. This is consistent with the refinancing incentive for prepayment.

The area unemployment rate, included as a proxy for trigger events, showed very little impact on our estimated variables. Rising unemployment rates are theorized to increase delinquency and default probabilities since they potentially increase the financial distress of these borrowers. We do not find this relationship using the last month's metropolitan area unemployment rate as an indication of trigger events.

Table 7 shows the percentage change in each of our discrete independent variables as the variable switches from 0 to 1. The first row reflects the impact of low documentation status on a loan's performance. Being "low doc" increases the probability of delinquency and the intensity of delinquency, but decreases slightly the probabilities of default and prepayment. The second row shows the impact of prepayment penalties. The existence of a prepayment penalty decreases the probability of prepayment by one-half.

The next series of variables in Table 7 represent the fixed effects of "MIC_group." MIC_group is a variable in the pool-level Loanperformance data indicating the source of the data (the data provider). Data providers include lenders and servicers in the subprime market. The coefficients can therefore reflect many different sources of heterogeneity in the subprime market derived from the origination, underwriting of the pools of loans, owners of the securities, and the servicing. The results are significant and substantial in all of our estimates. In addition, tests interacting the "MIC_group" with delinquency and credit scores proved unfruitful.

Conclusion

The emergence of subprime lending has lead to many challenges in the market place. Due to the high, and sometimes unexpectedly high, termination rates of subprime loans one of these challenges is to come to a more complete understanding of how mortgages terminate. For example, are there paths to termination that indicate whether a loan will ultimately default or prepay? This paper finds evidence that the long run delinquency of a loan leads to elevated probabilities of prepayment and default. But the magnitude of the response in terms of prepayment is much larger. These prepayments are made when a loan is delinquent, as well as being independent of interest rates, and as a result we interpret these types of prepayments as distressed prepayments. These results cannot be consistent with credit curing (improved credit history through time) refinances, because delinquency worsens not improves credit history. Therefore, the results in this paper provide an alternative interpretation for the observed high rate of out of the money prepayments of subprime loans which is consistent with further credit deterioration. In addition, the relationship between the extent or intensity of delinquency and default is nonlinear. In fact, if a loan spends most of its life in delinquency this actually implies a lower probability of default. These results are consistent with motivations such as free rent, income smoothing, and the value of delay.

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Table 1: Description of Variables and Source

Variable	Source	Description
D_q	Loan level data.	Provides the fraction of the observed life of the loan that it is delinquent -- or the observed intensity of delinquency. For example, 0 indicates the loan is never delinquent, 0.5 that the loan is delinquent one half of the time, and 1 indicates that the loan is always delinquent (this is possible because some loans are seasoned before any information is available).
D_p	Loan level data.	Indicates whether the loan is delinquent (=1) or not (=0).
d	Loan level data.	Indicates whether the loan is defaulted (=1) or not (=0). A loan is defined as defaulted if it enters foreclosure or become real estate owned by the lender/investor.
p	Loan level data.	Indicates whether the loan is prepaid (=1) or not (=0). Note that 1- d + p = c, where c indicates whether the loan continues or is terminated. Loan are defined as prepaid when the loan is paid in full and the previous months status was current or delinquent.
A	Loan level data.	Provides the age of the loan expressed in months since the date of origination. Age^2, A^2, is also included in the estimation to capture any non-linear effects.
L	Loan level data.	The origination loan to value ratio expressed in 100's so that 95 is a 95 percent loan to value ratio.
L_c	The Office of Federal Housing and Enterprise Oversight and loan level data.	Shows the current loan to value ratio derived from the balance on the loan and the updated value of the value of the property using the metropolitan area repeat sale price index. Also expressed in 100s.
F	Loan level data.	Provides the credit score at origination reported for the loan.
U	United States Bureau of labor and Statistics.	Provides the Metropolitan area reported unemployment rate for the previous month.
LD	Loan level data.	Indicates that the loan has low or no documentation.
ΔI	Freddie Mac.	Provides the change in prevailing prime interest rates from the date of origination to the current date. The Primary Mortgage Market Survey is used and available from Freddie Mac.
P	Loan level data.	Indicates whether a prepayment penalty is in effect for the current month. For example, for a loan with a prepayment penalty that lasts one year P=1 if months<=12 and P=0 if months>12.
S	Pool level data.	Identifies the eleven companies that provide the data to the repository (LoanPerformance.com). A dummy variable is constructed to capture any unique fixed effects associated with each data provider/servicer.

