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Quick on the Draw: Liquidity Risk Mitigation in Failing Banks

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Quick on the Draw: Liquidity Risk Mitigation in Failing Banks

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ABSTRACT

We study how banks limit their exposure to liquidity risk during financial stress by eliminating consumer access to cancelable credit lines. Using a proprietary set of transaction-level HELOC data from eight banks, we find that banks are more likely to revoke credit lines that exhibit potentially problematic characteristics at-origination and time-varying borrower "early warning signals" of risk. In the three months before each bank's failure date, when bank capital and liquidity constraints increase, we find that banks respond to these same borrower and loan characteristics more aggressively, while borrowers do not increase HELOC drawdown rates. Before the bank becomes distressed, we find that existing borrower relationships have no adverse effects on banks' decision to revoke credit. As failure approaches, however, banks are more likely to cut the HELOCs of borrowers with greater ability to demand liquidity from the bank, suggesting that lending relationships do not benefit borrowers during times of bank stress. Overall, we shed light on how banks manage their liquidity risk during times of idiosyncratic stress. Furthermore, while the bulk of the relationship banking literature has found that borrowers benefit from relationships during times of borrower distress, we show that relationships may harm borrowers during times of bank distress.

Keywords: financial crisis, HELOC, bank run, credit monitoring, failed bank
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Introduction

Financial institutions offer liquidity to borrowers and depositors through a variety of products. In turn, banks require liquidity to avoid selling the resulting relatively illiquid assets at a loss in a time of crisis to meet borrower and depositor demands (Diamond and Rajan, 2001). Policymakers have long managed bank liquidity risk via well-known tools such as central bank loans, deposit insurance, and reserve requirements, and researchers have analyzed the effects of liquidity risk on credit supply. However, banks' ability to reduce their own liquidity needs by limiting borrowers' ability to demand cash has received less attention. In this paper, we study how banks manage the liquidity risks resulting from a popular consumer credit line product both before and during times of bank distress.

Home equity lines of credit, or HELOCs, are open-ended loans that allow borrowers to use their properties as collateral. These loans usually have a draw period, where balances revolve for several years, and a repayment period, where the loans are amortized and repaid. Due to their low interest rates and favorable tax treatment compared to credit cards, HELOCs quickly grew in popularity and followed the boom-and-bust path of the housing market during the financial crisis. Between 2003 and 2006, in parallel with the increase in single-family, first-lien, closed-end residential loans, the volume of HELOCs held on bank balance sheets nearly doubled to $1.3 trillion (Figure 1). While both the amount of drawn credit card and HELOC balances was approximately $300 billion in 2003, HELOC drawdowns caused balances to approximately double by 2007, while credit card draws only realized proportionally modest increases (Figure 2). As the financial markets experienced turmoil, many borrowers experienced a need for credit and drew down on their HELOCs (Figure 3). When housing prices plummeted, banks realized a corresponding growth in HELOC charge-off rates, growing nearly seven-fold between 2007 and 2009 (Figure 4). The rise in HELOC lending increased the liquidity demands and balance sheet exposure for banks.

In the context of liquidity risk, HELOCs are useful to study because they are usually considered "unconditionally cancellable," meaning that the bank may, at any time, with or without cause, prohibit the extension of credit, reduce the credit line, or terminate the commitment.[1] HELOC contract terms reflect the authority of banks to cancel the credit line if it concludes that borrowers will not be able to repay.[2] Our focus on cancellable commitments distinguishes our work from that of Ivashina and Scharfstein (2010) and Cornett, McNutt, Strahan, and Tehranian (2011) on liquidity risk and credit supply. The ability to suspend drawdowns at will is similar to the "suspension of convertibility" seen in existing literature (e.g., for bank deposits in Diamond and Dybvig, 1983), which, in theory, should prevent borrower run-like actions.[3] The suspension of convertibility entails sub-optimal risk sharing and reputation risk to the bank.

As Figures 1-4 suggest, periods of stress for borrowers in aggregate can correspond with periods of stress for banks. Banks marketed HELOCs as a type of "emergency fund" alongside

[1] For further information on HELOC cancellability see Section 2 of the Regulatory Capital Rule https://www.federalreserve.gov/supervisionreg/srletters/sr1506a1.pdf

[2] For example, Regional Federal Credit Union notes that HELOCs may be suspended or reduced if "the value of your dwelling declines significantly below its appraised value" or "we reasonably believe that you will not be able to meet the repayment requirements due to a material change in your financial circumstances." See 2019-01-predisclosure-heloc.pdf (regionalfcu.org)

[3] Borrowers may be concerned that their access to credit will be curtailed in the event of bank stress or failure even if a new bank quickly acquires the troubled institution. Anecdotally, multiple banks froze or canceled HELOCs during the financial crisis (Morgenson, 2008). More recently, JP Morgan did not renew personal credit lines for First Republic borrowers post-acquisition. See https://finance.yahoo.com/news/jpmorgan-culling-first-republic-banks-174042441.html for more details.

credit cards, acknowledging the importance of consumer liquidity in crises.[4] As a result, banks were likely aware that consumers would have high demand for the liquidity available through credit lines at the same time that banks would have high demand for liquidity to avoid the greater risk of selling illiquid assets at low prices to meet consumer liquidity demands. This correlation heightens the importance of bank liquidity management and suggests that banks have a strong incentive to manage liquidity provision in times of stress. Figure 5 shows the trend in bank liquidity provision as our sample banks approach failure, using the preferred measure of bank liquidity creation from Berger and Bouwman (2009). In our sample, banks decrease liquidity provision beginning about 2 years prior to failure, with liquidity provision falling from approximately 47 percent to 30 percent of gross total assets.[5] Lower liquidity provision implies that the banks are offering fewer liquid products to borrowers and/or holding more liquid assets. We study how banks achieve the reduction in liquidity provision and liquidity risk seen in Figure 5 in part through eliminating some HELOCs.[6]

At first glance, it may not be obvious that banks would consider borrower characteristics when rationing credit. For example, within the Diamond (1984) framework, banks holding diversified loan portfolios could maintain the same level of diversification by cutting all loans equally. However, assuming a constant demand for credit, a contraction in the supply of credit increases the cost of lending and could result in the bank cutting riskier or less profitable loans,

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[4] A 2008 advertisement for Indymac's "Dynamic Line," a home equity line of credit coupled with a physical credit card to draw on the line, touted the product as "It's my money, and I'll (action) if I want to," advocating for its use in purchase of consumer goods. For a recent example, the first product mentioned in Fidelity Bank's discussion of "emergency funds" is the Home Equity Line of Credit (HELOC). https://www.fidelitybank.com/managing-your-emergency-fund/

[5] Gross total assets, as defined in Berger and Bouwman (2009), is total assets plus the allowance for loan and lease losses plus the allocated transfer reserve. The preferred measure of liquidity creation in Berger and Bouwman (2009), as identified by the authors, is the "catfat" measure.

[6] We note that failing banks may also be subject to supervisory actions. For more on the interaction between deposit insurance, bank supervisory actions, and bank liquidity provision, see Wang (2022).

analogous to a flight-to-quality effect modeled in Bernanke, Gertler, and Gilchrist (1996). Other studies suggest that banks may be more likely to insure borrowers with stronger relationships against these shocks (Berger and Udell, 1992, 1995; Berlin and Mester, 1999; Liberti and Sturgess, 2018) because the loans are more profitable (Sharpe, 1990; Rajan, 1992; Von Thadden, 1995; Bolton, Freixas, Gambacorta, and Mistrulli, 2016) and banks are more capable of monitoring these borrowers (Holstrom and Tirole, 1997; Cassar, Ittner, and Cavalluzzo, 2015; Sutherland, 2018). Chaderina, Laux, and Tengulov (2020) emphasize the role of accounting covenants in granting banks leeway to void credit commitments to individual firms in the commercial setting.

While there are relatively few existing HELOC studies, these studies tend to focus on the determinants of borrower HELOC default. Agarwal, Ambrose, Chomsisengphet, and Liu (2006) find that loans to borrowers with low credit scores and high loan-to-value (LTV) ratios at origination are more likely to default on HELOCs, while Norden and Weber (2010) find that increases in unsecured consumer credit line usage and limit violations are associated with future borrower default on individual credit lines using German data. In contrast, we focus on how banks use HELOC borrower information to manage liquidity risk by adjusting levels of committed credit in response to changing market conditions.

In this study, we use a unique and granular dataset featuring detailed daily loan-level data for HELOCs. The database contains detailed borrower-level characteristics, shocks to bank financial health, and an indication of whether the bank revoked the credit line. We use FDIC-collected data from eight U.S. banks shortly after their failure, with historic account-level data for each bank spanning between several months and several years prior to failure, allowing us to examine bank and borrower behavior during both times of bank solvency and months just prior to failure. After the banks failed and were placed into receivership, the FDIC collected their loan data. These data were made available to the authors under certain provisions, including keeping the names of the banks and customers confidential. Our data permit us to perform a number of cross-sectional analyses, as we observe all borrower-level and loan-level characteristics that the bank observes and at the same frequency as the bank. Our ability to observe borrower behavior at the loan level allows us to build on the work of Ivashina and Scharfstein (2010) and Cornett et al. (2011) in these areas.

