

# Quick on the Draw: Liquidity Risk Mitigation in Failing Banks

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## ABSTRACT

Analyzing proprietary transaction-level HELOC data, we find that during financial stress, banks manage liquidity risk by restricting consumer access to cancellable credit lines. Credit lines with riskier loan characteristics at origination and large undrawn balances over time are more likely to be revoked. Our findings intensify as banks approach failure, despite constant HELOC drawdown rates. Before bank distress, existing borrower relationships have no impact on credit revocation decisions. Banks close to failure cut HELOCs for borrowers with greater ability to demand liquidity, suggesting that relationships harm some borrowers during bank stress, thereby revealing a dark side of banking relationships.

**Keywords:** financial crisis, HELOC, bank run, liquidity risk, failed bank

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## 1. 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 and central bankers have long managed bank liquidity risk via well-known tools such as central bank loans, deposit insurance, and liquidity and reserve requirements, and researchers have analyzed the effects of liquidity risk on credit supply. In this paper, we show that banks approaching failure manage their own liquidity needs by revoking consumer credit lines, a previously unexplored area of liquidity risk management.

We analyze a unique and granular dataset featuring detailed daily loan-level data for 90,000 geographically diverse home equity credit lines (HELOCs) in nine U.S. banks to study how banks manage liquidity risks inside and outside of times of failure. Risk management as bank failure approaches is an area of debate in the literature with implications for bank shareholders, bondholders, and regulators.<sup>1</sup> We find that banks near failure provide less liquidity to borrowers, in part through cancelling HELOCs of borrowers with greater ability to demand liquidity and riskier loan characteristics. We find that the remaining HELOCs do not have elevated drawdown rates as banks approach failure, consistent with effective reduction of the liquidity risk posed by undrawn credit lines. We show that banks revoke HELOCs for borrowers with multiple loans at the bank, a proxy for bank knowledge of and exposure to a borrower's high liquidity needs. Our finding that relationships can be harmful to borrowers as bank failure approaches reveals a novel dark side of banking relationships.

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<sup>1</sup> See Freixas, Rochet, and Parigi (2004), Admati (2014), and Ben-David, Palvia, and Stulz (2019), among others.

In the context of liquidity risk, HELOCs are useful to study because they are usually considered “unconditionally cancellable.”<sup>2</sup> Unlike commercial and industrial lines of credit,<sup>3</sup> a bank may, at any time, with or without cause, prohibit the extension of a HELOC, or reduce or terminate the commitment.<sup>4</sup> 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 should prevent borrower run-like actions at the cost of sub-optimal risk sharing and reputation risk to the bank.<sup>5</sup> Our paper adds to this literature by being the first to examine whether consumer borrowers draw more on credit lines leading up to bank failure.

Empirical work examining equilibrium lending outcomes faces significant endogeneity challenges. Banks may cancel HELOCs because of borrower actions prior to revocation or because the bank observes events that researchers cannot, such as borrower job loss or non-payment on other debts. To focus on bank cancellation of credit lines, we exploit variation in the state corporate tax rate for bank earnings, a driver of bank but not borrower behavior. Banks in states with a higher earnings tax rate realize larger savings when charging off a nonperforming loan, giving them less incentive to cancel a HELOC preemptively than a bank in a low tax rate state. We find that our measure of HELOC cancellations responds strongly to differences in the bank earnings tax rate, indicating that we are capturing bank decisions to cancel HELOCs.

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

<sup>3</sup> When firms draw down on credit lines, banks can suspend liquidity transfers to the firm only if covenants are breached. Otherwise, the bank has no legal basis for suspending the credit, and the firm could pursue legal action.

<sup>4</sup> 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 \(regionalfcu.org\)](https://www.rfcu.org/predisclosure-heloc.pdf)

<sup>5</sup> 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.

Banks marketed HELOCs as a type of “emergency fund” alongside credit cards, acknowledging the importance of consumer liquidity during crises.<sup>6</sup> 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 seek to avoid selling illiquid assets at low prices to meet consumer liquidity demands. This correlation heightens the importance of and incentives for bank liquidity management in times of stress. Figure 1 shows the trend in bank liquidity provision as our sample banks approach failure, using the preferred measure from Berger and Bouwman (2009). In our sample, banks begin to decrease liquidity provision about 2 years prior to failure, with liquidity provision falling from approximately 47 percent to 30 percent of gross total assets.<sup>7</sup> Our work indicates that revoking HELOCs and denying liquidity to certain borrowers is one channel for banks to reduce liquidity provision and risk when nearing failure.<sup>8</sup>

We analyze how banks ration borrower credit immediately prior to failure when liquidity pressures are likely greatest. All nine banks within our sample have staggered failure dates between 2008-2011. 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 maintain 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

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<sup>6</sup> 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 purchasing consumer goods. For a recent example, the first product mentioned in Fidelity Bank’s discussion of “emergency funds” is the HELOC. <https://www.fidelitybank.com/managing-your-emergency-fund/>

<sup>7</sup> 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 is the “catfat” measure.

<sup>8</sup> 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).

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.

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, defined as borrower attempts to acquire credit in response to idiosyncratic stresses, could preempt default. We find no evidence that banks manage credit lines on this dimension. Banks are less likely to revoke loans with lower proportions of available credit, loans with recent available credit increases, and loans where borrowers reduced available credit via a drawdown over the previous month. Although line cuts prevent future draws, banks cannot easily claw back drawn balances. This is consistent with line cutting as a risk mitigation strategy, as a small undrawn balance gives the borrower little ability to demand liquidity in the future. We find no evidence that housing price declines affect 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 as banks approach failure. 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, though our focus on consumer borrowing and cancellable commitments distinguishes our work from theirs. 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 just before failure despite the higher likelihood that the bank management will render a line of credit unavailable, consistent with Diamond and Dybvig (1983). Our results contrast with existing studies that have found evidence of depositors running down the liability side of the bank balance sheet prior to failure (Iyer, Puri, and Ryan, 2016; Martin, Puri, and Ufier, forthcoming). Though some 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.