Table 2: Summary Statistics for the Estimation Data Set

	Mean	Std. Dev.	Minimum	Maximum
D_q	0.039	0.146	0	1
D_p	0.106	0.307	0	1
d	0.020	0.140	0	1
p	0.041	0.198	0	1
A	14.825	13.871	1	95
L	90.973	14.049	20	125
L_c	83.612	15.327	11.0	124.8
F	660.188	71.600	373	827
U	5.105	2.088	1.2	19.3
LD	0.294	0.455	0	1
ΔI	-0.501	0.743	-3.29	1.81
P	0.379	0.485	0	1
Absc	0.028	0.164	0	1
Cbass	0.026	0.159	0	1
Centex	0.030	0.171	0	1
Dlj	0.078	0.268	0	1
equicredit	0.064	0.245	0	1
Icifc	0.039	0.195	0	1
independent	0.026	0.159	0	1
Residential Funding Corporation	0.440	0.496	0	1
Ryland	0.190	0.392	0	1
Sasco	0.079	0.269	0	1
Number of observations	22,799			

D_q is the intensity of delinquency, D_p indicates when the loan is delinquent, d indicates the loan has defaulted, p indicates the loans has prepaid, A is age, L is the loan to value ratio, L_c is the current loan to value ratio, F is the FICO score, U is last months unemployment rate, LD is a low or no documentation loan, ΔI is the cumulative change in interest rates since origination, P is the prepay penalty is in force for the current month, and the remaining variables are dummy variables for each data provider.

Table 3: Double Hurdle Results

	Probability of Delinquency (Dp)		Intensity of Delinquency (Dq)	
	coeff	z	coeff	z
A	1.781	25.8	-0.188	-6.1
A^2	-1.009	-19.6	0.121	5.1
L	-0.238	-4.2	-0.073	-3.4
L_c	0.382	6.2	0.074	3.2
F	-0.356	-13.6	-0.116	-9.1
U	-0.023	-1.0	0.008	0.7
LD	0.064	2.6	-0.001	-0.1
absc	-0.002	-0.1	0.026	2.9
cbass	-0.033	-2.3	0.071	11.1
centex	0.033	1.8	-0.012	-1.6
dlj	0.108	4.8	-0.004	-0.4
equicredit	-0.266	-13.0	0.085	8.3
icifc	0.014	0.6	0.019	1.8
independent	0.035	1.6	-0.002	-0.3
ryland	0.023	1.0	0.019	1.8
sasco	-0.162	-5.8	0.081	4.6
constant	-1.217	-42.5	0.106	5.0
sigma			0.385	52.0

All variables are transformed so that the mean is zero and the standard deviation is 1. A age, A^2 age squared, L loan to value ratio, Lc current loan to value ratio, F FICO score, U last months unemployment rate, LD low or no documentation loan, and the remaining variables are fixed effects for each data provider.

Table 4: Seemingly Unrelated Bivariate Probit Results

	Probability of Default (π_d)			Probability of Prepay (π_p)		
	Coeff	Z-stat	Murphy Topel Z-stat	Coeff	Z-stat	Murphy Topel Z-stat
D_q	0.179	2.12	2.09	0.339	4.71	4.68
$(D_q)^2$	-0.054	-1.38	-1.37	-0.122	-2.79	-2.79
D_p	-0.232	-2.36	-2.33	-0.395	-5.87	-5.82
A	1.252	9.01	8.95	0.540	6.61	6.55
A^2	-0.780	-8.60	-8.53	-0.414	-7.73	-7.70
L	-0.508	-6.43	-6.42	0.161	3.80	3.78
L_c	0.593	7.27	7.26	-0.207	-4.86	-4.79
F	-0.273	-8.28	-8.24	0.073	3.43	3.42
U	-0.090	-2.30	-2.25	-0.066	-3.31	-3.31
ΔI	-0.060	-2.68	-2.68	-0.048	-2.60	-2.60
P				-0.144	-8.15	-8.15
cbass	-0.008	-0.33	-0.32	-0.032	-1.49	-1.49
centex	-0.026	-1.29	-1.29	0.013	0.72	0.72
dlj	0.021	0.81	0.80	0.066	4.28	4.27
equicredit	-0.012	-0.42	-0.39	-0.069	-3.03	-3.02
icifc	0.044	2.12	2.12	0.048	3.25	3.26
independent	0.065	3.71	3.71	0.036	2.58	2.54
ryland	0.021	0.91	0.91	0.074	4.38	4.28
sasco	-0.026	-0.76	-0.75	-0.035	-1.98	-1.97
constant	-2.341	-75.74	-75.74	-1.804	-109.24	-109.24
rho	-0.709	-1.00	-0.30			

