Determinants and Consequences of Mortgage Default*

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Abstract

We study a unique data set of borrower-level credit information from TransUnion, one of the three major credit bureaus, which is linked to a database containing detailed information on the borrowers' mortgages. We find that the updated credit score is an important predictor of mortgage default in addition to the credit score at origination. However, the 6-month change in the credit score also predicts default: A positive change in the credit score significantly reduces the probability of delinquency or foreclosure. Next, we analyze the consequences of default on a borrower's credit score. The credit score drops on average 51 points when a borrower becomes 30-days delinquent on his mortgage, but the effect is much more muted for transitions to more severe delinquency states and even for foreclosure.

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We study the determinants and consequences of mortgage default using a unique data set of borrower-level credit information from TransUnion, one of the three major credit bureaus. This database is linked to the LoanPerformance database, which contains detailed information on the borrowers' mortgages. Understanding the determinants of default, that is, which borrowers are more likely to be delinquent or to face foreclosure, is important for lenders and policy makers.[1] We also study the consequences of default and in particular how a borrower's credit score is affected by default. For instance, a commonly heard claim is that credit scores deteriorate substantially in cases of foreclosure. This may motivate borrowers to avoid foreclosure even if the value of their house is lower than the value of their mortgage. Hence, to understand the financial incentives borrowers face in case of default, it is important to obtain estimates of how delinquencies and foreclosures affect credit scores.[2]

Previous studies on the topic of the determinants and consequences of default face data limitations because they mostly rely on loan-level mortgage databases.[3] As a result, the determinants of default that can be analyzed are restricted to borrower and loan characteristics known at origination only. The consequences of default cannot be measured using these data, as no borrower identifier is provided, implying that one cannot follow borrowers after a loan ceases to exist.

We make use of two main data sources to overcome both issues. First, we use individual-level credit data from TransUnion's Consumer Credit Database. This is a comprehensive and rich database summarizing the credit situation of households. Second, we use the LoanPerformance database from CoreLogic, which contains loan-level data on U.S. subprime and Alt-A mortgage loans. This is the main database used by institutional investors to analyze the underlying collateral of non-agency mortgage-backed securities. CoreLogic and TransUnion have joined forces to provide a highly accurate match of the their two databases. We use the matched database, TransUnion Consumer Risk Indicators for RMBS, in this paper. We augment the data with a set of macroeconomic variables. Our results illustrate the improved ability of the merged database to predict future default and the effects on a borrower's credit score in response to a default. This is for instance relevant to value mortgage-backed securities contracts.

We consider four types of default: 30-day delinquency, 60-day delinquency, 90+-day delinquency, and foreclosure. We focus in each case on the first-lien mortgage. For the determinants of

[1]For instance, to the extent that foreclosure waves have a negative effect on neighboring house prices, see Campbell, Giglio, and Pathak (2010), micro-level data might be useful to identify areas that might be more prone to foreclosure waves.

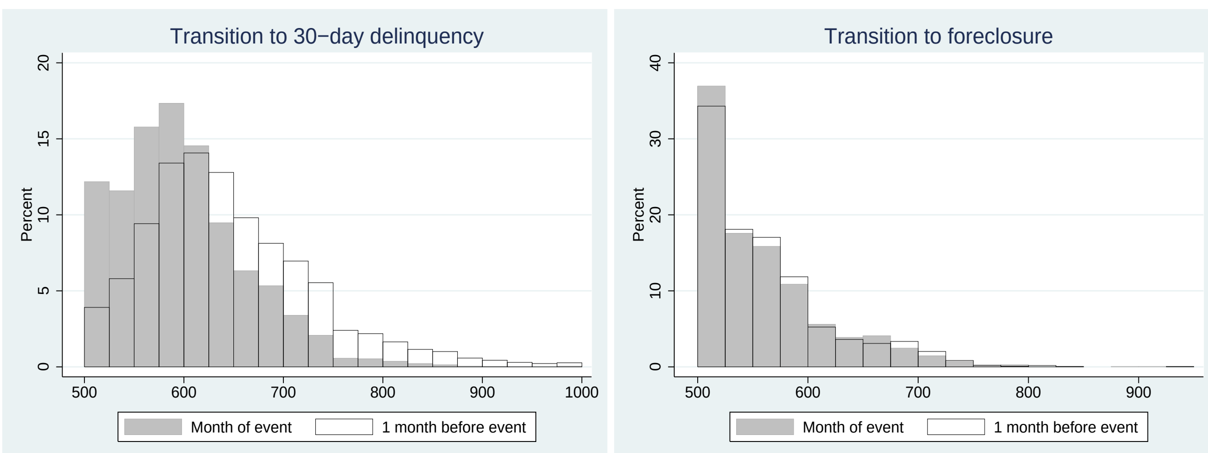
[2]Even if housing equity is negative, borrowers may decide not to default because of borrowing constraints, see Campbell and Cocco (2010). In addition, borrowers may decide not to default for non-financial reasons such as social stigma, see Guiso, Sapienza, and Zingales (2009).

[3]See for example, Demyanyk and Van Hemert (2010), Agarwal, Ambrose, Chomsisengphet, and Sanders (2010), Amromin and Paulson (2009), Gerardi, Lehnert, Sherlund, and Willen (2009), Archer and Smith (2010), Bajari, Chu, and Park (2008), and Jiang, Nelson, and Vytlacil (2010).

default we find that the data from TransUnion have predictive power in addition to LoanPerformance data only. First, a low credit score, the VantageScore in case of TransUnion, in the previous month substantially increases the probability of default, as one would expect. The VantageScore robustly predicts default for all types of default we consider. Second, we show that the current VantageScore is not a sufficient statistic, as past credit scores are also informative. In particular, holding constant the previous month's VantageScore, a higher VantageScore six months before forecasts a higher probability of default. For instance, if the VantageScore is 700 today, down from 800 six months before, the probability of default is substantially higher compared to a VantageScore of 700 today, up from 600 six months ago. We refer to this effect as the "VantageScore momentum."

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

The left panel shows the VantageScore distribution in the month before and in the month of a transition from current to 30-days delinquency. Similarly, the right panel shows the VantageScore distribution in the month before and in the month of a transition from 90+-days delinquency to foreclosure.



To analyze the consequences of default, we first focus on how the VantageScore is affected by default. We then link changes in the VantageScore to the cost of debt as measured by mortgage rates. To illustrate the impact of default on the VantageScore, we 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, we require the mortgage to be current the month before. For the transition to foreclosure, we require the mortgage to be 90+-day delinquent the month before, which is the case for 76% of the borrowers that enter foreclosure. Figure 1 shows that a transition from a current payment status to 30-day delinquency shifts the VantageScore distribution to the left. This implies that VantageScores decline substantially if a mortgage payment is missed. However, the VantageScore distribution is hardly affected in the case of foreclosure. We estimate that a transition from current to 30-day delinquent is on average associated with a drop of the VantageScore of 51 points. For transitions to 60-day delinquency, 90+-day delinquency, and foreclosure, the effect is increasingly muted at 25-, 14-, and 6-point drops, respectively. The common wisdom that "foreclosure ruins your credit score" does not seem to be the case for most foreclosure cases, which are already 90+-days delinquent in the month prior to foreclosure.[4]

Figure 2: Average VantageScore before and after transitioning to delinquency and foreclosure

The figure shows the average VantageScore during the 12 months preceding, and the 12 months following delinquency and foreclosure. The sample of borrowers is split into four groups according to the borrowers' VantageScores in the month prior to the credit event. Group 0 consists of borrowers with credit scores in the range [501,550]; Group 1: (550,700]; Group 2: (700,800]; Group 3: (800,990]. For each group, we report the number of borrowers in our sample by N.