At first glance, it may not be obvious that banks would consider borrower characteristics when rationing credit. Within the Diamond (1984) framework, banks could maintain the same level of portfolio 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, analogous to a flight-to-quality effect as 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). Our work differs from Hale, Kapan, and Minoiu (2020), which emphasizes the role of reciprocity in relationships among financial firms, and Chaderina, Laux, and Tengulov (2020), which explores the role of accounting covenants in voided credit commitments in the commercial setting.

Existing HELOC studies 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 credit commitments in response to changing market conditions.

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 low borrower or loan quality at origination, these borrowers may be least likely to find credit elsewhere during credit crunches. 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.

## **2. Background and Related Literature**

### **2.1 HELOC Background**

HELOCs are a special type of second mortgage that allows borrowers to borrow against their home equity. Borrowers have the ability to draw from a HELOC and repay a portion (or all) of it monthly, similar to a credit card. These loans usually have a draw period, where balances revolve for several years, and a repayment period, where the loans are amortized and repaid. 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 2a). 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 2b). As the financial markets experienced turmoil, many borrowers experienced a need for credit and drew down on their HELOCs (Figure 2c). When housing prices plummeted, HELOC charge-off rates grew nearly seven-fold between 2007 and 2009 (Figure 2d). The rise in HELOC lending increased the liquidity demands and balance sheet exposure for banks.

### **2.2 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; Hale, Kapan, and Minoiu, 2019; 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 examining the value of relationships when the bank is close to failure, as opposed to when borrowers are in distress. In contrast to the bulk of the relationship banking literature, 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; Kapan and Minoiu, 2014; Liberti and Sturgess, 2018; Kapan and Minoiu, 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 cancellable 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.

### 3. Data

We use data collected by the FDIC from bank servicing systems during the resolution process for failed banks. These data, collected from the nine 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 nine 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 1,373,638 HELOC-months spanning 90,848 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.<sup>9</sup> 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.<sup>10</sup> 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

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<sup>9</sup> 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.

<sup>10</sup> 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.

result, we define *Close 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.<sup>11</sup>

We present summary statistics for the 1,373,638 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 90,848 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 7,416 loans in Table 1B that meet our criteria as plausibly initiated by the bank.

Table 1B indicates that 17.69 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 \$86,500. At origination, the average credit score for borrowers on these loans was 735.57, the average LTV ratio was 60.55 percent, and the average origination spread was 2.59 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 have a historic delinquency. On the final day in the system, borrowers had drawn 38.63 percent

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<sup>11</sup> 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.

of credit lines, with their utilization falling on average -0.70 percent over the previous month. About 1 percent had a line increase at least 31 days prior to the failure date.

#### 4. 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:

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

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  $\delta_t$  that capture time variation common across all banks, including the level of the benchmark rate and macroeconomic conditions, and bank-level fixed effects  $\zeta_b$ , 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  $\gamma_{zy}$ , where zip codes are defined at the three-digit level (Zip 3). 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:

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

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,  $\nu_h$ , 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. As a preliminary analysis, we calculate the bank's HELOC revocation rate as the proportion of each bank's HELOCs that are cut each month. Then, within event-time, we calculate each the average revocation across banks. We plot these monthly revocation rate averages in Figure 3. As can be seen in the figure, there is an increase in the average bank HELOC revocation rates as failure, suggesting that banks are managing their own liquidity.



We further test this conjecture within a regression framework, whereby we interact our *Close to Fail* variable, indicating that the bank is less than three months from failure, with our time-invariant variables in Equation 3 and time-varying variables in Equation 4.<sup>12</sup>

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

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

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.

## 5. Results

### 5.1. 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

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<sup>12</sup> As noted above, *LoanChar<sub>hb</sub>* does not vary over time, and so the HELOC level fixed effects in Equation 4 absorb the direct effect of these variables.

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 5.271 percent more likely to cut a delinquent loan than a current loan and 0.944 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.

## **5.2 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 is 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.

### **5.3. 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.<sup>13</sup>

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.

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<sup>13</sup> 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.

## 6. Robustness

### 6.1. Callaway and Sant'Anna Estimator

While the staggered bank failure dates in our sample help us examine the effect of failure on bank liquidity management, recent developments in difference-in-difference estimation indicate that our interpretation of the effect of a bank being *Close to Fail* may be complicated by the lack of a suitable control group of banks that never fail. To address this concern, we use the approach designed by Callaway and Sant'Anna (2021) to correct our treatment group and avert potential concerns about the influence of variance weighting on our effect estimates. An event study design also allows us to examine our implicit assumption that banks and consumers do not significantly change their line revocation or drawdown behavior for HELOCs prior to the bank being close to failure.

In Figure 4, we plot the coefficients from our difference-in-difference estimation using the Callaway and Sant'Anna (2021) estimator. The pattern in Figures 3 and 4 are very similar and confirm our earlier empirical results indicating that bank liquidity management (HELOC revocations) become more aggressive as failure approaches. As shown in the raw data, we find evidence that HELOC revocations increase in the final month before bank failure, which may reflect the high cost of using line revocations as a liquidity management tool. Figure 4 also shows no change in the rate of HELOC revocations prior to the bank entering the *Close to Fail* period, supporting the implicit parallel trend assumption in our original interpretation of the coefficient estimates.<sup>14</sup>

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<sup>14</sup> In Appendix Figure A1, we apply the Callaway and Sant'Anna estimator to our results on borrower HELOC drawdowns. The results are quantitatively and qualitatively unchanged from those in text.

## **6.2. Additional 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 eight banks, our results are both qualitatively and quantitatively unchanged. In unreported results, we also perform 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 Appendix A.