All variables, including the dummy variables, are transformed so that the mean is zero and the standard deviation is 1. Dq predicted intensity of delinquency, $(D_q)^2$ predicted intensity of delinquency squared, D_p predicted probability of delinquency, A age, A^2 age squared, L loan to value ratio, Lc current loan to value ratio, F FICO score, U last months unemployment rate, ΔI cumulative change in interest rates since origination, P is prepay penalty is in force for the current month, cbass is C-BASS, Centex is Centex, DLJ is DLJ Mortgage Acceptance Corporation, Equicredit is Equicredit, ICIFC is ICIFC, Independent is Independent National, Ryland is Ryland Master Group, SASCO is SASCO. The excluded data provider is the Residential Funding Corporation, which includes both RFC Home Equity and RFC Master.

Table 5a. Predicted Probability of Prepayment for Various Current Equity Positions and Intensity of Delinquency

		Intensity of Delinquency	
		Low	High
Current LTV*	Low	0.031	0.080
	High	0.023	0.063

Table 5b. Predicted Probability of Default for Various Current Equity Positions and Intensity of Delinquency

		Intensity of Delinquency Rate	
		Low	High
Current LTV*	Low	0.001	0.004
	High	0.043	0.091

*Direct Effect Only, low and high is defined a one standard deviation above and below the mean.

Table 6: One Standard Deviation Elasticity

Variable	Probability Delinquent	Intensity of Delinquency (Percent of Life Delinquent)	Probability Default	Probability Prepay
F	-56%	-75%	-47%	22%
L	-41%	-57%	-80%	13%
L_c	90%	144%	316%	-33%
A	170%	66%	222%	-22%
U	-2%	1%	-13%	-5%
ΔI			-15%	-9%

A is age, L is loan to value ratio, Lc is current loan to value ratio, F is FICO score, U is the previous months unemployment rate, and ΔI is the cumulative change in interest rates since origination.

Table 7: Fixed and Discontinuous Effects – Percent Change

Variable	Probability Delinquent	Intensity of Delinquency (Percent of Life Delinquent)	Probability Default	Probability Prepay
LD	22%	20%	-4%	-9%
P				-49%
absc	29%	136%	10%	2%
cbass	24%	324%	36%	14%
centex	14%	-25%	-33%	9%
dlj	66%	54%	6%	30%
equicredit	-81%	-44%	5%	-15%
icifc	33%	101%	78%	66%
independent	32%	22%	154%	41%
ryland	20%	50%	14%	44%
sasco	-46%	41%	-1%	16%

Reference groups is full documentation, no prepay penalty, and RFC.
LD is a low or no documentation loan, and P is prepay penalty is in force for the current month.