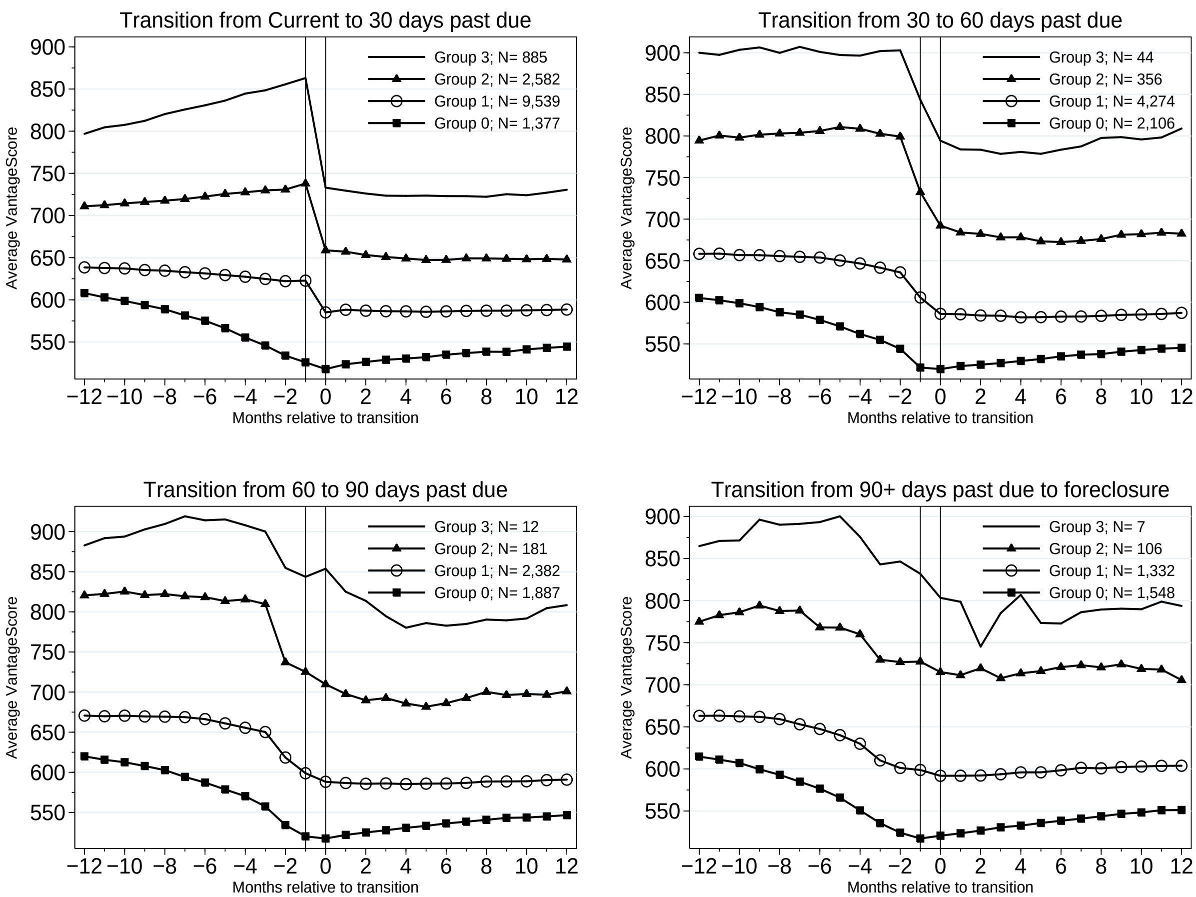


Figure 2 illustrates the muted response of the VantageScore to more severe credit events. The

[4]For examples see several news articles: "A foreclosure will drop the borrower's credit score by at least 100 points" (The New York Times, 25 October 2009) and "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).

figure displays the average VantageScore during the 12 months preceding, and the 12 months following, the credit event. The top left panel reports the results for a transition to 30-day delinquency, the top right panel for a transition to 60-day delinquency, the bottom left panel for a transition to 90-day delinquency, and the bottom right panel for a transition to foreclosure. We report the results for borrowers with different VantageScores, where we differentiate between four credit groups. As one may expect, Figure 2 also shows that the impact of any credit event is bigger for higher credit scores. The main insight is that the vast majority of borrowers that transition to foreclosure are 90+-day delinquent, and foreclosure has virtually no impact on their VantageScores. Hence, due to the cross-sectional distribution of credit scores prior to foreclosure, the average impact of a foreclosure is negligible.

We also study the VantageScore one year after default. Figure 3 shows the (cumulative) change in the VantageScore following the event in the month of, and 12 months after, a transition to 30-day delinquency (left panel) and foreclosure (right panel). We compute the cumulative change as a function of the VantageScore the month prior to the event.[5] Figure 3 illustrates that 30-day delinquency has a strong negative effect on VantageScores both at the moment of delinquency and one year after. Foreclosures, by contrast, have a small negative effect on VantageScores in the month of the event. In fact, for borrowers who are 90+-delinquent, we find a significant improvement in their VantageScores one year later, regardless of whether a foreclosure takes place or not.

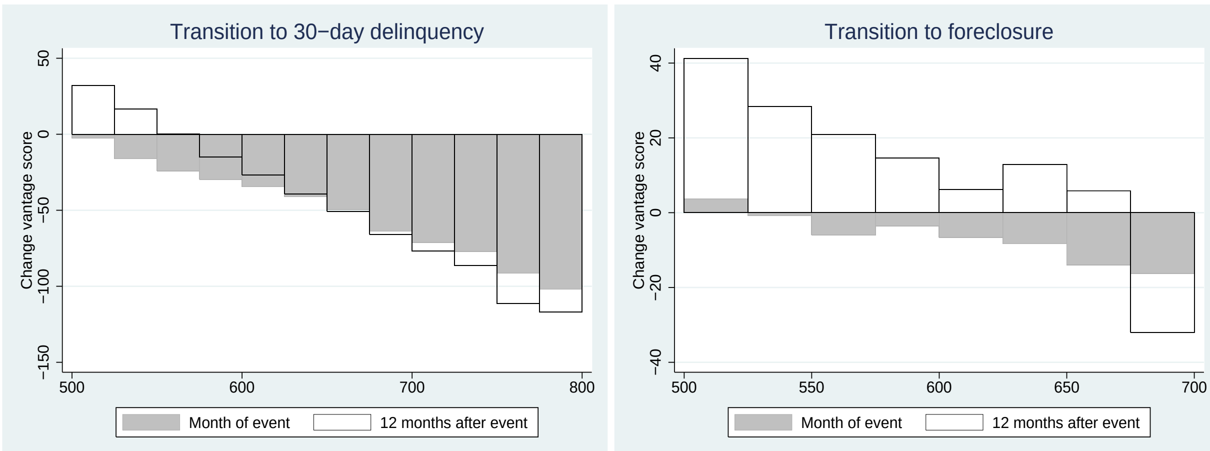
To better understand why the VantageScores of borrowers improve even after a foreclosure, we study delinquencies on bank and credit card debt and the number of credit inquiries in the last six months before the month of the foreclosure and one year later. One view contends that by not making mortgage payments, households can use 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, we find a substantial decline in the number of bank and credit card delinquencies and a similar decline in the number of credit inquiries for borrowers in foreclosure.

We then analyze the link between changes in VantageScores and mortgage rates to quantify the impact of delinquency and foreclosure on future mortgage rates. Our estimates suggest that, on average, a one-point drop in the VantageScore corresponds to approximately a one basis point increase in the mortgage rate for fixed-rate mortgages. This point estimate implies that the mortgage rate on a new mortgage increases by 51bp following 30-day delinquency, by another 25bp after 60-day delinquency, by 14bp following 90+-delinquency, and by 6bp following foreclosure.

[5] We truncate the plots at values of the VantageScore of 800 and 700 for the left and right panels, respectively, as too few borrowers have a sufficiently high VantageScore the month prior to a transition to a worse state, see Figure 1.

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

This figure plots the (cumulative) change of the 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) we require the mortgage to be current the month before the event. For transition to foreclosure (right panel), we require the mortgage to be 90+-day delinquent the month before the event.



The cumulative impact from a series of transitions from current to foreclosure is about 1% in total, which would increase the annual borrowing costs by $2,000 for a $200,000 mortgage.

Hybrid mortgages have a fixed-rate period, after which the mortgage rate will be floating and tied to a benchmark interest rate. The borrower pays the benchmark rate plus a margin during this latter period. For hybrid mortgages, we estimate the increase of the initial mortgage rate to be 0.6 to 0.7 basis points for a one-point drop in the VantageScore. For the two-year hybrid contract, the margin increases by 0.3 basis point, while for the three-year hybrid contract we estimate this number to be 0.8 basis point for a one-point drop in the VantageScore.

