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Bank Runs and Interest Rates: A Revolving Lines Perspective

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Abstract:
Revolving credit is at the core of the banking business. Corporate revolving credit lines are demandable claims; therefore, as with a traditional bank run on deposits, sudden widespread drawdowns on credit lines can destabilize the banking sector. However, we show that, unlike with deposits, credit-line utilization is highly sensitive to interest rates. A run on revolving lines is less likely in a high-interest-rate environment, but when the Federal Reserve cuts the interest rate to support a weak banking sector, the sector can become vulnerable to such a run.

JEL Classifications: G21, G32, G01
Keywords: Bank liquidity, corporate credit lines, bank runs, financial crisis

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Revolving credit is at the core of the banking business model. Data from the Shared National Credit Program, which covers more than 2,500 large US commercial borrowers, indicate that in 2023, approximately half of all newly originated bank credit took the form of revolving credit. Moreover, revolving credit is primarily offered by banks rather than nonbank financial institutions (NBFIs) such as private debt providers or institutional participants in the syndicated loan market. Indeed, in 2023, banks financed 97 percent of revolving credit but only 28 percent of term loans.

Typically, revolving credit lines are used to manage working capital, a crucial aspect of running a business that helps firms address short-term cashflow shortfalls and unexpected expenses.[1] Like a credit card, a revolving credit line can be used at the borrower's discretion, up to the committed amount of the line, and can be repaid and used repeatedly while the line remains outstanding. However, these characteristics of revolving credit also mean that, like uninsured deposits, unused revolving lines (or "revolvers") represent sizable demandable claims on banks, which can be subject to runs that threaten the stability of the banking system. The FR Y-14Q ("Y-14" hereafter) supervisory data used in this study indicate that banks' exposure to unused revolving lines accounts for about 20 percent of bank liabilities. In fact, runs on revolving lines—that is, widespread drawdowns—contributed significantly to banks' liquidity problems both in 2008 (Ivashina and Scharfstein, 2010) and at the beginning of the COVID-19 pandemic in early 2020.[2]

In this paper, we measure the interest rate sensitivity of runs on revolving lines. We show that this sensitivity is substantial and that runs on revolving lines are less likely to occur when interest rates are high. Like runs on deposits, runs on revolving credit lines are triggered by shocks to the perceived solvency of a bank, as documented in Diamond and Dybvig (1983). Yet, revolving lines are fundamentally different from deposits in that they are a liability, and the borrowing firm must pay interest on the drawn amount. (The borrower pays a small fixed fee on the undrawn amount.) As is common with many commercial loans, revolving lines are variable-rate contracts under which the borrower

[1] Recent research (e.g. Chodorow-Reich et al., 2022; Berrospide and Meisenzahl, 2022; Greenwald, Krainer and Paul, 2023) focuses on the economic importance of access to credit lines.

[2] For example, S&P reports large drawdowns through April 2020: https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/coronavirus-related-revolving-credit-drawdowns-grow-to-222b-via-414-issuers-58013811.

pays a fixed spread over a benchmark rate that varies with the market interest rate. Funds drawn for precautionary reasons are likely to be redeposited into safe accounts, but if there is a discrepancy between the interest rates on withdrawn and redeposited amounts, precautionary runs on revolving lines will remain sensitive to this interest rate gap.

Empirically, if the gap between the saving rate and the borrowing rate is small, we should not observe significant sensitivity of runs on revolving lines. However, Drechsler, Savov and Schnabl (2017) document that banks benefit from a deposit franchise, which is reflected in the limited sensitivity of deposit rates to base rates.[3] Overall, in a higher-interest-rate environment, companies face higher costs associated with precautionary withdrawals on revolving lines of credit. This has important implications for how runs on credit lines—and overall liquidity problems for banks—unfold. For example, in the context of the 2023 bank run episode, while unrealized portfolio losses for banks due to higher interest rates were a potential concern for deposit runs, revolving lines acted partly as an offsetting force.

We base our core empirical analysis on detailed facility-level supervisory Y-14 data collected by the Federal Reserve for stress testing purposes, as mandated by the 2010 Dodd–Frank Act. We exploit the commercial and industrial (C&I) loan schedule of this data set (schedule H), which contains information on all outstanding C&I loans with a committed amount of at least $1 million from US bank holding companies ("banks" hereafter) that are subject to stress testing (that is, the largest US banks). These data cover nearly 70 percent of all loans in the United States. Given our research focus, we examine revolving-line credit facilities as opposed to term loans. Importantly, for our study, schedule H contains detailed information on committed and utilized exposure, interest rate, maturity, and other contract characteristics, as well as borrower information at the quarterly frequency.

To measure the interest rate sensitivity of precautionary drawdowns of revolving lines, we need (1) exogenous variation in applicable interest rates and (2) an environment in which such withdrawals of revolving lines are likely. Given that Y-14 data do not start

[3]While the use of Treasury money market mutual funds for cash management could mitigate the cost that companies face when running on their revolving credit lines, as we discuss in the next section, a substantial portion of withdrawn capital seems to remain within the banking sector.

until 2011, the first requirement presents a significant empirical challenge, which we overcome by using an empirical design that explores a kink in applicable interest rates. As mentioned, credit-line facilities are generally variable-rate contracts, with the interest rate on the utilized portion linked to a base rate. (The relevant base rate for our sample is the London Interbank Offered Rate, or LIBOR.) To address the interest rate risk, we observe our data set's interest rate floors, which, in credit-line contracts, often prevent the applicable interest rate from falling below a contractually specified threshold. We exploit this feature to identify the interest rate sensitivity of credit-line utilization using a regression kink design (RKD) similar to the one used by Card et al. (2016). The basic intuition of this identification approach is that one can estimate the effect of changes in interest rates on credit-line utilization by comparing variation in utilization rates around the interest floor. More technically, this approach requires estimation of changes in the slope of the utilization rate (as a function of the distance to the floor) and does not require interest rates to be exogenous. We elaborate on this point in Section III.

Our main analysis focuses on the beginning of the COVID-19 pandemic, March 2020, when high uncertainty led firms to heavily draw down their committed credit lines for precautionary reasons. While we do not argue that uncertainty about banks' ability to honor the credit-line commitment was the only reason for the run on revolving lines, this period provides a unique opportunity to study the interest rate sensitivity of credit-line utilization when precautionary motives were a significant driver of withdrawals. Moreover, in early 2020, the Federal Reserve cut interest rates to zero, generating substantial variation in interest rates on revolving lines as floors became binding for many facilities.

We provide evidence of the validity of the RKD approach by directly testing some of the underlying identification assumptions. First, though manipulation of interest rates is unlikely in our set-up, we show that the density of the distance to the interest rate floor is relatively smooth at the kink. Second, we show that other key contract terms, such as committed amounts, loan maturity, and interest rate spread, do not exhibit kinks at the floor threshold—a key identification assumption for the RKD to work. Third, we confirm that our results are robust to changing the bandwidth around the kink and the inclusion of different orders of polynomials in the distance to the kink, thereby ensuring that we correctly identify the change of slopes at the kink.

Our key results show that the use of revolving lines is highly sensitive to changes in interest rates. Our most conservative estimates indicate that when interest rates increase by 1 percentage point, the line utilization ratio—that is, the percentage of committed credit drawn—falls by about 13 percentage points. We obtain these estimates from the pandemic period in 2020, when the motivation to draw down for precautionary purposes was high and, hence, credit-line utilization was presumably less sensitive to interest rates. We find substantially larger effects (in absolute values) outside the pandemic period. Our findings indicate that the line utilization ratio falls 20 to 30 percentage points when interest rates increase 1 percentage point. We identify these effects from within-facility variation, holding the borrower and other contract features constant. We also estimate heterogeneous effects across firms to further isolate the sensitivity of precautionary drawdowns to interest rates. To do so, we focus on firms that increased their line utilization in 2020:Q1 but repaid what they borrowed when the market stabilized following significant government intervention. We find that the elasticity of such precautionary drawdowns is large, in the order of a magnitude of –13. Finally, we substantiate that precaution was the predominant motive behind the temporary rise in the use of revolving lines in 2020 by ruling out potential payment frictions or that the increase was due to the use of revolving lines as "bridge" financing into other loans or bonds.

In the final section of the paper, we look holistically at bank liquidity management, using public FR Y-9C data on bank balance sheets to examine a longer period and a cross section of firms. We find that, historically, banks facing a greater threat of deposit outflows in response to interest rate increases have faced a lesser threat of revolving-line drawdowns because such drawdowns are less sensitive to interest rates. This indicates that the high interest rate sensitivity of credit-line utilization works as a counterforce to the liquidity squeeze stemming from deposit outflows.

As its main contribution, our study articulates a unique mechanism that explains the interest rate sensitivity of credit-line utilization, and it quantifies that sensitivity empirically. We find that this elasticity is economically substantial. Moreover, we find that—in the cross section of banks—interest rate elasticities of deposits and revolving lines appear to act as opposing forces.

The banking turmoil of March 2023 revealed a blind spot in the understanding of bank runs, particularly how bank runs relate to the interest rate environment. Drechsler et al. (2023) develop a model for understanding the relationship among interest rates, the value of securities holdings, and runs on unsecured deposits. Jiang et al. (2023) develop an empirical methodology for analyzing the effect of rising interest rates on the value of US bank assets and bank equity value. Our focus on revolving lines complements these studies. Specifically, we highlight that—unlike with deposits runs—the risk of a credit-line drawdown was low in the 2023 episode due to high interest rates.

More broadly, due to the significant growth of NBFIs and the continuous retreat of banks from information-sensitive credit origination (e.g., Hanson et al., 2024; Buchak et al., 2024), it has become increasingly important to understand other intrinsic elements of the bank business model, particularly liquidity management as it relates to the interaction of banks' assets and liabilities. Our paper contributes to the literature that follows the seminal work of Diamond and Dybvig (1983). Holmström and Tirole (1998) emphasize banks' key role as providers of liquidity to firms through the issuance of credit lines. Kashyap, Rajan and Stein (2002) provide the first integrated view of banks' advantage in liquidity management by articulating the synergy between deposit-taking and the issuance of revolving lines. Gatev and Strahan (2006) show that the existence of deposit insurance has given rise to additional sources of complementarity between deposits and the use of revolving lines in periods of economic instability. Ivashina and Scharfstein (2010) and Ippolito et al. (2016) bring attention to the run risk emanating from revolving lines. We contribute to this literature by emphasizing how liquidity pressures stemming from unused revolving lines respond to the interest rate environment.

The remainder of the paper is structured as follows. Section I provides institutional background on corporate revolving lines and derives theoretical predictions. Section II describes the micro data set that we use in our empirical analysis. Section III discusses our empirical identification strategy, and Section IV reports the results. Section V concludes.

I The Mechanism

To guide our analysis, we formulate a stylized model of precautionary credit-line drawdowns. We focus on the firm's problem of running depending on the interest rate environment.

I.1 Stylized Model

There are two periods and three dates, 0, 1, and 2. The firm has a positive net present value (NPV) project that requires an investment I at $t = 1$. The return on the investment is $f(I) = \theta \log(I)$, where $\theta > 0$ is a shift parameter. The log return function is assumed for simplicity and satisfies standard conditions imposed on more general return functions: $f' > 0, f'' < 0, f''' > 0$. The firm is assumed to be solvent (positive NPV) in all states. The project is financed with a credit line issued at $t = 0$ that matures at the end of the second period. In reality, revolving lines are typically taken out to finance future, uncertain working capital needs or acquisitions. For simplicity, we assume that the investment arrives with certainty in the future but that the credit line is outstanding for two periods. The interest rate on the drawn part of the credit line is r^l (per period); the interest rate on the undrawn amount is zero. The firm can either (i) draw down the line at $t = 1$ or (ii) draw down the line in $t = 0$ and keep funds in an insured deposit account paying $r^d < r^l$ until investment at $t = 1$. Debt is not amortizable, and the interest must be paid in cash.

At $t = 1$ (before investment), with probability p, the firm will not be able to access the unused amount of the credit line. This could be because the bank fails. The possibility of having financing cut off creates demand for precautionary liquidity drawdowns at $t = 0$ to fund the project at $t = 1$. If the bank fails, the line commitment will not be honored, so the firm prefers to draw down its credit line and hold the claim against the bank as an insured deposit. This time lag between drawdown and investment opportunity is a defining feature of a precautionary run. Instead of the funds being held as an insured deposit, we could assume that they would be held as a deposit at a different (safe) bank. Regardless of the lender's fate, the firm is required to pay interest on the drawn amount and repay the principal at maturity.[4]

In this simple set-up, we assume that the borrower has only one lender. This is equivalent to assuming that—in the short run—lender-switching costs are prohibitively high. This aligns with the broader academic literature highlighting the relevance of information frictions (e.g., Rajan, 1992).[5] We could allow for more than one bank and introduce lender-switching costs to reflect information costs in screening and monitoring. This latter point helps explain why many firms——especially those growing through acquisitions, as is common in private equity—typically secure a revolving credit line rather than obtaining a new loan each time they identify an acquisition target. One could incorporate switching costs formally, and doing so would imply that sufficiently high switching costs make precautionary withdrawals more likely. Ultimately, however, this is an intuitive conclusion, and we chose not to complicate the model further.

The firm maximizes expected profits, π, by choosing the precautionary drawdown (early line utilization) u at $t = 0$ and the residual drawdown l at $t = 1$, taking as given the probability of bank failure and interest rates:

$$\max_{u,l} \pi = (1-p)\Big(\theta \log(u+l) + (r^d - 2r^l)u - r^l l\Big) + p\Big(\theta \log(u) + (r^d - 2r^l)u\Big). \tag{1}$$

Any interior solution for late and early drawdowns satisfies the first-order conditions, which equate expected marginal return with expected marginal cost:

$$\begin{aligned} \frac{\partial \pi}{\partial u} &= 0 \;\Rightarrow (1-p)\frac{\theta}{u+l} + p\frac{\theta}{u} + r^d = 2r^l. \\ \frac{\partial \pi}{\partial l} &= 0 \;\Rightarrow \frac{\theta}{u+l} = r^l. \end{aligned}$$

It is important to point out that the early drawdown is associated with a marginal cost that is twice as large because the firm needs to pay the interest for two periods. Solving the

[4]In many ways, our model is similar to that of (Cooperman et al., 2025), but their model focuses on endogenizing the bank's problem, while our partial equilibrium model focuses on characterizing the firm's revolving-line utilization. Therefore, we take the probability of failure as an exogenous parameter. A more general version of the model would make the probability of the bank's failure endogenous.