Figure 1. Dynamic Role of Delinquency

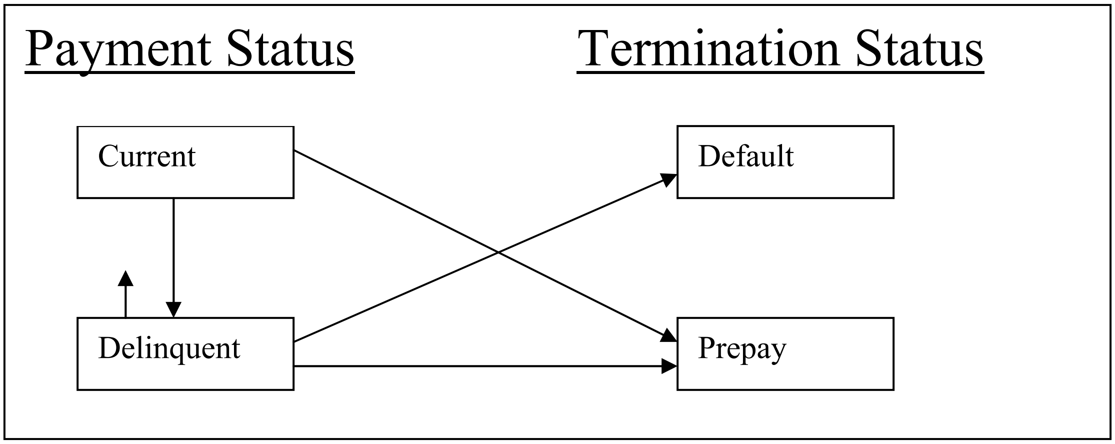

Figure 2. Direct and Indirect Effects of FICO on Default and Prepayment Probabilities

