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Michelle A. Danis
Securities and Exchange Commission

Anthony Pennington-Cross
Marquette University, anthony.pennington-cross@marquette.edu

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Michelle A. Danis
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Anthony Pennington-Cross
Marquette University

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Corresponding author: Michelle Danis, 100 F Street NE Mail Stop 6628, Washington, DC 20549, Phone 202-551-5534, Fax 202-772-9273, Email DanisM@sec.gov.

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Abstract

The lag between the time that a borrower stops making payments on a mortgage and the termination of the loan plays a critical role in the costs borne by both borrower and lender on defaulted loans. While the prior literature uses a multinomial logit approach, statistical tests indicate that we cannot accept the associated assumption of Independence of Irrelevant Alternatives (IIA). Using a nested logit specification our results suggest that the recipe for delinquency involves young loans to low credit score borrowers with low or no documentation in housing markets with moderately volatile and flat or declining nominal house prices.

1. Introduction

Subprime lending in the mortgage market has seen dramatic growth since the early 1990s. The share of total originations that is subprime has risen from 1.4 percent in 1994 to 18.7 percent in 2002. Lenders include both mono-line lenders (subprime only) and larger institutions that provide subprime loans as part of a continuum of alternatives. The securitized market for subprime loans has also been growing, with the securitization rate of subprime home mortgages rising from 31.6 percent in 1994 to 62.5 percent in 2002.[1] While the subprime securitization rate is still below the prime or conventional market rate (73.8 percent in 2002), it has helped bring the subprime market into a form more closely resembling the prime market (Inside Mortgage Finance, 2003).

Subprime lending can most easily be characterized as high risk lending, especially as compared to the conventional prime sector of the mortgage market. To compensate for these risks, which include elevated rates of prepayment, delinquency and default, lenders must charge higher risk spreads. The understanding of these risks is of crucial importance to both regulators and lenders. This paper focuses on one of the least studied risks, the delinquency of subprime loans. Delinquent loans increase the costs of servicing, increase losses for any institution guaranteeing timely payments, and impact payments to subordinate tranches. Even if the loans do not terminate, elevated rates of delinquency will impact pricing in the primary and secondary markets.

2. Motivation

The performance of a mortgage is often characterized by whether the loan has prepaid or defaulted, as well as the loss on any outstanding defaulted balance. Empirical models of these events can then be used to understand the sensitivity of a mortgage to economic conditions, loan type, and borrower information. Estimates of these relationships rely on option pricing techniques that allow the borrower to exercise the option to put the mortgage back to the lender or investor through default or to call the mortgage through prepayment.

Puts and calls can be motivated by financial considerations or by external events. A mortgage is put, at least in its simplest form, when the mortgage outstanding is greater than the value of the property

after accounting for costs such as transaction fees. These are often referred to as "ruthless" defaults. Similarly, a mortgage is called and prepaid, typically due to a drop in interest rates, if the gain from doing so outweighs the cost. Subprime borrowers may also put a mortgage when their history of paying financial obligations has improved, thus making lower cost credit available. Beyond the financial motivations, other factors, coined trigger events, have been identified as potential causes of loan defaults and prepayments. Typical trigger events include losing a job, a severe illness, or the breakup of a household. These unanticipated events, which can be either temporary or permanent, will likely change current and future income streams and make it difficult to continue paying a mortgage. Trigger events can lead to both defaults and prepayments depending on the amount of equity in the mortgage and expected income streams.

It is important to remember that the lender and borrower interact once a loan becomes delinquent. It is the outcome of this interaction that determines what status the loan will be in (cure, more delinquency, or termination and type of termination). Therefore, all observed loan outcomes reflect a mixture of lender and borrower objectives.

Before a loan enters foreclosure proceedings or the property becomes owned by the lender, there is a gray area in which a borrower is delinquent. While missing a single payment on a mortgage may violate the mortgage contract or agreement and thus could technically be considered a default, lenders prefer and are usually legally required to allow borrowers to be delinquent over a longer time period before pursuing foreclosure or alternative methods of collecting the debt. It is this time period as a loan moves from being one payment late, to two, and three payments late that is this paper's focal point. Delinquent loans consist of a mix of temporary delinquency, which will eventually cure, and delinquency that is driven by the standard option motivation to default or prepay.

The subprime mortgage market is a fertile segment of the market to examine delinquency because it includes borrowers who have already shown that they have trouble meeting their financial obligations. Therefore, subprime loans should exhibit high rates of delinquency and default. This should aid in identifying key factors that drive delinquency. These factors could include both time constant and time

varying factors. For example, borrowers in ruthless delinquency (delinquency driven by the financial desire to default) may find that by the time delinquency reaches 60 or 90+ days house prices have increased enough to make it no longer financially sensible to go all the way to foreclosure.

This paper uses a large and nationally representative sample of data from LoanPerformance.com (formerly MIC) to examine the monthly status of single-family 30-year fixed-rate subprime mortgages from 1996 through the middle of 2003.

This paper is one of the first examinations of the delinquency of subprime loans. It includes – 1) an examination of subprime mortgage performance using a large nationally representative sample of loans covering multiple lenders and servicers, 2) a model of multiple states of delinquency as well as termination states simultaneously, and 3) the utilization of nested logit in a hazard model framework.

3. Background and Literature Review

This paper draws from two lines of literature. The first line is the growing body of research on the subprime mortgage market. The second line focuses on the performance and modeling of mortgages and specifically the delinquency of mortgages.

3.1 Subprime

Over the last 10 years the growth in the subprime mortgage market, while substantial, has been uneven. The subprime market rapidly expanded in the mid- and early- 1990s. In 1998, however, the market was hit by two events that caused a liquidity crunch (Temkin, Johnson, and Levy, 2002). First, subprime lenders experienced unexpected losses after high default, delinquency, and prepayment rates occurred. Second, the Russian bond crisis during late 1998 caused investor confidence to decline. The resulting secondary market discipline led to a short time period of retrenchment followed by renewed growth in different market segments. Before 1998, growth in subprime came from a rapid expansion in lending to the riskiest portions of the market. After 1998, which was also associated with consolidation in the industry, growth has come in the least risky portions of the market. This segment is typically referred to as A- lending and includes borrowers with impaired credit histories that are willing to pay a premium

over the prime lending rate typically in excess of 290 basis points (Chomsisengphet and Pennington-Cross, 2004 and 2006).

In fact, subprime lenders provide a menu of mortgage options to borrowers with a variety of impairments. The most typical impairment is poor credit history. Borrowers with worse credit history pay higher premiums and must provide larger down payments to help defray some of the expected losses and expected delinquency of these types of loans. Another segment of the subprime market is referred to as Alt-A, which is short for Alternative A lending. These types of borrowers look just like prime borrowers in terms of credit history and assets to make down payments, but they usually provide limited or no documentation on their income or down payment. As a result, they typically pay a 100 basis point premium (Chomsisengphet and Pennington-Cross, 2004).

As should be expected given the impairments of subprime borrowers, the Mortgage Bankers Association of America (MBA) reports that in the third quarter of 2002 subprime loans were delinquent 5½ times the rate of conventional mortgages (14.28 versus 2.54 percent). In addition, subprime loans started foreclosure more than 10 times more often (2.08 versus 0.20 percent). There is also evidence that subprime lending is most often used in high-risk locations (Calem, Gillen, and Wachter 2004, and Pennington-Cross 2002). While subprime borrowers also tend to have less knowledge about the mortgage process, a borrower with a subprime mortgage is not necessarily stuck using high cost lending forever. Survey evidence indicates that of subprime borrowers who get another mortgage, 39.6 percent successfully transition into the prime market (Courchane, Surette, and Zorn, 2004).

The growing literature on subprime lending in the mortgage market consistently shows that subprime differs substantially from the prime market on many dimensions. The first and perhaps initially most curious fact regarding subprime is simply that it is segmented from the prime market. Theoretical models have explained this segmentation. Cutts and Van Order (2005) focus on the amount of underwriting a lender should do in each risk classification. They find that the most extensive underwriting will be done on the least risky loan types. Nichols, Pennington-Cross, and Yezer (2005) provide a different segmenting equilibrium in which lenders specialize in either subprime or prime

lending. In their model if a lender sets lending standards too close to the entrenched prime market, then application costs become so high that it becomes less costly to lower credit standards and accept more high-risk applicants. This result is driven by the costs associated with processing rejected applications. When a high proportion of applicants are rejected it can overwhelm any benefits associated with the lower risk borrowers. An optimum distance in credit quality space is then found, thus motivating the need for a segmented high-risk or subprime mortgage market.