[5]In reality, there are other frictions; for example, it takes time to apply for a new loan, and there is also a fixed cost for starting a new lending relationship.

system of equations shows that the optimal early drawdown is given by:

$$u = \frac{p\theta}{(1+p)r^l - r^d}.$$

Therefore, the optimal precautionary drawdown depends on the interest rate on the revolving line and the deposit rate, as well as the probability of bank failure. It also depends on the shift parameter θ.

From the first-order condition, it also follows that the total investment amount, $u + l = \theta/r^l$, is not a function of the probability of bank default but depends only on the loan rate and the shift parameter θ. Thus, the probability of bank default only affects the share of funds withdrawn early. Note also that expected investment is $pu + (1-p)(u+l)$, and production is $(1-p)f(u+l) + pf(u) < f(u+l)$; thus, bank default and the induced early credit-line drawdowns lead to inefficiencies. The output loss with $p > 0$ emerges because the firm engages in costly front-loading of the funding by drawing early, leading to reduced investment and output.

Differentiating the solution with respect to r^l shows that the interest rate elasticity of precautionary revolver utilization is decreasing in the interest rate:

$$\frac{\partial u}{\partial r^l} = -\frac{\theta p(1+p)}{\left((1+p)r^l - r^d\right)^2} < 0. \tag{2}$$

The derivative with respect to the probability of bank failure shows the intuitive results that the precautionary drawdown increases in the probability of bank failure:

$$\frac{\partial u}{\partial p} = \frac{\theta(r^l - r^d)}{\left(r^d - (1+p)r^l\right)^2} > 0.$$

Therefore, because bank distress is more likely, the demand for precautionary withdrawals shifts outward.

We can also analyze how the interest rate elasticity of revolving-line utilization changes with the probability of bank failure by examining the cross-derivative:

$$\frac{\partial^2 u}{\partial r^l \partial p} = \frac{\theta\Big((1+p)r^l - (1+2p)r^d\Big)}{\Big(r^d - (1+p)r^l\Big)^3} > 0$$

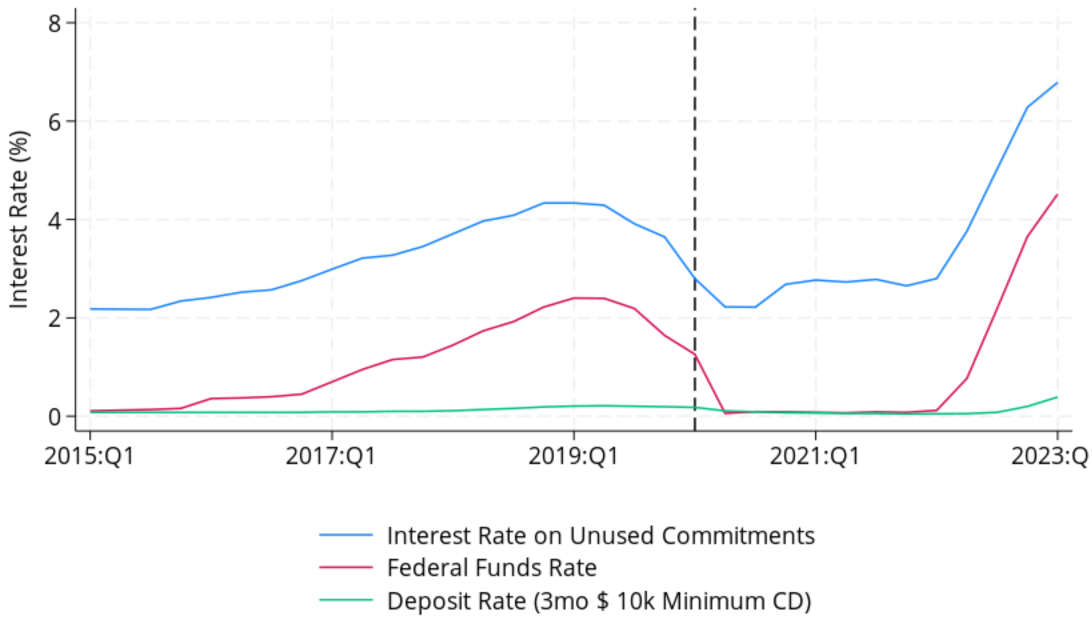
if the probability of bank failure is large enough. Given that the denominator has a negative sign, the ratio is positive if the numerator is negative, that is, if $(1+p)r^l < (1+2p)r^d$, which happens when the probability of failure is large enough. Expressed another way, if $p > \frac{r^l - r^d}{2r^d - r^l}$, the precautionary drawdowns become less sensitive to interest rate changes. This condition holds trivially if we set the deposit rate to zero.

To understand the intuition behind this result, note that the expected marginal return on the investment funded with precautionary drawdowns—that is, $(1-p)\frac{\theta}{u+l} + p\frac{\theta}{u}$—is increasing in p. When bank default becomes more likely, the marginal drawdown becomes worth more. Given the concavity of the investment return, this implies that, in response to a given interest rate change (marginal cost), credit-line utilization needs to change less to equalize marginal return and cost. Thus, the interest rate sensitivity of drawdowns is lower.

I.2 Understanding r^d

So far, we have assumed that the insured deposit rate and the loan rate are independent: If the borrowing rate moves, the deposit rate does not. This increases the net cost of precautionary drawdown, thus dampening the firm's incentive to run on the bank when borrowing rate increases. If both rates co-move perfectly (the other extreme), then the borrower would not react to changes in borrowing rates, since the change in the net cost of precautionary drawdown is zero. Our assumption is rooted in empirical observations that deposit rates tend to be insensitive to policy rate fluctuations, as documented by Drechsler, Savov and Schnabl (2017). Figure 1, which is based on the Y-14 data, shows that the applicable rates on outstanding revolving lines have been closely following the policy rate. This contrasts sharply with deposit rates, which—as Figure 1 illustrates—have been largely insensitive to policy rate changes.

Figure 1: Interest Rate on Revolving Credit Lines, Federal Funds Rate, and Deposit Rate



Notes: The figure shows the average interest rate on revolving lines that would apply if unused commitments were drawn. For comparison, the figure also shows the federal funds rate and deposit rate on three-month certificates of deposit with a minimum balance of $10,000. The vertical red line indicates 2020:Q1. *Sources:* FR Y-14Q, Haver, authors' computations.

However, more generally, we can relax this assumption and allow both the loan rate and deposit rate to depend on the policy rate in some way by writing:

$$\frac{\partial u}{\partial r} = -\frac{\theta p}{\left((1+p)r^l - r^d\right)^2}\left[(1+p)\frac{\partial r^l}{\partial r} - \frac{\partial r^d}{\partial r}\right]. \tag{3}$$

This shows that precautionary drawdowns will decrease in the policy rate whenever the loan rate is more sensitive to changes in the policy rate than the deposit rate. In our setting, the borrowing rate is effectively indexed to the policy rate, r, $r^l = r + spread$, such that the loan rate moves one-for-one with the policy rate and $\frac{\partial u}{\partial r^l} = \frac{\partial u}{\partial r}$. By contrast, the low policy rate sensitivity of deposit rates is well documented, as discussed earlier.[6] The condition $\frac{\partial r^l}{\partial r} > \frac{\partial r^d}{\partial r}$ is also consistent with the imperfect pass-through of the policy rate to Treasury

[6]While generally small, the pass-through of policy rate changes into deposit rates may be larger when interest rates are high (convex deposit beta). In that case, the interest rate elasticity of drawdowns would be smaller (in absolute values), all else being equal.

rates and imperfect substitutability of bank deposits and even government money market funds. Thus, our model encompasses the possibility that the firm holds its cash in a money market fund rather than a deposit account.

We can assess the role of money market funds as a substitute for deposits by examining weekly bank balance sheet data from the public FR H.8 during the 2023 regional bank turmoil. During the week of the Silicon Valley Bank (SVB) failure (March 13 through 19, 2023), there was a net outflow of $137.8 billion in deposits from small and mid-sized US commercial banks (outside the 25 largest banks in terms of assets). This deposit outflow was more than 10 times the standard deviation of weekly deposit changes of $13.29 billion during 2022. While small and mid-sized banks experienced a large deposit outflow during the week of March 13, 2023, there was a $44.4 billion net inflow to the 25 largest US banks and a $144.6 billion net inflow to government money market mutual funds during the same period. Note that the standard deviation of weekly deposit changes for large banks was $38.18 in 2022 and that the standard deviation of weekly asset changes for money market funds was $23.76.[7] Thus, while it is clear that a substantial fraction of deposits during the 2023 deposit run was moved to money funds, a non-trivial fraction of funds remained in the banking sector. In addition, it took a significant difference in rates and widespread banking panic for deposits to depart the banking sector, which aligns with the deposit franchise literature.[8]

Cooperman et al. (2025) provide additional evidence supporting this point. They analyze aggregate monthly movements of credit-line drawdowns in 2020 and find that 52 percent of drawdowns returned as deposits at the same bank. For regional banks, shares ranged from 28 percent to 41 percent. Their aggregate estimate for 2020 is 94 percent, implying that most of the funds remained within the banking system as opposed to being moved to money market funds.

Overall, the evidence suggests that even in 2023, a substantial amount of funding

[7] In 2022, the correlation between weekly deposit changes in small and mid-sized banks and weekly deposit changes in large banks was 0.184. During the same period, the correlation between weekly deposit changes in small and mid-sized banks and changes in money market funds assets was –0.046.

[8] "In the year after the Fed hikes began, MMF yields rose by 4.13 percentage points, meaning they had passed along 97% of the Fed rate change, while bank rates rose by 0.32 percentage point, or 8% of the Fed's hikes" (source: "Why US Banks Are Hemorrhaging Deposits to Money Funds," Bloomberg, March 31, 2024).

remained in the banking system. Combined with persistently low deposit rates, this points to the conclusion that borrowers incur a cost when drawing on revolving credit lines for precautionary purposes—a cost that depends on the prevailing interest rate environment.

I.3 Understanding p

In our model, p is a state in which the borrower cannot access the undrawn amount on its revolving credit line in a timely manner. Bank failure—such as the collapse of Lehman Brothers—is a clear example of borrowers being cut off from accessing the remaining funds on their revolvers. In the next section, we provide empirical evidence that, at the onset of the COVID-19 pandemic, concerns about the stability of even the largest banks were real, so our empirical evidence is consistent with this interpretation.

More broadly, p means that the borrower believes that the lender could cancel the credit line for reasons unrelated to the borrower's conditions. For example, loan agreements typically include a material adverse clause (MAC), which intends to protect the borrower from significant adverse changes. For reference, the Loan Syndication and Trading Association (LSTA; 2017) states, "A Catergory 5 hurricance that destroys the borrower's only manufacturing facility ... would likely result in a MAC." The same source notes that enforcing the MAC provision is a complex matter, and this cross checks with evidence suggesting that banks were unable to pool commercial lines on any significant scale in 2008 or 2020. However, if in 2020 borrowers believed that banks were trying to reduce credit in general and that the uncertainty around the COVID-19 pandemic could allow lenders to trigger MACs, this could be an alternative interpretation of p.

II Data

Our empirical analysis uses the C&I loan schedule (schedule H) from the supervisory quarterly Y-14 microdata. As part of the Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010, the Federal Reserve was mandated to collect and use the Y-14 data to assess the capital adequacy of large bank holding companies and support supervisory stress test models. Schedule H contains detailed information on all outstanding credit facilities with at least $1 million in committed exposure provided by the bank holding companies that are subject to the Dodd–Frank Act Stress Test. By the end of 2019, loans recorded in the Y-14 data covered close to 70 percent of all C&I loans held by US banks, and the data have been used in multiple recent studies (for example, Chodorow-Reich et al. (2022), and Greenwald, Krainer and Paul (2023) look specifically at the use of revolving lines.) We focus on credit lines, and since we study only the revolving facility within a loan package, we use “loan” and “facility" interchangeably.

For each outstanding revolving-line facility, the Y-14 data set tracks, at a quarterly frequency, the line utilization, its committed value, the interest rate, the interest rate spread, and the interest rate index type (for variable rate loans), as well as other detailed contract characteristics .[9] Crucially, for our identification strategy, the data also include applicable interest rate floors, enabling us to determine whether the interest rate of a given line in a given quarter is bound by a contracted rate floor.

In addition to those detailed loan characteristics, the Y-14 data set also includes information about the borrower. Important for our analysis is the borrower’s specific industry because the COVID-19 pandemic may have had heterogeneous demand effects across sectors. We also merge the Y-14 data with publicly available balance sheets and income statements of the banks reported in the FR Y-9C.[10] The data collection for Y-14 starts in 2011. Yet—as is frequently the case with new data sets—the Y-14 data are not reliably complete and consistent until later years. Our regression analysis uses data going back to 2015.

III Identification

An important difference between the economics of a deposit run and the economics of a revolving-line run is that a revolving line is a liability for the running firm (whereas deposits are an asset), and, therefore, using a revolving line is costly. As noted earlier,

[9] Our sample of loans also includes a small share of demand loans, which tend to be concentrated among smaller borrowers, as discussed in Chodorow-Reich et al. (2022). Results are robust to excluding those facilities from the sample.

[10] The FR Y-9C, like the Y-14, is at the bank-holding-company level, but we use the terms “bank” and “bank holding company” interchangeably in this paper.

commercial loans in the United States tend to be variable-rate contracts, priced as a fixed spread paid over a benchmark that closely follows the Fed's policy rate. Until recently, the dominant benchmark rate was LIBOR. Now, the dominant benchmark rate is the Secured Overnight Financing Rate (SOFR).[11] A commonly quoted pricing statistic for commercial loans is the all-in-drawn (AID) spread, which reflects the total cost to the borrower, including interest and fees paid on the drawn amount. On the undrawn amount of the line, the borrower pays a lower fixed cost or the all-in-undrawn (AIU) rate. So, a precautionary withdrawal of funds from the revolving line has a direct cost of SOFR + AID spread – commitment fee per dollar withdrawn.

Regression Kink Design. Our goal is to measure the interest rate elasticity of the utilization of the precautionary revolving line. We emphasize that our focus is on the precautionary motive of borrowers, which introduces an additional challenge for the identification. For example, even if we had an exogenous interest rate shock, we could not simply look at the utilization of revolving lines around such a shock because the fundamental credit demand could be downward sloping. Therefore, we need to not only address the fact that interest rates could be endogenous to firm fundamentals but also separate precautionary drawdowns from firms' fundamental demand for liquidity.