The first part of our paper, which analyzes determinants of default, complements a large literature on the topic by introducing variables linked to credit bureau information such as VantageScore momentum. Early contributions for instance include Von Furstenberg (1969), von Furstenberg and Green (1974), and Campbell (1983). Recent contributions include Deng, Quigley, and Order (2000), Crews and Order (2005), Pennington-Cross and Chomsisengphet (2007), Ghent and Kudlyak (2010), Agarwal, Chomsisengphet, and Liu (2010), and Elul, Chomsisengphet, Glennon, Hunt, and Souleles (2010).[6] This issue obviously received renewed attention during the great recessions. For papers analyzing the subprime mortgage crisis, see for instance Demyanyk and Van Hemert (2010), Mayer and Pence (2008), Gerardi, Shapiro, and Willen (2008), Mian and Sufi (2009), and Keys, Mukherjee, Seru, and Vig (2010). Closest to our paper are Gross and Souleles

[6]See also Fay, Hurst, and White (2002) for determinants of household bankruptcy.

(2002) and Elul, Chomsisengphet, Glennon, Hunt, and Souleles (2010). The former paper uses the updated credit score to predict credit card delinquency and personal bankruptcy. Gross and Souleles (2002) also find that the most recent credit score is not a sufficient statistic, consistent with our findings. Elul, Chomsisengphet, Glennon, Hunt, and Souleles (2010) find that the updated credit score helps to predict 60-day mortgage delinquencies. We show in addition that short-term trends in the VantageScore are highly informative about future delinquency and foreclosure, and comparable to the most recent VantageScore itself.

The second part of our paper that studies consequences of default for a borrower's VantageScore, has fewer directly-related papers, as we use a newly-merged database of credit and mortgage data for this purpose.[7] We then link these changes to changes in borrowing costs.

This paper continues as follows. In Section 1, we describe the data set we use. We study the determinants of default in Section 2. In Section 3, we analyze the consequences, in terms of a borrower's VantageScore, of delinquency and foreclosure, and we translate this to mortgage rates in Section 4. Section 5 concludes. Two appendices describe further robustness checks.

1 Data

In this section, we describe the data sources, the selection criteria we use, and the types of credit events we study. Table 1 provides an overview of the main definitions.

1.1 Data sources

We use borrower-level credit data from TransUnion's Consumer Credit Database. 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 have a securitized subprime or Alt-A mortgage. There are more than 250 attributes. For an exhaustive list of credit accounts, like mortgage, bank, and department store accounts, we know the payments status, utilization rates, and requests for new lines of credit. We have monthly updated information on the VantageScore.

Our 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. It is the main database used by institutional investors to analyze the underlying collateral of non-agency mortgage-backed securities. For each loan in the LP data set

[7] In a recent paper, Mian, Sufi, and Trebbi (2010) measure the impact of foreclosures on house prices, residential investment, and durable consumption.

we observe 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. The LP data set does not contain information about other loans, credit accounts, or the updated credit information after the mortgage has been originated, apart from the payment status.

CoreLogic and TransUnion recently developed an accurate link between both databases, and we study this linked database, which is called the TransUnion Consumer Risk Indicators for RMBS. The matching algorithm keys off of overlapping load data between the two databases. Actual borrower names and addresses are used to minimize false positive matches generated by the algorithm. The match rate is exceptionally high in comparison to other matched databases studied in the literature. The overall match rate of the LP data to credit data is 72%, but this varies depending on whether a mortgage is active or closed. The match rate on loans that are active is 84%, while it is 68% for mortgages that are closed.

We supplement these data 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 ZHVI does not require a home to be sold to be included in the calculation. The index is available monthly for 11,799 ZIP codes for the entire length of our study and loan origination dates.

We use data on monthly county-level unemployment rates from the Bureau of Labor Statistics. For our analysis we create a series of seasonally adjusted unemployment rates using a standard X-11 seasonal adjustment method. We use the six-month change in the log unemployment rate in our estimation. Finally, we get the average household income in the ZIP code, based on 2000 Census data, from the U.S. ZIP Code Database.[8] We also use this database to match counties and ZIP codes.

1.2 Variable definitions

We summarize in Table 1 the definitions of the variables we use in our analysis. For the status of the mortgage, we consider the following possibilities: current, 30/60/90+-days delinquent, and foreclosure.[9] The status is provided by TransUnion. We use the status of the first mortgage, which

[8]http://www.zip-codes.com/zip-code-database.asp.

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

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.

Variable	Description (source), and range for categorical variables
Mortgage status	The status of the borrowers largest mortgage (TU)
	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%,∞)
	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%,∞)
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%,∞)
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)

is defined by the largest mortgage balance.

The other variables in Table 1 are used as potential determinants of a transition from one mortgage status to another. To curb the impact of outliers in estimating our models and to allow for non-linear responses, for many of the key variables we use dummy variables that are set to a value of one if the variable of interest is within a certain range. We 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, we typically 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.

The VantageScore is provided by TransUnion. We define a variable, which we term "VantageScore momentum" as the six-month change in the VantageScore. 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 have predictive power in addition to the current VantageScore. Second, large swings in VantageScores could identify volatile borrowers. 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 changes during a period of six months.

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, we define a missing DTI dummy.

Elul, Chomsisengphet, Glennon, Hunt, and Souleles (2010) argue that liquidity constraints and negative equity are important drivers of 60-day mortgage delinquency. We proxy for liquidity constraints by a high level of credit card utilization, which is reported in the data from TransUnion. Housing equity for borrower i at time t is constructed using the combined loan-to-value ratio at origination (provided by LP) and the change in ZIP-code-level house prices:

$$\text{Equity}_{i,t} = 100\% - \frac{\text{Loan}_{i,0}}{\text{Value}_{i,0}} \times \frac{\text{ZipValue}_{i,0}}{\text{ZipValue}_{i,t}}.$$

This definition abstracts from amortization between the moment of origination (time 0) and the moment of evaluation (time t). In addition, we proxy for the change in the value of an individual property ($\text{Value}_{i,0}$) by the change in house prices in the ZIP code in which the property is located in ($\text{ZipValue}_{i,0}/\text{ZipValue}_{i,t}$). An equity value of zero means the loan and the updated value of the house are equal. A housing equity value of -100% means that the loan is twice the updated value of the house. With this definition, it is possible to have a housing equity value below −100%, but this is rare in our data set.

The mortgage interest rate is from LP and is updated monthly for mortgages with a variable mortgage rate. The FICO score is from LP and available only at the moment of origination of the mortgage.

1.3 Sample selection

We 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. We 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, we randomly pick 20,000 borrowers.

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

1.4 Summary statistics

We present summary statistics for our data in Table 2. The range of the VantageScore 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. We also use the FICO score in our analysis. As with the VantageScore, borrowers with higher FICO scores are deemed more creditworthy. The FICO credit score is measured only at origination. It has a mean of 658 and a standard deviation of 71.

The median (P50) VantageScore change 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 is reported in percentage points and 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

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 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

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 Determinants of mortgage default

We discuss in this section which loan characteristics, credit characteristics, and macro-economic variables predict mortgage default. We consider several specifications. The baseline specification (Section 2.1) utilizes the entire sample period. Second, to study the stability of our estimates over time, we repeat selected analyses, but separately for each year (Section 2.2). Third, we study the transition to foreclosure from a less severe payment status (Section 2.3). Fourth, we contrast VantageScore momentum with VantageScore volatility in Section 2.4.

2.1 Baseline-case specification

We estimate probit regressions where the dependent variable is a dummy variable taking the value one if a borrower transitions to a worse default state. For the baseline-case specifications we present both estimated coefficients, see Table 3, and the estimated marginal effect evaluated at the mean values of the variables, see Table 4.

To measure the probability of transition from one mortgage status to another, we use for each probit regression a set of criteria that need to be satisfied for a borrower to be included in the estimation. 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), we 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 columns of Table 3 and Table 4. Following the same logic, we have similar inclusion criteria when the dependent variable is a 60-day delinquency status dummy (D60), a 90+-day delinquency status dummy (D90+), and a foreclosure status dummy (F). For each explanatory variable considered in Table 3 and Table 4, we report the point estimate and, to assess the statistical significance, the z-score in parentheses. We include year dummy variables in all specifications and cluster standard errors at the borrower level.[10]

VantageScore The first block of explanatory variables are the dummy variables for the VantageScore groups. We lag all explanatory variables by one month, except for the year dummy variables. Recall from Table 1 that we always omit group 0, which corresponds to the lowest values for a variable. For example, the coefficient corresponding to "Score G1" measures the differential effect of borrowers with a VantageScore between 550 and 700 compared to borrowers with a VantageScore below 550.

