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The Impact of Missed Payments and Foreclosures on Credit Scores

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This paper debunks the common perception that "foreclosure will ruin your credit score." Using individual-level data from a credit bureau matched with loan-level mortgage data, it is estimated that the very first missed mortgage payment leads to the biggest reduction in credit scores. The effects of subsequent loan impairments are increasingly muted. Post-delinquency foreclosures have only a minimal effect on credit scores. Moreover, credit scores improve substantially a year after borrowers experience 90-day delinquency or foreclosure. The data supports one possible explanation of this improvement: the absence of mortgage payments relaxes the borrowers' budget constraint, allowing them to restore other forms of credit.

Keywords: Credit Score, Foreclosure, Delinquency, Crisis.

JEL codes: G2, D1, R2.

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Credit scores are used in many important areas of our lives, from applications for car loans, mortgages, credit cards, and car insurance to even some hiring decisions. It is well established that people with higher scores get better loans and pay lower insurance premiums than people with lower scores. Because credit scores matter so much, many consumers regularly monitor their scores and try to prevent events that could reduce their scores. The commonly heard claim that "credit scores deteriorate substantially in cases of foreclosure" may motivate borrowers to avoid or postpone defaulting on their mortgage even if is either inevitable or beneficial to do so.[1] News articles appearing after the wave of post-crisis foreclosures stressed this point. Examples include: "A foreclosure will drop the borrower's credit score by at least 100 points" (The New York Times, 25 October 2009); "If your house goes into foreclosure, you might take a hit of 150 points or more on your credit score" (Chicago Tribune, 31 January 2010); and "A foreclosure will cause a credit score to drop sharply, typically by 200 to 300 points" (Mint.com, 14 August, 2009). The impacts of foreclosure calculated by credit bureaus for hypothetical consumers generally supported these statements (Christie (2010)). Researchers have analyzed the *combined* impact of delinquency and foreclosure on the path of future credit scores (Brevoort and Cooper (2013)) and contributed to the belief that foreclosures do ruin one's credit score.[2]

This paper shows the opposite: foreclosure itself has a very limited impact on a borrower's credit score in most cases. Using individual-level credit report data that has been merged with loan-level mortgage data it is estimated that the very first missed mortgage payment leads to the biggest reduction in credit scores. The effect of subsequent loan impairments on the credit score is increasingly muted. Specifically, based on the estimates, the impact of a transition from current to 30-day delinquency on the credit score is a decline of 51 points (relative to households that stay current and have otherwise comparable observable characteristics). For a transition to 60-day delinquency, 90^{+}-day delinquency, and foreclosure, the effect is a 25-, 14-, and 6-point drop,

[1] For example, in a different setting, Fee and Fitzpatrick (2014) show that "the lingering effects of the foreclosure... costing taxpayers money and dragging down the recovery." Also, borrowers might decide to not default for other than financial reasons such as social stigma, see Guiso, Sapienza, and Zingales (2009).

[2] Other papers that studied the consequences of mortgage default are Demyanyk and Van Hemert (2011), Agarwal, Ambrose, Chomsisengphet, and Sanders (2012), Amromin and Paulson (2009), Gerardi, Lehnert, Sherlund, and Willen (2008), Archer and Smith (2013), Bajari, Chu, and Park (2008), and Jiang, Nelson, and Vytlacil (2013) among others.

respectively. This result is intuitive, as credit scores by construction have a lower bound, which is nearly approached after three or more missed payments. Hence, foreclosure itself has only a minimal impact on credit scores. Previous studies were unable to detect this effect as they did not have access to data on the monthly performance of mortgages and borrowers' credit scores in the same dataset. The data available for this paper allow to disentangle the beginning of foreclosure from previous delinquencies, in addition to controlling for loan-level mortgage characteristics, other non-mortgage credit, and consumer characteristics.

This study also presents evidence consistent with the notion that borrowers who take a first step down the road to default often slide further down, leading to a continuation of declines in the VantageScore. A 30-day delinquency has a strong negative effect on a credit score both at the moment of delinquency and one year after. Borrowers in foreclosure, on the other hand, experience a small drop of the score in the month of the event but show a significant improvement in their credit scores one year later. Moreover, there are similar improvements in the credit scores one year after borrowers missed more than three mortgage payments, regardless of whether foreclosure takes place or not.

To better understand why the credit scores of borrowers in foreclosure and 90-day delinquency improve a year after the events, I study delinquencies on credit card debt and the number of credit inquiries six months before the month of the event and one year later. One hypothesis is that by no longer making payments on the mortgage, households can save this income to make payments on other forms of credit. Also, by relaxing the budget constraint, these borrowers may not require new credit. Consistent with this interpretation, I find a substantial decline in the number of credit card delinquencies and a similar decline in the number of credit inquiries for borrowers in foreclosure.

Other recent papers have commented on different consequences of default. Guiso, Sapienza, and Zingales (2009) use survey data and conclude that relocation costs and moral and social considerations are important impediments to mortgage defaults. Ghent and Kudlyak (2011) find that homeowners with negative equity are less likely to default in recourse states than in non-recourse states. Bhutta, Dokko, and Shan (2010) compute an imputed cost of strategic default from the propensity to default at different levels of negative equity. White (2010) argues that guilt, shame, and fear of consequences are important impediments to strategic defaults. This paper adds to this literature by showing that the impact of mortgage default on borrowers' credit scores is not a factor.

This paper continues as follows. The data set and the variables used in this study are described in Section 1. The results are presented and discussed in Section 2, and conclusions are in Section 3.

1 Data

The first data source is the borrower-level credit data from TransUnion's Consumer Credit Database (TU). This data set contains detailed monthly information about the credit situation of mortgage borrowers. The data cover most borrowers who at some point during the September 2004 to July 2009 sample period had a securitized subprime or Alt-A mortgage. This is an ideal data set to study the impact of defaults on credit scores as the types of mortgages in it defaulted the most after the 2007 subprime mortgage crisis. There are more than 250 attributes in the data set. For an exhaustive list of credit accounts, like mortgage, bank, and department store accounts, there are the payments status, utilization rates, and requests for new lines of credit. Importantly, the data set contains monthly updated information on the credit score (VantageScore).

The second main data source is the loan-level LoanPerformance (LP) Securities database provided by CoreLogic. This data set contains information about loan and borrower characteristics at origination and monthly loan performance for about 85% of all U.S. subprime and Alt-A securitized mortgage loans. For each loan in the LP data set there are most of the underwriting criteria measured at the time of loan origination: FICO credit scores, debt-to-income ratios, and loan-to-value ratios. Also, for each mortgage we know the type (fixed-rate, adjustable-rate, hybrid, balloon, interest-only, et cetera), the structure (prepayment penalty, timing and types of rate resets, lien, et cetera), the location of the property (zip code and state), the mortgage rate at origination and thereafter, and the monthly performance after securitization.