## **7. 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 revocation to manage the liquidity risks from these lines of credit and whether consumer borrowers draw down lines of credit just prior to bank failure. 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 nine 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 and therefore pose less liquidity risk to the bank. 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 revoking unconditionally cancellable credit lines can be a tool for banks to manage their liquidity risks.

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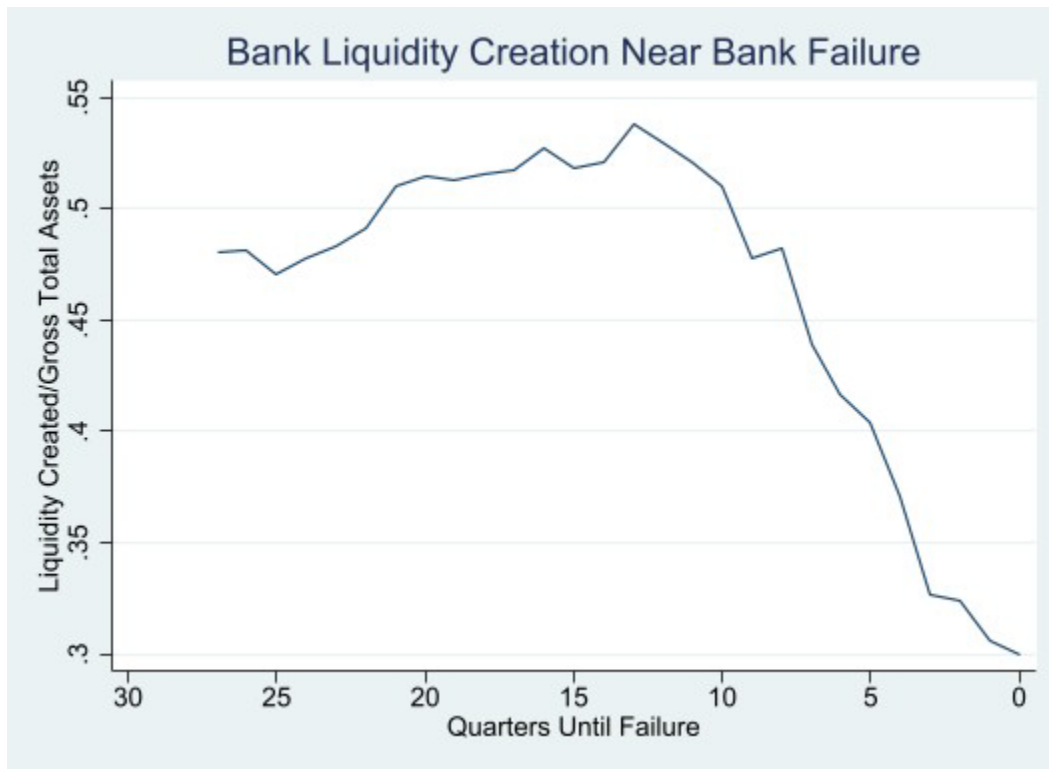


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## Tables and Figures

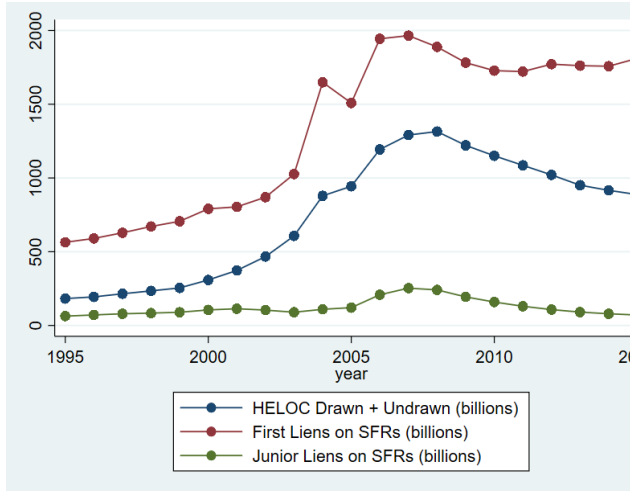
**Figure 1: Bank Liquidity Creation Near Bank Failure**

This figure shows bank liquidity failure as the sample banks approach bank failure. The Y-axis is total liquidity created as a share of bank gross total assets for all banks in sample where 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.