The estimates indicate that borrowers with higher VantageScores have a lower probability of transitioning to a worse state. The coefficients and marginal effects are monotonically declining in the VantageScore. The only exceptions to this are the insignificant results for the transition to 90+-day delinquency (D90+).

In Table 4, with marginal effects evaluated at the mean value for the explanatory variables, we see that the coefficients are smallest for the current to 30-day delinquency transition, which is merely a reflection of the fact that this transition has the lowest probability among the different transitions considered. Once a borrower reaches 30-day delinquency, transitioning to more severe states is more likely.

Based on the estimates reported in Table 4, borrowers with a VantageScore between 550 and 700 are on average 1% less likely to be 30-days past due on their mortgage than borrowers with scores below 550. Borrowers with scores above 800 are on average 3% less likely than those with scores below 550 to be 30 days past due. Once a borrower has already missed one mortgage payment, the

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

Table 3: Determinants of default

Each column reports the estimated coefficients for a multiple probit regression. The dependent variable equals one in case of a transition to a worse payment status on the first mortgage. The z-score is provided in parenthesis; errors are clustered at the borrower level. Row 4 presents the dependent variable of interest; a status dummy variable, with C = current, D30/D60/D90+ = 1, 2, 3+ months delinquent, and F = in foreclosure. We focus on transitions to the next worse payment status, and thus require the lagged status to be one notch better than the dependent variable (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-D30		C-D60		C-D90+		C-F	
Observations	266989		13459		6286		8604	
Dependent var.	D30		D60		D90+		F	
Score G1 (lag)	−0.30	(8)	−0.12	(3)	−0.11	(2)	−0.09	(2)
Score G2 (lag)	−0.75	(19)	−0.42	(6)	−0.07	(1)	−0.21	(2)
Score G3 (lag)	−0.99	(22)	−0.64	(4)	−0.28	(1)	−0.36	(1)
DScore G1 (lag)	−0.13	(5)	−0.21	(6)	−0.26	(6)	−0.24	(5)
DScore G2 (lag)	−0.23	(9)	−0.32	(8)	−0.65	(12)	−0.51	(11)
DScore G3 (lag)	−0.16	(6)	−0.52	(8)	−0.89	(10)	−0.71	(9)
DTI miss (orig.)	−0.02	(1)	−0.05	(1)	0.24	(2)	−0.03	(0)
DTI G1 (orig.)	−0.02	(1)	−0.01	(0)	0.17	(1)	−0.09	(1)
DTI G2 (orig.)	0.01	(0)	−0.13	(2)	0.13	(1)	0.05	(0)
DTI G3 (orig.)	0.05	(2)	−0.03	(1)	0.22	(2)	0.02	(0)
Credit G1 (lag)	−0.03	(1)	−0.11	(3)	−0.04	(1)	−0.10	(2)
Credit G2 (lag)	0.09	(4)	−0.16	(4)	−0.10	(2)	−0.04	(1)
Credit G3 (lag)	0.26	(9)	−0.17	(4)	−0.19	(3)	−0.16	(3)
Equity G1 (lag)	−0.17	(6)	−0.21	(4)	−0.24	(4)	−0.02	(0)
Equity G2 (lag)	−0.27	(10)	−0.32	(6)	−0.38	(6)	−0.12	(2)
Equity G3 (lag)	−0.32	(10)	−0.43	(7)	−0.38	(5)	−0.27	(4)
Int. rate (lag)	0.02	(5)	0.03	(2)	0.02	(1)	0.03	(2)
FICO/100 (orig.)	−0.21	(13)	0.09	(3)	0.10	(2)	0.11	(3)
Income (lag)	0.08	(3)	0.12	(2)	0.07	(1)	0.00	(0)
Unemp. (lag)	0.22	(3)	0.52	(3)	0.63	(3)	−0.15	(1)

likelihood of missing another payment increases. Borrowers with a VantageScore between 550 and 700 are 3.6% less likely to miss a second payment on their mortgage than borrowers with scores below 550. Borrowers with scores above 800 are 13.6% less likely to be 60 days past due, again compared to borrowers with scores below 550.

The VantageScore is designed to capture the creditworthiness of borrowers. It is therefore possible that the VantageScore is a sufficient statistic to predict default. In this case, other explanatory variables in a multiple regression would have no additional predictive power. We now turn to the discussion of other explanatory variables.

VantageScore momentum The second block of explanatory variables contains dummy variables for the VantageScore momentum groups. Again, group 0, with the lowest VantageScore momentum, is omitted from the estimation. Hence, the coefficients for groups 1, 2, and 3 measure the differential effect compared to group 0. The results are strongest for the transition to 60-day delinquency, 90+-day delinquency, and foreclosure: Higher VantageScore momentum lowers the probability of transitioning to a worse state. Put simply, if the VantageScore equals 700, but it declined from 800 six months before, the probability to transition to a worse state is higher compared to a VantageScore of 700 that increased from 600 six months before. The statistical significance of the VantageScore momentum variables is among the highest of all the explanatory variables. For the transition to 90+-day delinquency and foreclosure, its economic and statistical significance far exceeds the significance of the VantageScore itself.

The results in Table 4 imply that borrowers whose VantageScore improves by more than 30 points during the last six months are 12% less likely to switch from 30 days delinquency to 60 days delinquency, or 26% less likely to transition from 60 days delinquency to 90+ days delinquency, than borrowers whose VantageScore declined by more than 100 points.

Housing equity The effect of housing equity is significant and monotonic for each of the transitions that we consider. The direction of the effect is intuitive: An increase in housing equity lowers the probability of transitioning to a worse state.

Credit card utilization High credit card utilization (Credit G3) is associated with a higher probability of transitioning from current to 30-day delinquency, which is consistent with, for instance, Elul, Chomsisengphet, Glennon, Hunt, and Souleles (2010). We find this result even after controlling for a host of other variables, most notably the VantageScore, which takes into account the recent credit situation. For robustness, we re-estimate the probit regression including only the credit variables as explanatory variables and the year dummy variables. We find that the effect of credit card utilization is much stronger for the probability of transitioning from current to 30-day

Table 4: Determinants of default, marginal effects evaluated at the mean

Each column reports the estimated marginal effects (evaluated at the mean) for a multiple probit regression. The dependent variable equals one in case of a transition to a worse payment status on the first mortgage. The z-score is provided in parenthesis; errors are clustered at the borrower level. Row 4 presents the dependent variable of interest; a status dummy variable, with C = current, D30/D60/D90+ = 1, 2, 3+ months delinquent, and F = in foreclosure. We focus on transitions to the next worse payment status, and thus require the lagged status to be one notch better than the dependent variable (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-D30		C-D60		C-D90+		C-F	
Observations	266989		13459		6284		8604	
Dependent var.	D30		D60		D90+		F	
Score G1 (lag)	−0.009	(9)	−0.036	(3)	−0.039	(2)	−0.020	(2)
Score G2 (lag)	−0.021	(19)	−0.103	(7)	−0.027	(1)	−0.040	(2)
Score G3 (lag)	−0.029	(20)	−0.136	(6)	−0.098	(1)	−0.063	(2)
DScore G1 (lag)	−0.004	(6)	−0.060	(6)	−0.094	(6)	−0.049	(6)
DScore G2 (lag)	−0.008	(9)	−0.088	(9)	−0.222	(13)	−0.104	(12)
DScore G3 (lag)	−0.005	(6)	−0.122	(11)	−0.260	(15)	−0.111	(13)
DTI miss (orig.)	−0.001	(1)	−0.015	(1)	0.090	(2)	−0.006	(0)
DTI G1 (orig.)	−0.001	(1)	−0.004	(0)	0.063	(1)	−0.019	(1)
DTI G2 (orig.)	0.000	(0)	−0.037	(2)	0.049	(1)	0.010	(0)
DTI G3 (orig.)	0.002	(2)	−0.010	(1)	0.080	(2)	0.005	(0)
Credit G1 (lag)	−0.001	(2)	−0.031	(3)	−0.016	(1)	−0.022	(2)
Credit G2 (lag)	0.003	(4)	−0.044	(4)	−0.037	(2)	−0.008	(1)
Credit G3 (lag)	0.012	(7)	−0.046	(4)	−0.069	(3)	−0.032	(3)
Equity G1 (lag)	−0.005	(7)	−0.056	(4)	−0.085	(4)	−0.004	(0)
Equity G2 (lag)	−0.009	(10)	−0.089	(6)	−0.137	(6)	−0.026	(2)
Equity G3 (lag)	−0.010	(11)	−0.115	(7)	−0.134	(5)	−0.053	(4)
Int. rate (lag)	0.001	(5)	0.007	(2)	0.007	(1)	0.006	(2)
FICO/100 (orig.)	−0.007	(13)	0.026	(3)	0.038	(2)	0.025	(3)
Income (lag)	0.003	(3)	0.036	(2)	0.024	(1)	0.000	(0)
Unemp. (lag)	0.007	(3)	0.149	(3)	0.227	(3)	−0.032	(1)

delinquency. We do not report these results for brevity. For transitions to 60-day delinquency and worse, the effect of credit card utilization is weaker.