CoreLogic and TransUnion developed an accurate link between both databases, which is called the TransUnion Consumer Risk Indicators for RMBS. The match rate is exceptionally high in comparison to other matched databases studied in the literature. The match rate on loans that are active is 84%, while it is 68% for mortgages that are terminated.

For the analysis of this study, this matched data set is supplemented with the ZIP code-level Zillow Home Value Index (ZHVI) to estimate home values and account for housing market trends. Zillow appraises about three out of four homes in the U.S. several times a week and calculates historical values dating back to 1997. Then, Zillow aggregates these house-level valuations into indexes at the ZIP code level. The index is available monthly for 11,799 ZIP codes.

I use logarithm of average household income in the ZIP code based on Census 2000 data and a six-month change in the logarithm of county-level unemployment rate from the Bureau of Labor Statistics as other potential determinants of individual credit scores.

1.1 Variable definitions

Table 1 summarizes the definitions of the variables used in the analysis. For the status of the mortgage the following possibilities are considered: current, 30/60/90+ days delinquent, and foreclosure.[3] The status is provided by TransUnion. I use the status of the first mortgage, which is defined by the largest mortgage balance.

The other variables in Table 1 are used as potential determinants of the credit score. To curb the impact of outliers in estimating the model and to allow for non-linear responses, for many of the key variables I use dummy variables that are set to a value of one if the variable of interest is within a certain range. I typically divide up the possible range of values into four subsets (groups) and accordingly define the dummy variables G0, G1, G2, and G3, with G0 for the range with the lowest variable values and G3 for the range with the highest variable values. In the regression models, I omit the G0 dummy, and the coefficients corresponding to the G1, G2, and G3 dummy variables therefore measure the differential effect relative to group G0.

I define a variable "VantageScore momentum" as the six-month change in the VantageScore.

[3]Technically, 30/60/90+ days delinquent is defined as being 1/2/3+ months late with mortgage payments.

This variable can be interpreted in at least two ways. First, lagged VantageScores may be informative to the extent that deteriorating or improving VantageScores may predict the current VantageScore. Second, large swings in VantageScores could identify volatile borrowers, whose credit scores are likely to change due to frequent changes in financial situation or behavior. To interpret VantageScore momentum, it is important to realize that VantagesScores are relative measures, meaning that the cross-sectional distribution of VantageScores hardly fluctuates over time. Hence, VantageScore momentum measures how a borrower's position in the cross-sectional distribution of VantageScores moves during a period of six months.

Predicted housing equity for property i at time t is measured as:[4]

$$\%\text{Equity}_{i,t} = 100\left(1 - \frac{\text{Loan}_{i,0}}{\text{Value}_{i,0}} \times \frac{\text{ZIP HPI}_{i,0}}{\text{ZIP HPI}_{i,t}}\right)\%, \tag{1}$$

where the change in the value of an individual property since origination ($\text{Value}_{i,0}$) is proxied by the change in the ZIP code level of house price indices between the origination period ($\text{ZIP HPI}_{i,0}$) and time t ($\text{ZIP HPI}_{i,t}$). Actual home equity may be endogenous if, for example, homeowners who expect to default stop maintaining their house. In the regressions, I therefore use predicted instead of actual home equity; i.e., the home equity the homeowner would hold if he or she took out no further loans and if the value of the house varied with the average price level in the ZIP code. Because the variation in predicted home equity comes from exogenous house prices and the initial loan-to-value ratio, I consider the variation in predicted home equity exogenous.[5]

The debt-to-income (DTI) ratio is from LP and is reported only at the time a mortgage is originated. The DTI ratio is missing for about one-third of the borrowers; hence, I define a missing DTI dummy. Credit bureaus state that the level of credit utilization have an impact on credit scores. This variable as is available in the data from TransUnion. The mortgage interest rate is from LP and is updated monthly for mortgages with a variable mortgage rate. I also use the FICO score at origination in the analysis because FICO score is used for underwriting decisions and the

[4]This measure was used in Demyanyk, Hryshko, Luengo-Prado, and Sorensen (2013) in a similar way.

[5]this case of exogeneity is related to the argument in Acemoglu and Johnson (2007) for the exogeneity of instruments similarly generated.

VantageScore is not. FICO score is available from LP.

1.2 Sample selection

I construct a sample of borrower-level credit data from the merged data of TransUnion and LP. There are approximately 16.6 million borrowers in the original data set from TransUnion. Approximately 13.8 million of those borrowers have matched subprime or Alt-A mortgages reported in the LP data in our sample period, as of December 2009. These mortgages were originated for properties located in 34,125 ZIP codes of the U.S. I only select data for those ZIP codes for which the ZHVI is available. This selection results in approximately 10.6 million borrowers with 8 million loans for properties located in 11,761 ZIP codes. From this data set, I randomly pick 20,000 borrowers.

The unit of observation is a borrower in a given month. Hence, if several open mortgages co-exist at a given point in time, I collapse mortgage-level data provided by LP into a single observation per time period by taking an average of the combined loan-to-value ratio, DTI ratio, the FICO score at origination, the initial interest rate, and housing equity.

1.3 Summary statistics

Summary statistics for the data is provided in Table 2. The VantageScore range is 501 to 990, inclusive. Borrowers with higher VantageScores are deemed more creditworthy. The VantageScore has a mean of 724 and a standard deviation of 123. FICO credit score is measured at mortgage origination. As with the VantageScore, borrowers with higher FICO scores are deemed more creditworthy. It has a mean of 658 and a standard deviation of 71.

The median (P50) VantageScore momentum is 0, which is intuitive as VantageScore is a relative measure and our sample is representative of the general population. The 5th and 95th percentiles are -109 and $+78$, indicating that large swings in the VantageScore do occur over a six-month period. The standard deviation of VantageScore momentum is 57, further illustrating that the VantageScore can be quite volatile. The DTI ratio is reported in percentage points and has an average value of 39% with a standard deviation of 9%. The credit card utilization has an average value of 45% with a standard deviation of 37%. The 95th percentile is above 100% at 101%, which can happen if the credit limit is drastically reduced without a commensurate reduction in the amount of credit outstanding. Housing equity is reported in percentage points and is positive on average, at 17%, but with a standard deviation of 28%.

The interest rate is reported in percentage points and has a mean of 7.50% with a standard deviation of 1.75%. The interest rate distribution is skewed to the right, as can be seen from the percentiles, with a rate of 10.89% at the 95th percentile. Log income equals 10.76 on average, which corresponds to an income level of about $47,000. The average 6-month percentage change in the unemployment rate is positive at 8%.