We address the endogeneity of interest rates by using an RKD following Card et al. (2015), Card et al. (2016), and its recent application by Indarte (2023). In our setting, the RKD is possible due to the prevalence of interest rate floors in the pricing of commercial loans. As mentioned, commercial loans tend to be variable-rate contracts. The variable part is the base rate (or index rate), which is predominantly LIBOR during our sample period. The "floor" is the minimum base rate specified in the credit agreement.[12] The

[11] Both LIBOR and SFOR are short-term rates that co-move strongly with the federal funds rate (policy rate). The use of LIBOR as a reference rate ended in June 2023. Before the change, LIBOR was the dominant benchmark rate. For example, even as recently as May 2023, more than 50 percent of loans in the JPM Loan Index were still using LIBOR. For this reason, in our empirical analysis, we restrict the sample to credit-line facilities that use LIBOR as a base rate.

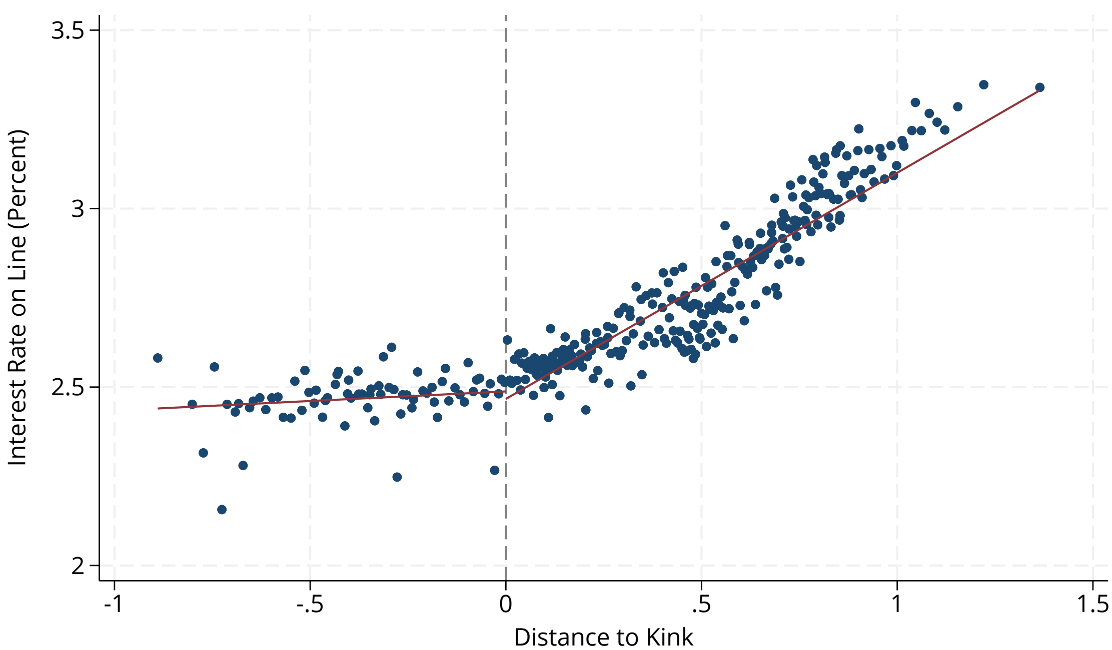
[12] The LSTA offers the following template for contractual language for the floor: " LIBOR means, [...]; provided that if such rate shall be less than [___], such rate shall be deemed to be [___] for the purposes of the Agreement; [...]." It adds: "It has also become common for LIBOR to have a floor rate below which LIBOR cannot go (even if the screen rate is in fact lower). These so-called LIBOR floors were first implemented in the wake of the 2008 credit crunch" (see LSTA 2017).

benchmark (variable) interest rate of credit line l at time t then effectively becomes:

$$r_{l,t} = \text{All-in spread}_l + \max(\text{LIBOR}_t, \text{Contracted LIBOR floor}_l). \tag{4}$$

The maximum function in the applicable interest rate on the line facility introduces a kink in the relationship between the index rate and the interest rate on the facility: There is a one-to-one relationship between LIBOR and the interest rate whenever LIBOR is above the contractual LIBOR floor, but when LIBOR is below the floor, the interest rate is flat and does not respond to LIBOR changes. Using the (unconditional) raw data underlying our analysis, Figure 2 illustrates non-parametrically the kink in the applicable interest rate that is at the core of our identification strategy.

Figure 2: Kink in Applicable Credit-line Interest Rate



Notes: The relationship between the interest rate that is applicable on the drawn part of the credit line is as a function of the distance between LIBOR and the contracted LIBOR floor. The applicable interest rate becomes insensitive to changes in LIBOR if the floor is binding. The sample period underlying this binned scatter plot is 2015:Q4 through 2020:Q4. *Sources:* Y-14, Haver, authors' calculations.

We use the RKD to examine the change in the slope of the relationship between the outcome of interest (line utilization) and the running variable (applicable interest rate) at the exact location of the kink that is imposed by the rule, which, in our case, is the LIBOR floors. It is important to stress that the regulation or market rule that governs the floors or the index rate does not have to be exogenous for the RKD to be valid. Provided that observations on either side of the kink threshold are similar—that is, they have a smooth density function at the threshold, a condition that holds in our application—any kink in the outcome can be attributed to the treatment effect of the policy variable (see Card et al. (2015) for technical details and additional standard regularity assumptions). Simply put, if we observe a kink in revolving-line utilization when the LIBOR floor becomes binding, we causally attribute this change to the change in the applicable interest rate.

Let $d_{l,t} \equiv \text{LIBOR}_t - \text{Contracted LIBOR floor}_l$ be the distance between the LIBOR and the contracted floor, that is, the running variable or forcing variable in terms of the RKD terminology.[13] We can express revolving-line utilization as a function of this distance, $u_{l,t} = u_{l,t}(d_{l,t})$. Dropping subscripts to ease notation, we can write the local average treatment effect as:

$$\tau = \frac{\lim_{d_0 \to 0^+} \frac{\mathrm{d}u(d)}{\mathrm{d}d}\Big|_{d=d_0} - \lim_{d_0 \to 0^-} \frac{\mathrm{d}u(d)}{\mathrm{d}d}\Big|_{d=d_0}}{\lim_{d_0 \to 0^+} \frac{\mathrm{d}r^l}{\mathrm{d}d}\Big|_{d=d_0} - \lim_{d_0 \to 0^-} \frac{\mathrm{d}r^l}{\mathrm{d}d}\Big|_{d=d_0}}, \tag{5}$$

that is, the change in the slope of the outcome variable (numerator) scaled by the change in the slope of the first stage (denominator). Note that the denominator simplifies to one with equation (4), in which case, the elasticity estimate is simply the change in the slope of line utilization at the threshold. As we discuss later, we use a fuzzy design in which the denominator can be different from one.

The empirical implementation of the RKD involves the estimation of regression models for the utilization and the interest rate for observations "close" to the kink using (local) polynomial regressions, similar to a regression discontinuity design. However, with the kink design, we are interested in estimating a slope change instead of a shift in the intercept. Later, we discuss the exact empirical regression model used to estimate the change in slopes at the kink.

[13]Note that we can rewrite the applicable interest rate on the credit line as a function of the distance: $r_{l,t} = \text{All-in spread}_l + \text{Contracted LIBOR floor}_l + \max(\mathrm{d}_{l,t}, 0)$.

Within our economic model, we can also derive the RKD estimand using equation (3). Because $\frac{\partial r^l}{\partial d} = 1$ when the floor is not binding and $\frac{\partial r^l}{\partial d} = 0$ when the floor is binding, we can write the derivative $\frac{\partial u}{\partial d}$ as a piecewise function:

$$\frac{\partial u}{\partial d} = \begin{cases} -\frac{\theta p}{\left((1+p)r^l - r^d\right)^2}\left[(1+p)\cdot 1 - \frac{\partial r^d}{\partial d}\right] < 0 & \text{if} \quad d_{l,t} \geq 0 \\ -\frac{\theta p}{\left((1+p)r^l - r^d\right)^2}\left[(1+p)\cdot 0 - \frac{\partial r^d}{\partial d}\right] > 0 & \text{if} \quad d_{l,t} < 0. \end{cases} \tag{6}$$

The difference between the limits of these two derivatives yields the interest elasticity of precautionary line utilization (equation 2). That is, the RKD estimand exactly recovers our main object of interest. Note from equation (6) that once the interest floor binds, $\frac{\partial u}{\partial d}$ is positive whenever $\frac{\partial r^d}{\partial d} > 0$. Mathematically, this happens because the differential between the change in the fixed loan rate (floor) and the change in the deposit rate—that is, $\frac{\partial r^l}{\partial r} - \frac{\partial r^d}{\partial r}$—decreases as the policy rate increases. Intuitively, the opportunity cost of withdrawing decreases at the floor when the policy rate increases, which in turn makes precautionary drawdowns relatively more attractive. On the other hand, when the floor is not binding, a higher policy rate increases the opportunity cost (given our assumption of a lower pass-through into the deposit rate), leading to a reduction of precautionary drawdowns.

While the RKD approach isolates the impact of an increase in the credit line's interest rate, holding fixed the macroeconomic environment, we acknowledge that the approach identifies a local average treatment effect (LATE) using only the interest rates of loan facilities that are close to their respective interest rate floors. Given that there is heterogeneity in the applicable interest rate across borrowers, the LATE estimate may not be representative of the average treatment effect (ATE) if the interest rate elasticities are heterogeneous and loans that are not in the RKD sample have different elasticities.[14] However, Appendix Figure A.1 shows that our sample covers facilities with a substantial range of interest rate floors. This means that when the policy rate (and, in turn, the base rate) falls, there is heterogeneity across borrowers in terms of the gap between the rate on revolving lines and the rate on "cash" holdings, which is what matters for precautionary revolving-line runs.

[14] See Angrist and Fernández-Val (2013) for a discussion.

A related concern is that when LIBOR floors are binding, the credit-line cost (applicable interest rate) is higher than the market interest rate. In this setting, there is an obvious disadvantage to drawing on the revolving line, even if a firm were to put 100 percent of the proceeds into a fund that yields the full market rate. This point relates to our discussion in Section 1 about the use of bank deposits, the strong evidence of the deposit franchise, and the degree of pass-through into deposits required for the identification to work.

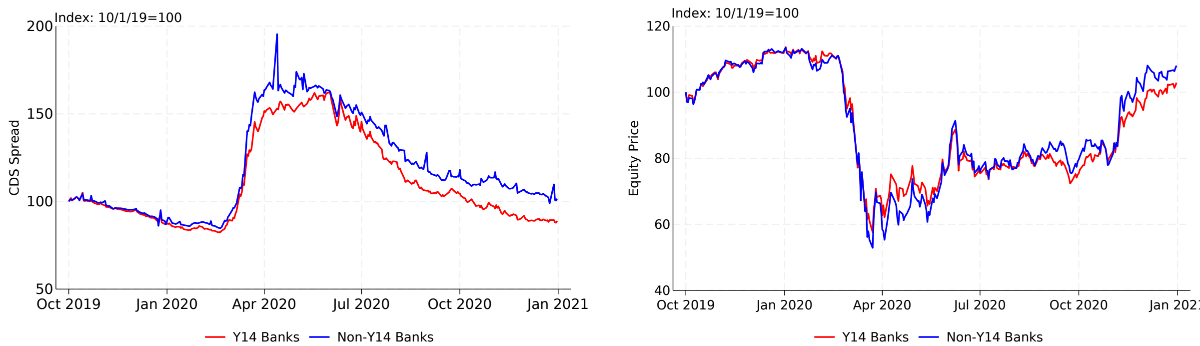
Isolating Precautionary Motives Given our focus, we need to identify a sample period with significant precautionary drawdown motives, that is, a period (covered by the available Y-14 data) when runs on banks were likely to take place. On the other hand, to implement the RKD, we also need the interest rate floors to bind for a sufficiently large group of borrowers. (As we discuss later, the RKD estimation focuses on a set of observations close to the floor.) Together, these conditions point to a period of high macroeconomic uncertainty.

Because the Y-14 data do not cover the 2008 Global Financial Crisis, we cannot study this episode. The 2023 regional banking crisis is not a good setting for our empirical identification due to the high interest rates at the time. Moreover, our data cover credit lines by large banks that were not at the center of the 2023 turmoil. Thus, in our main analysis, we focus on the 2019:Q4–2020:Q4 period, capturing the COVID-19 outbreak in early 2020.

As Figure 3 shows, this period was characterized by significant worries about the banking sector. Panel (a) shows a strong increase in CDS spreads—a standard market-based metric of default concerns—of more than 50 percent. Panel (b) shows a strong decline in bank stock prices of about 40 percent. Importantly, these movements are not limited to smaller banks (non–Y-14 banks); they are equally present in the larger banks (that is, Y-14 banks), suggesting material and broad concerns about bank health. Another advantage of focusing on the pandemic period is that monetary policy rates declined suddenly to zero due to an unexpected shock, making the LIBOR floors binding for a significant fraction of borrowers. Figure A.1 shows that the floors became binding for about 4 percent of facilities.