The literature on the performance of subprime mortgages has focused on default, prepayment, and losses on outstanding defaulted balances. In general, loss severity tends to be higher for high-risk borrowers and high-risk property. These losses tend to be larger even though subprime borrowers tend to put the mortgage earlier than prime borrowers -- when it is less in the money to default (Capozza and Thomson, 2005). Research has also found that loans originated by third parties tend to default at elevated rates and that high cost borrowers are less responsive to changing interest rates (Alexander et al 2002, and Pennington-Cross 2003). Evidence from a single subprime lender shows that risks tend to be higher for the higher cost segments in the market because the defaults are more highly correlated. For lower cost segments, such as A- and Alternative-A, subprime loans showed relatively low default correlation rates (Cowan and Cowan 2004).

3.2 Delinquency

Traditional option based mortgage-pricing research includes three possible states for a mortgage – 1) current or active, 2) prepaid, or 3) defaulted.[2] This approach typically ignores the fact that lenders are usually legally not allowed to begin foreclosure proceedings until two payments are missed and the third is due. Many options are available to lenders besides foreclosure to recover losses on defaulted loans and it can take a substantial period of time to complete a foreclosure. For example, the main feature of a ruthless default is that it makes financial sense because the mortgage is substantially larger than the value of the property. But, the relevant value of the property is at foreclosure, not when the first or even second payment is missed. Kau and Kim (1994) indirectly discuss this issue by showing that the value of a future default can impact whether an "in the money" default today will be exercised. For example, if

house prices continue to drop in the future the value of default will be larger in the future, and the borrower will wait. In a stochastic framework, the larger the variance of house prices the more value there may be in the future, so it is consistent for borrowers that are "in the money" to default to wait.

Ambrose, Buttimer, and Capone (1997) explicitly introduced into the option-pricing framework the delay of foreclosure and the concept that the decision to stop making payments is determined by expected values of the property well into the future (at the foreclosure date). The delay of foreclosure can be interpreted as an increase in the delinquency of the loan, but the model treats the delay of foreclosure as an exogenous variable and therefore, can be used to provide predictions about the probability of default given a foreclosure delay or delinquency time period. For instance, the probability that a loan defaults and becomes delinquent is sensitive to the delay before foreclosure, the loan to value (LTV) ratio at origination, and the variance of house prices. Specifically, longer delays (more expected delinquency) and higher LTVs are associated with higher default probabilities. The response to the variance of house prices in non-linear. In general, as the variance increases the probability of default increases because the probability of negative equity has increased. The direction of this effect can change to negative when there is a very long delay until foreclosure or the lender has no recourse to recover any losses from other assets beyond the value of the house. This is a natural result, because in these circumstances there may be time for the house price to drop even further in the future making a future default more valuable and at the same time the borrower can receive free rent while the loan is delinquent (not paying any mortgage or monthly rent).[3]

Empirical research dating back thirty years has already identified many of the same drivers of delinquency that have been included in more recent options oriented theoretical models. For instance, using sparse data sets from the 1960s and early 1970s, Morton (1975) and Furstenberg (1974) found evidence that the LTV at origination and income of the borrower were important determinants of the delinquency rates. The tenor of the results are remarkably similar in a more recent paper that examined delinquency rates in the United Kingdom (UK) using data from 1983 through 1992. Using a seemingly unrelated regression approach, Chinloy (1995) again found that LTV and income were the most important

empirical indicators of delinquency, whether defined as 6-12 months or greater than 12 months delinquent. Clarifying the role of LTVs, Getter (2003) uses the 1998 Survey of Consumer Finances to show that the best tool that borrowers have to avoid becoming late on a mortgage are financial assets, which can be used to cover financial obligations during unexpected periods of financial stress. To the extent that financial assets are correlated with down payments these results are consistent with earlier findings. Using an exponential hazard framework, Ambrose and Capone (2000) find that the probability of being 90+ days delinquent on FHA mortgages during the mid-1990s is sensitive to contemporaneous economic conditions in both the labor and housing markets. Similar to Ambrose and Capone (2000), using individual loan level data Calem and Wachter (1999) estimated the probability of being either 60 days or 90+ days delinquent using individual logits, thus implicitly assuming that the probability of being 60 and 90+ days are independent of each other. They find that credit scores matter for both delinquency categories, but LTV has no effect. Lastly, Baku and Smith (1998) use a case study approach to find that the performance of loans made by nonprofit lenders to low income households is sensitive to the incentive structure internal to the nonprofit agency. In short, the behavior of the lender does have an impact on loan delinquency.

Industry reports have examined transition matrices of subprime loans. In these reports various states of delinquency are collapsed into more aggregate groups, all states are assumed to be independent of each other, the estimation procedure is not reported, and the results cannot be extended beyond the single lender/servicer used in the report (Gjaja and Wang 2004). The results suggest that indicators have different impacts on the extent of delinquency.

This paper expands on this literature by recognizing that there are multiple states of delinquency and that these states are not independent of each other. But, in addition to the need to recognize the importance of various degrees of delinquency, any model must also recognize that loans can also prepay or default and that all these options are best viewed as competing risks.[4]

4. Estimation Technique

Several methods are available to model empirically the possible outcomes of a subprime mortgage loan. We discuss two of these alternatives, multinomial logit and nested logit, below.

4.1 Multinomial Logit

Multinomial logit is the standard estimator used in modeling outcomes with multiple possible states (>2). A drawback to the multinomial logit model is an undesirable property known as Independence from Irrelevant Alternatives (IIA). This implies that the odds ratio for any two alternatives *m* and *n* do not depend upon any other alternatives. A well-known example illustrates a problem with this assumption. A traveler has a choice of going to work by car or by a blue bus. Let the choice probabilities be equal, implying the ratio of probabilities equals one. Now introduce a choice of a red bus that the traveler considers equivalent to a blue bus. We would expect the probability of going to work by car to remain the same at 0.5, while the probabilities of going to work by bus would be split evenly between blue and red buses at 0.25. If this were true, then the ratio of probabilities between car and blue bus, formerly at 1, would now be equal to 2 (0.5 divided by 0.25).

The addition of a red bus alternative changed the ratio of probabilities between car and blue bus. The multinomial logit model does not allow this possibility. The ratio of probabilities between the car and blue bus alternatives must remain at one. Clearly, this result in nonsensical, because households will just evenly split between the blue and red bus. Recall that there are equal probabilities of taking a blue bus and a red bus. The only profile of probabilities that fit these two constraints puts equal probability of 0.33 on each choice. The multinomial logit would therefore overestimate the probability of taking a blue or a red bus and would underestimate the probability of taking a car.

4.2 Nested Logit

An alternative modeling strategy that partly solves this problem is to use nested logit models. Loan outcomes are partitioned such as shown in Figure 1. Each upper-level group is called a 'branch,' while each lower-level group of outcomes within a branch is called a 'nest.' The IIA property holds within nests but not between nests. For example, IIA holds between the choices prepay and default, but

does not hold between prepay and any of the other outcomes such as current. This suggests the hypothesis that removal of an alternative from the choice set results in equal proportional increases in the probabilities of the choices within a nest, but not different proportional changes across different nests. For example, removal of the prepay option would result in an equal proportional increases in the probabilities of 30 late, 60 late, and 90+ late, but no restrictions would be placed upon the increase in the probability of default and of current.

Estimation of the nested logit model is by Full Information Maximum Likelihood (FIML). The probability of an outcome is specified as the product of the probability of being at a branch and the probability of the outcome conditional on the chosen branch. Note that the nested logit structure does not assume that decisions by borrowers are made sequentially. This is a subtle but important point. Consider the outcome "prepay". The tree structure in Figure 1 does not assume that mortgage holders first decide to terminate a mortgage and then decide whether to terminate by prepaying or by defaulting. Rather, the tree structure implies that the probability of prepaying is specified as the probability of terminating the mortgage multiplied by the probability of prepaying conditional on terminating the mortgage.

Different formulations of the nested logit model appear in the literature. We use the Non-Normalized Nested Logit (NNNL) model that is estimated in STATA version 8.[5]

5. Data Description

We utilized data 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, and purchase price, as well as monthly updated information on loan status. Data on loans originated between January 1996 through May 2003 are included. The database contains information on over 1,000 pools of subprime loans representing over 3,500,000 individual loans. For our estimations, we choose a random cross-section sample of 100,000 30-year fixed rate loans for owner-occupied property from the LP database. After eliminating loans with missing data, a database of 97,852 observations resulted.

We matched data from several external data sources to the LP data. First, we matched data on the quarterly change in the OFHEO House Price Index (HPI) and on the standard error of the HPI to the loan data by state. We then matched Bureau of Labor Statistics data on the unemployment rate lagged by one month by state. Finally, we matched data on the prime interest rates on 30-year fixed mortgages from the Freddie Mac's Primary Mortgage Market Survey for the given month and for the origination month and computed the difference. Summary statistics for the data are in Table 1.