2 Impact of mortgage default on credit scores

In this section, I study the impact of credit events on a borrower's VantageScore. I first discuss the econometric framework in Section 2.1 and present the main empirical results in the subsequent sections.

2.1 Regression specification

I denote the VantageScore of borrower i at time t as V_{it} and let X_{it} be a vector of borrower characteristics. C_t is a dummy variable corresponding to a certain credit event. $C_t = 1$ if the credit event happens and $C_t = 0$ otherwise. I intend to answer questions of the type: "Suppose a borrower is 30 days delinquent on his or her mortgage. What is the impact on the VantageScore if the borrower misses another payment and transitions to a 60-days delinquent status?" I focus on the impact on the VantageScore in the next period, though I also report the impact on the VantageScore one year later. Formally, the object of interest is:

$$\Delta V_{it}(k) \equiv E\left(V_{i,t+k} \mid X_{i,t-1}, C_{it} = 1\right) - E\left(V_{i,t+k} \mid X_{i,t-1}, C_{it} = 0\right).$$

To this end, I run panel regressions of the form:

$$V_{i,t+k} = \beta_0^{(k)} + \beta_1^{(k)\prime} X_{i,t-1} + \beta_2^{(k)} V_{i,t-1} + \left(\gamma_0^{(k)} + \gamma_1^{(k)\prime} Y_{i,t-1}\right) C_{it} + \varepsilon_{i,t+k}, \tag{2}$$

where $Y_{i,t-1}$ a set of variables that might affect the impact of the credit event on the borrower's future VantageScore. From this regression equation, it follows:

$$\begin{aligned} E\left(V_{i,t+k} \mid X_{i,t-1}, C_{it} = 0\right) &= \beta_0^{(k)} + \beta_1^{(k)\prime} X_{i,t-1} + \beta_2^{(k)} V_{i,t-1}, \\ E\left(V_{i,t+k} \mid X_{i,t-1}, C_{it} = 1\right) &= \gamma_0^{(k)} + \gamma_1^{(k)\prime} Y_{i,t-1} + \beta_0^{(k)} + \beta_1^{(k)\prime} X_{i,t-1} + \beta_2^{(k)} V_{i,t-1}, \end{aligned}$$

which I in turn can combine into:

$$E\left(V_{i,t+k} \mid X_{i,t-1}, C_{it} = 1\right) - E\left(V_{i,t+k} \mid X_{i,t-1}, C_{it} = 0\right) = \gamma_0^{(k)} + \gamma_1^{(k)\prime} Y_{i,t-1}.$$

Hence, the estimates of $\gamma_0^{(k)}$ and $\gamma_1^{(k)}$ reveal the difference in VantageScores for households that are otherwise identical on observable characteristics. I use the VantageScore itself as the dependent variable. Causal statements based on these regressions cannot be made as an instrument generating exogenous variation in credit events is not available, even though a rich set of control variables used in the regressions should account for a large share of the heterogeneity.

2.2 Contemporaneous impact of delinquency and foreclosure on credit scores

In this section, I discuss the contemporaneous consequences of default in terms of changes in the VantageScore. To illustrate the impact, I first plot in Figure 1 the VantageScore distribution one month before and in the month of a transition to 30-day delinquency (left panel) and foreclosure (right panel). For the transition to 30-day delinquency I require the mortgage to be current the month before. For the transition to foreclosure, I require the mortgage to be 90+-day delinquent the month before. A transition to 30-day delinquency leads to a dramatic shift in the VantageScore distribution to the left. For the transition to foreclosure, the VantageScore distribution is already heavily tilted toward low values a month before foreclosure, and the VantageScore distribution after foreclosure hardly differs.

Next, in Table 3, I present results for the regressions with the VantageScore as the dependent variable. I include the lagged VantageScore as well as dummies related to the lagged VantageScore, VantageScore momentum, debt-to-income ratio, credit card utilization, and housing equity. I also include the lagged interest rate, FICO score, income, and unemployment. The main explanatory variable of interest is a dummy indicating that a borrower transitions to a worse state. For a borrower to be included in the estimation, a set of criteria needs to be satisfied. The first row displays the selection criteria for the previous month and the second row displays the criteria for the current month. For instance, to measure a transition from current (C) to 30-day delinquency (D30), I include only borrowers for whom the lagged status is current and for whom the status in the subsequent month is either current or 30 days delinquent. The results for this specification are reported in the first column of Table 3. Following the same logic, I have similar inclusion criteria when the dependent variable is a 60-day delinquency status dummy (D60), a 90-day or more delinquency status dummy (D90+), and a foreclosure status dummy (F). For each explanatory variable considered in Table 3, I report the point estimate and, to assess the statistical significance, the z-score in parentheses. I include year dummy variables in all specifications and cluster standard errors at the borrower level.[6]

Event dummy The impact of a transition from current to 30-day delinquency on the VantageScore is estimated to be a decline of 51 points (relative to households that stay current and have otherwise comparable observable characteristics). For a transition to 60-day delinquency, 90+-day delinquency, and foreclosure, the marginal effect is increasingly muted at 25-, 14-, and 6-point drops, respectively. Hence, by far the biggest hit on the VantageScore occurs at the very first step of the default process when borrowers transition from current to 30-day delinquency.

[6] I report the coefficient for FICO/100 instead of FICO, as the coefficient for FICO would be too small at the reported precision.

Other variables The effect of lagged VantageScore momentum is very significant and mostly monotonic: holding constant the current VantageScore group, households with positive VantageScore momentum, i.e., those who experienced increasing scores before the event, have a tendency to experience a greater deterioration in the VantageScore relative to households with negative VantageScore momentum.

Event dummy variables interacted with VantageScore group dummy variables In Table 4 I present the effect on the borrower's VantageScore of a transition to a worse state, for different lagged VantageScore groups. That is, compared to Table 3, I add interaction variables between the event and the lagged VantageScore group.

The event variable in Table 4 measures the effect for a borrower in the lowest VantageScore group, group 0, while the interaction variables between the event and groups 1-3 measure the effect of the event relative to a borrower in group 0. Focusing first on the event variable without interaction, one can see that a transition to 30-day delinquency, 60-day delinquency, 90+-day delinquency, and foreclosure has an increasingly muted effect on the VantageScore, similar to what was documented in Table 3. The impact on the VantageScore of a transition to a worse state is larger when starting from a higher VantageScore group. For example, transitioning from current to 30-day delinquency for a borrower in lagged VantageScore group 3, leads to a $-16-104=-120$ drop in the score on average. For transitions to more severe states there is less statistical power for the interaction variable between the event and the VantageScore group, as most borrower will be in VantageScore group 0 by the time they have reached these more severe states of delinquency.