Our sample consists of over 94,000 geographically diverse HELOCs, and bank failure dates range from 2008 to 2011. Our high frequency data and staggered bank failure dates enable us to include both HELOC loan-level and year-month fixed effects within the regression framework, controlling for HELOC-level characteristics that do not vary with time and time trends, such as the value of the benchmark rate and broader economic conditions, at the monthly frequency.

We also analyze how banks ration borrower credit during the time just prior to bank failure. A bank is classified as critically undercapitalized once its tangible equity falls below the regulatory minimum (2 percent of assets) and, by law, must be resolved within 90 days. If borrowers fear that they will be unable to acquire credit once their bank fails, or that the bank may close lines to manage its capital, they may have stronger incentives to draw down on their HELOCs. At the same time, bank stress may drive the bank to reduce leverage and risk (Ben-David, Palvia, and Stulz, 2019), gamble for resurrection by increasing their lending and risk-taking (Freixas, Rochet, and Parigi, 2004), or heighten the bank's need for liquidity and lead to aggressive credit rationing in an attempt to preempt borrower drawdowns. Thus, how banks treat liquidity risk as failure approaches is ultimately an empirical question.

The empirical work examining the unconditionally cancellable relationship between borrowers and lenders faces significant endogeneity challenges. Banks may cancel HELOCs because of borrower actions leading up to the revocation or because of events observed by the bank but not observable to researchers, such as borrower job loss or non-payment on other debts. Since we wish to study bank cancellation of credit lines, we check our definition of bank cancellation using differences in the state corporate tax rate applicable to bank earnings, a driver of bank but not borrower behavior. Banks in states with a higher tax rate on earnings realize larger tax savings when charging off a nonperforming loan or other bad debt, giving them less incentive to cancel a HELOC preemptively than a bank in a low tax state with less financial relief from a bad loan. We find that our measure of HELOC cancellations responds strongly to differences in the bank earnings tax rate, indicating that our definition is capturing bank decisions to cancel HELOCs.

We find that banks are more likely to revoke credit lines for loans with high loan-to-value ratios, high interest rates at origination, or a history of delinquency. Norden and Weber (2010) suggest that credit-seeking behavior, which they define as borrower attempts to acquire credit in response to idiosyncratic stresses, could preempt default. We find no evidence that banks manage credit lines along this dimension. Banks are less likely to revoke loans with lower proportions of available credit, loans that have recently had increases in their available credit (an uncommon event), and loans where borrowers drew down over the previous month and thereby reduced the amount of credit available to them. Although banks can cut borrower lines to prevent additional draws, they cannot easily claw back already drawn balances. This is consistent with line cutting as a risk mitigation strategy because the small undrawn balance leaves the borrower with little ability to demand liquidity in the future. We find no evidence that housing price declines are a meaningful determinant of credit line revocation.

Next, we examine whether stronger banking relationships reduce a bank's likelihood of revoking a HELOC. Although extant studies have shown that lending and non-lending relationships can be valuable during times of *borrower* distress (Berger and Udell, 1992, 1995; Berlin and Mester, 1999; Boot, Greenbaum, and Thakor, 1993; Liberti and Sturgess, 2018), to the best of our knowledge, no study examines the impact of relationships during times of *bank* distress. We find that banks are less likely to revoke the HELOCs of borrowers holding deposit accounts, indicating that a depositor relationship preserves borrower credit access. However, just prior to failure, banks are more likely to revoke lines of credit for borrowers with other loans. A single borrower with several loans represents a larger liquidity risk for the bank.

In the three months prior to each bank's failure, we find that the likelihood of HELOC cancellation increases and that most of our coefficients grow in magnitude, indicating that banks are more likely to cut a HELOC for a given change in loan characteristics when they face more capital and liquidity constraints close to failure. Our results are similar to Ivashina and Scharfstein (2010) on syndicated loans and Cornett et al. (2011) on aggregate lending. These findings are inconsistent with a story of banks gambling for resurrection as they are tolerating less risk from their borrowers, although this intolerance could be due to increased regulatory scrutiny. While reputational risk might deter bank management from cutting credit lines, this risk becomes less important as the franchise value of the bank falls close to failure.

We find no evidence that borrowers increase their drawdown rates during the time just before failure despite the elevated risk of a bank failure and a higher likelihood that the bank management will render a line of credit unavailable, consistent with Diamond and Dybvig

(1983). Although several existing studies have found evidence of depositors running down the liability side of the bank balance sheet just prior to failure (Iyer, Puri, and Ryan, 2016; Martin, Puri, and Ufier, forthcoming), to our knowledge, we are the first paper to examine whether consumer borrowers draw more on credit lines just prior to bank failure. Though certain cross-sections of borrowers increase (or decrease) their drawdown rates, we find that average HELOC utilization falls just prior to bank failure. This finding suggests that unconditional cancellability is an effective contract feature for deterring runs.

Our study contributes to a growing body of literature that explores how contractions in the supply of credit and deteriorating bank financial health affect both bank and borrower behavior. This paper also has implications for understanding what types of borrowers suffer the most harm when banks fail. Since we find that banks are more likely to manage loans associated with borrower-level characteristics that reflect low borrower or loan quality at origination, these borrowers may be least likely to find credit elsewhere during credit crunches. Our analysis has implications for understanding the welfare tradeoffs of liquidity provision to consumers through HELOCs. Although HELOCs may be useful for borrower consumption smoothing across certain kinds of idiosyncratic states, such as the need for home repairs, our results suggest that HELOCs do not help borrowers' smooth consumption across macroeconomic states when faced with idiosyncratic bank risk.

1. Related Literature

Our paper contributes to a rich literature examining the importance of bank relationships. Several studies show that relationships between banks and firms are largely valued during times of economic stress within a commercial lending environment (Jiménez et al., 2012; Sette and Gobi, 2015; Bolton et al., 2016; Beck, Degryse, DeHaas, and van Horen; 2018; Liberti and

Sturgess, 2018), though one recent study shows a dark side to firm-bank relationships during the COVID-19 crisis (Berger, Bouwman, Norden, Roman, Udell, and Wang, 2021). Another notable study finds that relationships are valuable for credit card borrowers during the COVID-19 pandemic (Berger, Bouwman, Norden, Roman, Udell, and Wang, 2023). Other papers show that relationship benefits to borrowers are associated with information production that can be particularly helpful in times of idiosyncratic firm stress (Cassar et al., 2015; Sutherland, 2018). Our paper builds on this literature by being the first of its kind to examine the value of relationships during bank distress, and we show a dark side to lending relationships.

We also directly contribute to a group of studies examining the conditions that cause banks to manage credit lines. Sufi (2009) finds that banks revoking credit lines following negative profitability shocks can incentivize firms to limit their liquidity risk optimally. Ivashina and Scharfstein (2010), Cornett et al. (2011), Berrospide, Meisenzahl, and Sullivan (2012), and Acharya and Mora (2015) show that bank funding sources impact bank willingness and ability to provide liquidity to borrowers. Acharya, Almeida, Ippolito, and Perez-Orive (2020) show that it can be theoretically optimal for banks to revoke lines of credit following negative profitability shocks, as doing so manages the firm’s liquidity risk expectation and strategies and provides incentives for bank monitoring that can contain the illiquidity transformation problem. Each of these papers focuses on bank credit line management for corporate borrowers, and to the best of our knowledge, we are the first study to examine credit line management of liquidity risk within the consumer market. Given the overall size of bank balance sheet exposure to HELOCs during the financial crisis and their importance to consumers in managing downside risk, it is especially important to understand the implications supply-shocks to banks have on consumer borrowing during crisis times.

Our paper is also related to an empirical literature documenting that deterioration in the financial health of banks affects bank-dependent borrowers through a contraction in credit supply (Kashyap and Stein, 2000; Peek and Rosengren, 2000; Ashcraft, 2006; Khwaja and Mian, 2008; Paravisini, 2008; Jiménez, Ongena, Peydró and Saurina, 2012; Liberti and Sturgess, 2018). This literature finds that banks ration credit for the same reasons during normal times and times of bank distress, but they are more sensitive to those factors when under constraints. Our finding that banks are more aggressive in closing HELOCs when close to failure and subject to liquidity and capital constraints shows that these basic results also apply to consumer credit markets.

Finally, our study contributes to a small body of literature on the conditions under which borrowers run or draw down on their credit lines. Kashyap, Rajan, and Stein (2002) emphasize that both deposits and credit lines are subject to runs, but existing empirical studies have found only limited evidence of corporate borrower runs during the financial crisis. Our findings and setting indicate that the nature of the credit contract may play a major role in realized behavior. Ippolito, Peydró, Polo, and Sette (2016) find that Italian firms with multiple credit lines draw preferentially down on the lines provided by banks more exposed to an interbank market liquidity shock. Ivashina and Scharfstein (2010) analyze corporate loans likely to have light covenants, where banks cannot easily limit borrower draws. We study unconditionally cancelable loans, a setting where banks have more options for managing liquidity risk. Furthermore, Kapan and Minoiu (2021) show that banks with higher risk of drawdowns tighten loan supply and the terms on new loans. In contrast to these studies focusing on corporate borrowers and syndicated loans, we analyze whether consumers draw down on their lines of credit before banks fail, potentially impeding their ability to acquire future credit.

