

**Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.**

**End of the Line: Behavior of HELOC Borrowers Facing Payment
Changes**

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2015-073

Please cite this paper as:

Johnson, Kathleen W., and Robert F. Sarama (2015). "End of the Line: Behavior of HELOC Borrowers Facing Payment Changes," Finance and Economics Discussion Series 2015-073. Washington: Board of Governors of the Federal Reserve System, <http://dx.doi.org/10.17016/FEDS.2015.073>.

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The End of the Line: Behavior of HELOC Borrowers Facing Payment Changes

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July 10, 2015

Abstract

An important question in the household finance literature is whether a change in required debt payments affects borrower behavior. One challenge in this literature has been identifying whether higher default rates observed after an increase in debt payments stem from the inability of borrowers to pay the higher amount, or the attrition of better borrowers in advance of the payment change. A related question is whether the higher default rate is a result of specific features of the debt product, or the type of borrower who chooses the product. We address both of these questions as they relate to a scheduled increase in payments on home equity lines of credit (HELOCs). Many existing HELOCs are structured such that when they reach the end of the draw period, they convert from open-ended, non-amortizing lines of credit to closed-end, amortizing loans. We compare the performance of HELOCs reaching end of draw with those not reaching end of draw and find that HELOCs that reach end of draw have a significantly higher cumulative default rate in the following months. We also show that, at end of draw, borrowers who have a HELOC with a balloon feature are more likely to have lower credit scores and higher LTVs than borrowers who have HELOCs with longer amortization periods. However, even controlling for borrower and loan characteristics, HELOCs with a balloon payment are more likely to default. This result provides evidence that HELOC defaults can be influenced both by the features of the product and the characteristics of borrowers who choose those features.

Keywords: home equity, HELOC, end of draw, consumer credit, payment changes

JEL classification: G21, R31, D14

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The End of the Line

Home equity lines of credit (HELOCs) are debt contracts that enable borrowers to access the equity in their home at their discretion. As home equity grew rapidly in the early part of the 2000s, the share of outstanding HELOCs relative to bank assets doubled from 2 percent in 2002, where it had lingered for about a decade, to 4 percent in 2005 (see figure 1). Although this share has declined somewhat, HELOCs currently account for the majority of the banking industry's home equity portfolios, and borrowers owed nearly \$390 billion on HELOCs to the largest bank holding companies as of December 2013.

Under typical HELOC contracts, borrowers can draw funds from the lines of credit at their discretion up to a fixed limit that is agreed upon when the HELOC is originated. Borrowers can continue to draw funds throughout the draw period and are generally required to make only interest payments on the outstanding debt during this period. Many existing HELOCs are structured to convert from open-ended, non-amortizing lines of credit to closed-end, amortizing loans at the end of the draw period. Many of the outstanding HELOCs were originated in the early 2000s with draw periods between 10 and 20 years; as a result, almost 60 percent of outstanding HELOCs will reach the end of draw in the next several years. The risk that these HELOCs will default has been cited with increasing frequency in the financial press,¹ and interagency guidance was issued on HELOCs nearing end of draw in July 2014 (see, Office of Comptroller of the Currency; Board of Governors of the Federal Reserve System; Federal Deposit Insurance Corporation; National Credit Union Administration; Conference of State Bank Supervisors [2014]).

Often, borrowers repay or refinance the HELOC just prior to the end of draw. However, if borrowers do not pay off the line and have insufficient income to cover the payment increase, or cannot refinance the debt, they will be more likely to default on the debt. This situation may be particularly common for borrowers whose credit characteristics make it costly or impossible to refinance into a new line of credit. Given the share of outstanding HELOCs that will reach end of draw in the next several years, an important question is whether the increase in required payments that accompany the end of draw will increase default rates.

Mortgage default decisions are influenced by both mortgage payment size and negative equity

¹For example, see Rieker [2013] or Gittelsohn [2014].

(e.g. Deng, Quigley, and van Order [2000]; Campbell and Cocco [2011]). Although early observers of the mortgage crisis in the late 2000s pointed to changes in mortgage payments as a cause for the rise in defaults, recent empirical literature has focused to a large extent on the role of negative equity (Bhutta, Dokko, and Shan [2011]). Estimating the effect of a change in mortgage payment on default in a cross section of borrowers is difficult in part because it is difficult to isolate the effect of the higher mortgage payment from that of other factors, such as borrower credit quality. For example, loans with higher mortgage rates may default at a higher rate due to either an inability of those borrowers to make the associated higher mortgage payments, or the greater riskiness of the borrowers, which is reflected in a higher mortgage rate. Estimating the effect in a time series of default rates is also difficult because better borrowers may choose to payoff the mortgage before the rate increase occurs. Suppose we observe higher default rates after a change in payments. Is the higher default rate associated with the inability of borrowers to make the higher mortgage payments (treatment effect) or with the attrition of the better borrowers (selection effect)? Fuster and Willen [2013] isolate the treatment effect from the selection effect by analyzing borrower behavior when their payment on a hybrid, interest-only mortgage *declined* and found that a decline in payments translated to a significant decline in defaults. Tracy and Wright [2012] find similar results in a sample of prime borrowers. The effects of selection are minimized in these studies, because one wouldn't expect better borrowers to payoff the loans in anticipation of a rate decline.

The end of draw feature of HELOCs provides a unique opportunity to study the effect of payment changes on default. Similar to Fuster and Willen [2013] and Tracy and Wright [2012], we are able to observe individual borrower behavior around the time of a payment change. Unlike the types of payment changes in those studies, the end of draw results in an increase in payment size, which requires us to carefully address the sample selection issue discussed in that work. However, a payment increase also allows us to identify the behavior of borrowing constrained consumers, a group that often reacts to payment increases differently than other consumers.

Our preferred method for measuring the effect of end of draw on HELOC defaults would be to estimate a model of HELOC default and payoff that explicitly accounts for the payment change that occurs at the end of draw, or at a minimum accounts for the timing of end of draw. However, to our knowledge no single dataset includes both data about the end of draw and a long history of HELOC performance on which to estimate a model of default. We address this problem by

combining information from two panel datasets: the CoreLogic home equity servicing data and a new dataset collected by the Federal Reserve (FR Y-14 data). The CoreLogic dataset includes information on HELOC performance that extends back to January 2002, but no information on end of draw, and the FR Y-14 dataset includes information on end of draw, but has only been collected since June 2012. To measure the effect of end of draw on HELOC defaults, we use CoreLogic data spanning the January 2002 to June 2012 period to estimate a competing hazards model of default and payoff as a function of loan, borrower, and market characteristics. Then, using the FR Y-14 data we compared the default and payoff behavior predicted by the model with actual behavior for households whose HELOCs have reached the end of their draw period and those whose HELOCs did not.

We find that HELOCs have significantly higher default and payoff rates around the end of the draw period. Our results suggest that reaching the end of draw increases the probability of default 2.9 percentage points. This difference is significantly greater for HELOCs originated to borrowers with lower credit scores that have high combined loan to value ratios (CLTVs) as they approach end of draw. For these “higher risk” HELOCs with a FICO score below 725 and a refreshed CLTV above 80 percent, reaching the end of draw increases the probability of default 8.8 percentage points. This suggests that borrowers who may have trouble refinancing into a new HELOC may be more likely to default when they reach end of draw than those who may find it easier to refinance. The size of the payment change also matters for these borrowers. For example, some HELOCs require a balloon payment of the principal due at the end of the draw period. We find that reaching the end of draw increases the likelihood that a HELOC defaults regardless of the size of the payment increase, but that HELOCs with balloon payments are significantly more likely to default.

We also consider the related issue of whether the end of draw effect on default rates results from features unique to the HELOC contract or from characteristics of borrowers who chose HELOCs with those features. For example, the significant increase in the payment for HELOCs with a balloon feature due may lead to an increase in default. However, if riskier borrowers choose HELOCs with this feature, this increase in default may in part reflect the composition of borrowers who choose this product. Borrowers who choose HELOCs with a balloon feature appear to be somewhat riskier than other borrowers, but even controlling for quality characteristics, the likelihood of default is higher for HELOCs with balloon payments. A higher risk HELOC with a balloon payment is

roughly 9.5 percentage points more likely to default when it reaches end of draw than HELOCs that have a small payment change at end of draw, suggesting a role for both selection into the product and the product itself. Garmaise [2013] addresses a similar issue of adverse selection into a mortgage program that offered borrowers flexibility in the timing of their payments. He found that riskier borrowers chose the program ex ante, but that ex post screening by the lender led to lower default rates for loans in the flexible payment program.