Transition to 30-day delinquency for different years For robustness, I verify that the results are not due to potential differences in models that credit bureaus may employ to measure the impact of delinquencies during the great recession. For the transition to 30-day delinquency there are enough observations to accurately measure the effect on the VantageScore year by year. In Table 5, I include the interaction between the event and the lagged VantageScore group, like I do in Table 4, and estimate the model separately for each year in our sample. The main takeaway is that the effect of a transition from current to 30-day delinquency on the VantageScore is very stable over time. For the lowest VantageScore group 0 the effect ranges from a 15- to an 18-point drop. For the highest VantageScore group 3, the effect (additional to the effect for group 0) ranges from an 82- to a 116-point drop. Also, the effect of other explanatory variables included is mostly stable. Hence, the evidence does not support the different-model hypothesis.

2.3 Impact of delinquency and foreclosure on credit scores after one year

To illustrate the effect of a credit event on credit scores one year after the event, Figure 2 shows the VantageScore distribution 1 month before and 12 months after a transition to 30-day delinquency (left panel) and foreclosure (right panel). The same inclusion criteria as before are applied. I make sure that the same set of borrowers is used for the distribution the month before and one year after, by including only borrowers for whom the VantageScore is given for both periods. A transition to 30-day delinquency leads to a dramatic shift in the VantageScore distribution to the left, even more dramatic than in the month of the transition, Figure 1. This is in the same spirit as the VantageScore momentum effect documented earlier: borrowers who take a first step down the road to default often slide further down, leading to a continuation of declines in the VantageScore. For the transition to foreclosure, the VantageScore distribution is already heavily tilted toward low values a month before foreclosure, and the distribution of the VantageScore 12 months after foreclosure actually shows a pronounced recovery. In particular, the percentage of borrowers in the lowest VantageScore bracket is much lower one year after the transition to foreclosure.

Then I repeat the regressions presented in Table 3, with the only difference that I use the VantageScore after one year as the dependent variable. More precisely, the dependent variable is measured in month $t + 12$, the event is in month t, and the lagged control variables are measured in month $t - 1$. The results are presented in Table 6.

Event dummy A year after transitioning from current to 30-day delinquency, the VantageScore is still 38 points lower, relative to households that did not transition to 30-day delinquency. The impact is -13 and -3 points for 60-day and 90-day delinquency, respectively. Interestingly, for the transition to foreclosure, the change in in the VantageScore over the subsequent year is similar to that of a household that did not experience foreclosure, evidenced by the (near) zero coefficient on the event dummy.

Table 6 shows that households that transition from 90+-delinquency to foreclosure have a 12-month change in their VantageScore comparable to the change experienced by households that did not transition from 90+-day delinquency to foreclosure. The large improvement in the VantageScore documented in Figure 2 (right panel) for households that transition from 90+-day delinquency to foreclosure then logically also implies that households that did not transition from 90+-delinquency to foreclosure experienced a comparable improvement in their VantageScores. I confirmed that this is indeed the case by constructing a similar figure for the households that do not transition to foreclosure (not reported). Hence, starting from a 90+ status, 12 months later the VantageScore is on average considerably higher, regardless of whether a foreclosure takes place. To provide a potential explanation for this improvement, I study in more detail what happens to the borrowers that are 90+-day delinquent but do not enter foreclosure. As it turns out, the VantageScore of these borrowers is very close to its lower bound. This implies that even if foreclosure does not occur and the borrower is still delinquent 12 months later, the VantageScore does not deteriorate. However, there are some borrowers that become current again and they experience a significant improvement in VantageScores. This behavior is similar for borrowers who do transition from 90+-delinquency into foreclosure.

To illustrate in another way how the VantageScore is differentially affected by a transition from current to 30-day delinquency in comparison to a transition from 90+-delinquency to foreclosure, I plot in Figure 3 the change in the VantageScore in the month of a transition to 30-day delinquency (left panel) and the cumulative change in the VantageScore 12 months after; I do the same for a transition into foreclosure (right panel). I plot the changes as a function of the VantageScore the month prior to the event. The plots are truncated above a VantageScore of 800 and 700 for the left and right panel respectively, as too few borrowers have a sufficiently high VantageScore the month prior to a transition to a worse state (see Figure 1).

The patterns are consistent with the results discussed above: the first delinquency has the largest effect on a borrower's VantageScore, while foreclosures on average have a small negative effect on VantageScores. Moreover, going forward, households that were 90+-day delinquent or in foreclosure tend to experience on average an improvement in VantageScores. One interpretation would be that households are able to make payments on other forms of credit when they no longer make the mortgage payments.

To document evidence consistent wit this interpretation, Figure 4 plots the number of months since the latest credit card delinquency (left panel), for both the month prior to the foreclosure and 12 months after. In the month prior to foreclosure more than 50% of households are delinquent on a credit card, while 12 months after foreclosure this number is less than 30%. More generally the distribution shows a dramatic shift to the right going from the month before to 12 months after foreclosure, showing how credit card problems improved following a foreclosure. The right panel of Figure 4 shows the number of inquires for credit over the last 6 months, for both the month prior to the foreclosure and 12 months after the foreclosure. The month prior to foreclosure less than 20% of households made no inquiry for credit, while 12 months after foreclosure more than 35% households made no inquiry. More generally the distribution shows a dramatic shift to the left, i.e., toward fewer inquiries, going from the month before to 12 months after foreclosure.[7]

3 Conclusions

A foreclosure is without any doubt a very disruptive event. It appears as a significant negative factor in one's credit history. A record of foreclosure stays on credit reports for seven years, which

[7] It is impossible to differentiate in the data whether borrowers apply less for new credit after foreclosure because they do not need as much credit anymore or because they are discouraged from applying. However, a number of recent credit inquiries is not only a measure of a household's distress, but also a determinant of future credit scores, where a large number of inquiries has a negative impact on the credit score. Therefore, both need- and discouragement-driven reductions in inquiries result in higher credit scores in the future.

may lead to less financially advantageous borrowing prospects for that period of time, as lenders may reject individuals with a record of foreclosure or charge high interest rates for the loans they would originate. Moreover, there may be a social stigma (Guiso, Sapienza, and Zingales (2009)) that causes embarrassment to those who have undergone foreclosure. Foreclosures induce people to leave their homes, alter their families' lifestyle and neighborhood, change their children's schools, etc. Homes in foreclosure distort home prices in the area (Campbell (2013) and Campbell, Giglio, and Pathak (2011)). However, this paper documents that one of the alleged negative impacts of foreclosure on consumers, namely foreclosures ruin credit scores, is not supported by the data. Based on our estimated results, foreclosures that were followed by missed mortgage payments—the vast majority of foreclosures—have a very limited impact on borrowers' credit scores. Also, on average, borrowers who missed more than three mortgage payments or entered a foreclosure have their credit scores substantially improved one year afterward. I show evidence for one potential explanation of this effect: borrowers who no longer make mortgage payments are better able to pay for other credit obligations (such as credit cards) and don't inquire as often for new credit, both of which in general drive credit scores up.