The monthly delinquency rate for our sample remains fairly constant from June 1999 to May 2003. The 30-day delinquency rate stays around the average 1.4% during this time period. There is a slight uptrend in the 30-day delinquencies since spring 2002. The 60-day delinquency rate is lower, with an average of 0.5%, and generally lags behind the 30-day delinquency rate. For example, there is a one-half percentage point decline in the 30-day rate in April 2000, followed by a decline of almost a third of percentage point in the 60-day rate in May. The 90+-day delinquency rate closely tracks the 30-day rate and has an average equal to 1.1%.

6. Results

As described above, two alternative econometric techniques are available to model subprime loan outcomes. Multinomial logit has been predominately used in the literature. Recall that multinomial logit makes the assumption of IIA on the alternative outcomes. To test whether this assumption is appropriate, we performed the Hausman (1984) and Small-Hsiao (1985) tests. The results of the tests, shown in Table 2, strongly suggest that IIA is not a valid assumption for this dataset. For each omitted category of dependent variable, the Small-Hsiao test unambigiously rejects the null hypothesis of IIA. The Hausman test rejects the null hypothesis of IIA for half of the omitted categories, and the negative values of the test statistic on two omitted categories, while suggesting that IIA is not violated, are difficult to interpret. In sum, we conclude that multinomial logit is not an appropriate estimation technique because the IIA assumption does not hold, and we therefore use nested logit.[6]

Instead of presenting the nested logit coefficient estimates, which are extremely difficult to interpret, Table 3 presents the one standard deviation elasticity estimates for continuous variables and

binary elasticity estimates for the discrete variables. Appendix A provides the coefficient and standard errors estimates. Appendix B includes sensitivity tests presented in graphical form for all exogenous variables. Table 3 estimates reflect the percent change in the probability of the event occurring, as indicated in each column, holding all other variables at their means. Since these impacts are not symmetric, elasticity estimates for both increasing the variable and decreasing the variable by one standard deviation are presented. Note that the lack of symmetry increases the larger the responsiveness. However, we do not know the statistical significance of the reported elasticities due to the highly nonlinear nature of the likelihood function.

When examining the results it is important to remember that this paper defines default as any loan that is in the foreclosure process or the property has become owned by the lender. Other papers occasionally use 90+ days late or the date the distressed property is sold (as real estate owned or at a foreclosure sale) as an alternative definition of default.

6.1 Impact of Credit Scores

The impact of credit scores is very strong and most of the results meet expectations. Loans with better credit scores are much more likely to stay current and less likely to enter delinquency or default. For example, the probability of 90+ delinquency falls from 1.89% for a FICO of 579 to 0.75% with a FICO of 649. This supports the notion that past performance on other financial obligations is a strong indicator of future ability or desire to pay.

In contrast with Pennington-Cross (2004) we find that borrowers with higher credit scores are slightly less likely to prepay. Figure B1 shows an inverted U-shaped relationship. For credit scores below 630, the results show a positive relationship between credit scores and the probability of prepayment. A borrower with a FICO score at the mean 649 has a 2.61% probability of prepaying. A borrower with a FICO one standard deviation above the mean, 718, has a prepay probability of 2.53%. This group of loans with high credit scores is unique because the FICO is sufficient to qualify for a prime loan, yet the borrower obtained a subprime loan. These results likely reflect the uniqueness of the borrowers with these loans and the permanence of their constraining circumstances.

6.2 Financial Incentives

Consistent with expectations, loans that are originated with higher LTVs are more likely to be delinquent. Serious delinquency (60 and 90+ days) is especially sensitive to homeowner equity at origination. The results are not consistent with the predictions of Ambrose, Buttimer, and Capone (1997) that higher LTVs are associated with higher probabilities of default. A loan with an 80% LTV has a probability of default of 2.71%, while a loan with a 100% LTV has a probability of default of 2.39%. This seems to indicate that original LTV does not in itself provide a good indicator of ruthless default types, but instead the inability or desire to provide a down payment indicates a proclivity to miss payments without the intent of losing the home. It could also indicate that lenders are less likely to foreclose on homes without equity but instead allow the borrowers to remain in delinquency.

When house prices are increasing, borrower equity should be growing, making it easier to prepay and less likely to default. In the model, the probability of delinquency and default decreases when prices increase. The model shows that prepayment is fairly unresponsive to changes in house prices, while was an unexpected result.

To more accurately calculate the equity of a borrower in each month we need to know the value of the property and the outstanding balance of the loan. State level house prices help to proxy for the house value, but there is a substantial dispersion of individual house prices around the mean appreciation rate through time. One way to measure this dispersion is to use estimates of the relationship between the variance of individual house price around the mean appreciation rate and time since the last transaction. We use this information to calculate what is labeled the standard error of house prices for each individual home in the sample. In essence, this provides an estimate of how confident we are that the individual house price has increased at the area rate. If we have little confidence then there is higher probability that the borrower has negative equity in the house. This makes it more likely that the borrower will attempt a ruthless default.[7]

We do find a strong positive impact of the standard error estimates on the probability of default and 90+ day delinquency in support of this interpretation. Areas with low standard errors, or areas in

which we have less confidence in the appreciation of the borrower's specific property, are much less likely to default than in areas with high standard errors. In conjunction with the effects of changes in house price, these results indicate that variation of individual house price appreciation rates and local market conditions are important predictors of default and serious delinquency in the subprime market. The evidence presented so far indicates that subprime loans do respond to the economic and financial incentives to put the mortgage through default.

To measure the volatility of average or typical house prices we include the standard deviation of the detrended OFHEO HPI in each state. Kau and Kim (1994) theorized that when prices are volatile borrowers may wait longer to default, because the value of the option to default may be larger in the future. Ambrose, Buttimer, and Capone (1997) theorized that the result is indeterminate depending on the length of delay (delinquency) and the extent of recourse. The empirical evidence does not find support for a nonlinear relationship.[8] Instead, as volatility increases loans are less likely to default or prepay. Delinquency is fairly unresponsive to the volatility measure, which is consistent with free rent motivations for many delinquent subprime loans. In total, these results provide supporting evidence that the value of delaying default is an important component needed to understand the behavior of subprime loans.

Subprime loans are also responsive to changes in interest rates. As interest rates drop, the loan is more likely to prepay. A loan has a 2.5% probability of prepaying if interest rates do not change, and a 2.8% probability of prepaying as interest rates fall 100 basis points. This is consistent with the notion that financial considerations are a driver in prepayments even for the financially constrained subprime borrowers.

6.3 Trigger Events

Trigger events, as proxied by last month's state unemployment rate, in general do not act as expected. Higher unemployment rates are associated with lower delinquency probabilities. The probability of default is insensitive to local labor market conditions proxied by the state unemployment rate. In addition, worse labor market conditions are also associated with lower prepayment probabilities.

In summary, future research needs to come to a more complete understanding of how subprime loans react differently to economic conditions and exogenous trigger events.

6.4 Loan Characteristics

Prepayment penalties tend to act as designed and reduce prepayments. A loan with a prepayment penalty is 27.6% less likely to prepay. However, loans with prepayment penalties are also associated with higher likelihoods of delinquency (7.0% more likely to be 30 days late and 2.5% more likely to be 90+ late) and default (2.6% more likely to default). Loans with limited documentation also are delinquent (87.6% more likely to be 30 days late and 87.9% more likely to be 90+ late) and default (19.8% more likely) more frequently than full documentation loans. The impact for loans with no documentation is even larger. This implies that these types of loans are especially risky.

We also included a baseline in the estimation. The nested results show a peak in defaults after the first 12 months. The model shows steady declines in prepayments as the loan ages.

7. Conclusion

This paper examines the performance of a large national sample of securitized private label loans. It includes multiple lenders and therefore provides a broad examination of the performance of subprime loans. The results reinforce the notion that all loans, including subprime loans, respond to incentives to default and prepay a mortgage. In addition to default and prepayment, the delinquency behavior of subprime loans is examined in an econometric framework that captures all the potential outcomes for the loan.

We find that financial incentives strongly explain subprime loan outcomes. Borrower credit scores are robust predictors of delinquency, default and prepayment and LTV at origination is positively correlated with delinquency. Several measures of housing market conditions indicate that subprime loans are strongly affected by all incentives to become delinquent and default on a mortgage. The change in interest rates affects prepayment, default, and delinquency. In addition, we find that loan characteristics are important determinants of loan outcomes. Prepayment penalties extend the duration of subprime loans, and documentation status is associated with higher delinquency status.

