The Impact of Positive Payment Shocks on Mortgage Credit Risk – a Natural Experiment from Home Equity Lines of Credit at End of Draw

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Abstract

Using a unique loan-level residential home equity data from the largest US mortgage servicers that contains a large number of loan attributes and borrower characteristics, we find that default risk of home equity lines of credit (HELOCs) increases with the size of positive payment shocks. Furthermore, default risk increases at end of draw (EOD) when borrowers first experience liquidity constraints and cannot refinance under tightened lending standards. Our findings are robust across different model specifications and risk segments, using clustered standard errors and controlling for the sample selection bias from HELOC payoffs prior to EOD. Since an unprecedented number of HELOCs are expected to reach their EOD period in 2016-2017, we provide several prudential recommendations for lenders and regulators. These include (i) capturing payment shocks and liquidity constraints in credit risk models, (ii) smoothing payment shocks in contract designs as well as work out process, and (iii) coordination in loosening or tightening HELOC lending standards.

Keywords

Default, End of Draw, Home Equity Lines of Credit, Lending Standards, Payment Shock, Payoff, Refinance, Utilization

JEL classification

G2 (Financial Institutions and Service), C3 (Econometric Methods: Multiple/Simultaneous Equation Models)

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1. Motivation

Mortgage defaults tend to increase when house prices drop and when borrowers face liquidity constraints. While the impact of house price fluctuations on mortgage default risk has been fairly well studied, very little is known about the role consumer liquidity constraints play in mortgage defaults. This has motivated us to analyze the impact of positive payment shocks on borrower default. Such payment shocks are common to a wide range of financial instruments. Prominent examples are adjustable rate mortgages that are subject to reference rate increases, especially those with teaser rates that expire at the end of promotional period. Understanding the link between positive payment shocks and HELOC default risk is important as it can help assess the risk of deterioration in loan serviceability for various mortgage products when borrowers experience loss of income due to unemployment, loss of benefits, or demotion.

Home equity lines of credit (HELOCs) allow homeowners to borrow up to the equity value of their house. During the draw period borrowers enjoy access to a credit line and low monthly payments. At the end of the draw period (EOD), access to the credit line ends, the outstanding loan amount is converted into a fixed term mortgage, and monthly payments may go up substantially due to principal repayment. Consequently, default risk can increase significantly as HELOCs reach their end of draw periods. As such, HELOCs offer a natural experiment for the analysis of positive payment shocks as many HELOCs have experienced EOD payment shocks. Other mortgage products were generally repriced at lower interest rates due to low base rates in the aftermath of the Global Financial Crisis (GFC).

As can be seen in Figure 1, default rates of HELOCs that are close to or post EOD (test sample) are nearly three times as high as compared to those in the draw period (control sample).[4] While the liquidity shock from loss of credit line access may affect all HELOCs, the payment shock should be most pronounced for interest-only and balloon loans when refinance is difficult and an immediate payment cannot be avoided.

HELOCs are very popular financial instruments used by homeowners to extract equity from real estate investments in the US, in part because interest paid is typically tax deductible and in part because of its flexibility both in terms of borrowing and repayment. Many HELOCs in the US were originated in the early 2000s with loose underwriting standards. An unprecedented number of HELOCs are expected to reach their EOD periods soon with the peak in May 2017. Some industry

[4] The default rate spike in late 2012 was due to the OCC accounting guidance requiring banks to write down loans discharged in Chapter 7 bankruptcy judgements. We have analysed longer performance horizons, such as 12, 24 and 36 month, and find that increases in default risk around EOD are consistent.

statistics show that as of the first quarter in 2013 outstanding HELOC volume for the entire banking system was $552 billion with an additional $486 billion available to be drawn down. There continues to be significant growth in HELOCs - the dollar amount of HELOC outstanding grew 38% for a twelve-month period ending in December 2013 at US national banks. Thus understanding and measuring the risks of HELOCs in the US is important to financial system resilience and financial intermediation. The materiality of risk has prompted the US bank regulators to issue interagency guidance on HELOC EOD risk management programs and expectations.[5] HELOC EOD risk has received continued media attention.[6]

Despite the importance, the literature on positive payment shocks and borrowers' ability to service mortgages is limited. The existing studies on mortgage default have uncovered many risk factors affecting a borrower's ability and willingness to repay, such as credit score, loan to value, and macroeconomic variables. Few studies have focused on measuring positive payment shock and its impact on mortgage default. This is in part because default data on positive payment shock events is limited for mortgages due to decreases in interest rates, in conjunction with increases in default rates during, and in the aftermath, of the recent financial crisis. Adjustable rate mortgages with low teaser rate were quite popular during the boom years before the GFC and some papers have highlighted the positive causality of rate resets and delinquency risk (see e.g., Mayer et al, 2009) without further analyzing the payment shock. Most existing studies have focused on the impact of negative payment shocks on default risk as base interest rates have decreased post GFC. For example, negative payment shocks are found to be associated with lower default risk of hybrid mortgages at the rate reset (Fuster and Willen, 2013), lower default rates in prime adjustable-rate mortgages (Tracy and Wright, 2012), and lower re-default rates in modified loans (Adelino et al., 2013, Haughwout et al., 2010 and Agarwal et al., 2011) and among the 30-year fixed-rate borrowers with little or negative home equity refinanced through the Home Affordable Refinance Program (Zhu et al., 2014).

Although HELOC default data had been previously extremely limited because very few HEOLCs had reached the EOD, this has changed recently with the bulk of those outstanding entering the EOD phase as shown in Figure 2. Through this study, we aim to analyze the positive payment shock and liquidity shock around HELOC EOD and their impact on HELOC default. We also aim to make prudential recommendations based on our empirical results.

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5 http://www.occ.gov/news-issuances/bulletins/2014/bulletin-2014-29.html.

6 See, for example, http://www.marketwatch.com/story/the-bill-for-home-equity-lines-is-coming-due-2014-03-26.

To the best of our knowledge, there are only three studies on HELOC EOD risk so far. All three studies, Johnson and Sarama (2015), Tong (2015), and Epouhe and Hall (2016), have identified an increased level of HELOC default risk at EOD, despite different samples and modeling methodologies. Johnson and Sarama (2015) estimate a competing hazard model using historical data that contains no information on EOD to predict default risk for a sample of HELOCs that reach EOD in a short test period of June-Dec 2013. They report that the model predicts default risk well for HELOCs that do not reach EOD during the test period, but significantly underestimates risk for HELOCs that do reach EOD. Underestimation is greater for low quality HELOCs with low credit score and high refreshed combined loan to value (CLTV), especially those with balloon payments at EOD. The paper has several limitations, such as payment shocks and liquidity constraints are not measured or included in the model, the EOD effect might have been overstated due to omitting variables often found significant in the literature (e.g., asset/income documentation type, type of loan – Interest Only/Balloon, loan source – retail/wholesale/correspondent/bulk purchased, etc., utilization rate, owner occupancy, property type, property price, refreshed FICO, house price index and GDP growth.

Compared to Johnson and Sarama (2015), Tong (2015) uses a larger sample over a longer sample period and a more comprehensive set of default risk factors. However, HELOC EOD effect is analysed using a dummy variable for EOD and a categorical variable measuring the number of months in which a HELOC will reach EOD. Since change in payment size and line frozen indicator are not included in the model, it is not clear whether the higher default and payoff rates are caused by payment shocks and/or liquidity constraints, and whether the impact is consistent across loans with different risk characteristics.

Epouhe and Hall (2016) is the first study to include both the timing and size of payment increases. However, their sample period is less than three years starting in June 2012 all in benign economic conditions despite wide coverage, the two confounding effects are not disentangled, the role of refinance does not consider changes in bank lending standards, the size of the payment shock is not relative to the size of the property, and many variables often found significant in the literature (e.g., line frozen indicator, asset/income documentation type, lien position, loan source, property type, securitized/portfolio loan indicator, house price index, state foreclosure laws) are not included in the model. We overcome the limitations in the existing studies in analyzing the impact of payment shocks and liquidity constraints on mortgage default.

Our study is also related to the strand of literature studying household liquidity constraints and default risk. Using credit card utilization rates to proxy for consumer liquidity constraint, Elul et al. (2010) and Demyanyk et al. (2011) find that mortgage default is driven by both liquidity constraint and negative home equity. Gerardi et al. (2013) analyze the impact of liquidity shock on mortgage default and find that loss of income due to unemployment dominates negative equity as a cause of default during the GFC.

HELOC utilization can serve as another proxy for borrowers' financial constraints. Based on survey data, Yamashita (2007) finds that households increase home equity borrowing in response to house price appreciation, especially among those facing liquidity constraints and having low wealth-to-income. Calem et al. (2011) use public HELOC data and find that borrowers obtain and expand home equity credit lines when house prices increase (e.g., to purchase an additional property). Furthermore, consumers are drawing on new credit lines when consumer confidence has declined (liquidity draws) and are more likely to fall behind in their payments. Agarwal, Ambrose, and Liu (2006) use private bank data and analyze HELOC utilization conditional on default risk and find that higher HELOC utilization increases the risk of mortgage delinquencies.

HELOCs are subject to payoffs, which are triggered by prepayments or refinance. Keys et al. (2014) show that about one in five mortgage borrowers does not refinance when it is optimal to do so. Deng et al. (2000) and most mortgage papers thereafter control for the possible selection bias resulting from payoffs by applying competing hazard and multinomial logit models and by including empirically important variables that drive the default process.

Our paper contributes to the literature in a number of important aspects. First, this paper is first to analyze both the size and the timing of positive payment shocks on HELOC default risk along with other loan, collateral, borrower characteristics and macroeconomic variables. We analyze alternative measures for the size of payment shocks and quantify the impact in terms of the probability of default.

Second, our study is based on the OCC Home Equity Dataset which contains monthly loan-level residential home equity data from the largest US mortgage servicers, covering HELOCs that were originated since 1985.[7] The data contains 10.8 million HELOCs and 1.8 million end-of-draw events during the sample period from January 2010 to March 2015, which is considerably more than the 45,265 EOD events contained in the data used by Johnson and Sarama (2015). The large dataset allows us to analyze the impact of the payment shock and liquidity shock effect over time for the same HELOCs before and after the end of draw.

Third, we control for sample selection bias from payoffs by including a large number of risk factors, such as current utilization rate, refreshed FICO, and refreshed combined LTV in all models.

[7] Some earlier originations exist but are below 100 observations per month. The number of HELOCs originated in a given month exceeds 100 observations from 1985 onwards.

We also perform various robustness checks on different subsamples and use alternative models, such as competing hazard models, data filtering for non-payoffs, models that control for the Inverse Mills Ratio, and bivariate probit models.

The paper proceeds as follows. The data is described in Section 2. We report the empirical analysis in Section 3. Robustness of the findings and economic significance are reported in Section 4. Concluding remarks are provided in Section 5, along with prudential policy and best practice risk measurement recommendations for lenders and regulators.

2. Data and Empirical Design

2.1. Data description

Our analysis is based the OCC Home Equity Loan-Level Data. The data is in panel format and loans are observed monthly. Figure 2 shows the HELOC volume (in $ billion) by origination, EOD, and maturity date.

The grey shaded area highlights our observation period from January 2010 to March 2015 for loan performance and risk characteristics. As of March 2013, the outstanding HELOC volume is $310bn and the undrawn HELOC line is $247bn in our data. The total HELOC volume is $557bn, which represents approximately half of the total HELOC volume in the US.

Figure 2 shows that the majority of loans were originated prior to the GFC and a large number of HELOCs will reach EOD in the near future with the peak in May 2017. During the next four years (i.e., 2016-2019), another 6 million HELOCs in our sample will reach end of draw, which may cause an unprecedented number of HELOC payoff and default events. It is apparent that the draw period is in many instances ten years, and the post EOD repayment period is either zero for balloon loans (B), or 20 years for non-balloon loans (NB).

The majority of the loans is contracted at a variable rate and is first or second lien. We create a more homogeneous dataset by excluding fixed rate HELOCs, third or higher liens, HELOCs which have zero credit balance in all observation months, and loans that are already in default as of each observation month. The remaining data is further cleaned by excluding observations with erroneous or missing critical information for our analysis, such as utilization rates less than zero or greater than one, missing EOD, negative loan balance or credit line, and implausible time stamps.[8]

[8] This includes observation time before origination time, EOD time before observation time, maturity time before origination time, and maturity time before EOD time.

Payment shock is predominantly observed at EOD and we generate a test sample: panel data set of HELOCs that have reached EOD and are observed from one year prior to EOD to one year after EOD in our data.[9] This data has 28.3 million monthly observations, with 632,554 payoff events and 191,118 default events.

We also generate a control sample that includes a panel data set of HELOCs that have not reached EOD by March 2015. This data has 436.4 million monthly observations. Variable definitions are contained in Table 1. The summary statistics of the continuous and categorical variables are reported in Tables 2 and 3, respectively. The next three subsections provide a more detailed discussion of the dependent variables, test variables, and control variables used in our study.