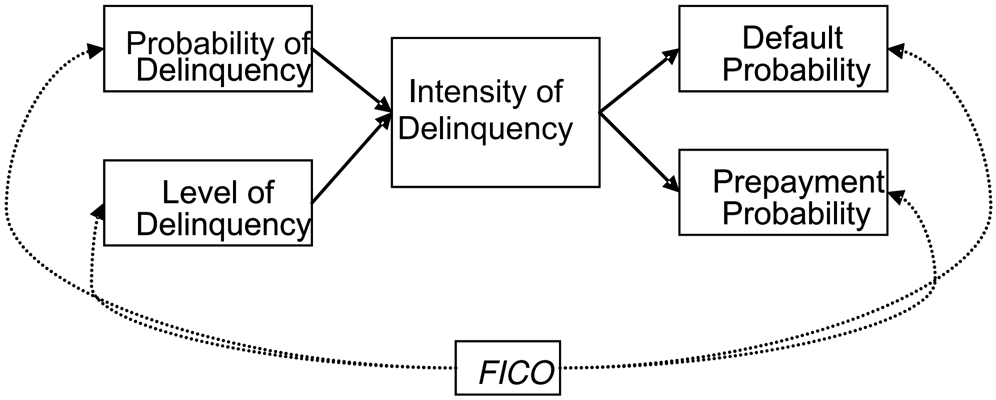

Figure 3. Effect of Predicted Intensity of Delinquency on Termination

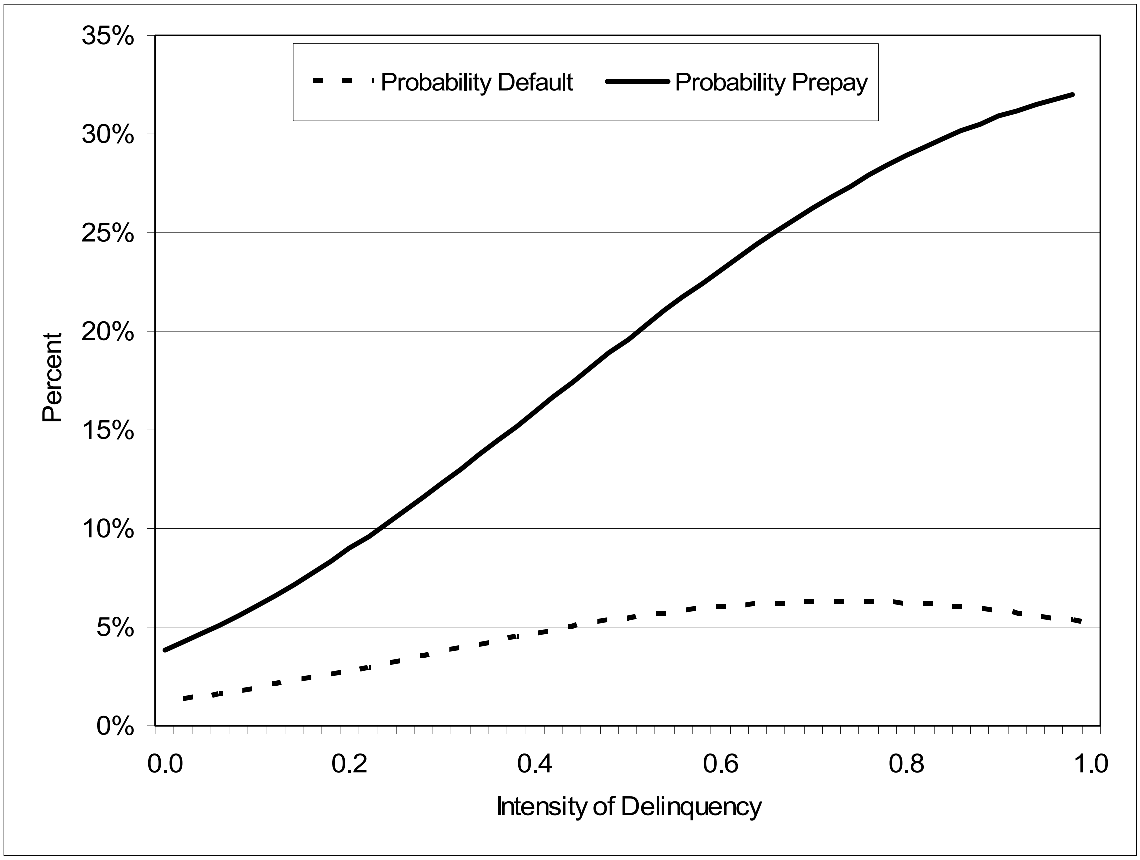

Figure 4a. Effect of LTV at Origination on First and Second Stage Estimates