2. Data

We use data collected by the FDIC from bank servicing systems during the resolution process for failed banks. These data, collected from the eight failed banks in our sample, were made available to the authors for this analysis under the condition that the banks and the borrowers remain anonymous. The foundation of our analysis is transaction-level HELOC data which we then link to term loans, non-HELOC lines of credit, and deposits to construct daily balances, interest rates, line amounts, and linkages for each line of credit to other products. We collapse our data to the monthly level, retaining one observation of each HELOC-month. These data come from eight banks, spanning anywhere from months to years prior to failure, with banks failing at various points throughout the 2008-2013 crisis. These banks had various primary lines of business and strategies, but like many banks that failed during that period, most invested materially in loans backed by residential real estate. We can observe borrower and bank behavior both during periods of bank solvency and in the months immediately prior to failure, allowing us to study bank management of liquidity risk through varying bank-specific and economy-wide conditions. Our final sample consists of 1,531,232 HELOC-months spanning 94,294 HELOCs, with both banks and credit lines spread geographically throughout the country.

Dependent Variables. Two of the primary goals of this study are to understand the determinants of bank HELOC line management, including during the time just prior to failure when banks are most likely to be capital and liquidity constrained, and whether borrowers draw down their HELOCs in the time just prior to failure. Accordingly, our two primary dependent variables identify instances when the banks revoked the credit line and whether the borrowers drew down on the HELOC prior to failure. To isolate closures plausibly motivated by bank line management, we keep loans where the line was closed, revoked, or cut to a limit of zero dollars, as identified by the bank and servicer systems. Although it is possible for a bank to reduce the amount of credit available to borrowers through their HELOCs incrementally, we find very little evidence of this occurring within our dataset. Instead, we find that banks tend to revoke these lines entirely. To limit the possibility of consumer-initiated management, such as a refinance or sale that closed the line, we omit line cuts where the balance is zero at time of the bank closing and the balance was non-zero 31 days before from our regressions. This usage pattern is consistent with a consumer paying off and then eliminating a HELOC.[7] The variable *Line Cut* represents plausibly bank-initiated HELOC revocations and takes a value of 100 in the first month where the HELOC is marked as closed or has a credit limit of 0 after having a positive credit limit on the previous month.[8] After a HELOC is revoked, we drop all further observations on the loan from the panel.

The variable *Used Proportion Change Past Month* is the difference between the proportion of the credit line drawn in the previous month and the proportion drawn in the current month. A fully drawn line in the current month that was undrawn in the previous month has a *Used Proportion Change Past Month* equal to 100. The Federal Deposit Insurance Act (FDICIA) mandates that failed banks be resolved within 90 days of becoming critically undercapitalized. Because of Call Report timing and Call Report amendments, this 90-day period may not be an exact match for when public information about a bank's financial distress becomes available, but it is a good approximation that can be broadly applied across banks. As a result, we define *Close*

[7] This leaves open the possibility of zero-balance HELOCs being closed as part of a refinance process, which would look identical to a bank closing a zero-balance loan.

[8] We maintain all HELOCs that have buyer-initiated closures (as identified by the above metrics based on zero closing balance and a positive balance one month before close), such as sales of the underlying real estate or refinances (indicating that usage was nonzero in the month prior) in our sample for baseline comparisons as untreated observations, described in the variable *Line Cut or Closed*. We omit the days that actually have the cut, since they are not manifestations of active bank line management, but retain all other days.

to Fail to be an indicator variable that equal to 1 for all loans in the three months prior to the bank's failure date.

Loan-Level Characteristics. We construct both time-invariant and time-varying loan-level characteristics, and all specifications include month fixed effects to capture economic conditions. Our time-invariant characteristics include borrower FICO score at time of origination (*Credit Score*) and the ratio of the loan to the value of its collateral (*LTV*). Although a borrower's LTV or FICO score may change over time, the banks in our sample reporting this variable only retained its value from the time of loan origination. Banks split HELOCs into draw and repayment periods, and our outcome variables of interest cover to the draw phase. Furthermore, at origination, HELOC interest rates are typically a function of a benchmark, such as the prime rate, and a positive spread. We calculate the interest rate spread at origination, *Origination Spread*, by taking the difference between the interest rate that the bank charged the borrowers on the first day of the HELOC approval and the effective federal funds rate on that day. The interest rates that banks offer borrowers should reflect the borrower's total risk, as reflected in both hard information, such as *LTV* and *FICO*, but also soft information that the bank has about the borrower, such as the borrower's employer or business, and any discretionary changes that may occur over time. We record the variables *LTV* and *Origination Spread* as percentages, with a 5 percent interest rate or 100 percent loan-to-value ratio expressed as 5 and 100.

For each month a HELOC appears in our sample, we calculate several time-varying variables that capture borrower "early warning signals" to banks or indications of borrowers likely seeking credit. For each day, we create two indicator variables related to delinquency. *Recent Delinquency* takes a value of 1 for loans currently more than 60 days past due and became so within the past two months. *Historic Delinquency* takes a value of 1 for loans that were more than 60 days past due at some point more than two months in the past. We also quantify the proportion of the line in use one month ago (*Used Proportion Past Month*) and whether the borrower had a line increase in the time between the loan origination and the previous month (*Previous Line Increase*). The indicator variables *Deposit Account* and *Other Loan* each respectively takes a value of 1 if the HELOC borrower has a deposit account or other loan with the bank in that month.[9]

We present summary statistics for the 1,369,100 HELOC-months in our sample in Table 1A. Missing values arise because not all banks retained the necessary information to compute all variables. Table 1B shows summary statistics for a total of 90,730 loans on the final month that the loan is in the bank's system prior to failure. Table 1C reports summary values for the subset of 7,354 loans in Table 1B that meet our criteria as plausibly initiated by the bank.

Table 1B indicates that approximately 18 percent of loans in our sample were closed. Some of these closures were bank-initiated while others were consumer-initiated, such as with the sale of property. Table 1C shows that the HELOCs with bank-initiated closures have an average credit commitment of $86,417. At origination, the average credit score for borrowers on these loans was 736, the average LTV ratio was 61 percent, and the average origination spread was 2.64 percent over the effective fed funds rate. Approximately 35 percent of borrowers with cut HELOCs have other loans at the bank and 56 percent have a deposit account. Delinquency is a rare event for these borrowers. Only 4 percent of them are currently delinquent and 5 percent

[9] Wherever possible in the data, we include closed-end, first-lien, residential mortgages recovered from servicing systems. In general, and especially immediately before the financial crisis, the originator bank making the mortgage loan, investors holding the credit risk, and servicer maintaining the loan are not necessarily coincident and can change rapidly over time, and thus linking data for these loans in particular is difficult.

have a historic delinquency. On the final day in the system, borrowers had drawn 38.87 percent of credit lines, with their utilization falling on average -0.71 percent over the previous month. About 1 percent had a line increase at least 31 days prior to the failure date.

3. Empirical Design

In our first set of analyses, we explore whether banks manage borrower liquidity demand by terminating HELOCs when the observable characteristics suggest that the loan is at a higher risk of default. Our first specification focuses on time-invariant default risk factors. Agarwal, Ambrose, Chomsisengphet, and Liu (2006) show that HELOC default is negatively related to FICO score (*Credit Score*) and positively related to the loan-to-value ratio (*LTV*). We also include *Origination Spread* as a potential early warning signal, since the spread that the bank offers the borrower should reflect the bank's overall assessment of the borrower's risk. We analyze the relationship between each of these loan-level variables and the bank's propensity to cut HELOC lines using the empirical framework in Equation 1:

$$Line\ Cut_{hbt} = \alpha_{hbt} + \beta_1 LoanChar_{hb} + \delta_t + \zeta_b + \gamma_{zy} + \epsilon_{hbt} \tag{1}$$

where *t* represents the month of the observation for HELOC *h* in bank *b*. $LoanChar_{hb}$ represents the HELOC-level variable of interest held in bank *b*. Since all HELOC-level variables are calculated at loan origination and therefore fixed over time, we cannot include loan-level fixed effects in this baseline specification. However, we include year-month fixed effects δ_t that capture time variation common across all banks, including the level of the benchmark rate and macroeconomic conditions, and bank-level fixed effects ζ_b, capturing time-invariant differences between banks, such as lending practices. We control for changes in the value of the underlying collateral through zipcode-year level fixed effects γ_{zy}, where zip codes are defined at the three-digit level. We also include the month-over-month changes within the Zillow Price Index, which is calculated at the three-digit zipcode level, to account for any changes in the underlying property value.

We then examine the influence of time-varying covariates on the likelihood of HELOC revocation. Specifically, we test whether banks are more likely to cut lines for borrowers with high delinquency rates, borrowers holding other types of bank products, or borrowers exhibiting credit-seeking behaviors, as evidenced by increased borrower drawdown or increased line changes, using the empirical framework in Equation 2:

$$Line\ Cut_{hbt} = \alpha_{hbt} + \beta_1 Var_{hbt} + \delta_t + \nu_h + \gamma_{zy} + \epsilon_{hbt} \tag{2}$$

where t represents the month of the observation for HELOC h in bank b and Var_{hbt} represents the HELOC-month variable of interest. We include both month fixed effects and zipcode-year level fixed effects, where zipcodes are defined at the three-digit level as in Equation 1. We also include HELOC-level fixed effects, ν_h, to absorb time-invariant HELOC-level characteristics, such as the variables measured at origination and the identity of the loan officer responsible for making the loan.