In line with precautionary drawdowns being at play, Figure 5 illustrates that 2020:Q1

Figure 3: Bank CDS Spreads and Stock Prices during the COVID-19 Pandemic



(a) CDS Spread

(b) Stock Price

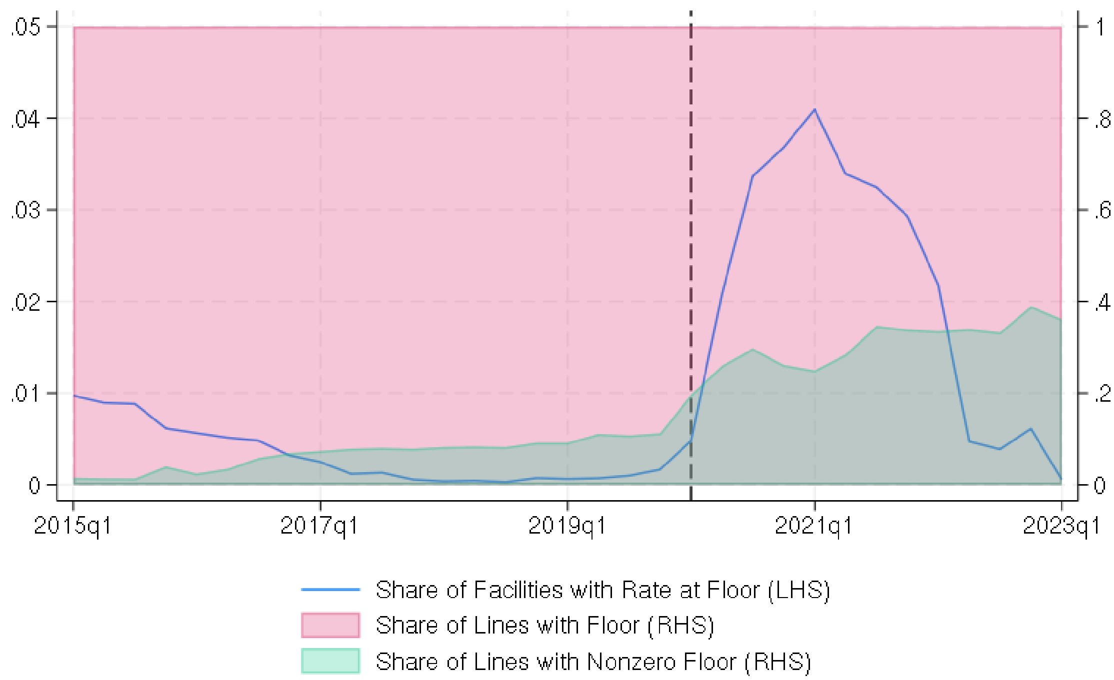
Notes: Panel (a) shows a strong increase in the average CDS spreads for both Y-14 banks and non–Y-14 banks during the pandemic. Panel (b) shows a strong decline in the average stock price for both Y-14 banks and non–Y-14 banks. *Sources:* Bloomberg, authors' calculations.

was a period with a sudden and significant jump in the use of revolving lines, but utilization returned to its normal level the next quarter. Appendix Figure A.2 shows the same developments, focusing on only LIBOR-indexed facilities. In Appendix Table B.1, we report detailed summary statistics of drawdowns in 2020:Q1 at the facility, bank, firm, and industry levels from the Y-14 data, confirming a widespread increase in drawdowns in the cross section as well. Similar patterns of credit-line drawdowns emerge from S&P's Global Market Intelligence "US COVID-19 Related Revolver Drawdown" firm-level data set, which covers an aggregate of $28 billion in drawdowns of syndicated lines in March 2020. This data set indicates that 707 firms had drawn down their line by that point.[15] As Figure 5 shows, we do not find a similar stark increase in drawdowns during the SVB failure in 2023:Q1, which is consistent with high interest rates muting precautionary drawdowns during this period.

For further supporting evidence of precautionary motives being at play during 2020, we examine data on stated motives for public firms' revolving-line drawdowns at the onset of the pandemic. These data were collected by King & Spalding (2020) and include

[15] In Appendix Figure A.3, we zoom in on the cross section of drawdowns by looking at the median, 90th percentile, 95th percentile, and maximum of drawdowns on revolvers in the cross section of banks in our sample. Figure A.3 clearly picks up the run on the revolving lines in 2020:Q1 and its economic importance. For most exposed banks in our sample, this represented about 7 percent of liabilities. In US dollars, the largest bank-level drawdown was about $35 billion.

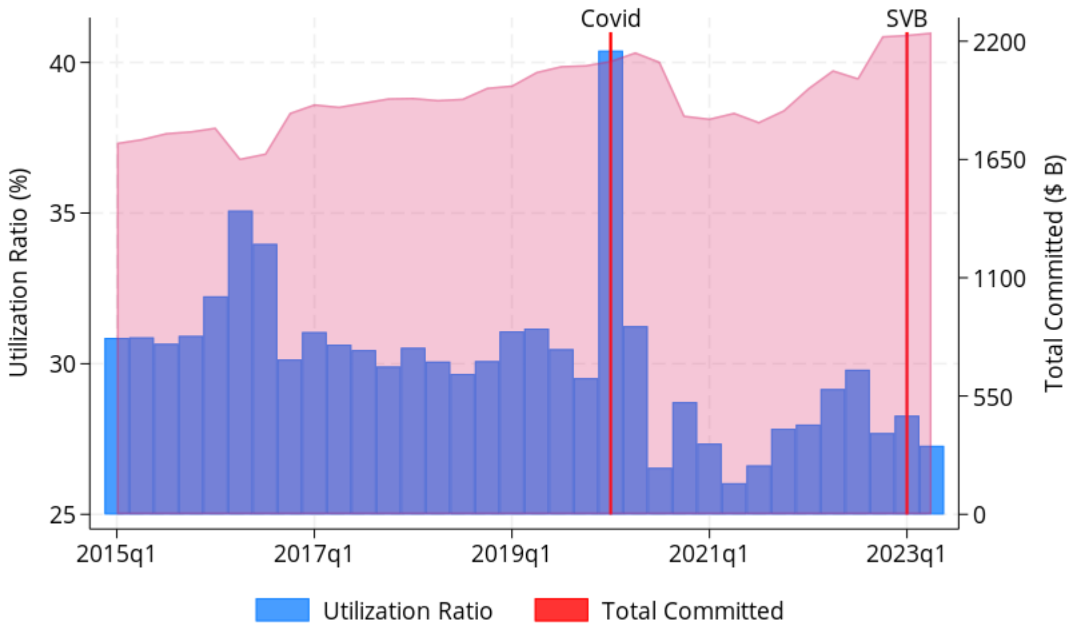
Figure 4: Interest Rate Floors on Line Commitments



Notes: On the left scale, this figure shows the share of revolving-line facilities with a binding interest rate floor (blue solid line). On the right scale, the figure shows the share of revolving-line facilities with a contractual interest rate floor (red area), and we overlay the share of facilities with nonzero interest rate floors (green area). The figure shows that virtually all facilities have a floor, although for the majority of facilities in our sample, the floor is zero. The vertical red line indicates 2020:Q1. *Sources:* Y-14, authors' computations.

information on the drawing firm and the lead arranger bank as well as a description of the reason for the drawdown. Table 1 reports, for each Y-14 bank in the data in King & Spalding (2020), the number of dollars drawn that were associated with mentions of "caution" and the number of dollars drawn that were associated with no mention of "caution." The table highlights that the stated concerns about caution were widespread among firms with credit lines from Y-14 banks. This serves as additional and direct evidence that worries about bank health were widespread at the onset of the pandemic, including among the Y-14 banks that are the focus of our analysis. Also, Cooperman et al. (2025) show that drawdowns at the onset of the pandemic were for precautionary reasons by examining borrowers' cash balances. They argue that precautionary drawdowns should be associated with increases in cash holdings, and they confirm that this is indeed the case

Figure 5: Utilization Rates and Total Line Commitments over Time



Notes: On the left axis, the figure shows the aggregate utilization ratio, defined as total utilized line credit as a percentage of total committed line credit. On the right axis, the graph shows the total committed credit lines in billions of dollars. The figure is based on revolving-line commitments irrespective of their index rate. The vertical red line labeled "COVID" indicates 2020:Q1, and the vertical red line labeled "SVB" indicates 2023:Q1. *Sources:* Y-14, authors' computations.

with the 2020 drawdowns.

A potential concern about focusing on the pandemic period is that in 2020, there was a fundamental shift in demand for revolving credit. To be clear, all drawdowns are driven by fundamental demand, but under normal conditions, capital needs and drawdowns are contemporaneous. As in the model, the lag between drawdowns and potential capital needs is at the core of what defines a precautionary drawdown. We may expect the rise in use of revolving lines in 2020:Q1 for fundamental reasons, given that firms' general demand for cash was pervasive due to pandemic-related disruptions. This, however, cannot explain the abrupt reversal of the utilization of revolving lines in 2020:Q2.

We should consider, however, that the lag between drawdown and future capital needs could occur due to payment frictions. If the expected settlement of funds under revolving lines takes a significant amount of time, the firm could draw the lines ahead of anticipated capital needs. However, in speaking with CFOs for this study, we learned that while there

Table 1: Reasons for Credit-line Drawdowns during the COVID-19 Pandemic

	Stated Rational for Drawdowns				
	"Caution" Appears		"Caution" Doesn't Appear		Total
	$M	%	$M	%	$M
Bank of America	15,603.8	58	11,298.8	42	26,902.6
Citigroup	4,938.9	23	16,935.0	77	21,873.9
Citizens	350.4	58	250.0	42	600.4
Credit Suisse	1,215.0	100	0.0	0	1,215.0
Deutsche Bank	3,844.8	100	0.0	0	3,844.8
First Citizens	33.0	100	0.0	0	33.0
JPMorgan Chase	20,192.9	24	65,586.4	76	85,779.3
Keycorp	1,685.0	66	879.0	34	2,564.0
M & T Bank	125.0	90	14.1	10	139.1
MUFG Bank	970.0	100	0.0	0	970.0
Morgan Stanley	211.0	31	469.6	69	680.6
PNC	138.0	15	800.0	85	938.0
Royal Bank of Canada	79.0	100	0.0	0	79.0
Truist	123.8	44	158.8	56	282.6
US Bancorp	47.0	5	887.0	95	934.0
Wells Fargo	5,121.8	48	5,542.9	52	10,664.7

Note: This table was compiled using data from King & Spalding (2020), who track revolving-line drawdowns and identify the motives of public firms from the onset of the COVID-19 pandemic through April 2020. Separately, we collect the identities of the lead arrangers on revolving lines from SEC filings. This table does not use any confidential Y-14 information. *Sources:* King & Spalding (2020), SEC filings, authors' computations.

is indeed a minor transactional delay, such time lags (conservatively) do not exceed five days for small firms and two days for large firms. Thus, payment frictions seem to be an unlikely explanation for the surge in revolving-line utilization during the pandemic.

We should also consider the possibility that revolving credit was used as "bridge" financing, with firms using other forms of credit, at a later stage, to pay back the additional credit-line debt drawn at the onset of the pandemic. Although corporate bond markets recovered after the Fed interventions (Darmouni and Siani, 2024), bank credit was still extremely tight in 2020:Q2. New term loan origination was well below its pre-pandemic levels (Bräuning, Fillat and Wang, 2024), suggesting that it is unlikely that a large set of borrowers without access to the bond markets obtained bridge financing. Nevertheless, we conduct several empirical tests to explore this possibility, concluding that precautionary motives were the first-order explanation behind the 2020 surge in revolving-line utilization. We discuss the results in Section IV.

Empirical Model Focusing on the kink in the relationship between revolving-line utilization and the distance to the interest rate floor, we estimate the following regression model:

$$u_{l,t} = \begin{cases} \beta_1 d_{l,t} + f_1(d_{l,t}) + \theta_1 X_{l,t} + u_{l,t}, & \text{for } d_{l,t} > 0 \\ (\beta_1 + \beta_2) d_{l,t} + f_2(d_{l,t}) + \theta_2 X_{l,t} + u_{l,t}, & \text{for } d_{l,t} \leq 0, \end{cases} \tag{7}$$

where $u_{l,t}$ is the utilization rate (as a percentage of total committed credit under the revolving-line agreement), and $d_{l,t}$ is the difference between LIBOR and the applicable LIBOR floor, since all the other components of the interest rate are fixed. This number can be negative, indicating that the applicable interest rate on the line equals LIBOR floor + spread. The piecewise regression equation means that we allow all parameters to vary freely on either side of the kink point; that is, we do not enforce pooled parameters, as is common in the RKD literature.

The coefficient β_1 equals the derivative of utilization with respect to the distance as the distance approaches zero from above, and the coefficient β_2 measures the *change* in the derivative at $d_{l,t} = 0$, the kink point. Flexible polynomial functions f_1 and f_2 are included to account for a potential nonlinear relationship between the distance to the floor and line utilization away from the kink point so that the linear terms accurately measure the derivative as the distance approaches zero. In our baseline specifications, we follow Card et al. (2015) and include polynomial functions of order 2, but we show robustness to alternative specifications.

The vector $X_{l,t}$ collects all control variables, which we also allow to change flexibly depending on whether the floor is binding. Throughout the analysis, we control for the (log) loan committed amount, the (log) maturity, and the interest rate spread. We include these controls because, for a small share of loans, the terms change over time. Moreover, the regression includes loan fixed effects, industry-quarter fixed effects, and bank-quarter fixed effects.

Our analysis includes loan fixed effects, so the identification is driven by within-loan variation. This means that changes in the applicable interest rate come from variations in LIBOR. As noted earlier, changes in LIBOR are likely to be endogenous, and to the degree that such changes are correlated with changes in investment opportunities, RKD design helps us address this issue. An additional concern could be that changes in LIBOR also correlate with the perception of banking-sector stability, thus accelerating the run. Inclusion of bank-quarter fixed effects should address this concern.

The Y-14 data contain very detailed contract information at the facility level, including the applicable interest rate on the line and the base-rate type. Yet, given the complexity of contractual interest rate schedules, the mapping between the base rate and the applicable interest rate is not fully captured in the data due, for example, to the lack of information when variable-rate contracts reset after base-rate changes. Typically, data sets, including Y-14, do not capture these nuanced features of credit agreements. However, the lack of such detail necessitates a fuzzy RKD design, in which the "first-stage" assignment rule—in our case, the mapping between the index rate and the applicable interest rate on the line—is also modeled as a regression. Therefore, as with the utilization ratio, we estimate a similar piecewise model for the interest rate of the line facility:

$$r_{l,t} = \begin{cases} b_1 d_{l,t} + g_1(d_{l,t}) + \gamma_1 X_{l,t} + e_{l,t}, & \text{for } d_{l,t} > 0 \\ (b_1 + b_2) d_{l,t} + g_2(d_{l,t}) + \gamma_2 X_{l,t} + e_{l,t}, & \text{for } d_{l,t} \le 0. \end{cases} \tag{8}$$

The key parameter of interest is b_2, the change in the slope of the relationship between the (observed) interest rate and the LIBOR distance at the kink point.

As is common practice in RKD applications (Card et al., 2016), we estimate both quantity and price models for observations within a given bandwidth around the interest rate floors, which allows for a narrow identification of the slope near the kink. The baseline results are estimated for a bandwidth of 1 percent around the floor, and later we show the robustness of the effect for several bandwidth selections. Moreover, we adopt a commonly used uniform kernel that implies equal weighting of observations in our regressions.

The fuzzy RKD estimate of the interest rate elasticity of line utilization is then obtained as the ratio of the estimated changes in the slopes of the utilization ratio and the estimated change in the slope of the interest rate:

$$\hat{\tau} = \frac{\hat{\beta}_2}{\hat{b}_2}. \tag{9}$$

We compute standard errors using the delta method and based on multi-way clustered errors at the bank and industry levels.

IV Results

IV.1 Interest Rate Elasticity of Drawdowns

Table 2 presents our baseline elasticity estimates using the COVID-19 episode. Panel A reports the estimated interest rate elasticity, while Panels B and C report the estimates of the underlying parameters of the change in slope for the interest rate and revolving-line utilization. Throughout the analysis, we include loan-facility fixed effects and quarter fixed effects; that is, the results are identified from within-loan variation after common time trends in utilization and rates have been netted out. All columns include the log of the committed-line amount, log maturity, and interest rate spread, as discussed earlier. In addition, column (2) includes bank-quarter fixed effects, and column (3) includes borrower-industry-quarter fixed effects.