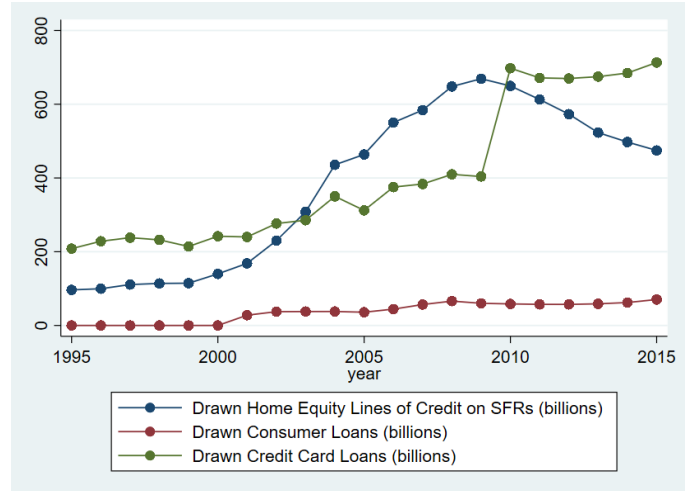


## Figure 2: Bank Credit Products Over Time.

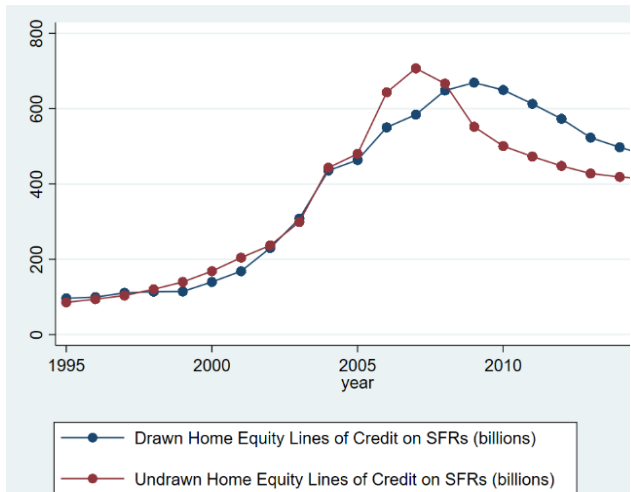
This figure shows the time-varying size of HELOC holdings relative to all mortgages for banks (sub-figure a), size of HELOC market relative to other selected consumer borrowing for banks (sub-figure b), HELOC draw patterns (sub-figure c), and charge-off rates for single-family residential (SRF) and HELOC lending (sub-figure d). All figures are constructed using Call Report data.



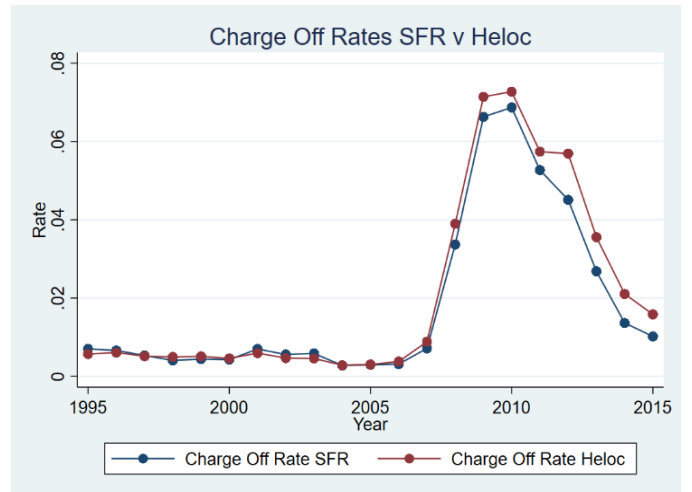
a. Size of HELOC Holdings Relative to All Mortgages for Banks



b. Size of HELOC Market Relative to Other Selected Consumer Borrowing for Banks



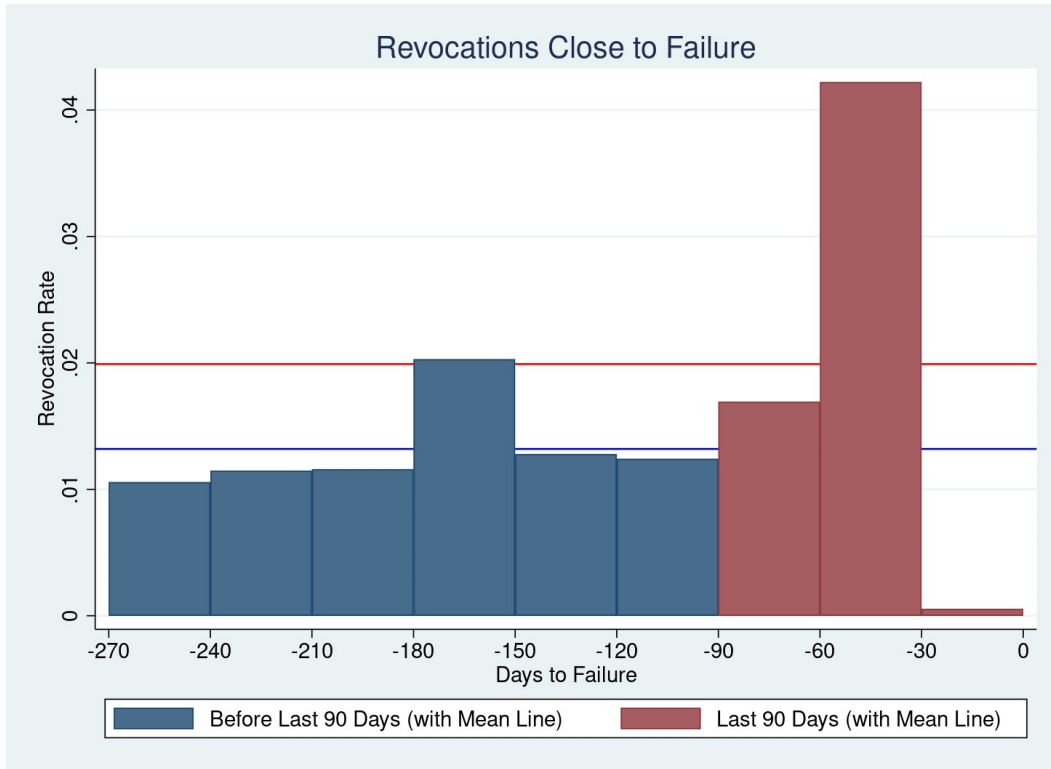
c. HELOC Draw Patterns using Call Report data



