Bank Funding Risk, Reference Rates, and Credit Supply

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Abstract

Corporate credit lines are drawn more heavily when funding markets are more stressed. This covariance elevates expected bank funding costs. We show that credit supply is inefficiently dampened by the associated debt-overhang cost to bank shareholders. Until 2022, this impact was reduced by linking the interest paid on lines to credit-sensitive reference rates such as LIBOR. We show that transition to risk-free reference rates may exacerbate this friction. The adverse impact on credit supply is offset if the majority of drawdowns are expected to be left on deposit at the same bank, which happened at some of the largest banks during the COVID shock.

JEL: G00, G01, G02, G20, G21, E4, E43

Keywords: bank funding risk, credit supply, reference rates, credit lines, revolvers, London Interbank Offered Rate (LIBOR), Secured Overnight Financing Rate (SOFR)

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1 Introduction

In the US, most bank credit to corporate borrowers takes the form of revolving credit lines that give borrowers the option to draw any amount of credit, up to an agreed line limit, at any time before maturity and at committed pricing terms. Until 2022, the majority of US corporate loans, including revolvers, had interest rates set to the London interbank offered rate (LIBOR) plus a fixed spread.[1] In most of the world, however, banking has made a transition from credit-sensitive interest rate benchmarks such as LIBOR to new "risk-free" benchmark reference rates such as the secured overnight financing rate (SOFR). Credit-sensitive reference rates like LIBOR reduce borrowers' incentives to draw on committed credit lines when the banks' costs of funding drawdowns are high, for example during the global financial crisis (GFC) and the COVID recession. Risk-free loan reference rates, in contrast, typically fall when markets are stressed, thus encouraging borrowers to draw more heavily on credit lines just when bank funding costs rise sharply. Because of this, a collection of large US banks have argued that transitioning to risk free reference rates may reduce ex-ante incentives for providing bank credit.[2]

This paper shows how the choice of loan reference rate affects the supply of revolving credit lines. Bank shareholders bear a disproportionate share of the interest expense for funding line draws, a form of debt overhang. This debt-overhang wedge is priced ex-ante into credit lines. The resulting adverse impact on credit provision is mitigated by using credit-sensitive reference rates such as LIBOR that reduce borrowers' incentives to draw on their lines when LIBOR is high, which is also when bank funding expenses are high. We find that the transition from LIBOR to SOFR will lead to much heavier drawdowns when bank credit spreads rise sharply. Our calibrated representative bank prices this behavior into the terms of new lines, increasing the expected cost of drawn credit by about 14 basis points, reducing total line commitments by about 3%, and reducing the expected quantity of drawn credit by about 2%. The corresponding welfare loss is about 2%. For our representative bank, a welfare-maximizing reference rate has about 70% of the credit sensitivity of LIBOR. The welfare-maximal reference rate is estimated to be much closer to SOFR for those banks with much lower funding costs than our representative calibrated bank.

Our analysis proceeds in three steps. In the first part of our analysis, we provide a simple equilibrium

[1] We find that at the end of 2019 in the US, around 70% of all bank-firm lending referenced LIBOR as the underlying floating interest rate.

[2] See the letter of September 23, 2019 of banks in the Credit Sensitivity Group to Randall Quarles, vice chair of supervision of the Board of Governors of the Federal Reserve System, Joseph Otting, Comptroller of the Currency, and Jelena McWilliams, Chair Federal Deposit Insurance Corporation.

model of credit provision in which revolving credit lines give borrowers the option to draw funds at a pre-agreed fixed spread over a floating reference rate. We show that this induces a debt-overhang cost to bank shareholders that is roughly equal to the covariance between bank funding spreads and the quantity of line draws. This debt-overhang wedge inefficiently dampens banks' incentives to offer committed lines of credit. However, the adverse impact on the provision of credit lines is attenuated to the extent that (1) reference rates are credit-sensitive, which reduces borrowers' incentives to draw heavily under stressed-market conditions; and (2) draws on lines offered by a bank are expected to be left on deposit at the same bank, thus reducing the bank's funding costs.

The second part of our analysis is an empirical evaluation of funding costs associated with the provision of revolving credit. We use several data sources, including confidential bank-level data from the Federal Reserve, such as reporting forms FR 2052a, FR Y-14Q, and FR 2420, which cover the largest US bank holding companies (BHCs). The high granularity of the balance-sheet data collected in the FR2052a dataset—designed to monitor the liquidity profile of large US BHCs—allows us to pin down the composition and dynamics of bank funding costs for large US BHCs in much more detail than was possible in prior work.

As of the end of 2019, for our main sample consisting of the 20 largest US BHCs, non-financial firms borrow more from large banks by utilizing credit lines ($544 billion) than with conventional term loans and other forms of commercial and industrial (C&I) lending ($444 billion). Moreover, the largest 20 banks alone had around $1.3 trillion of undrawn credit-line commitments, more than the total utilized credit from term lending and revolving credit combined. Contractually, these lines can be drawn at any time, including during times in which funding markets are stressed and when wholesale bank funding spreads, typified by the difference between LIBOR and overnight index swap (OIS) rates, are elevated.

Consistent with the premise of our theoretical model, we find that banks were indeed subject to substantial drawdowns on credit lines during recent stress episodes, such as the GFC and the COVID recession. However, we show that bank funding sources were much different across these two episodes. During the GFC, most draws were not left on deposit. Instead a large fraction of the funds left the banking sector (Ivashina and Scharfstein, 2010; Acharya and Mora, 2015), causing banks to fund the drawdowns with other new borrowing, just when wholesale bank funding spreads were extremely high. In contrast, during the COVID recession, drawdowns were generally of a "precautionary" nature. That is, firms largely kept the drawn funds in their corporate deposit accounts. Given their uncertainty regarding their own future credit quality over the course of the ensuing pandemic, many firms plausibly chose to draw the cash on their lines before their banks might have invoked covenants that could have blocked them from doing so. We estimate that for every dollar drawn, an average of 89 cents was placed into low-interest-rate corporate deposit accounts at the same set of banks. Moreover, rates on uninsured corporate deposits did not exhibit sensitivity to the LIBOR-OIS spread. Banks raised the remaining needed funds with secured advances from the Federal Home Loan Bank (FHLBs), which tended to be cheaper than unsecured wholesale funding. Unlike during the GFC, the high fraction of line draws that were left on deposit during COVID significantly insulated bank shareholders from the costs of funding the draws, on average across banks. Nevertheless, some large regional banks funded a substantially larger part of their drawdowns with FHLB advances. Thus, even during the COVID recession, elevated funding costs arising from committed credit lines did materialize for this subset of banks.

Were it not for the debt-overhang cost to bank shareholders of funding line draws, the choice of reference rate would merely determine how funding-cost risks are shared between banks and their corporate borrowers. With risk-free reference rates, banks bear the majority of this risk, whereas with credit-sensitive reference rates, corporate borrowers absorb the bulk of this risk. However, our paper brings to light a funding-cost wedge that is not related to risk sharing: the ex-ante expected debt-overhang cost to bank shareholders associated with funding committed credit to corporate borrowers at a pre-agreed spread to a reference rate. This wedge, roughly equal to the covariance between bank funding spreads and the quantity of drawn credit, is higher under new risk-free reference rates than under legacy credit-sensitive reference rates. For the alternative of term lending, transitioning to risk-free reference rates does not affect this wedge because the quantity of credit is fixed, eliminating the covariance component of bank funding costs. Reference rate transition therefore has a negligible impact on the incentives of banks to supply term loans.

In the third and final part of our analysis, we combine our theoretical and empirical results into a calibrated equilibrium model of credit-line provision that allows us to estimate the impact on credit supply of the ongoing transition from the legacy credit-sensitive reference rate LIBOR to the risk-free reference rate SOFR. For our calibrated representative bank, we find that transition from LIBOR to SOFR implies only a moderate reduction—about 3%—in aggregate credit-line commitments. However, our model predicts a substantial change in line utilization across states of the world. The transition from LIBOR to SOFR increases the amount drawn by borrowers when LIBOR-OIS is high. Borrowers will exploit the fact that the drawn interest rate for SOFR-linked lines does not increase under stressed market conditions. Because of this, in equilibrium, the fixed spread over SOFR offered to credit line customers incorporates the increased cost to bank shareholders of funding more line draws when LIBOR-OIS is elevated. As a consequence, in "normal times" when bank funding spreads are relatively low, borrowers will draw less credit on lines linked to SOFR than they would have on lines linked to LIBOR.

