Bank Runs and Interest Rates: A Revolving Lines Perspective*

Falk Bräuning[1] and Victoria Ivashina[2]

[1]Federal Reserve Bank of Boston

[2]Harvard University and NBER

February 12, 2025

Abstract

Revolving credit is at the core of the banking business. Corporate revolving credit lines are demandable claims; thus, similar to a traditional bank run on deposits, sudden widespread drawdowns on credit lines can be destabilizing to the banking sector. However, we show that, unlike deposits, credit line utilization has a large interest rate sensitivity. A revolving line run is less likely in a high-interest-rate environment, but can introduce vulnerability when the Fed cuts the interest rate to support a weak banking sector.

Keywords: bank liquidity, corporate credit lines, bank runs, financial crisis

JEL Codes: G21, G32, G01

*We thank participants at seminars at the Federal Reserve Bank of Boston, Columbia University, as well as the OCC Bank Research Symposium, and Santiago Finance Workshop for valuable feedback. We thank Mark Adams (discussant), Olivier Darmouni, Gustavo Joaquim, Tano Santos, Alexi Savov, and Jeremy Stein for insightful comments. Justin Sun provided outstanding research assistance. The views expressed in this papers do not necessarily reflect the opinions of the Federal Reserve Bank of Boston or the Federal Reserve System.

Disclosure Statement

I have nothing to disclose.

Falk Braeuning

Boston, February 10, 2025

Disclosure Statement

In addition to Harvard University, in the past three years, I received significant financial support from the Federal Reserve Bank of Boston, Superintendency of Banking and Insurance of Peru, Carlyle AlpInvest Private Markets Fund (independent trustee), and Cornerstone.

Victoria Ivashina

Boston, February 10, 2025

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. Revolving credit also continues to be offered primarily by banks. Compared to non-bank financial institutions (NBFIs) such as private debt providers or institutional participants in the syndicated loan market, banks financed 97% of revolving credit, but only 28% of term loans.

Typically, revolving lines are used to manage working capital, a crucial aspect of running a business that helps firms handle short-term cash flows shortfalls and unexpected expenses.[1] Like a credit card, revolvers 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, this characteristic of revolving credit also means that, like uninsured deposits, unused revolving lines are sizable demandable claims on the banks, which can be subject to runs, posing a threat to the stability of the banking system. The FR Y-14Q supervisory data used in this study indicate that banks' exposure to unused revolving lines accounts for about 20% of bank liabilities. Indeed, revolving lines runs were a significant contributing force to banks' liquidity problems both in 2008 (Ivashina and Scharfstein, 2010) and also during the outbreak of the pandemic in early 2020.[2]

In this paper, we measure the interest-rate sensitivity of revolving line runs. Our central point is that this sensitivity is substantial and 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 in Diamond and Dybvig (1983). Yet, revolvers are fundamentally different from deposits in that they are a liability, and the borrowing firm has to pay interest on the drawn amount. (The borrower pays a small fixed fee on an undrawn amount.) As is common for many commercial loans, revolving lines are variable-rate contracts, paying a fixed spread over a benchmark rate, which varies with the market interest rate. Funds drawn for precautionary reasons are likely to be redeposited

[1] Recent work (e.g. Chodorow-Reich et al., 2022; Berrospide and Meisenzahl, 2022; Greenwald, Krainer and Paul, 2023) studies 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.

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 saving rate and borrowing rate is small, we should not observe significant sensitivity of runs on revolvers. But it has been documented that banks benefit from a deposit franchise Drechsler, Savov and Schnabl (2017), 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.

Our empirical analysis is based on detailed facility-level supervisory FR Y-14Q ("Y-14") data collected by the Federal Reserve for stress testing purposes, as mandated by the 2010 Dodd-Frank Act. Specifically, we exploit the commercial and industrial (C&I) loan schedule of this dataset (schedule H), which contains information on all outstanding C&I loans with at least $1 million committed amount by the largest US bank holding companies ("banks", hereafter) that are subject to stress testing. Overall, these data cover close to 70% of all loans in the United States. Given our question, we focus on revolving line credit facilities as opposed to term loans. Important 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 precautions revolving lines draw-downs we need: (i) exogenous variation in applicable interest rates, and (ii) an environment where such revolving lines withdrawals are likely. Given that Y-14 data does not start until 2011, the first point presents a significant empirical challenge. To overcome it, we use an empirical design that explores a kink in applicable interest rates. As we already

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

mentioned, credit line facilities are generally variable rate contracts, with the interest rate on the utilized portion being linked to a base rate. (The relevant base rate for our sample is LIBOR.) To deal with the interest rate risk, credit line contracts often include interest rate floors that prevent the applicable interest rate from falling below a contractually specified threshold. We observe the interest rate floors in our dataset and exploit this feature to identify the interest rate sensitivity of credit line utilization using a regression kink design (RKD) similar to 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 in Section III.

In our main analysis, we focus on the period around the beginning of the COVID pandemic in 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 line commitment was the only reason for the run on revolvers, 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, during 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 direct evidence for the validity of the RKD approach by directly testing some of the underlying identification assumptions. First, while manipulation of interest rates is unlikely in our setup, 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 revolving line usage 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 falls by about 8.2 percentage points. These estimates are obtained from the COVID period during 2020, a period when precautionary drawdown motives were high, and hence presumably line utilization was less sensitive to interest rates. We find substantially larger effects (in absolute values) outside of the COVID period, indicating that line utilization ratio falls by up to 30 percentage points as interest increases by 1 percentage point. These effects are identified from within-facility variation, hence holding constant borrower and other contract features. We also estimate heterogeneous effects across firms to further isolate the sensitivity of precautionary drawdowns. To do so, we focus on firms that increased their line utilization in 2020q1, but repaid it after the market was stabilized following significant government intervention. We find that the elasticity of such precautionary drawdowns is large and in the order of magnitude of –13. Finally, we substantiate the predominance of precautionary motive behind the temporary rise in use of revolving lines in 2020 by ruling out potential payment frictions or use of revolvers as "bridge" financing was replaced with other loans or bonds.

In the last section of the paper, we take a holistic look at bank liquidity management examining a longer time period and cross-section of firms using the public FR Y-9C data on bank balance sheets. We find that banks with a higher threat of deposit outflows in response to interest rate increases historically faced a lower threat of revolving line drawdowns as their drawdowns are less interest sensitive. This indicates that the high interest rate sensitivity of credit line utilization works as a counterforce to the liquidity squeeze stemming from the deposit outflow.

The main contribution of our study is to articulate a distinct mechanism that explains the interest-rate sensitivity of credit line utilization and to quantify it 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 March 2023 banking turmoil unveiled a blind spot in the understanding of bank runs, and particularly how bank runs relate to the interest rate environment. Drechsler et al. (2023) developed a model to understand the relationship between interest rates, the value of securities holdings, and runs on unsecured deposits. Jiang et al. (2023) develop an empirical methodology to analyze the effect of rising interest rates on the value of US bank assets and bank equity value. We focus on revolving lines, and our work is complementary to these studies. Specifically, we highlight that—unlike deposits runs—the risk of credit line drawdown was low in the 2023 episode due to high interest rates.

More broadly, with the significant growth of non-bank financial institutions and the continuous retreat of banks from information-sensitive credit origination (e.g., Hanson et al., 2024; Buchak et al., 2024), there has been increased pressure 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 this literature which follows the seminal work by Diamond and Dybvig (1983). Holmström and Tirole (1998) emphasize the key role of banks as providers of liquidity to firms through issuance of lines of credit. Kashyap, Rajan and Stein (2002) provide the first integrated view of banks' advantage in liquidity management by articulating the synergy between deposit-taking and revolving lines issuance. Gatev and Strahan (2006) show that existence of deposit insurance gives rise to additional sources of complementarity between deposits and 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 coming 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 dataset used in the empirical analysis. Section III discusses the 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. Our focus is on the firm's problem to run depending on the interest rate environment.

There are two-periods, three dates, 0, 1, and 2. The firm has a positive 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 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 insured deposit account paying $r^d < r^l$ until investment at $t = 1$. Debt is not amortizable, and the interest has to 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. Possibility of getting 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 holding an insured deposit, we could assume that the funds would be held as deposit at a different (safe) bank. Naturally, if we would allow more than one bank, we would also need to introduce lender switching costs to reflect information costs in screening and monitoring (e.g., Rajan, 1992) . Regardless of the lender's fate, the firm is required to pay interest on drawn amount and repay the principal at maturity.[4]

The firm maximizes expected profits, π, by choosing the precautionary drawdown (early

[4]In many aspects, our model is similar to Cooperman et al. (2023), but their focus is on endogenizing the bank's problem, while the focus of our partial equilibrium model is to characterize 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 bank failure probability endogenous.

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:

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

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

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

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

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

Hence, 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 FOC it also follows that the total investment amount, $u + l = \theta/r^l$, is not a function of the probability of bank default, but only depends 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 leads to inefficiencies. The output loss with $p > 0$ emerges because the firm engages in costly front-loading 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:

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

Hence, because bank distress is more likely, the demand for precautionary withdrawals shifts outwards.