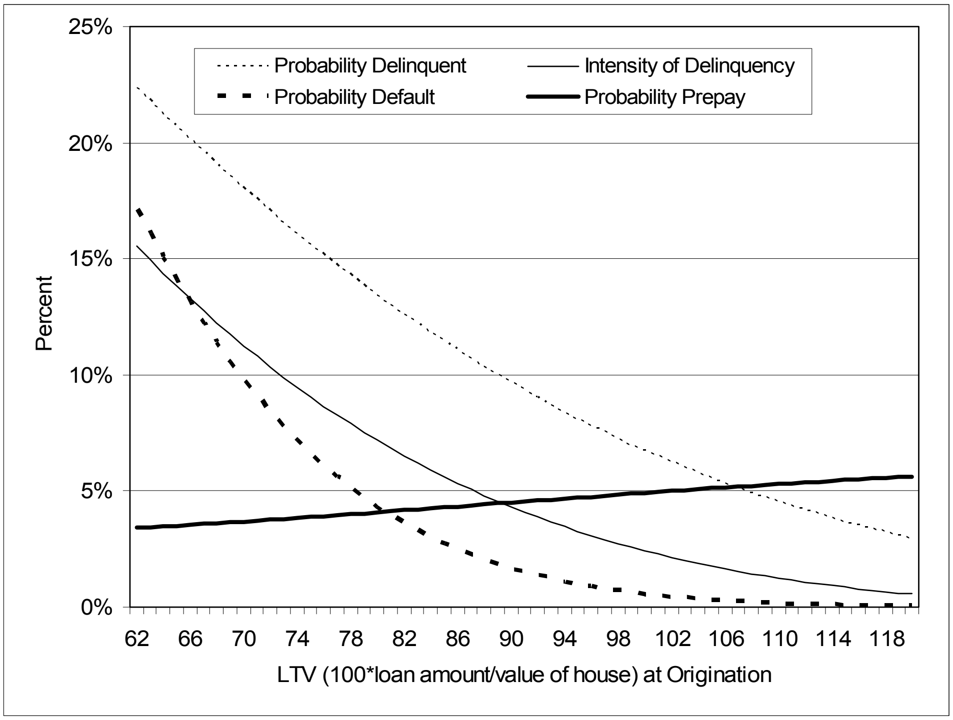

Figure 4b. Effect of Current LTV on First and Second Stage Estimates

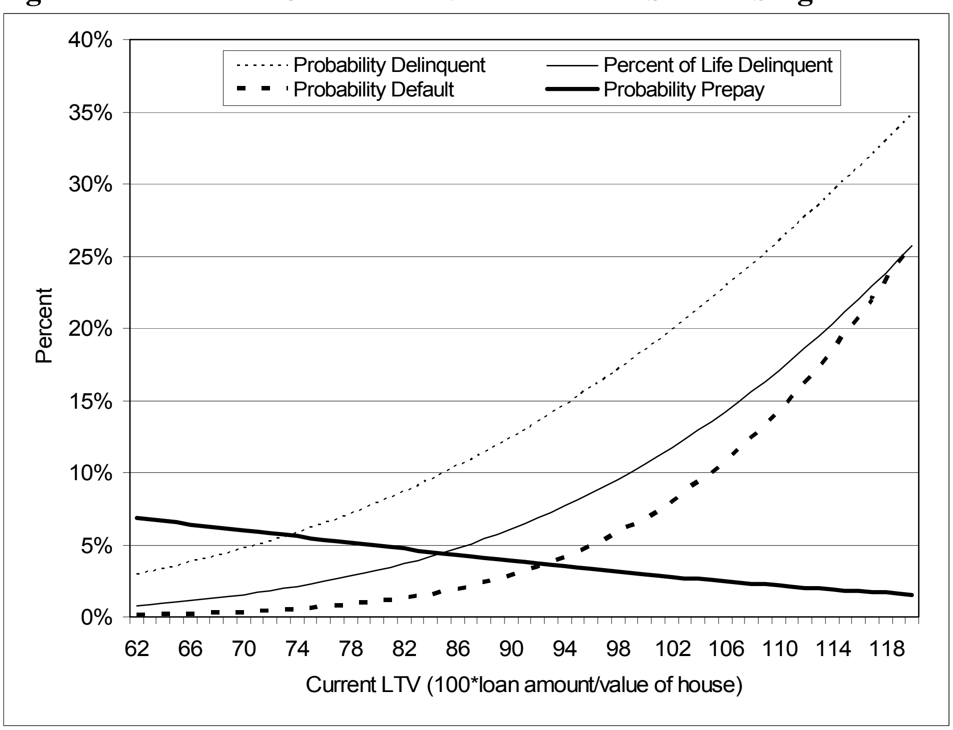

Figure 5. Effect of FICO on Delinquency