Our calibration also implies that the impact of LIBOR-SOFR transition on credit supply varies markedly across types of banks. Banks that face less severe debt overhang—whether due to lower wholesale funding spreads or higher expected deposit inflows from drawn credit—will be less affected by the transition, or may even increase overall credit provision and prefer a credit sensitivity substantially below that of LIBOR. As we discuss in more detail in Section 6, our analysis suggests that low-debt overhang banks may gain market share and that the aggregate impact on credit provision of the transition from LIBOR to SOFR is thus likely to be more muted than would be suggested by our partial-equilibrium analysis, especially for a borrower with a low cost of switching its banking relationship to a new bank. A broader equilibrium analysis that incorporates the industrial organization of banking relationships is, however, beyond the scope of this paper.

Our analysis helps explain why some US banks have argued that the transition to risk-free reference rates will exacerbate bank funding shocks and reduce incentives for credit provision. In September 2019, a collection of banks, predominantly large regional banks that, according to our analysis, are the most affected by such a transition,[3] wrote to bank regulators, stating:

"*Specifically, borrowers may find the availability of low cost credit in the form of SOFR-linked credit lines committed prior to the market stress very attractive and borrowers may draw-down those lines to 'hoard' liquidity. The natural consequence of these forces will either be a reduction in the willingness of lenders to provide credit in a SOFR-only environment, particularly during periods of economic stress, and/or an increase in credit pricing through the cycle. In a SOFR-only environment, lenders may reduce lending even in a stable economic environment, because of the inherent uncertainty regarding how to appropriately price lines of credit committed in stable times that might be drawn during times of economic stress.*"

Banking regulators responded by convening the Credit Sensitivity Group,[4] a group of these banks that were invited to a series of meetings at the New York Fed to discuss this issue and eventually to consider a "credit sensitive rate/spread that could be added to SOFR."

[3]Our empirical analysis shows that regional banks experienced significantly less depositing of line draws during the COVID recession than did the larger money-center banks, and that regional banks have historically had somewhat higher funding spreads.

[4]See Transition from LIBOR: Credit Sensitivity Group Workshops, Federal Reserve Bank of New York, February 04, 2021.

Since January 2022, supervisory guidance provided in interagency statements has suggested that US banks should not reference LIBOR in their loan contracts.[5] Banks have generally followed the guidance of the Alternative Reference Rates Committee (ARRC) and now use primarily SOFR as their loan reference rate. For example, ARRC reported that over 95% of US syndicated loans issued in April 2022 referenced SOFR.[6]

LIBOR is no longer acceptable as a reference rate because of the small number of wholesale unsecured funding transactions at short maturities that are available to support a robust daily fixing of LIBOR. The reporting of US dollar LIBOR is scheduled to end on June 30, 2023.[7] This does not rule out the possibility that some banks may choose to link some of their corporate lending contracts to other credit-sensitive reference rates.[8]

Our work is the first to probe the implications of reference rate choice for incentives to provide credit, and the first to quantify the impacts of reference rate transition based on detailed data on bank assets and liabilities.

The rest of the paper unfolds as follows. Section 2 relates our work to the most relevant prior research. Section 3 provides a simple equilibrium model of credit-line provision. Section 4 describes our data. Our main empirical analysis, in Section 5, consists of mapping bank funding risk for large US BHCs and quantifying the importance of reference rates in mitigating funding shocks. In Section 6, we calibrate our theoretical model to key empirical moments in order to quantify the effects of the LIBOR-SOFR transition on credit-line supply and welfare-maximal reference rates. Section 7 concludes.

2 Related Literature

Our paper is related to at least three strands of the literature. First, we contribute to the literature on bank liquidity provision through revolving credit lines. Credit lines allow firms to access funds on demand and can thus provide insurance against liquidity shocks (Holmström and Tirole, 1998). Banks that are financed by deposits are naturally well positioned to provide this type of liquidity insurance

[5]See, for instance, SR 20-27 which states: "*Given consumer protection, litigation, and reputation risks, the agencies believe entering into new contracts that use USD LIBOR as a reference rate after December 31, 2021, would create safety and soundness risks and will examine bank practices accordingly.*"

[6]See Alternative Reference Rates Committee May 18 Meeting Readout, May 18, 2022.

[7]See "Federal Reserve Board invites comment on proposal that provides default rules for certain contracts that use the LIBOR reference rate, which will be discontinued next year," Press Release, Federal Reserve Board, July 19, 2023.

[8]Alternative US dollar credit sensitive reference rates currently include Ameribor, BSBY, and AXI. One of the authors of this paper, Duffie, is a co-author of the proposal for AXI (Berndt, Duffie, and Zhu, 2020), but has no related compensation or affiliation with its commercialization.

(Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006).[9] Existing work on the pricing of credit lines typically emphasizes that drawdowns are more likely when a borrower's financial condition deteriorates (Thakor, Hong, and Greenbaum, 1981). Adverse selection with respect to borrower credit quality thus creates incentives for banks to screen borrowers and to price credit lines with a combination of spreads and fees (Thakor and Udell, 1987; Berg, Saunders, and Steffen, 2016).[10] Our paper focuses on a previously unstudied aspect of credit-line provision that stems from bank debt overhang costs. We show that an extra source of debt overhang arises from the covariance between bank funding spreads and the quantity of line draws. The associated cost to bank shareholders is priced into line terms and inefficiently dampens the provision of revolving credit. We further show that credit-sensitive reference rates mitigate the adverse impact of this debt-overhang wedge, relative to risk-free reference rates.

Our paper also adds to prior work on elevated drawdowns during times of distress. During the GFC, many non-financial firms drew on committed credit lines (see, for example, Ivashina and Scharfstein, 2010; Campello, Giambona, Graham, and Harvey, 2011; Acharya and Mora, 2015).[11] Drawdowns possibly resulted from concern by borrowers about their banks' abilities to provide credit in the future (Ivashina and Scharfstein, 2010; Ippolito, Peydró, Polo, and Sette, 2016). During the COVID recession, firms drew on existing credit lines to an even larger extent than during the GFC, with $300 billion to $500 billion drawn in March 2020 alone (Li, Strahan, and Zhang, 2020; Acharya and Steffen, 2020). But these draws were accompanied by a large increase in deposits (Li et al., 2020; Levine et al., 2021).[12]

Using the novel FR 2052a data, we provide more detailed information on drawdowns and deposit flows during the COVID recession. In contrast to the GFC, we show that drawing induced by COVID was largely precautionary, in that borrowers left most of their drawn funds on deposit. Our evidence bearing on the dynamics of bank balance sheets during the COVID recession thus emphasizes that most banks did not need to raise costly external funding. Banks may have nonetheless been constrained in their term lending because of regulatory capital requirements and the expansion of their balance sheets caused by drawdowns, increased deposits, and other effects (Acharya, Engle, and Steffen, 2021;

[9]Empirical evidence from Brown, Gustafson, and Ivanov (2021) and Santos and Viswanathan (2020) suggests that credit lines indeed insure firms against liquidity shocks, although Chodorow-Reich, Darmouni, Luck, and Plosser (2021) find that this insurance is only available to large firms but not to small firms. Other important work on credit lines includes Sufi (2009), Acharya, Almeida, Ippolito, and Perez (2014), and Acharya, Almeida, Ippolito, and Orive (2020). Kiernan, Yankov, and Zikes (2021) studies how interbank fronting networks mitigate bank funding risk in syndicated credit lines, from the perspective of the borrower's ability to quickly receive funds.

[10]For example, accepting a higher spread and lower commitment fee would signal a lower probability of drawing.

[11]See also Berrospide, Meisenzahl, and Sullivan (2012), Acharya, Almeida, Ippolito, and Orive (2020), and Chodorow-Reich and Falato (2022).

[12]After the 1998 Russian default, banks also experienced both credit-line drawdowns and transaction deposit inflows (Gatev, Schuermann, and Strahan, 2007).

Greenwald, Krainer, and Paul, 2020; Kapan and Minoiu, 2021).