d. Charge Off Rates for SFR and HELOC using Call Report data

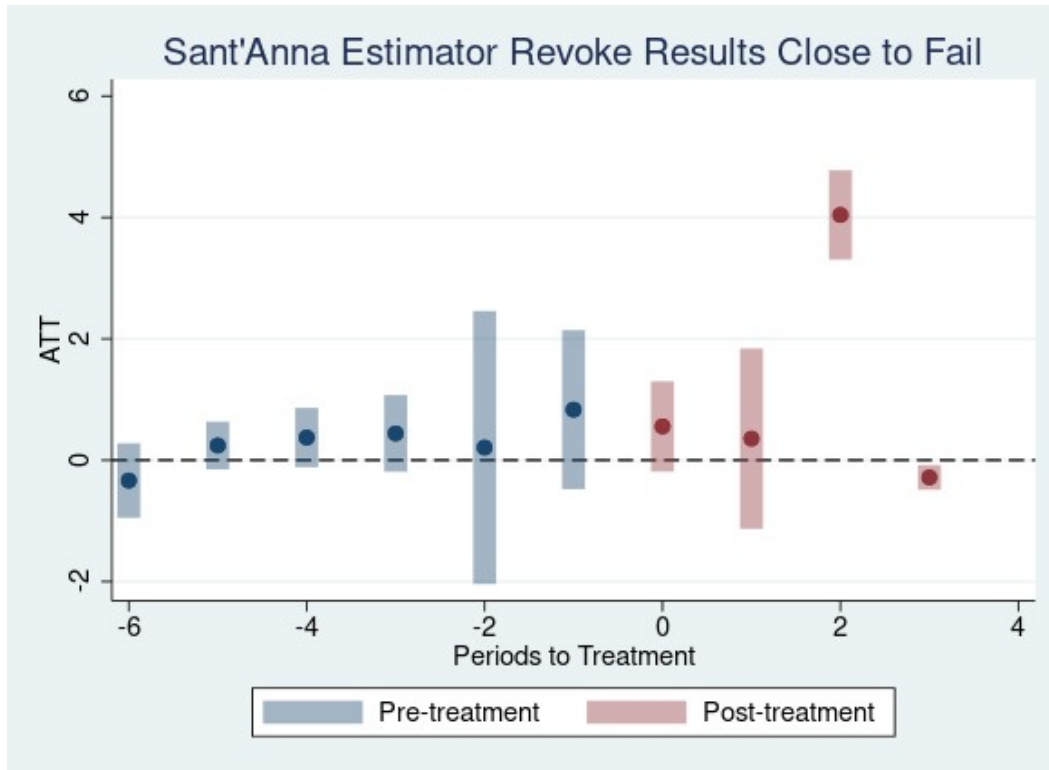
### Figure 3: Event Study HELOC Revocations

This figure displays the average bank HELOC revocation rate as bank failure approaches where the bank-level revocation rate is calculated as the fraction of the number of HELOCs the bank has that are revoked. The y-axis represents the monthly revocation rate, and the x-axis is days until failure where date 0 is the bank's failure date.



### Figure 4: Callaway and Sant'Anna Revocation Results

This figure displays the coefficient estimates from an event study using the Callaway and Sant'Anna (2021) difference-in-difference estimator. Periods are 30 day intervals. We define treatment for a bank as the 90 day period before bank failure, as represented by the *Close to Fail* variable defined in text. Y-axis reports the average difference from baseline in the probability of a HELOC being revoked during that period. X-axis indicates the current periods.



**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 B.

| (1)<br>Variable                    | (2)<br>Mean | (3)<br>SD | (4)<br>N  |
|------------------------------------|-------------|-----------|-----------|
| Original Loan Commitment Amount    | 79,800      | 183,000   | 1,373,638 |
| Line Cut or Closed                 | 0.53        | 7.31      | 1,373,638 |
| Credit Score                       | 734.12      | 61.66     | 985,720   |
| LTV                                | 43.25       | 32.64     | 1,316,955 |
| Origination Spread                 | 2.33        | 2.06      | 1,319,247 |
| End of Month Principal             | 43,000      | 119,000   | 1,373,638 |
| End of Month Line                  | 81,200      | 184,000   | 1,373,638 |
| Historic Delinquency               | 0.04        | 0.19      | 1,373,638 |
| Recent Delinquency                 | 0           | 0.06      | 1,373,638 |
| Used Proportion. Past Month        | 53.17       | 38.72     | 1,373,638 |
| Used Proportion. Past Month Change | 0.08        | 16.81     | 1,373,638 |
| Previous Line Increase             | 0.02        | 0.14      | 1,373,638 |
| Deposit Account                    | 0.57        | 0.49      | 1,373,638 |
| Other Loan                         | 0.26        | 0.44      | 1,373,638 |
| Zillow Price Index Growth          | -0.25       | 1.19      | 1,156,410 |
| Close to Fail                      | 0.08        | 0.27      | 1,373,638 |
| N                                  |             |           | 1,373,638 |

**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 B.

| (1)<br>Variable                    | (2)<br>Mean | (3)<br>SD | (4)<br>N |
|------------------------------------|-------------|-----------|----------|
| Original Loan Commitment Amount    | 88,800      | 129,000   | 90,848   |
| Line Cut or Closed                 | 17.69       | 38.16     | 90,848   |
| Credit Score                       | 717.3       | 66.78     | 78,060   |
| LTV                                | 46.03       | 29.57     | 86,760   |
| Origination Spread                 | 3.62        | 1.83      | 88,125   |
| End of Month Principal             | 60,700      | 88,400    | 90,848   |
| End of Month Line                  | 89,100      | 130,000   | 90,848   |
| Historic Delinquency               | 0.02        | 0.15      | 90,848   |
| Recent Delinquency                 | 0.02        | 0.14      | 90,848   |
| Used Proportion. Past Month        | 70.71       | 36.54     | 90,848   |
| Used Proportion. Past Month Change | -0.22       | 11.97     | 90,848   |
| Previous Line Increase             | 0.01        | 0.10      | 90,848   |
| Deposit Account                    | 0.20        | 0.40      | 90,848   |
| Other Loan                         | 0.44        | 0.50      | 90,848   |
| Zillow Price Index Growth          | -1.38       | 1.31      | 86,007   |
| Close to Fail                      | 0.83        | 0.38      | 90,848   |
| N                                  |             |           | 90,848   |