We also examine whether banks manage the liquidity risk presented by HELOCs differently as they approach failure and their capital position worsens. We interact our *Close to Fail* variable, indicating that the bank is less than 3 months from failure, with our time-invariant variables in Equation 3 and time-varying variables in Equation 4.[10]

[10] As noted above, $LoanChar_{hb}$ does not vary over time, and so the HELOC level fixed effects in Equation 4 absorb the direct effect of these variables.

$$Line\ Cut_{hbt} = \alpha_{hbt} + \beta_1 Close\ to\ Fail_{bt} + \beta_2 Close\ To\ Fail_{bt} * LoanChar_{hb} + \delta_t + \zeta_b + \gamma_{zy} + \epsilon_{hbt} \tag{3}$$

$$Line\ Cut_{hbt} = \alpha_{hbt} + \beta_1 Close\ to\ Fail_{bt} + \beta_2 Close\ To\ Fail_{bt} * Var_{hbt} + \delta_t + \nu_h + \gamma_{zy} + \epsilon_{hbt} \tag{4}$$

We also use Equations 3 and 4 to examine if borrowers have an increased likelihood of drawing down on their HELOCs prior to bank failure, which may reflect borrower liquidity demand or uncertainty about access to future credit. In these specifications, our dependent variable of interest is *Used Proportion Change Past Month*, which we measure at the monthly frequency for each HELOC. We cluster standard errors at the HELOC level to allow for arbitrary correlations within loan observations over time.

4. Results

4.1 Overall determinants of Bank HELOC Management

We first examine whether banks are more likely to revoke credit lines for loans that have higher risk profiles using HELOC-level information available to the bank at the time of loan origination. We follow Agarwal, Ambrose, Chomsisengphet, and Liu (2006) by using the loan-to-value ratio (*LTV*) as a determinant of HELOC termination. We add the initiation spread (*Origination Spread)*, reflecting the bank's assessment of the borrower's overall level of borrower risk, as a new potential predictor of a bank's decision to terminate a HELOC, similar to the spread used to explain business lending decisions in Liberti and Sturgess (2018). We examine the relationship between bank credit line revocation and loan risk factors using the empirical framework in Equation 1 and present results in Column 1 of Table 2. We use the empirical framework in Equations 3 and 4 to explore any changes in these associations as banks approach failure and present analogous results in Column 2.

Consistent with our predictions, we find in Column 1 that banks are more likely to revoke HELOCs for loans that exhibit higher risk profiles at loan origination for both measures that we examine. Both higher loan-to-value ratios (*LTV*) and spreads at origination (*Origination Spread*) are positively correlated with line revocation. When lending, banks set interest rates based on the overall risk profile of a borrower, considering both hard and soft information. As discussed in Section 2.1, banks typically set HELOC interest rates as a function of both a benchmark rate (such as prime) as well as a positive spread above the benchmark. The monthly fixed effects in Equation 1 absorb the monthly levels of the benchmark rate, indicating that the coefficient on *Origination Spread* should primarily reflect differences in the spread. Since we do not use HELOC fixed effects in this table, loans with higher overall interest rates could reflect correspondingly higher levels of risk. The positive coefficient on *Origination Spread* in Column 1 may reflect a negative correlation between higher spreads and unobservable borrower quality.

In Column 2, we add Close to Fail, an indicator variable that takes a value of 1 in the three months just prior to each bank's failure. We find that the coefficient on *Close to Fail* is negative but not statistically significant. The direct coefficients on *LTV* and *Origination Spread* indicate that when a bank is not close to failure, it is more likely to revoke HELOCs with higher loan-to-value ratios and interest rates. The interaction terms between *Close to Fail*, *LTV*, and *Origination Spread* are consistent in sign with their direct effects and the interactions with *LTV* and *Origination Spread* are statistically significant in Column 2, suggesting that banks revoke HELOCs more aggressively just prior to failure.

Next, we examine whether time-varying differences in borrower payment and drawdown behavior affect how banks manage HELOCs. We use the framework in Equation 2 and present the results in Table 3. We use HELOC-level fixed effects, which subsume all bank fixed effects and account for all time-invariant characteristics of the loan, such as the address and value of the collateral and the origination characteristics presented in Table 2 Column 1. By including HELOC fixed effects, we identify the effects of borrower delinquency and liquidity demand through variation within a given HELOC over time.

Table 3, Column 1 indicates that banks are 5.216 percent more likely to cut a delinquent loan than a current loan and 0.930 percent more likely to revoke a loan if it has a more distant history of delinquency. Since delinquency is a common precursor to default, the positive signs on both coefficients are consistent with banks actively managing HELOCs in response to this early warning signal.

We also examine whether borrowers exhibiting credit-seeking behavior or liquidity demands are more likely to have their lines revoked. Norden and Weber (2010) suggest that borrower credit-seeking behavior, such as large borrower drawdowns, precedes default in their sample of personal credit lines in Germany. However, after a drawdown, a borrower has less credit available for future drawdowns, leaving less potential future liquidity demand for the bank to manage.

Our results indicate that banks are less likely to revoke the credit lines of borrowers that have lower usage levels as of the previous month. The negative coefficient on *Used Proportion Past Month* shows that banks are less likely to revoke credit lines with smaller potential for future drawdowns. We also find that banks are less likely to revoke credit for borrowers who have drawn down a greater proportion of their balance within the previous month, since the coefficient on *Used Proportion Change Past Month* is negative and statistically significant. The negative coefficients on both *Used Proportion Past Month* and *Used Proportion Change Past Month* indicate that banks are less likely to manage credit for borrowers with less credit to draw upon. The negative coefficient on *Previous Line Increase* indicates that banks are less likely to cut credit lines of borrowers that had previously received credit line increases. This finding may reflect a preference across banks for keeping credit lines that offer lower balance sheet exposure or for borrowers who have improved their unobservable risk factors since origination. Since loan losses are a function of both probability of default and bank exposure at default, both interpretations are consistent with banks being less likely to manage loans when expected losses are lower.

In Column 2, we examine whether banks change the way they manage delinquent borrowers and those with greater credit availability in the time just prior to failure. The positive and significant coefficient on *Close to Fail* suggests that banks revoke access to home equity lines more often in the time shortly before failure. The direct effects are highly consistent with those in Column 1. The interaction terms for each of these variables and the *Close to Fail* indicator show that these effects grow in magnitude in the time just prior to failure. The result indicates that banks' credit line management decisions are more sensitive to changes in these variables in the time just prior to failure. Thus, in the three months prior to failure when banks are both liquidity and capital constrained, banks are less likely to revoke credit lines of borrowers without a history of delinquency and those who pose less liquidity risk to the institution.

We now turn to the question of whether stronger borrower-bank relationships, as indicated by whether borrowers hold other loans or a deposit account with the bank, are associated with a decreased likelihood of banks revoking credit from HELOCs. In Table 4, we apply the framework in Equation 2 and examine whether HELOC closure is a function of the other products that a borrower may hold within a bank. When we include HELOC fixed effects in Column 1, we find that a borrower holding a deposit account with the bank reduces the probability of a bank revoking a credit line, while a borrower holding another loan with the bank increases probability of line revocation. We also examine whether banks are more or less likely to revoke credit for borrowers when the value of the underlying collateral increases, as measured by the Zillow pricing index. As above in Table 3 when controlling for HELOC characteristics, we find no evidence that the value of the underlying collateral meaningfully impacts the probability of banks revoking credit lines when controlling for borrower relationship characteristics.

In Column 2, we show that the direct effects on each of the three relationship variables are broadly consistent with those in Column 1. As the bank nears failure, the probability of all line cuts increases, as shown by the positive and statistically significant coefficient on *Close to Fail*. Additionally, the interaction between *Close to Fail* and *Other Loan* is positive and statistically significant. This positive coefficient suggests that banks may grow concerned about possible correlated defaults across multiple lending relationships with the same borrower as failure grows closer and liquidity constraints grow tighter.

Our results use all available observations from our sample of banks, including those from times close to failure and times of normal bank operation. Additionally, the analyses presented in Tables 3 and 4 may suffer from bias due to time-varying unobservable loan characteristics that may drive both borrower behavior and the closure of the credit line. When we examine the time period just prior to failure when banks have stronger incentives to manage HELOCs, we find that bank HELOC management is consistent with the effects found in the full sample, yet more sensitive to changes in the determinants. Banks are more likely to revoke credit for HELOCs with riskier profiles, greater ability to demand liquidity, and for borrowers with other lending relationships. However, while certain cross-sections of borrowers may be more or less likely to have their home equity loans revoked, we find that banks manage HELOCs more aggressively just prior to failure.

4.2 Borrower Drawdown Behavior Close to Bank Failure

In this section, we search for evidence that borrowers change their draw behavior just prior to bank failure. Each borrower in our sample has an established banking relationship through their HELOC, and pending bank failure may introduce uncertainty for the borrower and change draw behavior. Borrowers may also anticipate the bank's decision to close lines as part of liquidity and capital management as failure approaches and draw on their available credit. It is not clear ex ante if the net effect should be more draws, as the borrowers access liquidity and credit that may soon be unavailable to them, or less draws, as the bank has power to restrict draws effectively at the cost of future profits. We study whether borrowers draw down on a HELOC using the same specifications as we use above for line revocations.