2.2. Dependent variables: payoff and default

Default and payoff indicators are defined in Panel A of Table 1. Common default events include delinquency of 30, 60 and 90 days past due (DPD), the interaction between bankruptcy (BK) and delinquency (BK current, BK 30 DPD, BK 60 DPD), foreclosure and real estate owned (REO) where a lender retains property ownership after foreclosure.

We apply a “seriously delinquent” or worse definition as this is commonly used and implies lower cure rates.[10] Mortgages that are 60 or more DPD, and all mortgages held by bankrupt borrowers with payments past due for 30 days or more are considered seriously delinquent. Thus the following events trigger default in our paper:

- Payment delinquency of 60 days or more;
- Payment delinquency of 30 days or more if the borrower is in bankruptcy;
- Foreclosure;
- At short sale of loan;
- Real estate owned (REO);
- Loss/write-down amount is positive;
- Involuntary Liquidation;
- Debt modification as a positive interest, expense, or principle forgiveness.

9 We tried longer and shorter observation windows and found the results are consistent.

10 See, for example, http://www.occ.gov/publications/publications-by-type/other-publications-reports/mortgage-metrics-2014/mortgage-metrics-q2-2014.pdf.

We have checked other common default definitions for robustness and obtain similar results throughout. One of such alternative default definitions is the Basel definition, which differs from the above as it is based on a payment delinquency of 180 days or more and a payment delinquency of 60 days or more if the borrower is in bankruptcy.

Figure 1 shows that default risk is higher for the test sample than for the control sample. Two alternative explanations may exist. First, a liquidity shock and a payment shock experienced by the borrowers who did not or could not refinance may lead to an increase of default risk. Second, borrowers of better credit quality are more likely to drop out of the test sample because they are more likely to be able to refinance with the same or another HELOC lender prior to or at EOD to maintain their access to the credit line and low monthly payment. This can introduce sample selection bias and thus higher risk among borrowers who actually experienced EOD.

To control for payoff, we generate a payoff indicator, which is equal to one if a loan drops out of the sample without experiencing a default or maturity, and zero otherwise. Payoff events are impacted by similar risk factors as default events, however, in the opposite way as loans with good credit quality are more likely to be repaid before maturity or refinanced under better terms with the same or another lender. Figure 3 shows that the payoff risk is higher for the test sample than for the control sample.

HELOCs default rates increased in late 2012 and early 2013. This is largely driven by a change in accounting practice from an OCC supervisory guidance issued in October 2012, which requires all national banks to write down to collateral value (one of our default triggering events, see above) retail exposures not reaffirmed after Chapter 7 bankruptcy judgments that discharged the obligors' debts, irrespective of delinquency status. Before October 2012, the borrower must also have missed at least two payments before write-down took place at many banks, even if the bank was notified that the debt has been discharged by the bankruptcy court. We have coded the three months November 2012, December 2012 and January 2013 by a separate dummy (Write Down) to control for this unusual increase of the default rate in the data. We include this dummy in all multivariate models.

2.3. Test variables

Our research analyzes how payment shock and liquidity shock impact HELOC delinquency risk. The test variables are listed and defined in Panel B of Table 1. We measure Payment Shock (PS) using the change in minimum payment from one year prior to EOD to the current period divided by the latest available house price.[11]

We divide raw payment shock by current house price in order to make a meaningful comparison of the payment shocks for borrowers of different wealth levels. A payment shock of 0.001 implies an increase in the monthly minimum payment of $1,000 per $1 million property value. Borrowers generally fund the mortgage payment and payment increase from their post-tax, post-consumption income and a payment shock may be equivalent to a higher pre-tax income shock. Note that the payment shock is in addition to payments to other debt, such as credit card, auto and most importantly other mortgage debts. We expect the payment shock to 'bite at the margin' and to increase the default risk of the HELOC borrower considerably.

Table 5 shows this calculation in more detail for all HELOCs (Panel A), non-balloon HELOCs (Panel B) and balloon HELOCs (Panel C). The mean minimum payment at EOD (MP EOD, column 1) is much higher for balloon HELOCs than for non-balloon HELOCs, while the mean minimum payment one year prior to EOD (MP Pre-EOD, column 2) is comparable for all panels. The raw payment shock is the difference between the MP EOD and MP pre-EOD (column 3), which is mostly driven by MP EOD. Payment shock (column 5) shown is calculated as the raw payment shock divided by the current house price (column 4). The payment shocks show a significant variation with the 5th percentile of -0.00022 and the 95th percentile of 0.00357.

The numbers tend to be very small and hence the parameter estimates tend to be larger relative to other variables in the model as the payment shocks are computed from dividing changes in monthly payment by updated house prices. We do not apply any scaling, as we are interested in the sign and raw magnitude of parameter estimates of this variable.

Some loans in our data show no change of minimum payment at EOD. We suspect that this is caused by lenders not updating the minimum payment and insisting on payment by maturity without further draws. Hence, we augmented the reported minimum payment as follows:

[11] We have tested alternative payment shock definitions with consistent results: (i) the ratio of the difference in minimum payment of the current period and the minimum payment at origination and the house price, and (ii) the ratio of the difference of the minimum payment of the current period and the minimum payment of the previous period (i.e., one month lag) and the latest available house price. Furthermore, Section 4.1.2 shows consistent results using alternative house price definitions: (i) house prices at origination, and house prices updated by changes in the house price index since the last evaluation. We have also related the raw payment shock to credit line.

- Loans prior to EOD with liquidity facility (i.e., line not frozen/closed and current utilization <95%): minimum payment is set to the reported minimum payment; [12]
- Loans prior to EOD without liquidity facility (i.e., line frozen/closed or current utilization >=95%): minimum payment is equal to the minimum of the reported minimum payment and the current interest rate times outstanding balance;
- Loans post EOD: minimum payment = annuity payment based on current interest rate, outstanding and time to maturity.

Note that the payment shock at EOD may also be negative or zero, which may appear counterintuitive at first sight. Negative payment shocks imply that consumers repay principal around EOD as they may no longer require the loan or have found other sources of finance including refinance with a different lender. The drop in outstanding balance explains the drop in minimum payment and hence negative payment shock at EOD. A zero payment shock is common for amortizing HELOCs. We have confirmed our intuition by reviewing a large number of individual cases. Furthermore, alternative payment shock definitions are tested in Section 4.1.2.

With regard to liquidity shock, we analyze HELOC performance before, at and after EOD. TSEOD is analyzed by including quarterly splines in the models to allow for non-monotone impact of quarters before and after EOD. Current utilization rate (CUR), defined as the ratio of the outstanding principal balance and the credit limit, has been used in the literature as a measure of borrower liquidity. A lower utilization ratio implies greater loss of liquidity at EOD if no refinance is available. Calem et al. (2011) argue that the credit limit does not only reflect the perceived default risk but also the amount of home equity that the borrower has prior to obtaining the HELOC. We find as borrowers approach EOD, the higher HELOC utilization rate is associated with higher default risk, consistent with the findings in the existing literature.

Our models also include other variables that measure borrower liquidity. One such variable is the refreshed CLTV. The outstanding loan amount used in the CLTV calculation includes the balances of the HELOC and other more senior liens on the property. The property value used in CLTV calculation is the latest available property value and is often updated by the lending financial institutions. A higher refreshed CLTV ratio implies lower liquidity as borrowers are less likely to be able to refinance or obtain a smaller HELOC facility when needed. Another such variable is CEP, which measures the cumulative excess payments (i.e., payments in excess of the required minimum

[12] This assumes that minimum payment is not a constraint for borrowers prior to EOD when an unused liquidity facility is available to the borrower. We have tested the minimum payment provided by the lender prior to EOD with consistent results.

payment) relative to the property value at origination. We report the parameter estimates for CUR, CLTV and CEP in all models.

2.4. Control variables

Our models include a large set of other control variables that are commonly used in the mortgage literature, such as refreshed FICO score, natural log of the updated property value, and refreshed CLTV. They are listed and defined in Panels C and D of Table 1.

The original combined loan to value ratio (CLTV) is the original committed loan amount in addition to any senior liens divided by the property value at the time of HELOC origination. CLTV is periodically refreshed using the current loan balance and updated property value. The bank may use an updated first mortgage balance, if serviced in house. For property value, the bank should use the most recent estimate of property value. The origination value may be used if the bank has not refreshed the value since loan origination. Furthermore, the refreshed CLTVs take into account whether the same borrower holds multiple second lien HELOCs with the same or other lenders. The final CLTV is computed as the combined outstanding balances from the first lien mortgage and all HELOCs divided by the property value estimate. We use the CLTVs refreshed this way if available. Approximately 46% of the CLTVs are refreshed this way.

Other HELOC-specific control variables are interest rate at origination, the cumulative excess payment (CEP), and the rate spread. CEP is the cumulative difference of monthly payment and minimum payment since 2008 divided by property price at origination.

Table 2 shows summary statistics for continuous variables. All variables demonstrate sufficient cross-sectional and time series variation. We do not include time since origination and time to maturity in the analysis as this would confound with the test variable TSEOD, as the draw period and maturity are generally standardized with 10 years between origination and EOD, zero years between EOD and maturity for balloon HELOCs and 20 years between EOD and maturity for non-balloon HELOCs (see Figure 2). Table 3 shows the pairwise correlation coefficients for the continuous variables for all observations in the test sample. The correlation is generally low between the continuous variables indicating limited multicollinearity.

We include a number of categorical variables in the models and report summary statistics in Table 4 These include indicator variables for HELOCs that have balloon repayment (B=1), interest only (IO=1), asset documentation (ADOC=1), income documentation (IDOC=1), owner occupied (OC=1), multi-family properties (PRT=1), second lien (Lien=1), non-retail loans (Loan source=1), are observed in the period that the OCC BK7 write down guidance became effective (OCC=1), and indicate particular foreclosure laws, such as judicial procedure (JP=1), statutory right of redemption (SRR=1) and prohibit deficiency judgment (PDJ=1). The reference category is coded zero for all binary variables.

We also flag loans that have a frozen or closed credit line (CLF=1). Many accounts approaching EOD may already have line availability suspended due to collateral value declines or performance problems. These accounts warrant particular attention. As is reported in the media, in 2008 major home equity lenders began informing borrowers that their home equity lines of credit had been frozen, reduced, suspended, rescinded or restricted in some other manner.

Finally, we include a number of macroeconomic variables in our models. The term spread is the difference between the ten-year Treasury bond rate and the one-year Treasury bond rate and is the same value for all HELOCs in a given observation month. We assign macro-economic variables by Metropolitan Statistical Area (MSA) level and if a direct match is not possible, by the state level of the mortgaged property. The variables are the annual growth in the house price index (HPI), and the unemployment rate (UER).[13] A last macro-economic variable is the bank lending standard, which is the net percentage of domestic banks tightening standards for HELOCs from the Federal Reserve Board Senior Loan Officer Survey.

We checked all variables for missing values and found that all variables have missing values in less than 10% of all observations with the exception of current utilization, and interest rate at origination, which are less than 20% for all observations in the test sample.

We have replaced missing values by cross-sectional means for given time periods (i.e., the replacement values are time-varying) to minimize the loss of observations in the test data set. We have assured the robustness of our results by comparing the results for models with missing values and the models applying the cross-sectional means replacement for given variables. The number of missing values is low and the means replacement for missing values has no impact on our findings as it affects only very few second variables among our large number of controls variables.[14]

HELOCs at payoff generally have better credit quality, with lower payment shock, lower utilization, higher FICO score, lower CLTV, higher cumulative excess payment, lower interest rate at

[13] We have tested other macro-economic variables such as the annual growth in real GDP, which were not included as the model fit did not improve.

[14] The unemployment rate was unavailable from January 2015 onwards and we used the December 2014 values for February 2015 and March 2015. The numbers shown in Table 2 to Table 4 are without replacing the missing values. They are largely consistent after replacement but standard errors are slightly higher due to the lower number of observations.

origination, lower rate spread, higher house price appreciation and lower unemployment rate.[15] HELOC payoff rate is higher for balloon loans, interest-only loans, full income documentation, non-owner occupied homes, single-family homes, first liens, retail loans, loans when the credit line is not frozen, not securitized, owned or held on a bank's balance sheet, and a somewhat higher payoff rate during the Nov 2012 − Jan 2013 write down, in states with non-judicial procedures, that prohibit deficiency judgment and without statutory right of redemption.[16]

It is apparent from Table 2 that relative to the rest of the HELOCs, HELOCs at default generally have poorer credit quality which coincides with greater payment shock, higher line utilization, lower FICO score, higher CLTV, lower cumulative excess payment ratio, higher interest rate at origination, higher rate spread, greater average term spread, lower house price appreciation and higher unemployment rate.[17]

HELOC default rates are higher for non-balloon loans, non-interest-only loans, loans with limited income documentation, non-owner occupied homes, multi-family homes, second liens, loans not originated from retail channel, loans when the credit line is frozen, securitized loans, loans not owned or help on a bank's balance sheet, during the Nov 2012 − Jan 2013 write down and somewhat higher default rates in states with non-judicial procedures, that prohibit deficiency judgment and with statutory right of redemption.