Panel A, column (1), reports an estimated elasticity of –13.37; that is, when interest rates increase by 1 percentage point, revolving-line utilization decreases by 13.37 percentage points. Consistent with equation (9), this elasticity estimate is the ratio of the slope changes in the utilization rate and the applicable interest rate at the interest floor. For example, in column (1), the elasticity estimate of –13.37 (Panel A) is the ratio of 6.845 (Panel C) and –0.512 (Panel B).

Table 2: Interest Rate Sensitivity of Revolving-line Utilization

	(1)	(2)	(3)
Panel A: Interest Rate Elasticity			
Elasticity	-13.37***	-13.71***	-12.95**
	(2.49)	(4.15)	(5.24)
Panel B: Dep. Var. is Interest Rate			
Distance to Floor	0.506***	0.533***	0.560***
	(0.021)	(0.040)	(0.049)
At Floor * Distance to Floor	-0.512***	-0.511***	-0.533***
	(0.023)	(0.039)	(0.063)
Panel C: Dep. Var. is Utilization Rate			
Distance to Floor	-2.088**	-3.178	-2.233
	(0.545)	(1.408)	(1.370)
At Floor * Distance to Floor	6.845**	7.005**	6.903*
	(1.237)	(2.053)	(2.672)
Controls	Yes	Yes	Yes
Facility FE, Time FE	Yes	Yes	Yes
Bank*Time FE	No	Yes	Yes
Industry*Time FE	No	No	Yes
N	18157	18147	18126

Notes: The elasticity reported in Panel A is computed as the ratio between the changes in slope at the kink point (At Floor * Distance to Floor) estimated from the utilization rate model (Panel C) and the interest rate model (Panel B). All results are based on bandwidth = 1 percentage point around the floor and uniform kernel, and they control for second-order polynomial terms on each side of the kink. Controls include the (log) committed amount, the (log) maturity, and the interest rate spread. The sample period runs from 2019:Q4 through 2020:Q4. Standard errors are two-way clustered at the facility and time levels. * (**) [***] indicate significance at the 10 percent (5 percent) [1 percent] level.

The coefficient estimates reported in Panels B and C are economically meaningful.[16] In Panel B, we find that when the floor is not binding, the applicable interest rate on the line decreases by about 50.6 basis points when the LIBOR decreases by 1 percentage point.[17] On the other hand, when the interest rate is at the floor, changes in the LIBOR have no effect on the applicable interest rate of the line ($0.506–0.512 \approx 0$). Panel C shows that when the floor is not binding, line utilization decreases when the LIBOR increases (estimate of –2.088). However, when the floor is binding, and the applicable interest rate on the line is insensitive to LIBOR changes, this effect reverts and becomes positive (–2.088 + 6.845), consistent with our model prediction in equation (6). The intuition is that when the applicable interest rate on the line is insensitive to LIBOR changes (at the floor), an increase in the LIBOR makes the line relatively more attractive than other sources of funding that become more costly.

Column (2) shows that the elasticity estimate increases slightly to –13.71 once we include bank-time fixed effects, driven by a somewhat larger change in the slope of utilization (Panel C). Column (3) reports the estimates from our most saturated model, which includes both industry-time fixed effects and bank-time fixed effects to the baseline controls. Panel A implies an interest rate elasticity of about –12.95: When the interest rate increases by 1 percentage point, the precautionary revolving-line utilization decreases by 12.95 percentage points.

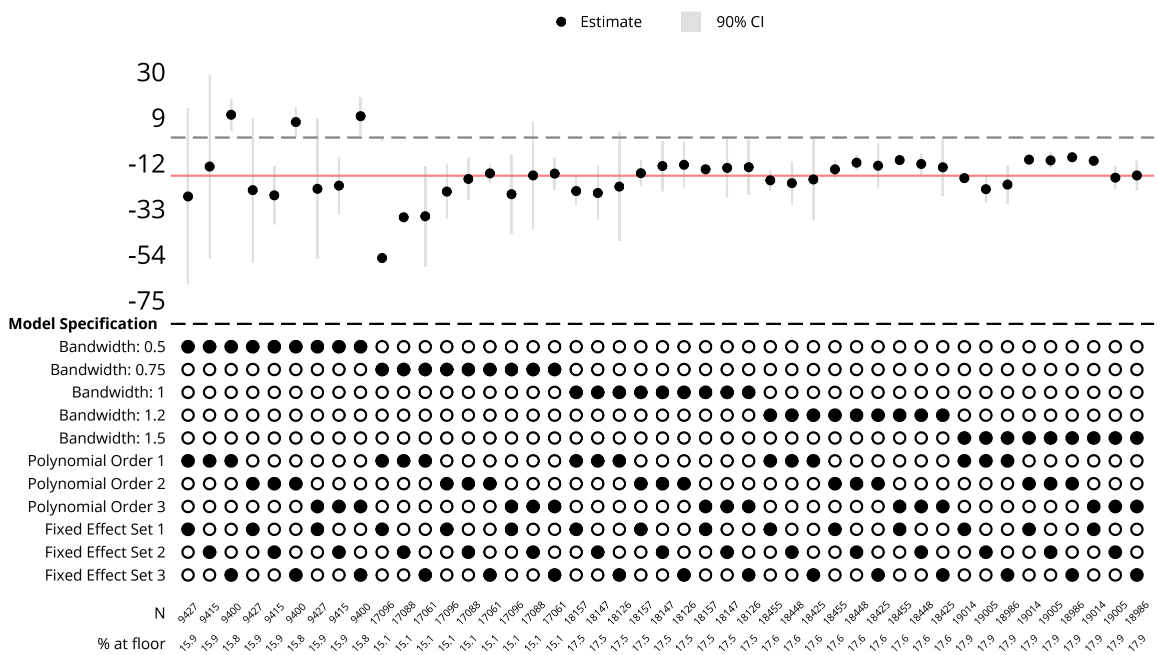
We directly test the validity of the RKD identification approach in several ways. First, we verify that other key variables do not exhibit a kink at the threshold. For example, in the Y-14 data, we observe the active loan contract over time, and if a loan was amended, we observe the amended terms. There is a small possibility that the kink in the applicable interest rate is associated with an amendment, which could include other loan modifications, triggering a kink in other variables. Empirically, we find that changes in other core terms (loan amount, maturity, spread) are very rare around the kink where the LIBOR floor becomes binding. Nevertheless, in Table B.2, we show that if such amendments are made,

[16]The coefficient estimates in Panels B and C are not causally identified. Only the ratio of the two slope changes allows for causal identification in the RKD set-up. We report these results for transparency.

[17]Notice that the first-stage coefficient estimate is smaller than one, consistent with measurement problems related to the policy function. For this reason, we cannot use the standard RKD and must resort to the fuzzy design that allows for fairly general measurement error types (see Card et al. (2016)).

these variables behave smoothly around the interest rate kink; that is, interaction terms with the distance to the LIBOR floors are mostly insignificant. This is an important point because the smoothness of covariates at the threshold is the RKD's central identification assumption. Second, we verify that the distance to the floor variable is smooth around the threshold. Figure A.4 shows the density estimate, suggesting that there is no discontinuity at the threshold.

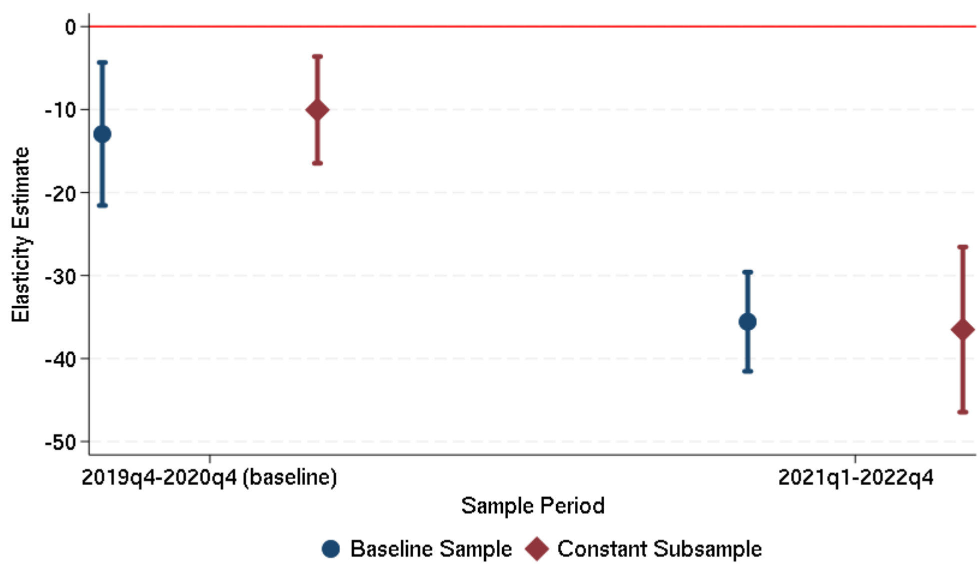
Figure 6: Robustness to RKD Specification



Notes: This figure shows the robustness of our baseline elasticity estimates (Table 2) to changes in key parameter choices underlying the regression kink design. We consider the following key parameters: bandwidth, degree of polynomial, and fixed effects. For each parameter combination indicated with black dots in the bottom panel of the figure, we estimate the elasticity. Point estimates shown in the top part of the figure are depicted as black dots, and 90 percent confidence intervals are shown as gray bars. For presentation purposes, we omit the confidence intervals if they exceed ±70. The red vertical line is the average of the estimates across all models in this plot. Fixed Effect Set 1 corresponds to the fixed effects in column 1 of Table 1. Fixed Effects Set 2 corresponds to column 2, and so forth. *Sources:* Y-14, authors' computations.

Figure 6 shows the results of a sensitivity analysis of the baseline estimates reported in Table 2. Two key parameters in the RKD are (1) the bandwidth of the running variable around the kink and (2) the order of polynomials included as controls. The dark circles at the bottom of the graph indicate the active specification. The upper panel plots the estimated elasticity; that is, each dot in the upper panel corresponds to a different estimate. We consider bandwidths of 50 (most stringent), 75, 100 (baseline), 120, and 150 basis points around the kink. We also consider polynomials of order 1, 2, and 3, with 2 being the baseline, which aligns with standard practice in the literature (Card et al., 2015). We report results for all three fixed-effect specifications in Table 2. In sum, Figure 6 presents elasticity estimates for 5 x 3 x 3 = 45. Naturally, for very small bandwidths, we make few observations near the kink point, introducing some variation in the estimates. The order of the included polynomial does not seem to be crucial for our estimates. Overall, these additional results validate the RKD design and suggest a relatively large interest rate sensitivity of line utilization, with estimates close to the magnitudes reported in Table 2 for most specifications.

Figure 7: Time Variation in Interest Rate Elasticity of Revolving-line Utilization



Notes: The blue elasticity estimates are obtained by estimating the baseline model (all fixed effects) on the indicated subsamples. The red elasticity estimates are obtained by estimating the RKD model with facility and time fixed effects for a constant set of facilities that are present in both periods. The whiskers represent 90 percent confidence intervals based on two-way clustered standard errors at the facility and time levels. *Sources:* Y-14, authors' computations.

We can further ensure that the elasticities we estimate are predominantly those of precautionary drawdowns by looking at the time variation in the estimates. Figure 7 summarizes our baseline estimates presented in Table 2 for different sample periods. During the 2021:Q1–2022:Q4 reference period, the fundamental motive behind the demand for liquidity is likely to dominate precautionary motives, given that bank stock volatility is low. As Figure 7 shows, and as is consistent with our theoretical predictions, the elasticity estimates for this low-uncertainty period are substantially larger (in absolute values), with values of about –35. One potential concern about estimating elasticities for different periods is that the set of loans used in our tightly identified RKD bandwidth estimation changes over time. Hence, variation in the estimated interest rate elasticities may be driven by sample selection. As shown in Figure 7, we address this concern by including estimates that use the same constant sample of facilities in both periods. Given the smaller sample of facilities, we include only time and facility fixed effects rather than the broader set of fixed effects that we apply in our baseline analysis, and we also cluster standard errors only at the time level. That said, results using the constant sample analysis are very similar to those obtained from our baseline analysis and confirm a higher-interest-rate elasticity for the 2021:Q1–2022:Q4 period.[18]

The results in Figure 7 align with our model predictions. Precautionary drawdowns are driven by *future* fundamental demand. In the model, the central decision is when to draw the credit line, and timing is the key distinguishing feature of a precautionary draw. In the case of precautionary drawdowns, the firm has a greater interest expense, so its marginal cost rises, which, with investment opportunities remaining constant, makes investment more sensitive to changes in interest rates, given the curvature of the return function. With a concave return function, the firm will move its optimal investment into a region with a higher marginal return on investment. As a result, the firm will change its investment less in response to interest rate changes because the investment return is higher. Thus, when precautionary motives become stronger, the interest rate elasticity should decline in absolute values, as shown in Figure 7. In the absence of a precautionary motive, the shift in the slope in 2020 would not take place.

Another way to isolate a precautionary motive is to analyze heterogeneous elasticities

[18]Appendix Figure A.5 presents additional results for time variation in elasticities, showing weighted regression and full sample estimates for the 2015:Q1–2022:Q4 period. Given the small share of facilities near the floor in the pre–COVID-19 period (see Figure A.1), we cannot zoom in further on the time variation during this period.

Table 3: Interest Rate Elasticity of Revolving-line Utilization in the Cross Section

	Borrowers with Precautionary Drawdown?			
	Definition 1		Definition 2	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Elasticity (No COVID)	-22.37***	-19.40***	-21.74***	-23.04***
	(3.46)	(4.55)	(3.09)	(4.72)
Between-Group Diff	-2.97		1.30	
	(0.406)		(0.764)	
Elasticity (COVID)	-11.24***	-16.86***	-12.22***	-16.54***
	(3.88)	(2.07)	(3.81)	(2.57)
Between-Group Diff	5.63*		4.31	
	(0.094)		(0.421)	
COVID Effect:	-11.13**	-2.53	-9.52*	-6.51
(p-value)	(0.035)	(0.617)	(0.054)	(0.219)
N	60647	15727	65463	10911

Notes: This table represents elasticities that are separately estimated for different groups of firms during the COVID-19 period. "Yes" identifies borrowers with precautionary drawdowns, and "No" identifies those without precautionary drawdowns. We use two different definitions to identify firms with precautionary drawdowns. Under definition 1, a firm had a precautionary drawdown if it increased its utilization in 2020:Q1 by more than the median firm and in 2020:Q2 reverted to its 2019:Q4 utilization level (within a 5 percentage point margin). Under definition 2, the logic is the same, but we allow the median utilization to change by NAICS2 industry. Standard errors are two-way clustered at the facility and time levels. * (**) [***] indicates significance at the 10 percent, (5 percent) [1 percent] level. Full estimation output is reported in Table B.3 *Sources:* Y-14, Compustat, authors' computations.

across firms during the COVID-19 period. The loan-panel structure of our data allows us to identify firms that were increasing their line utilization when the pandemic shock hit in 2020:Q1 but then repaid the line in 2020:Q2, when the run on revolving lines had largely ended. In our first proxy for precautionary drawers (definition 1), we flag firms that increased their line utilization from 2019:Q4 to 2020:Q1 by more than the median firm but then repaid the increase in line utilization in 2020:Q2, such that the level of utilization in 2020:Q2 equals that of 2020:Q4 (up to a margin of 5 percentage points). In our second proxy, we conduct a similar analysis based on a within-industry threshold for the 2020:Q1 increases in utilization (definition 2).