I. Data used for analysis

We used data from two sources in our analysis: the FR Y-14M regulatory report and the CoreLogic Loan Performance Home Equity Servicing data.² The FR Y-14M is a set of monthly schedules that has been collected since June 2012 from any top-tier bank holding company (other than a foreign banking organization) that has \$50 billion or more in total consolidated assets. The main schedule used for this analysis was the Domestic Home Equity Loan and Home Equity Line schedule, which includes detailed information on each loan held in the respondent's portfolio, or serviced by the respondent. These data include 10.6 million loans, representing almost 70 percent of the outstanding balance of home equity loans.

The CoreLogic data are collected from a number of large home equity servicers. As of the end of 2012, these data include 8.4 million loans, representing about 50 percent of the outstanding balance of home equity loans. Unlike the FR Y-14M data, which have only been collected since June 2012, the CoreLogic data include a long performance history dating back to the first quarter of 2002.

In our main analysis, we focus on a subset of HELOCs that were originated in 2003 because we are able to observe most of this cohort from origination to the end of the draw period and beyond. Because the CoreLogic data do not contain reliable information about the timing of the end of draw, we use information about end of draw in the FR Y-14 data. The sample statistics for the two sets of loans used in the analysis is in table 1. The CoreLogic data set used to estimate our hazard model includes about 96,400 loans at the time they are first observed. Due to default or payoff, only about 21,600 loans survive to October 2012. At that time, the characteristics of the CoreLogic and FR Y-14 are remarkably similar. The distribution of credit score at origination for the two samples is nearly identical, as is the distribution of the combined loan-to-value. However, the geographic

²The FR Y-14 schedules are available at www.federalreserve.gov/apps/reportforms/default.aspx.

distribution of the two samples is somewhat different. HELOCs in the CoreLogic data are more concentrated in states that experienced a significant house price bubble during the mid-2000s, and the CoreLogic data had a significantly higher share of missing geographic information. They are also slightly more likely to be a junior lien HELOC.

We define default as occurring in the month in which the HELOC transitions to 90 or more days past due or into foreclosure. Because many HELOCs are interest only and the borrowers can draw and paydown multiple times during the life of the line, prepayment is not really a meaningful concept for open lines of credit. As such, we define the competing hazard to default as “payoff,” which is inferred if at the last period the HELOC is observed, it has a zero balance and is not in default. This measure captures both HELOCs that reach maturity and those that borrowers voluntarily close prior to reaching maturity.

II. Empirical Approach

A HELOC that reaches end of draw is both more likely to payoff and more likely to default than a HELOC that has not reached the end of draw. As shown in figure 2, 25 percent of HELOCs that reached end of draw in June 2013 were paid off 6 months later, compared to less than 5 percent of HELOCs that had not reached end of draw. A similar pattern is evident in loans that reach end of draw in December 2013. The higher likelihood of payoff is of course unsurprising as required principal payoff at end of draw is a contractual feature of HELOCs. Some HELOC contracts specify full repayment of principal at end of draw in a single “balloon” payment. What is perhaps less expected is the increased likelihood of default at end of draw. About 4.5 percent of HELOCs that reached end of draw were delinquent 6 months later, compared with 0.3 percent of HELOCs that had not reached end of draw.

Figure 2 is compelling, and one may want to view the difference between the two default curves as a rough estimate of the effect of the end of draw on a borrower’s probability of default. However, the cumulative default curves shown do not account for the differences in HELOCs or borrower characteristics between the two groups that could affect either the probability that the HELOC survived to the time period shown or the probability of default or repayment given that the HELOC survived. For example, better borrowers may be more likely to pay off the loan prior to the payment change, causing selection bias among the sample of loans observed after the payment

change. In this case, the simple difference between the two default curves as measured after the HELOCs reach end of draw would overstate the effect of end of draw. To get a sense of the selection bias, one could start the analysis several months prior to end of draw, as shown in figure 3. Here the selection issue becomes immediately apparent as the cumulative payoff rate begins to rise for HELOCs approaching the end of the draw period.

Our empirical approach attempts to overcome the challenges highlighted by the simple empirical default and prepayment curves shown in figures 2 and 3. Rather than compare the empirical default curves between HELOCs that reach end of draw and those that do not, we (1) subtract from each empirical default curve, the curve predicted by a competing hazard model estimated on a long panel of HELOC performance data from CoreLogic and (2) compare the errors between HELOCs that reached end of draw and those that did not. This method controls for differences in default caused by observed factors and helps to isolate the end of draw effect. Specifically, we use CoreLogic data spanning the January 2002 to June 2012 period to estimate the competing hazards of default and payoff as a function of loan, borrower, and market characteristics. We cannot directly measure the end of draw effect by including an appropriate variable in the hazard model because, as noted earlier, the CoreLogic data used to estimate the competing hazard model do not include information on the end of draw. Instead, we use the parameters estimated on the CoreLogic data to predict default and prepayment around the end of draw period in the FR Y-14 data.

A key feature of our strategy to isolate the end of draw (treatment) effect from the prepayment (selection) effect is to examine cumulative default rates on a pool of HELOCs that are about to reach end of draw. Let D_t be the number of defaults in period t , and let R_t be the number of at risk HELOCs in period t . Given that, the cumulative default rate over any T month period can be written as:

$$H^D(T) = \frac{\sum_{t=1}^T D_t}{R_1} \tag{1}$$

We can calculate $H^D(T)$ directly from the data for any T month period.

Using a competing hazard model and loan characteristics at $t = 1$, we can calculate the predicted cumulative default rate as

$$\hat{H}^D(T) = \sum_{t=1}^T s_t h_t^d \quad (2)$$

Where s_t is the probability the HELOC survives for t periods, and h_t^d is the instantaneous default hazard in period t . Importantly, the predicted cumulative default curve is a function of the characteristics of the *full set of HELOCs at risk at $t = 1$* . The difference between the predicted cumulative default curve calculated in this way and the actual curve is the model error, including that arising from omitted variables. We calculate the effect of end of draw as the difference in the model error for HELOCs that reach end of draw and the model error for HELOCs that do not reach end of draw:

$$\epsilon_{eod=1}^D(T) = H_{eod=1}^D(T) - \hat{H}_{eod=1}^D(T). \quad (3)$$

$$\epsilon_{eod=0}^D(T) = H_{eod=0}^D(T) - \hat{H}_{eod=0}^D(T). \quad (4)$$

$$EOD(T) = \epsilon_{eod=1}^D(T) - \epsilon_{eod=0}^D(T). \quad (5)$$

This strategy is intended to isolate the error in the model that is associated only with reaching the end of the draw period.

It is critical to our strategy that all of the attrition associated with end of draw occurs during the time period over which we calculate the cumulative default rate. To capture the end of draw effect, the start date, $t = 1$, must be before HELOC attrition due to end of draw begins to occur and the end date, $t = T$, must be after attrition associated with end-of-draw begins to subside.

III. Competing Hazard Model

Following the literature on first mortgage default (e.g. Kau and Keenan [1995]; Deng, Quigley, and van Order [2000]), we estimate a model that attempts to account for two reasons for default: (1) the borrower optimally exercises a financial option associated with the termination of the mortgage and (2) the borrower faces liquidity constraints that prevent the servicing of the debt. The financial options theory can be understood by considering the assets involved in the purchase of a residential

property with a mortgage. In such transactions, the borrower simultaneously purchases a piece of real estate and issues a bond collateralized by the real estate (i.e. the mortgage). Two options embedded in the bond characterize the borrower’s choice to terminate the mortgage: (1) the option to prepay and (2) the option to forgo future debt payments in exchange for the collateral. The vast majority of the literature on mortgage termination focuses on measuring factors that affect the value of those options.

Recent papers, including Campbell and Cocco [2011], Elul, Souleles, Chomsisengphet, Glennon, and Hunt [2010], and Fuster and Willen [2013] have promoted the “double trigger” theory of mortgage termination in which borrowers who encounter a negative shock to their budget constraints must also have negative equity in order to default; otherwise they will sell or refinance the house. The “double trigger” theories of mortgage termination place more weight on the effect of tightening budget constraints than some of the more option-theoretic mortgage termination theories.