2.5. Modeling framework

In our data set, we observe three potential competing outcomes for HELOCs: (i) non-default and non-payoff, (ii) default, and (iii) payoff.[18] We are only able to observe default/non-default of HELOCs that have not been paid off. As such, our data might not be representative of all HELOCs originated by lenders covered in the dataset if the HELOCs that were prepaid or refinanced with a different lender are different from those that remain observable in the dataset.

[15] The payoff event in Table 2 is defined as a payoff event within one month from the observation period. The numbers presented are robust for longer horizons (e.g., 12, 24 and 36 months).

[16] US bankruptcy and foreclosure laws allow for judicial and non-judicial foreclosures. In a judicial foreclosure, a court orders the foreclosure and supervises the whole foreclosure process. A deficiency judgment allows the recourse to other borrower assets if assets fall short of the outstanding loan amount. Statutory right of redemption give the borrower a right to buy the house after a foreclosure adding uncertainty about ownership and providing for less efficient workout processes. The signs on these variables are generally mixed or insignificant and driven by inclusion/exclusion of other key factors.

[17] The default event in Table 2 is defined as a default event within one month from the observation period. The numbers presented are robust for longer horizons (e.g., 12, 24 and 36 months).

[18] Deng et al. (2000) analyse mortgage termination with regard to payoff, default, missing information and end of observation period.

Such sample selection bias should be somewhat contained because of the extensive coverage of the OCC Home Equity dataset. This implies that we continue to observe and analyze those borrowers who refinance with another lender in the OCC Home Equity dataset, albeit under a different loan identification number in the data.

Nevertheless, we apply a number of econometric techniques to control for, as opposed to assuming no selection bias. We apply three different techniques: multinomial logit models, models that control for the Inverse Mills Ratio, and bivariate probit models. Our main findings are based on the multinomial logit models (see Section 3), whereas the models controlling for the Inverse Mills Ratio and bivariate probit models are included in the robustness section of this paper (see Section 4).

Multinomial logit models are common in mortgage delinquency modeling (see, for example, Deng et al., 2000, Agarwal et al., 2011). We model a potential selection bias stemming from payoff events by a separate equation for the dependent outcomes (payoff and default) whereby one outcome (non-default and non-payoff) serves as the reference category. Multinomial logit models are comparable to competing hazard models and may result in identical parameter estimates for discrete ties (Allison, 1995). [19]

For the multinomial logit modeling, we assume that every outcome is subject to an unobservable (latent) propensity score:

$$\mathrm{y}_{\mathrm{it,k}}^{*} = \beta_{\mathrm{k}} x_{it-1} + \varepsilon_{\mathrm{it,k}}, \tag{1}$$

where $\mathrm{k} \epsilon \{0,1,2\}$, representing the three potential competing outcomes for the i^{th} HELOC at time t: (i) non-default and non-payoff: $y_{it} = 0$, (ii) default: $y_{it} = 1$, and (iii) payoff: $y_{it} = 2$; the risk factors $x_{\mathrm{it}-1}$ are time lagged with regard to the dependent variable and include borrower, collateral and macroeconomic characteristics; $\varepsilon_{\mathrm{it,k}}$ are independent error terms following a type I (Gumbel) extreme value distribution with cumulative density function $F(\varepsilon_{\mathrm{it,k}}) = exp\left(-exp(-\varepsilon_{\mathrm{it,k}})\right)$.[20] This independence assumption has the advantage that the likelihood function is computationally

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[19] We have confirmed consistency in a simulation study.

[20] The Gumbel distribution is chosen as it has the property that the difference of two error variables, which follow the Gumbel distribution, follows the logistic distribution. The difference is the dependent variable after consideration of the reference category.

simple.[21] The models require the same control and test variable set and the outcome of one category (in particular payoff) does not impact the relative odds of the other two outcomes (in particular default and non-default/ non-payoff). This is also known as the Independence of Irrelevant Alternatives Assumption. Hence, to control for adverse selection, we will allow for correlated errors in a sequential structure for latent variables as a robustness check due to a heavy computational burden (see Section 4.2.2).

The observable dependent outcome variable y_{it} is linked with the latent propensity score:

$$y_{it} = \mathrm{k}, \text{if } \mathrm{y}^*_{\mathrm{it,k}} = \max\{\mathrm{y}^*_{\mathrm{it,0}}, \mathrm{y}^*_{\mathrm{it,1}}, \mathrm{y}^*_{\mathrm{it,2}}\}. \tag{2}$$

The probability for the outcome y_{it} is:

$$\begin{aligned} \mathrm{P}(\mathrm{y_{it}} = \mathrm{k}) &= \mathrm{P}\big(\beta_\mathrm{k}\mathrm{x}_{\mathrm{it}-1} + \varepsilon_{\mathrm{it,k}} > \beta_\mathrm{j}\mathrm{x}_{\mathrm{it}-1} + \varepsilon_{\mathrm{it,j}}, \forall \mathrm{j} \neq \mathrm{k}\big) \\ &= \mathrm{P}\big(\varepsilon_{\mathrm{it,j}} < \mathrm{x}_{\mathrm{it}-1}(\beta_\mathrm{k} - \beta_\mathrm{j}) + \varepsilon_{\mathrm{it,k}}, \forall \mathrm{j} \neq \mathrm{k}\big) \\ &= \int_{-\infty}^{\infty} \prod_{\mathrm{j}\neq\mathrm{k}} \exp\Big[\big(-\exp\big(-\mathrm{x}_{\mathrm{it}-1}(\beta_\mathrm{k} - \beta_\mathrm{j}) \\ &\quad + \varepsilon_{\mathrm{it,k}}\big)\big)\Big] \exp\big(-\exp(-\varepsilon_{\mathrm{it,k}})\big) \exp(-\varepsilon_{\mathrm{it,k}}) \mathrm{d}\varepsilon_{\mathrm{it,k}} \\ &= \frac{exp(\beta_\mathrm{k} x_{it-1})}{\sum_{k=0}^{2} exp(\beta_\mathrm{k} x_{it-1})}. \end{aligned} \tag{3}$$

Normalization of the default parameters to zero (see Maddala, 1983) results in:

$$\mathrm{P}(y_{it} = \mathrm{k}) = \frac{exp(\beta_\mathrm{k} x_{it-1})}{1 + \sum_{k=1}^{2} exp(\beta_\mathrm{k} x_{it-1})} \tag{4}$$

for $\mathrm{k} \epsilon \{1,2\}$. The probability for a non-payoff and non-default (i.e., $\mathrm{k} = 0$) is:

[21] We apply parallel computing to allow for faster execution of models.

$$\mathrm{P}(y_{it} = 0) = \frac{1}{1 + \sum_{k=1}^{2} exp(\beta_{\mathrm{k}} x_{it-1})} \tag{5}$$

The log-likelihood is:

$$lnL = \sum_{i=1}^{I} \sum_{t=1}^{T} lnP(y_{it} = k, \beta_k) \tag{6}$$

The parameters $\beta_{\mathrm{k}}, \mathrm{k} \epsilon \{1,2\}$ are estimated by maximizing the log likelihood function.

It is possible that statistics of interest may not be simple linear functions of the observed data for survey data with unequal size clusters. We compute the standard errors based on the Taylor Series Linearization Method clustering by state. The linearization approach applies the Taylor method to derive an approximate form of the estimator that is linear in statistics for which variances and pairwise co-variances can be directly estimated (Rust, 1985 and Wolter, 1985).

3. Empirical Results

Table 6 shows the parameter estimates, clustered standard errors, statistical significance and various model performance measures, including pseudo R-squared, Accuracy Ratio and Area under the Receiver Operating Characteristic curve (AUROC) for the baseline competing hazard model predicting default and payoff within one month. We use a range of other prediction horizons and receive consistent results. The one-year models are reported later to show the robustness of the findings.

The parameter estimates of our key variables of interest have the sign and magnitude that are consistent with our expectation. Specifically, the payment shock has a positive and highly significant impact on the default probability, and the default risk increases and peaks approximately one quarter prior to EOD, peaks at EOD and then decreases over the year post-EOD.

The economic impact of a payment shock is considerable. We have computed iso-curves, i.e., combinations for the payment shock and FICO as well as payment shock and CLTV that result in the same probability of default. For the one-year default probability, a payment shock of \$500 per month would have to be offset by an increase of the FICO score by 31 and a decrease of CLTV by 44 percent. This shows that the estimated sensitivities are of comparable magnitude to other major drivers of mortgage and HELOC delinquency risk.

The control variables explaining the default events are also consistent with our expectation from the univariate analysis (see Table 2 and Table 4) and the literature. Control variables have generally the opposite impact on payoff than on default as a lower default risk borrower is more likely to refinance and pay off the existing HELOC exposure. Current line utilization rate has a positive impact on the default probability, consistent with impact of liquidity constraint on default found in the literature (e.g., Agarwal et al., 2006). Lower FICO score and higher CLTV are associated with higher likelihood to default. House price appreciation and unemployment rate change since origination have a positive impact on the default probability.[22] State foreclosure laws (judicial procedure, prohibit deficiency judgment and statutory right of redemption) are not significant drivers of default probability after controlling for other more important risk drivers.

We test the following alternative model specifications to confirm robustness of our results and show the relative importance of the test variables:

- Model 1: all variables including payment shock, liquidity shock, and TSEOD, the same as the baseline model reported in Table 6;
- Model 2: all variables except payment shock;
- Model 3: all variables except liquidity shock;
- Model 4: all variables except TSEOD;
- Model 5: all variables except payment shock, liquidity shock, TSEOD;
- Model 6: only those control variables used in Johnson & Sarama (2015).

Table 7 shows the parameter estimates, clustered standard errors, statistical significance for the key variables of interest in these models, along with model performance measures (pseudo R-squared, accuracy ratio and AUROC). The parameter estimates of our key variables of interest consistently show the expected sign and comparable magnitude across alternative specifications: the payment shock has a positive and highly significant impact on the default probability, the default risk increases significantly within the quarter since EOD and then decreases over the year post-EOD, with higher utilization rate, lower FICO and higher CLTV associated with higher default risk.

The standard performance measures (pseudo R-squared, accuracy ratio, and AUROC) in Table 7 indicate that Model 1 dominates the alternative models. In unreported tests we compared the estimated Model 5 using the control sample and applied the resulting equation to the test sample.

[22] The positive impact of HPA on default is counterintuitive, this is likely due to multicollinearity as HPA has fairly high correlation with other variables, such as CLTV, RS and UER.

Again, Model 1 outperforms Model 5. The other control variables are consistent with the ones reported in Table 6.

The results from the one-year models (shown in Table 8) are largely consistent with those from the one-month models, with the exception of Model 3 that marginally outperforms the other models based on accuracy ratio and AUROC and the negative sign on current utilization rate.

4. Robustness checks

4.1. Payment shock

4.1.1. Non-linearity

To account for non-linearity in metric variables, we have added relative splines above various thresholds for some metric variables as follows:

$$\text{spline (variable, threshold)} = \begin{cases} 0, & \text{if variable} < \text{threshold} \\ \text{variable} - \text{threshold}, & \text{if variable} \geq \text{threshold} \end{cases} \tag{7}$$

The splines capture the additional impact in excess of the variable's impact for values above the threshold level. For example, we introduce three spline effects for the current FICO score with the threshold levels 620, 660 and 700. The parameter for spline (FICO, threshold) describes the additional impact of FICO levels above the threshold and the total parameter effect is

- β_{FICO} for FICO<620;
- $\beta_{FICO}+\beta_{FICO\ 620}$ for 620<=FICO<660;
- $\beta_{FICO}+\beta_{FICO\ 620}+\beta_{FICO\ 660}$ for 660<=FICO<725;
- $\beta_{FICO}+\beta_{FICO\ 620}+\beta_{FICO\ 660}+\beta_{FICO\ 725}$ for FICO>=725.

In addition, we include spline terms for underwater mortgages (i.e. refreshed CLTV in excess of 100%), time since EOD in quarterly intervals (i.e., EOD-0.75, EOD-0.5, ……, EOD+1), and payment shock in 0.0005 intervals (i.e., $500 increase in monthly payment on a $1 million property).

To account for the nonlinearity in payment shock, specifically, we include the payment shock as a categorical variable as opposed to a continuous variable in Model 1 along with other risk characteristics. The impact on the probability of default (PD) is computed as follows: the reference category (reference category -0.0005) of the payment shock dummies is assumed to imply a base value of 0.5% for the one-month PD and 5% for the one-year PD. The PDs are then adjusted to reflect the respective estimate for payment shock categories assuming all other variables remain constant. We plot the one-month and one-year estimated PDs (left axis) along with the frequency distribution (right axis) across the payment shock intervals in Figure 4.

The dashed lines represent the boundaries of 95% confidence intervals based on the estimated standard errors clustered by state and a normal distribution assumption with the parameter estimate being the mean. Non-clustered standard errors would imply similar parameter estimates but lower standard errors, and hence, somewhat narrower confidence intervals.

It is obvious from Figure 4 that default risk increases monotonically with payment shock and rises exponentially when payment shock is above 0.0025 (i.e., $2,500 increase in monthly payment on a $1 million property). For a $1 million property, a $3,000 increase in monthly payment results in a one-month (one-year) default probability that is approximately 3.7 (2.1) times higher than the default probability when there is no payment shock (e.g., prior to EOD).