In Table 5, we investigate whether HELOC characteristics at the time of loan origination influence borrower drawdown behavior in the three months prior to failure. The dependent variable is *Used Proportion Change Past Month*, which is the difference in the dollar amount of the HELOC drawn over the previous month as a percentage of the total HELOC borrowing limit. Higher values of *Used Proportion Change Past Month* indicate that borrowers drew down greater amounts of credit relative to their limits over the previous month. In Column 1, the coefficient on *LTV* is negative and statistically significant, indicating that on average, borrowers with greater initial loan to value ratios draw smaller shares of their available credit while borrowers in regions with greater home price appreciation draw more. In the three months prior to bank failure, we find that borrowers with a greater spread at origination draw less from their unused HELOC balances. The negative coefficient on origination spread when the bank if close to failure suggests that banks may be effective in cutting HELOCs to the riskier borrowers who are more likely to borrow, as indicated by our results in Table 2. The findings on *LTV* and house price growth are consistent with greater draws coming from borrowers with more equity on which to draw.

In Table 6, we examine the time-varying elements of borrower delinquency and credit-seeking behavior. As in Table 5, we find that higher home price appreciation is correlated with larger draws. We also find a negative coefficient on *Close to Fail* and no evidence that the borrowers who were most credit rationed exhibit increased abnormal drawdowns when bank failure is imminent in our model with HELOC fixed effects. The coefficient on *Historic Delinquency***Close to Fail* is negative, statistically significant, and larger in magnitude than the coefficient on *Historic Delinquency*, indicating that borrowers with a history of delinquency are less likely to draw down as bank failure approaches. Recently delinquent borrowers are no more (or less) likely to drawdown on their HELOCs in the three months prior to bank failure, possibly because banks restrict delinquent borrowers' credit access without specifically revoking it. However, the corresponding interaction terms show that borrowers with less available credit (high values of *Used Proportion Past Month*) are relatively more likely to increase their drawdown rates. When the interaction term between *Close to Fail* and each independent variable is evaluated at its mean from Table 1A and the negative effect of the *Close to Fail* indicator variable is included, our model predicts that the average borrower will draw down an extra 0.3 percent of their available HELOC limit when the bank is close to failure. Our estimate reflects only a 0.6 percent increase in average line utilization as bank failure approaches.

We also examine whether borrowers with stronger banking relationships draw down more on their HELOCs just prior to bank failure and present results in Table 7. If relationships provide borrowers with value and borrowers anticipate that they will have difficulty acquiring outside credit or liquidity post-failure, they may be more likely to draw on their existing HELOC. In Column 1, we find that borrowers with other loans from the bank are less likely to drawdown on their available credit. However, the interaction terms between *Close to Fail* and *Deposit Account* or *Other Loan* are not statistically significant, indicating that the effects of a banking relationship on drawdown propensity do not change when the bank nears failure. Again, we find that great home price growth predicts larger draws on available equity credit.

Overall, our results indicate that borrowers do not significantly increase their HELOC drawdown rates as bank failure approaches. While certain cross-sections of borrowers increase or decrease their *relative* drawdown rates, we do not find consistent evidence that borrowers less likely to obtain outside credit or liquidity, such as those with riskier HELOC characteristics, or borrowers with stronger banking relationships, increase their HELOC usage just prior to bank failure. Our findings are consistent with three interpretations. First, it is possible that borrowers are unable to anticipate bank failure and thus do not draw down on their HELOCs. Second, even if they do anticipate bank failure, they may not respond by drawing down specifically on credit available through home equity lines. Third, banks may successfully manage borrowers by not allowing them to draw down on the credit they have available, thus preempting any HELOC drawdown, which has the most interesting implications for the literature.

This finding highlights features of the contract here that may have implications for similar settings. Kasyhap, Rajan, and Stein (2002) emphasize the parallel between borrower runs on deposits and lines of credit, but they note that the contracts in their analysis are hard to revoke. Other studies have found only limited evidence of corporate drawdown behavior consistent with run behavior in cross-sectional studies (Ivashina and Scharfstein, 2010; Ippolito, Peydro, Polo, and Sette, 2016), but those settings involve banks being possibly unwilling but still able to honor credit lines and contracts written to make runs less likely. While *ex ante* it may be reasonable to look for draw behavior before banks elect to turn lines off, this would be a setting very similar to deposits with the threat of suspension of convertibility in Diamond and Dybvig (1983). In such a setting, borrowers do not run and there is merely some sub-optimal risk sharing as borrowers are unable to convert their claims to cash. Since banks can easily revoke credit lines in our setting, we accordingly do not see large drawdowns. As the franchise value of the bank falls and the risk of failure increases, future costs are less relevant to the bank. Accordingly, the threat of revocation becomes even more credible, which would be consistent with the observation in our paper that borrowers draw even less close to failure.

4.3. Bank Earnings Tax Rate

Throughout our analysis, we attempt to isolate HELOCs that banks, rather than borrowers, terminate in order to study banks' determinants for ending the credit relationship and mitigating the liquidity risk. However, this is challenging because many features of the relationship between the borrower and creditor are unobservable to researchers. For example, borrowers may have significant income shocks that are known to the bank but unobservable in our data, and these income shocks may be correlated with determinants such as *Recent Delinquency* or *Used Proportion Change*.

In this section, we add the bank earnings tax rate as an additional determinant to our regressions to investigate whether the observed HELOC terminations result from bank or consumer actions. In a state with a higher bank tax rate, a bank receives a larger tax benefit from charging off a bad loan and so faces weaker incentives to end a potentially failing HELOC early, affecting both the decision to cut the line and the timing of the cut (Coles et al, 2022). However, the corporate tax rate is unlikely to influence the behavior of HELOC borrowers directly.[11]

We use the bank tax rate to test whether the line cuts captured in our dependent variable reflect bank or consumer behavior. If consumer behavior determines HELOC cancellations, then variation in the bank tax rate should be unrelated to the behavior and should not predict HELOC line cuts. If the banks initiate line cuts, then variation in the bank tax rate may influence the decision to cancel a HELOC. We present results in Table 8. In Column 1, we find that the bank tax rate is a statistically significant predictor of HELOC termination in our data, suggesting that bank incentives matter for line cuts. In Column 2, we show that the coefficient on the tax rate grows larger when adding controls for bank behavior near failure. We interpret these findings as evidence that bank incentives influence in HELOC cancellations under the definition of line terminations in our sample.

5. Robustness

To alleviate the concern that one bank is driving the overall results presented in this paper, we rerun our analyses dropping each bank in turn. In each set of seven banks, our results are both qualitatively and quantitatively unchanged. In unreported results, we also perform

[11] Bank earnings tax rates are equal to or directly derived from corporate earnings tax rates in most states, which apply to C-corporations and are not immediately tied to a borrower's ability to repay. We will address possible endogeneity from individual's awareness of changes in corporate tax rates in future work.

regression analyses including all covariates and find that our regression results are qualitatively similar. The only notable exception is that borrowers with higher credit scores are less likely to have their lines cut, with the coefficient is negative and significant at the 5 percent level when all covariates are included. We discuss possible reasons for this result in the Appendix.

6. Conclusion

In the years before the financial crisis, bank balance sheet exposure to HELOCs rapidly expanded, and consumers actively drew down on these lines as the economy deteriorated. Our paper is the first to examine whether banks used common HELOC contract terms allowing credit revocation to manage the risks from these lines of credit. We contribute to a growing body of literature exploring how credit supply contractions and deteriorating bank financial health are associated with both bank and borrower behavior.

Using a unique set of proprietary, daily transaction-level data from eight banks, we find that banks are more likely to revoke credit for loans that have riskier characteristics at loan origination and time-varying borrower "early warning signals." We show that banks are less likely to revoke HELOCs that have lower amounts of credit available. In further analysis, we find that banks are more likely to revoke HELOCs for all borrowers in the three months prior to failure, when the banks are most likely to be liquidity and capital constrained and face stronger incentives to deploy resources strategically. This effect attenuates slightly for higher quality loans, more profitable loans, and loans with less unutilized credit. Our results suggest that these unconditionally cancellable credit lines can be a tool for banks to manage their liquidity risks.

Furthermore, to our knowledge, this is the first paper to examine whether consumer borrowers draw down lines of credit just prior to bank failure, and this analysis has implications for understanding the welfare tradeoffs of HELOCs. Although HELOCs may be useful for borrower consumption smoothing across certain kinds of idiosyncratic shocks, such as the need for home repairs, our results suggest that bank management of the associated liquidity risks may make it more challenging for consumers to smooth across macroeconomic states when we introduce idiosyncratic bank risk.

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Appendix

In Tables 2 and 5, we investigate whether HELOC characteristics at the time of loan origination influence bank decisions to terminate the HELOC and borrower drawdown behavior. In Appendix Tables A1 and A2, we replicate these analyses adding borrower credit score at origination to the regressions. Since credit score was not a variable retained by all banks or for all loans, we also include an indicator for whether a credit score exists in the data to enable us to use the entire sample in the regression to make the comparison to the results in Tables 2 and 5 as close as possible. For observations with a missing credit score, the credit score variable is set to 0.