Our baseline model is a reduced form model that implicitly captures the degree to which borrower, loan, and macroeconomic factors contribute to the likelihood of mortgage termination through both of these channels. We jointly model the default and payoff in a discrete-time hazard model that assumes that the hazard rate at time t , h_t , is the sum of the hazards associated with default, h_t^d , and payoff, h_t^p :

$$h_t = h_t^d + h_t^p \tag{6}$$

Under this specification, the probability of surviving for k periods is:

$$s_k = \prod_{t=1}^k [1 - h_t]. \tag{7}$$

Following Allison [1982] and using the methods similar to those described in Jenkins [2005], we organize our data so that we can estimate the model using a multinomial logit.

In the baseline specification, two variables proxy for the borrower’s incentive to payoff the line, based on variables suggested in the literature on adjustable rate first lien mortgage prepayment.³ First, the rate spread variable proxies for the borrower’s incentive to refinance into a new adjustable

³For example, see Ambrose and LaCour-Little [2001].

rate HELOC. In general, this incentive is driven by changes in the market price of risk.⁴ The rate spread is defined as the percent difference between the interest rate on the HELOC in period t and the contemporaneous interest rate associated with an adjustable rate HELOC indexed to the Prime rate:

$$SPREAD_{i,t}^{RATE} = \frac{r_{i,t} - (prime_t + margin_t)}{prime_t + margin_t} \quad (8)$$

where $r_{i,t}$ is the interest rate on HELOC i at time t , $prime_t$ is the market prime rate at time t , and $margin_t$ is the average margin rate charged at time t for newly originated HELOCs indexed to prime. When the rate spread is positive and there are no frictions, the prepayment option is “in-the-money” and the borrower has the incentive to pay off. Second, the term spread variable proxies for borrower expectations about future interest rates:

$$SPREAD_{i,t}^{TERM} = TBOND_t^{10Y} - TBOND_t^{1Y} \quad (9)$$

where $TBOND_t^{10Y}$ is the interest rate on 10-year treasury bonds at time period t and $TBOND_t^{1Y}$ is the interest rate on 1-year treasury bonds at time period t .

To proxy for the strategic default option, we use a measure of combined loan-to-value (CLTV) that is refreshed for both changes in property value and changes in the size of the draw on the HELOC since origination. The value of the option to put the collateral back to the lender in exchange for future mortgage payments is higher for larger CLTVs. Loans with CLTVs above 100 are often referred to as being “underwater” because the borrower owes more on the mortgage than the house is worth. We use a spline function of CLTV, where the break points are at 80 and 100.

$$CLTV_{i,t}^{REFRESHED} = \frac{UPB_{i,0}^{FL} + UPB_{i,t}^{SL}}{VALUE_{i,0} * (HPI_{i,t}/HPI_{i,0})} \quad (10)$$

where $UPB_{i,0}^{FL}$ is the unpaid principal balance on the first lien at the time the HELOC was originated, $UPB_{i,t}^{SL}$ is the unpaid principal balance on the second lien at time t , $VALUE_{i,0}$ is the value of the property at the origination date of HELOC i , and $HPI_{i,t}/HPI_{i,0}$ is the gross change in local house prices since the origination of the HELOC. We do not have information on the amount of

⁴Because not all HELOCs are indexed to the prime rate, some variability in this measure may be associated with basis risk if the index rate is not sufficiently correlated with the prime rate.

unpaid principal balance on the first lien as of time $t > 0$ or on the seasoning of the first lien at the time of the origination of the second. Lacking such information, we assume that there has been no amortization on the first lien between $t = 0$ and t .

To control for relative differences in credit conditions across borrowers, we use a spline function of the FICO score of the borrower at the time of origination. The break points for the spline are at a FICO score of 620 and at 725. Higher FICO scores are associated with more credit worthy borrowers, and we interpret them as a proxy for a lower likelihood of the budget constraint binding. We control for the likelihood that an individual borrower’s budget constraint tightened during the time since origination by including the change in the local unemployment rate since the origination of the loan. Larger changes are associated with a higher likelihood that the borrower became unemployed since the loan was originated.

We also include a suite of variables that control for other potential differences in the borrower or loan characteristics. That suite of variables includes a dummy for whether the HELOC is a junior lien and state dummies to capture differences in macroeconomic and demographic characteristics across geography.

Estimation sample

We estimate the model on a ten percent sample of first and second lien HELOCs that were originated in 2003. We define current loans as loans that are less than 90 days past due, and current loans may transition to one of three states: default, payoff, and unresolved. All non-default, non-payoff observations in the last observed time period are classified as unresolved.

To reduce the effect of outliers, we Winsorise the calculated continuous variables (refreshed CLTV and the spread between the loan interest rate and the prevailing market interest rate) at the first and ninety-ninth percentiles. To limit the effects of left censoring, we restrict the sample to HELOCs that survive for at least 18 months and for which the first observation we observe is at most 18 months from the closing date.⁵ We drop 2,706 of the 99,139 loans that survived for at least 18 months entered the sample after they were 18 months old.

⁵This assumption implies that our estimated baseline hazards will be conditional on the loan surviving 18 months. Because the period we’re interested in studying (the time around end-of-draw) typically occurs 60 to 120 months after origination, conditioning the baseline model on the loan surviving for 18 months will not affect our results. Left censoring thresholds of 6 and 12 months were considered.

Summary statistics of the retained sample of loans are presented in the first four columns of table 1. In general, HELOCs that default are to borrowers with lower origination FICO scores than HELOCs that don't default. This likely reflects that borrowers who have more frequently missed debt payments in the past are more likely to have trouble making debt payments going forward. Refreshed CLTVs are also higher for HELOCs that default. Almost 20 percent of the HELOCs that eventually defaulted were originated with CLTVs above 95.

Exponentiated model parameter estimates are shown in table 3 and plots of the predicted CPR and CDR in the FICO and CLTV splines are in figure 4. As expected, higher FICO scores are associated with lower defaults, but FICO does not appear to materially affect the probability of payoff. Consistent with the strategic default motive, HELOCs with negative equity are significantly less likely to payoff and significantly more likely to default.

An increase in the unemployment rate since origination is associated with a lower probability of payoff, and a higher probability of default. An increase in term spread, which is a proxy for borrower interest rate expectations, is associated a lower probability of payoff. An increase in the rate spread is associated with a higher probability of payoff, which is consistent with an incentive to refinance due to low market interest rates relative to the borrowers HELOC rate. It is also associated with higher probability of default. Because the rate spread measure is based on the average margin on a newly originated HELOC, we believe the positive relationship may be driven by borrowers with higher than average margins, which is an indicator of a higher risk borrower.

IV. Default and payoff around the end of draw

We can now observe the actual behavior of HELOCs that reach the end of draw relative to what the baseline model would predict. As discussed above, we measure our variable of interest – the difference between actual cumulative default rate (CDR) and predicted CDR – starting at a time period before borrowers start to select out of the sample. This difference is essentially the model prediction error. Consider figure 5, which shows the difference around the end of draw for two different cohorts: those with an end of draw in June 2013 and those with an end of draw in December 2013. If the model perfectly predicted the likelihood of payoff and default, the plots of adjusted CDRs and CPRs would equal zero. For loans not reaching end of draw, the adjusted CDRs and CPRs remain very close to zero during the entire period, reflecting the model's generally good

out-of-sample predictive power. For loans reaching end of draw, the model begins to under-predict payoff approximately 4 to 6 months before the end of draw and under-predict default 2 to 4 months after end of draw. Based on this finding, in our following analysis, we calculate the adjusted CDRs and CPRs starting at least ten months before end of draw and ending at least eight months after end of draw.

EOD effect

Because the FR Y-14 sample used to identify end of draw spans October 2012 to August 2014, we will look at loans that reach end of draw between June 2013 and December 2013. HELOCs that reached end of draw during this period both defaulted and paid off more often than HELOCs scheduled to reach end of draw in 2015 or later (figure 6). In figure 7 we plot the EOD effect (calculated as described above) for default and payoff.

The plot on the left side of figure 7 shows the EOD effect on default, which is just under 3 percent for HELOCs reaching EOD in the second half of 2013. That is, reaching EOD increases the likelihood a HELOC will default by a little less than 3 percent. The plot on the right side shows a large increase in the payoff rate associated with HELOCs reaching the end of draw. Reaching EOD increases the payoff probability by nearly 30 percent; that large increase in payoffs may reflect borrowers electing to refinance into a new HELOC when the line on their existing HELOC closes.