The results shown in Table 3 highlight that outside the pandemic period, the elasticity for both groups—those marked as having a higher precautionary motive and those marked as having a lower motive—is very similar. Under the first definition, the estimates are about −19 and −22, respectively. During the pandemic period, the elasticity drops for both groups, but it is more negative (an estimate of −16.86 under the first definition) for firms flagged as having used their line for precautionary reasons. This difference is also statistically significant for the first definition.

Table 4: Interest Rate Elasticity of Precautionary Revolving-line Utilization

	Excluding Firms with New:			
	Bonds (1)	Loans (2)	PPP (3)	Any (4)
Panel A: Interest Rate Elasticity, Definition 1				
Elasticity (COVID)	-16.80*** (2.30)	-16.44*** (1.92)	-9.01*** (3.35)	-8.32*** (3.13)
N	15367	14839	12143	11034
Panel B: Interest Rate Elasticity, Definition 2				
Elasticity (COVID)	-16.58*** (4.17)	-16.06*** (4.22)	-12.25** (5.54)	-10.56** (5.13)
N	10584	10268	8719	7857

Notes: This table refines our estimates of precautionary drawdowns during the COVID-19 pandemic (Table 3). As in Table 3, we use two definitions of precautionary drawdowns. In Panel A, we restrict the sample to firms that increased their credit-line utilization in 2020:Q1 by more than the median firm and in 2020:Q2 reverted to their 2019:Q4 utilization level (within a 5 percentage point margin). In Panel B, the logic is the same, but we allow the median utilization to change by NAICS2 industry. To rule out bridge financing motives, we exclude firms that received new sources of funding during 2020:Q2. We focus on three key funding sources, as indicated in the column titles: bonds, term loans, and the Paycheck Protection Program (PPP). Standard errors are two-way clustered at the facility and time levels. * (**) [***] indicates significance at the 10 percent (5 percent) [1 percent] level. *Sources:* Y-14, Mergent FSID, Compustat, authors' computations.

As mentioned earlier, we need to consider the possibility that the large increase in revolving-line utilization during 2020:Q1 was a "bridge" for firms' financing needs. If that were the case, then, on average, other forms of financing would have increased as the revolving lines were repaid. We see that, in general, the median firms in our sample increased their total debt by 1.3 percent in 2020:Q1 and reduced it by 4.9 percent in 2020:Q2 (a 9.8 percent increase and an 8.9 percent decrease on average.) Nevertheless, we zoom in on this conceptual possibility by refining our estimates, presented in Table 3, of elasticities of precautionary drawdowns during the pandemic.

We do so by collecting information on three main funding sources other than credit lines for all borrowers in our sample. First, we collect bond issuance data from Mergent FSID and identify firms that issued bonds in 2020:Q2. Second, we flag firms that received a new term loan from a Y-14 bank during 2020:Q2. Third, we identify firms that received funds through the Paycheck Protection Program (PPP). Table 4 reports the elasticity estimates for precautionary drawdowns during the pandemic (compare with Table 3) after excluding firms that received additional funding from one of the aforementioned sources. The results remain robust and indicate that while some firms may have tapped into credit lines as a means of bridge financing, the interest rate elasticity of precautionary credit-line drawdowns was sizable.[19]

IV.2 Financial Stability Implications

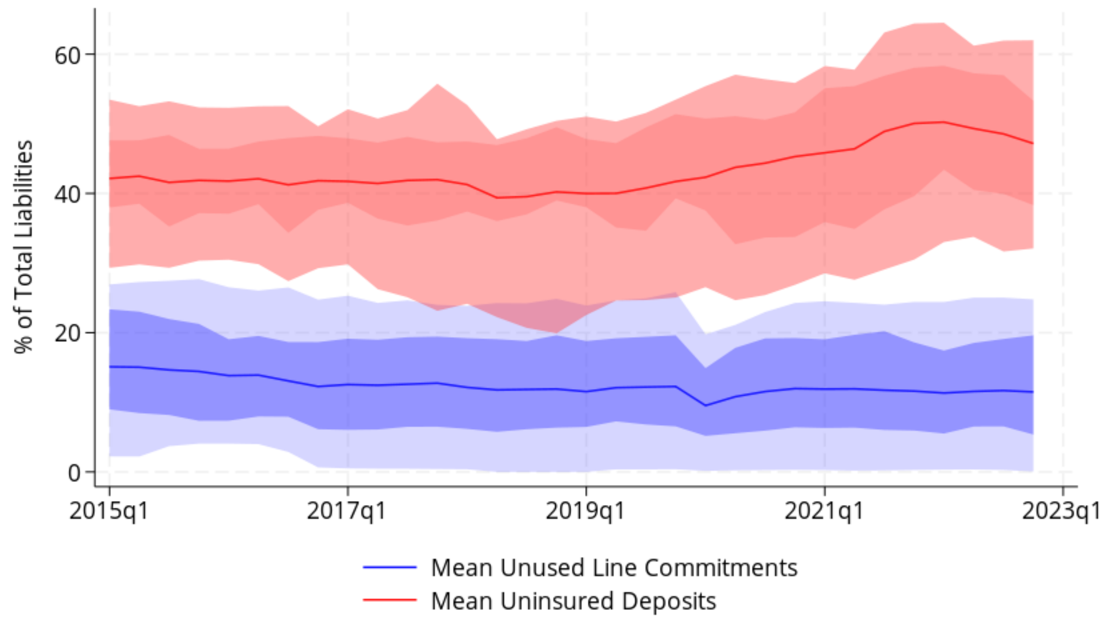
Revolving credit and deposit-taking are at the core of the banking business (Kashyap, Rajan and Stein, 2002). Importantly, the rise of nonbank credit intermediation in recent decades has not eroded bank credit's dominance of revolving credit. To better understand the financial stability risk associated with revolving-line drawdowns, we need to gauge the size of the exposure to credit-line drawdowns and assess overall bank liquidity management. This entails examining the correlation between deposit drawdowns and revolving-line utilization and the extent to which this correlation depends on the interest rate.

Banks' exposure to unused revolving lines is economically large. Figure 8 compares the stock of uninsured deposits with the stock of unused revolving lines expressed as a fraction of liabilities and focusing on the set of banks observed in the Y-14 data. Before the post-2020 increase in deposits, average uninsured deposits represented nearly 40 percent of the liabilities of the banks in our sample.[20] The exposure on revolving credit represents about one-third of the exposure on deposits, but some banks' exposure accounts for more than 30 percent of their total liabilities and therefore still presents substantial liquidity risk for those banks.

[19] Because we have a sizable number of facilities in our sample, we can slice the data according to borrower characteristics. One caveat about Y-14 data is that they only cover the largest U.S. banks. In a larger sample of banks, we could have also explored cross-bank variation in exposure to precautionary drawdowns. However, our identification approach requires a sufficient amount of data (focusing on observations near the floor), which prohibits us from pursuing a credible cross-bank analysis.

[20] This counts only the uninsured portion of the deposit amount. For example, if the deposit balance is $300,000, the figure counts only $50,000, which is not covered by the insurance of $250,000.

Figure 8: Unused Line Commitments and Uninsured Deposits



Notes: The figure shows the unused commercial revolving-line commitments and uninsured deposits as a percentage of total liabilities. The mean shares are depicted by the solid lines, and the dark (light) shaded areas represent 25 percent–75 percent (10 percent–90 percent) bands of the cross-bank distribution. The sample includes all Y-14 banks. *Sources:* Y-14, FR Y-9C, FFIEC 031, authors' calculations.

Our central contribution is that we measure how precautionary drawdowns on revolving lines respond to a rise in interest rates. In the preceding subsection, we isolated this key parameter, leveraging identification through application of the RKD approach to our microdata. Due to data limitations, we cannot apply the same method to causally identify the interest rate sensitivity of deposit drawdowns. Therefore, to understand the interaction between the flow of uninsured deposits and precautionary drawdowns on revolving lines, we follow Drechsler, Savov and Schnabl (2021) and compute "deposit betas" that measure how changes in deposits co-move with changes in the federal funds rate.

This analysis uses quarterly bank-level data compiled from publicly available call reports, enabling us to cover a broader set of banks and a longer time period than with the Y-14 data. The key regression equation in the deposit beta approach relates deposit growth to the federal funds rate:

$$\Delta y_{i,t} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta FF_t + \epsilon_{i,t}, \tag{10}$$

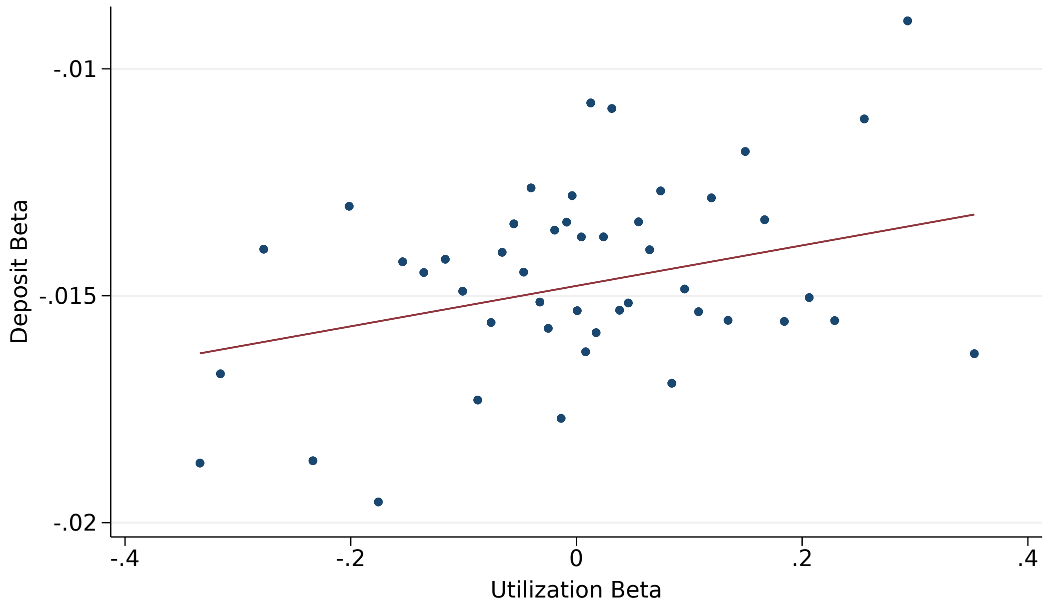
where $\Delta y_{i,t}$ is the log change in the total deposits (deposit flow) of bank i from t to $t+1$, and ΔFF_t is the contemporaneous change in the federal funds rate. The coefficient of interest is the sum of the coefficients on the funds rate: $\beta_i^{deposits} = \sum_{i,\tau}^{3} \beta_{i,\tau}$. While this (flow) beta does not present an identified effect of interest rates on deposit growth, results from these predictive regressions are still informative and help us understand the co-movement (statistical correlation) between the two variables.

We compute similar betas for credit-line utilization. For this exercise, we again use the publicly available call reports, given the small sample period covered by the Y-14 data. However, call reports do not include information about committed and utilized amounts at the facility level. Therefore, we proxy the credit-line utilization rate at the bank-quarter level by computing used commercial loan commitments—that is, the total utilization of revolving lines and term loans—as a percentage of total (used and unused) commitments.[21] Another caveat regarding this analysis is that we cannot isolate precautionary drawdowns. We therefore estimate a model similar to equation (10) but use the log change in the credit-line utilization ratio as the dependent variable. We call the credit-line utilization beta $\beta_i^{utilization}$. Our data run from 2001:Q1 through 2024:Q3, and we focus on banks with at least 30 observations for both deposit and utilization variables, leaving us with a cross section of 6,077 banks.

Figure 9 shows a binned scatter plot of deposit betas and utilization betas (the underlying data are at the bank level). For deposits, a lower deposit beta means that in response to a funds-rate increase, there is a larger deposit outflow. For revolving lines, a lower utilization beta means that in response to a funds-rate increase, revolving-line utilization declines, resulting in a lower outflow of liquidity for the bank. The positive association between the

[21] We proxy for unused commitments of commercial lines using variable rcfd3818, which includes commitments to extend credit through overdraft facilities or commercial lines of credit and also retail check credit and related plans. We proxy utilized commitments as the sum of C&I loans and loans to financial institutions (see Appendix Table B.5 for details).

Figure 9: Relationship between Deposit Flow Beta and Line Utilization Beta



Notes: The figure shows a binned scatter plot of deposit flow betas and line utilization betas. The betas are bank-specific estimates of the sensitivity of deposit withdrawals and credit-line utilization to changes in the federal funds rate. *Sources:* FFIEC 031, Haver, and authors' calculations.

two betas means that banks with a higher threat of deposit outflows in response to interest rate increases face a lower threat of revolving-line runs. Therefore, the high interest rate sensitivity of credit-line utilization works as a counterforce to the liquidity squeeze stemming from the deposit outflow. In Appendix Table B.6, we show that the relationship also holds when we focus on uninsured deposits. In fact, the estimated coefficients on the utilization beta are larger, suggesting a stronger relationship.