Figure 5 shows the one-month and one-year estimated PD (left axis) and frequency distribution (right axis) across various time since EOD intervals. Default risk increases at EOD and then decreases over the twelve months following EOD. At its peak, the one-month (one-year) probability of default is approximately 3.3 (1.6) times higher than the level prior to EOD. Note that the impact of time since EOD has to be interpreted in conjunction with the model outcome horizon of one month or one year – the probability of default within one year peaks much sooner than the probability of default within one month as HELOCS approach EOD.

In summary, the results are consistent with our findings presented in Section 3. Default risk increases with payment shock monotonically and exponentially above the level of 0.0025 in both the one-month and one-year models. Delinquency risk increases in the quarter post-EOD in the one-month model and starting two quarters prior to EOD in the one-year model.

4.1.2. Alternative payment shock definitions

The main results presented in Section 3 are based on the payment shock measure normalized by the latest available house price. This might bring in the effect of a house price change. To make sure payment shock only captures the change in monthly minimum payment, we include two alternative payment shock measures that are normalized by time-invariant variables: property value at origination and credit limit. Using property value at origination in payment shock definition should result in payment shocks that are comparable to those using the updated property value if property values do not change much, whereas using the credit limit could result in much larger payment shocks given it is usually a lot smaller than the updated property value.

In Table 9, we compare the results from the two alternative definitions of payment shock (Models 7 and 8) to the baseline model (Model 1) from Table 6. The number of observations in Models 7 and 8 is less than that in Model 1 as we did not apply a cross-sectional mean replacement for the all payment shock test variables. Nevertheless, the results of Models 7 and 8 are largely consistent with those of the baseline model, i.e., default risk increases with payment shock and also increases as the loan approaches and soon after EOD, but then decreases within one year post-EOD. Note that unlike in Models 1 and 7, current utilization rate is not significant in Model 8, possibly caused by its correlation with PS_Credit Line due to the common denominator and smaller sample size.

4.1.3. Pooled regressions from the combined test and control samples

In addition, we run a regression with the combined test and control samples that includes payment shock and time since EOD. The control sample is a random sample of all control data with roughly the same number of observations as the test sample. Table 10 presents the results which are consistent with those presented in the previous tables. In particular, the payment shock and current utilization has a positive and highly significant impact on the default risk, and default risk increases approximately one month prior to EOD, peaks at EOD and then decreases over the year following EOD. The coefficients and significance of the control variables are also consistent with those in the previous tables.

4.1.4. Sensitivity across risk segments

We further analyze the impact of payment shock on default probability across various risk segments. We run Model 1 specification for a number of risk segments defined by:

- Post-draw payment characteristics (balloon payments, interest-only payments);
- Origination channel (retail and non-retail);
- Borrower characteristics (credit score, and utilization rate bands); and
- Home equity (CLTV).

The results in Table 11 suggest that the payment shock is positive for all but two risk segments, the quarter post EOD has a greater risk and one year post EOD has a lower risk. Higher utilization rate is associated with higher default risk. Results in Table 11 also show that the payment shock impact on default risk is stronger for non-balloon loans, non-interest only, wholesale loans, FICOs under 700, high utilization, and 95%-100% CLTV.

4.2. Sample selection bias

Our sample changes over time due to loan origination, reaching maturity, payoff and default. Sample selection bias may exist if a large proportion of loans is paid off non-randomly prior to maturity, which may imply that bad credits remain while good credits leave the sample. This problem is more pronounced in HELOCs that are close to or have reached the end of the draw period as borrowers are required to repay their loans at EOD in the instance of balloon loans or within a period of time for non-balloon loans. Lower risk HELOC borrowers can more readily refinance their loans either with the same or another lender.

To address potential sample selection bias, we apply the following strategies:

- Control for a large number of characteristics. Generally speaking, this control information may be able to address sample selection bias if all risk factors are captured in the model, payoff is infrequent, or if the prediction horizon is short. However, it is not clear if these conditions hold in our case. In other words, the borrowers who are "remaining in the sample-period" may exhibit a greater risk profile than controlled by the risk factors included in our models (for both the test/treatment and control samples) and we may wrongly conclude that the increase in risk at EOD is due to the payment shock and liquidity constraint.
- Estimate multinomial logit models common in the mortgage literature to control for prepayment risk and to disentangle the EOD effect from the sample selection bias from payoff and other risk characteristics.
- Estimate the models for HELOCs that did not pay off during the observation period by excluding all the observations from the loans that experienced payoff any time from January 2008 to March 2015. The results are consistent with the presented models.

We now perform two additional robustness checks: control for the Inverse Mills Ratio (IMR) and a bivariate probit analysis.

4.2.1. Inverse Mills Ratio

We include the Inverse Mills Ratio from a probit model for payoff (reference non-payoff) into the probit model for default (reference non-default) equation as a first robustness check for sample selection bias.[23] This approach controls for observable information explaining the payoff selection and default model process. Selection bias may relate to omitted information. In addition to analyzing the competing outcomes payoff and default we now analyze payoff and default driven by separate information.[24] We discuss the additional instrumental variables that explain payoff but not default below.

We now assume that default (D_{it}) is observed if a second, unobserved latent variable $\mathrm{p}_{\mathrm{it}}^{*}$ (i.e., a proxy for the likelihood of the borrower to **not** payoff) exceeds a particular threshold (here zero):

$$\mathrm{P}_{\mathrm{i,t}} = \begin{cases} 0, \text{if } \mathrm{p}_{\mathrm{it}}^{*} \geq 0 \\ 1, \text{if } \mathrm{p}_{\mathrm{it}}^{*} < 0 \end{cases}, \text{with } \mathrm{p}_{\mathrm{it}}^{*} = \beta_{P}\mathrm{x}_{\mathrm{it-1,P}} + \varepsilon_{\mathrm{it,P}} \tag{8}$$

Following, Heckman (1976) we assume that the error term $\varepsilon_{\mathrm{it,P}}$ follows a standard normal distribution and that the probability for a non-payoff outcome, and hence the opportunity to observe the outcome of the default probability, is explained by a probit model:

$$\begin{aligned} \mathrm{P}\left(p_{it} = 0 | \mathrm{x}_{\mathrm{it-1,P}}, \beta_{\mathrm{P}}\right) &= \mathrm{P}\left(\beta_{P}\mathrm{x}_{\mathrm{it-1,P}} + \varepsilon_{\mathrm{it,P}} \geq 0\right) = \mathrm{P}\left(\varepsilon_{\mathrm{it,P}} \leq \beta_{P}\mathrm{x}_{\mathrm{it-1,P}}\right) \\ &= \Phi\left(\beta_{P}\mathrm{x}_{\mathrm{it-1,P}}\right) \end{aligned} \tag{9}$$

We estimate the model by maximizing the log likelihood:

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23 We apply logit link functions and probit link functions in the robustness test. It has been shown that the distinction between logit and probit does not lead to materially different results for the sign of parameters and the impact on the dependent variables (i.e., probability of payoff and default, see e.g., Hamerle et al, 2006). Furthermore, we choose for the presentation of our model framework a latent variable derivation to contrast the three techniques to control for selection bias (multinomial logit, Inverse Mills Ratio and bivariate probit analysis).

24 The majority of models in political science make some form of Imbens' (2004) exogeneity assumption: systematic differences in treated and control units with the same values for the covariates are attributed to the treatment.

$$\ln\mathrm{L} = \sum_{i=1}^{I}\sum_{t=1}^{T} \ln\left[p_{it}\mathrm{P}\left(p_{it} = 1, \mathrm{x}_{\mathrm{it-1,P}}, \beta_{\mathrm{P}}\right) + (1 - p_{it})\left(1 - \mathrm{P}\left(p_{it} = 1, \mathrm{x}_{\mathrm{it-1,P}}, \beta_{\mathrm{P}}\right)\right)\right] \tag{10}$$

The parameters β_{P} are estimated by maximizing this log likelihood function.

As a next step, we compute the Inverse Mills Ratio:

$$\lambda\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right) = \frac{\phi\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right)}{\Phi\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right)}, \tag{11}$$

with the probability density function of the standard normal distribution $\phi(.)$ and the cumulative density function of the standard normal distribution $\Phi(.)$.

In a second step, following Agarwal, Ambrose, and Liu (2006), we include the Inverse Mills Ratio (IMR) into a probit model for default to control for the adverse selection in relation to payoff and other risk characteristics. The default model assumes that default occurs if a latent variable conditional on the risk factors and the Inverse Mills Ratio falls below a threshold (here zero):

$$\mathrm{D}_{\mathrm{i,t}} = \begin{cases} 1, \text{if } \mathrm{d}_{\mathrm{it}}^* \geq 0 \\ 0, \text{if } \mathrm{d}_{\mathrm{it}}^* < 0 \end{cases}, \text{with } \mathrm{d}_{\mathrm{it}}^* = \beta_D \mathrm{x}_{\mathrm{it-1,D}} + \beta_\lambda \lambda\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right) + \varepsilon_{\mathrm{it,D}} \tag{12}$$

The probability for a default outcome is explained by a probit model:

$$\begin{aligned} &\mathrm{P}\left(d_{it} = 1 | \mathrm{x}_{\mathrm{it-1,D}}, \beta_{\mathrm{D}}, p_{it} = 0\right) = \mathrm{P}\left(\beta_D \mathrm{x}_{\mathrm{it-1,D}} + \beta_\lambda \lambda\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right) + \varepsilon_{\mathrm{it,D}} \ \geq 0\right) = \\ &= \mathrm{P}\left(\varepsilon_{\mathrm{it,D}} \ \leq \beta_D \mathrm{x}_{\mathrm{it-1,D}} + \beta_\lambda \lambda\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right)\right) = \Phi\left(\beta_{\mathrm{D}} \mathrm{x}_{\mathrm{it-1,D}} + \beta_\lambda \lambda\left(\beta_{\mathrm{P}} \mathrm{x}_{\mathrm{it-1,P}}\right)\right) \end{aligned} \tag{13}$$

We estimate the model by maximizing the log likelihood:

$$\ln\mathrm{L} = \sum_{i=1}^{I}\sum_{t=1}^{T} \ln\left[d_{it}\mathrm{P}\left(d_{it} = 1, \mathrm{x}_{\mathrm{it-1,D}}, \beta_{\mathrm{D}}, \beta_\lambda\right) + (1 - d_{it})\left(1 - \mathrm{P}\left(d_{it} = 1, \mathrm{x}_{\mathrm{it-1,D}}, \beta_{\mathrm{D}}, \beta_\lambda\right)\right)\right] \tag{14}$$

The parameters β_{D} and β_{λ} are estimated by maximizing this log likelihood function.

Note that the estimated parameter β_{λ} is negative (see Table 12) for all our empirical models, which implies that a higher default risk (of borrowers remaining in the population) coincides with a lower likelihood to prepay.

We have tested these advanced models in a simulation study with known data generating processes and found: (i) adverse selection does not cause bias in parameters if our models capture all data generating variables, (ii) adverse selection causes bias in parameters if our models do not capture all data generating variables (in addition to the bias from the omitted variables).

The Inverse Mills Ratio provides for a correction if at least one variable explaining censoring/payoff is new (see Sartori, 2002). Thus, we include two further instrumental variables in the selection equation: loan owner type and lending standard.[25] Loan owner type includes Securitized (10.6% of all HELOCs), Portfolio (87.5% of all HELOCs) and Serviced For Others (SFO). Portfolio HELOCs are expected to have lower default risk than Securitized and SFO HELOCs (see for example, LaCour-Little and Zhang, 2014 who show that loss rates for Securitized HELOCs are greater than for Portfolio HELOCs). Furthermore, we control for the lending standards (STD) by including the net percentage of domestic banks tightening standards for HELOCs, which is reported by the Federal Reserve Bank. Negative values mean fewer banks reported tightening their standards than those reporting loosening their standards. Easing lending standards might result in higher origination volume and relatively higher delinquency rates at a later stage.

Table 12 shows the resulting parameter estimates for the payoff (selection) and the default (model) equation. Note that the number of observations is slightly lower than those in previous tables as we did not apply a cross-sectional mean replacement for instrumental variables. IMR is significant in the one-month model and insignificant in the one-year model, indicating some degree of sample selection bias in the one-month model. Nevertheless, the results after including IMR are still directionally consistent with those presented in the previous tables. In particular, the payment shock has a positive and highly significant impact on the default risk, and default risk increases approximately one quarter prior to EOD, peaks at EOD and then decreases over the year following

[25] Furthermore, we have included the rate spread in both selection and default equation. The rate spread is the difference between average HELOC rate per month and current interest rate of the HELOC. A lower value indicates a greater incentive to refinance as the rate provided by other lenders is likely to be lower. Table 6 shows that the impact is negative as a higher rate spread would imply a higher contract rate after refinance.

EOD. The coefficients and significance of the control variables are also consistent with those in the previous tables.

4.2.2. Bivariate probit

One critique for the multinomial logit model or competing hazard models is that these models only control for factors that are known but not factors that are unknown (Rosenmann et al. 2010). The same critique applies to the Inverse Mills Ratio with the prime innovation there that the approach accommodates separate control variables in the payoff and the default model.