The likelihood that a HELOC borrower who reaches end of draw will default depends in part on the ability of the borrower to cover the payment increase or to refinance the debt. We suspect that borrowers whose credit characteristics make it costly or impossible to refinance into a new line of credit will default more often than other borrowers. To explore this hypothesis, we segmented the HELOCs that reached end of draw between June 2013 and December 2013 into three groups. The first group, the lower risk group, includes HELOCs with a refreshed CLTV less than 80 percent and a borrower FICO score above 725. The second group, the higher risk group, includes HELOCs with a refreshed CLTV greater than 80 percent and a borrower FICO below 725. The third group, the intermediate quality group, includes the remaining HELOCs. Sample statistics for the two groups of interest, the lower risk and higher risk groups, are presented in table 2. Higher risk HELOCs reaching EOD tended to have higher unpaid principal balances than other HELOCs: more than 40 percent of higher risk HELOCs reaching EOD had unpaid principal balances of more than \$50,000.

Further, 30 percent of the low credit quality HELOCs reaching the end of draw will experience more than a 100 percent increase in required payments as a result of the HELOC beginning to amortize. Roughly 90 percent of higher risk HELOCs in our sample are junior liens, which suggests that the lenders may have limited ability to recover collateral should the HELOCs default.

The EOD effect on default is much more pronounced for higher risk HELOCs than for lower risk HELOCs, while the opposite is true for the EOD effect on payoff (figure 8). Borrowers with better credit scores, who have greater access to credit markets, may be more likely to refinance into new HELOCs. The payoffs we observe in our data may, in part, be capturing those sort of refinances.

The double trigger theories of mortgage default suggest that, liquidity shocks or other abrupt changes in required payments that cause a tightening of the budget constraint play an important role in determining borrower default behavior. Borrowers who have demonstrated difficulty in making debt payments in the past (i.e. those with low FICO scores) who are near the negative equity threshold may be particularly sensitive to payment changes. To explore this hypothesis, we further segmented the HELOCs into three additional groups based on payment change size. Small payment changes are payment changes less than 75 percent (representing approximately the bottom half of the distribution); large payment changes are non-balloon HELOCs that have payment changes greater than 75 percent; and, balloon HELOCs, defined as HELOCs with an amortization period (the period between end of draw and maturity) of less than three months.

The size of the effect on default is increasing in the size of the required payment change for both high and high risk HELOCs; however, for lower risk HELOCs the EOD effect is economically small for non-balloon payment increases (figure 9). For higher risk HELOCs, the EOD effect is sizable (greater than 5 percent) even for relatively small increases in required payments, and it rises to above 10 percent for balloon payment HELOCs.

These results also provide evidence that HELOC defaults may be influenced both by the features of the product, as well as by the characteristics of borrowers who choose the product. The balloon feature at the end of draw appears to be chosen slightly more often by households with a high CLTV and low FICO score. About 12 percent of these households have a HELOC with a balloon feature, compared with 9 percent of households with a lower CLTV and higher FICO (table 2). Riskier borrowers are more likely to default at end of draw than less risky borrowers (figure 8).

However, even controlling for the riskiness of the borrower, borrowers with a balloon payment are more more likely to default than borrowers with amortizing payments (figure 9).

Statistical significance

We employ a bootstrap technique to better understand whether the EOD effects on default that were plotted in the previous section are statistically significant. Specifically, we test whether the difference between the observed cumulative default rate and the predicted cumulative default rate for loans reaching end of draw is greater than for loans not reaching end of draw. Using the same notation as before, we want to test that

$$EOD(T) = \epsilon_{eod=1}^D(T) - \epsilon_{eod=0}^D(T) > 0 \quad (11)$$

We calculate the model predicted cumulative default rate for the 25 months between October 2012 and October 2014 for all loans in the sample. We make 1,000 random draws of 10,000 observations of HELOCs (with replacement), retaining: (1) predicted 25 month cumulative default rate, (2) the outcome of the HELOC during that period (payoff/default/unresolved), and (3) whether the loan reached end of draw between June and December of 2013. Then we calculate the difference between actual and predicted cumulative default rate as of October 2014 for each of the 1,000 draws for 16 unique segments resulting in 16,000 observations. The 16 segments include four quality segments for HELOCs not reaching end of draw, and 12 quality/payment change segments for HELOCs that reach end of draw. We stack those observations to form the dataset we use in our regressions. In all of the regressions, we weight the observations by the number of loans in the segment associated with an observation.

In the first specification, we regress the model errors on a constant term. The coefficient captures both forecast error of our model and the EOD effect. The second specification includes a dummy for segments that reach end of draw and implies the model underpredicts the 25 month cumulative default rate by approximately 2.1 percent. The 2.9 percent EOD effect is statistically significant and similar in magnitude to the effect shown in figure 7.

In the third specification, we decompose the end of draw effect to discern whether lower credit quality HELOCs reaching end of draw are more likely to default than higher credit quality HELOCs

reaching end of draw. The end of draw effect for lower risk HELOCs is 0.6 percent, while the end of draw effect for high risk HELOCs is 8.8 percent (table 4, column 3). Finally, we find that reaching the end of draw increases the likelihood that a HELOC defaults regardless of the increase in the payment, but that HELOCs with balloon payments are significantly more likely to default. A high risk HELOC with a balloon payment was 16.1 percentage points more likely to default when it reached end of draw than HELOCs that did not reach end of draw (table 4, column 4).

The magnitude of these results are in line with previous studies of payment changes. Tracy and Wright [2012] report that a 26 percent decrease in monthly payments leads to a decline in the 5 year cumulative default rate from 17.3 percent to 13 percent. In other words, a 26 percent decline in payment size results in a 24.8 percent decline in the five year default hazard. Fuster and Willen [2013] report that cutting a borrowers payment in half (i.e. a 50 percent decline) reduces the default hazard by 55 percent.

Using a bootstrap technique, we estimate that a 25 percent increase in required payment results in an increase in the default hazard by 17 percent, and doubling the required payments increases the default hazard by 75 percent.⁶ However, we also find that the sensitivity of default to increases in required payment changes varies significantly across high and higher risk HELOCs. For example, our analysis suggests that a 25 percent increase in required payments would only increase the default hazard for low risk borrowers by 7 percent, whereas the same percent increase would increase the default hazard for high risk borrowers by 47 percent.

V. Conclusions

In this paper, we used the end of draw feature of HELOCs to study the effects of payment changes on default. Because the timing of end of draw is exogenous to borrower credit characteristics, we were able to examine the effect changes in required payments have on borrowers who likely face credit constraints.

We use a combination of two datasets to examine this issue because we know of no single dataset that includes both data about the end of draw and a long history of HELOC performance on which to estimate a model of default. We use CoreLogic performance data (spanning January 2003 to June 2012) on 2003 vintage HELOCs to estimate a competing hazards model of default

⁶See appendix A for more detail.

and payoff as a function of loan, borrower, and market characteristics. Then, using the regulatory data collected by the Federal Reserve, we identify the HELOCs that reach end of draw between June 2013 and December 2013 and, controlling for observable differences in HELOCs, compare their performance to the performance of HELOCs reaching end of draw in 2015 or later.

We find that HELOCs reaching the end of draw are 2.9 percent more likely to default than HELOCs not reaching end of draw. However, we also find that there is significant variation in this effect. The end of draw effect is significantly larger for HELOCs originated to borrowers with lower credit scores and that have high combined loan to value ratios (CLTVs) as they approach end of draw. For these “higher risk ” HELOCs with a FICO score below 725 and a refreshed CLTV above 80 percent, reaching end of draw increases the default rate by nearly 9 percent. This suggests that borrowers who may have trouble refinancing into a new HELOC may be more likely to default when they reach end of draw than those who may find it easier to refinance. The size of the payment change also matters for these borrowers. We find that reaching the end of draw increases the likelihood that a HELOC defaults regardless of the increase in the payment, but that HELOCs with balloon payments are significantly more likely to default. A high risk HELOC with a balloon payment was roughly 16 percentage points more likely to default when it reached end of draw than HELOCs that did not reach end of draw.

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Appendix A: Sensitivity of default to size of payment change

The approach we used in the paper to identify the end of draw effect relies on grouping loans into groups, which makes it difficult for us to estimate sensitivity of default to incremental changes in required payments. However, we can use a bootstrap technique to approximate the sensitivity of default to incremental changes in required payments.