Table 5 further explores the relationship between the deposit beta and the utilization beta in a regression framework. Overall, the results confirm a statistically significant positive correlation between the two variables. Column (2) shows that controlling for size and the share of deposits and unused commitment does not change the coefficient. (The coefficient on the utilization beta of 0.0043 needs to be viewed under the large standard deviation of the utilization beta of about 0.285 relative to a standard deviation of 0.063 for the deposit beta.) Notably, the results from the size-weighted regressions, shown in columns (3) and (4), suggest a stronger relationship between the deposit beta and the

Table 5: Relationship between Deposit Beta and Utilization Beta

	Dependent Variable: Deposit Beta			
	(1)	(2)	(3)	(4)
Utilization Beta	0.0045**	0.0043**	0.0498**	0.0481***
	(0.0018)	(0.0018)	(0.0214)	(0.0172)
Log Assets		-0.0004*		-0.0024***
		(0.0002)		(0.0008)
Deposits/Liabilities		-0.0000		-0.0003*
		(0.0001)		(0.0002)
Unused Commitment/Liabilities		-0.0000		0.0001
		(0.0000)		(0.0000)
Constant	-0.0148***	-0.0048	-0.0200***	0.0428*
	(0.0003)	(0.0071)	(0.0020)	(0.0251)
Weighted?	No	No	Yes	Yes
N	6,077	6,077	6,077	6,077

Notes: This table shows the coefficient estimates of regressing the deposit beta on the utilization beta. Columns (1) and (2) are unweighted regressions, and columns (3) and (4) are asset weighted. Balance sheet characteristics refer to the average values during the 2001:Q2–2024:Q3 estimation sample period. Robust standard errors are shown in parentheses. *Sources:* FFIEC 031, Haver, authors' calculations

utilization beta.

We can also compute the sensitivity of deposit flows and utilization to exogenous monetary policy shocks (rather than to endogenous interest rate changes). We focus on the monetary policy shocks presented in Jarociński and Karadi (2020) and Bauer and Swanson (2023), who exploit high-frequency changes in asset prices and additional information to construct shocks. In Table 6, we confirm that with betas constructed using monetary policy shocks, deposit betas and utilization betas are positively correlated. The coefficient on the utilization beta is only slightly larger than the one in Table 5.

Notably, Figure 9 and Tables 5 and 6 reveal a purely empirical relationship. A framework that provides a conceptional explanation for this result is beyond the scope of this paper. However, one possibility is that this relationship is endogenous to banks' risk management. For example, banks with borrowers who are more interest-sensitive may

Table 6: Relationship between Deposit Beta and Utilization Beta Constructed Using Monetary Policy Shocks

	Dependent Variable: Deposit Beta			
	(1)	(2)	(3)	(4)
Utilization Beta	0.0055***	0.0053***	0.0058***	0.0059***
	(0.0018)	(0.0018)	(0.0016)	(0.0016)
Log Assets		-0.0261***		-0.0174***
		(0.0050)		(0.0051)
Deposits/Liabilities		-0.0019		-0.0019
		(0.0012)		(0.0012)
Unused Commitment/Liabilities		0.0001		-0.0009
		(0.0008)		(0.0006)
Constant	-0.2751***	0.2295	-0.1705***	0.2297
	(0.0059)	(0.1490)	(0.0059)	(0.1539)
Weighted?	No	No	No	No
N	6,077	6,077	6,077	6,077

Notes: This table shows the coefficient estimates of regressing the deposit beta on the utilization beta (all unweighted), computed using monetary policy shocks. Columns (1) and (2) use the Bauer and Swanson (2023) shocks, and columns (3) and (4) use the Jarociński and Karadi (2020) shocks. Balance sheet characteristics refer to the average values during the 2001:Q2–2024:Q3 estimation sample period. Robust standard errors are shown in parentheses. *Sources:* FFIEC 031, San Francisco Fed website, Jarocinski's personal website, authors' calculations

price their deposits less competitively.[22]

[22] As a reminder, the identification of our main results in the previous section is at the bank level.

V Conclusion

Liquidity management is at the core of the bank business model. Uninsured deposits comprise a significant fraction of US banking-sector liabilities. Similarly, unused revolving commitments represent sizable demandable claims—nearly 20 percent of bank liabilities. Given the importance of revolving lines for the management of working capital and other financial needs, firms have, in the past, responded to uncertainty surrounding the banking sector by drawing down their revolving lines, similarly to how they have responded to such uncertainty by running on their deposits. Precautionary runs on credit lines in both 2008 and 2020 contributed significantly to banks' liquidity pressures.

We argue, however, that precautionary drawdowns are highly sensitive to interest rates. Unlike deposit runs, revolving-line runs are costly, and this cost is higher when policy rates are high. This substantially reduces the probability of a run on revolving lines. In this paper, we quantify the sensitivity of precautionary drawdowns to interest rates. We estimate that, as a lower bound, each 1 percentage point increase in the policy rate leads to a 13 percentage point reduction in precautionary drawdowns, or about 2.6 percent of bank liabilities.

The drawdown sensitivity to interest rates is therefore an important part of bank liquidity management. The discussions that followed the 2023 regional bank run focused on the sensitivity of deposit outflows to interest rates. Our findings suggest that, in the high-interest-rate environment of 2023, the reduced risk of revolving-line drawdowns was likely a sizable stabilizing force that prevented the broader banking sector from facing liquidity issues.

More generally, holistic bank liquidity management is complex and remains only partially understood. In this paper, we show a complementarity between management of deposits and revolving credit, depending on the interest rate environment. Our insights can help supervisors and bank risk managers model credit-line drawdowns for liquidity stress test scenarios.

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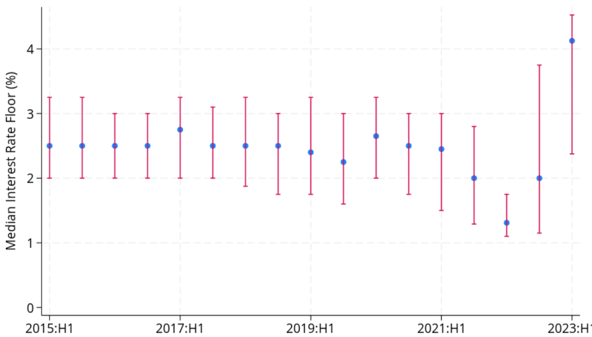
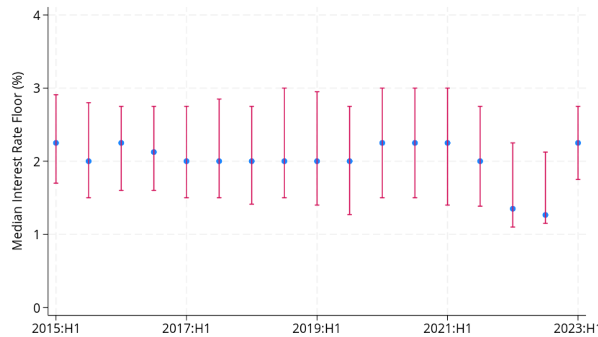
A Additional Figures

Figure A.1: Interest Rate Floor Distribution over Time

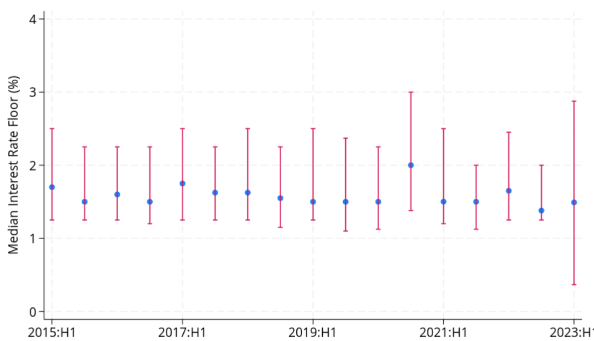
(a) Committed Exposure < 33rd percentile



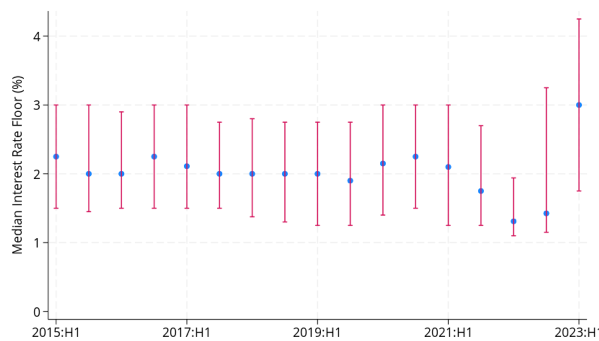
(b) Committed Exposure 33rd–67th percentiles



(c) Committed Exposure > 67th percentile

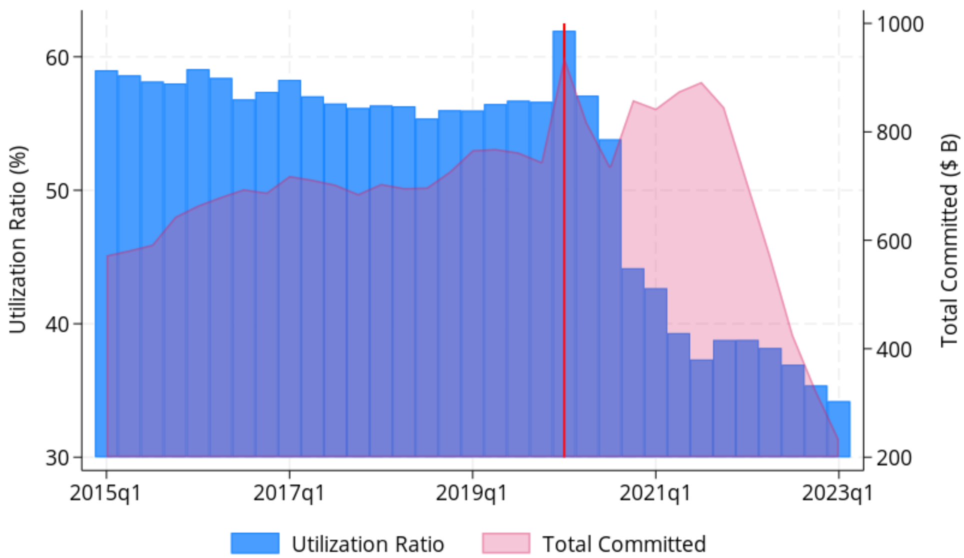


(d) All Facilities



Notes: This figure shows the distribution of floors on applicable interest rates on revolving credit lines over time for different loan sizes. The blue dots represent medians, and the red whiskers represent the interquartile ranges. The sample contains LIBOR-indexed facilities from 2015:H1 to 2023:H1. Dates refer to loan origination dates. The correlation coefficient between the interest rate floor and the interest rate spread for the sample in panel (a) is 0.7509, (b) 0.1442, (c) 0.6460, (d) 0.2738 *Sources*: FR Y-14Q, authors' computations.

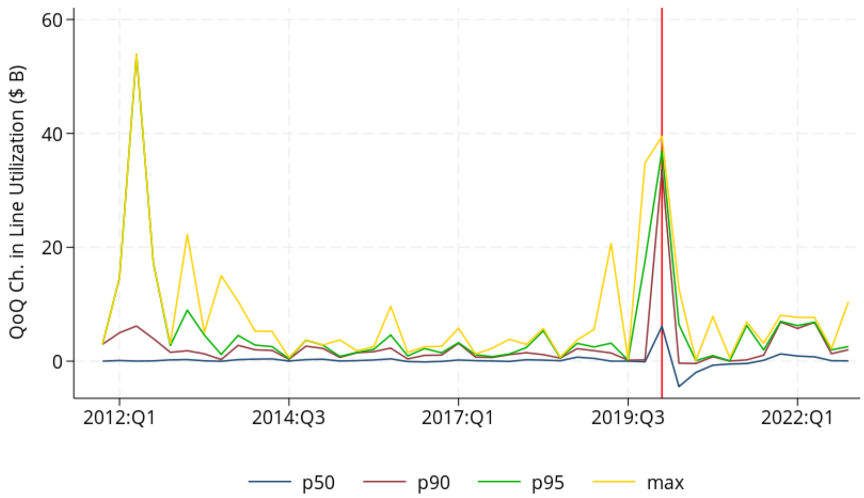
Figure A.2: Utilization Rates and Commitments over Time of LIBOR Facilities



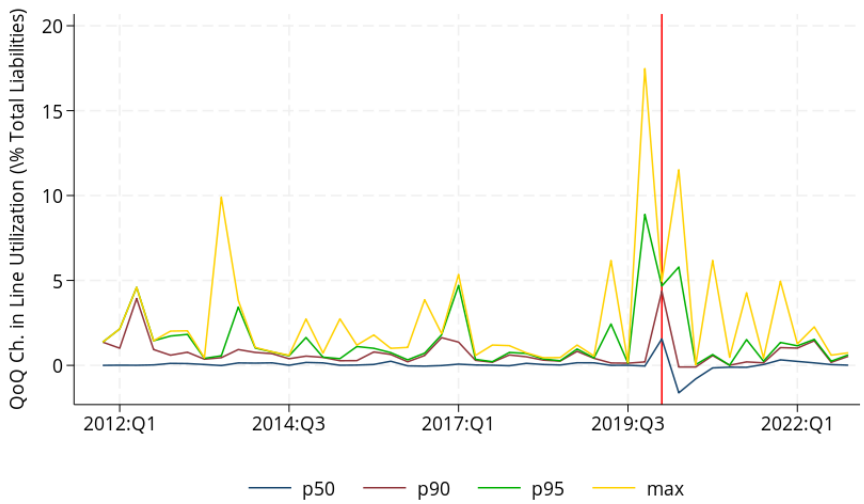
(a) Only LIBOR-based

Notes: On the left axis, the figure shows the aggregate utilization ratio, defined as total utilized line credit as a percentage of total committed line credit. On the right axis, the graph shows the total committed line credits in billions of dollars. The figure is based on revolving-line commitments indexed to LIBOR. The vertical red line indicates 2020:Q1. *Sources:* Y-14, authors' computations.