We can also analyze how the interest rate elasticity of revolver utilization changes with the probability of bank failure by looking at the cross-derivative:

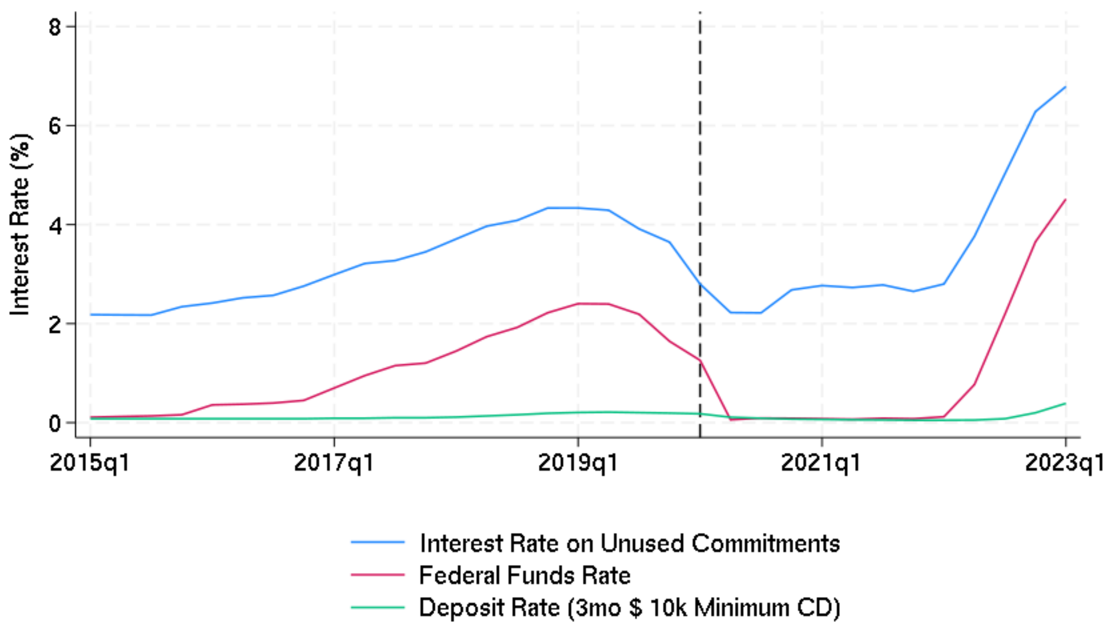
$$\frac{\partial^2 u}{\partial r^l \partial p} = \frac{\theta\left((1+p)r^l - (1+2p)r^d\right)}{\left(r^d - (1+p)r^l\right)^3} > 0$$

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, i.e., if $(1+p)r^l < (1+2p)r^d$, which happens when the probability of failure is large enough. That is, if $p > \frac{r^l - r^d}{2r^d - r^l}$, the precautionary drawdowns become less sensitive to interest rates. 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. That is, 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. Hence, a lower interest rate sensitivity of drawdowns.

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 perfectly comove (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 rates fluctuations as documented by Drechsler, Savov and Schnabl (2017). Figure 1, drawn from the Y-14 data, shows that the applicable rates on outstanding revolving lines have been closely following the policy rate. This is in sharp contrast with deposit rates, which—as Figure 1 illustrates—are largely insensitive to the policy rate changes.

Figure 1: Interest Rate on Revolving Line Credit, Fed 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 3-month certificates of deposits with a minimum balance of $10k. The vertical red line indicates 2020q1. *Sources:* FR Y-14Q, Haver, authors' computations.

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

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

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 $\frac{\partial u}{\partial r^l} = \frac{\partial u}{\partial r}$. In contrast, the low policy rate sensitivity of deposit rates is a well-documented fact as discussed above.[5] 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 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 to deposits by looking at weekly bank balance sheet data from the public FR H.8 during the 2023 regional bank turmoil. During the week of the SVB failure (2023w11), there was net outflow of $137.8 billion in deposits from small and mid-sized US commercial banks (outside the largest 25 banks in terms of assets). This deposit outflow was more than 10 times the standard deviation of weekly deposit changes during 2022 of $13.29 billion. While in 2023w11 small and mid-sized banks experienced a large deposit outflow, there has been 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. This is as compared to the standard deviation of weekly deposit change of $38.18 for large banks, and the standard deviation of weekly asset changes of $23.76 for money market funds during 2022.[6] 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 is line with the deposit franchise literature.[7]

[5] 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 this case, the interest-rate elasticity of drawdowns would be smaller (in absolute values), all else equal.

[6] In 2022, the correlation between weekly deposit changes in small and mid-sized banks and weekly deposit changes in large banks was 0.184. Over 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.

[7] "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, 3/31/2024.

II Data

Our empirical analysis uses the C&I loan schedule (Schedule H) from the supervisory quarterly micro data FR Y-14Q (Y-14, hereafter). As part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, the Federal Reserve was mandated with the Y-14 data collection 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 Dodd-Frank Stress-Testing. By end of 2019, loans recorded in the Y-14 data cover close to 70% of all C&I loans held by US banks, and the data has been used in multiple recent studies (e.g., Chodorow-Reich et al. (2022), and Greenwald, Krainer and Paul (2023) specifically look at the use of revolving lines.) Our focus is on credit lines. Since we only look at the revolving facility within a loan package, in what follows, we use interchangeably "loan" and "facility".

The Y-14 dataset tracks for each outstanding revolving line facility at the quarterly frequency, the line utilization, its committed value, the interest rate, interest rate spread, and the interest rate index type (for variable rate loans) as well as other detailed contract characteristics.[8] 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 dataset also includes information about the borrower. Important to our analysis is specifically the industry of the borrower since COVID may have had heterogeneous demand effects across sectors. We also merge the Y-14 data with publicly available balance sheet and income statement of the banks reported in the FR Y-9C.[9] The data collection for Y-14 starts in 2011. But—as is frequent with new datasets—completeness and consistency of the Y-14 data is not reliable until later years. In the regression analysis we use data going back to 2015, this relates to

[8] Our sample of loans also include 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.

[9] 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.

the size of the sample where our identification is feasible.

III Identification

An important difference between the economics of a deposit run and the economics of a revolving lines run is that revolvers are a liability for the running firm (whereas deposits are an asset) and thus using a revolving line is costly. As mentioned earlier, commercial loans in the US tend to be variable rate contracts, priced as a fixed spread paid over a benchmark that closely follows the Fed's policy rate. The dominant benchmark rate was the London Interbank Offered Rate (LIBOR) until recently, and now Secured Overnight Financing Rate (SOFR).[10] A commonly quoted pricing statistic for commercial loans is All-in-Drawn Spread (AID), 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 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. This 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. So, not only do we need to address the fact that interest rates could be endogenous to firm fundamentals, we also need to make sure that we are separating precautionary drawdowns from firm's fundamental demand for liquidity.

Our way to get around the endogeneity of interest rates instead is to use the regression

[10]Both LIBOR and SFOR are short-term rates that strongly comove with the federal funds rate (policy rate). The use of LIBOR as a reference rate has ended in June 2023. Before the change, LIBOR was the dominant benchmark rate. For example, even in May 2023, over 50% 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.

kink design (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 earlier, 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 level specified in the credit agreement.[11] Hence, the benchmark (variable) interest rate of credit line l at time t effectively becomes:

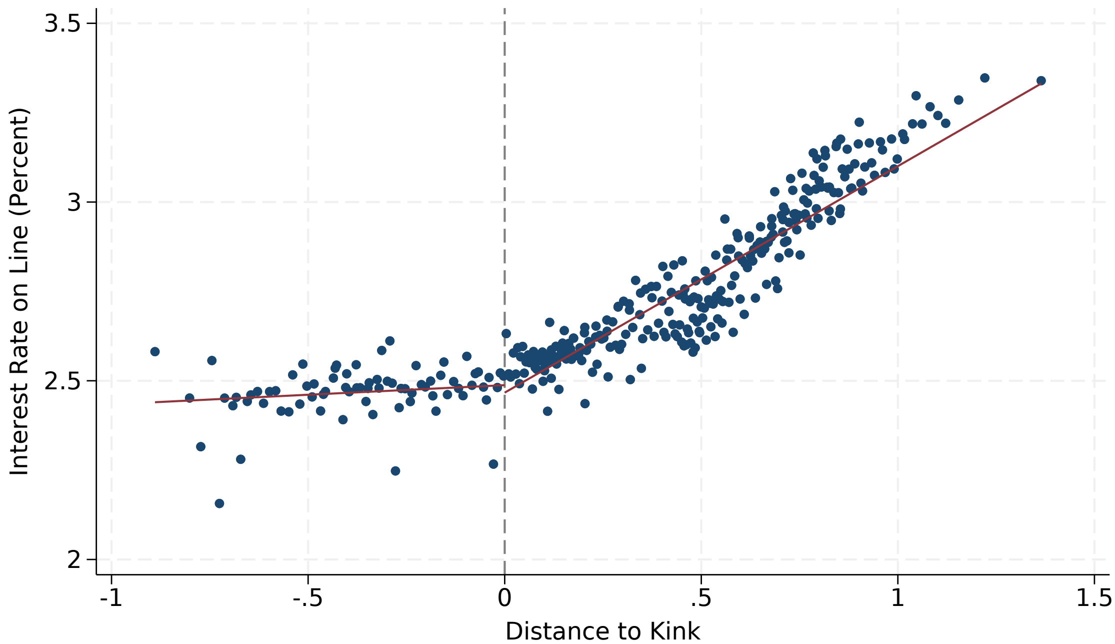
$$r_{l,t} = \text{All-in spread}_l + \max(\text{LIBOR}_t, \text{Contracted LIBOR floor}_l). \tag{4}$$

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.

The idea of the RKD is 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, that is, LIBOR floors in our case. It is important to stress that, for the RKD to be valid, it is not required that the regulation or market rule that govern the floors or the index rate is exogenous. Provided that observations on either side of the kink threshold are similar—i.e., 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 lines utilization when LIBOR floor becomes binding, we

[11] Loan Syndication and Trading Association indicates the following template 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 further elaborates: "(I)t 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).

Figure 2: Kink in Applicable Credit Line Interest Rate



Notes: Relationship between interest rate applicable on the drawn part of the credit line as a function of the distance between LIBOR and the contracted LIBOR floor. The applicable interest rate become insensitive to changes in LIBOR if the floor is binding. The sample period underlying this binned scatter plot covers 2015q4-2020q4. *Sources:* FR Y-14Q, Haver, authors' calculations.

causally attribute this change to the change in applicable interest rate.

Let $d_{l,t} \equiv \text{LIBOR}_t$ - Contracted LIBOR floor_l be the distance between the LIBOR rate and the contracted floor, the running variable or forcing variable in terms of the RKD terminology.[12] 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, the local average treatment effect can be written 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 1 with equation (4), in which case the elasticity estimate is simply the change in the slope of

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

line utilization at the threshold. As we discuss below, we use a fuzzy design in which case the denominator can be different than 1.