We address the potential concern from this critique by estimating a bivariate probit model that controls for both observed and unobserved factors that explain the latent processes for payoff and default. Following Equations (8) and (12) and the correlation ρ between the two random processes:

$$\rho = corr(\varepsilon_{\mathrm{it,P}}, \varepsilon_{\mathrm{it,D}}). \tag{15}$$

The joint probability of a non-payoff and a default is:

$$\begin{aligned} &\mathrm{P}(p_{it} = 0, d_{it} = 1 | \mathrm{x}_{\mathrm{it-1,P}}, \mathrm{x}_{\mathrm{it-1,D}}, \beta_{\mathrm{P}}, \beta_{\mathrm{D}}) \\ &= \mathrm{P}(\beta_P \mathrm{x}_{\mathrm{it-1,P}} + \varepsilon_{\mathrm{it,P}} \geq 0, \beta_D \mathrm{x}_{\mathrm{it-1,D}} + \varepsilon_{\mathrm{it,D}} \geq 0) \\ &= \mathrm{P}(\varepsilon_{\mathrm{it,P}} \leq \beta_P \mathrm{x}_{\mathrm{it-1,P}}, \varepsilon_{\mathrm{it,D}} \leq \beta_D \mathrm{x}_{\mathrm{it-1,D}}) \\ &= \int_{-\infty}^{\beta_P \mathrm{x}_{\mathrm{it-1,P}}} \int_{-\infty}^{\beta_D \mathrm{x}_{\mathrm{it-1,D}}} f(\varepsilon_{\mathrm{it,P}}, \varepsilon_{\mathrm{it,D}}) d\varepsilon_{\mathrm{it,P}} \varepsilon_{\mathrm{it,D}} \\ &= \int_{-\infty}^{\beta_P \mathrm{x}_{\mathrm{it-1,P}}} \int_{-\infty}^{\beta_D \mathrm{x}_{\mathrm{it-1,D}}} \phi_2(\varepsilon_{\mathrm{it,P}}, \varepsilon_{\mathrm{it,D}}, \rho) d\varepsilon_{\mathrm{it,P}} \varepsilon_{\mathrm{it,D}} \\ &= \Phi_2(X_{i,t-1} \beta_P \mathrm{x}_{\mathrm{it-1,P}}, \beta_D \mathrm{x}_{\mathrm{it-1,D}}, \rho), \end{aligned} \tag{16}$$

where Φ_2 is the cumulative density function of the bivariate standard normal distribution. Note that according to Equation (9), the probability of a payoff is $\mathrm{P}(p_{it} = 1 | \mathrm{x}_{\mathrm{it-1,P}}, \beta_{\mathrm{P}}) = 1 - \Phi(\beta_P \mathrm{x}_{\mathrm{it-1,P}})$. We estimate the parameters by maximizing the log likelihood:

$$\ln \mathrm{L} = \sum_{i=1}^{I} \sum_{t=1}^{T} \ln\left[p_{it} 1 - \Phi\left(\beta_P \mathrm{x}_{\mathrm{it-1,P}}\right) + (1 - p_{it}) d_{it} \Phi_2\left(X_{i,t-1} \beta_P \mathrm{x}_{\mathrm{it-1,P}}, \beta_D \mathrm{x}_{\mathrm{it-1,D}}, \rho\right)\right.$$
$$\left. + (1 - p_{it})\left(1 - (1 - p_{it})\right) d_{it} \Phi_2\left(X_{i,t-1} \beta_P \mathrm{x}_{\mathrm{it-1,P}}, -\beta_D \mathrm{x}_{\mathrm{it-1,D}}, \rho\right)\right] \tag{17}$$

Again, the number of observations is slightly lower than in Model 1 as we did not apply a cross-sectional mean replacement for instrumental variables. The results from bivariate probit models shown in Table 13 are still directionally consistent with those presented in the previous tables. In particular, the payment shock has a positive and highly significant impact on the default risk, and default risk increases approximately one quarter prior to EOD, peaks at EOD and the decreases over the year following EOD. The coefficients and significance of the control variables are also consistent with those in the previous tables.

4.3. Ability to refinance and payment shock effect

Our payoff models (see Table 6, Table 12 and Table 13) show that HELOC borrowers are more likely to refinance when rate spread is low, lending standards are loosened, and their HELOCs are not securitized. Portfolio HELOCs are associated with payoff risk lower than securitized and other HELOCs which is consistent with our priors. This may indicate that lenders may retain HELOCs with a lower pre-payment risk on their books. Note that only a very small percentage of all HELOCs are serviced for others, which is the reference category.

Underwriting standards have tightened in recent years. For example, following the great financial crisis in 2008-2009, the mean CLTV and mean utilization rate have decreased while the mean FICO has increased. However, the tightening of lending standards has slowed down resulting in an increased volume of newly originated HELOCs since 2014.

Tightening lending standards may lead to a number of consequences:

- Some of the EOD HELOCs may not be able to refinance under new tightened underwriting standards.
- Low quality borrowers find it harder (indeed may not be able to refinance) under the new tightened underwriting standards. In addition, borrowers may pay a higher price (in terms of spread) for refinance. For example, industry estimates show that there are \$70 billion HELOCs with high LTV in excess of 90%, which may have difficulty refinancing.

- Loans remaining on banks' books may be very different from those that originated in early 2000, and those that had been paid off or refinanced. We control for underwriting effects by measuring various variables at origination and control for any remaining lending standard effects via origination year dummies following Alp (2013) and Blume et al. (1998).

Furthermore, we analyze whether the payment shock corresponds to a changing ability to refinance by analyzing its interaction with several proxy variables. Our prior expectation would be that tighter bank lending standards imply a larger effect of payment shock on HELOC default as it is more difficult for HELOC borrowers to mitigate the payment shock through HELOC refinance. We test the following alternative proxies for the ability to pay off or refinance:

- Model 9: Net percentage of domestic banks tightening standards for HELOCs, reported by the Federal Reserve Bank (expectation: **positive** sign): a greater measure may indicate that refinance is more difficult and may hence strengthen the impact of payment shock;
- Model 10: Rate spread or the difference between the current interest rate and the average HELOC rate (expectation: **positive** sign): a greater measure may indicate a lower credit worthiness and greater difficulty to refinance despite a stronger incentive to do so and may hence strengthen the impact of payment shock;
- Model 11: Voluntary HELOC balance payoff defined as the sum of total HELOC balances in the data that has been paid off (expectation: **negative** sign): a lower measure may indicate that refinance is more difficult and may hence strengthen the impact of payment shock.

We have also tested voluntary credit line termination, i.e., the sum of total HELOC balances in the data that is terminated by borrowers (expectation: negative sign): a lower measure may indicate that refinance is more difficult and may hence strengthen the impact of payment shock. The results for this model are almost identical to Model 11 and we chose not to report the estimates for brevity.

Table 14 shows the parameter estimates for the interaction between payment shock and the ability to refinance proxies (standard) and the standalone effects (which can only be interpreted in conjunction with the interaction). The empirical results support the hypothesis that the lower ability to refinance (i.e., a higher percentage of banks tightening underwriting standards, higher rate spread and lower total HELOC balance paid off or credit lines termination), the higher the payment shock impact on HELOC default.

Note that the number of observations is slightly lower as in previous tables as we did not apply a cross-sectional mean replacement for missing values of the ability to refinance proxies in Model 11. The number of observations is not reduced for Panel B (default within one year) as the missing values coincide with the last observation months that are not analyzed as HELOC outcomes are not observed for a complete year.

5. Conclusions

We study the end of draw risk of home equity lines of credit using a large representative data set covering the largest US mortgage servicers. We find that the default risk increases due to a combination of payment shock and loss of liquidity facility as a HELOC approaches EOD. We investigate the key drivers of the increased default risk and have two important findings.

First, payment shock has a positive and significant impact on default risk. Our empirical analysis shows that the monthly probability of default increases by approximately 3.7 times and the annual probability of default by 2.1 times for a payment shock of $3,000 on a $1 million property. Our analysis is based on a rigorous approach that allows for non-monotonicity, controls for a large number of control variables, and provides for confidence levels based on clustered standard errors. We find that the payment shock is more pronounced if HELOC borrowers are somewhat surprised by the loss of liquidity facility through a greater difficulty to refinance.

Second, default risk increases at EOD and then decreases over the twelve months following EOD. The probability of default is approximately 3.3 times higher at its peak (and the annual probability of default by approximately 1.6 times higher) than the probability of default prior to EOD.

These findings hold after controlling for a large number of observable information on the borrower, the loan, the collateral and the economy. The findings also hold for alternate payment shock definitions, lending standard definitions and after control for a potential sample selection effect through the payoff channel. All results, in particular reported significance levels, and confidence levels are based on clustered standard errors.

An unprecedented number of HELOCs are about to experience the transition from interest-only payments to interest plus principal payments and our models project an increase of both HELOC payoff as well as defaults.

Our study has a number of important prudential policy recommendations for lenders and regulators for HELOC risk measurement, contract design, and risk mitigation. First, banks' loss projection models and debt impairment evaluations for HELOCs approaching EOD should include variables that measure payment shock and loss of line utility. Where volumes warrant, HELOCs approaching EOD should form a separate risk segment in the allowance process. Our study captures payment shock and liquidity constraint explicitly and thus should help financial institutions improve their HLEOC credit risk models and be prepared for this anticipated surge in default risk. Cumulative risk profile, factors affecting the ability to refinance, and borrower liquidity measures are extremely useful for financial institutions to appropriately cover HELOC risk through product pricing, provisioning and capital allocation.

Second, our study highlights the importance of better HELOC and mortgage contract design at origination. Examiners have seen some high risk HELOC contracts with liberal repayment terms and that are meant to be refinanced not repaid. For example, some loans have a 10-year draw period plus 30-year repayment period, a total of 40 years of term. It is highly unlikely that financial institutions can accurately price HELOCs with such long term.

Third, risk mitigation techniques, such as troubled debt restructuring, forbearance, workout, and modification programs should include payment terms that are affordable, but also promote orderly and systematic repayment of principal. Speculative elements, like interest-only, balloon maturity, or negative amortization, should be avoided. Our study measures the link between payment shock and default risk. Furthermore, lenders and regulators may include the smoothing of the payment shock during economic downturn periods.

Lastly, the impact of positive payment shock and loss of liquidity at HELOC EOD on the financial system is likely to depend on the future state of the economy. Other key variables, such as FICO and CLTV, can deteriorate and can exacerbate the level of default risk in stressed economic conditions. Hence, our models may be used for stress-testing that captures both the end of draw and economic downturn effects. For example, during and post economic downturn lenders have tightened underwriting standards, cut credit lines and reduced borrower liquidity.

In summary, measuring payment shock and time to EOD and quantifying their impact on mortgage default risk is of great importance to lenders and the resilience of the financial system. Payment shock and loss of liquidly facility (due to a HELOC reaching end of draw period) can exacerbate the impact of house price decline on mortgage default risk.

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Table 1: Variable definitions

Variable (Abbreviation)	Definition
	Panel A: dependent variables
Payoff within one month (P1)	0: No payoff event, 1: Payoff event
Payoff within one year (P12)	0: No payoff event, 1: Payoff event
Default within one month (D1)	0: No default event, 1: Default event
Default within one year (D12)	0: No default event, 1: Default event
	Panel B: test variables
Payment shock (PS)	(Minimum payment current - Minimum payment 1 year prior to EOD) / updated property value
Time since EOD (TSEOD)	Years between observation time and EOD
	Panel C: control variables (continuous)
Current utilization rate (CUR)	Outstanding principal balance / credit limit
FICO	Borrower credit score in current period, scaled by 1,000
Combined loan to value (CLTV)	Total outstanding loan amount / updated property value
Cumulative excess payment (CEP)	(Cumulative payments over minimum payment) / property value at origination
Interest rate at origination (IRO)	Contractual interest rate at origination
Log property value (LPV)	Natural logarithm of the updated property value
Rate spread (RS)	(Current interest rate-Average HELOC rate) / Average HELOC rate
Average term spread (ATS)	Ten-year Treasury bond yield - one-year Treasury bond yield
Change in HPI (HPA)	Annual growth in house price index at MSA level
UER change since origination (UER)	Unemployment rate change since origination at MSA level
Lending standards (STD)	Net percentage of domestic banks tightening standards for HELOCs from Federal Reserve Board Senior Loan Officer Survey
	Panel D: control variables (categorical)
Balloon (B)	1: Balloon loan (B), 0: Non-balloon loan (NB)
Interest Only (IO)	1: Interest-only payments, 0: Otherwise
Asset documentation (ADOC)	1: Full / verified, 0: Otherwise
Income documentation (IDOC)	1: Full / verified, 0: Otherwise
Owner occupancy (OC)	1: Owner occupied, 0: Non-owner occupied
Property type (PRT)	1: Multi-family property/ others, 0: Single family residence
Lien	1: Second lien, 0: First lien
Loan source (LS)	1: Non-retail (wholesale, correspondent, servicing rights purchased, bulk purchased, and wealth management / private banking), 0: Retail
Credit line frozen (CLF)	1: HELOC closed or frozen 6 months prior EOD, 0: Otherwise
OCC BK7 write down guidance (OCC)	1: 3 months after OCC issued guidance to write down loans discharged in Chapter 7 bankruptcy judgments, 0: Otherwise
Judicial procedure (JP)	1: Judicial procedure, 0: Non judicial procedure
Statutory right of redemption (SRR)	1: Statutory right of redemption, 0: Otherwise
Prohibit deficiency judgment (PDJ)	1: Prohibit deficiency judgement, 0: recourse
HELOC owner: securitized (SEC)	1: Securitized, 0: Otherwise
HELOC owner: bank portfolio (POR)	1: Portfolio, 0: Otherwise
Origination year (Oyear) 2001 to 2010	1: 2001 to 2010, 0: Otherwise