Second, our paper adds to recent research concerning the transition from LIBOR to risk-free reference rates.[13] Jermann (2019) shows that LIBOR-linked loan revenues act as a form of insurance to banks against risks to their funding costs. Jermann (2021) shows, in effect, that SOFR is not as effective as LIBOR for hedging his risk. Kirti (2022) models how reference rate choice affects loan provision in a model with risk-averse banks and risk-averse borrowers. The risk-sharing properties of alternative reference rates are not our concern. We focus instead on the implications of reference rate choice for the equilibrium supply of credit lines. We calibrate an equilibrium model of credit line provision and estimate the impact to both prices and quantities of switching from LIBOR to SOFR. We find that the expected pricing of drawn credit is likely to be higher under SOFR, relative to LIBOR, because banks adjust the terms of revolvers to reflect debt-overhang costs to their shareholders. By contrast, our theory implies essentially no impact on term lending. This aligns with recent evidence provided by Klingler and Syrstad (2022), who find only a small effect of reference rate transition on the pricing of floating-rate bonds.

Third, we contribute to the theoretical literature on reference rates. Santomero (1983), Chang, Rhee, and Pong (1995), and Kirti (2020) provide a rationale for floating-rate loans based on the assumption that banks are risk averse. Ho and Saunders (1983) analyze hedging in the context of fixed-rate unfunded loan commitments. Their model also highlights the importance of the covariance between borrower draws and loan costs for pricing at origination. Risk aversion plays no role in our analysis. In any case, only the credit-spread component of bank funding costs matters in our analysis because uncertain changes in risk-free interest rates do not contribute to debt overhang in this setting. By contrast, prior work that focuses on hedging total interest expense, including the above cited work and Bowman, Scotti, and Vojtech (2020), applies even to banks that have no credit spreads. More generally, in our model, banks maximize equity market value; they are not risk averse.

[13] There is also work on LIBOR as a measure of bank funding costs, documenting historical divergences between LIBOR and risk-free rates, such as SOFR or SOFR proxies. For example, Schrimpf and Sushko (2019) and Abate (2020) document that the LIBOR-SOFR was extremely elevated for extended periods of time during past financial market stress and recessions. Kuo, Skeie, and Vickery (2018) find that during the GFC, LIBOR broadly tracked alternative measures of short-term bank funding costs but they also document a large dispersion in bank borrowing costs not captured by LIBOR. However, Bowman, Scotti, and Vojtech (2020) question whether LIBOR is even a good measure of the marginal funding costs of banks, noting that (1) wholesale unsecured funding is a tiny fraction of GSIB and non-GSIB liabilities and (2) depending on time period and type of term SOFR (in arrears versus in advance), SOFR can be more correlated with average funding costs than LIBOR.

3 A Model of Credit Line Provision

The following simple equilibrium model of credit lines allows us to show the degree to which the banks' incentives to provide credit lines are affected by the choice of the floating reference rate. In Section 6, we calibrate this model to the empirical experience with LIBOR credit lines originated by large US banks in order to illustrate the potential impact of reference rate transition and the key economic channels at work.

Credit lines are contracted at time 0, giving a borrower the option to draw on the line at time 1 at an interest rate equal to a fixed contractual spread over the reference rate. We also analyze special cases in which the reference rate R is either a credit-sensitive rate like LIBOR or the risk-free rate r. These interest rates apply to loans funded at time 1 and maturing at time 2. We ignore risk aversion throughout.

At time 0, as depicted in Figure 1, the bank offers the borrower a menu $\{(L, s(L)) : L \geq 0\}$ of credit-line terms distinguished by the size L of the line and the associated fixed spread $s(L)$ over the variable loan benchmark rate R. The borrower selects its preferred choice $(L, s(L))$ from this menu. At time 1, information reveals the rates R, r, and the credit spread S of the bank for unsecured wholesale funding maturing at time 2. By "wholesale," we mean that bank creditors break even in market value by providing marginal quantities of new funding to the bank at the interest rate $r + S$.

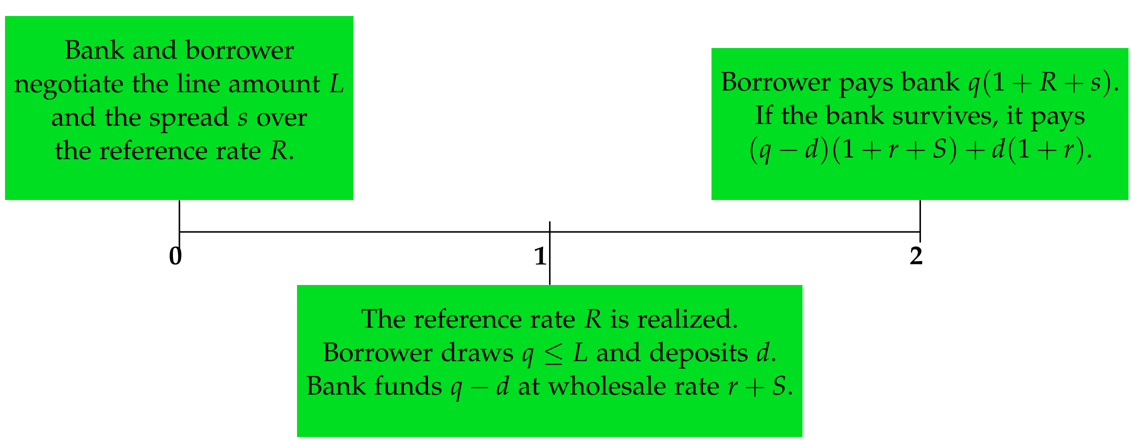


Figure 1: **Model timeline.** A credit-sensitive reference rate R such as LIBOR is of the form $r + W$, for some credit-spread benchmark W. A risk-free reference rate, for example SOFR is $R = r$.

At time 1, after observing S, r, and R, the borrower chooses the quantity $q \leq L$ of cash to draw, and leaves $d \leq q$ of the drawn funds on deposit at the same bank. In this basic version of the model, the deposited fraction $\varphi = d/q$ can be contingent on the state of the market at time 1, but is exogenously chosen. In Appendix Section E, we endogenize φ based on the borrower's fear that the condition of the borrower or the bank may deteriorate so as to block drawing on the line at an intermediate date before maturity.

As shown in Figure 1, the undeposited quantity $q - d$ of drawn cash is funded by the bank at its unsecured wholesale rate $r + S$. The interest rate offered to the borrower on the deposited amount d is assumed to be the risk-free rate r. (Empirically, we will later show that the interest rate paid on corporate transaction deposits is near the risk free rate.) At time 2, the bank's total assets and total liabilities are revealed and the bank is either solvent or not. For simplicity, the bank will not default before time 2 because the bank has no liabilities maturing before time 2. If solvent at time 2, the bank pays back $(q-d)(1+r+S) + d(1+r)$ on the funding that it obtained at time 1. The corporate borrower repays $q(1 + R + s(L))$ on the line, and receives $d(1+r)$ in interest, whether or not the bank is solvent at time 2. For simplicity, our basic model assumes that the borrower will not default on the credit line. We defer a consideration of borrower default risk.

It remains to specify the preferences of the bank's shareholders and the borrower, and then solve for the equilibrium line size L, contractual spread $s(L)$, and amount q drawn.