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Figure 1: VantageScore distribution one month before and the month of a transition to worse state

The left panel of this figure shows the change in VantageScore distribution for households that are 30 days delinquent in a particular month. For the transition to 30-day delinquency the mortgage is required to be current the month before. The right panel displays the change in VantageScore distributions at the moment of foreclosure. For transition to foreclosure, the mortgage is required to be 90+-day delinquent the month before. The sample period is September 2004 until May to July 2009.

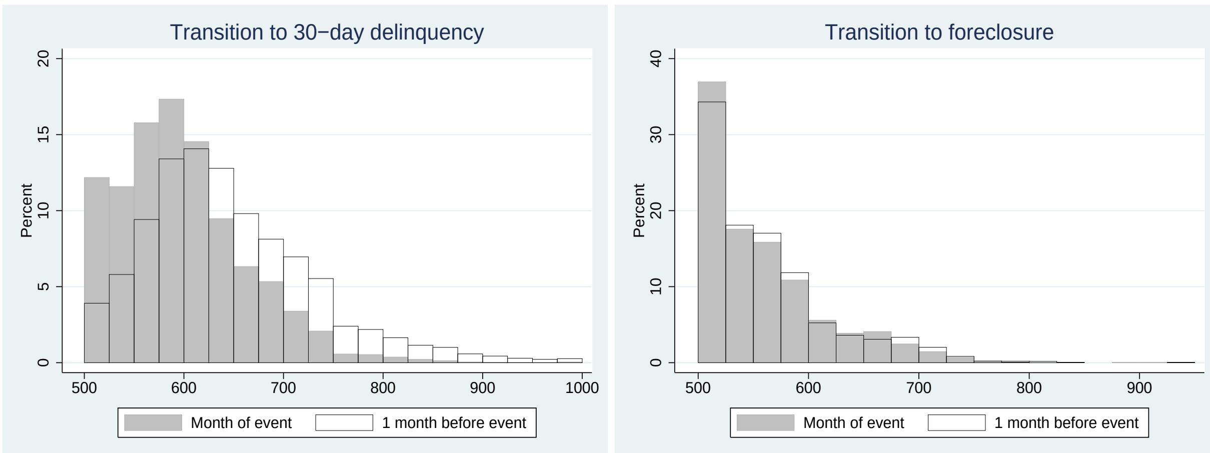

Figure 2: VantageScore distribution 1 month before and 12 months after a transition to a worse state

The left panel of this figure shows the change in VantageScore distribution 1 month before and 12 months after a transition to 30 days delinquency. For the transition to 30-day delinquency the mortgage is required to be current the month before. The right panel displays the change in VantageScore distributions 1 month before and 12 months after a transition to foreclosure. For transition to foreclosure, the mortgage is required to be 90+-day delinquent the month before. The sample period is September 2004 until May to July 2009.

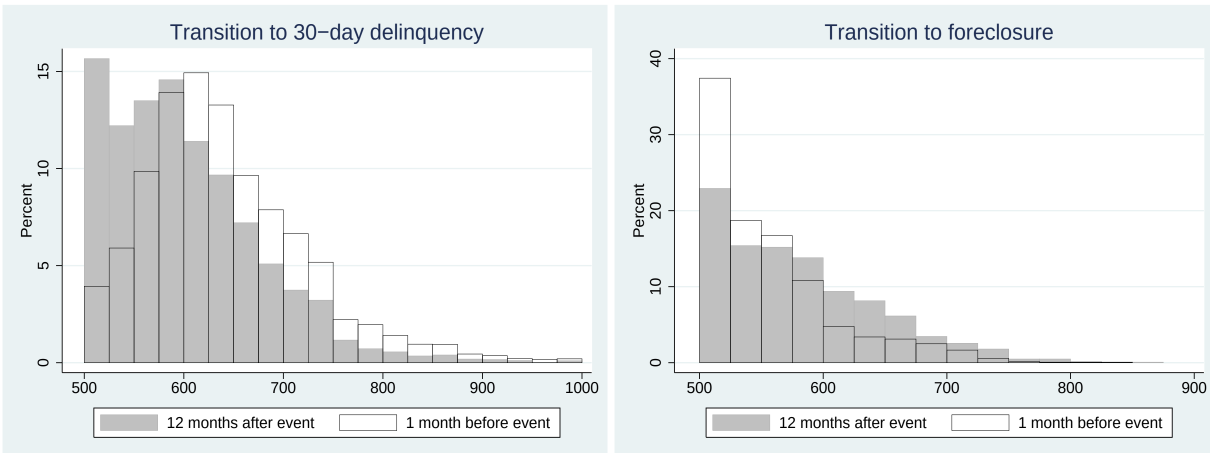

Figure 3: Cumulative change of VantageScore in the month of a transition to worse state and 12 months after

This figure plots the cumulative change of VantageScore in the month of a transition to a worse state and 12 months after, as a function of the VantageScore the month prior to the credit event. For the transition to 30-day delinquency (left panel) the mortgage is required to be current the month before the event. For transition to foreclosure (right panel), the mortgage is required to be 90+-day delinquent the month before the event. The sample period is September 2004 until May to July 2009.

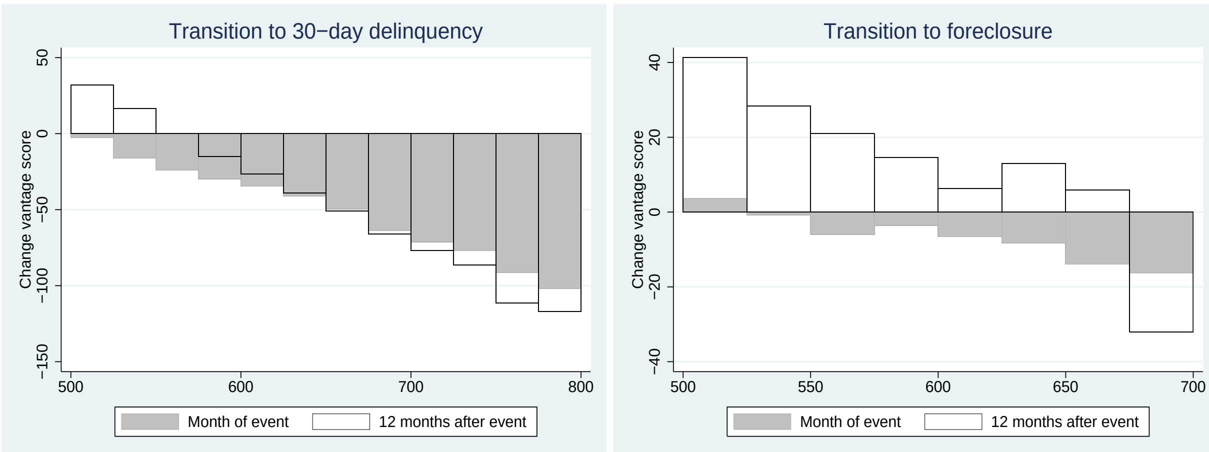

Figure 4: General credit situation 1 month before and 12 months after foreclosure