Subprime mortgages represent an increasingly important segment of the securitized mortgage market. These loans are typically more risky than prime mortgages, and are characterized by higher rates of prepayment, delinquency, and default. This research seeks to explain the sources of the higher rates of prepayment, delinquency, and default of subprime mortgages. By better understanding the sources of the risk, subprime lenders can implement better risk management policies.

Footnotes

[1] Securities that include subprime loans are often referred to as Asset Backed Securities (ABS) instead of Mortgage Backed Securities (MBS).
[2] For a summary of this line or research see Vandell (1995) and Kau and Keenan (1995). Typically these papers consider a loan "defaulted" when the mortgage is terminated through foreclosure or other adverse means.
[3] Another line of literature looks at the time from a default, which is typically defined as being 90+ days delinquent, to resolution of the mortgage. Resolution could include many of the available loss mitigation tools used by lenders such as foreclosure, curing, pre-foreclosure sale or short sale, or even assumption of the mortgage. While some theoretical work has been done most of the work focuses on empirical determinants of the various possible outcomes, typically using multinomial logit in a hazard style framework (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, Geppert and Karels 2001).
[4] While default has been defined in many different ways, in the empirical work explained in the following sections default is defined as whenever the lender initiates foreclosure proceedings (the acceleration note) or the lender becomes the owner of the property which will be sold to help cover any losses associated with the default and period of delinquency.
[5] See Koppelman and Wen (1998) and Hunt (2000) for an explanation of the different formulations of the nested logit model.
[6] We estimated the multinomial logit model in addition to the nested logit model and found several differences in the relationships implied between the two.
[7] While this line of reasoning is commonly used to motivate the importance of equity in a home, it is only valid to the extent that lenders do not attempt to recover losses on defaulted loans from other assets the borrower may have (recourse or deficiency judgment lending). Ambrose, Buttimer, and Capone (1997) show in their model that when a lender has full recourse and fully exercises it that borrowers have no incentive to default.
[8] Future research needs to focus on measuring the time to default and the extent that redemption is actually used by lenders to see if the non-linear relationship does exist in empirical models.

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Figure 1. Nested Logit Model of Mortgage Loan Performance

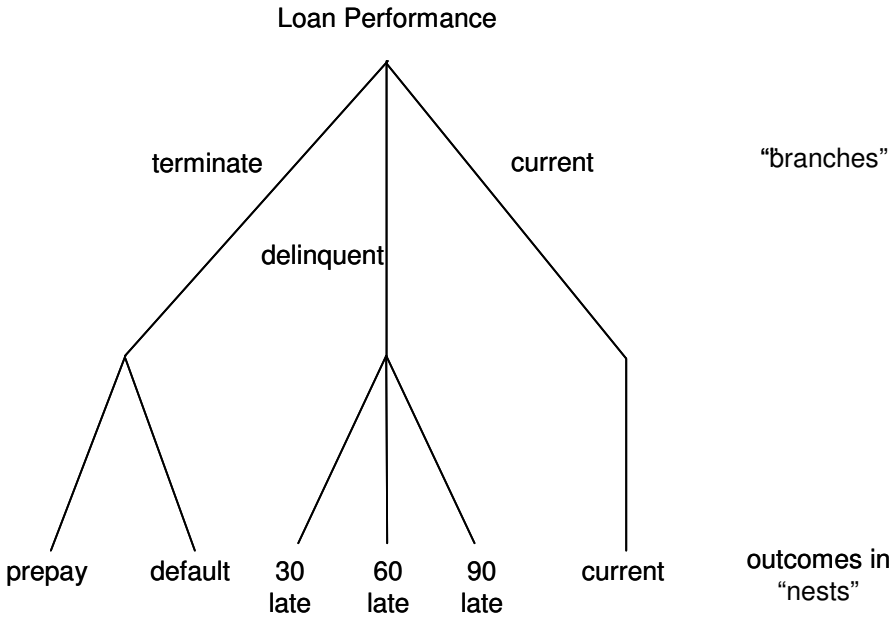

Table 1. Summary Statistics for Variables in the Database

Variable	Description	Mean	StDev	Min	Max
Vector of dependent variables					
Current status	Indicates the loan is current.	0.914	0.28	0	1
30-Late status	Indicates the loan is 30-59 days delinquent.	0.014	0.12	0	1
60-Late status	Indicates that the loan is 60-89 days delinquent.	0.006	0.07	0	1
90+- Late status	Indicates that the loan is 90+ days delinquent.	0.013	0.11	0	1
Default status	Indicates that the loan is in default - footnote 3.	0.018	0.13	0	1
Prepaid status	Indicates that the loan has been paid off.	0.035	0.18	0	1
Vector of explanatory variables					
Age of loan	Age of the loan is defined in months so that the first payment is due in month 0.	16.40	14.48	1	89
Loan to value ratio at origination (LTV)	LTV is expressed in one hundreds and indicates what fraction of the house price is purchased with a mortgage.	86.32	20.50	20.03	183
FICO score at origination	The FICO score is the Fair Isaac consumer credit score calculated at origination.	648.69	69.81	332	888
Quarterly change house prices (chHPI)	The quarterly change in the state repeat sales house price index as reported by the Office of Federal Housing Enterprise Oversight.*	0.09	0.10	-0.09	0.89
Standard error of house prices (seHPI)	Calculated using the time between transactions in the second stage of the repeat sale price index procedure.** Collected from OFHEO.	0.07	0.03	0.02	0.21
Standard deviation of detrended HPI (sdHPI)	The variance of the detrended state-level house price index. A four period moving average was utilized to detrend the series.	0.02	0.01	0.01	0.12
Unemployment rate lagged one month (Urate)	The unemployment rate at the state level collected from Bureau of Labor and Statistics.	5.32	1.15	1.7	9.6
Low documentation (Low Doc)	The borrower provided limited documentation of income and down payment sources.	0.21	0.41	0	1
No documentation (No Doc)	The borrower provided no documentation of income and down payment sources.	0.02	0.13	0	1
Prepayment penalty (Penalty)	Penalty indicates that in the current month a prepayment penalty is active, as defined in the loan agreement.	0.45	0.50	0	1
Change in interest rates (chIR)	The change in the 30-year fixed prime mortgage rate since origination. Collected from the Freddie Mac PMMS.	-0.50	0.73	-3.04	1.81

* Note that the growth in house prices is calculated from loans purchased by Fannie Mae and Freddie Mac and therefore, will include very few subprime transactions. If housing purchased with subprime loans appreciate at a different rate than housing purchased with prime loans then the results may be biased.

** See Dreiman and Pennington-Cross (2004) for a discussion of the variance and dispersion issues surrounding repeat sales house price indices.

Table 2. Hausman and Small-Hsiao Tests of IIA Assumption

	Hausman Test		Small-Hsiao Test	
Omitted Variable	**χ^2 Test Statistic**	**Supports IIA?**	**χ^2 Test Statistic**	**Supports IIA?**
Current	323.344	No	70.971	No
30 Late	56.770	Yes	29.889	No
60 Late	101.562	No	42.567	No
90+ Late	-12.391	Yes	39.907	No
Default	76.436	No	35.367	No
Prepaid	-101.350	Yes	42.427	No

Note: The tests were performed using the mlogtest function in Stata. The Hausman test has 48 degrees of freedom and the Small-Hsiao test has 12 degrees of freedom.

Table 3. One Standard Deviation Elasticity Estimates

	Current	30-Late	60-Late	90+-Late	Default	Prepaid
FICO up	2.5%	-67.5%	-53.7%	-64.8%	-32.2%	-3.1%
FICO down	-3.7%	175.1%	92.9%	153.5%	23.7%	-13.5%
LTV up	-0.1%	19.4%	33.3%	53.0%	-11.9%	-13.9%
LTV down	-0.1%	-20.1%	-28.5%	-37.7%	13.2%	15.8%
Change in HPI up	1.3%	-46.0%	-26.8%	-51.2%	-11.6%	2.1%
Change in HPI down	-1.4%	62.5%	19.9%	79.6%	9.9%	-4.9%
Standard error of HPI up	-10.0%	202.2%	-38.0%	147.9%	41.1%	222.7%
Standard error of HPI down	6.7%	-95.9%	-80.1%	-95.0%	-71.1%	-87.4%
Standard deviation of HPI up	0.6%	-2.9%	4.2%	7.4%	-9.2%	-12.9%
Standard deviation of HPI down	-0.6%	2.1%	-4.8%	-7.6%	9.8%	14.5%
Change in Interest Rates up	0.7%	-11.1%	-11.1%	-11.1%	-8.4%	-8.4%
Change in Interest Rates down	-0.8%	12.3%	12.3%	12.3%	9.0%	9.0%
Unemployment Rate up	1.0%	-19.6%	-6.1%	-21.5%	-4.0%	-18.1%
Unemployment Rate down	-0.9%	21.0%	3.7%	24.0%	0.9%	18.3%
Prepayment Penalty	0.7%	7.0%	4.4%	2.5%	2.6%	-27.6%
Low Doc	-1.9%	87.6%	16.6%	87.9%	19.8%	1.7%
No Doc	-5.8%	270.7%	23.7%	336.8%	24.3%	5.8%

This table represents the percent change (not percentage points) in the probability of the event occurring holding all other variables at their means. The last three variables are indicators or dummy variables and report the percent change in the event occurring if the loan has a prepayment penalty relative to not having a prepayment penalty, or is low doc relative to full documentation, or is no doc relative to full documentation.