Table 2: Summary statistics for the continuous variables for all observations, payoff observations and default observations in the test sample

	PS	TSEOD	CUR	FICO	CLTV	CEP	IRO	LPV	RS	ATS	HPA	UER	STD
All Observations (N=28,329,688)													
Mean	0.00025	-0.259	0.588	0.743	0.647	0.071	0.059	12.467	-0.053	0.023	0.022	0.027	-0.014
Median	0.00000	-0.340	0.753	0.764	0.630	0.012	0.053	12.445	-0.167	0.024	0.012	0.023	-0.028
SD	0.00074	0.559	0.406	0.075	0.418	0.160	0.020	0.735	0.357	0.005	0.066	0.022	0.056
P5	-0.00011	-1.000	0.000	0.586	0.070	-0.014	0.037	11.293	-0.394	0.015	-0.073	-0.004	-0.071
P95	0.00166	0.830	1.000	0.830	1.407	0.338	0.098	13.717	0.789	0.033	0.154	0.069	0.074
Missing	0.00000	0.000	0.189	0.024	0.012	0.000	0.279	0.000	0.006	0.000	0.037	0.019	0.000
Payoffs (P1=1, N=632,554)													
Mean	0.00018	-0.134	0.291	0.777	0.554	0.110	0.056	12.528	-0.125	0.023	0.029	0.023	-0.018
Median	0.00000	-0.090	0.000	0.794	0.550	0.031	0.050	12.496	-0.184	0.023	0.017	0.020	-0.028
SD	0.00072	0.413	0.385	0.055	0.328	0.198	0.018	0.748	0.232	0.005	0.062	0.020	0.045
P5	-0.00007	-0.920	0.000	0.669	0.060	-0.002	0.037	11.347	-0.390	0.015	-0.059	-0.005	-0.071
P95	0.00124	0.660	0.997	0.837	1.070	0.506	0.092	13.818	0.281	0.032	0.147	0.060	0.062
Missing	0.00000	0.000	0.236	0.042	0.035	0.000	0.594	0.000	0.004	0.000	0.061	0.036	0.000
Defaults (D1=1, N=191,118)													
Mean	0.00052	-0.101	0.778	0.682	0.795	0.044	0.062	12.458	0.052	0.023	0.018	0.031	-0.010
Median	0.00000	-0.090	0.971	0.691	0.786	0.000	0.055	12.448	-0.131	0.024	0.012	0.026	-0.028
SD	0.00109	0.517	0.347	0.104	0.519	0.157	0.023	0.738	0.462	0.005	0.072	0.025	0.063
P5	-0.00015	-0.920	0.000	0.514	0.068	-0.048	0.037	11.250	-0.391	0.015	-0.090	-0.005	-0.071
P95	0.00338	0.830	1.000	0.824	1.848	0.249	0.106	13.696	1.155	0.033	0.154	0.076	0.107
Missing	0.00000	0.000	0.477	0.035	0.008	0.000	0.150	0.000	0.007	0.000	0.019	0.006	0.000

Table 3: Correlation between the continuous variables

	TSEOD	CUR	FICO	CLTV	CEP	IRO	LPV	RS	ATS	HPA	UER	STD
PS	0.404	0.155	-0.063	0.035	0.030	-0.023	-0.098	-0.042	0.021	-0.055	0.032	0.010
TSEOD	1.000	0.103	-0.092	0.065	-0.091	0.023	-0.062	0.100	0.027	-0.123	0.087	0.030
CUR		1.000	-0.453	0.252	-0.159	0.155	-0.067	0.198	0.069	-0.012	0.068	0.000
FICO			1.000	-0.248	0.174	-0.224	0.118	-0.266	-0.102	0.122	-0.168	-0.050
CLTV				1.000	-0.078	0.359	-0.246	0.350	0.116	-0.253	0.354	0.080
CEP					1.000	-0.118	-0.069	-0.161	-0.072	0.137	-0.186	-0.080
IRO						1.000	-0.181	0.437	0.114	-0.248	0.343	0.050
LPV							1.000	-0.213	-0.051	0.197	-0.133	-0.060
RS								1.000	0.177	-0.228	0.241	0.060
ATS									1.000	-0.189	0.293	0.100
HPA										1.000	-0.564	-0.270
UER											1.000	0.270

Table 4: Summary statistics of the categorical variables for all observations, payoff observations, and default observations in the test sample

	B	IO	ADOC	IDOC	OC	PRT	LIEN	LS	CLF	OCC	JP	PDJ	SRR	SEC	POR
Relative frequency															
0	0.690	0.327	0.880	0.818	0.104	0.420	0.176	0.808	0.588	0.955	0.607	0.888	0.717	0.894	0.125
1	0.310	0.672	0.120	0.177	0.884	0.573	0.824	0.191	0.329	0.045	0.393	0.112	0.283	0.106	0.875
Missing	0.000	0.001	0.000	0.006	0.013	0.007	0.000	0.000	0.083	0.000	0.000	0.000	0.000	0.000	0.000
Payoff rate (P1=1)															
0	0.014	0.018	0.023	0.022	0.030	0.024	0.027	0.023	0.027	0.022	0.024	0.022	0.023	0.024	0.011
1	0.041	0.024	0.016	0.025	0.021	0.020	0.021	0.019	0.015	0.023	0.020	0.029	0.021	0.008	0.024
Missing	0.000	0.049	0.010	0.011	0.031	0.064	0.000	0.038	0.016	0.000	0.000	0.000	0.000	0.000	0.000
Default rate (D1=1)															
0	0.071	0.071	0.056	0.060	0.061	0.045	0.039	0.053	0.035	0.056	0.059	0.056	0.053	0.052	0.093
1	0.025	0.049	0.063	0.042	0.056	0.060	0.060	0.073	0.088	0.066	0.053	0.058	0.065	0.096	0.051
Missing	0.000	0.003	0.018	0.063	0.030	0.476	0.000	0.042	0.085	0.000	0.000	0.000	0.000	0.000	0.000

Table 5: Descriptive statistics for minimum payment, raw payment shock and payment shock. MP EOD is minimum payment at EOD, MP pre-EOD is minimum payment one year before EOD, raw payment shock is the difference between MP EOP and MP pre-EOD, payment shock is raw payment shock divided by current property value.

	MP EOD	MP Pre-EOD	Raw payment shock	Property value	Payment shock
			Panel A: all HELOCs		
Mean	1,161.885	165.804	996.081	342,326.321	0.00076
Median	225.000	52.415	91.795	247,444.500	0.00039
SD	13,646.300	1,705.745	13,515.740	355,321.876	0.00112
P5	0.000	0.000	-43.000	78,100.000	-0.00022
P95	1,491.139	654.000	1,063.721	881,454.000	0.00357
Missing	0.000	0.000	0.000	0.000	0.00000
			Panel B: non-balloon HELOCs		
Mean	451.595	177.889	273.706	346,917.777	0.00073
Median	238.000	70.000	92.385	253,167.500	0.00039
SD	3,722.847	1,878.523	3,204.107	353,915.163	0.00103
P5	0.000	0.000	-25.204	81,278.000	-0.00012
P95	1,373.052	677.501	919.527	883,973.000	0.00307
Missing	0.000	0.000	0.000	0.000	0.00000
			Panel C: balloon HELOCs		
Mean	4,412.387	110.497	4,301.890	321,314.416	0.00092
Median	150.000	0.000	87.000	221,180.500	0.00037
SD	31,018.268	267.991	30,957.388	360,946.366	0.00145
P5	0.000	0.000	-141.000	67,465.000	-0.00066
P95	17,875.622	502.575	17,775.000	867,229.000	0.00443
Missing	0.000	0.000	0.000	0.000	0.00000

Table 6: Baseline one-month payoff and default models (Model 1). Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

Variable	Payoff (P1)		Default (D1)		Variable	Payoff (P1)		Default (D1)	
Intercept	-10.111	(0.334)***	-5.320	(0.389)***	Income doc.	0.170	(0.034)***	-0.482	(0.074)***
Payment shock	-86.839	(26.01)***	248.483	(32.816)***	OC	0.037	(0.076)	-0.289	(0.180)
TSEOD (-0.75 to -0.5)	-0.001	(0.030)	0.117	(0.014)***	Property type	-0.088	(0.037)**	0.262	(0.056)***
TSEOD (-0.5 to -0.25)	0.770	(0.151)***	0.415	(0.035)***	Second lien	0.084	(0.018)***	0.075	(0.044)*
TSEOD (-0.25 to 0)	2.426	(0.074)***	0.616	(0.053)***	Loan source	-0.167	(0.050)***	0.194	(0.071)***
TSEOD (0 to 0.25)	1.841	(0.105)***	1.197	(0.086)***	CLF	0.437	(0.071)***	0.312	(0.066)***
TSEOD (0.25 to 0.5)	1.310	(0.124)***	0.526	(0.067)***	OCC	-0.072	(0.047)	0.250	(0.033)***
TSEOD (0.5 to 0.75)	1.117	(0.121)***	0.224	(0.069)***	ATS	-0.666	(2.328)	-1.916	(1.521)
TSEOD (0.75 to 1)	1.131	(0.107)***	0.129	(0.075)*	HPA	0.328	(0.332)	0.968	(0.492)**
CUR	-1.204	(0.052)***	0.384	(0.053)***	UER	-2.390	(1.065)**	2.830	(1.421)**
FICO	5.449	(0.302)***	-4.442	(0.217)***	JP	-0.116	(0.058)**	-0.087	(0.070)
FICO (from 620)	-0.005	(0.002)**	-0.019	(0.001)***	PDJ	-0.264	(0.057)***	-0.020	(0.068)
FICO (from 660)	0.006	(0.002)***	0.014	(0.001)***	SRR	0.226	(0.051)***	0.126	(0.112)
FICO (from 725)	-0.003	(0.001)***	0.015	(0.001)***	Oyear 2001	0.185	(0.041)***	0.016	(0.270)
CLTV	-0.052	(0.041)	0.426	(0.026)***	Oyear 2002	0.061	(0.047)	0.638	(0.145)***
CLTV (from 100)	-1.078	(0.139)***	0.019	(0.009)**	Oyear 2003	-0.089	(0.056)	1.112	(0.119)***
CEP	0.568	(0.067)***	-0.003	(0.231)	Oyear 2004	-0.029	(0.086)	0.908	(0.114)***
IRO	-0.532	(0.843)	-0.415	(0.758)	Oyear 2005	-0.248	(0.068)***	0.667	(0.071)***
LPV	0.121	(0.029)***	0.168	(0.022)***	Oyear 2006	-0.659	(0.106)***	0.744	(0.078)***
Rate spread	-0.328	(0.075)***	0.226	(0.081)***	Oyear 2007	-0.009	(0.110)	0.788	(0.089)***
Balloon	0.997	(0.095)***	-0.573	(0.203)***	Oyear 2008	-0.548	(0.114)***	0.438	(0.117)***
Interest only	-0.054	(0.057)	0.189	(0.172)	Oyear 2009	-0.695	(0.200)***	0.214	(0.315)
Asset doc.	0.039	(0.046)	-0.009	(0.055)	Oyear 2010	0.356	(0.157)**	1.708	(0.472)***
Pseudo R-square	0.164		0.164		AUROC	0.795		0.786	
Accuracy ratio	0.591		0.572		Observations	28,329,688		28,329,688	

Table 7: Alternative model specifications, default within one month. Model 1: the baseline one-month model, Models 2-4: alternative models, Model 6: the same variables as in Johnson & Sarama (2014). Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PS	248.483(32.816)***		261.761(32.579)***	324.720(32.884)***		
TSEOD (0.25)	1.197 (0.086)***	1.374(0.100)***	1.208 (0.088)***			
TSEOD (1)	0.129 (0.075)*	0.301(0.064)***	0.138 (0.078)*			
CUR	0.384 (0.053)***	0.462(0.050)***		0.410 (0.049)***		
FICO current	-4.442 (0.217)***	-4.422(0.243)***	-4.689 (0.205)***	-4.616 (0.184)***	-4.881(0.227)***	
CLTV	0.426 (0.026)***	0.465(0.028)***	0.441 (0.025)***	0.439 (0.028)***	0.527(0.030)***	0.371(0.058)***
CEP	-0.003 (0.231)	0.055(0.206)	-0.050 (0.229)	-0.037 (0.242)	-0.069(0.215)	
Other borrower characteristics	Included	Included	Included	Included	Included	Included
Other loan characteristics	Included	Included	Included	Included	Included	Included
Macroeconomic variables	Included	Included	Included	Included	Included	Included
Pseudo R-square	0.164	0.163	0.151	0.092	0.078	0.083
Accuracy ratio	0.572	0.565	0.572	0.530	0.511	0.370
AUROC	0.786	0.782	0.786	0.765	0.756	0.685
Observations	28,329,688	28,329,688	28,329,688	28,329,688	28,329,688	28,329,688