At time 1, the benefit to the borrower of receiving x in cash is $b(x, \psi)$, where ψ is a liquidity-preference variable that is revealed at time 1 and b is a function in two non-negative variables such that (i) for any y, $b(x, y)$ is increasing, differentiable, and strictly concave with respect to x, and (ii), for any x, the marginal benefit $b_x(x, y)$ of cash is at least 1 and is increasing in the outcome y of ψ.[14]

At time 1, given the committed size L of the credit line, the borrower chooses the amount $Q(L)$ to draw that maximizes the benefit of receiving the cash, net of the present value of the loan repayment less deposit proceeds. That is, state by state, $Q(L)$ solves

$$\sup_{q \le L} \; b(q, \psi) - q\varphi - q\delta(1 + R + s(L)) + \delta q \varphi (1+r), \tag{1}$$

where $\delta = 1/(1+r)$. In the event that $b_x(0, \psi) \le \delta(1 + R + s(L))$, the optimal cash draw $Q(L)$ is zero. In the event that $b_x(L, \psi) \ge \delta(1 + R + s(L))$, the optimal cash draw $Q(L)$ is L. Otherwise, from the

[14]Our modeling of the liquidity benefit to the borrower is of a reduced form. Benefits from liquidity insurance can be motivated, for instance, by a borrower's ability to avoid liquidating otherwise profitable projects when obtaining an amount of credit q when subject to a liquidity shock (see for example, Holmström and Tirole, 1998).

first-order condition for optimality,

$$Q(L) = B\left(\delta(1+R+s(L)), \psi\right), \tag{2}$$

where $B(\,\cdot\,, y)$ is the inverse of $b_x(\,\cdot\,, y)$, meaning that $b_x(B(z,y),y) = z$. At time 0, the borrower chooses the size L^* of the credit line that achieves the maximal expected net benefit

$$\sup_L E\left[b(Q(L), \psi) - Q(L)\delta(1+R+s(L))\right] - fL, \tag{3}$$

where fL is the line fee, for some constant $f \geq 0$. To simplify, we assume that the line fee fL compensates bank shareholders for the cost of meeting any capital requirements associated with the committed line size L. There is also an equity capital requirement $CQ(L)$ for the drawn[15] amount $Q(L)$, for some constant capital ratio C.

From Theorem 1 of Andersen, Duffie, and Song (2019), the marginal increase[16] at time 1 in the equity value of the bank associated with the given contractual credit line terms $(L, s(L))$ is

$$G(L) = p_1\pi_L - p_1\delta(1+C)(1-\varphi)Q(L)S, \tag{4}$$

where p_1 is the conditional probability[17] at time 1 of bank solvency at time 2, and

$$\pi_L = \delta Q(L)(1+R+s(L)) - Q(L)$$

is the bank's profit on the drawn line, which is the discounted loan payoff net of the loan proceeds. The first term of (4) is the expectation at time 1 of credit-line profit going to bank shareholders, noting that

[15]The impacts of capital requirements on credit provision are widely discussed in the literature. For example, Favara, Infante, and Rezende (2022) show how drawdowns during March 2020 reduced bank participation in Treasury markets.

[16]In the context of Andersen, Duffie, and Song (2019), the market value $V(c)$ of the bank's equity at time 1, for some incremental quantity c of credit-line customers, is $\delta E_1^*[(X+cY)^+]$, where E_1^* denotes risk-neutral conditional expectation at time 1, X is the payoff at time 2 of the bank's legacy assets net of its legacy liabilities, and Y is the cash flows at time 2 for one unit of credit-line customers, net of the associated funding costs. Under mild technical regularity conditions, the marginal value of a credit line customer at time 1 is shown in Andersen, Duffie, and Song (2019) to be $G(L)$, which is the right derivative $\partial_+ V(0)/\partial c$ of the market value $V(c)$ of the bank's equity with respect to the incremental quantity c of customers contracting credit lines with the bank, evaluated at $c = 0$.

[17]Given the fractional loss ℓ at default to the bank's unsecured creditors, we can solve for the credit spread $S = (1-p_1)\ell$, and substitute $p_1 = 1 - S/\ell$ into (4). As shown by Andersen, Duffie, and Song (2019), for a borrower with default risk that is positively correlated with the default risk of the bank, there is also a risk-shifting benefit to bank shareholders of $\delta\,\mathrm{cov}_1(1_H, Y_L)$, where 1_H is the indicator of the event H of bank solvency and cov_1 denotes covariance conditional on information available at time 1. This term is zero in our setting because the borrower is default free.

equity owners get paid at time 2 if and only if the bank is solvent. The second term

$$\tau = p_1 \delta(1 + C)(1 - \varphi)Q(L)S \tag{5}$$

of (4) is the debt-overhang cost to bank shareholders of funding $(1 - \varphi)Q(L)$ at the wholesale rate S. For large US banks, the factor $\delta p_1(1 + C)$ is typically close to 1 and the majority of the debt-overhang wedge is the product of the bank's wholesale credit spread S and the quantity $(1 - \varphi)Q(L)$ of required wholesale (non-deposit) funding.

When the credit line is contracted at time zero, the bank prices the expected debt-overhang wedge $E(\tau)$ into the terms of the line. This expected wedge includes the effect of covariance between the credit spread S and the required quantity $(1 - \varphi)Q(L)$ of wholesale funding. Section 5 explains that, empirically, this covariance has been significantly positive for LIBOR credit lines because firms have tended to draw heavily on their revolvers when bank credit spreads are sharply elevated. In Section 6, we calibrate this model to empirical evidence for LIBOR-linked credit lines. With the resulting calibrated model, we show that most corporate borrowers will draw even more heavily on SOFR-linked lines when bank wholesale funding spreads spike, because of the opportunity to borrow at a drawn rate that is far below LIBOR. This increases the covariance between the bank's required amount wholesale funding per credit line and the bank's wholesale funding spread, exacerbating the debt-overhang wedge for the representative calibrated large bank.[18]

We also show in Section 6 that the resulting potential adverse impact of reference rate transition on credit provision is mitigated for banks with low debt overhang wedges, whether due to high levels of capitalization (low S), or an expectation of a high fraction φ of depositing of line draws.

We assume that the bank maximizes the initial market value of its equity and Bertrand-competes against other banks of the same credit quality for providing credit lines. At time 0, the bank therefore offers the borrower, for any line size L, a fixed spread $s(L)$ at which the bank's shareholders break even on marginal new credit lines, implying that $E[G(L)] = 0$. This pins down the contractual spread

$$s(L) = \frac{E[p_1 Q(L)(1 - \delta(1 + R - (1 + C)(1 - \varphi)S))]}{E[\delta p_1 Q(L)]}. \tag{6}$$

[18]As calibrated in Section 6 to empirical data for our sample of large banks, spanning 2015-2021, the borrower's liquidity shock ψ and the bank's funding spread S are affiliated random variables. This is so because the calibrated model has $\psi = (K(S) + \epsilon)^+$, where K is strictly increasing and ϵ is independent of S. The affiliation of ψ and S and the concavity of the liquidity benefit function $b(\,\cdot\,, \psi)$ imply that the drawn quantity $B\,(\delta(1 + r + s(L))), \psi)$ and S are also affiliated for the risk-free reference, and this covariance $\mathrm{cov}(Q(L), S)$ is anticipated to be higher than for the case of a credit-sensitive reference rate.

The borrower then solves (3) for the optimal line amount L^*. An alternative would be to model imperfect competition between banks, which would be more realistic with respect to the magnitudes of profit markups, but would not alter the thrust of our characterization of the effect of reference rate choice on incentives for loan provision.

In summary, in our setting, the switch from credit-sensitive reference rates like LIBOR to risk-free reference rates could increase the expected pricing of credit obtained on committed lines, because borrowers will draw more credit when bank funding costs are sharply elevated. Section 6 shows, however, that this simple effect is sharply reduced, or even reversed, if corporate borrowers deposit a sufficiently high fraction of their drawn credit. In Section 5 we therefore focus attention on the extent to which corporate borrowers deposit their line draws under stressed market conditions, such as during the COVID recession. We show that this propensity to deposit depends significantly on the type of bank. We also show in Section 6 that the impact of reference rate choice on borrower welfare has a somewhat different character, and also depends importantly on bank quality.

4 Data

Our empirical analysis builds mainly on two confidential data sets available at the Federal Reserve: the FR 2052a and the FR Y-14Q. We use several additional sources such as the FR Y-9C, FR 2420, FRED, RateWatch, Bloomberg, S&P Compustat, and Capital IQ. Here, we briefly describe these data. A more detailed documentation of the data can be found in Appendix Section A.

Our primary data source is the FR 2052a data collection, which is designed to monitor the liquidity profile of large US bank holding companies (BHCs). The respondent panel consists of BHCs designated as global systemically important banks (G-SIBs) and foreign banking organizations (FBOs) with US broker-dealer assets greater than \$100 billion. The data collection was started in December 2015 and expanded to a larger panel of banks in July 2017. This data source has two crucial advantages over publicly available regulatory bank filings such as the FR Y-9C. First, the FR 2052a data are more granular and report assets and liabilities by product type, maturity, collateral status, and counterparty. This additional granularity allows us to establish several previously unreported facts about US banks' funding structures and exposures to variation in bank funding spreads. For instance, Appendix Figure A.1 illustrates how the FR2052a data allow us to break down deposits and wholesale funding by more detailed categories than would be possible from the publicly available data in FR Y-9C. Second, the data are collected at a higher frequency. Firms with $700 billion or more in total consolidated assets or $10 trillion or more in assets under custody must submit a report on each business day. Firms with more than $50 billion but less than $700 billion in consolidated assets report at the end of each month. These higher frequencies allow us to document how bank balance sheets evolved during the COVID recession more precisely than was possible in previous work.