Appendix A – Nested Logit Coefficient and Standard Error Estimates

Variable	Coefficient	Standard Error
Estimates for nests		
Age		
Prepay	-0.161*	0.012
30-Late	-0.241*	0.025
60-Late	0.145*	0.038
Current	0.127*	0.010
Default	0.223*	0.011
LTV		
Prepay	-0.006	0.008
30-Late	-0.248*	0.018
60-Late	-0.138*	0.022
Current	0.057*	0.007
Default	0.017*	0.008
FICO		
Prepay	0.038*	0.008
30-Late	-0.082*	0.014
60-Late	0.273*	0.020
Current	0.364*	0.006
Default	-0.319*	0.007
chHPI		
Prepay	0.102*	0.010
30-Late	0.100*	0.023
60-Late	0.404*	0.036
Current	-0.037*	0.009
Default	-0.042*	0.012
seHPI		
Prepay	0.140*	0.025
30-Late	0.198*	0.055
60-Late	-1.386*	0.078
Current	-0.078*	0.022
Default	-0.687*	0.026
sdHPI		
Prepay	-0.021*	0.008
30-Late	-0.100*	0.015
60-Late	-0.030	0.018
Current	0.060*	0.006
Default	0.021*	0.007
Urate		
Prepay	-0.037*	0.007
30-Late	0.025	0.015
60-Late	0.179*	0.020
Current	-0.030*	0.006
Default	0.121*	0.007
Low Doc		
Prepay	-0.045*	0.007
30-Late	-0.001	0.014
60-Late	-0.194*	0.022
Current	-0.002	0.006
Default	0.022*	0.007
No Doc		
Prepay	-0.016*	0.007
30-Late	-0.021	0.011
60-Late	-0.159*	0.020
Current	-0.001	0.005
Default	0.004	0.007
Penalty		
Prepay	-0.056*	0.008
30-Late	0.022	0.014
60-Late	0.009	0.019
Current	-0.027*	0.006
Default	0.117*	0.007
Estimates for branches		
chIR		
Terminate	-0.095*	0.013
Delinquent	-0.125*	0.015

"90-Late" is the omitted category for the nest estimates and "Current" is the omitted category for the branches. Variable definitions are in Table 1. * denotes the coefficient is significant at the 95% confidence level.

Appendix B – Sensitivity Tests

Figure B1: Credit Scores (FICO)
FICO=consumer credit score at origination.

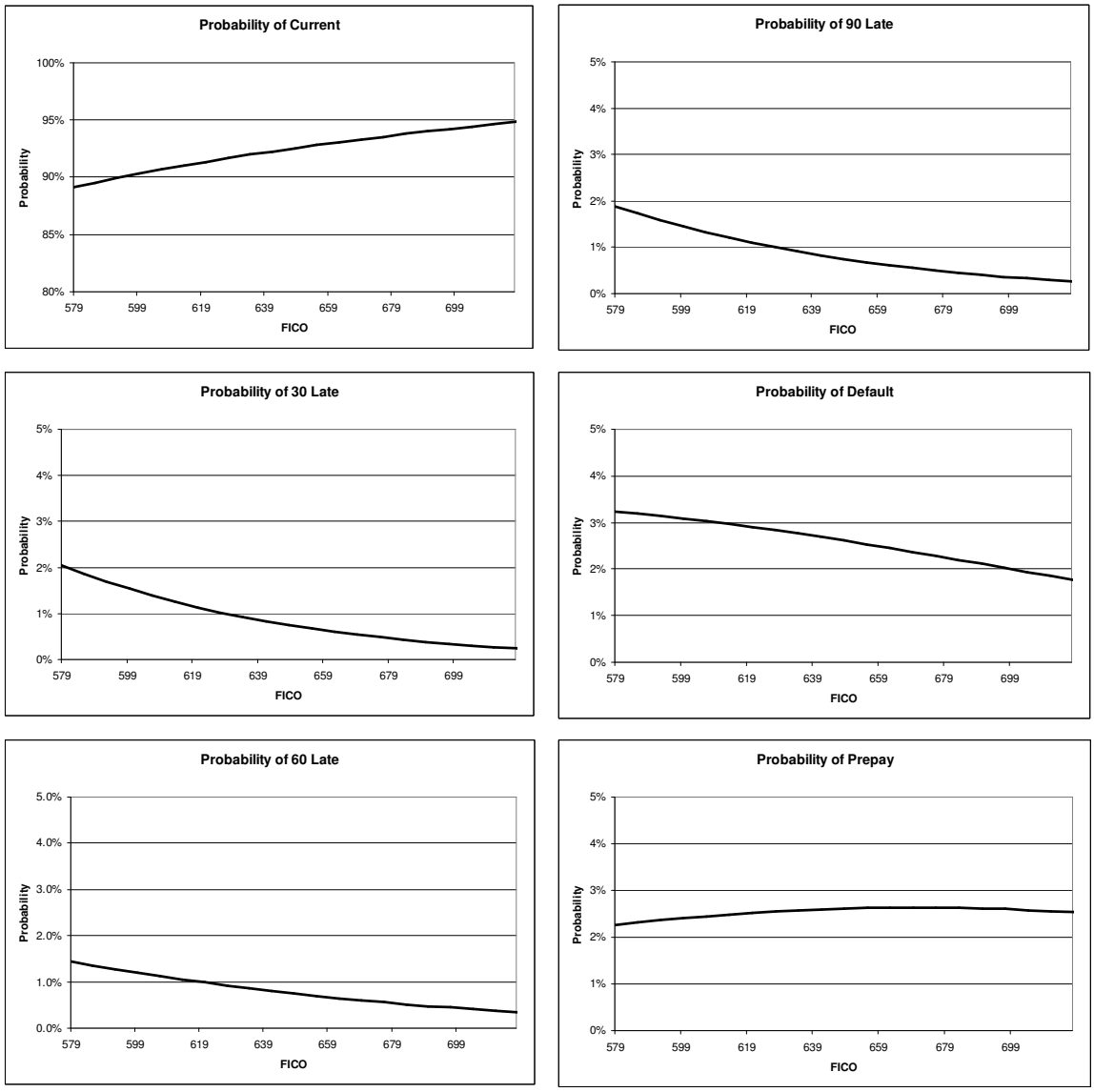

Figure B2: LTV at Origination
LTV=loan to value ratio at origination.