We use a bootstrap to calculate cumulative default rates (CDRs) on 24 segments of loans:

- **6 payment change size buckets:** not reaching EOD, 0 to 30 percent increase, 30 to 60 percent increase, 60 to 90 percent increase, greater than 90 percent increase, and balloon payments;
- **2 credit score buckets:** less than 725 and greater than 725; and,
- **2 CLTV buckets:** less than 80 and greater than 80.

For each bucket, we calculate the number of loans in the bucket, the difference between the realized CDR and the model predicted CDR, and the average percent increase in payments. We repeat the procedure 1,000 times randomly sampling 10,000 observations for each draw.

With that dataset in hand, we calculate the three HELOC credit quality segments, indexed by k , using the same definition as we used in the body of the paper. Then we calculate the weighted (by loan counts) average $\bar{\epsilon}_{eod=0}^D$ for each HELOC credit quality segment:

$$\bar{\epsilon}_{eod=0,k}^D = \frac{1}{J} \sum_{j=1}^J \epsilon_{eod=0,j,k}^D \quad (12)$$

Then we divide $\epsilon_{eod=1,j,k}^D$ for the segments of HELOCs that reach end of draw (excluding the balloon payment segments) by the corresponding $\bar{\epsilon}_{eod=0,k}^D$. This yields a measure that is analogous to an odds ratio in a typical hazard model:

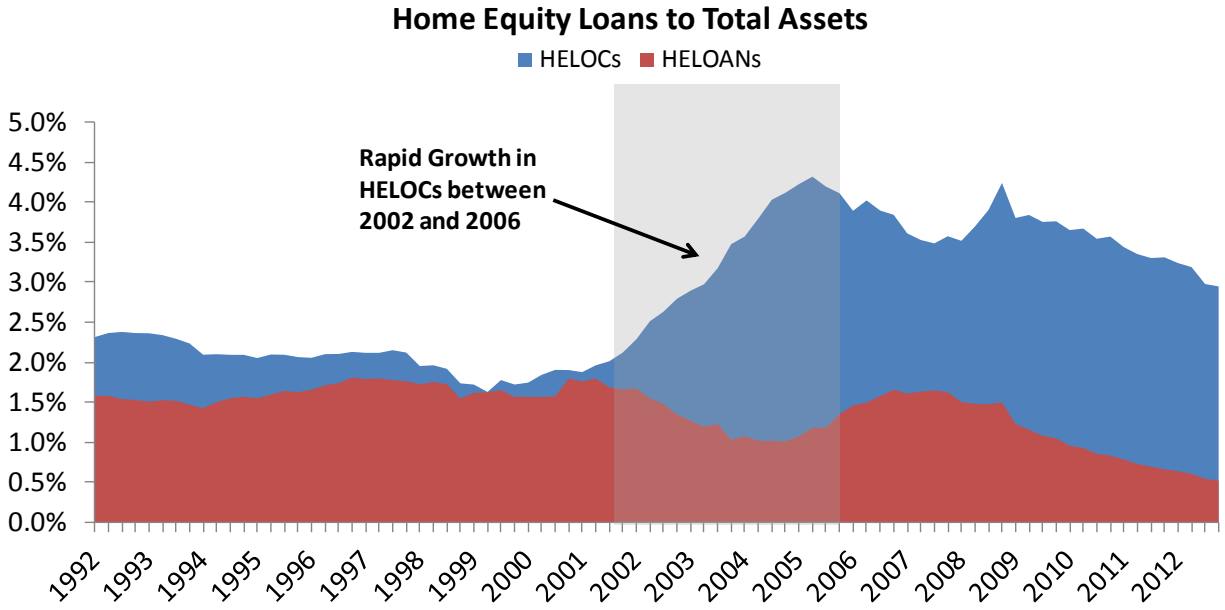
$$M_{j,k} = \frac{\epsilon_{eod=1,j,k}^D}{\bar{\epsilon}_{eod=0,k}^D} \quad (13)$$

Then we regress the $M_{j,k}$ on a constant and interactions of the three quality segments with the average percent increase in payments:

$$M_{j,k} = \alpha + \beta_1 D_{high} * p_{j,k} + \beta_2 D_{other} * p_{j,k} + \beta_3 D_{low} * p_{j,k} + \eta_{j,k} \quad (14)$$

The parameter estimates can be used to estimate the increase in default hazard for different size payment changes, conditional on having a lower or higher risk HELOC.

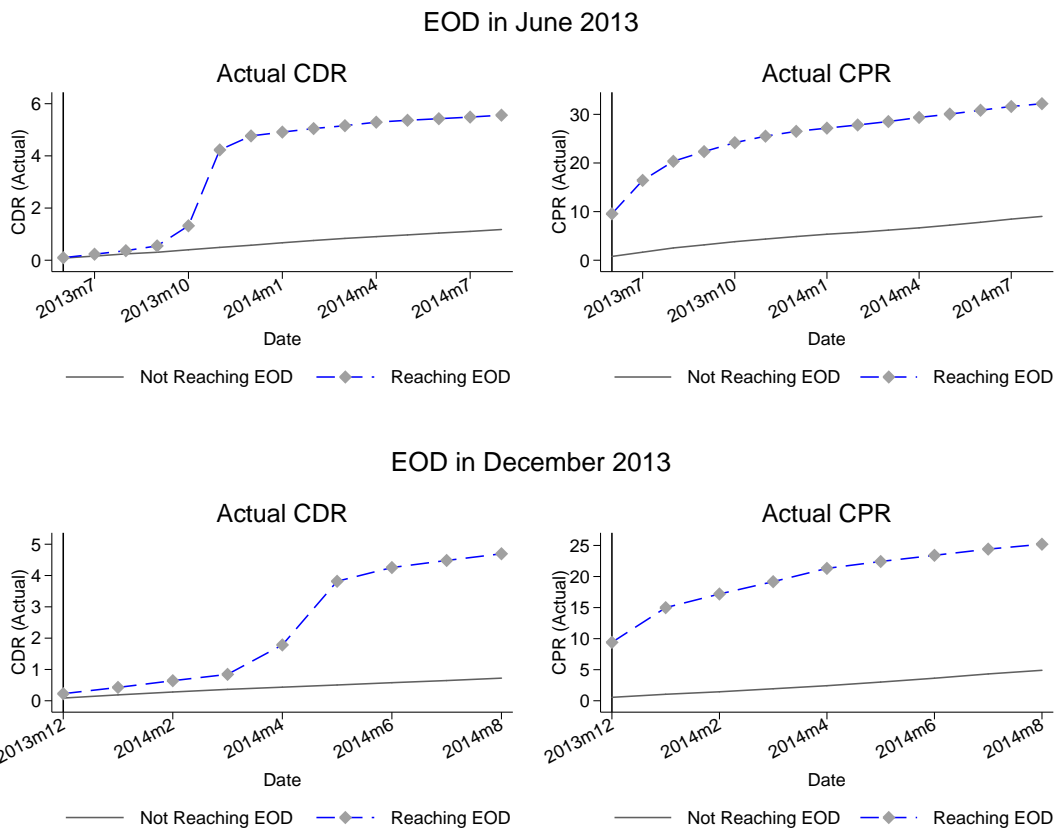
Figure 1: Home equity share of bank portfolios.



Source: FR Y-9C, all BHCs.

Source: Federal Reserve Board of Governors, Y-9C "Consolidated Financial Statements for Holding Companies"; Author Calculations