Other variables The DTI ratio is a static variable from the LP database, which means that it is not updated after origination. The variable is often missing, hence the inclusion of a missing DTI ratio group. This variable is in most cases not significant.

A high current interest rate is associated with an increased probability of transitioning to a worse state, as one might expect, and it is particularly significant for the transition to 30-day delinquency. The current interest rate captures two effects: (i) it is positively related to the the size of monthly payments and (ii) it may reflect information about the riskiness of a borrower that is unobserved to us, but observable to the lender who sets the rate.

The FICO score at origination carries a positive coefficient for the transition to 60-day and 90+-day delinquency and foreclosure. This at first sight may seem odd, as a high FICO score borrower should be a more creditworthy borrower. Notice however that we run a multiple probit regression in which we also include the most recent VantageScore. It is therefore yet another manifestation of credit score momentum, this time measured relative to the moment of mortgage origination. That is, given a current VantageScore, a borrower starting from a low FICO score (and thus a borrower who has made improvements in credit scoring variables since origination) is less likely to transition to a worse mortgage status.

Log income is the only variable with a counterintuitive sign, as a higher income level is related to an increased probability of transitioning to a worse state. It is significant only for the transition to 30- and 60-day delinquency. The univariate effect of income on the probability of default is negative and thus has the intuitive sign (results not reported).

An increase in the unemployment rate over the past six months increases the probability of transitioning to 30-, 60-, and 90+-day delinquency. For the transition to foreclosure the effect is insignificant.

2.2 Transition to 30-day delinquency for different years

For the transition to 30-day delinquency we have enough observations to accurately measure the effect of the different determinants year by year, see Table 5. The coefficient for VantageScore (Score G1-G3) decreases monotonically over time, even though it remains one of the most important variables. The effect of VantageScore momentum is very stable over time though. Also the effect of housing equity is stable as of 2007, while its effect is measured imprecisely in 2006.

Table 5: Determinants of default, transition to 30-day delinquency year-by-year

Each column reports the estimated coefficients for a multiple probit regression. The dependent variable equals one in case of a transition to a 30-day delinquency payment status on the first mortgage. Each probit regression uses data of only one year (specified in row 3). The z-score is provided in parenthesis; errors are clustered at the borrower level. Row 5 presents the dependent variable of interest; a status dummy variable for 30-day delinquency (D30). We focus on transitions to the next worse payment status, and thus require the lagged status to be current (C, see inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 4. We include a constant and year dummies (not reported).

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	
Dependent var.	D30		D30		D30		D30	
Score G1 (lag)	−0.47	(6)	−0.36	(6)	−0.30	(5)	0.03	(0)
Score G2 (lag)	−1.01	(11)	−0.85	(13)	−0.72	(11)	−0.25	(3)
Score G3 (lag)	−1.26	(12)	−1.11	(15)	−0.97	(14)	−0.53	(5)
DScore G1 (lag)	−0.13	(2)	−0.11	(2)	−0.16	(4)	−0.11	(2)
DScore G2 (lag)	−0.27	(5)	−0.19	(4)	−0.22	(5)	−0.26	(4)
DScore G3 (lag)	−0.19	(3)	−0.12	(3)	−0.12	(3)	−0.18	(3)
DTI miss (orig.)	−0.06	(1)	−0.05	(1)	0.01	(0)	0.03	(0)
DTI G1 (orig.)	−0.08	(1)	−0.05	(1)	0.03	(0)	−0.10	(1)
DTI G2 (orig.)	−0.08	(1)	−0.03	(1)	0.05	(1)	0.08	(1)
DTI G3 (orig.)	0.05	(1)	−0.01	(0)	0.07	(1)	0.07	(1)
Credit G1 (lag)	−0.01	(0)	−0.03	(1)	0.00	(0)	−0.10	(2)
Credit G2 (lag)	0.10	(2)	0.11	(3)	0.11	(3)	0.05	(1)
Credit G3 (lag)	0.23	(4)	0.35	(7)	0.24	(5)	0.20	(3)
Equity G1 (lag)	0.14	(0)	−0.16	(2)	−0.17	(5)	−0.09	(2)
Equity G2 (lag)	0.20	(1)	−0.24	(2)	−0.29	(8)	−0.27	(6)
Equity G3 (lag)	0.16	(0)	−0.29	(3)	−0.34	(8)	−0.38	(6)
Int. rate (lag)	0.03	(3)	0.03	(4)	0.02	(3)	0.01	(1)
FICO/100 (orig.)	−0.25	(8)	−0.18	(7)	−0.17	(7)	−0.20	(6)
Income (lag)	0.17	(3)	0.14	(3)	−0.01	(0)	−0.04	(1)
Unemp. (lag)	0.19	(1)	0.05	(0)	0.23	(2)	0.53	(3)

2.3 Transition to foreclosure from a less severe payment status

In Section 2.1, we consider a transition to foreclosure from a 90+-delinquency status, which is the most common status prior to foreclosure (76% of the transitions to foreclosure were preceded by a 90+-delinquency status). In Appendix A, we also consider the transitions of a current, a 30-day delinquency, and a 60-day delinquency status to foreclosure, which account for 3%, 4%, and 17% of all transitions to foreclosures, respectively. These foreclosures are arguably less anticipated. Interestingly, we find that low housing equity is a strong determinant of foreclosures in these cases. This suggests that these foreclosures seem more sensitive to changes in negative housing equity than those borrowers whose status has already deteriorated to 90+-delinquency.

2.4 VantageScore momentum versus VantageScore volatility

We find that VantageScore momentum helps to predict the transition to worse delinquency states and foreclosure. One may wonder whether VantageScore momentum is effectively measuring VantageScore volatility instead of trends in VantageScores that tend to continue. In Appendix B, we include VantageScore momentum alongside a measure of VantageScore volatility in the probit model. We find that for the transition from current to 30-day delinquency, VantageScore volatility is more important than VantageScore momentum. However, for the transition to worse delinquency states and foreclosure, VantageScore momentum is more important, and VantageScore volatility has no significant impact.

These results suggest that VantageScore volatility identifies inattentive borrowers who every now and then miss a payment. For the more important delinquencies and foreclosure, VantageScore momentum is the more important variable to explain the transition.

3 Consequences of mortgage default

In this section, we study the impact of credit events on a borrower's VantageScore. We first discuss the econometric framework in Section 3.1 and present the main empirical results in the subsequent sections.

3.1 Regression specification

We 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. We 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?" We focus on the impact on the VantageScore in the next period, though we also report the impact on the VantageScore one year later. Formally, the object of interest is:

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

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

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

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 we 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. We use the VantageScore itself as the dependent variable.

3.2 Contemporaneous consequences of default

In this section, we discuss the contemporaneous consequences of default in terms of changes in the VantageScore. In Table 6, we present results for regressions with the VantageScore as the dependent variable. We 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. We 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. We study the same transitions as in Table 3 and we therefore also use the same criteria for including observations.

Event dummy The impact on the VantageScore of a transition from current to 30-day delinquency 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

Table 6: Consequences of default

Each column reports the estimated coefficients for a multiple regression, with the VantageScore as dependent variable. The z-score is provided in parenthesis; errors are clustered at the borrower level. Each regression evaluates the effect on the VantageScore of transitioning to a worse payment status; the new (worse) status, referred to as "Event" is reported in row 4. We focus on transitions to the next worse payment status, and thus require the lagged status to be one notch better than the event variable (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

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)
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)

delinquency, and foreclosure, the 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.