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. Instead of estimating a shift in the intercept, however, in the kink design we are interested in estimating a slope change. We will discuss the exact empirical regression model used to estimate the change in slopes at the kink below.

We can also derive the RKD estimand within our economic model 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 piece-wise 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 deposit rate, that is, $\frac{\partial r^l}{\partial r} - \frac{\partial r^d}{\partial r}$, decreases as the policy rates 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 on lower pass-through into deposit rate), leading to a reduction of precautionary drawdowns.

We should acknowledge that RKD approach identifies a local average treatment effect (LATE) using only the interest rates of loan facilities that are in the close neighborhood to their respective interest rate floors. Given that there is heterogeneity in the applicable interest rate across borrowers, the LATE estimate could be not representative of the average treatment effect (ATE).[13] However, Figure A.1 in the appendix 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) come down, there is heterogeneity across borrowers in terms of the gap between the rate on revolving lines and the rate on the "cash" holdings, which is what matters for precautionary revolver runs. A related concern, is that when LIBOR floors are binding, the credit line cost is floored above the market interest rate. In this setting, there is an obvious disadvantageous to draw on the line, even if the firm were to put 100% of the proceeds in a fund that gives one a full market rate. This goes back to our discussion about use of bank deposits, the strong evidence of the deposit franchise, and the degree of path through in deposits required for the identification to work (Section I).

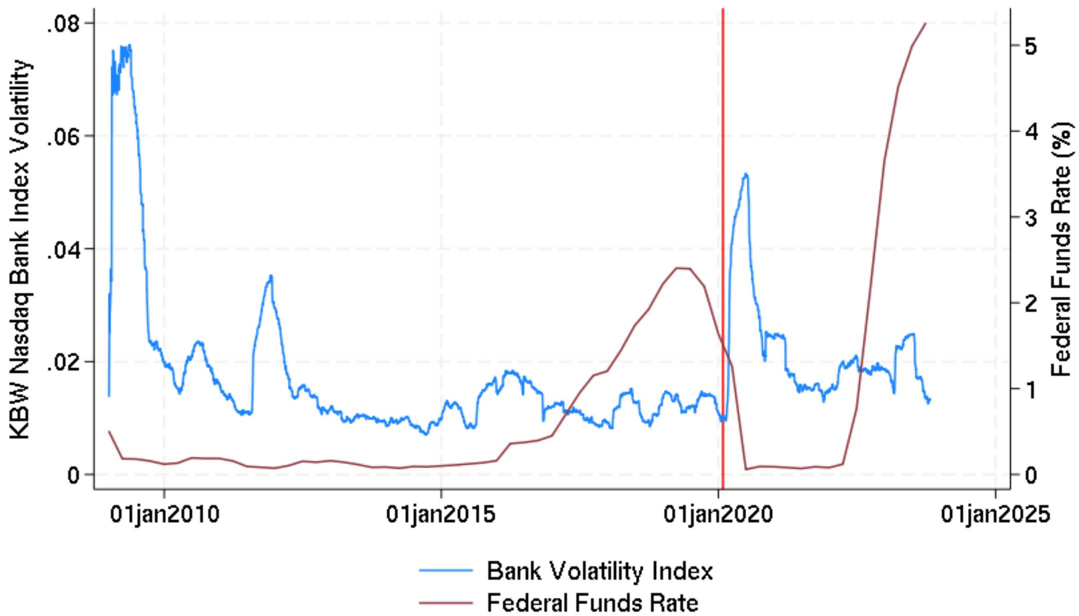
Isolating Precautionary Motives Given our focus, we need to identify a sample period with significant precautionary drawdown motives. That is, a setting where runs on banks (in the available Y-14 sample) were likely to take place. On the other hand, to implement the RKD, we also need the interest rate floors to bind for a large enough group of borrowers. (As we will discuss below, 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 does not cover the 2008 financial crisis, we cannot study this episode. The 2023 regional banking crisis is not a good setting for our empirical identification given the high level of interest rates. Moreover, our data covers credit lines by large banks that were not at the center of the 2023 turmoil. Thus, in our main analysis, we will focus on the 2019q4–2020q4 period, capturing the sudden COVID outbreak during early 2020.

As Figure 3 shows, this period was characterised by a strong increase in uncertainty about banks' health as measured by the volatility of the KBW Nasdaq Bank Index. Another advantage of focusing on the COVID 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 roughly 4% of

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

Figure 3: Bank Index Volatility and FFR



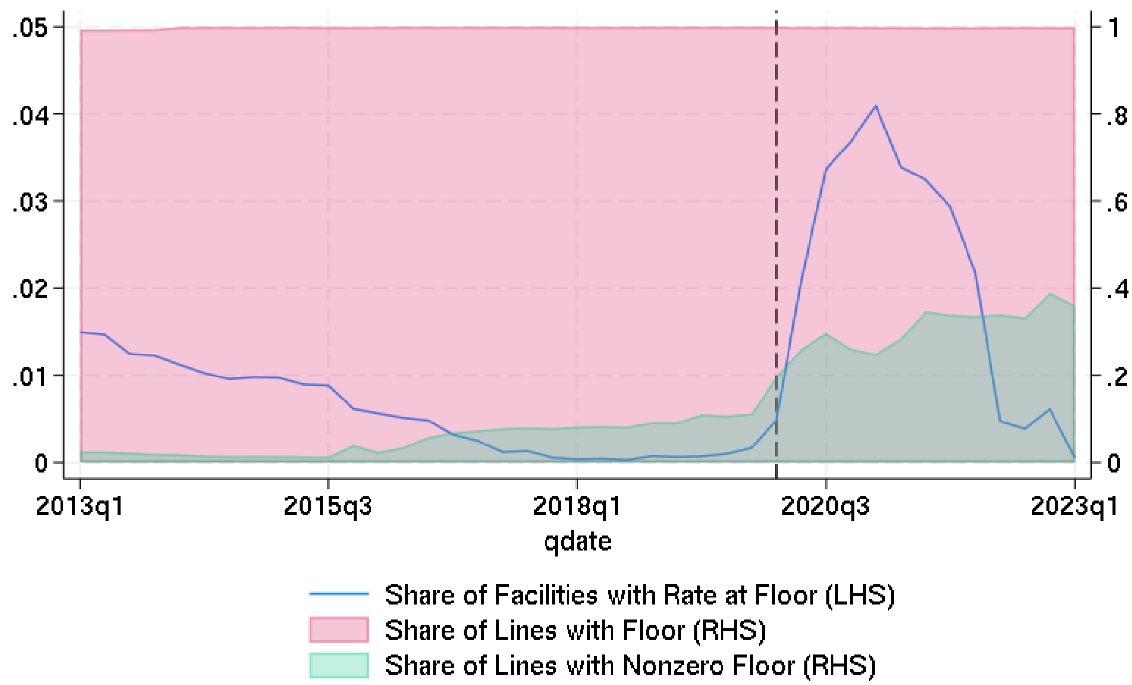
Notes: This figure plots the 90-day rolling window standard deviation of the KBW Nasaq Bank Index (on the left axis) and the Effective Federal Funds Rate (in %, on the right axis). *Sources:* HAVER, authors' calculations.

facilities.

In line with precautionary drawdowns being at play, Figure 5 illustrates that 2020q1 has been a period with a sudden and significant jump in the use of revolving lines, only to return to its normal level next quarter. Appendix Figure A.2 shows the same developments focusing only on LIBOR-indexed facilities. In Appendix Table B.1, we report detailed summary statistics of drawdowns in 2020q1 at the facility, bank, firm, and industry level using the Y-14 data, confirming the widespread increase in drawdowns also in the cross-section. Similar patterns of credit line drawdowns emerge from S&P's Global Market Intelligence, "US COVID-19 Related Revolver Drawdown" firm-level dataset, which covers an aggregate of $28 billion in drawdowns of syndicated lines in March 2020. This dataset indicates that 707 firms had drawn their line at that point.[14]

[14]In Appendix, Figure A.3, we zoom in on the cross-section of draw-downs by looking at the median, 90th percentile, 95th percentile and maximum of draw-downs on revolvers in the cross-section of banks in our sample. Figure A.3 clearly picks up the run on the revolving lines in 2020q1 and its economic importance. For most exposed bank in our sample this represented about 7% of liabilities. In US dollars, the largest bank-level drawdown was about $35 billion.

Figure 4: Interest Rate Floors on Line Commitments

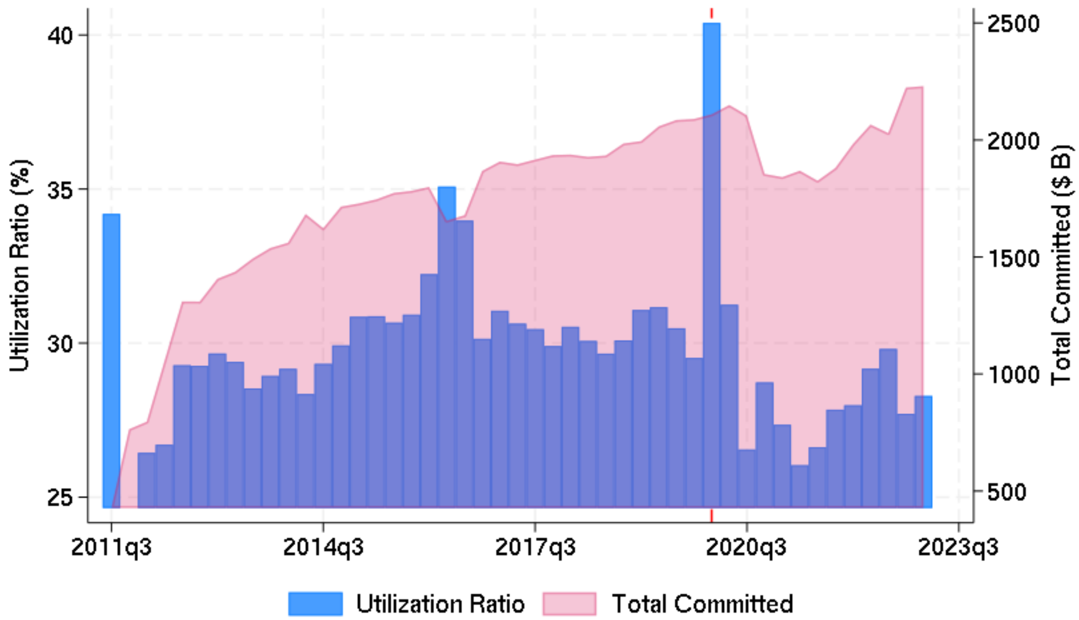


Notes: On the left scale, this figure shows the share of revolving line facilities with a binding interest rate floor (blue solid line). On the right scale, the figure shows the share of revolving line facilities with a contractual interest rate floor (red area) and we overlay the share of facilities nonzero interest rate floors (green area). The figure shows that virtually all facilities do have a floor, although for the majority of facilities the floor is zero in our sample. The vertical red line indicates 2020q1. *Sources:* FR Y-14Q, authors' computations.