Figure A.3: Bank-quarter-level Change in Line Utilization



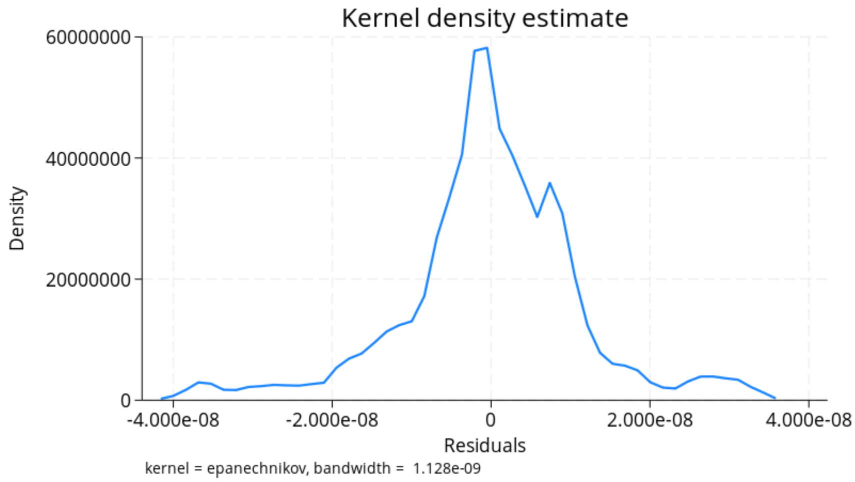
(a) Change in Line Utilization



(b) Change in Line Utilization (% Total Liabilities)

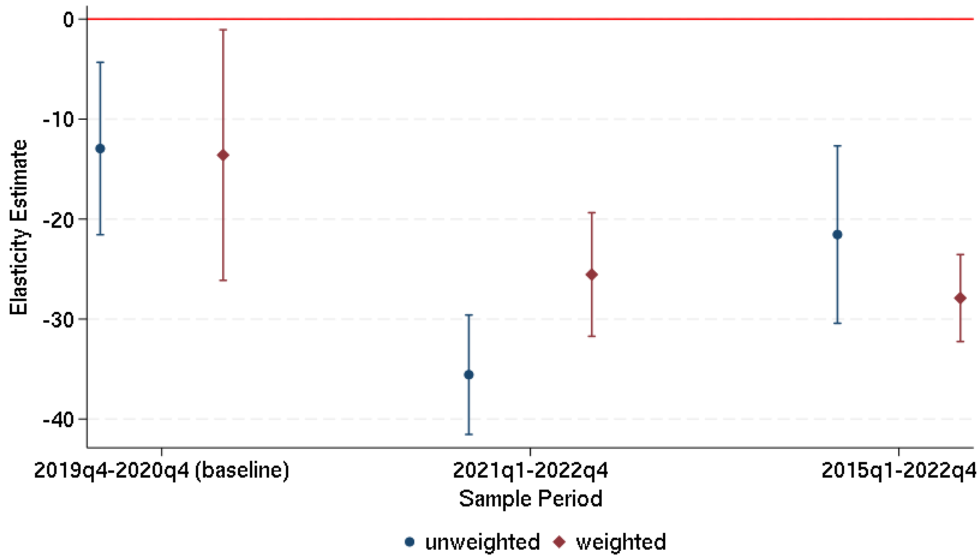
Notes: The figure shows select percentiles of the cross-bank distribution of changes in line commitment over time. Panel (a) is based on changes in billions of dollars, while Panel (b) shows the changes of utilization as a percentage of total liabilities. The sample includes all Y-14 banks. The vertical line indicates 2020:Q1.
Sources: Y-14, FR Y-9C, authors' computations.

Figure A.4: Distribution of Distance to Floor



Notes: Density estimate of the distance to the floor, orthogonalized with respect to the fixed effects of the baseline model.

Figure A.5: Additional Results for Time Variation in Elasticity



Notes: Elasticity estimates are obtained by estimating the baseline model (all fixed effects) on the indicated subsamples. The whiskers represent 90 percent confidence intervals based on two-way clustered standard errors at the facility and time levels. The estimates are obtained using unweighted (baseline) or commitment-weighted regressions. *Sources:* Y-14, authors' computations.

B Additional Tables

Table B.1: Summary Statistics, 2020:Q1

Panel A: Facility Level

	Mean	SD	p5	p25	p50	p75	p95
Utilized Dollars (M)	15.33	32.21	0.40	1.71	5.32	16.58	61.00
Committed Dollars (M)	24.74	43.96	1.20	3.00	8.98	28.57	100.00
Utilized / Committed (%)	64.77	29.40	11.87	42.47	67.57	94.43	100.00
Δ (Utilized / Committed)	10.08	27.77	-22.38	-2.00	0.29	17.48	74.06
Interest Rate Floor (%)	0.44	0.97	0.00	0.00	0.00	0.00	2.50
Interest Rate Spread (%)	2.12	0.99	0.88	1.40	2.00	2.75	3.75
Maturity (years)	6.59	5.64	1.00	3.09	5.01	8.17	17.24
Observations	37959						

Panel B: Firm Level

	Mean	SD	p5	p25	p50	p75	p95
Utilized Dollars (M)	20.95	68.12	0.39	1.75	5.32	15.66	85.77
Committed Dollars (M)	33.81	98.68	1.20	3.01	8.76	25.00	137.55
Utilized / Committed (%)	64.55	28.51	12.10	44.00	67.16	90.64	100.00
Δ (Utilized / Committed)	8.57	26.10	-22.41	-2.78	0.26	15.36	66.30
Observations	27777						

Panel C: Bank Level

	Mean	SD	p5	p25	p50	p75	p95
Utilized Dollars (B)	21.55	30.59	0.34	3.40	10.85	24.11	102.35
Committed Dollars (B)	34.79	50.54	0.62	4.38	16.38	36.28	166.79
Utilized / Committed (%)	65.73	10.16	56.08	57.99	61.53	70.44	89.68
Δ (Utilized / Committed)	18.03	14.98	0.08	9.26	13.57	20.74	44.74
Assets (B)	580.99	769.21	108.74	136.11	236.75	487.67	2426.33
Tier 1 Leverage Ratio	9.26	1.49	6.83	8.22	9.32	9.93	11.94
Liquid Assets (%)	10.96	9.39	1.62	4.55	8.82	13.41	34.53
Uninsured / Liabilities (%)	37.16	15.47	6.02	24.74	41.28	48.49	56.73
Line Concentration	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Observations	27						

Panel D: Industry Level

	Mean	SD	p5	p25	p50	p75	p95
Utilized Dollars (B)	6.32	10.90	0.19	1.24	3.03	6.60	24.85
Committed Dollars (B)	10.21	16.52	0.27	1.87	4.92	10.10	43.30
Utilized / Committed (%)	62.42	11.92	46.07	53.24	61.09	70.99	81.68
Δ (Utilized / Committed)	20.47	15.73	0.57	9.56	17.75	28.53	57.81
Observations	92						

Notes: Summary statistics shown for 2020:Q1 are based on LIBOR-indexed lines. The utilization ratio is calculated as utilized over committed. For each panel, facility-level ratios are then aggregated to the respective unit of observation (that is, firm, bank, or industry) using commitment-weighted averages.

Table B.2: Check for Kink in Covariates

	(1)	(2)	(3)
Panel A: IR Spread			
Distance to Floor	0.357***	0.362***	0.344***
	(0.036)	(0.019)	(0.020)
At Floor*Distance	-0.024	-0.010	0.041
	(0.044)	(0.028)	(0.019)
Panel B: Maturity			
Distance to Floor	0.025**	0.010	0.015
	(0.007)	(0.011)	(0.009)
At Floor*Distance	-0.048	-0.047	-0.015
	(0.027)	(0.044)	(0.045)
Panel C: Committed Amount			
Distance to Floor	-0.000	-0.002	0.002
	(0.005)	(0.003)	(0.003)
At Floor*Distance	-0.039*	-0.008	-0.023
	(0.016)	(0.009)	(0.010)
Controls	No	No	No
Facility FE, Time FE	Yes	Yes	Yes
Bank*Time FE	No	Yes	Yes
Industry*Time FE	No	No	Yes
N	18157	18147	18126

Notes: This table shows that key facility-level variables other than the interest rate do not exhibit a slope change at the kink. We test this by estimating model (7) for different dependent variables. Each panel corresponds to a different dependent variable, which is indicated in the panel title. The dependent variables Maturity (Panel B) and Committed Amount (Panel C) are in logs. The sample period runs from 2019:Q4 through 2020:Q4. Standard errors are two-way clustered at the facility and time levels. * (**) [***] indicates significance at the 10 percent (5 percent) [1 percent] level.

Table B.3: Precautionary Elasticities in Cross Section

	Borrowers with Precautionary Drawdown?			
	Definition 1		Definition 2	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Panel A: Interest Rate Elasticity				
Elasticity (No COVID)	-22.37***	-19.40***	-21.74***	-23.04***
	(3.46)	(4.55)	(3.09)	(4.72)
Between-Group Diff	-2.97		1.30	
	(0.406)		(0.764)	
Elasticity (COVID)	-11.24***	-16.86***	-12.22***	-16.54***
	(3.88)	(2.07)	(3.81)	(2.57)
Between-Group Diff	5.63*		4.31	
	(0.094)		(0.421)	
COVID Effect:	-11.13**	-2.53	-9.52*	-6.51
(p-value)	(0.035)	(0.617)	(0.054)	(0.219)
Panel B: Dep. Var. is Interest Rate				
Distance to Floor	0.939***	0.842***	0.930***	0.838***
	(0.015)	(0.027)	(0.014)	(0.045)
Distance to Floor * COVID	0.536***	0.645***	0.547***	0.630***
	(0.048)	(0.038)	(0.047)	(0.044)
At Floor * Distance to Floor	-0.925***	-0.851***	-0.915***	-0.856***
	(0.044)	(0.042)	(0.046)	(0.056)
At Floor * Distance to Floor * COVID	-0.505***	-0.640***	-0.522***	-0.601***
	(0.059)	(0.070)	(0.061)	(0.057)
Panel C: Dep. Var. is Utilization Rate				
Distance to Floor	-1.522	1.583	-1.242	1.627
	(1.288)	(1.396)	(1.209)	(1.421)
Distance to Floor * COVID	-1.005	-6.204***	-1.495	-5.926**
	(1.289)	(1.606)	(1.226)	(2.335)
At Floor * Distance to Floor	20.686***	16.512***	19.897***	19.725***
	(3.053)	(3.786)	(2.647)	(3.837)
At Floor * Distance to Floor * COVID	5.675***	10.787***	6.378***	9.937***
	(1.843)	(0.598)	(1.840)	(1.222)
Controls	Yes		Yes	
Facility FE, Time FE	Yes		Yes	
Bank*Time FE	Yes		Yes	
Industry*Time FE	Yes		Yes	
N	60647	15727	65463	10911
COVID-Floor N	2603	568	2785	386
nonCOVID-Floor N	14228	2168	14838	1558
COVID-nonFloor N	11006	3949	12346	2609
nonCOVID-nonFloor N	32810	9042	35494	6358

Notes: This table reports the full estimation details of Table 3. See details in the caption of Table 3.

Table B.4: Variation in Interest Rate Spreads

Dependent Variable:	Interest Rate Spread (pp)				
	(1)	(2)	(3)	(4)	(5)
Log Maturity	-0.045***	-0.033**	0.264***	0.009	0.195***
	(0.016)	(0.016)	(0.035)	(0.017)	(0.034)
Log Comm. Exp.	-0.158***	-0.161***	-0.199***	-0.153***	-0.178***
	(0.008)	(0.008)	(0.010)	(0.009)	(0.011)
Libor (Orig. %)		-0.049***		-0.043***	
		(0.010)		(0.010)	
Origination Quarter FE	No	No	Yes	No	Yes
Industry FE	No	No	No	No	Yes
Bank FE	No	No	No	Yes	Yes
R^2	0.047	0.050	0.090	0.096	0.192
Within R^2	0.047	0.050	0.055	0.040	0.040
Observations	7072	7072	7057	7072	7053

Table B.5: FFIEC 031 Call Data Variable Key

Variable	Call Variables	Start	End	Description
Deposits	rconf045	2006-06-30	Current	Amount of Retirement Deposits Accounts of $\leq \$250,000$
	rconf047	2006-06-30	Current	Amount of Retirement Deposit Accounts of $\geq \$250,000$
	rconf049	2006-06-30	Current	Amount of Deposit Accounts (Ex Retirement) of $\leq \$250,000$
	rconf051	2006-06-30	Current	Amount of Deposit Accounts (Ex Retirement) of $\geq \$250,000$
	rcon2702	1983-06-30	2006-03-31	Amount of Deposit Accounts of $\leq \$100,000$
	rcon2710	1983-06-30	2006-03-31	Amount of Deposit Accounts of $> \$100,000$
Uninsured Deposits	rcon2604	1997-03-31	2009-12-31	Total Time Deposits of $\geq \$100,000$
	rconj474	2010-03-31	Current	Total Time Deposits of $\geq \$250,000$
Utilized Commitments	rcfd1763 (U)	1984-03-31	Current	Commercial and Industrial Loans to US Addressees
	rcfd1764 (U)	1984-03-31	Current	Commercial and Industrial Loans to US Addressees
	rcfd1563 (U)	1984-03-31	2024-09-30	Other Loans
	rcfdb532 (U)	2001-03-31	Current	Loans to US Branches and Agencies of Foreign Banks
	rcfdb533 (U)	2001-03-31	Current	Loans to Other Commercial Banks in the US
	rcfdb534 (U)	2001-03-31	Current	Loans to Other Depository Institutions in the US
	rcfdb535 (U)	2001-03-31	Current	Loans to Banks in Foreign Countries
	rcfdb536 (U)	2001-03-31	Current	Loans to Foreign Branches of Other US Banks
	rcfdb537 (U)	2001-03-31	Current	Loans to Other Banks in Foreign Countries
Unused Commitments	rcfd3818 (Unc)	1969-06-30	Current	Unused Commitments–Other

Notes: Utilization Ratio = U/(U + UnC), where U = utilized commitments and UnC = unused commitments. We proxy used commitments as U = rcfd1763 + rcfd1764 + rcfd1563 + rcfdb532 + rcfdb533 + rcfdb534 + rcfdb535 + rcfdb536 + rcfdb537. Unused Commitments are taken as UnC = rcfd3818.

Table B.6: Relationship between Uninsured Deposit Beta and Utilization Beta

	Dependent Variable: Uninsured Deposit Beta			
	(1)	(2)	(3)	(4)
Utilization Beta	0.0141**	0.0158***	0.1830**	0.1708**
	(0.0055)	(0.0056)	(0.0805)	(0.0815)
Log Assets		0.0028***		0.0049
		(0.0007)		(0.0031)
Deposits/Liabilities		-0.0004**		-0.0002
		(0.0002)		(0.0004)
Unused Commitment/Liabilities		0.0002**		-0.0001
		(0.0001)		(0.0004)
Constant	0.0442***	0.0421*	0.0802***	0.0041
	(0.0009)	(0.0221)	(0.0072)	(0.0805)
Weighted?	No	No	Yes	Yes
N	6,060	6,060	6,060	6,060

Notes: This table shows the coefficient estimates of regressing the uninsured deposit beta on the utilization beta. Columns (1) and (2) are unweighted regressions, and columns (3) and (4) are asset weighted. Balance sheet characteristics refer to average values during the 2001:Q2–2024:Q3 estimation sample period. Uninsured deposits are time deposits greater than $100,000 until 2009 and greater than $250,000 after that. Robust standard errors are shown in parentheses. *Sources:* FFIEC 031, Haver, authors' calculations