In Column 1 of Appendix Table A1, we find that credit score at origination conditional on a score existing does not explain a bank's later decision to eliminate a HELOC. However, banks are more likely to terminate a HELOC belonging to a borrower without a recorded score. This may indicate that borrowers without recorded scores are more likely to be riskier borrowers, as suggested by the coefficient on spread at origination. The other two coefficients do not show any significant change. In Column 2, we find that adding credit score makes the estimated effect of being close to failure negative and significant for the probability of line cuts, while the coefficient on the interaction term *Credit Score * Close to Fail* has an unexpected positive sign. We believe that these unexpected signs are likely driven by multicollinearity between *Credit Score* and the other loan risk measures in the regression and presented in Table 2. The regression in Column 2, for example, requires that a borrower's interest rate spread at origination remain constant when estimating the marginal effort of a change in credit score. If the origination rate spread is already an accurate measure of borrower risk including factors beyond the borrower's credit score, then a higher credit score at origination with a given interest rate spread may be correlated with other negative credit information that the bank has about the borrower, leading to the positive correlation with bank line closure observed here. The minimal change in regression R^2 values between Table 2 and Appendix Table A1 also suggests that adding credit score to our regressions does not add meaningful predictive power to our specifications beyond the variables already included in Table 2 in text.

The results in Appendix Table A2 replicate those in Table 5 for the percentage of the available credit that borrowers use. When we add our credit score variables and compare the results between the two tables, we find a similar pattern as above in Appendix Table 1. The coefficients on the variables included in Table 5 do not show major changes with the addition of the credit score variables with the exception of the *Close to Fail* dummy. The coefficient on the interaction variable *Credit Score * Close to Fail* has an unexpected positive sign, and the regression R^2 value shows no change to the thousandth place. Again, we interpret these results as indicating that the *LTV* and *Origination Spread* variables in Tables 2 and 5 capture borrower risk in a way that is closely correlated with *Credit Score*, so adding our credit score controls directly does not meaningfully improve our regression models.

Appendix A: Variable Description

Variable	Full Text	Source
Close to Fail	*Close to Fail* is an indicator variable equal to 1 if the account-month observation is three months or fewer away from the failure date of the bank and 0 otherwise.	FDIC
Credit Score	*Credit Score* is a FICO score on the range of 300 to 850. As this is time invariant it is removed by loan level fixed effects unless interacted. Note we do not always have credit score status, but due to its removal from fixed effects this does not negatively affect most specifications.	FDIC
Deposit Account	*Deposit Account* is an indicator variable equal to 1 if the customer has a deposit account with the bank during the month and 0 otherwise. We can identify checking, savings, and CD accounts for most banks.	FDIC
End of Month Line	*End of Month Line* is equal to the maximum limit of the line in dollars at the end of the month.	FDIC
Historic Delinquency	*Historic Delinquency* is an indicator variable equal to 1 if the account month is after the loan has become 60 days or more past due more than two months in the past and 0 otherwise. Note this will be a regime change, as even if the loan cures it will still have been delinquent.	FDIC
Line Cut or Closed	*Line Cut or Closed* is a variable equal to 100 if the line's credit limit is cut to 0 (a 100 percent cut) after having a positive credit limit or is marked as closed, and 0 otherwise.	FDIC
Line Cut	*Line Cut* is a variable equal to 100 if the line's credit limit is cut to 0 (a 100 percent cut) after having a positive credit limit or is marked as closed, which we identify as a bank initiated closure, and 0 otherwise.	FDIC
Line Increase	*Line Increase* is an indicator variable equal to 1 if the line's credit limit was ever increased in the past and 0 otherwise	FDIC
Loan Term	*Loan Term* is equal to the term of the loan in years. As this is time invariant it is removed by loan level fixed effects unless interacted. Note we do not currently have separate draw and repayment periods in this draft.	FDIC
LTV	*LTV* is defined as the size of the loan divided by the size of the underlying collateral. As this is time invariant, it is removed by loan level fixed effects unless interacted. Note we do not always have other lien status for the property or lien order, so we rely on loan level fixed effects to correct for this. A loan that is exactly fully secured but is not over-collateralized has an LTV of 100.	FDIC
Original Loan Commitment Amount	*Original Loan Commitment Amount* is equal to the original maximum limit of the loan in dollars.	FDIC

Origination Spread	*Origination Spread* is defined as the interest rate spread above the federal funds rate as of the loan's origination. A spread of 5 percent is listed as 5. As this is time invariant, it is removed by loan level fixed effects unless interacted.	FDIC
Other Loan	*Has Other Loans with Bank* is an indicator variable equal to 1 if the customer has either a term loan or other line of credit at the bank and 0 otherwise.	FDIC
Previous Line Increase	*Previous Line Increase* is an indicator variable equal to 1 if credit line increased anytime between one month in the past and the opening date of the credit line, assuming the line has been open for more than 31 days and, 0 otherwise. Several banks did not employ this management strategy.	FDIC
Rate	*Rate* is defined as the interest rate of the loan on the day measured. A rate of 5 percent is listed as 5.	
Recent Delinquency	*Recent Delinquency* is an indicator variable equal to 1 if the account month is after the loan has become 60 days or more past due for the first time in the past two months and 0 otherwise. Note this will be a regime change, as even if the loan cures it will still have been delinquent.	FDIC
Tax Rate	*Tax Rate* is the yearly state-level corporate tax rate.	
Used Proportion Change Past Month	*Used Proportion Change* is the difference between the proportion of the credit line that was already drawn at the end of the month and the proportion of the credit line that was already drawn one month in the past. This is also a left hand side variable in some specifications. A fully drawn line has a used proportion of 100.	FDIC
Used Proportion, Past month	*Used Proportion, Past Month* is equal to the proportion of the credit line that was already drawn one month in the past in the regressions and unlagged in the summary statistics tables. A fully drawn line has a used proportion of 100.	FDIC
Zillow Price Index Growth	Zillow Price Index Change is the change in the past month at the zip code level of the Zillow housing price index.	FDIC

Tables and Figures

Figure 1: Size of HELOC Holdings Relative to All Mortgages for Banks using Call Report data

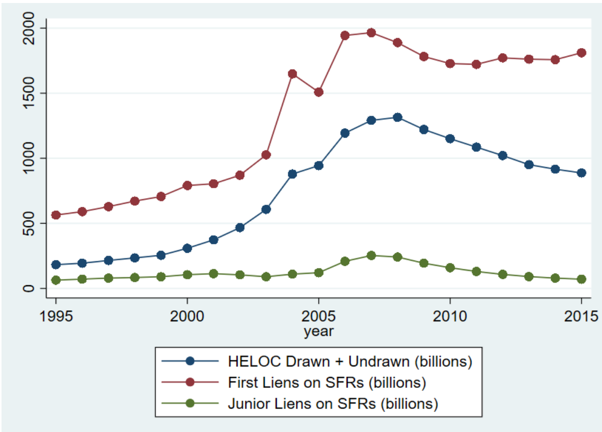


Figure 2: Size of HELOC Market Relative to Other Selected Consumer Borrowing for Banks using Call Report data

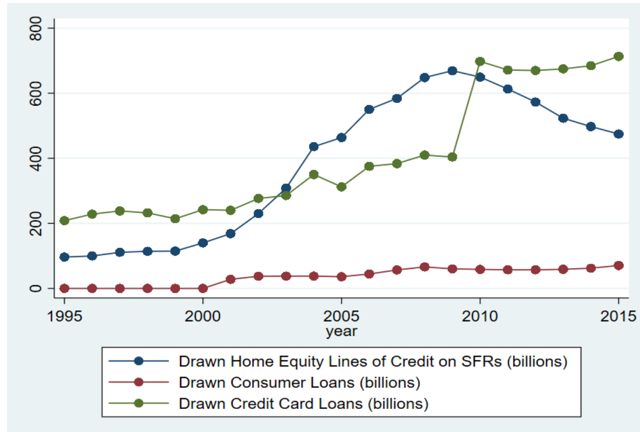


Figure 3: HELOC Draw Patterns using Call Report data

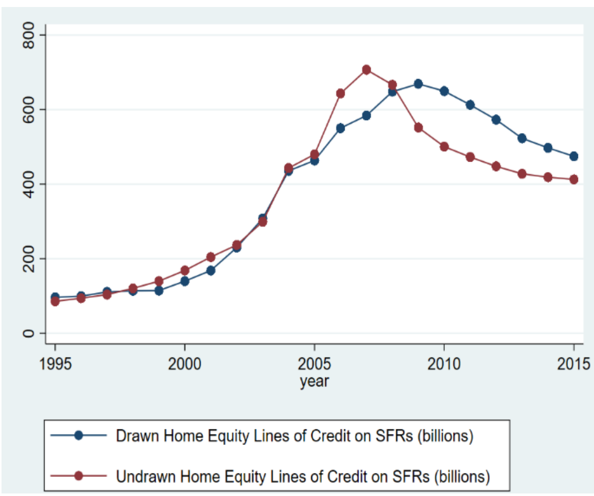
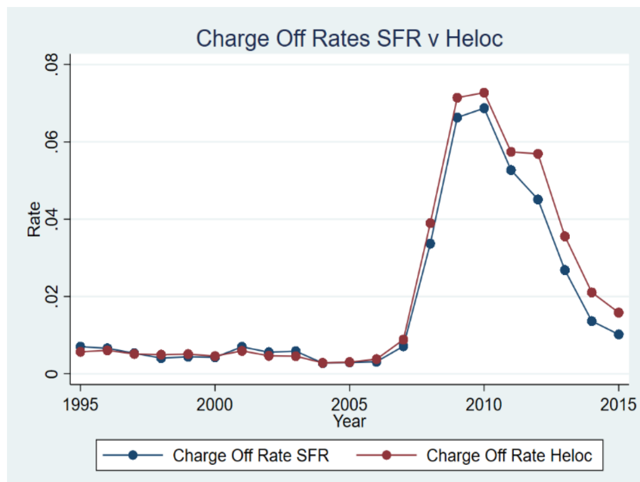


Figure 4: Charge Off Rates for SFR and HELOC using Call Report data



Source: FDIC Call Report Data

Figure 5: Bank Liquidity Creation Near Bank Failure

Y-axis is total liquidity created as a share of bank gross total assets for all banks in sample. Liquidity created is defined by the catfat measure of liquidity from Berger and Bouwman (2009). Gross total assets is bank total assets plus the allocation for loan lease and losses plus the allocated transfer reserve. X-axis is the number of quarters prior to the quarter in which bank failure occurs.