A potential concern is that 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 draw-downs and potential capital needs is at the core of what defines a precautionary draw down. We may expect the rise in usage of revolving lines in 2020q1 for fundamental reasons given that general firms' demand for cash was pervasive due to COVID disruptions. This, however, cannot explain the abrupt reversal of usage in revolving lines in 2020q2.

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, from talking to CFOs, we have learned that, while indeed there is

Figure 5: Utilization Rates and Total Line Commitments over Time



Notes: The figure shows the aggregate utilization ratio, defined as total utilized line credit as a percent of total committed line credit, on the left axis. On the right axis, the graph shows the total committed line credits in $ billion. The figure is based on a revolving line commitments irrespective of their index rate. The vertical red line indicates 2020q1. *Sources:* FR Y-14Q, authors' computations.

a minor transactional delays, 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 behind the surge in revolving lines usage during COVID.

We should also consider the possibility that revolving credit was used as a "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. While after the Fed inventions corporate bond markets recovered ((Darmouni and Siani, 2024)), bank credit was still extremely tight in 2020q2 with new term loan origination well below their pre-pandemic levels (e.g., Bräuning, Fillat and Wang, 2024) suggesting that bridge financing for a large set of borrowers without access to bond markets is unlikely. Nevertheless, we do several empirical tests to explore this possibility further, concluding that precautionary motives were the first-order explanation behind the 2020 surge in revolver usage. We will discuss the results in Section IV.

Empirical Model Our empirical estimation focuses on estimating the kink in the relationship between the revolving line utilization and the distance to interest rate floor. We do so by estimating 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 (in percent of total committed), 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 freely vary on either side of the kink point; that is, we are not enforcing pooled parameters as 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 in order for the the linear terms to 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 flexibly change depending on whether the floor is binding or not. Throughout the analysis we control for the (log) loan committed amount, the (log) maturity, and 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 effect, and bank*quarter fixed effects.

The analysis includes loan fixed effects, so the identification is driven by within loan variation, that means that changes in applicable interest rate come from variation in LIBOR. As we already said, 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 overcome it. An additional concern could be that changes in LIBOR also correlate with the perception banking sector stability, thus accelerating the run. Inclusion of bank*quarter fixed effects should address this concern.

The Y-14 data has 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, for example due to the lack of information when variable rate contracts reset after base rate changes. Typically, datasets, including Y-14, do not capture these nuanced features of credit agreements. However, lack of such detail requires a fuzzy RKD design where 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. As with the utilization ratio, we therefore estimate a similar piecewise model for the interest rate of the line facility:

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

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 sloped near the kink. The baseline results are estimated for a bandwidth of 1% around the floor, and we will show the robustness of the effect for several bandwidth selections below. Moreover, we adopt a commonly used uniform kernel implying 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 level.

IV Results

IV.1 Interest Rate Elasticity of Drawdowns

Table 1 presents our baseline elasticity estimates using the COVID episode. Panel A reports the estimated interest rate elasticity. 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 effect and quarter fixed effect. That is, the results are identified from within-loan variation after netting out common time trends in utilization and rates. All columns also include log of committed line amount, log maturity and interest rate spread, as discussed above. In addition, column (2) includes bank-quarter fixed effects, and column (3) additionally includes borrower industry-quarter fixed effect.

Panel A, column (1), reports an estimated elasticity of -12.66. That is, when interest rates increase by 1 percentage point, revolving line utilization decreases by 12.66 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 -12.66 (Panel A) is the ratio of 6.025 (Panel C) and -0.476 (Panel B).

The coefficient estimates reported in Panels B and C are economically meaningful.[15] In Panel B, we find that, when the floor is not binding, the applicable interest rate on the line decreases by about 46.3 basis points when the LIBOR rate decreases by 1 percentage point.[16] On the other hand, when the interest rate is at the floor, changes in the LIBOR rate have no effect on the applicable interest rate of the line ($0.463-0.476 \approx 0$). Panel C shows

[15]Coefficient estimates in Panel B and C are not causally identified, only the ratio of the two slope changes allows for causal identification in the RKD setup. We report these for transparency.

[16]Notice that the first stage coefficient estimate is smaller than one, consistent with measurement problems of the policy function. This is exactly why we cannot use the standard RKD, but resort to the fuzzy design that allows for fairly general measurement error types, see Card et al. (2016).

Table 1: Interest Rate Sensitivity of Revolving Line Utilization

	(1)	(2)	(3)
Panel A: Interest Rate Elasticity			
Elasticity	-12.66***	-9.18***	-8.18**
	(1.88)	(3.21)	(3.94)
Panel B: Dep. Var. is Interest Rate			
Distance to Floor	0.463***	0.532***	0.559***
	(0.032)	(0.042)	(0.049)
At Floor * Distance to Floor	-0.476***	-0.515***	-0.537***
	(0.031)	(0.052)	(0.067)
Panel C: Dep. Var. is Utilization Rate			
Distance to Floor	-2.047*	-1.724	-1.167
	(0.667)	(1.538)	(1.523)
At Floor * Distance to Floor	6.025***	4.724*	4.396
	(0.802)	(1.580)	(2.045)
Controls	Yes	Yes	Yes
Facility FE, Time FE	Yes	Yes	Yes
Bank*Time FE	No	Yes	Yes
Industry*Time FE	No	No	Yes
N	20198	20188	20170

Notes: The elasticity reported in Panel A is computed as the ratio between the change 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 pp around floor and uniform kernel, and control for second order polynomial terms on each side of the kink. Controls include the (log) committed amount, the (log) maturity as well as interest rate spread. The sample period runs from 2019q4-2020q4. Two-way clustered standard errors at facility and time level. * (**) [***] indicates significance at the 10% (5%) [1%] level.

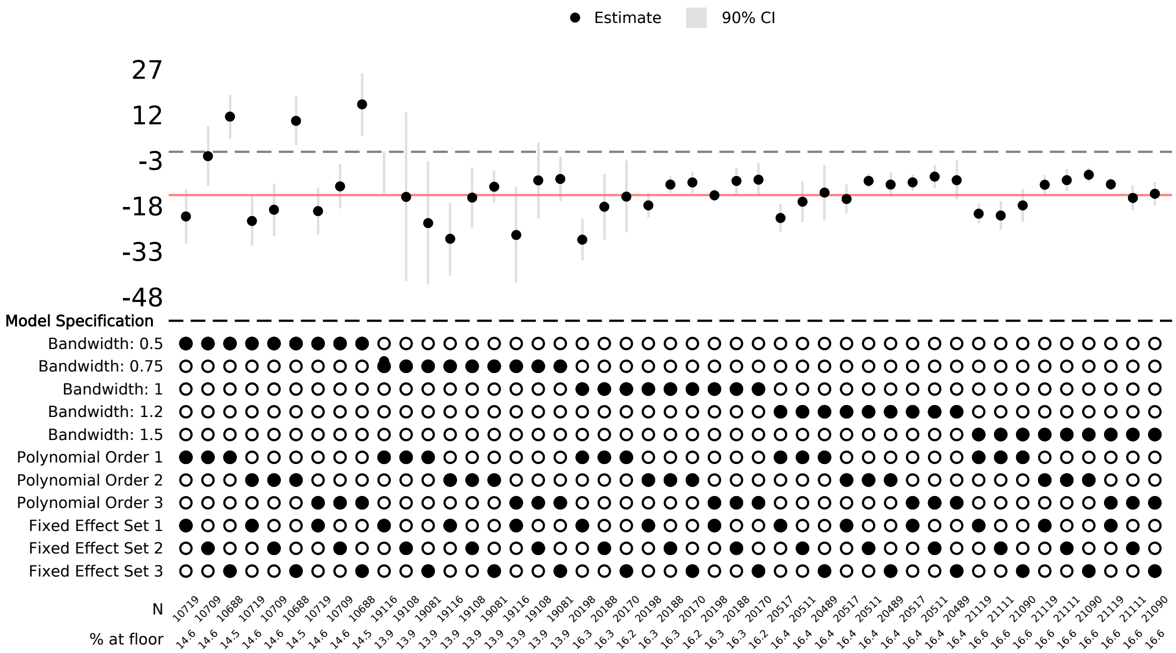
that, when the floor is not binding, line utilization decreases when the LIBOR rate increases (estimate of -2.047). On the other hand, when the floor is binding, and the applicable interest rate on the line is insensitive to LIBOR changes, we see that this effect reverts and becomes positive (-2.047 + 6.025), 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 decreases somewhat to -9.18 once we include bank*time fixed effects, driven by a smaller change in the slope of utilization (Panel C). Thus, part of the variation captured in column (1) was driven by cross-bank differences in firms' interest sensitivity to credit line utilization. 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 –8.2: For a 1 percentage point increase in the interest rate, the precautionary revolving line utilization decreases by 8.2 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 narrow possibility that the kink in the applicable interest rate is associated with an amendment, which in turn could also carry 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 LIBOR floor becomes binding. Nevertheless, in Table B.2, we show that, if such amendments occur, 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 as the smoothness of covariates at the threshold is the central identification assumption of the RKD. Second, we also verify that the distance to floor variable is smooth around the threshold. Figure A.4 shows the density estimate suggesting no discontinuity at the threshold.