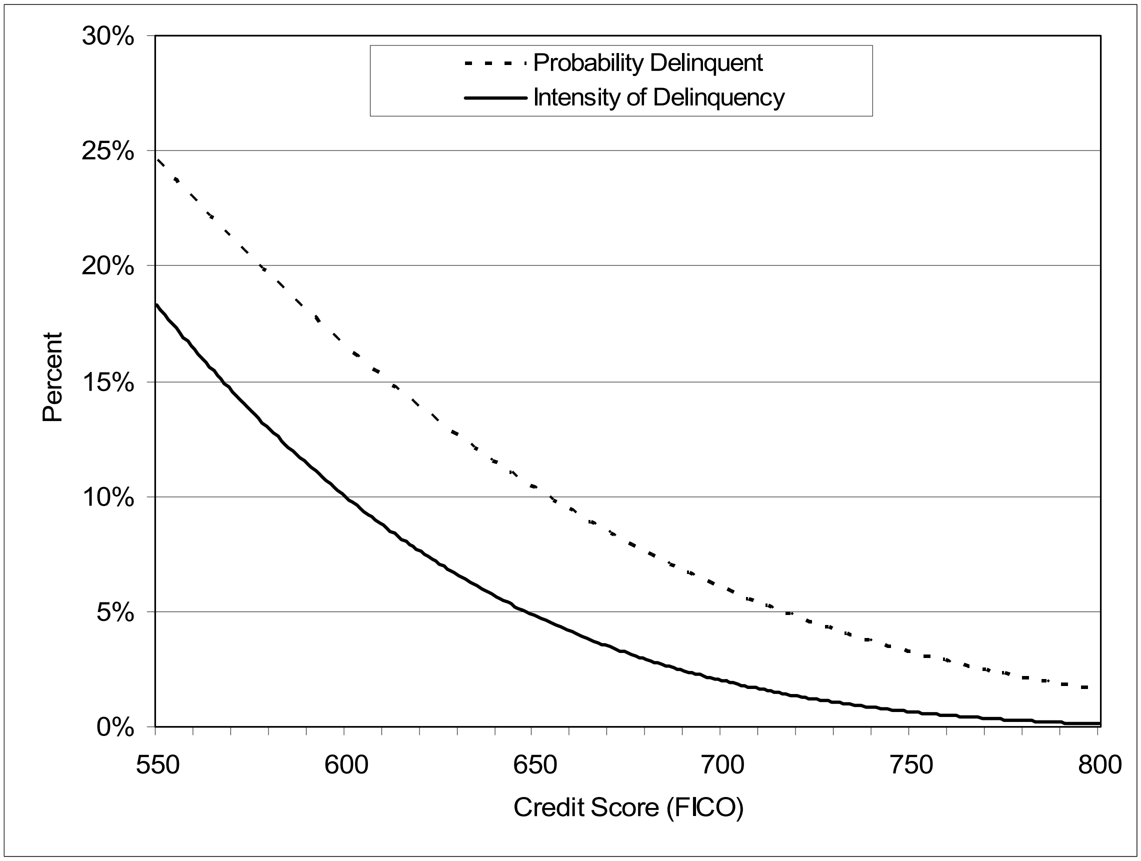

Figure 6. Effect of Credit Score on Termination

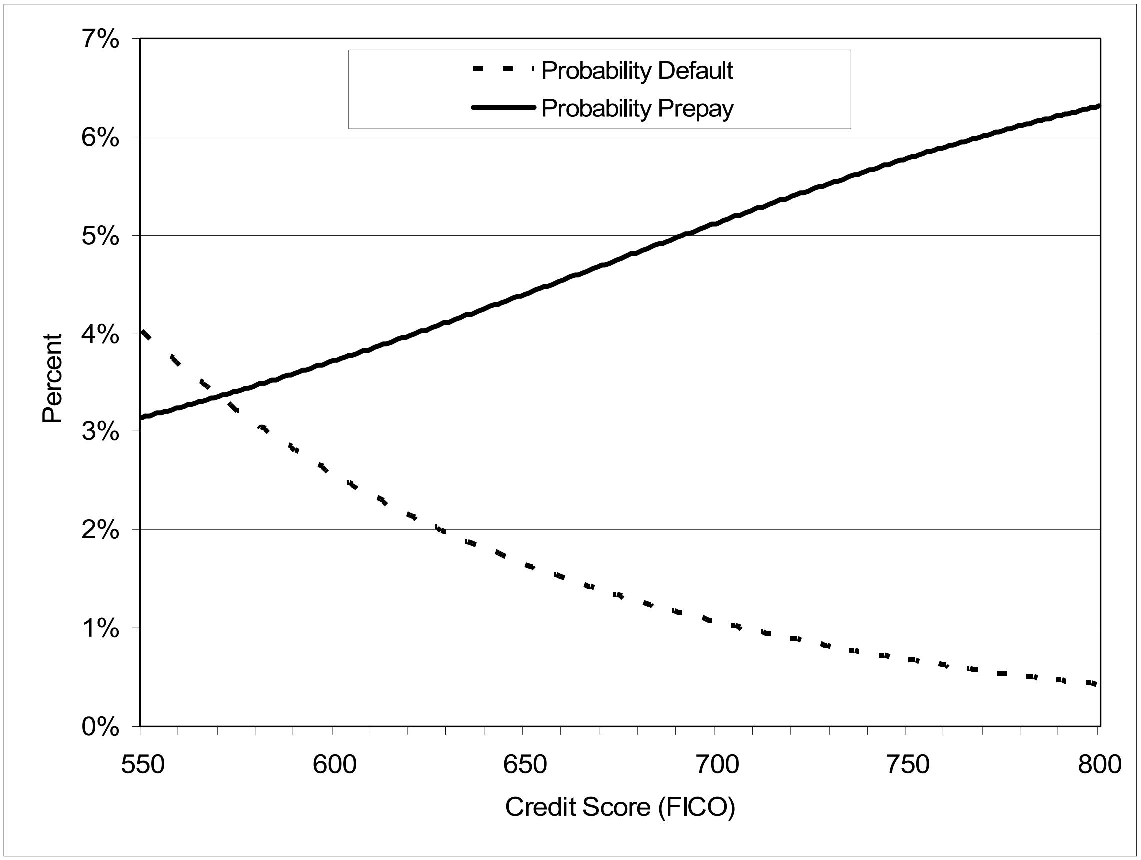

Figure 7. Effect of the Change in Interest Rates on Termination