**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 B.

| (1)<br>Variable                    | (2)<br>Mean | (3)<br>SD | (4)<br>N |
|------------------------------------|-------------|-----------|----------|
| Original Loan Commitment Amount    | 86,300      | 222,000   | 7,416    |
| Line Cut or Closed                 | 100         | 0         | 7,416    |
| Credit Score                       | 735.57      | 57.01     | 4,325    |
| LTV                                | 60.55       | 33.96     | 6,921    |
| Origination Spread                 | 2.59        | 1.95      | 7,140    |
| End of Month Principal             | 33,000      | 111,000   | 7,416    |
| End of Month Line                  | 86,500      | 223,000   | 7,416    |
| Historic Delinquency               | 0.05        | 0.22      | 7,416    |
| Recent Delinquency                 | 0.04        | 0.19      | 7,416    |
| Used Proportion. Past Month        | 38.63       | 41.95     | 7,416    |
| Used Proportion. Past Month Change | -0.70       | 25.29     | 7,416    |
| Previous Line Increase             | 0.01        | 0.12      | 7,416    |
| Deposit Account                    | 0.56        | 0.50      | 7,416    |
| Other Loan                         | 0.35        | 0.48      | 7,416    |
| Zillow Price Index Growth          | -0.50       | 1.04      | 6,243    |
| Close to Fail                      | 0.15        | 0.36      | 7,416    |
| N                                  |             |           | 7,416    |



**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 B. 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)<br>Line Cut       | (2)<br>Line Cut       |
|------------------------------------|-----------------------|-----------------------|
| LTV                                | 0.00727***<br>(26.62) | 0.00614***<br>(21.46) |
| Origination Spread                 | 0.0255***<br>(7.37)   | 0.0166***<br>(5.11)   |
| Close to Fail                      |                       | -0.146<br>(-1.46)     |
| LTV * Close to Fail                |                       | 0.0129***<br>(8.82)   |
| Origination Spread * Close to Fail |                       | 0.106***<br>(5.95)    |
| Zillow Price Index Growth          | Yes                   | Yes                   |
| Bank FE                            | Yes                   | Yes                   |
| Month FE                           | Yes                   | Yes                   |
| Zip 3 * Year FE                    | Yes                   | Yes                   |
| N                                  | 1,055,087             | 1,055,087             |
| R-sq                               | 0.036                 | 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 B. 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)<br>Line Cut         | (2)<br>Line Cut         |
|---|-------------------------|-------------------------|
| Recent Delinquency                                | 5.271***<br>(15.09)     | 4.981***<br>(13.58)     |
| Historic Delinquency                              | 0.944***<br>(9.93)      | 0.912***<br>(9.40)      |
| Used Proportion Past Month                        | -0.00842***<br>(-18.54) | -0.00764***<br>(-16.93) |
| Previous Line Increase                            | -0.605***<br>(-8.37)    | -0.482***<br>(-6.73)    |
| Used Proportion Change Past Month                 | -0.00353***<br>(-5.27)  | -0.00290***<br>(-4.41)  |
| Close to Fail                                     |                         | 1.713***<br>(10.11)     |
| Recent Delinquency * Close to Fail                |                         | 2.468**<br>(2.17)       |
| Historic Delinquency * Close to Fail              |                         | 0.119<br>(0.49)         |
| Used Proportion Past Month * Close to Fail        |                         | -0.0181***<br>(-9.60)   |
| Previous Line Increase * Close to Fail            |                         | -1.478***<br>(-10.69)   |
| Used Proportion Change Past Month * Close to Fail |                         | -0.0197***<br>(-2.83)   |
| Zillow Price Index Growth                         | -0.0107<br>(-0.81)      | -0.00816<br>(-0.62)     |
| HELOC FE  | Yes                     | Yes                     |
| Bank FE   | No                      | No                      |
| Month FE  | Yes                     | Yes                     |
| Zip 3 * Year FE                                   | Yes                     | Yes                     |
| N   | 1,156,410               | 1,156,410               |
| R-sq  | 0.037                   | 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 B. 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)<br>Line Cut      | (2)<br>Line Cut     |
|---------------------------------|----------------------|---------------------|
| Deposit Account                 | -0.154***<br>(-2.58) | -0.145**<br>(-2.40) |
| Other Loan                      | 0.154**<br>(2.10)    | 0.0978<br>(1.34)    |
| Close to Fail                   |                      | 0.299**<br>(2.37)   |
| Deposit Account * Close to Fail |                      | -0.0315<br>(-0.25)  |
| Other Loan * Close to Fail      |                      | 1.139***<br>(6.72)  |
| Zillow Price Index Growth       | -0.0107<br>(-0.81)   | -0.0114<br>(-0.92)  |
| HELOC FE                        | Yes                  | Yes                 |
| Bank FE                         | No                   | No                  |
| Month FE                        | Yes                  | Yes                 |
| Zip 3 * Year FE                 | Yes                  | Yes                 |
| N                               | 1,156,410            | 1,156,410           |
| 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 B. 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)<br>Used Proportion Change<br>Past Month |
|------------------------------------|---|
| LTV                                | -0.00327***<br>(-7.02)                      |
| Origination Spread                 | 0.00987<br>(1.57)                           |
| Close to Fail                      | 0.0423<br>(0.36)                            |
| LTV * Close to Fail                | 0.000837<br>(0.63)                          |
| Origination Spread * Close to Fail | -0.0295*<br>(-1.71)                         |
| Zillow Price Index Growth          | 0.0823***<br>(3.65)                         |
| HELOC FE                           | No  |
| Bank FE                            | Yes   |
| Month FE                           | Yes   |
| Zip 3 * Year FE                    | Yes   |
| N                                  | 1,055,087                                   |
| R-sq                               | 0.02  |