Figure 6 shows results of a sensitivity analysis of the baseline estimates reported in Table 1. Two key parameters in the RKD are (i) the bandwidth of the running variable around the kink, and (ii) what order of polynomials to include as controls. At the bottom of the graph, dark circles 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 bandwidth 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 in line with the standard practice in the literature (Card et al., 2015). We

Figure 6: Robustness to RKD Specification

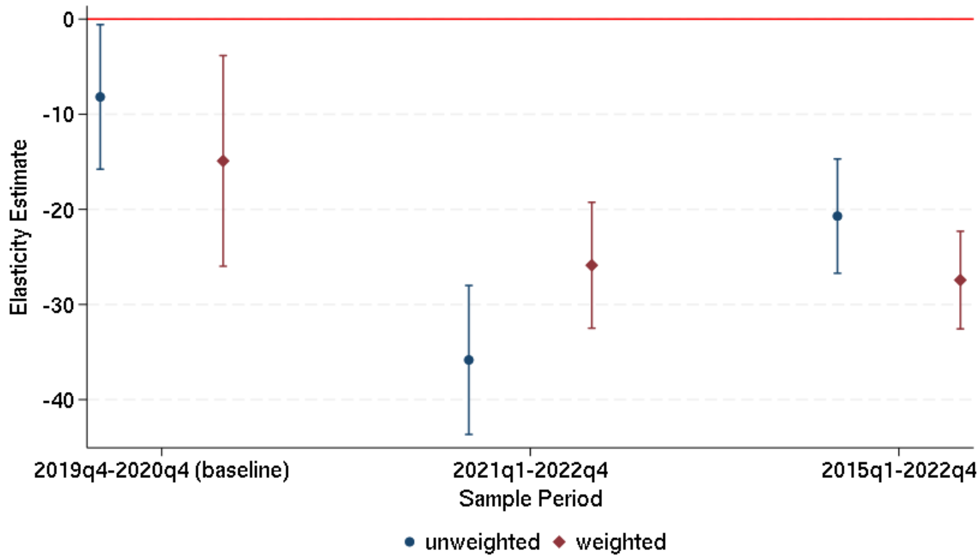


Notes: This figure shows the robustness of our baseline elasticity estimates to changes in key parameters choices underlying the regression kink design. We consider the following key parameters: bandwidth, degree of polynomial, fixed effects. For each parameter combination indicated with black dots in 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% confidence intervals are shown as gray bars. The red vertical line is average of estimate 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 to column 2, and so forth. *Sources:* FR Y-14Q, authors' computations.

report results for all three fixed effects specifications reported in Table 1. In sum, Figure 6 presents elasticity estimates for 5 x 3 x 3 = 45. Naturally, for very small bandwidths, we have 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 estimated close to magnitudes reported in Table 1 for most specifications.

We can further gain assurance that we are estimating predominantly elasticities of precautionary drawdowns by looking at the time variation in the estimates. Figure 7 summarizes estimates for different sample periods. Based on Figure 3 which displays the bank equity index volatility, 2021q1-2022q4 is the period where fundamental motive in

Figure 7: Time-Variation in Elasticity



Notes: Elasticity estimates are obtained by estimating the baseline model (all FEs) on the indicated subsamples. The whiskers represent 95% confidence intervals based on two-way clustered standard errors at facility and time level. The estimates are obtained using unweighted (baseline) or commitment-weighted regressions. *Sources:* FR Y-14Q, authors' computations.

the demand for liquidity is likely to dominate given that bank stock volatility is low. As Figure 7 shows, and consistent with our theoretical predictions, the elasticity estimates for this low-uncertainty period are substantially larger. Similarly, in the 2015q1-2022q4 sample, we find elasticities of up to -30.[17] The figure also includes commitment-weighted results, which are roughly similar to the baseline unweighted results.

Results in Figure 7 are in line with our model predictions. Precautionary drawdowns are driven by *future* fundamental demand. In the model, it is just about when you draw, and that is the key difference. In the case of precautionary drawdowns, the firm has a higher interest expense, so its marginal cost goes up, which, with investment opportunities constant, makes it more sensitive to 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 higher marginal return on investment. As a result, the firm will change its investment less to interest rate changes, because the investment return is just higher. Thus, when

[17] Given the small share of facilities near the floor in the pre-COVID period (see Figure A.1), we cannot zoom in more on the time variation during this period.

precautionary motives become stronger, the interest rate elasticity should go down in absolute values which is what we see in Figure 7. In absence of precautionary motive, the shift in the slope in 2020 would not take place.

Table 2: Precautionary Elasticities in Cross-Section

	Borrowers with Precautionary Drawdown?			
	Definition 1		Definition 2	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Elasticity (No COVID)	-21.20***	-20.98***	-20.72***	-24.26***
	(3.77)	(4.52)	(3.18)	(4.98)
Between-Group Diff	-0.23		3.54	
	(0.962)		(0.519)	
Elasticity (COVID)	-6.02**	-13.60***	-7.16**	-13.37***
	(3.05)	(3.25)	(3.13)	(4.39)
Between-Group Diff	7.57**		6.21	
	(0.020)		(0.275)	
COVID Effect:	-15.18***	-7.38	-13.56***	-10.89*
(p-value)	(0.002)	(0.185)	(0.002)	(0.098)

Notes: This table represents elasticities separately estimated for different groups of firms during the COVID period. "Yes" identifies borrowers with precautionary drawdowns, and "No" those without. We use two different definitions to identify firms with precautionary drawdowns. Under definition 1, a firm had a precutions drawdown if it increased its utilization in 2020q1 by more than the median firm, and in 2020q2 reverted back to its 2019q4 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. Two-way clustered standard errors at facility and time level. * (**) [***] indicates significance at the 10% (5%) [1%] level. Full estimation output is reported in Table B.3 *Sources:* FR Y-14Q, Compustat, authors' computations.

Another way to isolate a precautionary motive is to analyze heterogeneous elasticities across firms in the COVID period. The loan-panel structure of our data allows us to identify firms that were increasing their line utilization when the COVID shock hit in 2020q1, but then repaid the line in 2020q2 when the run on revolvers was largely over. In our first proxy for precautionary drawer (Definition 1), we flag firms that increase their line utilization from 2019q4 over 2020q1 by more than the median firm but the repaid the increase in line utilization in 2020q2, such that the level of utilization in 2020q2 equals that of 2020q4 (up to a margin of 5 percentage points.) In our second proxy, we do a similar analysis based on a within-industry threshold for the 2020q1 increases in utilization (Definition 2).

The results in Table 2 highlight that outside of the COVID period, the elasticity for both groups—those marked as higher and lower precautionary motive—is very similar. Under the first definition, the estimates are around -21. During the COVID period, the elasticity drops for both groups, but is more negative (estimate of -13.6 under the first definition) for firms flagged as using their line for precautionary reasons. This differences are also statistically significant for the first definition.

As mentioned earlier, we need to consider possibility that revolving lines were drawn as a "bridge" to firms' financing needs. If that is the case, on average, we would need to see that other forms of financing went up just as when the revolving lines were repaid. In general, we see that, the median firms in our sample increased its total debt by 1.3% in 2020q1, and decreased it by 4.9% in 2020q2 (9.8% increase and 8.9% decrease on average.) Nevertheless, Appendix Table B.4 shows that our results are robust to excluding firms that (i) received Paycheck Protection Program (PPP) funds and/or (ii) issued new debt, including both bonds and loans. In sum, it appears that some of the firms might have been using revolving credit as a bridge financing, but this cannot explain the broader pattern of the increase and drop in revolving lines utilization at the start of the COVID pandemic.

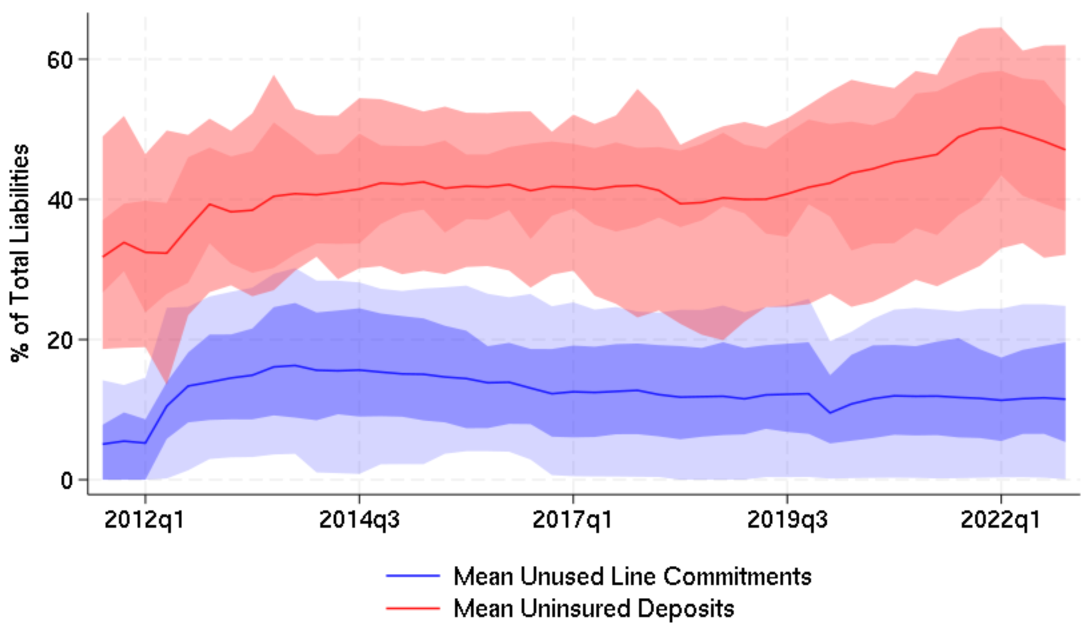
One caveat of Y-14 data is that it only covers the largest U.S. banks. In a bigger sample of banks, we could have explored cross-bank variation in exposure to precautionary drawdowns. However, our identification approach requires sufficient amount of data (focusing on observations near the floor), which prohibits us from pursuing a credible cross-bank analysis.