Other variables We include the same set of control variables as in Table 3. The effect of lagged VantageScore momentum is very significant and mostly monotonic: holding constant the current VantageScore group, households with positive VantageScore momentum have a tendency to experience a smaller improvement (greater deterioration) in the VantageScore relative to households with negative VantageScore momentum. However, for households with positive VantageScore momentum the subsequent change in their scores also has a smaller standard deviation (not reported). The latter effect dominates in determining the probability of a large drop in the VantageScore; hence the presented results are not inconsistent with the previous result that positive VantageScore momentum is, in fact, less likely to be accompanied by a deterioration in mortgage status (which would typically be accompanied by a large drop in the VantageScore).

In our control variables, we do not include dummy variables to indicate whether a state is recourse or non-recourse, or whether foreclosures are judicial or non-judicial. The motivation is that TransUnion does not use these variables in their credit model. In unreported results, we follow Ghent and Kudlyak (2010) to classify states as recourse versus non-recourse and judicial versus non-judicial. We indeed do not find significant differences across states, after controlling for all other variables.

Event dummy without controls For robustness, we re-estimate the regressions reported in Table 6, now only including the event dummy variables and not the list of other explanatory variables. We find quantitatively very similar results, indicating that the measured effect is not an artefact resulting from a strong correlation with one of the other explanatory variables (results are not reported). To further illustrate the effect of a credit event without controls, we plot in Figure 1 the VantageScore distribution 1 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 we require the mortgage to be current the month before. For the transition to foreclosure, we 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.

Event dummy variables interacted with VantageScore group dummy variables In Table 7 we 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 6, we add interaction variables between the event and the lagged VantageScore group.

The event variable in Table 7 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. If we first focus on the event variable without interaction, we find 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 we documented in Table 6. 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 we have 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.

3.3 Transition to 30-day delinquency for different years

For the transition to 30-day delinquency we have enough observations to accurately measure the effect on the VantageScore year by year. In Table 8, we include the interaction between the event and the lagged VantageScore group, like we do in Table 7, 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, we find no evidence to support a hypothesis that the credit bureau has modified its model to measure the impact of delinquencies during the great recession.

3.4 Consequences of default after one year

We repeat the regressions presented in Table 6, with the only difference that we 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 9.

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

Table 7: Consequences of default, event-VantageScore group interaction effects

Each column reports the estimated coefficients for a multiple regression, with the VantageScore as dependent variable. The z-score is provided in parenthesis; errors are clustered at the borrower level. Each regression evaluates the effect on the VantageScore of transitioning to a worse payment status; the new (worse) status, referred to as "Event" is reported in row 4. We focus on transitions to the next worse payment status, and thus require the lagged status to be one notch better than the event variable (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

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)
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)

Table 8: Consequences of default, transition to 30-day delinquency year-by-year

Each column reports the estimated coefficients for a multiple regression, with the VantageScore as dependent variable. The z-score is provided in parenthesis; errors are clustered at the borrower level. Each regression evaluates the effect on the VantageScore of transitioning to a 30-day delinquency (D30), the "Event" reported in row 5, using data from different calendar years (reported in row 3). We focus on transitions to the next worse payment status, and thus require the lagged status to be current, C (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 4. We include a constant and year dummies (not reported).

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)

Table 9: Consequences of default, effect after one year

Each column reports the estimated coefficients for a multiple regression, with the VantageScore 12 months after a prescribed event as dependent variable. The z-score is provided in parenthesis; errors are clustered at the borrower level. Each regression evaluates the effect on the VantageScore one-year out of transitioning to a worse payment status; the new (worse) status, referred to as "Event" is reported in row 4. We focus on transitions to the next worse payment status, and thus require the lagged status to be one notch better than the event variable (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

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)
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)

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.

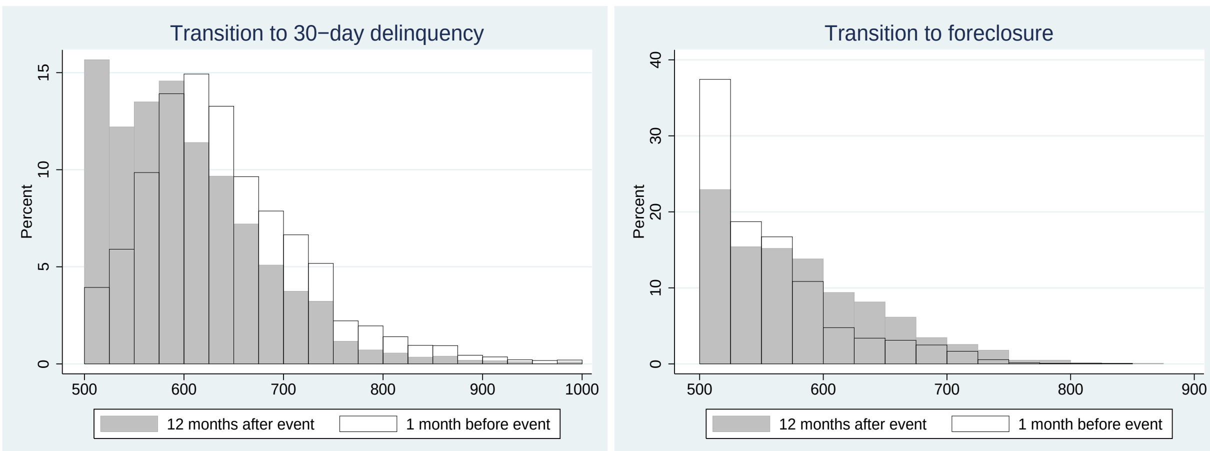
Event dummy without controls We re-estimate the regressions reported in Table 9, including now only the event dummy variables and not the list of other explanatory variables, and find quantitatively similar results. This indicates that the measured effect is not an artefact resulting from a strong correlation with one of the other explanatory variables (results are not reported). To further illustrate the effect of a credit event without controls, in Figure 4 we plot the VantageScore distribution 1 month before and 12 months after a transition to 30-day delinquency (left panel) and foreclosure (right panel). For the transition to 30-day delinquency we require the mortgage to be current the month before. For the transition to foreclosure, we require the mortgage to be 90+-days delinquent the month before. We make sure that we use the same set of borrowers 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 what we saw in the month of the transition, Figure 1. This is in the same spirit as the VantageScore momentum effect we documented: 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.

Recall from our discussion of Table 9 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 4 (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. We 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 or not.

We study in more detail what happens to the borrowers that are 90+-day delinquent. As it turns out, the VantageScores of these borrowers are very close to the lower bound of the VantageScore range. This implies that even if a 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 transition from 90+-delinquency into foreclosure.

Figure 4: VantageScore distribution 1 month before and 12 months after a transition to a worse state

The figure shows the VantageScore distribution 1 month before and 12 months after a transition to a worse state. For the transition to 30-day delinquency (left panel), we require the mortgage to be current the month before. For transition to foreclosure (right panel), we require the mortgage to be 90+-day delinquent the month before.