**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 B. 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)<br>Used Proportion Change<br>Past Month |
|--|---|
| Recent Delinquency                         | 0.371<br>(1.62)                             |
| Historic Delinquency                       | 0.736***<br>(3.20)                          |
| Used Proportion Past Month                 | -0.333***<br>(-77.72)                       |
| Previous Line Increase                     | 2.526***<br>(6.82)                          |
| Close to Fail                              | -0.750***<br>(-3.66)                        |
| Recent Delinquency * Close to Fail         | 0.437<br>(0.77)                             |
| Historic Delinquency * Close to Fail       | -1.153***<br>(-5.27)                        |
| Used Proportion Past Month * Close to Fail | 0.0203***<br>(8.55)                         |
| Previous Line Increase * Close to Fail     | -0.232<br>(-0.80)                           |
| Zillow Price Index Growth                  | 0.0708***<br>(2.61)                         |
| HELOC FE                                   | Yes   |
| Bank FE                                    | No  |
| Month FE                                   | Yes   |
| Zip 3 * Year FE                            | Yes   |
| N  | 1,156,410                                   |
| R-sq                                       | 0.197                                       |

**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 B. 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)<br>Used Proportion Change<br>Past Month |
|---------------------------------|---|
| Deposit Account                 | 0.118<br>(1.35)                             |
| Other Loan                      | -0.479***<br>(-4.52)                        |
| Close to Fail                   | 0.0949<br>(0.70)                            |
| Deposit Account * Close to Fail | 0.0952<br>(0.88)                            |
| Other Loan * Close to Fail      | -0.0883<br>(-0.54)                          |
| Zillow Price Index Growth       | 0.0781***<br>(3.20)                         |
| HELOC FE                        | Yes   |
| Bank FE                         | No  |
| Month FE                        | Yes   |
| Zip 3 * Year FE                 | Yes   |
| N                               | 1,156,410                                   |
| 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 B. 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)<br>Line Cut         | (2)<br>Line Cut         |
|--|-------------------------|-------------------------|
| Tax Rate                                   | -0.0709***<br>(-3.77)   | -0.114***<br>(-4.19)    |
| LTV  | 0.00782***<br>(28.84)   | 0.00697***<br>(24.69)   |
| Origination Spread                         | 0.0244***<br>(7.03)     | 0.0164***<br>(4.70)     |
| Recent Delinquency                         | 5.168***<br>(14.39)     | 4.816***<br>(12.79)     |
| Historic Delinquency                       | 0.306***<br>(7.05)      | 0.302***<br>(7.07)      |
| Used Proportion Past Month                 | -0.00413***<br>(-18.45) | -0.00341***<br>(-15.01) |
| Previous Line Increase                     | -0.0886*<br>(-1.94)     | 0.00431<br>(0.09)       |
| Deposit Account                            | -0.0289*<br>(-1.82)     | -0.0385**<br>(-2.48)    |
| Other Loan                                 | 0.0356*<br>(1.86)       | 0.0124<br>(0.61)        |
| Used Proportion Change                     | -0.00212***<br>(-3.25)  | -0.00146**<br>(-2.27)   |
| Close to Fail                              |                         | 0.101<br>(0.69)         |
| LTV * Close to Fail                        |                         | 0.0114***<br>(7.74)     |
| Origination Spread * Close to Fail         |                         | 0.102***<br>(5.79)      |
| Recent Delinquency * Close to Fail         |                         | 2.888**<br>(2.42)       |
| Historic Delinquency * Close to Fail       |                         | 0.0248<br>(0.09)        |
| Used Proportion Past Month * Close to Fail |                         | -0.0104***<br>(-9.31)   |
| Previous Line Increase * Close to Fail     |                         | -1.414***<br>(-9.37)    |
| Used Proportion Change * Close to Fail     |                         | -0.0141**<br>(-2.45)    |
| Deposit Account * Close to Fail            |                         | 0.369***<br>(2.84)      |
| Other Loan * Close to Fail                 |                         | 0.106<br>(1.51)         |
| Zillow Price Index Growth                  | -0.0126<br>(-1.05)      | -0.00935<br>(-0.78)     |
| HELOC FE                                   | No                      | No                      |
| Bank FE                                    | No                      | No                      |
| Month FE                                   | Yes                     | Yes                     |
| Zip 3*Year FE                              | Yes                     | Yes                     |
| N  | 1,052,917               | 1,052,917               |
| R-sq                                       | 0.038                   | 0.039                   |

## Appendix A: Additional Discussion

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 A1. 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 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 B. 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)<br>Line Cut       | (2)<br>Line Cut        |
|-------------------------------------|-----------------------|------------------------|
| Credit Score                        | -0.00015<br>(-1.34)   | -0.000270**<br>(-2.26) |
| Credit Score Exists                 | -0.240***<br>(-2.79)  | -0.202**<br>(-2.26)    |
| LTV                                 | 0.00647***<br>(23.83) | 0.00517***<br>(18.21)  |
| Origination Spread                  | 0.0218***<br>(6.28)   | 0.0128***<br>(3.71)    |
| Close to Fail                       |                       | -0.921***<br>(-5.58)   |
| Credit Score * Close to Fail        |                       | 0.00160***<br>(3.46)   |
| Credit Score Exists * Close to Fail |                       | -0.268<br>(-0.73)      |
| LTV * Close to Fail                 |                       | 0.0136***<br>(9.35)    |
| Origination Spread * Close to Fail  |                       | 0.118***<br>(6.26)     |
| Zillow Price Index Growth           | Yes                   | Yes                    |
| Bank FE                             | Yes                   | Yes                    |
| Month FE                            | Yes                   | Yes                    |
| Zip 3 * Year FE                     | Yes                   | Yes                    |
| N                                   | 1,055,087             | 1,055,087              |
| R-sq                                | 0.037                 | 0.037                  |