Table 8: Alternative model specifications, default within one year. Model 1: the baseline one-month model, Models 2-4: alternative models, Model 6: the same variables as in Johnson & Sarama (2014). Numbers in parenthesis are standard error clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
PS	143.122(14.836)***		131.701(14.288)***	100.715(16.404)***		
TSEOD (0.25)	0.285 (0.044)***	0.381(0.054)***	0.274 (0.042)***			
TSEOD (1)	-0.150 (0.052)***	-0.055(0.059)	-0.156 (0.050)***			
CUR	-0.264 (0.061)***	-0.231(0.061)***		-0.257 (0.062)***		
FICO current	-3.839 (0.324)***	-3.776(0.339)***	-3.547 (0.286)***	-3.844 (0.326)***	-3.517(0.297)***	
CLTV	0.311 (0.079)***	0.324(0.079)***	0.281 (0.080)***	0.306 (0.079)***	0.290(0.081)***	-0.024(0.116)
CEP	-0.259 (0.206)	-0.226(0.194)	-0.230 (0.210)	-0.182 (0.202)	-0.150(0.199)	
Other borrower characteristics	Included	Included	Included	Included	Included	Included
Other loan characteristics	Included	Included	Included	Included	Included	Included
Macroeconomic variables	Included	Included	Included	Included	Included	Included
Pseudo R-square	0.328	0.324	0.288	0.316	0.264	0.204
Accuracy ratio	0.507	0.505	0.514	0.506	0.509	0.359
AUROC	0.754	0.752	0.757	0.753	0.755	0.680
Observations	20,749,241	20,749,241	20,749,241	20,749,241	20,749,241	20,749,241

Table 9: Model results based on alternative payment shock definitions. PS, PS_Orig PV and PS_Credit Line is raw payment shock divided by the updated property value, property value at origination, and credit line, respectively. Models 1, 7 and 8 are estimated using PS, PS_Orig PV and PS_Credit Line, respectively. Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Payment shock descriptive statistics			
	PS	**PS_Orig PV**	**PS_Credit Line**
Mean	0.00025	0.00024	0.00048
Median	0.00000	0.00000	0.00000
SD	0.00074	0.00073	0.00172
P5	-0.00011	-0.00010	-0.00047
P95	0.00166	0.00169	0.00395
Missing	0.00000	0.03738	0.15902
Panel B: default within one month			
	Model 1	**Model 7**	**Model 8**
PS	248.483 (32.816)***	197.474 (34.100)***	195.901 (8.511)***
TSEOD (0.25)	1.197 (0.086)***	1.219 (0.078)***	0.339 (0.146)**
TSEOD (1)	0.129 (0.075)*	0.167 (0.075)**	-0.205 (0.041)***
CUR	0.384 (0.053)***	0.395 (0.055)***	-0.013 (0.075)
FICO current	-4.442 (0.217)***	-4.465 (0.252)***	-5.481 (0.337)***
CLTV	0.426 (0.026)***	0.346 (0.052)***	0.268 (0.113)**
CEP	-0.003 (0.231)	0.065 (0.207)	-0.427 (0.295)
Other borrower characteristics	Included	Included	Included
Other loan characteristics	Included	Included	Included
Macroeconomic variables	Included	Included	Included
Pseudo R-square	0.164	0.154	0.197
Accuracy ratio	0.572	0.563	0.621
AUROC	0.786	0.782	0.811
Observations	28,329,688	27,270,747	23,824,637
Panel C: default within one year			
	Model 1	**Model 7**	**Model 8**
PS	143.122 (14.836)***	113.053 (17.603)***	82.107 (6.856)***
TSEOD (0.25)	0.285 (0.044)***	0.296 (0.039)***	-0.038 (0.041)
TSEOD (1)	-0.150 (0.052)***	-0.131 (0.050)***	-0.308 (0.048)***
CUR	-0.264 (0.061)***	-0.257 (0.059)***	-0.373 (0.070)***
FICO current	-3.839 (0.324)***	-3.872 (0.356)***	-4.459 (0.419)***
CLTV	0.311 (0.079)***	0.309 (0.085)***	0.325 (0.090)***
CEP	-0.259 (0.206)	-0.219 (0.179)	-0.448 (0.209)**
Other borrower characteristics	Included	Included	Included
Other loan characteristics	Included	Included	Included
Macroeconomic variables	Included	Included	Included
Pseudo R-square	0.328	0.308	0.360
Accuracy ratio	0.507	0.502	0.541
AUROC	0.754	0.751	0.770
Observations	20,749,241	19,797,120	17,983,234

Table 10: Test and control samples combined (Model 1). Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Panel A: within one month				Panel B: within one year			
Variable	**Payoff**		**Default**		**Payoff**		**Default**	
PS	-55.45	(20.098)***	362.157	(24.561)***	-213.574	(31.500)***	233.231	(12.581)***
TSEOD (-1 to -0.75)	0.065	(0.033)**	0.249	(0.051)***	1.286	(0.078)***	0.867	(0.046)***
TSEOD (-0.75 to -0.5)	0.116	(0.035)***	0.351	(0.053)***	1.753	(0.084)***	1.242	(0.059)***
TSEOD (-0.5 to -0.25)	0.885	(0.141)***	0.652	(0.063)***	1.824	(0.083)***	1.287	(0.059)***
TSEOD (-0.25 to 0)	2.504	(0.080)***	0.872	(0.077)***	1.720	(0.076)***	1.215	(0.059)***
TSEOD (0 to 0.25)	1.822	(0.101)***	1.502	(0.099)***	1.339	(0.120)***	1.030	(0.060)***
TSEOD (0.25 to 0.5)	1.287	(0.109)***	0.827	(0.080)***	1.121	(0.123)***	0.679	(0.057)***
TSEOD (0.5 to 0.75)	1.091	(0.109)***	0.53	(0.082)***	1.141	(0.123)***	0.625	(0.060)***
TSEOD (0.75 to 1)	1.100	(0.095)***	0.441	(0.087)***	1.062	(0.115)***	0.585	(0.061)***
CUR	-1.010	(0.033)***	0.551	(0.076)***	-1.115	(0.031)***	0.262	(0.076)***
FICO	7.067	(0.381)***	-4.82	(0.177)***	5.222	(0.403)***	-4.441	(0.229)***
CLTV	-0.096	(0.041)**	0.349	(0.040)***	0.056	(0.029)*	0.262	(0.069)***
CEP	0.652	(0.062)***	0.038	(0.192)	0.157	(0.054)***	-0.356	(0.139)**
Other borrower characteristics	Included		Included		Included		Included	
Other loan characteristics	Included		Included		Included		Included	
Macroeconomic variables	Included		Included		Included		Included	
Pseudo R-square	0.155		0.155		0.274		0.274	
Accuracy ratio	0.560		0.657		0.556		0.617	
AUROC	0.780		0.829		0.778		0.809	
Observations	56,659,376		56,659,376		46,247,385		46,247,385	

Table 11: One-month baseline default model by risk segment. Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

Segment	PS		TSEOD(0.25)		TSEOD(1)		CUR		Others	R-square	AR	AUROC	Observation
All	248.483	(32.816)***	1.197	(0.086)***	0.129	(0.075)*	0.384	(0.053)***	Included	0.164	0.572	0.786	28,329,688
Balloon (0)	189.850	(20.384)***	1.049	(0.085)***	0.243	(0.059)***	0.33	(0.053)***	Included	0.099	0.511	0.755	19,547,317
Balloon (1)	252.420	(160.255)	2.309	(0.108)***	0.235	(0.222)	0.534	(0.175)***	Included	0.242	0.807	0.903	8,782,371
Interest-only (0)	369.902	(60.556)***	0.199	(0.150)	-0.528	(0.092)***	0.571	(0.057)***	Included	0.177	0.690	0.845	9,298,619
Interest-only (1)	-19.933	(129.262)	1.881	(0.051)***	0.639	(0.117)***	0.214	(0.053)***	Included	0.173	0.567	0.783	19,031,069
Loan source (0)	166.368	(21.780)***	1.329	(0.082)***	0.201	(0.079)**	0.365	(0.050)***	Included	0.170	0.565	0.782	22,911,331
Loan source (1)	495.821	(55.288)***	0.845	(0.138)***	-0.06	(0.046)	0.474	(0.064)***	Included	0.158	0.612	0.806	5,418,357
FICO (300 to 620)	327.201	(18.203)***	0.583	(0.084)***	-0.082	(0.032)**	0.913	(0.051)***	Included	0.149	0.395	0.698	2,904,653
FICO (620 to 660)	394.783	(47.738)***	0.857	(0.152)***	0.006	(0.051)	0.253	(0.083)***	Included	0.092	0.437	0.718	1,596,562
FICO (660 to 700)	402.419	(51.022)***	1.037	(0.124)***	-0.016	(0.086)	0.422	(0.085)***	Included	0.108	0.430	0.715	5,287,016
FICO (from 700)	-109.058	(75.908)	1.939	(0.091)***	0.527	(0.139)***	0.067	(0.047)	Included	0.164	0.573	0.787	18,541,457
CUR (0% to 50%)	469.563	(156.494)***	1.118	(0.239)***	0.326	(0.179)*			Included	0.225	0.622	0.811	9,250,770
CUR (50% to 70%)	467.467	(82.131)***	0.767	(0.151)***	0.013	(0.106)			Included	0.112	0.649	0.824	2,003,052
CUR (70% to 95%)	446.518	(44.563)***	0.366	(0.123)***	-0.263	(0.068)***			Included	0.114	0.639	0.819	4,937,314
CUR (95% to 100%)	520.304	(22.947)***	0.316	(0.120)***	-0.056	(0.058)			Included	0.105	0.575	0.787	7,633,501
CLTV (0% to 80%)	92.568	(71.626)	1.699	(0.039)***	0.46	(0.081)***	0.248	(0.031)***	Included	0.166	0.551	0.776	18,617,827
CLTV (80% to 90%)	224.653	(42.205)***	1.623	(0.086)***	0.382	(0.097)***	0.366	(0.064)***	Included	0.140	0.614	0.807	2,714,724
CLTV (90% to 95%)	259.118	(30.601)***	1.359	(0.143)***	-0.08	(0.188)	0.429	(0.070)***	Included	0.150	0.629	0.814	1,167,168
CLTV (95% to 100%)	409.904	(41.102)***	0.728	(0.114)***	-0.112	(0.097)	0.362	(0.090)***	Included	0.163	0.630	0.815	913,383
CLTV (from 100%)	423.583	(22.372)***	0.221	(0.115)*	-0.338	(0.028)***	0.765	(0.097)***	Included	0.162	0.613	0.807	4,916,586

Table 12: Robustness check for sample selection bias. Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Panel A: within one month		**Panel B: within one year**	
	Payoff	**Default**	**Payoff**	**Default**
PS	-48.538(10.865)***	106.589(12.989)***	-138.319(24.106)***	88.977(10.278)***
TSEOD (0.25)	0.766 (0.041)***	0.330 (0.040)***	0.187 (0.107)*	0.133 (0.036)***
TSEOD (1)	0.484 (0.039)***	-0.040 (0.025)	0.026 (0.100)	-0.072 0.025)***
CUR	-0.48 (0.020)***	0.226 (0.030)***	-0.954 (0.032)***	0.089 (0.078)
FICO current	2.222 (0.136)***	-2.213 (0.092)***	3.346 (0.200)***	-2.500 (0.336)***
CLTV	-0.030 (0.019)	0.190 (0.014)***	-0.016 (0.023)	0.225 (0.036)***
CEP	0.286 (0.031)***	-0.083 (0.075)	0.171 (0.051)***	-0.159 (0.082)*
IMR		-3.891 (0.594)***		-0.150 (0.902)
STD	-0.273 (0.106)***		-0.059 (0.067)	
SEC	-0.292 (0.034)***		-0.056 (0.07)	
POR	-0.328 (0.027)***		-0.567 (0.053)***	
Other borrower characteristics	Included	Included	Included	Included
Other loan characteristics	Included	Included	Included	Included
Macroeconomic variables	Included	Included	Included	Included
Pseudo R-square	0.175	0.102	0.351	0.153
Accuracy ratio	0.595	0.576	0.639	0.536
AUROC	0.798	0.788	0.819	0.768
Observations Used	27,592,375	27,592,375	20,157,141	20,157,141