IV.2 Financial Stability Implications

Revolving credit and deposit-taking are at the core of the banking business (Kashyap, Rajan and Stein, 2002). Importantly, revolving credit is one area where the dominance of bank credit has not been eroded in recent decades through the rise on nonbank credit intermediation. To better understand the financial stability risk of revolving line drawdowns, we need to gauge the size of the exposure as well as overall bank liquidity management. This entails assessing the correlation between deposit drawdowns and revolving line utilization, and how it depends on the interest rate.

Banks' exposure to unused revolving lines is economically large. Figure 8 compares the stock of uninsured deposits to the stock of unused revolving lines expressed as a fraction of liabilities, focusing on the set of banks observed in the Y-14 data. Previous to the post-2020 rise in deposits, the average uninsured deposits were close to 40% of liabilities for the banks in our sample.[18] The exposure on revolving credit is about a third of the exposure on deposits, but with some banks' exposure accounting for more than 30% of total liabilities, and therefore still presents substantial liquidity risk for banks.

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 with the solid lines and the dark (light) shaded areas represent 25pct-75pct (10pct-90pct) bands of the cross-bank distribution. The sample includes all Y-14 banks. *Sources:* FR Y-14Q, FR Y9, FFIEC 031, authors' calculations.

Our central contribution is to measure how precautionary drawdowns on revolving lines respond to a rise in interest rates. In the last subsection, we have isolated this key parameter leveraging identification through application of the RKD approach to our micro data. Due to data limitations, we cannot apply the same methodology to causally identify

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

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 comove with changes in the federal funds rate.

This analysis uses quarterly bank-level data compiled from publicly available call reports. Which also means that we can cover a broader set of banks than with the Y-14 data. The key regression equation in the deposit beta approach relates deposit growth to the federal funds rate:

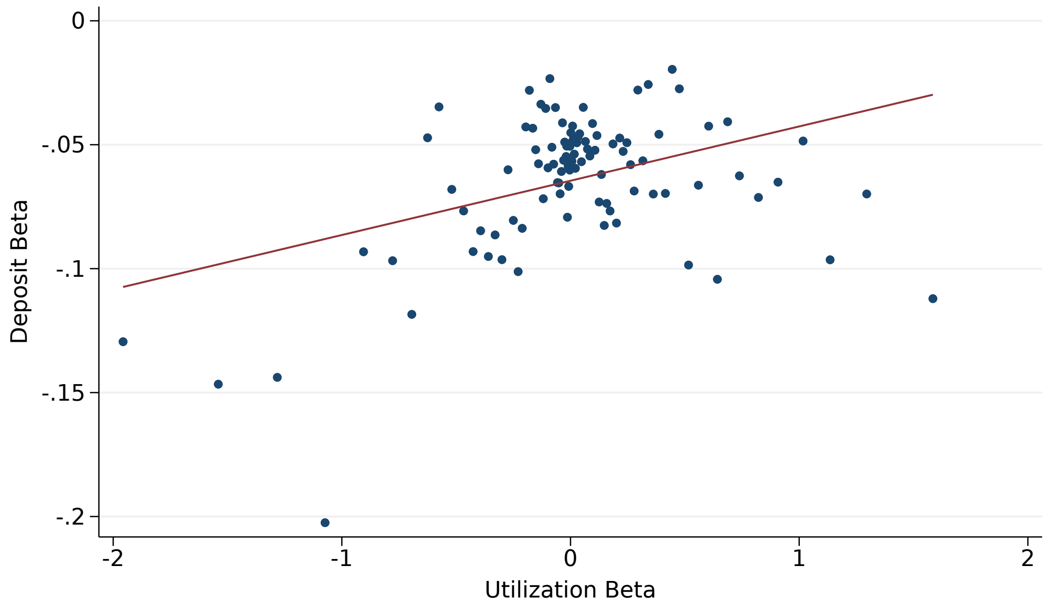
$$\Delta y_{i,t} = \alpha_i + \eta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta FF_t + \epsilon_{i,t}, \tag{10}$$

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 beta does not present an identified effect of interest rates on deposits growth, results from these predictive regressions are still informative to understand the comovement (statistical correlation) between the two variables.

We compute similar betas for the credit line utilization. For this exercise, we again use the publicly available call reports given that the small sample period covered in the Y-14 data. However, call reports do not have information of committed and utilized amounts at the facility level. Instead, we proxy the credit line utilization rate, at the bank level-quarter, by computing used C&I loan commitments—that is, the total utilization of revolving lines and term loan—as a percent of total (used and unused) C&I loan commitments. Another caveat of this analysis is that we cannot isolate precautionary drawdowns. We then estimate a model similar to equation (10), but using the log change in the credit line utilization ratio as the dependent variable. We call the credit line utilization beta $\beta_i^{utilization}$.

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

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



Notes: The figure shows a binned scatter plots between uninsured deposit flow betas and line utilization beta. The betas are bank-specific estimates of the sensitivity of desposit withdrawal and credit line utilization to changes in the federal funds rate. *Sources:* FR Y-9C, Haver, and authors' calculations.

positive association between the 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 run. Therefore, the high interest rate sensitivity of credit line utilization works as a counterforce to the liquidity squeeze stemming from the deposit outflow.

Table 3 further explores the relationship between deposit beta and 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 Utilization Beta of 0.0045 needs to be viewed under the large standard deviation of Utilization Beta of about 0.449 relative to a standard deviation of 0.045 for the utilization beta.) Interestingly, size-weighted regressions, shown in columns (3) and (4), suggest a stronger relationship between the deposit beta and utilization beta.

We should acknowledge that Figure 9 and Table 3 uncover a purely empirical relationship. A framework that provides a conceptional explanation for this result is beyond the

Table 3: Relationship Between Deposit Beta and Utilization Beta

	Dependent Variable: Deposit Beta			
	(1)	(2)	(3)	(4)
Utilization Beta	0.0045***	0.0045***	0.0210***	0.0160***
	(0.0016)	(0.0016)	(0.0039)	(0.0038)
Log Assets		-0.0015***		-0.0029***
		(0.0005)		(0.0003)
Desposit/Liabilities		-0.0129		0.0133***
		(0.0134)		(0.0040)
Unused Commitment/Liabilities		-0.0009		0.0126**
		(0.0055)		(0.0060)
Constant	-0.0238***	0.0077	-0.0436***	0.0009
	(0.0007)	(0.0163)	(0.0006)	(0.0076)
Weighted?	No	No	Yes	Yes
N	4,500	4,490	4,500	4,490

Notes: This table shows the coefficient estimates of regressing Deposit Beta on Utilization Beta. Column (1) and (2) are unweighted regressions, columns (3) and (4) are asset weighted. Balance sheet characteristics refer to average values during estimation sample from 2010-2023. *Sources:* FR Y-9C, authors' calculations

scope of this paper. However, one possibility could be that this relationship is endogenous to banks' risk management. For example, banks with borrowers that are more interest sensitive may be pricing their deposits less competitively.[19]

V Conclusion

Liquidity management is at the core of the bank business model. Uninsured deposits are a significant fraction of US banking sector liabilities. Similarly, unused revolving commitments are sizable demandable claims representing close to 20 percent of the banks liabilities. As with deposits, given the importance of revolving lines for management of working capital and other financial needs, in the past, firms have responded to uncertainty surrounding the banking sector by drawing down their revolving lines. Precautionary runs on credit lines, both in 2008 and 2020, were a significant contributing force to banks' liquidity pressures.

In this paper, however, we argue that precautionary drawdowns are highly sensitive to

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

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 revolving lines run. In this paper, we quantify the sensitivity of precautionary drawdowns to interest rates. As a lower bound, we estimate that each 1-percentage point increase in the policy rate leads to an 8-percentage point reduction in precautionary drawdowns, or about 1.6 percent of 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 effect of interest rates on the sensitivity of deposit outflows. Our findings suggest that, in the high interest rate environment of 2023, 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 complementary that emerges between management of deposits and revolving credit depending on interest rate environment. Our insights can help supervisors and bank risk managers modelling credit line drawdowns for liquidity stress test scenarios.

References

Angrist, Joshua D., and Iván Fernández-Val. 2013. "ExtrapoLATE-ing: External Validity and Overidentification in the LATE Framework." *Advances in Economics and Econometrics: Tenth World Congress*, , ed. Daron Acemoglu, Manuel Arellano and EddieEditors Dekel *Econometric Society Monographs*, 401–434. Cambridge University Press. 16

Berrospide, Jose, and Ralf Meisenzahl. 2022. "The Real Effects of Credit Line Drawdowns." *Interantional Journal of Central Banking*, 18(3): 321–397. 1

Bräuning, Falk, José L. Fillat, and J. Christina Wang. 2024. "Did High Leverage Render Small Businesses Vulnerable to the COVID-19 Shock?" *Journal of Money, Credit and Banking*. 19

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2024. "The Secular Decline of Bank Balance Sheet Lending." National Bureau of Economic Research Working Paper 32176. 5

Card, David, David S. Lee, Zhuan Pei, and Andrea Weber. 2015. "Inference on Causal Effects in a Generalized Regression Kink Design." *Econometrica*, 83(6): 2453–2483. 13, 20, 24

Card, David, David S Lee, Zhuan Pei, and Andrea Weber. 2016. "Regression Kink Design: Theory and Practice." National Bureau of Economic Research Working Paper 22781. 3, 13, 21, 22

Chodorow-Reich, Gabriel, Olivier Darmouni, Stephan Luck, and Matthew Plosser. 2022. "Bank liquidity provision across the firm size distribution." *Journal of Financial Economics*, 144(3): 908–932. 1, 11

Cooperman, Harry R, Darrell Duffie, Stephan Luck, Zachry Z Wang, and Yilin Yang. 2023. "Bank Funding Risk, Reference Rates, and Credit Supply." National Bureau of Economic Research Working Paper 30907. 6