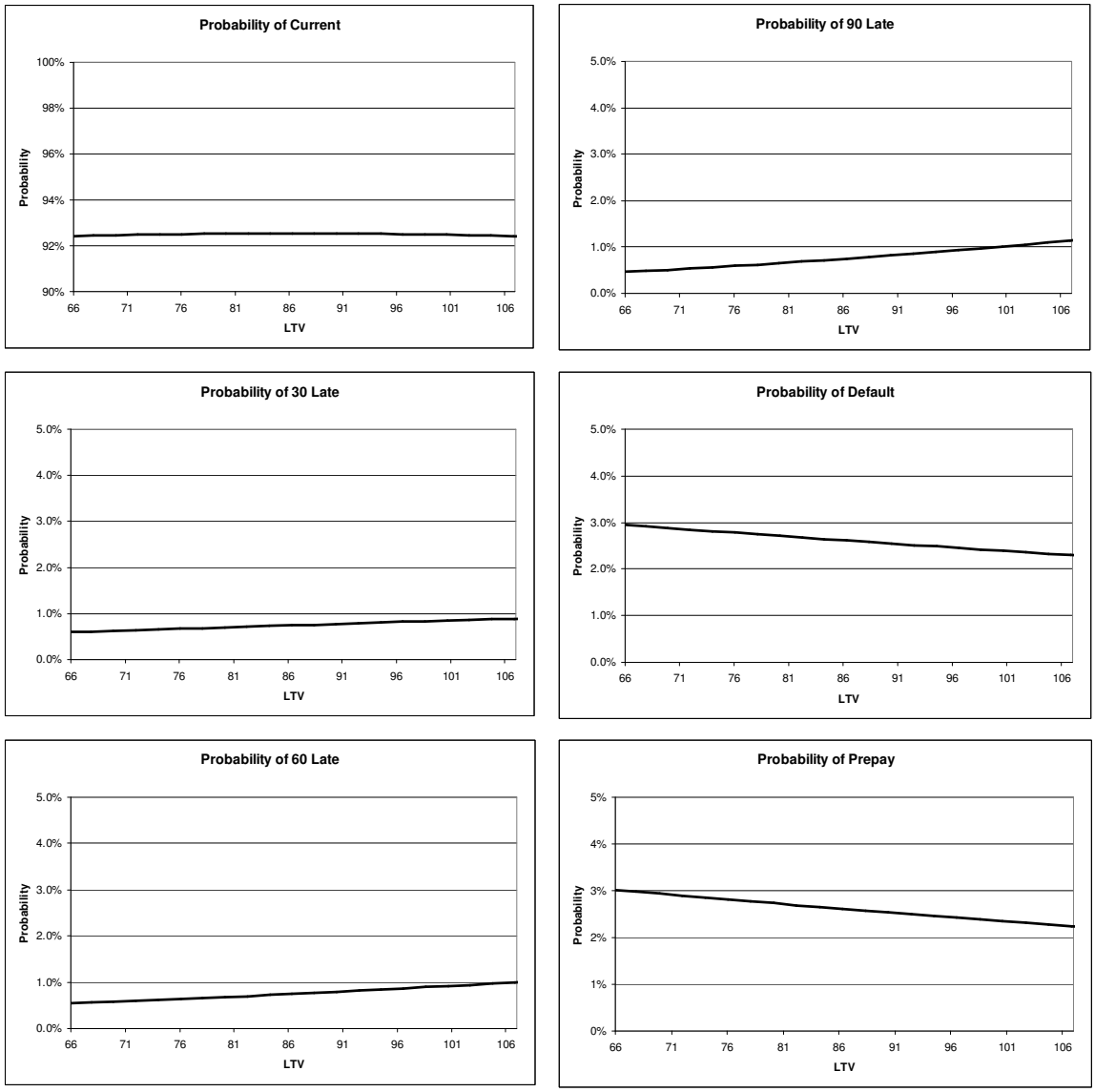

Figure B3: Change in House Prices

Change in House Prices = percent change in house prices since origination.

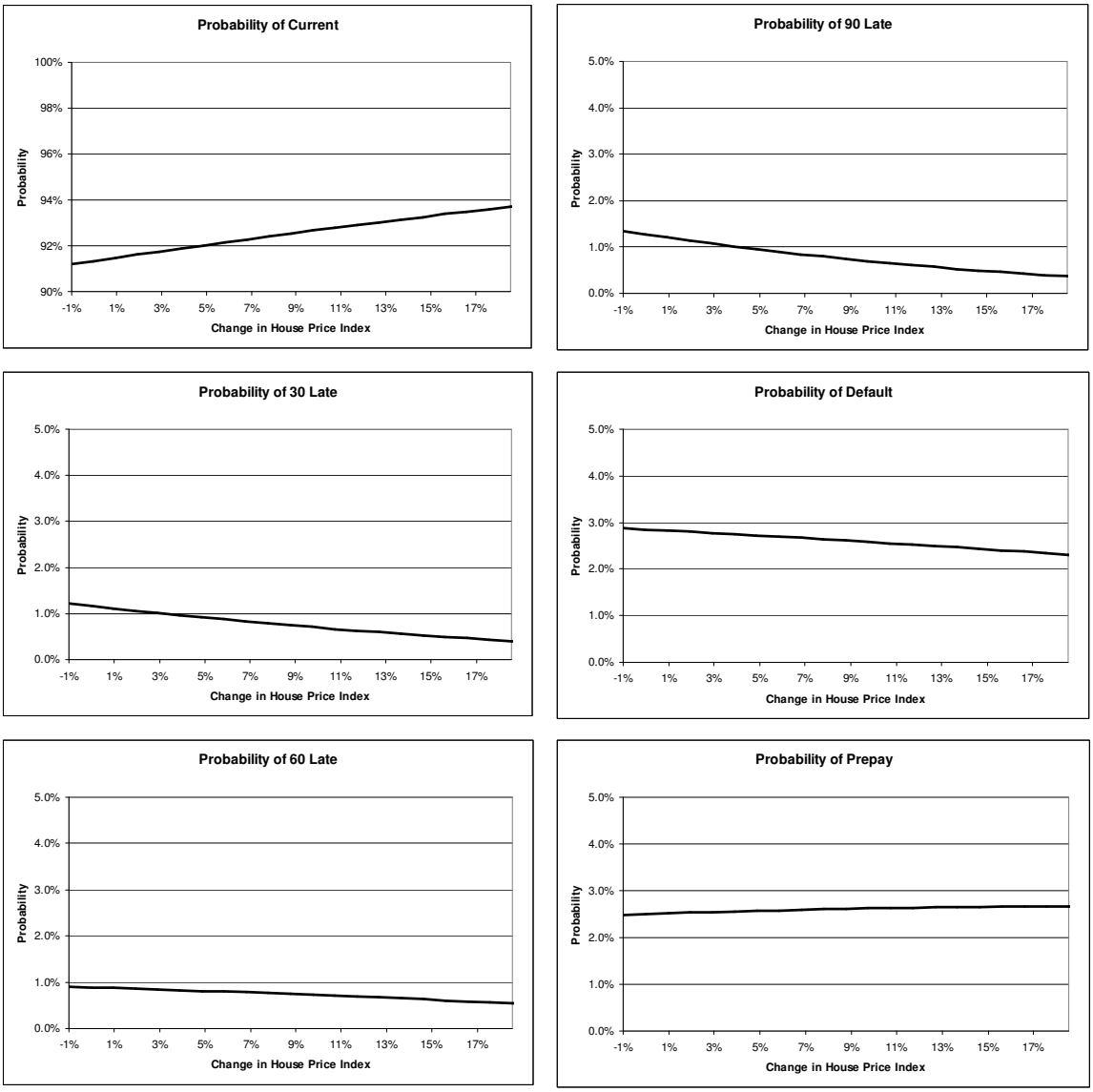

Figure B4: House Price Confidence (Standard Error of Individual House Price)
Standard Error of Individual House Price = diffusion estimate of individual house prices around the index estimate, as it relates to months since the date of origination.