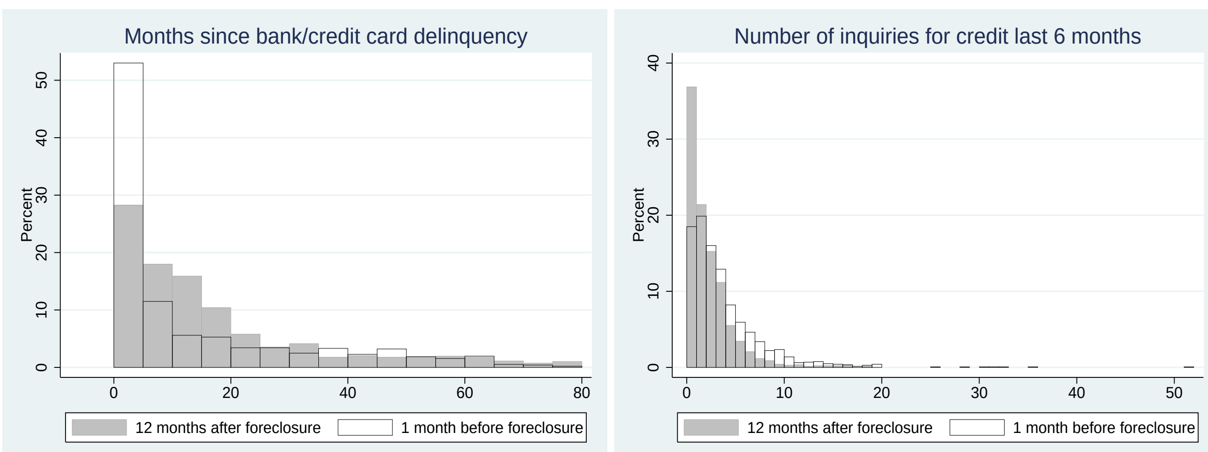


To illustrate in another way how the VantageScore is differentially affected by a transition from current to 30-day delinquency in comparison to a transition from 90+-delinquency to foreclosure, we plot in Figure 3 the change in the VantageScore in the month of a transition to 30-day delinquency (left panel) and the cumulative change in the VantageScore 12 months after; we do the same for a transition into foreclosure (right panel). We plot the changes as a function of the VantageScore the month prior to the event. We truncate the plots 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 are 90+-day delinquent tend to experience on average an improvement in VantageScores. One interpretation in the case of foreclosure would be that households are able to make payments on other forms of credit when they no longer make the mortgage payments. To illustrate the improvement in the credit situation following a foreclosure, we plot in Figure 5 (left panel) the number of months since the latest bank or credit card delinquency, 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 bank or 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 bank and credit card problems improved following a foreclosure. In Figure 5 (right panel), we depict 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. Credit inquiries are interesting to look at not just because they are a measure of a household's distress, but also because the credit bureaus may use them as an input to determine the credit score, where a large number of inquiries has a negative impact on the credit score. 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 going from the month before to 12 months after foreclosure.

Figure 5: General credit situation 1 month before and 12 months after foreclosure

We focus on transitions to foreclosure where the mortgage was 90+-day delinquent the month before. 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, we show both the month prior to the foreclosure and 12 months after the foreclosure.



4 The price of credit

In this section, we document the link between the price of credit and both the VantageScore and the loan-to-value ratio.[11] This link is useful for interpreting changes in VantageScores in the

[11] Rajan, Seru, and Vig (2010) also study the link between mortgage rates and both the FICO score and the loan-to-value ratio.

previous section in terms of the cost of obtaining new credit. If households, for instance, enter the foreclosure process, the change in VantageScores can be translated into the change in mortgage rates charged on a new mortgage. This argument of course assumes that the borrower is able to successfully apply for a new mortgage.

We focus on three types of mortgages, namely, fixed-rate mortgages (FRM), 2-year hybrid mortgages, and 3-year hybrid mortgages.[12] In the case of the last two contracts, the interest rate is fixed for two or three years, respectively, and floating in all subsequent periods. In the case of hybrid mortgages, the contract has both an initial interest rate and a margin. The margin is what the borrower pays over a benchmark rate during the period in which the rate is floating. We restrict attention to mortgages that are not refinancings and that are for owner-occupied homes.

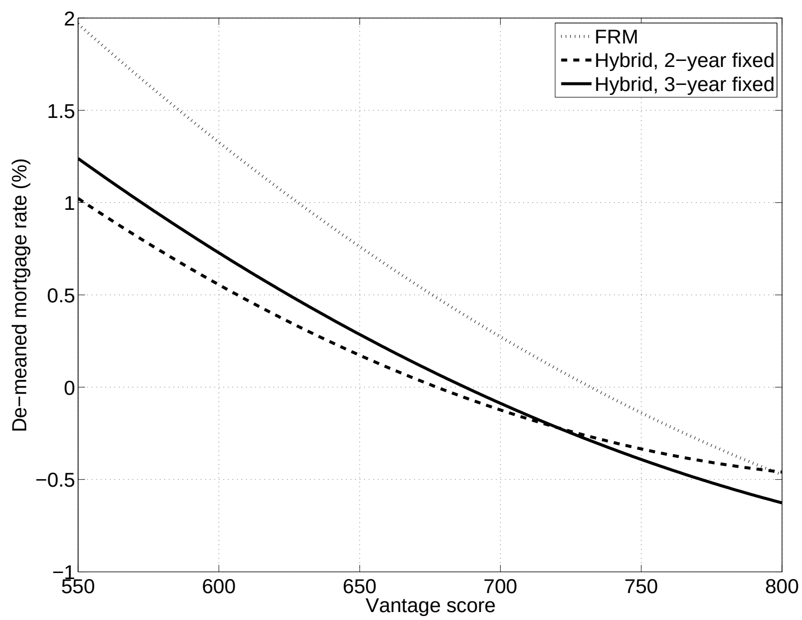
For each mortgage type, we first regress mortgage rates on year dummy variables to remove the aggregate time series variation in mortgage rates. We collect the residuals and regress these in turn on the loan-to-value ratio, the VantageScore, and the squared VantageScore. It is potentially important to allow for non-linearities, as the price of credit may be less sensitive to the VantageScore for high VantageScores. We measure the VantageScore in the month of the mortgage origination. We then evaluate the polynomial at the average loan-to-value ratio and at different values of the VantageScore to map out the price of credit.

The results are summarized in Figure 6, which shows that in all cases the initial mortgage rate declines for higher VantageScores. The figure shows that initial rates on FRM contracts are somewhat more sensitive to changes in the VantageScore, once we fix the loan-to-value ratio. Both hybrid contracts result in very similar pricing curves, as might be expected. The R-squared values corresponding to the regressions of mortgage rates on the loan-to-value ratio, the VantageScore, and the squared VantageScore is around 30%. In all cases, we find that the pricing curve displays some convexity, confirming that initial mortgage rates are less sensitive to the VantageScore for high-quality borrowers. Quantitatively, we find that, on average, a 1-point drop in the VantageScore results in a about a 1-basis point (0.01%) increase in the mortgage rate, ceteris paribus, for FRM contracts. This point estimate implies that the mortgage rate on a new mortgage increases by 51bp following 30-day delinquency, by another 25bp after 60-day delinquency, by 14bp following 90+-delinquency, and by 6bp following foreclosure. The cumulative impact from a series of transition from current to foreclosure about 1% in total, which would increase the annual borrowing costs by $2,000 for a $200,000 mortgage. Table 7 shows that the impact of delinquencies and foreclosure is larger for borrowers with higher VantageScores before the credit event. For instance, 30-day delinquency already- corresponds to a 120-point decline of the VantageScore if the VantageScore exceeds 800 before delinquency.

[12] Koijen, Van Hemert, and Van Nieuwerburgh (2009) study the determinants of mortgage choice between adjustable- and fixed-rate mortgages.

Figure 6: Initial mortgage rates for various contract types and VantageScore

The figure shows how initial mortgage rates relate to a borrower's VantageScore at origination. We focus on three types of mortgages, namely, fixed-rate mortgages (FRM), 2-year hybrid mortgages, and 3-year hybrid mortgages. For each mortgage type, we first regress mortgage rates on year dummy variables to remove the aggregate time series variation in mortgage rates. We collect the residuals and regress these in turn on the loan-to-value ratio, the VantageScore, and the squared VantageScore. It is potentially important to allow for non-linearities, as the price of credit may be less sensitive to the VantageScore for high VantageScores. We measure the VantageScore in the month of origination. We then evaluate the polynomial at the average loan-to-value ratio and at different values of the VantageScore to map out the price of credit.



For the hybrid contracts, we estimate the sensitivity to be around a 0.6-0.7 basis point increase for a 1-point drop in the in VantageScore. Finally, we also study the impact on the margins in the case of hybrid contracts. For the 2-year hybrid contract, the margin increases by 0.3 basis points, while for the 3-year hybrid contact this number is estimated to be 0.8 basis points for a 1-point drop in the VantageScore.

5 Conclusion

In this paper we look at determinants and consequences of default on the first-lien mortgage. We add to the literature on determinants, by including credit information from TransUnion, one of the three major credit bureaus. We find that the updated credit score is an important predictor of mortgage default in addition to the credit score at origination. However, the 6-month change in the credit score also predicts default: A positive change in the credit score significantly reduces the probability of delinquency or foreclosure.

We add to the literature on consequences of default, by providing a detailed study on the impact of default on a borrower's credit score. The credit score drops on average 51 points when a borrower becomes 30-days delinquent on his mortgage, but the effect is much more muted for transitions to more severe delinquency states and even foreclosure.

We also analyze the link between changes in VantageScores and mortgage rates to quantify the impact of delinquency and foreclosure on future mortgage rates. Our estimates suggest that, on average, a one-point drop in the VantageScore corresponds to approximately a one basis point increase in the mortgage rate for fixed-rate mortgages. This point estimate implies that the mortgage rate on a new mortgage increases by 51bp following 30-day delinquency, by another 25bp after 60-day delinquency, by 14bp following 90+-delinquency, and by 6bp following foreclosure. The cumulative impact from a series of transitions from current to foreclosure is about 1% in total, which would increase the annual borrowing costs by $2,000 for a $200,000 mortgage.