Darmouni, Olivier, and Kerry Siani. 2024. "Bond Market Stimulus: Firm-Level Evidence." Working paper. 19

Diamond, Douglas W., and Philip H. Dybvig. 1983. "Bank Runs, Deposit Insurance, and Liquidity." *Journal of Political Economy*, 91(3): 401–419. 1, 5

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The Deposits Channel of Monetary Policy*." *The Quarterly Journal of Economics*, 132(4): 1819–1876. 2, 9

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2021. "Banking on Deposits: Maturity Transformation without Interest Rate Risk." *The Journal of Finance*, 76(3): 1091–1143. 30

Drechsler, Itamar, Alexi Savov, Philipp Schnabl, and Olivier Wang. 2023. "Banking on Uninsured Deposits." National Bureau of Economic Research Working Paper 31138. 4

Gatev, Evan, and Philip E. Strahan. 2006. "Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market." *The Journal of Finance*, 61(2): 867–892. 5

Greenwald, Dan, John Krainer, and Pascal Paul. 2023. "The Credit Line Channel." *The Journal of Finance*, Forthcoming. 1, 11

Hanson, Samuel, Victoria Ivashina, Laura Nicolae, Jeremy Stein, Adi Sunderam, and Daniel Tarullo. 2024. "The Evolution of Banking in the 21st Century." Brookings Insitution, BPEA Conference Draft. 5

Holmström, Bengt, and Jean Tirole. 1998. "Private and Public Supply of Liquidity." *Journal of Political Economy*, 106(1): 1–40. 5

Indarte, Sasha. 2023. "Moral Hazard versus Liquidity in Household Bankruptcy." *The Journal of Finance*, 78(5): 2421–2464. 13

Ippolito, Filippo, Jose-Luis Peydro, Andrea Polo, and Enrico Sette. 2016. "Double bank runs and liquidity risk management." *Journal of Financial Economics*, 122(1): 135–154. 5

Ivashina, Victoria, and David Scharfstein. 2010. "Bank lending during the financial crisis of 2008." *Journal of Financial Economics*. 1, 5

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2023. "Monetary Tightening and U.S. Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?" National Bureau of Economic Research, Inc NBER Working Papers 31048. 5

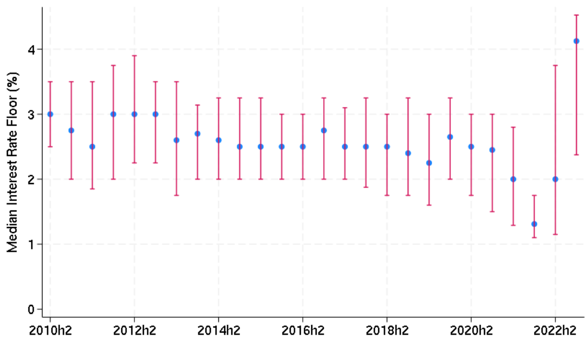
Kashyap, Anil K., Raghuram Rajan, and Jeremy C. Stein. 2002. "Banks as Liquidity Providers: An Explanation for the Co-Existence of Lending and Deposit-Taking." *Journal of Finance*, LVII(1). 5, 28

Rajan, Raghuram G. 1992. "Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt." *The Journal of Finance*, 47(4): 1367–1400. 6

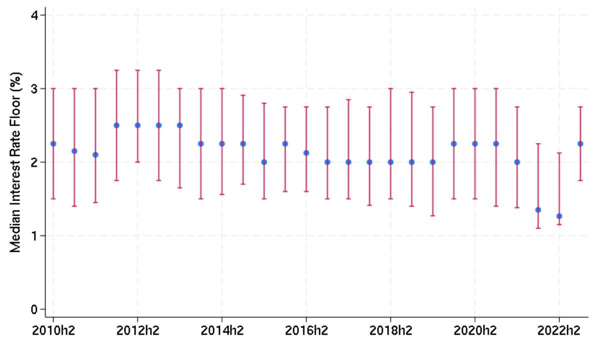
A Additional Figures

Figure A.1: Interest Rate Floor Distribution over Time

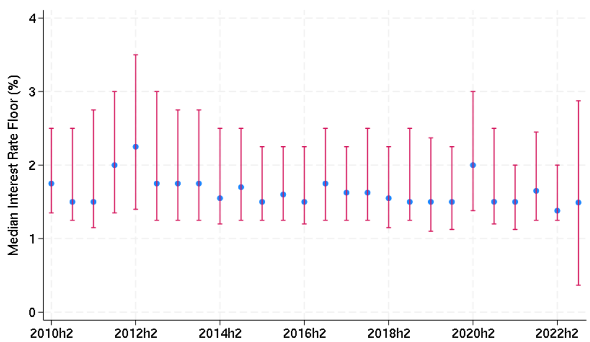
(a) Committed Exposure < 33rd percentile



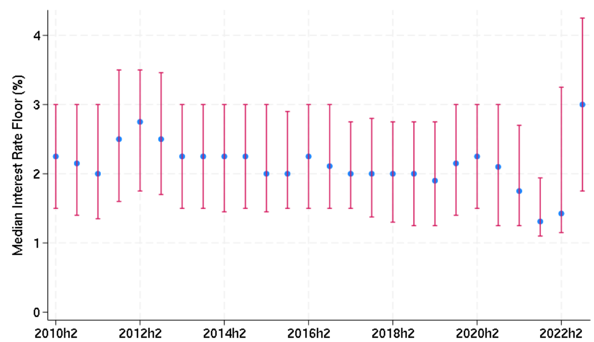
(b) Committed Exposure 33rd-67th percentile



(c) Committed Exposure > 67th percentile

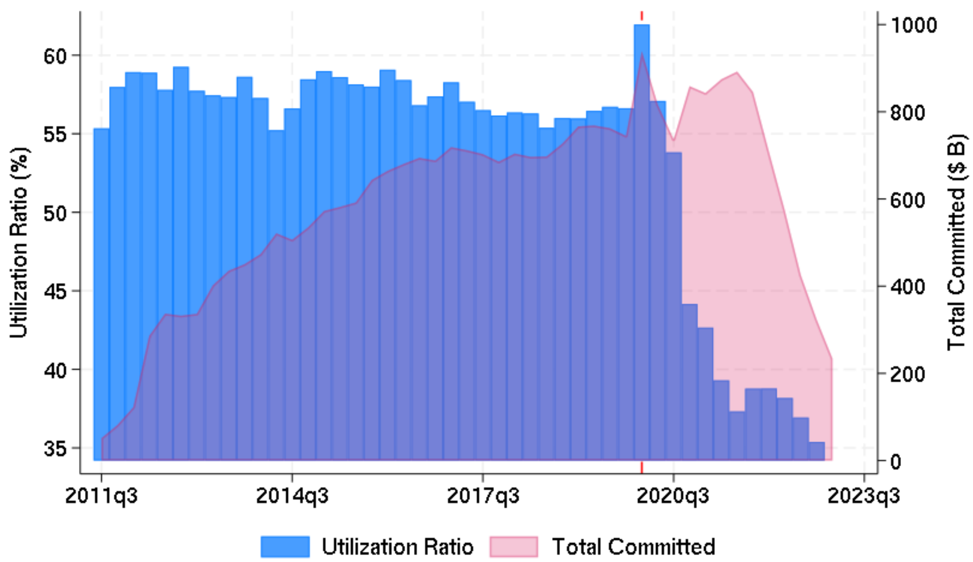


(d) All facilities



Notes: This figure shows the distribution of floors on applicable interest rates on revolving credit lines over time, for different loan sizes. Blue dots represent medians, and the red whiskers represent the interquartile ranges. The sample contains LIBOR-indexed facilities from 2010h2 to 2023h1. Date is by loan origination date. The correlation coefficient between interest rate floor and interest rate spread for the sample in panel (a) is 0.1667, (b) 0.1215, (c) 0.1399, (d) 0.1415 *Sources*: FR Y-14Q, authors' computations.

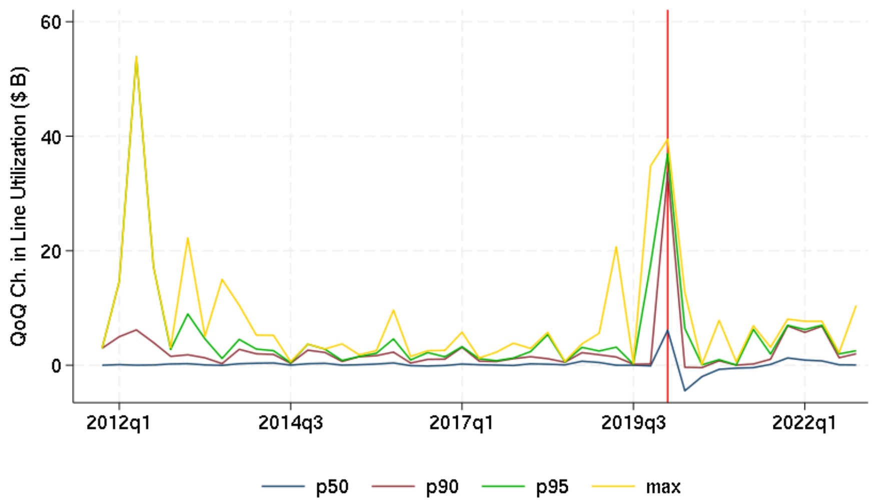
Figure A.2: Utilization Rates and Commitments over Time of LIBOR Facilities



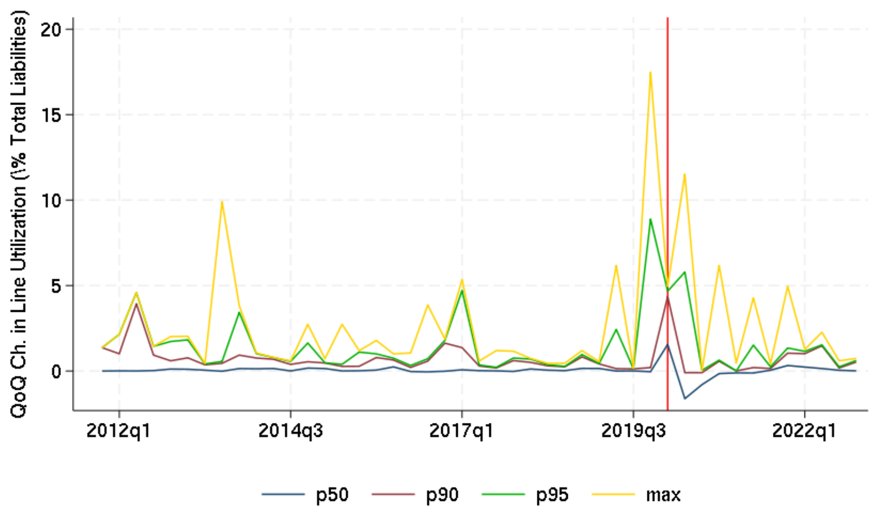
(a) only LIBOR-based

Notes: The figure shows the aggregate utilization ratio, defined as total utilized line credit as a percent of total committed line credit, on the left axis. On the right axis, the graph shows the total committed line credits in $ billion. The figure is based on a revolving line commitments indexed to LIBOR. The vertical red line indicates 2020q1. *Sources:* FR Y-14Q, authors' computations.