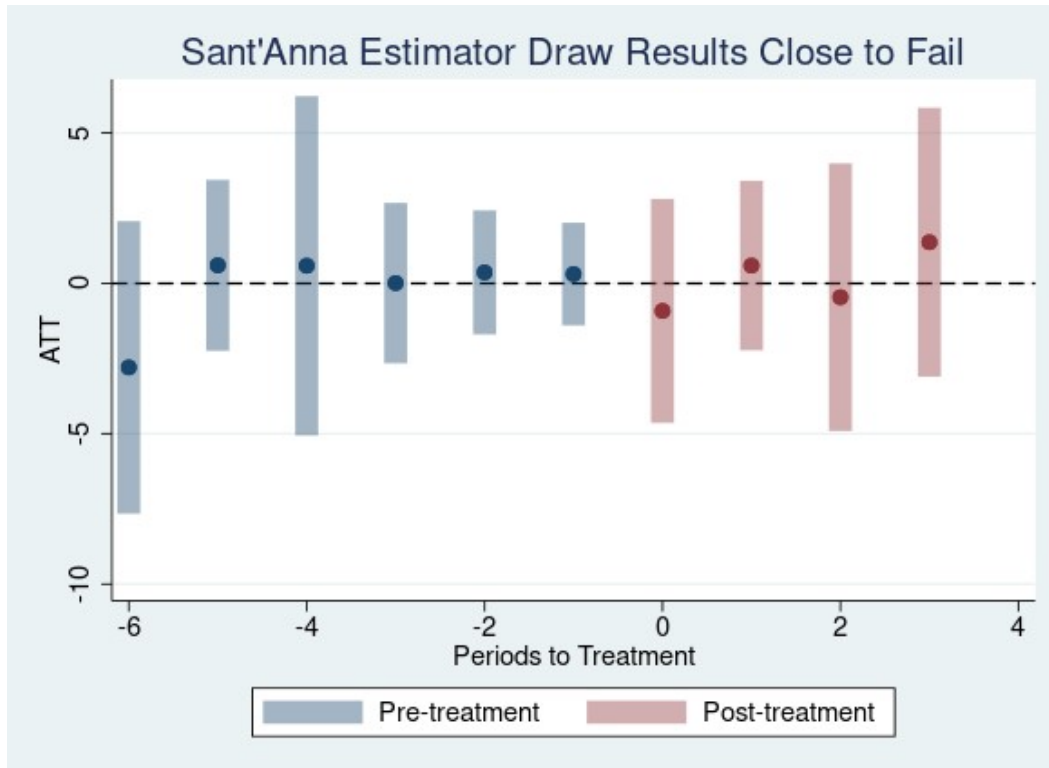
## Appendix Table A2: Line Draws with Fixed Loan Characteristics Close to Failure.

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 B. 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)<br>Used Proportion Change |
|-------------------------------------|-------------------------------|
| Credit Score                        | -0.000522**<br>(-2.07)        |
| Credit Score Exists                 | 0.211<br>(1.13)               |
| LTV                                 | -0.00371***<br>(-7.78)        |
| Origination Spread                  | 0.00722<br>(1.14)             |
| Close To Fail                       | -0.264*<br>(-1.87)            |
| Credit Score * Close to Fail        | 0.00244***<br>(4.49)          |
| Credit Score Exists * Close to Fail | -1.471***<br>(-3.60)          |
| LTV * Close to Fail                 | 0.00124<br>(0.92)             |
| Origination Spread * Close to Fail  | -0.0105<br>(-0.59)            |
| Zillow Price Index Growth           | 0.0805***<br>(3.56)           |
| Month FE                            | Yes                           |
| Zip 3 * Year FE                     | Yes                           |
| N                                   | 1,055,087                     |
| R-sq                                | 0.020                         |

### Appendix Figure A1: Callaway and Sant'Anna Draw Results

This figure displays the coefficient estimates from an event study using the Callaway and Sant'Anna (2021) difference-in-difference estimator. Periods are 30 day intervals. We define treatment for a bank as the 90 day period before bank failure, as represented by the *Close to Fail* variable defined in text. Y-axis reports the average difference from baseline in the percentage of a HELOC that is drawn during that period. X-axis indicates the current periods.



## Appendix B: Variable Descriptions

| Variable                               | Full Text   | Source |
|--|---|--------|
| <i>Close to Fail</i>                   | <i>Close to Fail</i> 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   |
| <i>Credit Score</i>                    | <i>Credit Score</i> 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   |
| <i>Deposit Account</i>                 | <i>Deposit Account</i> 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   |
| <i>End of Month Line</i>               | <i>End of Month Line</i> is equal to the maximum limit of the line in dollars at the end of the month.  | FDIC   |
| <i>Historic Delinquency</i>            | <i>Historic Delinquency</i> 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   |
| <i>Line Cut or Closed</i>              | <i>Line Cut or Closed</i> 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   |
| <i>Line Cut</i>                        | <i>Line Cut</i> 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   |
| <i>Line Increase</i>                   | <i>Line Increase</i> is an indicator variable equal to 1 if the line's credit limit was ever increased in the past and 0 otherwise  | FDIC   |
| <i>Loan Term</i>                       | <i>Loan Term</i> 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   |
| <i>LTV</i>                             | <i>LTV</i> 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   |
| <i>Original Loan Commitment Amount</i> | <i>Original Loan Commitment Amount</i> is equal to the original maximum limit of the loan in dollars.   | FDIC   |

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| <i>Origination Spread</i>                | <i>Origination Spread</i> 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 |
| <i>Other Loan</i>                        | <i>Has Other Loans with Bank</i> 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 |
| <i>Previous Line Increase</i>            | <i>Previous Line Increase</i> 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 |
| <i>Rate</i>                              | <i>Rate</i> is defined as the interest rate of the loan on the day measured. A rate of 5 percent is listed as 5.   |      |
| <i>Recent Delinquency</i>                | <i>Recent Delinquency</i> 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 |
| <i>Tax Rate</i>                          | <i>Tax Rate</i> is the yearly state-level corporate tax rate.  |      |
| <i>Used Proportion Change Past Month</i> | <i>Used Proportion Change</i> 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 |
| <i>Used Proportion, Past month</i>       | <i>Used Proportion, Past Month</i> 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 |
| <i>Zillow Price Index Growth</i>         | <i>Zillow Price Index Change</i> is the change in the past month at the zip code level of the Zillow housing price index.  | FDIC |