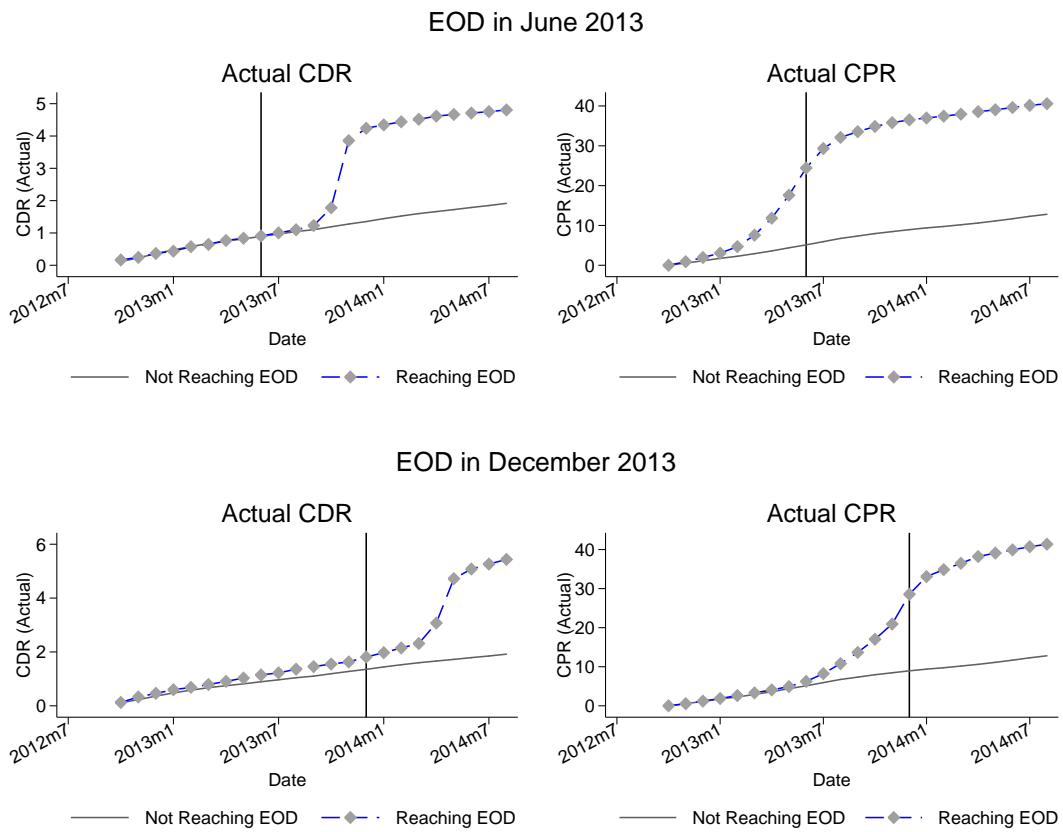
Figure 2: Empirical CDR and CPR, Starting at End of Draw. This figure was created using the sample of data described in the last column of table 1. We dropped HELOCs that reach the end of their term before the start of the projection period. The sample is segmented by whether the HELOCs reach end of draw – HELOCs “Not Reaching EOD” are scheduled to reach end of draw in 2015m1 or later. Once segmented, the realized CDRs and CPRs are calculated over the performance window.



Source: Federal Reserve Board of Governors, Y-14; Author Calculations

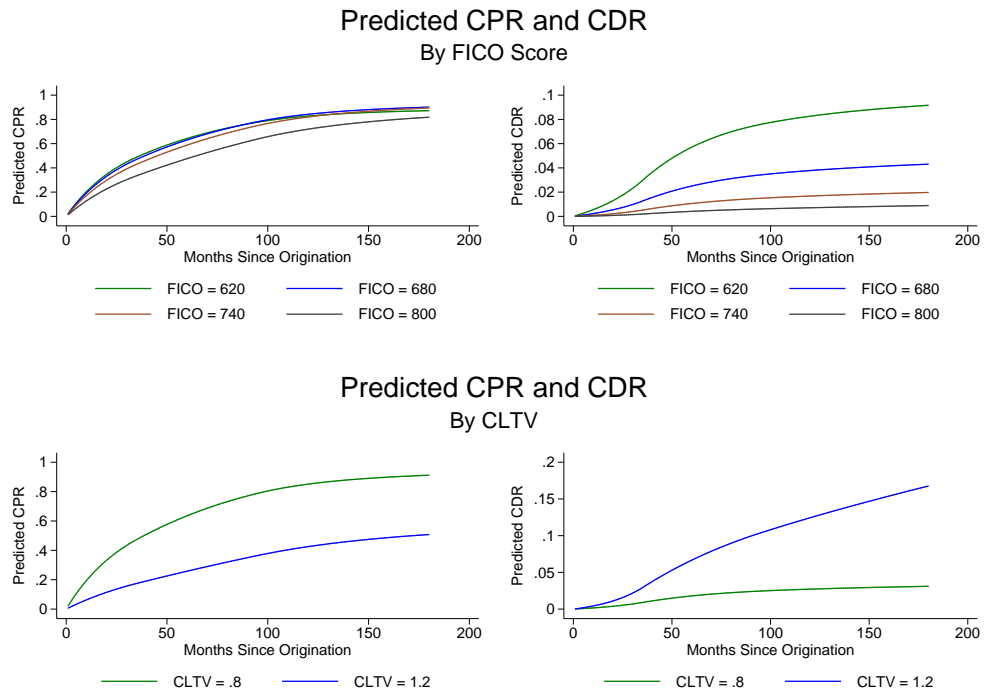
Figure 3: Empirical CDR and CPR, Starting Several Months Before End of Draw.

This figure was created using the sample of data described in the last column of table 1. We dropped HELOCs that reach the end of their term before the start of the projection period. The sample is segmented by whether the HELOCs reach end of draw – HELOCs “Not Reaching EOD” are scheduled to reach end of draw in 2015m1 or later. Once segmented, the realized CDRs and CPRs are calculated over the performance window.



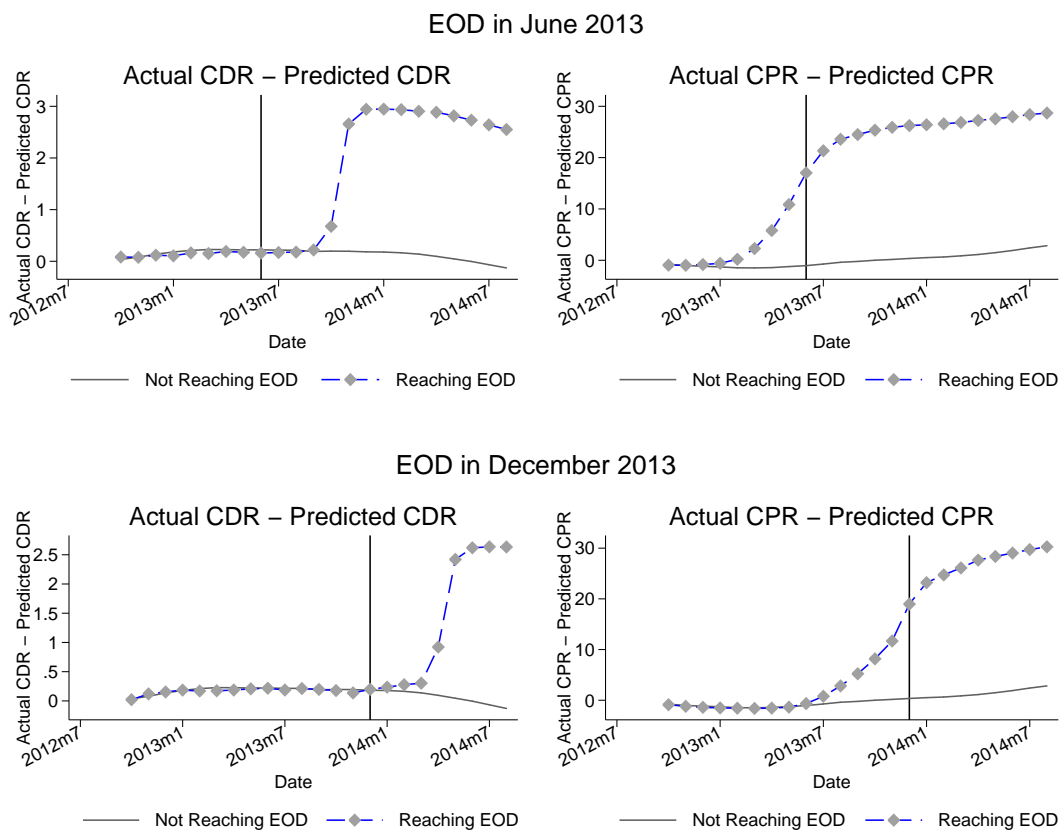
Source: Federal Reserve Board of Governors, Y-14; Author Calculations

Figure 4: Plots of Predicted Payoff and Default Rates. Calculated cumulative payoff and default curves associated with model parameters in table 3. Model predictions are plotted assuming the average characteristics of the other variables in the model.