Figure A.3: Bank-Quarter Level Change in Line Utilization



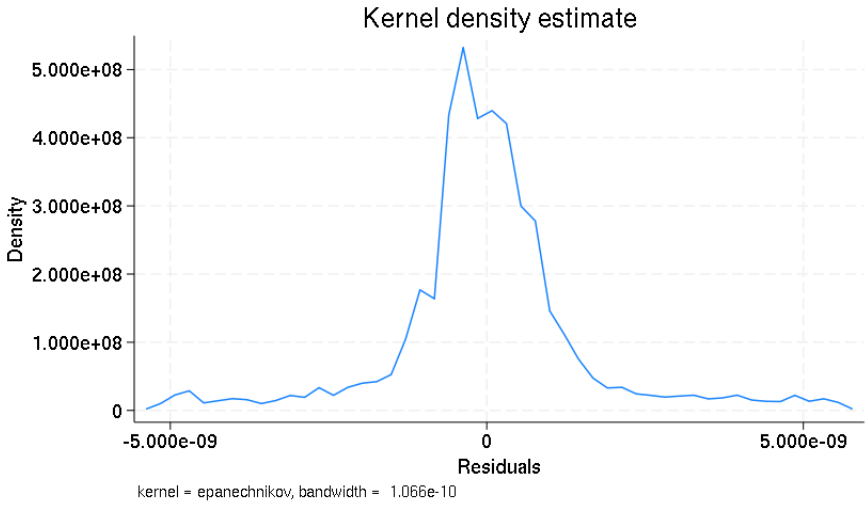
(a) Change in Line Utilization



(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 $ billion, while Panel (b) shows the changes of utilization as a percent of total liabilities. The sample includes all Y-14 banks. The vertical line indicates 2020q1. *Sources:* FR Y-14Q, FR Y9, authors' computations.

Figure A.4: Distribution of distance to floor



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

B Additional Tables

Table B.1: Summary statistics, 2020q1

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)	5.03	5.67	0.00	0.93	4.89	6.87	15.54
Observations	37959						

Panel B: Firm Level

	Mean	SD	p5	p25	p50	p75	p95
Utilized Dollars (M)	20.94	68.12	0.39	1.75	5.32	15.66	85.75
Committed Dollars (M)	33.81	98.67	1.20	3.01	8.75	25.00	137.53
Utilized / Committed (%)	64.55	28.51	12.10	44.00	67.16	90.65	100.00
Δ (Utilized / Committed)	8.58	26.10	-22.41	-2.78	0.26	15.36	66.30
Observations	27780						

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	16.51	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)	20.51	15.68	1.27	9.56	17.75	28.53	57.81
Observations	92						

Notes: Sum stats shown for 2020q1 based on Libor-indexed lines. Utilization ratio is utilized over committed. For each panel, facility-level ratios are then aggregated to the respective unit of observation (i.e., 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	0.378***	0.362***	0.345***
	(0.034)	(0.018)	(0.020)
At Floor*Distance	-0.047	-0.011	0.038
	(0.050)	(0.028)	(0.023)
Panel B: Maturity			
Distance to Floor	0.024*	0.014	0.022
	(0.010)	(0.016)	(0.020)
At Floor*Distance	0.049*	-0.017	0.010
	(0.017)	(0.038)	(0.030)
Panel C: Committed Amount			
Distance to Floor	0.006	0.001	0.006
	(0.005)	(0.003)	(0.003)
At Floor*Distance	-0.045*	-0.012	-0.032
	(0.017)	(0.011)	(0.015)
Controls	Yes	Yes	Yes
Facility FE, Time FE	Yes	Yes	Yes
Bank*Time FE	No	Yes	Yes
Industry*Time FE	No	No	Yes
N	20205	20195	20177

Notes: This table tests shows hat other key facility-level variables 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 2019q4-2020q4. Two-way clustered standard errors at facility and time level. * (**) [***] indicates significance at the 10% (5%) [1%] level.

Table B.3: Precautionary elasticities in cross-section

	Borrowers with Precautionary Drawdown?			
	Definition 1		Definition 2	
	0	1	0	1
	(1)	(2)	(3)	(4)
Panel A: Interest Rate Elasticity				
Elasticity (No COVID)	-21.20***	-20.98***	-20.72***	-24.26***
	(3.77)	(4.52)	(3.18)	(4.98)
Between-Group Diff	-0.23		3.54	
	(0.962)		(0.519)	
Elasticity (COVID)	-6.02**	-13.60***	-7.16**	-13.37***
	(3.05)	(3.25)	(3.13)	(4.39)
Between-Group Diff	7.57**		6.21	
	(0.020)		(0.275)	
COVID Effect:	-15.18***	-7.38	-13.56***	-10.89*
(p-value)	(0.002)	(0.185)	(0.002)	(0.098)
Panel B: Dep. Var. is Interest Rate				
Distance to Floor	0.933***	0.841***	0.924***	0.838***
	(0.000)	(0.001)	(0.000)	(0.002)
Distance to Floor * COVID	0.535***	0.643***	0.546***	0.629***
	(0.002)	(0.002)	(0.002)	(0.002)
At Floor * Distance to Floor	-0.914***	-0.831***	-0.904***	-0.838***
	(0.003)	(0.002)	(0.003)	(0.002)
At Floor * Distance to Floor * COVID	-0.510***	-0.645***	-0.526***	-0.608***
	(0.004)	(0.006)	(0.004)	(0.004)
Panel C: Dep. Var. is Utilization Rate				
Distance to Floor	-1.320	1.463	-1.068	1.499
	(1.095)	(1.626)	(0.887)	(1.275)
Distance to Floor * COVID	-0.014	-5.038	-0.403	-5.051
	(2.087)	(6.492)	(1.736)	(12.506)
At Floor * Distance to Floor	19.374*	17.427	18.734***	20.320
	(10.560)	(13.316)	(6.932)	(16.068)
At Floor * Distance to Floor * COVID	3.068	8.765***	3.762	8.128
	(2.267)	(3.244)	(2.496)	(6.353)
Controls	Yes		Yes	
Facility FE, Time FE	Yes		Yes	
Bank*Time FE	Yes		Yes	
Industry*Time FE	Yes		Yes	
N	67065	16805	72363	11507
COVID-Floor N	2696	576	2884	388
nonCOVID-Floor N	15061	2242	15695	1608
COVID-nonFloor N	12591	4307	14106	2792
nonCOVID-nonFloor N	36717	9680	39678	6719

Notes: This table reports the full estimation details of Table 2, see details in the caption of Table 2.

Table B.4: As Table 2, but Excluding PPP Borrowers or Borrowers with Debt Increase

Panel A: Excluding Firms with PPP loans

	Borrowers with Precautionary Drawdown?			
	Definition 1		Definition 2	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Elasticity (No COVID)	-21.63***	-19.86***	-21.15***	-20.95***
	(3.49)	(5.96)	(3.20)	(5.26)
Between-Group Diff	-1.77		-0.20	
	(0.728)		(0.973)	
Elasticity (COVID)	-5.75*	-8.95*	-7.26*	-14.73***
	(3.27)	(4.79)	(3.95)	(4.57)
Between-Group Diff	3.20		7.47	
	(0.440)		(0.140)	
COVID Effect:	-15.88***	-10.92	-13.89***	-6.23
(p-value)	(0.001)	(0.155)	(0.006)	(0.369)
N	67062	12259	72362	8700

Panel B: Excluding firms with Debt Increase

	Borrowers with Precautionary Drawdown?			
	Definition 1		Definition 2	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Elasticity (No COVID)	-20.94***	-19.83***	-20.50***	-23.49***
	(3.61)	(4.44)	(3.18)	(4.71)
Between-Group Diff	-1.11		2.99	
	(0.827)		(0.590)	
Elasticity (COVID)	-5.69	-14.90***	-7.25**	-13.34***
	(3.48)	(4.16)	(3.51)	(4.41)
Between-Group Diff	9.21**		6.09	
	(0.040)		(0.310)	
COVID Effect:	-15.25***	-4.93	-13.26***	-10.16
(p-value)	(0.003)	(0.422)	(0.006)	(0.125)
N	67061	14418	72359	9749

Notes: This table, similar to Table 2, represents elasticities separately estimated for different groups of firms during the COVID period. "Yes" identifies borrowers with precautionary drawdowns, and "No" those without. We have the same two definitions of precautionary drawdowns, see details Table 2. Here, we restrict the set of precautionary drawdowns further by dropping firms that, in principle, could have used revolving credit as bridge financing. First, the upper panel excludes firms that received PPP loans from the sample. Second, the lower panel excludes firms from the sample for which either merged Compustat or supervisory Y14 data show an increase in total debt in 2020q2. Two-way clustered standard errors at facility and time level. * (**) [***] indicates significance at the 10% (5%) [1%] level. Full estimation output is reported in Table B.3 *Sources:* FR Y-14Q, Compustat, authors' computations.