Our second main data source is the FR Y-14Q data collection, which is a supervisory data set maintained by the Federal Reserve to support capital stress testing. The reporting institutions comprise US BHCs, intermediate holding companies (IHCs) of foreign banking organizations, and savings and loan holding companies with more than $100 billion in total consolidated assets. We use the corporate loan schedule (H.1) and the commercial real estate schedule (H.2). Both schedules contain loan-level information for commitments of at least $1 million. These data allow us to study how reference rates are used in C&I and CRE lending. The corporate loan schedule (H.1) also includes borrower reference information such as employer identification numbers (EINs), stock tickers, and CUSIPs. We use these reference data to merge firm financials from S&P Compustat and Capital IQ to analyze firm-level drawdowns and cash management during the COVID shock.

Combining the above data sets with publicly available information from the FR Y-9C and bank call reports, our primary sample of banks consists of 24 of the largest US banks. We exclude the US operations of foreign banks from the parts of our analysis that rely on the FR 2052a, as we do not observe the full liability profile for these institutions. For our analysis, we distinguish between different bank types: "universal" banks, "regional" banks, credit-card firms, trusts, and investment banks. For some analyses, namely when using the FR Y-14Q to identify details on bank loan terms, we restrict our sample further to a subset of 20 banks that reported Y-14Q data as of December 31, 2019. A list of all banks in our sample, their types, and the panels in which they report can be found in Appendix Table A.1.

We also construct measures of bank funding rates using various sources. First, we use the FR 2420 to construct these measures for corporate deposits, interbank deposits, and other deposit and wholesale funding rates. The FR 2420 is a transaction-based report that collects daily liability data on federal funds purchased, certificates of deposits (CDs), and selected deposits by counterparty type, allowing us to distinguish between rates paid by financial versus non-financial counterparties. The reporting panel comprises US commercial banks and thrifts that have $18 billion or more in total assets. Bank savings and checking deposit rates are taken from RateWatch. Additional information on bank funding costs is sourced from FRED and Bloomberg, including term LIBOR, SOFR, and BSBY rates. We also source data on fixed-rate advances provided by the Federal Home Loan Banks (FHLBs) of Des Moines, Pittsburgh and Dallas.

5 Bank Funding Exposures and Revolving Credit at Large US Banks

In this section, we analyze the empirical implications of the provision of revolving credit for bank funding risk. First, we provide a set of key facts about the composition of bank funding and document the historical sensitivity of various bank funding rates to measures of bank funding spreads such as the LIBOR-OIS spread. We measure LIBOR-OIS as the difference between three-month LIBOR and three-month overnight index swap rates (OIS), for which the underlying rate is the effective fed funds rate. Second, we investigate the extent to which revolving credit could pose bank funding risk by studying the outstanding amounts of revolving credit for BHCs and the funding of drawdowns, during both the COVID recession and the GFC.

5.1 The Composition of Bank Deposit and Wholesale Funding

Table 1 provides evidence bearing on the composition of bank funding, as reported in the FR 2052a, allowing us to establish several novel facts about the composition of bank funding. In Panel A of Table 1 we report deposits by counterparty, maturity, and type. The level of granularity offered by the FR 2052a was not available for US banks before the recent introduction of the FR 2052a dataset.

As of December 2019, deposits account for 59% of total bank assets. The largest providers of bank deposits are retail customers, who provide around 50% of all deposit funding. The second most important source of deposit funding is non-financial corporate deposits (23%) followed by deposits from financial institutions (15%) and small businesses (7%). Most financial deposits are held by non-bank financial institutions (NBFIs), around 11%.[19]

Across all counterparty types, more than 91% of all deposits are without maturity and are available on demand—this form of deposit is referred to as “open." Time deposits are uncommon. The share of deposits with a fixed term is largest among retail depositors, at less than 14%. Retail and small-business deposits are mostly FDIC insured, in contrast to deposits from all other counterparties, which are

[19]There is also heterogeneity across banks, see for instance Table G.1 in the Appendix that shows cross-bank distributions. While most banks predominantly rely on retail deposits, the reliance on these deposits varies, as the interquartile range varies from 43% to 83%. See also Table G.2 in the Appendix, which restricts the sample to “regional” banks. Regional banks are slightly more reliant on retail and small business deposits than the rest of the industry.

almost entirely uninsured. Further, most deposits – around 62% – are considered stable, labeled as "relationship" accounts in Table 1, and are thus unlikely to cause an increase in banks' funding costs under stressed market conditions.[20] Finally, only a small portion of deposits (under 5%) are brokered deposits, which are less stable and more rate-sensitive.

We turn next to the composition of wholesale funding in Panel (B) of Table 1. Around 16% of outstanding bank assets are financed by wholesale funding. Reflecting regulatory reforms after the GFC, the majority of wholesale funding of large US BHCs is longer term. As of December 2019, less than one-third of outstanding wholesale funding was expected to mature within 12 months and only 13% within one month (see also Anderson, Du, and Schlusche, 2021). Most wholesale funding is provided through unstructured or structured long-term debt issues, which together account for 71% of total wholesale funding[21] and are mostly fixed rate.[22]

The second most important type of wholesale funding is an advance from a Federal Home Loan Bank (FHLB). Banks that join the FHLB system can obtain secured loans from FHLBs, which in turn raise funds from money market funds (Gissler and Narajabad, 2017). FHLB advances are typically secured by real estate mortgages and a "super lien" on other bank assets. The maturity of FHLB advances can range from very short term (overnight) to very long term (30 years). Overall, FHLB funding is an important source of bank funding and accounts for 8% of wholesale funding.[23]

There is relatively little reliance on other forms of wholesale funding, especially types of funding that are most credit-sensitive. For instance, large US banks rely very little on unsecured funding sources such as wholesale certificates of deposits (2.4%) and commercial paper (1.2%).[24] Instead, banks more

[20]We use categories of funding as defined in the liquidity coverage ratio (LCR) rule to identify these types of deposits. For retail and small business deposits, relationships accounts consist of transaction accounts (for example, demand deposits) or non-transaction accounts (for example, savings accounts). For corporates and other counterparty types, relationship accounts are operational deposits, defined as those used for cash management, clearing, or custody services.

[21]Structured debt refers to debt instruments with original maturity greater than one year whose principal or interest payments are linked to an underlying asset (for example, commodity-linked notes). Unstructured debt refers to vanilla products with original maturity greater than one year, for instance floating rate notes linked to indexes like LIBOR or effective fed funds or with standard embedded options (that is, call/put).

[22]According to data obtained from Bloomberg, we find that most of long-term bank debt is fixed rate. Only 29% of claims are floating rate, and of those only 11% reference LIBOR, see Table G.4. We match the data on long-term debt with public balance sheets data only for a subset of the banks in our sample which consists mostly of banks classified as "regional" banks. See Section G for details on our match quality.

[23]There is also cross-sectional variation in the types of wholesale funding used. For instance, regional banks rely more on FHLB advances, which made up around 30% of their wholesale funding as of December 31, 2019, see Panel (B) of Table G.2 in the Appendix. These regional banks' overall lending tends to have a larger share of C&I lending. They also rely relatively more on deposit funding than the average bank, as 76% of all assets are financed by deposits and only around 11% by wholesale funding. The US operations of FBOs also have a substantially different funding profile than the domestic U.S. banks, see Table G.3. Nearly all deposits are uninsured, and the US operations of FBOs rely primarily on corporate deposits and internal funding from overseas branches (via deposits or wholesale funding). We exclude FBOs from our primary analyses because we do not observe the full consolidated asset and liability profile of the institution – only that of their US operations.