Table 13: Bivariate probit model. Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Panel A: within one month		**Panel B: within one year**	
	Payoff	**Default**	**Payoff**	**Default**
PS	-36.871(0.869)***	85.269(0.935)***	-111.113(0.572)***	78.587(0.601)***
TSEOD (0.25)	0.539(0.002)***	0.301(0.002)***	0.182(0.001)***	0.137(0.002)***
TSEOD (1)	0.245(0.003)***	-0.134(0.004)***	0.034(0.002)***	-0.071(0.002)***
SEC	-0.295(0.005)***		-0.180(0.003)***	
POR	-0.339(0.004)***		-0.409(0.002)***	
STD	-0.297(0.012)***		-0.042(0.006)***	
Score	0.459(0.001)***	0.382(0.001)***	0.596(0.000)***	0.553(0.001)***
Other borrower characteristics	Included	Included	Included	Included
Other loan characteristics	Included	Included	Included	Included
Macroeconomic variables	Included	Included	Included	Included
AIC	7,111,609		26,307,477	
Obs. Used	27,592,375		20,157,141	

Table 14: Ability to refinance and payment shock impact. Model 9: lending standards (STD), Model 10: rate spread, Model 11: total balance paid off. Numbers in parenthesis are standard errors clustered by state. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Descriptive stats			
	STD	rate spread	cum. bal. payoff
Mean	-0.014	-0.007	21.500
Median	-0.028	-0.004	21.510
SD	0.056	0.027	0.165
P5	-0.071	-0.084	21.220
P95	0.074	0.025	21.769
Missing	0.000	0.000	0.026
Panel B: default within one month			
	Model 9 (STD)	**Model 10 (rate spread)**	**Model 11 (cum. bal. payoff)**
PS	251.553 (32.310)***	255.801 (32.290)***	2687.496 (1022.755)***
standard	0.322 (0.226)	-2.915 (0.785)***	0.118 (0.057)**
PS*standard	377.171(145.157)***	2227.412(401.329)***	-113.301 (48.288)**
Other variables	Included	Included	Included
Pseudo R-square	0.164	0.164	0.166
Accuracy ratio	0.572	0.573	0.574
AUROC	0.786	0.787	0.787
Observations	28,329,688	28,329,688	27,592,375
Panel C: default within one year			
	Model 9 (STD)	**Model 10 (rate spread)**	**Model 11 (cum. bal. payoff)**
PS	144.131 (14.84)***	127.702 (16.385)***	1513.191(414.736)***
standard	0.260 (0.111)**	-4.982 (1.278)***	0.023 (0.023)
PS*standard	345.131(72.637)***	6381.916(701.661)***	-63.754 (19.638)***
Other variables	Included	Included	Included
Pseudo R-square	0.328	0.328	0.328
Accuracy ratio	0.507	0.507	0.507
AUROC	0.754	0.754	0.754
Observations	20,749,241	20,749,241	20,749,241

Figure 1: Monthly HELOC default rate of the control and test samples from the OCC Home Equity Loan-Level data, January 2010 to March 2015.

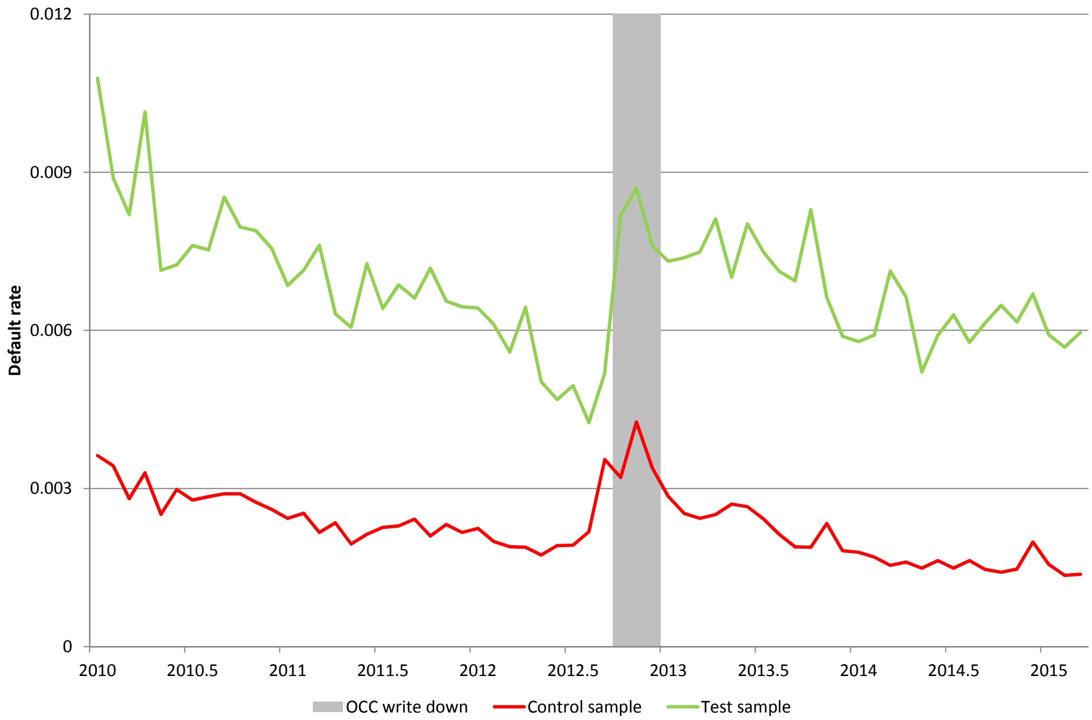

Figure 2: HELOC volume by origination, EOD and maturity date (entire sample from the OCC Home Equity Loan-Level data).

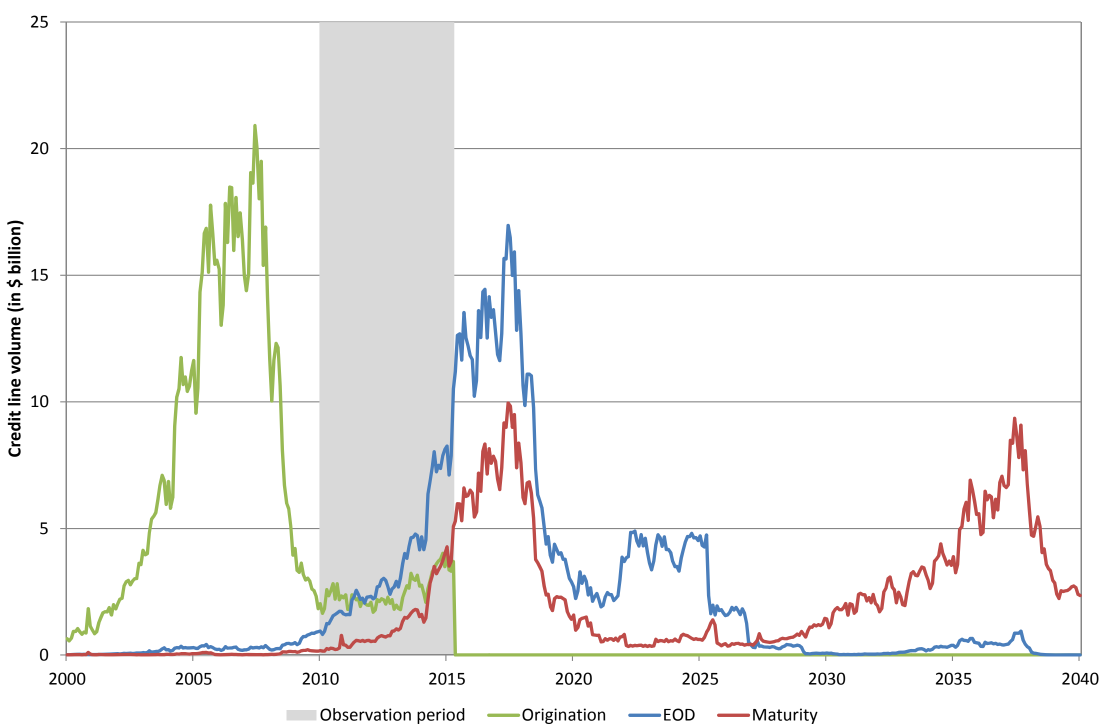

Figure 3: Monthly payoff rate of the control and test samples from the OCC Home Equity Loan-Level data, January 2010 to March 2015.

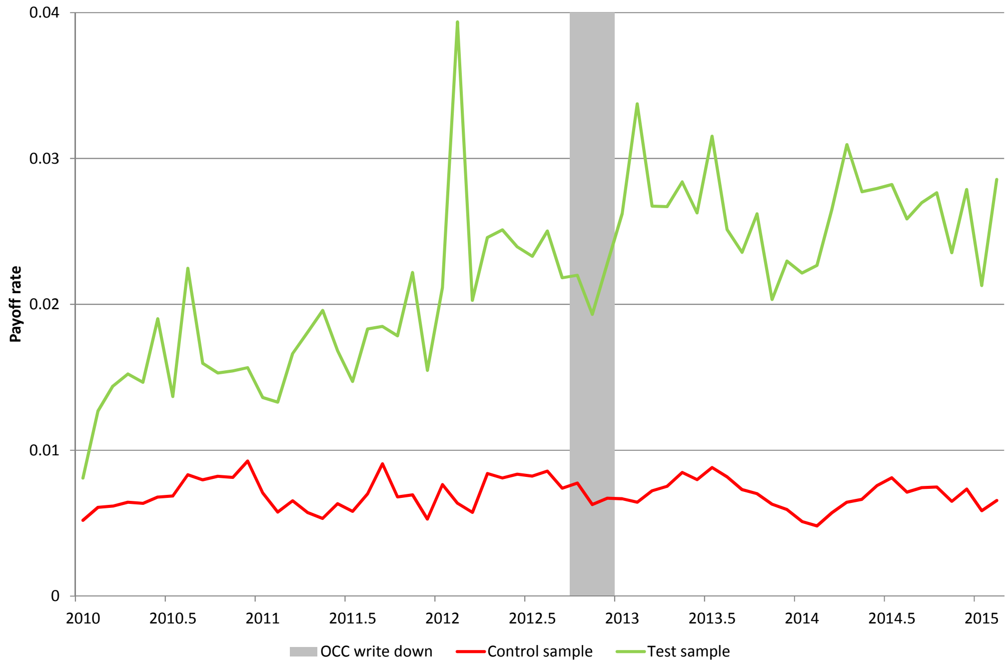

Figure 4: Implied probabilities of default and payment shock normalized by updated property value. The figure plots the one-month and one-year default probability (left axis) and frequency (right axis) across payment shock ranges for all HELOCs. The dashed lines represent 95% confidence intervals. The reference category (-0.002) has a set default probability of 0.5% for the one month default probability and 5% for the one-year default probability.

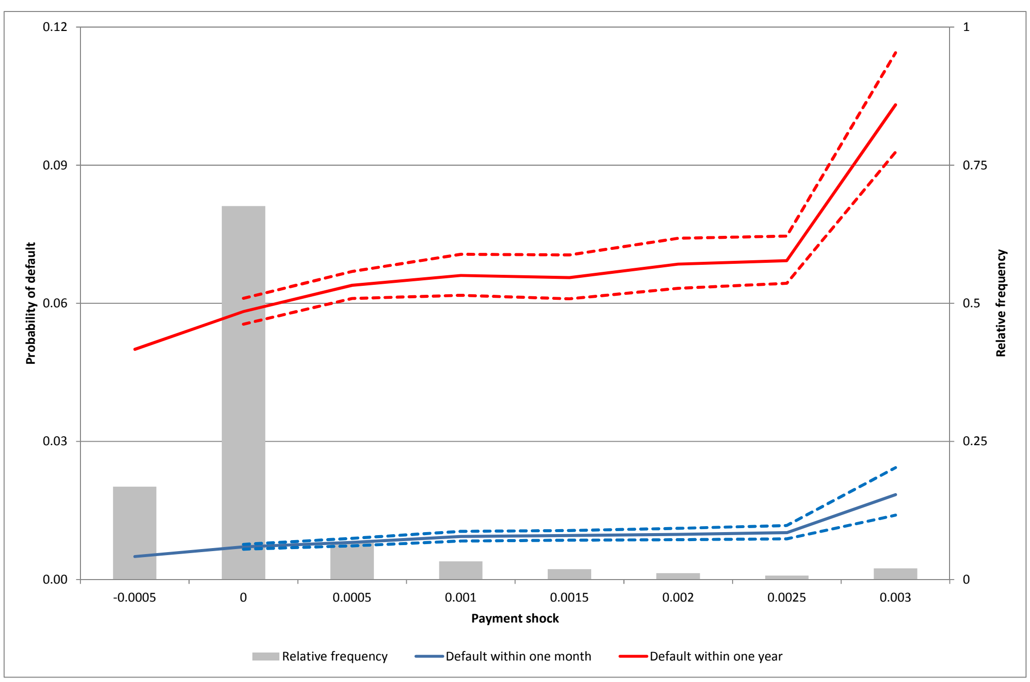

Figure 5: Implied probabilities of default and time since EOD. The figure plots the one-month and one-year default probability (left axis) and frequency (right axis) across payment shock ranges for all HELOCs. The dashed lines represent 95% confidence intervals. The reference category (-0.002) has a set default probability of 0.5% for the one month default probability and 5% for the one-year default probability.