The left panel depicts the number of months since the latest bank or credit card delinquency. The right Panel shows the number of inquires for credit over the last 6 months. In both panels, I show both the month prior to the foreclosure and 12 months after the foreclosure. I focus on transitions to foreclosure where the mortgage was 90+-day delinquent the month before. The sample period is September 2004 until May to July 2009.

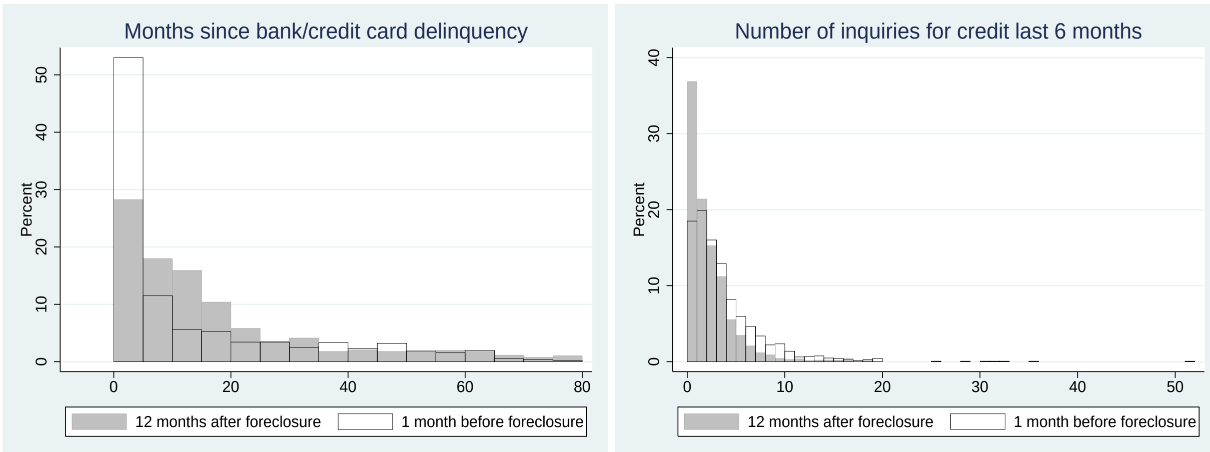

Table 1: Variable definitions

This table present definitions for the main variables used in the statistical analyses. In the table, "TU" stands for TransUnion and "LP" for LoanPerformance. The sample period is September 2004 until May to July 2009.

Variable	Description (source), and range for categorical variables
Mortgage status	The status of the borrowers largest mortgage (Credit bureau)
	C: current
	D30, D60, D90+: 1,2,3+ months delinquent
	F: in foreclosure
VantageScore	The VantageScore (TU)
	Score G0: score in [501,550]
	Score G1: score in (550,700]
	Score G2: score in (700,800]
	Score G3: score in (800,990]
VantageScore momentum	VantageScore current month minus VantageScore 6-months earlier (TU)
	Dscore G0: [-489,-100]
	Dscore G1: (-100,-30]
	Dscore G2: (-30,30]
	Dscore G3: (30,489]
Debt-to-income ratio	Debt-to-income ratio, weighted-average of the values reported at origination (LP)
	DTI G0: value in [0%,30%]
	DTI G1: value in (30%,35%]
	DTI G2: value in (35%,40%]
	DTI G3: value in (40%,+Inf%]
	DTI miss: DTI not provided
Credit utilization	Percentage of available credit utilized (TU)
	Credit G0: value in [0%,50%]
	Credit G1: value in (50%,80%]
	Credit G2: value in (80%,100%]
	Credit G3: value in (100%,+Inf%]
Equity in the house	Computed from CLTV at origination (LP) and ZIP-code level house price data (Zillow)
	Equity G0: value in [-Inf%,-20%]
	Equity G1: value in (-20%,0%]
	Equity G2: value in (0%,25%]
	Equity G3: value in (25%,+Inf%]
Interest rate	Interest rate, updated to reflect current rate for adjustable-rate mortgages (LP)
FICO	FICO credit score, weighted-average of the values reported at origination (LP)
Year dummy variables	We include year dummy variables for all but the first sample year (which is the reference year)
Log income	Logarithm of the average household income in the ZIP code based on 2000 Census data
Unemployment	Six-month change in log county-level unemployment rates (Bureau of Labor Statistics)

Table 2: Descriptive statistics

This table reports mean, standard deviation, and the 5th, 25th, 50th, 75th, 95th percentile of the distribution of the variables used in the statistical analysis. The sample period is September 2004 until May to July 2009.

	Mean	St. dev.	P5	P25	P50	P75	P95
VantageScore	723.61	122.57	530.00	631.00	718.00	809.00	943.00
VantageScore momentum	−5.61	57.23	−109.00	−30.00	0.00	24.00	78.00
DTI ratio	39.29	9.43	21.60	33.80	40.80	46.40	52.00
Credit utilization	44.53	37.15	0.00	9.40	38.60	76.50	100.70
Housing equity	16.52	27.61	−31.55	2.56	18.04	33.86	57.31
Interest rate	7.50	1.75	5.38	6.25	7.15	8.40	10.89
FICO	658.04	70.71	536.00	609.00	659.00	709.00	776.00
Log income	10.76	0.33	10.24	10.53	10.75	10.99	11.28
Unemployment	0.08	0.15	−0.12	−0.03	0.06	0.19	0.34

Table 3: Contemporaneous impact of delinquency and foreclosure on credit scores

Constant and year dummy variables included but not reported. Z-score in parenthesis (errors clustered at borrower level). The sample period is September 2004 until May to July 2009. The detailed variable definitions are provided in Table 1 and regression specification is described in Section 2.1.