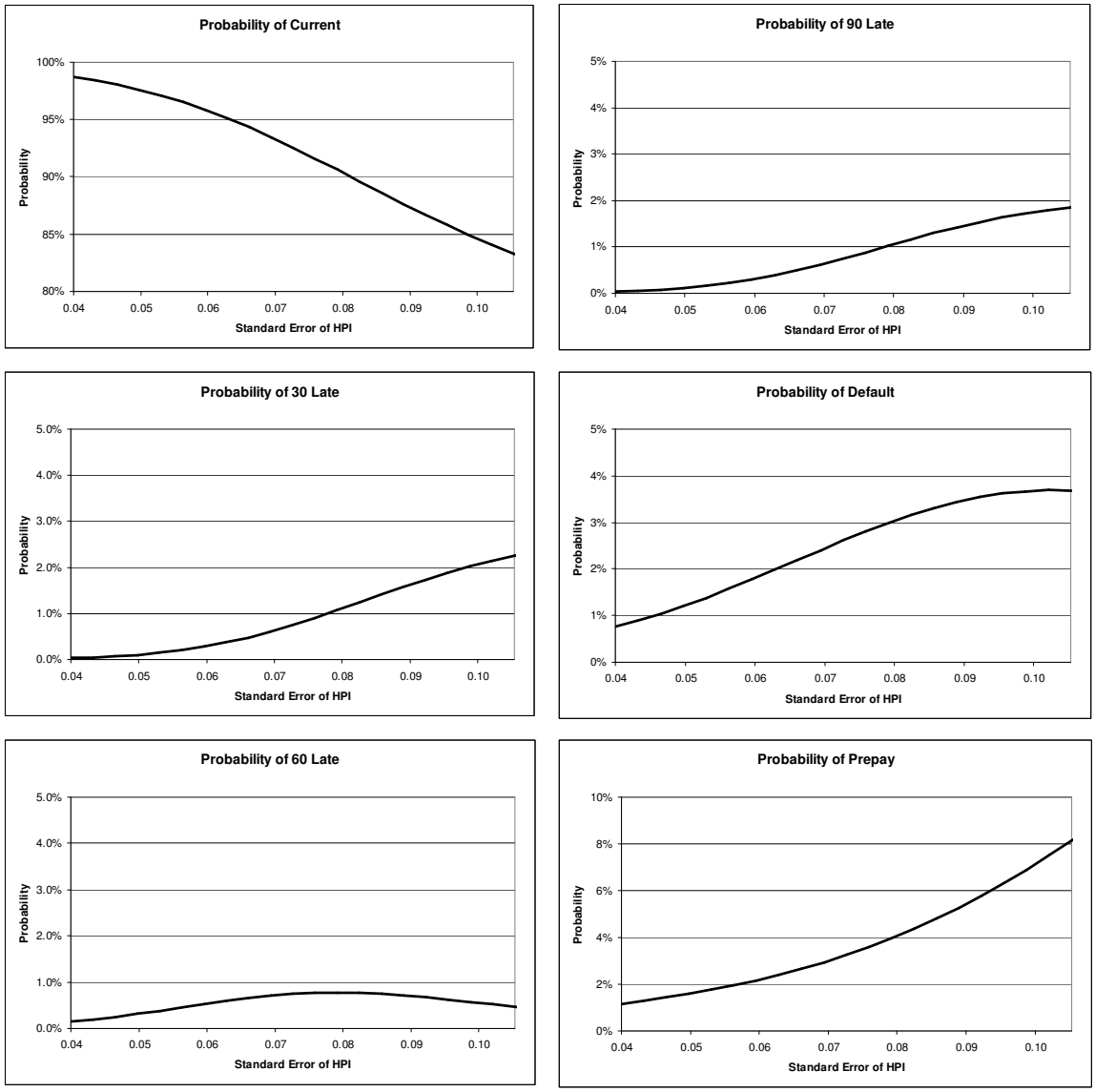

Figure B5: Stability of House Prices (Variance of the De-trended House Price Index)
Variance of the De-trended House Price Index = variance estimated from the standard deviation of the difference between actual and 4-period moving average of house price change.

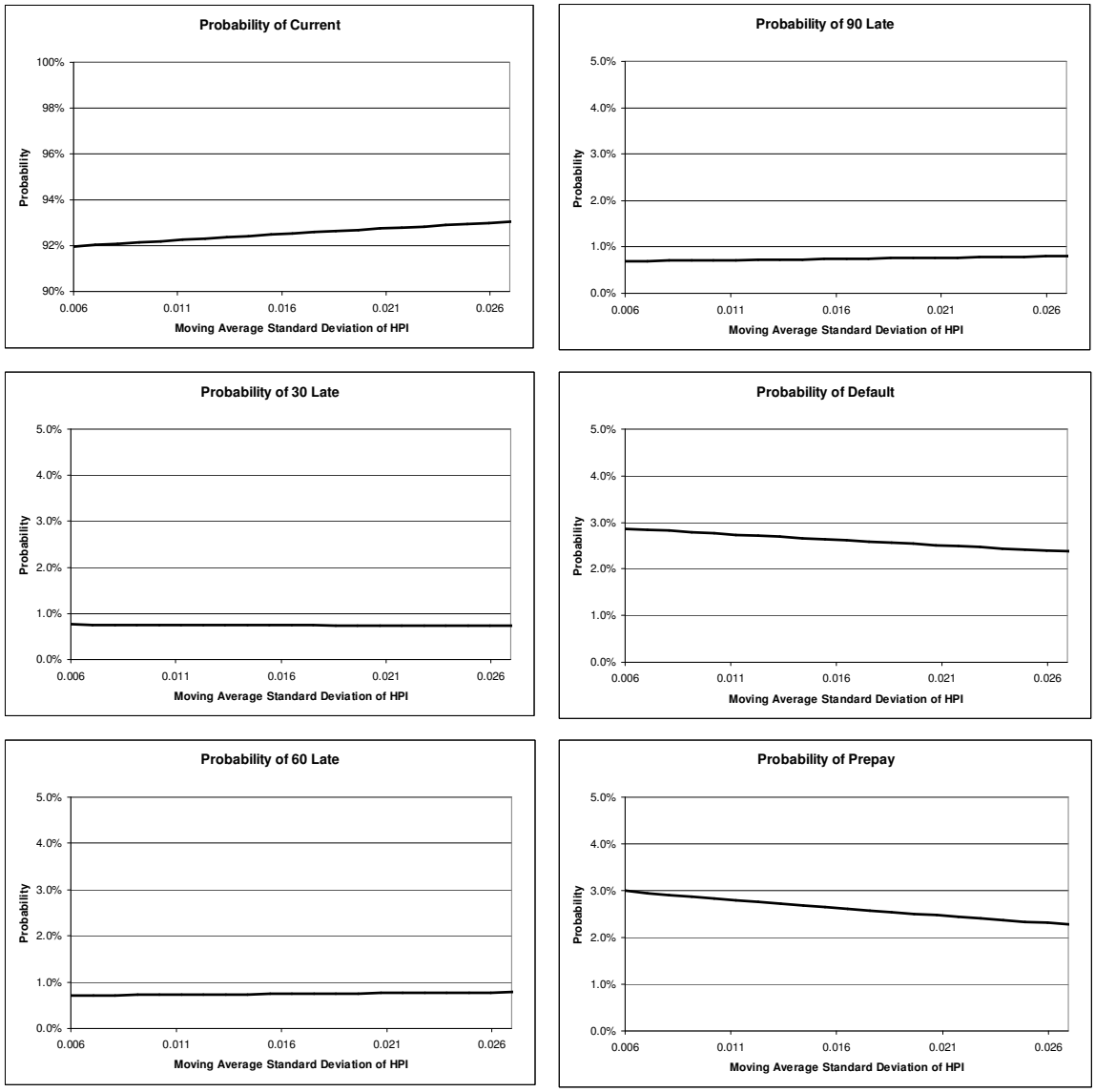

Figure B6: Change in Interest Rates

Change in Interest Rates = the change in 30 year fixed rate interest rates from the date of origination.

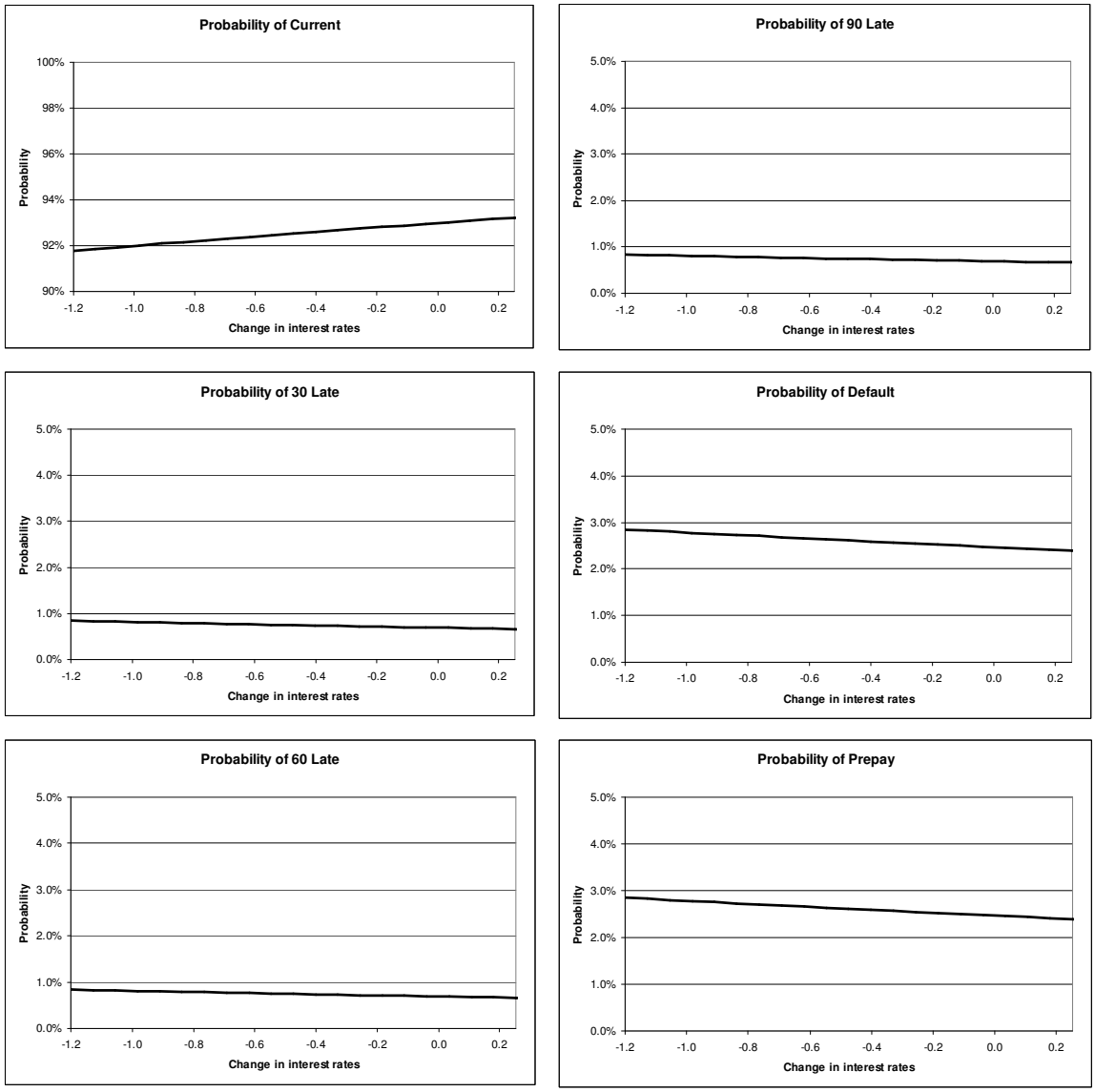

Figure B7: Trigger Events (Unemployment Rate)
Unemployment Rate = the state level unemployment rate in the previous month.