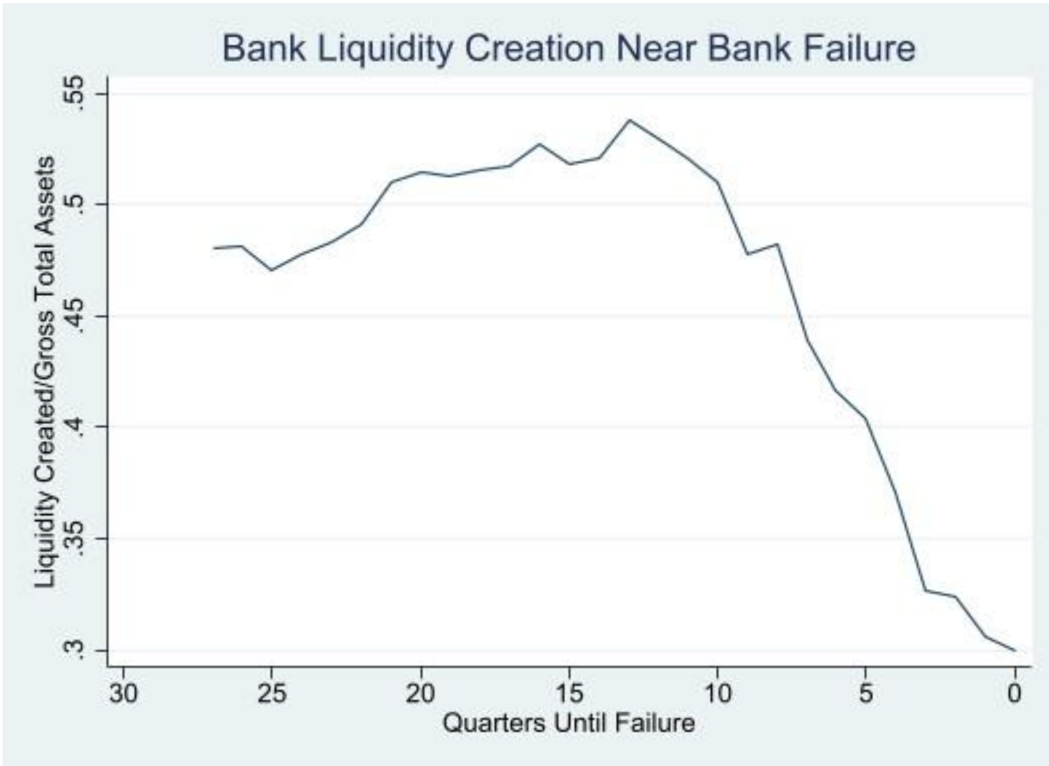


Table 1A: Loan and Borrower-Level Characteristics. Panel A: All Loan-Months.

This table displays summary statistics for each month at each HELOC. All variables defined in Appendix A.

(1) Variable	(2) Mean	(3) SD	(4) N
Original Loan Commitment Amount	79,808.45	183,000	1,369,100
Line Cut or Closed	0.54	7.31	1,369,100
Credit Score	734.16	61.65	984,388
LTV	43.24	32.65	1,313,350
Origination Spread	2.34	2.04	1,314,714
End of Month Principal	42,124.51	116,000	1,369,100
End of Month Line	81,148.87	184,000	1,369,100
Historic Delinquency	0.04	0.19	1,369,100
Recent Delinquency	0.00	0.06	1,369,100
Used Proportion Past Month	53.33	38.67	1,369,100
Used Proportion Change Past Month	0.08	16.81	1,369,100
Previous Line Increase	0.02	0.14	1,369,100
Deposit Account	0.57	0.49	1,369,100
Other Loan	0.26	0.44	1,369,100
Zillow Price Index Change	-0.25	1.19	1,152,076
Close to Fail	0.08	0.27	1,369,100
N			1,369,100

Table 1B: Loan and Borrower-Level Characteristics. Panel B: Last loan-month.

This table displays summary statistics for one observation for each HELOC on the last month it appears in the servicing system or on the month the bank failed, if it continued to be in the servicing system post failure. All variables defined in Appendix A.

(1) Variable	(2) Mean	(3) SD	(4) N
Original Loan Commitment Amount	88,722.71	129,000	90,730
Line Cut or Closed	17.64	38.12	90,730
Credit Score	717.31	66.78	78,054
LTV	46.04	29.57	86,642
Origination Spread	3.63	1.82	88.008
End of Month Principal	60,753.18	88,000	90,730
End of Month Line	89,127.34	129,000	90,730
Recent Delinquency	0.02	0.12	90,730
Historic Delinquency	0.02	0.15	90,730
Used Proportion Past Month	70.80	36.48	90,730
Used Proportion Change Past Month	-0.22	11.98	90,730
Previous Line Increase	0.01	0.10	90,730
Deposit Account	0.20	0.40	90,730
Other Loan	0.44	0.50	90,730
Zillow Price Index Growth	-1.38	1.31	85,896
Close to Fail	0.83	0.38	90,730
N			90,730

Table 1C: Loan and Borrower-Level Characteristics. Panel C: Treated Loan-Month.

This table displays summary statistics for one observation for each HELOC on the first day it appeared in the servicing system as a closed loan and met our criteria for being a bank-initiated closure, a *Line Cut*. All variables defined in Appendix A.

(1) Variable	(2) Mean	(3) SD	(4) N
Line Cut	100.00	0	7,354
Original Loan Commitment Amount	86,175.02	223,000	7,354
Credit Score	735.64	56.96	4,312
LTV	60.65	33.97	6,867
Origination Spread	2.64	1.88	7,078
End of Month Principal	33,453.37	111,000	7,354
End of Month Line	86,417.68	224,000	7,354
Recent Delinquency	0.04	0.19	7,354
Historic Delinquency	0.05	0.22	7,354
Used Proportion Past Month	38.87	41.97	7,354
Used Proportion Change Past Month	-0.71	25.40	7,354
Previous Line Increase	0.01	0.12	7,354
Deposit Account	0.56	0.50	7,354
Other Loan	0.35	0.48	7,354
Zillow Price Index Growth	-0.50	1.05	6,182
Close to Fail	0.14	0.36	7,354
N			7,354

Table 2: Line Cuts with Loan Characteristics at Origination.

This table presents the estimates from an OLS regression where the dependent variable, *Line Cut*, is an indicator variable that takes a value of 100 on the first day of a bank-initiated closure where the bank either revoked the HELOC by either dropping the available credit limit to 0 or marking it as closed and 0 otherwise. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	(1) Line Cut	(2) Line Cut
LTV	0.00726***	0.00614***
	(26.63)	(21.51)
Origination Spread	0.0263***	0.0174***
	(7.65)	(5.11)
Close to Fail		-0.197
		(-1.95)
LTV * Close to Fail		0.0127***
		(8.67)
Origination Spread * Close to Fail		0.105***
		(5.89)
Zillow Price Index Growth	Yes	Yes
HELOC FE	No	No
Bank FE	Yes	Yes
Month FE	Yes	Yes
Zip 3 * Year FE	Yes	Yes
SE Clustered at Loan Level	Yes	Yes
N	1,051,691	1,051,691
R-sq	0.037	0.037

Table 3: Line Cuts with Early Warning Signals.