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-D30		C-D60		C-D90+		C-F	
Observations	266989		13459		6284		8604	
Event	D30		D60		D90+		F	
Dependent var.	Score		Score		Score		Score	
Event	−50.90	(79)	−25.28	(38)	−13.69	(18)	−6.27	(8)
Score (lag)	0.96	(647)	0.92	(105)	0.90	(70)	0.92	(95)
Score G1 (lag)	−2.42	(5)	−0.63	(1)	1.56	(1)	1.86	(2)
Score G2 (lag)	−3.51	(6)	2.48	(1)	2.25	(1)	5.74	(2)
Score G3 (lag)	−2.10	(3)	8.51	(2)	21.82	(3)	2.66	(0)
DScore G1 (lag)	−3.69	(9)	−1.02	(1)	0.15	(0)	−1.74	(2)
DScore G2 (lag)	−6.26	(15)	−2.74	(3)	−2.60	(3)	−2.27	(3)
DScore G3 (lag)	−10.14	(24)	−6.54	(6)	−6.95	(4)	−5.19	(5)
DTI miss (orig.)	0.35	(2)	0.47	(0)	−1.33	(1)	−1.50	(1)
DTI G1 (orig.)	−0.03	(0)	1.93	(2)	−1.11	(1)	−1.45	(1)
DTI G2 (orig.)	−0.31	(1)	0.20	(0)	−1.77	(1)	−1.01	(1)
DTI G3 (orig.)	−0.13	(1)	0.26	(0)	−1.03	(1)	−0.59	(1)
Credit G1 (lag)	−2.78	(18)	−4.42	(6)	−1.92	(2)	−2.80	(3)
Credit G2 (lag)	−3.50	(19)	−5.02	(7)	−3.00	(3)	−4.04	(6)
Credit G3 (lag)	−2.44	(7)	−4.39	(5)	−3.30	(3)	−1.91	(2)
Equity G1 (lag)	1.01	(4)	0.38	(0)	0.97	(1)	0.15	(0)
Equity G2 (lag)	2.43	(9)	3.18	(3)	1.62	(1)	0.89	(1)
Equity G3 (lag)	3.87	(14)	6.03	(6)	5.30	(4)	2.31	(2)
Int. rate (lag)	−0.28	(7)	−0.46	(3)	0.11	(1)	0.10	(1)
FICO/100 (orig.)	2.16	(19)	−0.49	(1)	0.10	(0)	0.70	(1)
2006 dummy	0.07	(0)	0.96	(1)	−1.32	(1)	−1.10	(1)
2007 dummy	0.01	(0)	1.17	(1)	−0.17	(0)	−2.27	(1)
2008 dummy	0.16	(1)	1.05	(1)	1.10	(1)	−0.81	(1)
2009 dummy	1.35	(5)	2.87	(2)	5.62	(3)	1.52	(1)
Income (lag)	1.78	(10)	0.72	(1)	0.08	(0)	0.41	(0)
Unemp. (lag)	−3.46	(6)	−9.36	(3)	−9.66	(3)	−5.55	(2)
Constant	7.87	(4)	52.43	(4)	58.68	(4)	43.72	(4)

Table 4: Contemporaneous impact of delinquency and foreclosure on credit scores; Event-VantageScore group interaction effects

Constant and year dummy variables included but not reported. Z-score in parenthesis (errors clustered at borrower level). The sample period is September 2004 until May to July 2009. The detailed variable definitions are provided in Table 1 and regression specification is described in Section 2.1.

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-D30		C-D60		C-D90+		C-F	
Observations	266989		13459		6284		8604	
Event	D30		D60		D90+		F	
Dependent var.	Score		Score		Score		Score	
Event	−16.03	(18)	−11.36	(13)	−10.09	(11)	−3.04	(4)
Event*Score G1 (lag)	−23.41	(22)	−16.88	(15)	−6.15	(5)	−4.89	(3)
Event*Score G2 (lag)	−56.12	(35)	−32.30	(9)	−3.74	(1)	−15.17	(3)
Event*Score G3 (lag)	−104.16	(33)	−27.37	(2)	29.51	(3)	−16.67	(1)
Score (lag)	0.96	(655)	0.93	(105)	0.90	(71)	0.92	(95)
Score G1 (lag)	1.42	(3)	3.63	(4)	3.84	(3)	2.67	(3)
Score G2 (lag)	1.22	(2)	9.06	(4)	3.63	(1)	7.70	(3)
Score G3 (lag)	2.72	(4)	13.53	(3)	14.52	(2)	4.42	(1)
DScore G1 (lag)	−3.65	(9)	−1.21	(2)	0.16	(0)	−1.77	(2)
DScore G2 (lag)	−6.19	(15)	−3.20	(4)	−2.73	(3)	−2.33	(3)
DScore G3 (lag)	−10.07	(24)	−7.49	(7)	−7.10	(4)	−5.43	(5)
DTI miss (orig.)	0.37	(2)	0.27	(0)	−1.66	(1)	−1.33	(1)
DTI G1 (orig.)	−0.03	(0)	1.86	(1)	−1.29	(1)	−1.28	(1)
DTI G2 (orig.)	−0.28	(1)	0.03	(0)	−2.01	(1)	−0.86	(1)
DTI G3 (orig.)	−0.10	(1)	0.21	(0)	−1.28	(1)	−0.47	(0)
Credit G1 (lag)	−2.71	(18)	−4.74	(6)	−1.96	(2)	−2.81	(3)
Credit G2 (lag)	−3.46	(19)	−5.28	(7)	−3.17	(3)	−4.08	(6)
Credit G3 (lag)	−2.77	(8)	−4.55	(6)	−3.39	(3)	−1.88	(2)
Equity G1 (lag)	0.65	(2)	0.10	(0)	1.05	(1)	0.18	(0)
Equity G2 (lag)	1.91	(8)	2.95	(3)	1.44	(1)	1.01	(1)
Equity G3 (lag)	3.32	(13)	5.47	(5)	5.16	(4)	2.43	(3)
Int. rate (lag)	−0.28	(8)	−0.45	(3)	0.10	(1)	0.09	(1)
FICO (orig.)	2.15	(19)	−0.55	(1)	0.12	(0)	0.72	(1)
2006 dummy	0.04	(0)	0.85	(1)	−1.26	(1)	−1.22	(1)
2007 dummy	0.00	(0)	1.14	(1)	−0.16	(0)	−2.33	(1)
2008 dummy	0.15	(1)	1.10	(1)	1.13	(1)	−0.81	(1)
2009 dummy	1.40	(5)	3.16	(2)	5.83	(3)	1.51	(1)
Income (lag)	1.74	(10)	0.83	(1)	−0.01	(0)	0.43	(1)
Unemp. (lag)	−3.42	(6)	−9.19	(3)	−10.14	(3)	−5.43	(2)
Constant	4.32	(2)	47.83	(4)	58.72	(4)	42.59	(4)

Table 5: Contemporaneous impact of 30-day delinquency on credit scores year-by-year

Constant and year dummy variables included but not reported. Z-score in parenthesis (errors clustered at borrower level). The sample period is September 2004 until May to July 2009. The detailed variable definitions are provided in Table 1 and regression specification is described in Section 2.1.