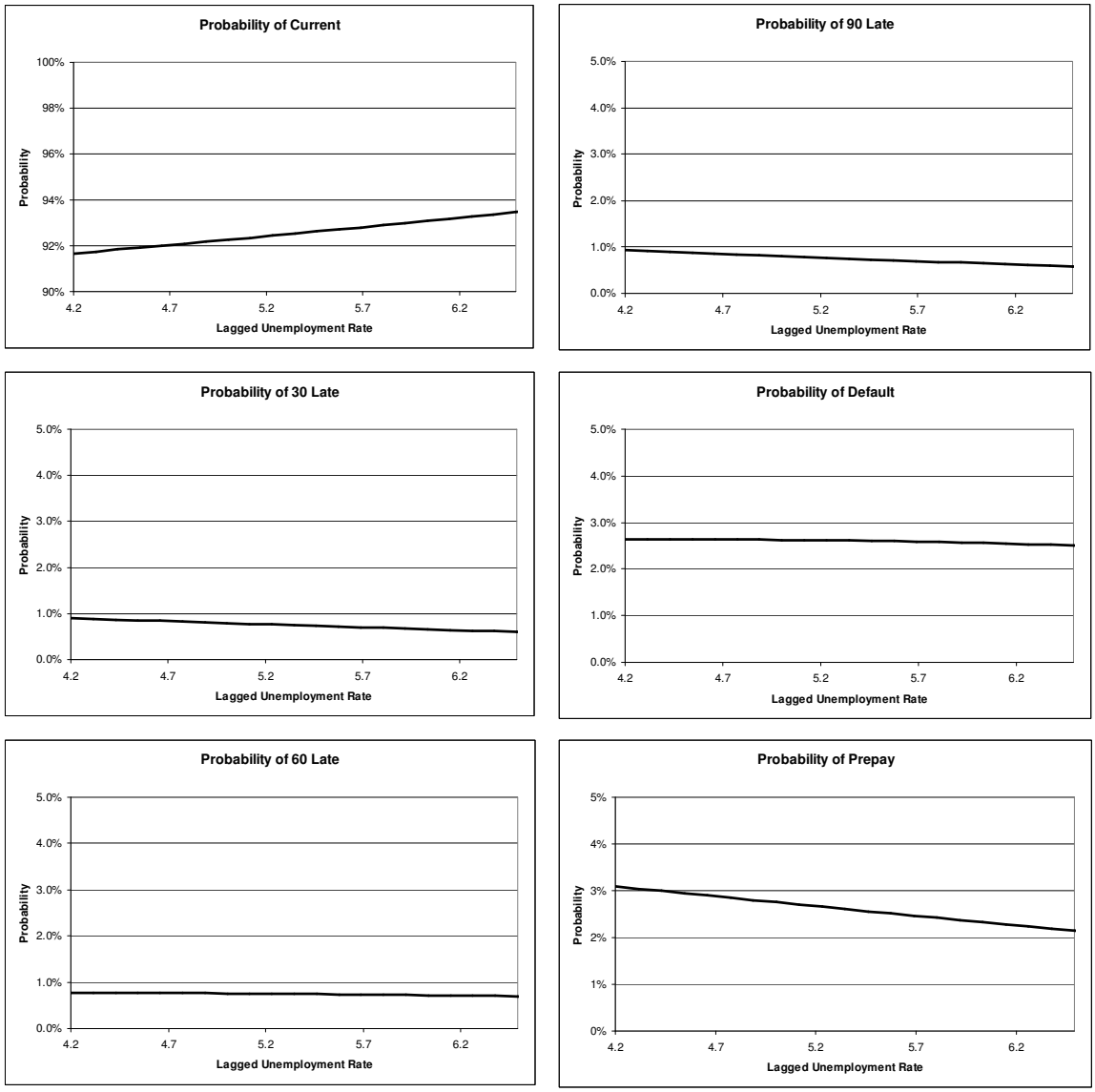
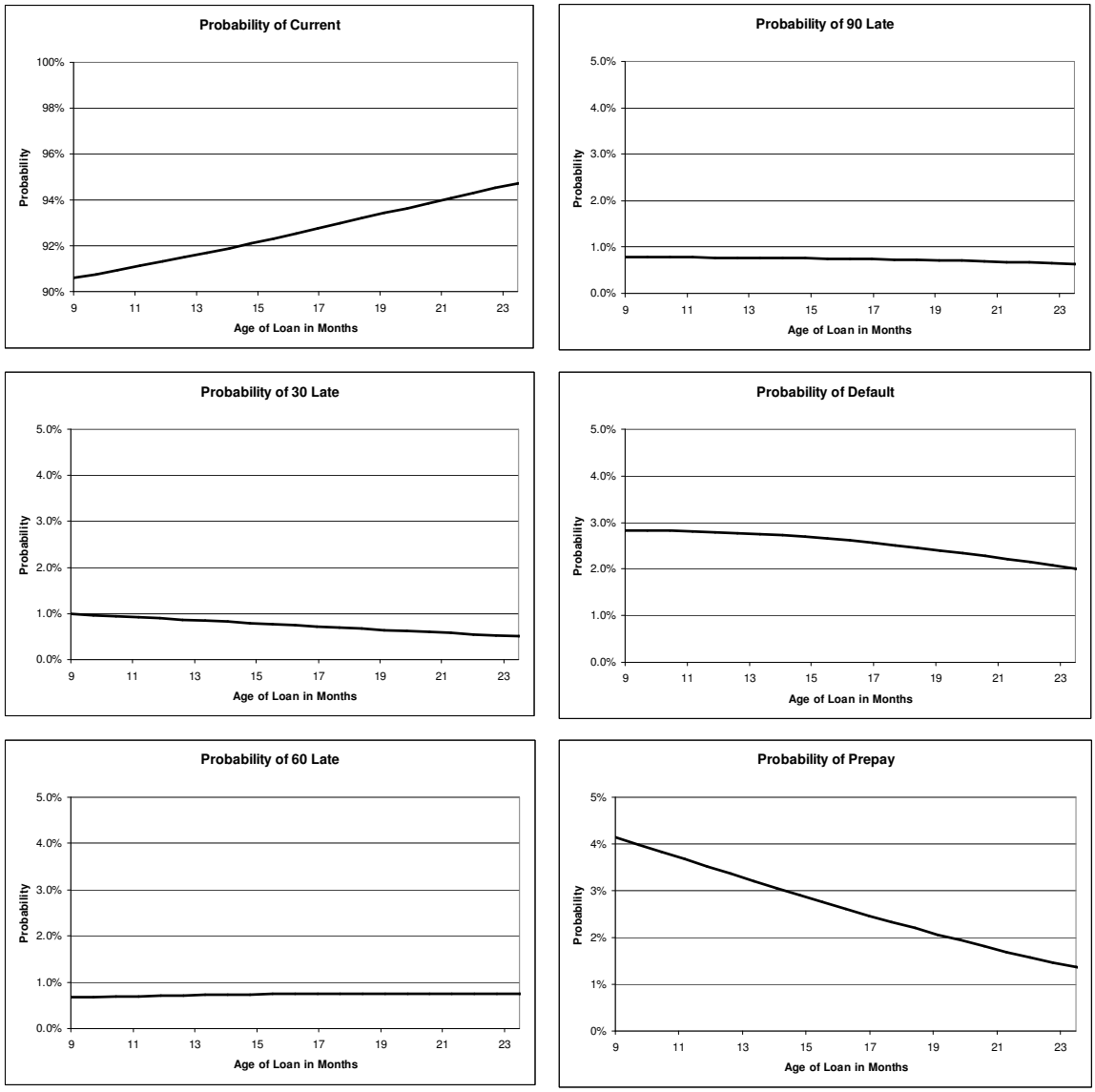
Figure B8: Baseline (Age of Loan)
Age of Loan = the number of months the loan has survived.