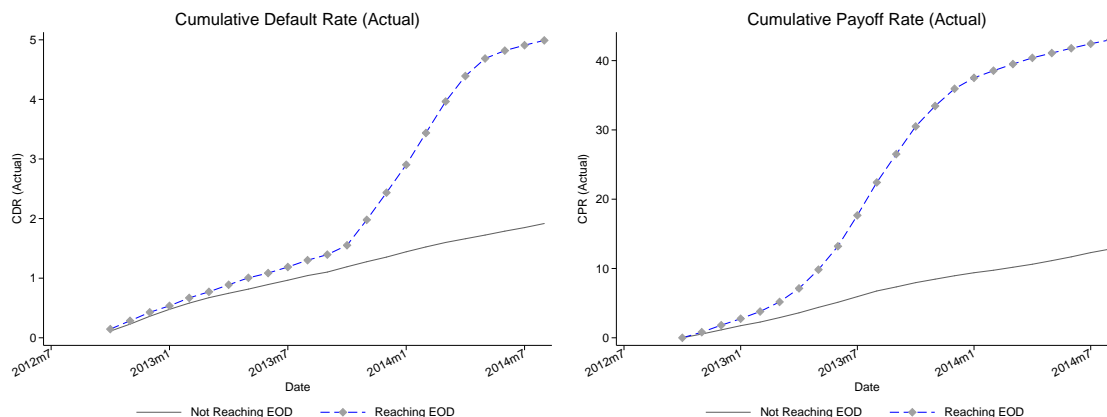
Source: CoreLogic; Author Calculations

Figure 5: CDR and CPR, Controlling for Observable Loan and Borrower Characteristics. The plotted series are the empirical CDR and CPR less the model projected CDR and CPR. This figure was created using the sample of data described in the last column of table 1. We dropped HELOCs that reach the end of their term before the start of the projection period. The sample is segmented by whether the HELOCs reach end of draw – HELOCs “Not Reaching EOD” are scheduled to reach end of draw in 2015m1 or later. Once segmented, the realized CDRs and CPRs are calculated over the performance window.



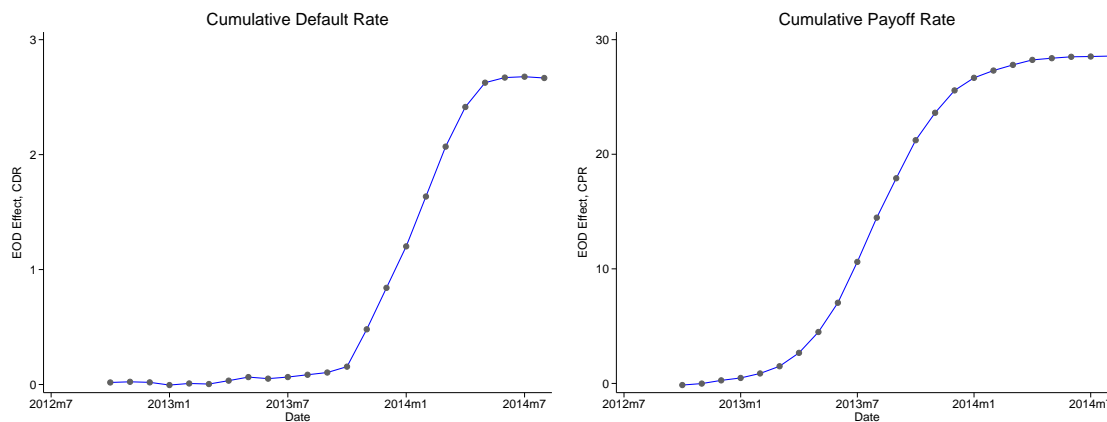
Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations

Figure 6: Empirical CDR and CPR, Full Sample. This figure was created using the sample of data described in the last column of table 1. We dropped HELOCs that reach the end of their term before the start of the projection period. The sample is segmented by whether the HELOCs reach end of draw – HELOCs “Not Reaching EOD” are scheduled to reach end of draw in 2015m1 or later. HELOCs reaching EOD reach EOD between July 2013 and December 2013. Once segmented, the realized CDRs and CPRs are calculated over the performance window.



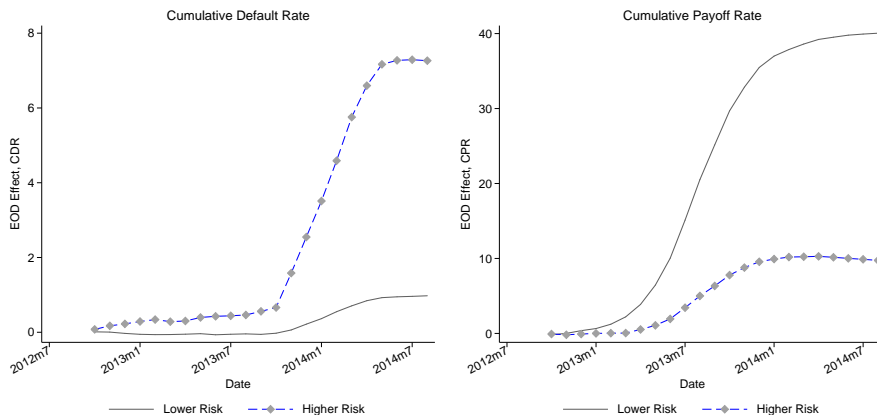
Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations

Figure 7: EOD effect, CDR and CPR, all HELOCs. This figure shows the EOD effect on cumulative defaults and payoffs for HELOCs reaching the EOD between July 2013 and December 2013. The EOD effect is calculated in two steps. First, we calculate model forecast errors of CDR and CPR as the empirical CDR/CPR minus the model projected CDR/CPR. We do this separately for loans reaching EOD and for loans not reaching EOD. Second, subtract the model forecast errors for loans not reaching EOD from the model forecast errors of loans reaching EOD. This figure was created using the sample of data described in the last column of table 1. We dropped HELOCs that reach the end of their term before the start of the projection period.



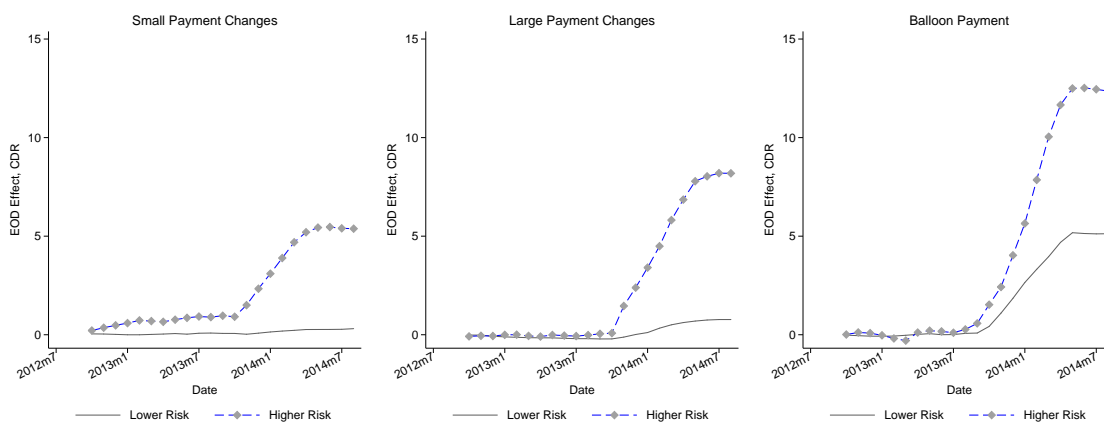
Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations

Figure 8: EOD effect, Lower and Higher Risk HELOCs. This figure shows the EOD effect on cumulative defaults and payoffs for HELOCs reaching the EOD between July 2013 and December 2013 for lower and higher risk HELOC segments. *Lower Risk* HELOCs have an origination FICO Score 725 or greater and a refreshed CLTV (as of September 2012) of less than 80 and *Higher Risk* HELOCs have an origination FICO Score less than 725 and a refreshed CLTV (as of October 2012) of greater than 80. For each segment, the EOD effect is calculated in two steps. First, we calculate model forecast errors of CDR and CPR as the empirical CDR/CPR minus the model projected CDR/CPR. We do this separately for loans reaching EOD and for loans not reaching EOD. Second, subtract the model forecast errors for loans not reaching EOD from the model forecast errors of loans reaching EOD. This figure was created using the sample of data described in table 2. We dropped HELOCs that reach the end of their term before the start of the projection period.



Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations

Figure 9: EOD effect, Lower and Higher Risk HELOCs, by Payment Change Size. This figure shows the EOD effect on cumulative defaults and payoffs for HELOCs reaching the EOD between July 2013 and December 2013 for lower and higher risk HELOC segments, by size of the payment change. *Lower Risk* HELOCs have an origination FICO Score 725 or greater and a refreshed CLTV (as of September 2012) of less than 80 and *Higher Risk* HELOCs have an origination FICO Score less than 725 and a refreshed CLTV (as of October 2012) of greater than 80. Small payment changes are the bottom 50 percent of the payment change size distribution (payment change less than 75 percent), and large payment changes are the top 50 percent of the distribution. Balloon HELOCs are HELOCs with amortization periods of less than 3 months. For each segment, the EOD effect is calculated in two steps. First, we calculate model forecast errors of CDR and CPR as the empirical CDR/CPR minus the model projected CDR/CPR. We do this separately for loans reaching EOD and for loans not reaching EOD. Second, subtract the model forecast errors for loans not reaching EOD from the model forecast errors of loans reaching EOD. This figure was created using the sample of data described in table 2. We dropped HELOCs that reach the end of their term before the start of the projection period.



Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations

Table 1: Sample Statistics - Estimation and Projection Samples This table shows sample statistics for the estimation and projection samples. The first four columns of the table show sample statistics for the estimation sample, and all statistics are calculated as of the first observation. The fifth column shows the HELOCs surviving (as of 2012m10) in the 2003 vintage of the CoreLogic sample. The sixth column shows the HELOCs observed in the FR Y-14 data as of 2012m10.

	Payoff	CoreLogic* Outcome		All	CoreLogic As-of 2012m10	Y-14 As-of 2012m10
Number of Loans:	74,370	2,613	19,450	96,433	21,594	210,161
Origination Credit Score, share						
Less than 620	0.01	0.03	0.01	0.01	0.01	0.01
620 to 679	0.11	0.31	0.12	0.12	0.09	0.11
680 to 724	0.24	0.34	0.24	0.24	0.20	0.22
725 and above	0.61	0.31	0.60	0.60	0.68	0.66
Missing	0.03	0.02	0.03	0.03	0.03	0.00
Origination Combined Loan-to-Value, share						
80 or less	0.50	0.40	0.55	0.51	0.64	0.63
81 to 90	0.28	0.31	0.29	0.28	0.24	0.26
91 to 95	0.10	0.10	0.09	0.10	0.06	0.05
96 or greater	0.12	0.19	0.07	0.11	0.06	0.06
Missing	0.00	0.00	0.00	0.00	0.00	0.00
Geography, share						
CA, FL, AZ, and NV	0.37	0.31	0.31	0.35	0.32	0.24
OH, IN, MI	0.05	0.14	0.06	0.05	0.07	0.15
GA, NC, SC, AL, TN, MS	0.04	0.06	0.06	0.05	0.03	0.13
Other	0.39	0.32	0.38	0.39	0.38	0.47
Missing	0.15	0.16	0.19	0.16	0.20	0.00
Junior Lien, share	0.87	0.86	0.86	0.87	0.80	0.71
Origination Limit, mean	80,481	67,639	77,793	79,591	88,630	85,675

* Estimation sample. Measured as of first observation.

Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations

Table 2: Sample Statistics - End of Draw and non-End of Draw HELOCs This table shows sample statistics for the lower and higher risk HELOC segments of the projection sample. *Lower Risk* HELOCs have an origination FICO Score 725 or greater and a refreshed CLTV (as of September 2012) of less than 80 and *Higher Risk* HELOCs have an origination FICO Score less than 725 and a refreshed CLTV (as of October 2012) of greater than 80. The first two columns of the table show sample statistics for HELOCs not reaching EOD, the third and fourth columns show sample statistics for HELOCs reaching EOD.

	Reaching EOD?			
	No		Yes	
	Lower Risk	Higher Risk	Lower Risk	Higher Risk
Number of Loans:	63,916	13,877	41,287	13,247
UPB, share				
1 to 1,000	0.03	0.00	0.04	0.00
1,001 to 10,000	0.20	0.10	0.16	0.07
10,000 to 50,000	0.48	0.53	0.43	0.49
More than 50,000	0.29	0.37	0.37	0.43
Payment Change Increase, percent				
Less than 50 percent	N/A	N/A	0.06	0.15
50 to 75 percent	N/A	N/A	0.24	0.27
75 to 100 percent	N/A	N/A	0.44	0.27
Greater than 100 percent	N/A	N/A	0.17	0.18
Balloon Payment	N/A	N/A	0.09	0.12
Missing	N/A	N/A	0.00	0.00
Geography, share				
CA, FL, AZ, and NV	0.15	0.18	0.36	0.29
OH, IN, MI	0.12	0.28	0.09	0.29
GA, NC, SC, AL, TN, MS	0.18	0.27	0.03	0.08
Other	0.55	0.27	0.52	0.34
Missing	0.00	0.00	0.00	0.00
Junior Lien, share	0.57	0.88	0.69	0.89
Outcomes				
Default	720	579	897	1,536
Payoff	9,636	1,444	23,800	2,749

Source: Federal Reserve Board of Governors, Y-14; Author Calculations

Table 3: Model Estimates Exponentiated coefficients reported and standard errors are in brackets. The model is estimated on the sample described in the first four columns of table 1. * for $p < 0.05$, ** for $p < 0.01$, *** for $p < 0.001$

	Outcome	
	Payoff	Default
Duration Spline: 36 Months or fewer	0.987*** [0.001]	1.053*** [0.006]
Duration Spline: 36 to 96 Months	1.004*** [0.001]	0.995 [0.003]
Duration Spline: More Than 96 Months	0.992 [0.005]	1.003 [0.017]
FICO Spline: 620 or Less	1.005*** [0.001]	1.009*** [0.003]
FICO Spline: 621 to 725	0.999*** [0.000]	0.985*** [0.001]
FICO Spline: Greater Than 725	0.995*** [0.000]	0.982*** [0.001]
Refreshed CLTV Spline: 80 or Less	1.941*** [0.047]	17.512*** [2.943]
Refreshed CLTV Spline: 80 to 100	0.005*** [0.001]	22.271*** [9.072]
Refreshed CLTV Spline: More Than 100	0.504*** [0.099]	3.773*** [0.882]
Unemployment Rate Change Since Origination	0.667*** [0.020]	1.740*** [0.204]
Term Spread	0.764*** [0.007]	0.934 [0.039]
Rate Spread	2.183*** [0.061]	2.326*** [0.250]
Controls		
Constant, state dummies, and dummies for junior lien, missing FICO, missing CLTV.		
Pseudo R2	0.034	
Log-likelihood	-331,659	
Observations	3,820,341	
Exponentiated coefficients		

Source: CoreLogic; Author Calculations

Table 4: Statistical significance of EOD effects. OLS estimates reported on regressions of the 13-month CDR model prediction error on segment dummies. The credit quality segments are: *Lower Risk* HELOCs with origination FICO Score 725 or greater and a refreshed CLTV (as of September 2012) of less than 80; *Higher Risk* HELOCs with origination FICO Score less than 725 and a refreshed CLTV (as of October 2012) of greater than 80; and *Other* which contains the rest of the end of draw HELOCs in the sample. The payment change size segments are: *Small Payment Changes* are the bottom 50 percent of the payment change size distribution (payment change less than 75 percent), and *Large Payment Changes* are the top 50 percent of the distribution. *Balloon HELOCs* are HELOCs with amortization periods of less than 3 months. We use weighted regression in which we weight the segment-level observations by the number of loans in the segment.

	(1)	(2)	(3)	(4)
Constant	0.034*** [0.000]	0.021*** [0.000]		
EOD Dummy		0.029*** [0.001]		
Lower Risk			0.010*** [0.000]	0.010*** [0.000]
Other			0.028*** [0.000]	0.028*** [0.000]
Higher Risk			0.044*** [0.001]	0.044*** [0.000]
EOD, Lower Risk			0.006*** [0.000]	
EOD, Other			0.030*** [0.000]	
EOD, Higher Risk			0.088*** [0.001]	
EOD, Lower Risk, Small Paychange				0.002*** [0.000]
EOD, Lower Risk, Large Paychange				0.004*** [0.000]
EOD, Lower Risk, Balloon HELOC				0.036*** [0.001]
EOD, Other, Small Paychange				0.014*** [0.000]
EOD, Other, Large Paychange				0.028*** [0.000]
EOD, Other, Balloon HELOC				0.108*** [0.001]
EOD, Higher Risk, Small Paychange				0.066*** [0.001]
EOD, Higher Risk, Large Paychange				0.092*** [0.001]
EOD, Higher Risk, Balloon HELOC				0.161*** [0.001]
Observations	16,000	16,000	16,000	16,000
Adjusted R-squared	0.47	0.55	0.87	0.96

Source: Federal Reserve Board of Governors, Y-14; CoreLogic; Author Calculations