Incl. status (lag)	C		C		C		C	
Incl. status	C-D30		C-D30		C-D30		C-D30	
Incl. year	2006		2007		2008		2009	
Observations	61685		74258		68651		30240	
Event	D30		D30		D30		D30	
Dependent var.	Score		Score		Score		Score	
Event	−17.71	(7)	−14.77	(10)	−16.19	(10)	−17.71	(8)
Event*Score G1 (lag)	−22.76	(8)	−25.62	(14)	−23.80	(13)	−17.11	(6)
Event*Score G2 (lag)	−50.30	(13)	−63.82	(24)	−55.89	(20)	−49.87	(14)
Event*Score G3 (lag)	−82.13	(8)	−97.08	(19)	−115.61	(26)	−110.39	(17)
Score (lag)	0.95	(309)	0.95	(362)	0.96	(384)	0.97	(291)
Score G1 (lag)	2.87	(2)	3.29	(4)	−1.15	(1)	−0.14	(0)
Score G2 (lag)	2.64	(2)	3.80	(4)	−1.62	(2)	−0.89	(1)
Score G3 (lag)	3.94	(3)	5.51	(5)	0.24	(0)	0.10	(0)
DScore G1 (lag)	−6.58	(7)	−3.69	(5)	−2.26	(3)	−1.36	(1)
DScore G2 (lag)	−9.76	(10)	−6.23	(9)	−4.23	(6)	−3.29	(4)
DScore G3 (lag)	−13.73	(14)	−10.07	(13)	−7.57	(10)	−7.21	(7)
DTI miss (orig.)	−0.29	(1)	0.75	(2)	0.00	(0)	1.29	(3)
DTI G1 (orig.)	−0.74	(2)	0.34	(1)	0.30	(1)	1.04	(2)
DTI G2 (orig.)	−1.18	(3)	0.09	(0)	−0.21	(0)	−0.28	(0)
DTI G3 (orig.)	−1.09	(3)	0.00	(0)	−0.09	(0)	1.52	(3)
Credit G1 (lag)	−2.77	(9)	−2.66	(9)	−2.95	(10)	−2.77	(7)
Credit G2 (lag)	−3.29	(9)	−3.50	(10)	−3.57	(10)	−3.64	(7)
Credit G3 (lag)	−2.53	(3)	−2.87	(4)	−2.95	(5)	−2.52	(3)
Equity G1 (lag)	2.49	(1)	0.25	(0)	0.37	(1)	1.07	(3)
Equity G2 (lag)	3.52	(1)	1.89	(2)	1.56	(4)	1.41	(4)
Equity G3 (lag)	5.25	(2)	3.41	(4)	2.75	(7)	2.22	(5)
Int. rate (lag)	−0.36	(5)	−0.33	(5)	−0.27	(4)	−0.08	(1)
FICO/100 (orig.)	3.19	(15)	2.49	(12)	1.60	(8)	0.51	(2)
Income (lag)	2.10	(6)	1.67	(5)	1.54	(5)	1.40	(3)
Unemp. (lag)	−4.14	(3)	−1.82	(2)	−6.33	(7)	−0.62	(0)
Constant	1.66	(0)	3.50	(1)	7.81	(2)	6.50	(1)

Table 6: Impact of delinquency and foreclosure on credit scores after one year

Constant and year dummy variables included but not reported. Z-score in parenthesis (errors clustered at borrower level). The sample period is September 2004 until May to July 2009. The detailed variable definitions are provided in Table 1 and regression specification is described in Section 2.1.

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-D30		C-D60		C-D90+		C-F	
Observations	207192		9555		4081		4181	
Event	D30		D60		D90+		F	
Dependent var.	Score (lead)		Score (lead)		Score (lead)		Score (lead)	
Event	−38.39	(30)	−13.23	(8)	−3.49	(2)	0.28	(0)
Score (lag)	0.78	(78)	0.70	(25)	0.63	(14)	0.68	(14)
Score G1 (lag)	−29.98	(14)	−10.58	(4)	−4.95	(1)	−2.90	(1)
Score G2 (lag)	−31.48	(12)	−3.08	(0)	−1.93	(0)	2.54	(0)
Score G3 (lag)	−24.42	(7)	38.68	(3)	85.96	(4)	−1.49	(0)
DScore G1 (lag)	−8.53	(5)	2.86	(1)	−3.08	(1)	−0.85	(0)
DScore G2 (lag)	−9.14	(5)	−0.05	(0)	−4.90	(2)	−6.99	(2)
DScore G3 (lag)	−24.09	(14)	−7.41	(2)	−11.36	(2)	−11.65	(2)
DTI miss (orig.)	2.09	(1)	−1.23	(0)	−5.49	(1)	−6.85	(1)
DTI G1 (orig.)	0.32	(0)	−4.60	(1)	−7.92	(1)	−11.45	(1)
DTI G2 (orig.)	−3.15	(1)	1.33	(0)	−10.86	(2)	−12.29	(1)
DTI G3 (orig.)	−4.31	(3)	−1.23	(0)	−6.16	(1)	−5.22	(1)
Credit G1 (lag)	−10.28	(9)	−8.37	(3)	−9.72	(2)	−7.65	(2)
Credit G2 (lag)	−10.67	(8)	−4.70	(2)	−6.73	(2)	−10.34	(2)
Credit G3 (lag)	−3.23	(2)	−1.41	(0)	−5.83	(2)	−6.23	(1)
Equity G1 (lag)	13.36	(4)	−0.24	(0)	5.08	(1)	0.66	(0)
Equity G2 (lag)	31.72	(9)	6.44	(1)	4.85	(1)	0.10	(0)
Equity G3 (lag)	49.89	(14)	25.62	(5)	15.62	(3)	8.69	(1)
Int. rate (lag)	−2.02	(6)	−0.93	(1)	−0.22	(0)	1.00	(1)
FICO/100 (orig.)	16.35	(17)	7.47	(4)	10.06	(4)	11.40	(3)
2006 dummy	−8.51	(9)	−10.71	(4)	−12.98	(2)	−18.11	(3)
2007 dummy	−16.03	(14)	−18.60	(6)	−11.44	(2)	−19.19	(3)
2008 dummy	−18.80	(14)	−14.34	(4)	−8.28	(1)	−15.86	(2)
Income (lag)	7.56	(5)	0.25	(0)	0.44	(0)	13.72	(2)
Unemp. (lag)	−43.02	(11)	−40.39	(4)	−46.86	(3)	−44.24	(3)
Constant	−0.57	(0)	163.99	(4)	186.69	(3)	11.86	(0)