[24]By contrast, the US operations of FBOs rely more heavily on wholesale CDs, which account for 25% of third-party assets,

Table 1: **Deposit and Wholesale Funding Breakdown as of December 31, 2019**

Panel A: Deposit Funding by Counterparty (percent)								
Counterparty	Open	1 Day- 1 Year	1 Year+	Uninsured	Relation -ship	Brokered	Total Deposits	Total Assets
Retail	86.6	9.2	4.2	28.6	67.8	7.2	50.0	29.5
Non-Financial Corp.	96.5	3.3	0.1	96.1	45.2	1.0	23.3	13.7
NBFI	94.7	3.7	1.6	94.6	60.2	1.6	11.2	6.6
Small Business	98.0	1.9	0.1	45.8	80.5	6.0	6.6	3.9
Bank	96.7	2.8	0.5	97.3	65.4	0.1	4.2	2.5
Other Counterparty	90.1	8.9	1.0	95.6	59.1	0.1	2.5	1.5
Public Sector Entity	96.0	3.7	0.2	97.3	50.6	0.3	2.4	1.4
All Counterparties	91.3	6.3	2.4	59.0	61.8	4.4		

Panel B: Wholesale Funding by Type (percent)								
Product	Open- 30 Days	1-6 Months	6 Months- 1-Year	Long- Term	Collateral -ized	Prime Brokerage	Wholesale Funding	Total Assets
Unstructured LTD	1.1	4.5	5.3	89.1	0.0	0.0	59.1	9.1
Structured LTD	3.1	8.4	9.3	79.2	0.0	0.0	12.4	1.9
FHLB	22.5	31.9	13.0	32.6	100.0	0.0	8.1	1.3
Conduit and SPV	13.9	23.3	8.3	54.5	99.4	0.0	6.5	1.0
Free Credits	100.0	0.0	0.0	0.0	0.0	50.7	6.3	1.0
Other Wholesale	55.7	30.8	10.5	3.1	0.0	0.0	4.0	0.6
Wholesale CDs	15.9	54.9	25.3	3.8	0.0	0.1	2.4	0.4
CP	27.8	64.9	7.3	0.0	0.0	0.0	1.2	0.2
All Products	13.0	11.2	7.0	68.9	14.6	3.2		

Notes: Data Sources: FR2052a, FR Y-9C. Panel A represents the distribution of deposit characteristics by counterparty type across 24 banks in the monthly FR 2052a panel. Other Counterparty includes central banks, debt-issuing special purpose entities (SPEs), GSEs, multilateral development banks, sovereigns, other supranationals, counterparties categorized as "other" and deposits with missing information on counterparty type. Maturity information reflects remaining maturity as of Dec. 31, 2019, and not maturity at origination. Relationship deposits reflect retail and small business deposits classified as transactional accounts (for example, demand deposits) or non-transactional relationship accounts (e.g. savings accounts), and operational deposits at all other counterparties. Panel B represents the distribution of wholesale funding characteristics by product type in the monthly FR 2052a panel across all banks. Conduit and SPV financing includes asset-backed commercial paper, other asset-backed securities, collateralized CP, covered bonds, and tender option bonds. Other Wholesale Funding includes banks' draws on committed lines, government supported debt, onshore and offshore borrowing (for example, fed funds), structured notes, and unsecured notes.

often use secured funding provided by conduits (e.g. asset-backed commercial paper) which constitutes around 6% of wholesale funding. Free credits (deposits placed at broker-dealers) account for around 6% of wholesale funding, half of which come from prime-brokerage clients.

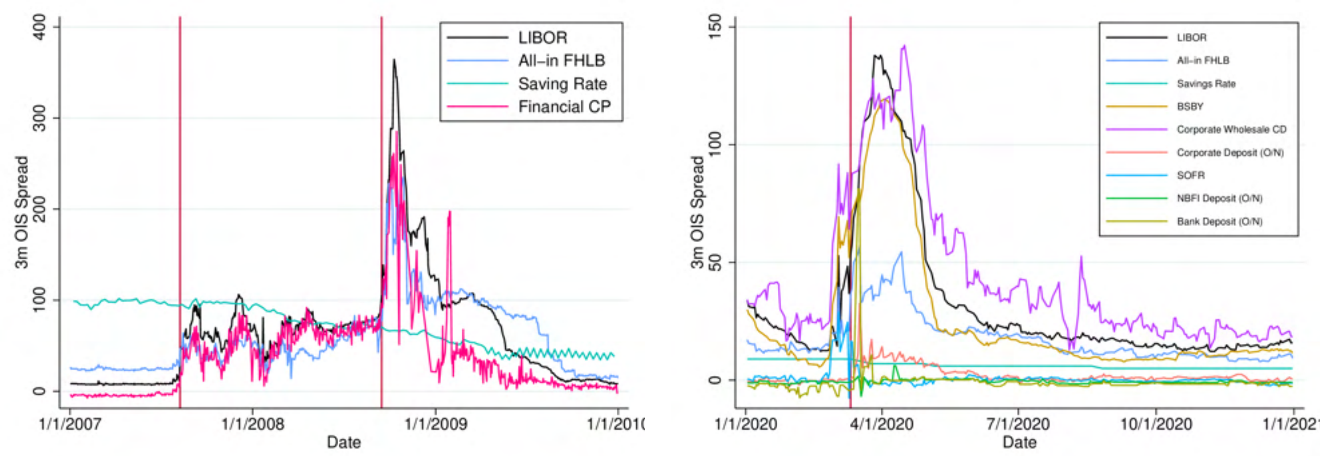
5.2 Sensitivity of Bank Funding Rates to the LIBOR-OIS Spread

We next study the sensitivity of various types of bank funding rates to changes in funding conditions. Given the variation in market power, riskiness, sophistication or opportunity costs across different counterparties and product types, the extent to which the various types of short-term debt empirically correlate with the LIBOR-OIS spread may vary. Understanding this variation is key to understand which types of funding sources are relatively more expensive to bank shareholders when used to fund drawdowns .

see Table G.3.

We thus study the historical sensitivity of bank funding rates that correspond to the different funding sources listed in Table 1 to the LIBOR-OIS spread during periods of financial distress. Figure ?? shows data bearing on some key funding rates during the GFC in Panel (a) and during the COVID recession in Panel (b). During the GFC, LIBOR-OIS started to increase around August 2007, at the collapse of the asset-backed commercial paper (ABCP) market (Covitz, Liang, and Suarez, 2013). Between the summer of 2007 and September 2008, LIBOR-OIS remained elevated and just below 100bp. Reported LIBOR rates, however, were downward biased by manipulative reporting (Duffie and Stein, 2015). LIBOR-OIS returned toward normal levels near the end of the crisis.

During the GFC, rates for retail deposits (proxied by savings and checking account rates from RateWatch) were not sensitive to movements in LIBOR-OIS spreads. This is unsurprising. Most retail deposits are insured and banks exhibit substantial market power over depositors, implying a low sensitivity to changes in economic conditions (Driscoll and Judson, 2013; Drechsler, Savov, and Schnabl, 2017). Rates on financial CP, however, rise sharply with increases in LIBOR-OIS, as shown in Figure 2. As documented by Ashcraft, Bech, and Frame (2010), rates on “safer" borrowing—such as collateralized advances from FHLBs—were significantly lower than LIBOR in the early stages of the crisis, but rates on these somewhat lower-risk instruments also increased at the peak of the GFC.



(a) Global Financial Crisis

(b) COVID-19 Recession

Figure 2: **Bank funding rates during financial distress**. Various wholesale and deposit funding rates are shown for periods covering the GFC (Panel (a)), and COVID pandemic (Panel (b)). Data Sources: FR2420, FRED, Bloomberg, FDIC, RateWatch, FHLB Des Moines Historical Rate File. “All-in” FHLB spreads are calculated similarly to Ashcraft, Bech, and Frame (2010), with additional parameters to capture equity cost for FHLB stock. Appendix Section A provides details. In the COVID figure, Corporate Wholesale CD and Bank, Corporate, and NBFI O/N deposit rates are calculated from bank-level transactions in the FR 2420 report. 3M CD rates reflect issuances with maturities between 89 and 92 days. "O/N" refers to overnight rates. We aggregate trades by date, calculating the median daily interest rate weighted by transaction amount. We exclude dates with fewer than 10 transactions, and carry forward the prior date’s rate. We then calculate a rolling average rate that averages the interest rates paid on the five most recent trading dates, to smooth our series.