This table presents the estimates from an OLS regression where the dependent variable, *Line Cut*, is an indicator variable that takes a value of 100 on the first day of a bank-initiated closure where the bank either revoked the HELOC by either dropping the available credit limit to 0 or marking it as closed and 0 otherwise. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1) Line Cut	(2) Line Cut
Recent Delinquency	5.216***	4.912***
	(14.99)	(13.46)
Historic Delinquency	0.930***	0.894***
	(9.82)	(9.26)
Used Proportion Past Month	-0.00845***	-0.00769***
	(-18.61)	(-17.02)
Previous Line Increase	-0.607***	-0.483***
	(-8.39)	(-6.75)
Used Proportion Change Past Month	-0.00353***	-0.00292***
	(-5.26)	(-4.42)
Close to Fail		1.642***
		(9.67)
Recent Delinquency * Close to Fail		2.602*
		(2.28)
Historic Delinquency * Close to Fail		0.139
		(0.57)
Used Proportion Past Month * Close to Fail		-0.0178***
		(-9.49)
Previous Line Increase * Close to Fail		-1.467***
		(-10.61)
Used Proportion Change Past Month * Close to Fail		-0.0190**
		(-2.76)
Zillow Price Index Growth	-0.00971	-0.00683
	(-0.74)	(-0.52)
HELOC FE	Yes	Yes
Bank FE	No	No
Month FE	Yes	Yes
Zip 3 * Year FE	Yes	Yes
SE Clustered at Loan Level	Yes	Yes
N	1,152,076	1,152,076
R-sq	0.038	0.038

Table 4: Line Cuts with Relationship Variables

This table presents the estimates from an OLS regression where the dependent variable, *Line Cut*, is an indicator variable that takes a value of 100 on the first day of a bank-initiated closure where the bank either revoked the HELOC by either dropping the available credit limit to 0 or marking it as closed and 0 otherwise. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1) Line Cut	(2) Line Cut
Deposit Account	-0.159**	-0.150*
	(-2.65)	(-2.48)
Other Loan	0.147*	0.089
	(1.99)	(1.21)
Close to Fail		0.253*
		(1.99)
Deposit Account * Close to Fail		-0.0414
		(-0.32)
Other Loan * Close to Fail		1.131***
		(6.70)
Zillow Price Index Growth	-0.0105	-0.0114
	(-0.08)	(-0.92)
HELOC FE	Yes	Yes
Bank FE	No	No
Month FE	Yes	Yes
Zip 3 * Year FE	Yes	Yes
SE Clustered at Loan Level	Yes	Yes
N	1,152,076	1,152,076
R-sq	0.035	0.035

Table 5: Line Draws with Fixed Loan Characteristics Close to Failure.

This table presents the estimates from an OLS regression where the dependent variable is a change in the proportion of the HELOC utilized over the last month. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1) Used Proportion Change Past Month
LTV	-0.00339***
	(-7.34)
Origination Spread	0.00897
	(1.45)
Close to Fail	0.0906
	(0.76)
LTV * Close to Fail	0.00126
	(0.94)
Origination Spread * Close to Fail	-0.0357*
	(-2.04)
Zillow Price Index Growth	0.0830***
	(3.66)
HELOC FE	No
Bank FE	Yes
Month FE	Yes
Zip 3 * Year FE	Yes
SE Clustered at Loan Level	Yes
N	1,051,691
R-sq	0.020

Table 6: Line Draws with Early Warning Signals Close to Failure.

This table presents the estimates from an OLS regression where the dependent variable is a change in the proportion of the HELOC utilized over the last month. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1) Used Proportion Change Past Month
Recent Delinquency	0.376
	(1.65)
Historic Delinquency	0.731**
	(3.18)
Used Proportion Past Month	-0.332***
	(-77.68)
Previous Line Increase	2.523***
	(6.83)
Close to Fail	-0.706***
	(-3.44)
Recent Delinquency * Close to Fail	0.412
	(0.72)
Historic Delinquency * Close to Fail	-1.125***
	(-5.13)
Used Proportion Past Month * Close to Fail	0.0193***
	(8.18)
Previous Line Increase * Close to Fail	-0.222
	(-0.76)
Zillow Price Index Growth	0.0709**
	(2.61)
HELOC FE	Yes
Bank FE	No
Month FE	Yes
Zip 3 * Year FE	Yes
SE Clustered at Loan Level	Yes
N	1,152,076
R-sq	0.196

Table 7: Line Draws with Relationship Variables Close to Failure.

This table presents the estimates from an OLS regression where the dependent variable is a change in the proportion of the HELOC utilized over the last month. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	(1) Used Proportion Change Past Month
Deposit Account	0.138
	(1.57)
Other Loan	-0.482***
	(-4.58)
Close to Fail	0.0761
	(0.55)
Deposit Account * Close to Fail	0.126
	(1.14)
Other Loan * Close to Fail	-0.0852
	(-0.52)
Zillow Price Index Growth	0.0787**
	(3.22)
HELOC FE	Yes
Bank FE	No
Month FE	Yes
Zip 3 * Year FE	Yes
SE Clustered at Loan Level	Yes
N	1,152,076
R-sq	0.016

Table 8: Line Cuts with Bank Corporate Earnings Tax Rate.

This table presents the estimates from an OLS regression where the dependent variable, *Line Cut*, is an indicator variable that takes a value of 100 on the first day of a bank-initiated closure where the bank either revoked the HELOC by either dropping the available credit limit to 0 or marking it as closed and 0 otherwise. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. All other variables are defined in Appendix A. Standard errors are clustered by state. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1)	(2)
	Line Cut	Line Cut
Tax Rate	-0.0711***	-0.109***
	(-3.78)	(-4.00)
LTV	0.00784***	0.00699***
	(28.89)	(24.76)
Origination Spread	0.0241***	0.0159***
	(6.94)	(4.57)
Recent Delinquency	5.168***	4.815***
	(14.39)	(12.79)
Historic Delinquency	0.305***	0.301***
	(7.04)	(7.05)
Used Proportion Past Month	-0.00416***	-0.00346***
	(-18.61)	(-15.23)
Previous Line Increase	-0.0890	0.00338
	(-1.95)	(0.07)
Deposit Account	-0.0308	-0.0399*
	(-1.94)	(-2.57)
Other Loan	0.0363	0.0132
	(1.90)	(0.64)
Used Proportion Change	-0.00215**	-0.00150*
	(-3.29)	(-2.32)
Close to Fail		0.0456
		(0.31)
LTV * Close to Fail		0.0112***
		(7.56)
Origination Spread * Close to Fail		0.105***
		(5.92)
Recent Delinquency * Close to Fail		2.892*
		(2.43)
Historic Delinquency * Close to Fail		0.035
		(0.13)
Used Proportion Past Month * Close to Fail		-0.0101***
		(-9.08)
Previous Line Increase * Close to Fail		-1.402***
		(-9.28)
Used Proportion Change * Close to Fail		-0.0140*
		(-2.43)
Deposit Account * Close to Fail		0.344**
		(2.63)
Other Loan * Close to Fail		0.105
		(1.50)
Zillow Price Index Growth	-0.0121	-0.00868
	(-1.01)	(-0.72)
HELOC FE	No	No
Bank FE	No	No
Month FE	Yes	Yes
Zip 3*Year FE	Yes	Yes
SE Clustered at State Level	Yes	Yes
N	1,036,308	1,036,308
R-sq	0.039	0.040

Appendix Table A1: Line Cuts with Loan Characteristics at Origination.

This table presents the estimates from an OLS regression where the dependent variable, *Line Cut*, is an indicator variable that takes a value of 100 on the first day of a bank-initiated closure where the bank either revoked the HELOC by either dropping the available credit limit to 0 or marking it as closed and 0 otherwise. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. *Credit Score Exists* is an indicator variable that takes on a value of 1 for observations where the credit score variable is not missing. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1) Line Cut	(2) Line Cut
Credit Score	-0.000149	-0.000263*
	(-1.30)	(-2.20)
Credit Score Exists	-0.245**	-0.209*
	(-2.86)	(-2.34)
LTV	0.0064***	0.00516***
	(23.81)	(18.22)
Origination Spread	0.0227***	0.0136***
	(6.55)	(3.96)
Close to Fail		-0.959***
		(-5.76)
Credit Score * Close to Fail		0.00157***
		(3.40)
Credit Score Exists * Close to Fail		-0.266
		(-0.73)
LTV * Close to Fail		0.0135***
		(9.21)
Origination Spread * Close to Fail		0.118***
		(6.22)
Zillow Price Index Growth	Yes	Yes
HELOC FE	No	No
Bank FE	Yes	Yes
Month FE	Yes	Yes
Zip 3 * Year FE	Yes	Yes
SE Clustered at Loan Level	Yes	Yes
N	1,051,691	1,051,691
R-sq	0.037	0.037

Appendix Table A2: Line Draws with Fixed Loan Characteristics Close to Failure.

This table presents the estimates from an OLS regression where the dependent variable is a change in the proportion of the HELOC utilized over the last month. The variable *Close to Fail* is an indicator variable that takes a value of 1 for observations within the three months prior to failure. *Credit Score Exists* is an indicator variable that takes on a value of 1 for observations where the credit score variable is not missing. All other variables are defined in Appendix A. Standard errors are clustered by HELOC. T-statistics are presented in parentheses, and significance is denoted by * p <0.05, ** p < 0.01, and *** p<0.001.

	(1) Used Proportion Change
Credit Score	-0.000496*
	(-1.97)
Credit Score Exists	0.191
	(1.02)
LTV	-0.00383***
	(-8.10)
Origination Spread	0.00634
	(1.01)
Close To Fail	-0.218
	(-1.50)
Credit Score * Close to Fail	0.00235***
	(4.34)
Credit Score Exists * Close to Fail	-1.408***
	(-3.45)
LTV * Close to Fail	0.00167
	(1.24)
Origination Spread * Close to Fail	-0.017
	(-0.93)
Zillow Price Index Growth	0.0811***
	(3.58)
HELOC FE	No
Bank FE	No
Month FE	Yes
Zip 3 * Year FE	Yes
SE Clustered at Loan Level	Yes
N	1,038,140
R-sq	0.020