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A Transition to foreclosure from different states

In this appendix, we study the determinants of a transition to foreclosure from starting states other than 90+-day delinquency. Foreclosure is preceded by a current, a 30-day delinquency, a 60-day delinquency, and a 90+-day delinquency state in 3%, 4%, 17%, and 76% of the cases, respectively. In the previous analyses we consider only the most common starting state, 90+-day delinquency. We report the main results in Table 10. The last column (transition from 90+-day delinquency to foreclosure) corresponds to the last column in Table 3. From our discussion of Table 3, recall that VantageScore momentum in particular is a strong determinant of foreclosure. Because we have less foreclosure events preceded by less severe states (current, 30-day delinquency, and 60-day delinquency), we have less statistical power. Also we do not have any observations for some dummy variables, in which case we report an "na" in Table 10. We find less statistical evidence that foreclosure from a less severe state is predicted by VantageScore momentum. Instead, the housing equity dummies have the most statistical power to predict foreclosures from a less severe state. The sign is consistent with standard economic intuition: higher housing equity lowers the probability transitioning to foreclosure. This suggests that these foreclosures seem more sensitive to changes in negative housing equity than those borrowers whose status has already deteriorated to 90+-delinquency.

We do not report results for the consequences of a transition that starts from a less severe payment status to foreclosure because of a lack of observations and thus statistical power.

Table 10: Determinants of default, transition to foreclosure from different states

Each column reports the estimated coefficients for a multiple probit regression. The dependent variable equals one in case of a transition to a foreclosure payment status on the first mortgage. The z-score is provided in parenthesis; errors are clustered at the borrower level. Row 4 presents the dependent variable of interest; F = in foreclosure. We vary the lagged payment status, reported in row 1, where C = current and D30/D60/D90+ = 1, 2, 3+ months delinquent. For this table, the status in the evaluation month is unrestricted (row 2 shows it can be any of C-F). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-F		C-F		C-F		C-F	
Observations	166919		12476		5858		8604	
Dependent var.	F		F		F		F	
Score G1 (lag)	−0.69	(5)	−0.24	(2)	−0.14	(2)	−0.09	(2)
Score G2 (lag)	−1.30	(7)	−0.20	(1)	−0.16	(1)	−0.21	(2)
Score G3 (lag)	*na*		*na*		*na*		−0.36	(1)
DScore G1 (lag)	−0.12	(1)	−0.33	(3)	0.01	(0)	−0.24	(5)
DScore G2 (lag)	−0.31	(2)	−0.12	(1)	−0.14	(2)	−0.51	(11)
DScore G3 (lag)	−0.18	(1)	−0.15	(1)	−0.35	(2)	−0.71	(9)
DTI miss (orig.)	0.12	(1)	0.24	(1)	0.18	(1)	−0.03	(0)
DTI G1 (orig.)	0.25	(1)	*na*		0.33	(2)	−0.09	(1)
DTI G2 (orig.)	0.29	(1)	0.19	(1)	0.21	(1)	0.05	(0)
DTI G3 (orig.)	0.23	(1)	0.23	(1)	0.14	(1)	0.02	(0)
Credit G1 (lag)	−0.17	(1)	−0.23	(2)	−0.03	(0)	−0.10	(2)
Credit G2 (lag)	−0.19	(2)	−0.12	(1)	−0.08	(1)	−0.04	(1)
Credit G3 (lag)	−0.30	(2)	0.09	(1)	−0.21	(2)	−0.16	(3)
Equity G1 (lag)	−0.50	(2)	−0.23	(2)	−0.11	(1)	−0.02	(0)
Equity G2 (lag)	−0.51	(4)	−0.24	(2)	−0.28	(3)	−0.12	(2)
Equity G3 (lag)	−0.55	(4)	−0.33	(2)	−0.32	(3)	−0.27	(4)
Int. rate (lag)	0.04	(2)	0.03	(1)	0.02	(1)	0.03	(2)
FICO/100 (orig.)	0.03	(0)	−0.01	(0)	0.03	(0)	0.11	(3)
Income (lag)	−0.03	(0)	0.03	(0)	−0.03	(0)	0.00	(0)
Unemp. (lag)	0.01	(0)	−0.37	(1)	0.23	(1)	−0.15	(1)

B VantageScore Volatility

In this appendix, we study the effect of VantageScore volatility, which we measure as the absolute value of the VantageScore momentum variable. For this table we choose not to use dummies for VantageScore and VantageScore momentum, as the measured effect for the highly related absolute VantageScore momentum variable may depend on the particular choice of cut-offs for the dummies.

In Table 11 one can see that 30-day delinquency is positively predicted by VantageScore volatility. The VantageScore volatility variable does not significantly predict more severe states of delinquency or foreclosure, suggesting that the VantageScore volatility variable helps identify inattentive borrowers who every now and then are late with their monthly payment but have no real solvency issues. In contrast, the VantageScore momentum variable has hardly any predictive power for 30-day delinquency, but it is a powerful determinant borrowers which will transition into progressively worse delinquency states and foreclosure.[13]

[13]We report the coefficient for VantageScore/100 rather than the VantageScore, as the coefficient for VantageScore would be too small at the reported precision.

Table 11: Determinants of default, effect of score volatility

Each column reports the estimated coefficients for a multiple probit regression. The dependent variable measures the probability of a transition to a worse payment status on the first mortgage. The z-score is provided in parenthesis; errors are clustered at the borrower level. Row 4 presents the dependent variable of interest; a status dummy variable, with C = current, D30/D60/D90+ = 1, 2, 3+ months delinquent, and F = in foreclosure. We focus on transitions to the next worse payment status, and thus require the lagged status to be one notch better than the dependent variable (inclusion criterion specified in row 1). Also we restrict the status in the evaluation month to be at most one-notch worse than the month before, and thus omit the rare occurrences of the payment status deteriorating more than one notch in a month (inclusion criterion specified in row 2). The number of observations, taking into account both inclusion criteria, is presented in row 3. We include a constant and year dummies (not reported).

Incl. status (lag)	C		D30		D60		D90+	
Incl. status	C-D30		C-D60		C-D90+		C-F	
Observations	266989		13459		6286		8604	
Dependent var.	D30		D60		D90+		F	
Score/100 (lag)	−0.39	(31)	−0.17	(5)	−0.08	(2)	−0.06	(2)
Dscore/100 (lag)	0.03	(2)	−0.24	(5)	−0.46	(6)	−0.33	(6)
abs(Dscore/100) (lag)	0.11	(6)	0.00	(0)	−0.10	(1)	−0.06	(1)
DTI miss (orig.)	−0.01	(0)	−0.05	(1)	0.22	(2)	−0.02	(0)
DTI G1 (orig.)	−0.02	(1)	−0.01	(0)	0.14	(1)	−0.11	(1)
DTI G2 (orig.)	0.00	(0)	−0.14	(2)	0.11	(1)	0.06	(1)
DTI G3 (orig.)	0.05	(2)	−0.03	(1)	0.21	(2)	0.03	(0)
Credit G1 (lag)	−0.07	(4)	−0.11	(3)	−0.06	(1)	−0.10	(2)
Credit G2 (lag)	0.03	(2)	−0.18	(4)	−0.12	(2)	−0.04	(1)
Credit G3 (lag)	0.13	(5)	−0.20	(4)	−0.18	(3)	−0.13	(2)
Equity G1 (lag)	−0.16	(6)	−0.21	(4)	−0.23	(4)	−0.02	(0)
Equity G2 (lag)	−0.26	(9)	−0.33	(6)	−0.37	(5)	−0.13	(2)
Equity G3 (lag)	−0.29	(9)	−0.44	(7)	−0.38	(5)	−0.28	(4)
Int. rate (lag)	0.02	(4)	0.03	(2)	0.02	(1)	0.03	(2)
FICO (orig.)	−0.15	(9)	0.07	(2)	0.09	(2)	0.09	(2)
Income (lag)	0.10	(4)	0.12	(2)	0.05	(1)	0.00	(0)
Unemp. (lag)	0.23	(3)	0.53	(3)	0.62	(3)	−0.15	(1)