A similar pattern holds for the COVID recession, as shown in Panel (b) of Figure 2. LIBOR-OIS increased throughout March, especially once the World Health Organization announced on March 11 that COVID-19 had become a global pandemic. However, LIBOR-OIS reached a much lower peak than it had during the GFC. For the COVID episode, we have more precise measures for bank funding costs. For instance, we can obtain the rates for overnight corporate deposits and rates on deposits held by other banks or non-bank financial institutions (NBFI). These rates, unlike retail deposit rates, are sensitive to the effective fed funds rate. However, spreads of deposit rates over the effective federal funds rate are relatively insensitive to LIBOR-OIS during the COVID episode.[25] We find that an increase in LIBOR-OIS of 100 basis points is associated with a mere 10-basis-point increase in overnight corporate deposit spreads, a 5-basis-point increase in bank deposit spreads, and a 1-basis-point increase in NBFI deposit spreads, as illustrated in Appendix Figure G.1.

As expected, wholesale bank funding spreads, such as spreads of corporate wholesale CDs over OIS, closely track LIBOR-OIS during the COVID recession.[26] A recently introduced Bloomberg credit-sensitive three-month bank funding rate index, BSBY, also closely tracks LIBOR during the COVID pandemic. In line with patterns observed during the GFC, the "All-in" FHLB spreads also rose, but peaked at less than 40% of LIBOR-OIS.

Our analysis of funding rate sensitivity shows that deposit funding is a cheap source of funding for banks. While this is less surprising for retail deposits, it also holds for corporate deposits and for open deposits from financial institutions, which are sensitive to risk-free rates but not to LIBOR-OIS. Wholesale funding is, in contrast, credit sensitive and more expensive. As per our analysis in Section 5.1, banks make little use of such relatively credit-sensitive forms of funding and, to the extent it is used, it is longer term and fixed rate. This analysis, of course, does not preclude the use of unsecured wholesale funding—which is expensive for bank shareholders especially during times of distress—to fund drawdowns. We now address this in more depth.

5.3 Undrawn Commitments

Our theoretical analysis in Section 3 emphasizes that banks may be exposed to funding risk when providing revolving credit. Table 2 shows that this risk is economically large. For the banks in our main

[25]We construct these spread by averaging across overnight deposits held by either non-financial corporates, banks or NBFIs as reported in the FR 2420 and subtract the effective fed funds rate.

[26]Section G provides additional evidence on the cross-sectional variation in CD rates for both non-financial corporates and non-bank financial institutions (NBFIs). We can see that even across the trade distribution, spreads widened for term CDs while spreads remained relatively flat for overnight deposits.

Table 2: **Bank Credit by Loan Type for Large U.S BHCs as of December 31, 2019**

Loan Type	Util ($B)	Comm ($B)	% Utilized	No. Banks
All Loans	1579.16	3551.52	44.46	21
Credit Line	543.76	1876.39	28.98	20
Term Loan	310.37	375.26	82.71	20
Other C&I	133.88	540.05	24.79	21
Commercial Real Estate	591.16	759.82	77.80	20

This table displays the distribution of utilized and committed credit across loan products. We source exposures from the FR Y-14Q Schedule H1 B (corporate loans) and Schedule H2 (commercial real estate). Data are as of 2019q4. We include only domestic C&I and CRE lending. US subsidiaries of foreign banks are excluded from our analysis. "Other" C&I loans include non-revolving credit lines, capitalized lease obligations, standby letters of credit, other assets, fronting exposures, commitments to commit, and exposures classified as "other."

sample, overall commitments sum to more than $3.5 trillion—more than twice the $1.6 trillion in funded credit across C&I and CRE lending. Further, approximately 70% of these loans are indexed to LIBOR as of 2019, see Table G.9 in the Appendix.

These unfunded commitments represent a substantial risk to bank liquidity and may become even more of a funding risk when LIBOR is replaced with a risk-free alternative such as SOFR. If borrowers draw on their lines in periods of distress, banks may need to pay expensive funding costs in order to obtain the cash demanded by their borrowers.[27] As we show in Section 3, these costs are borne by bank shareholders and benefit existing debt-holders. However, the costs to shareholders may be reduced depending on how banks fund these draws. If borrowers leave all of their draws on deposit at the same bank, the relevant funding credit spread is near zero and the cost to shareholders is minimal. If, however, banks are forced to obtain funding at more credit-sensitive rates, shareholders can bear a substantial cost.

5.4 Dynamics of Assets and Liabilities During Times of Distress

Given the large outstanding unfunded credit commitments of banks and the high associated potential funding cost to bank shareholders, we next ask: How have bank balance sheets historically evolved during times of distress that featured elevated bank funding costs? Is the covariance between drawdowns and bank funding costs—a key determinant of credit supply according to our theory in Section 3—positive and large? And how are drawdowns actually funded?

As descriptive evidence bearing on the evolution of bank balance sheets, Figure 3 shows cumulative

[27] For revolving credit lines, borrowers can draw and repay funds at their discretion, at least "on paper." In practice, however, not all commitments can be drawn, because covenants (Sufi, 2009) or other loan terms can limit the ability or the incentives of borrowers to draw (Chodorow-Reich, Darmouni, Luck, and Plosser, 2021). Nonetheless, the extent to which credit line draws need to be funded is largely out of a bank's control.

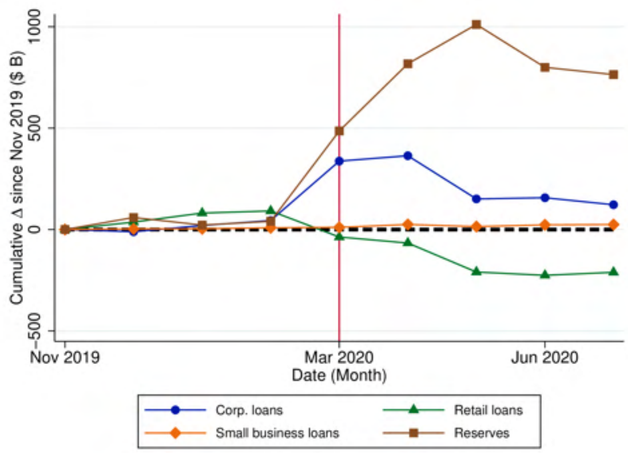
industry-level changes, in billions of dollars, of various balance sheet items in the periods surrounding the COVID recession and for the GFC. For the GFC, we rely on publicly available data from the Federal Reserve H8 series, sourced via FRED. These data allow us to distinguish between broad loan types (for example, C&I and home equity lines) on the asset side and, on the liability side: deposits, interbank funding, and other borrowing (which pools wholesale funding, FHLB funding, and borrowing from the Federal Reserve). For the COVID recession, we use the FR 2052a data, which are more detailed. For instance, the FR 2052 gives us the ability to distinguish within both loans and deposits between counterparty types, allowing us to separate C&I lending to large corporates and to small businesses. Figure 3 shows the dynamics of bank balance sheets, split into assets and liabilities. Panels (a) and (b) show the dynamics for large US BHCs, which report monthly in the FR2052a, around the COVID recession. Panels (c) and (d) show the dynamics for large domestically chartered banks around the Lehman failure.

There is substantial growth in C&I lending following both shocks, partly or entirely driven by credit line drawdowns, as shown in Panels (a) and (c) of Figure 3. During the COVID recession, we observe that drawdowns on corporate credit lines increase by close to $300 billion by April, which is an increase of almost 20% in total C&I lending (Li, Strahan, and Zhang, 2020; Acharya and Steffen, 2020). Most of these drawdown were in LIBOR-linked facilities[28] and were driven by the largest firms (Greenwald, Krainer, and Paul, 2020; Chodorow-Reich, Darmouni, Luck, and Plosser, 2021). In line with firms drawing lines to weather the bond market turmoil, lines are repaid quickly after the bond market started to recover (Darmouni and Siani, 2022). Following Lehman's failure, there was a $50 billion (6%) increase in C&I lending overall, as large corporations drew on their lines in fear of future bank failures (Ivashina and Scharfstein, 2010).[29]

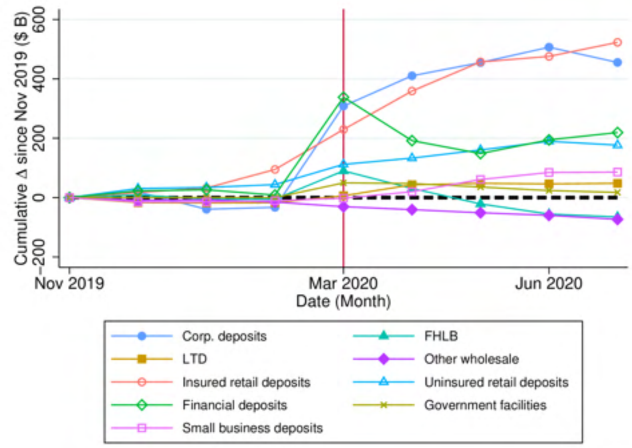
We next turn to the evolution of bank liabilities, in Panels (b) and (d) of Figure 3. In contrast to corporate lending, which increased in both periods of distress, the evolution of bank liabilities varied more between the COVID pandemic and the Lehman failure. Starting with the COVID pandemic, we notice that the increase in bank liabilities was driven by liabilities that exhibited limited sensitivity bank credit risk (as measured by LIBOR-OIS). Both corporate and financial deposits increased by around $340

[28]See Panel (a) of Figure G.4 in the Appendix.

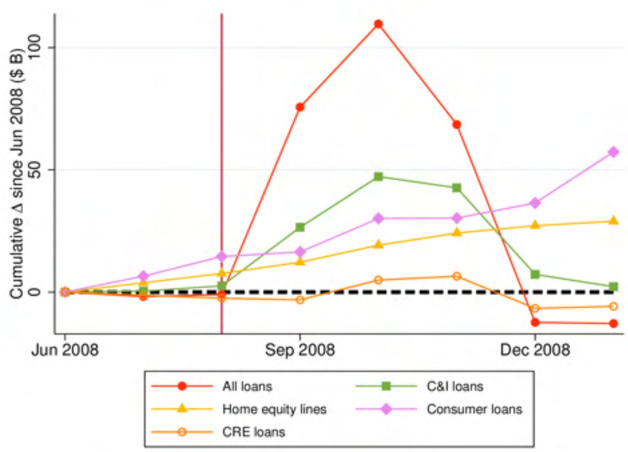
[29]There was also a sustained increase in C&I lending after the ABCP run in 2007, partly due to draws on corporate credit lines (Berrospide, Meisenzahl, and Sullivan, 2012). Further, there was limited growth in other loans after the COVID shock. Following the March 2020 pandemic declaration, there was a decrease in aggregate retail lending. Small business only increased in April with the launch of the Paycheck Protection Program (PPP) (Granja, Makridis, Yannelis, and Zwick, 2022). After Lehman's collapse, there were continued draws on home equity lines and consumer loans (and, possibly, credit cards), although both increases generally followed pre-Lehman growth trends.



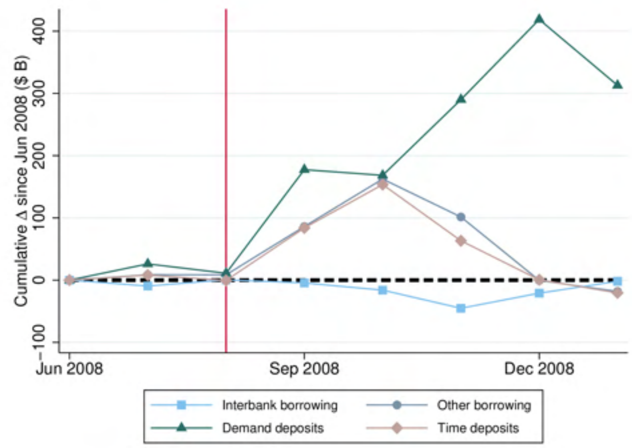
(a) Loans During COVID Recession



(b) Funding During COVID Recession



(c) Loans Around the Lehman Failure



(d) Funding Around the Lehman Failure

Figure 3: **Industry Assets & Liabilities in Periods of Distress.** This figure shows the evolution of aggregate assets and liabilities during the GFC (following Lehman's collapse) and during the COVID pandemic (following the declaration of the global pandemic in March 2020). Values represent cumulative growth/decreases compared to the starting month in billions of dollars. Data from the GFC are sourced from the FRED series for large domestically chartered banks, adjusted for large M&A based on public notes to H8 series. Data from COVID are sourced from the FR 2052a monthly balanced panel of 24 banks. Due to balance reclassifications between business segments in the FR 2052a, we exclude one bank from our aggregate series for: small business loans, small business deposits. We include a similar version of these figures, based on log-change vs. the pre-shock values, in Appendix Figure G.5. We also include a version of the COVID graphs for U.S. Branches of FBOs in Appendix Figure G.6.

billion (20%) in March 2020, almost entirely in open maturity deposits (see Appendix Figure G.4). Rates on these deposits largely tracked the federal funds rate during the COVID recession and were thus cheaper than unsecured wholesale funding (see Figure G.1). We also notice a striking increase in FHLB advances—nearly $100 billion, or 40% of funding—in March 2020. The reliance on FHLB advances in distress aligns with evidence from the GFC (Ashcraft, Bech, and Frame, 2010; Acharya and Mora, 2015), as FHLBs provide cheaper funding than unsecured wholesale markets.

Retail deposits also rose significantly in March, by $200 billion, with steady increases in subsequent months. The increase in retail deposits can be explained in part by government stimulus checks and precautionary savings (Cox, Ganong, Noel, Vavra, Wong, Farrell, Greig, and Deadman, 2020). Small business deposits also increased starting in April-May, likely related to the disbursement of PPP funds. We also see a *decrease* in more expensive sources of short-term wholesale funding, such as commercial paper (CP), certificates of deposits (CDs), and funding from off-balance sheet conduits. The sole increase in expensive funding was in the form of long-term debt issuance, starting in April-May 2020, which may have been a response to reduced yields that came on the back of the Fed's announcement on March 23 that it would purchase corporate bonds.[30]

Following Lehman's failure, we see an increase of around $160 billion (approximately 15%) in "other borrowing"—a broad category of liabilities that includes short-term unsecured wholesale funding, as well as advances from FHLBs. Deposits grew by over $300 billion (about 9%), of which a significant portion (by October 2008, nearly 50%) was in more expensive large time deposits. A crucial difference between the GFC and the COVID recession is that the GFC saw a collapse of interbank borrowing following Lehman's failure (Afonso, Kovner, and Schoar, 2011), requiring some banks to raise additional funds to make up for the lost interbank funding.

While both of these episodes saw significant credit line drawdowns, the composition of aggregate bank funding appears to tilt toward more expensive sources during the GFC than during the COVID recession. During the COVID recession, cheap deposit funding increased and relatively expensive wholesale funding decreased. In contrast, the evidence suggests that the increase of deposit funding during the GFC was in the form of relatively more expensive time deposits, especially at weaker banks (Acharya and Mora, 2015). Further, corporate drawdowns during the GFC were akin to a run on some banks (Ivashina and Scharfstein, 2010), forcing some banks to turn to relatively expensive wholesale

[30] See Federal Reserve announces extensive new measures to support the economy, Board of Governors of the Federal Reserve System, March 23, 2021 as well as Boyarchenko, Kovner, and Shachar (2022). Further, note that most of these aggregate trends for the COVID pandemic also hold true in the cross-section of banks.

funding.

5.5 How Credit-Line Drawdowns Are Funded

We next address how banks finance drawdowns. At the bank level, we can exploit the granularity of FR 2052a data and use cross-sectional variation to tighten our empirical understanding of how drawdowns are funded during the COVID recession. At the borrower level, we use data from FR Y-14Q, Compustat, and Capital IQ to study the relationships between drawdowns and cash holdings during both the COVID recession and the GFC.

Bank-level Evidence We first study the raw data and correlate changes in outstanding utilized C&I exposure from the end of February 2020 through end of April 2020 with changes in corporate deposits, FHLB advances, and unsecured wholesale funding. The left panel of Figure 4 shows linear fits. Here, for confidentiality reasons, we group BHCs into bins, with several BHCs per bin.

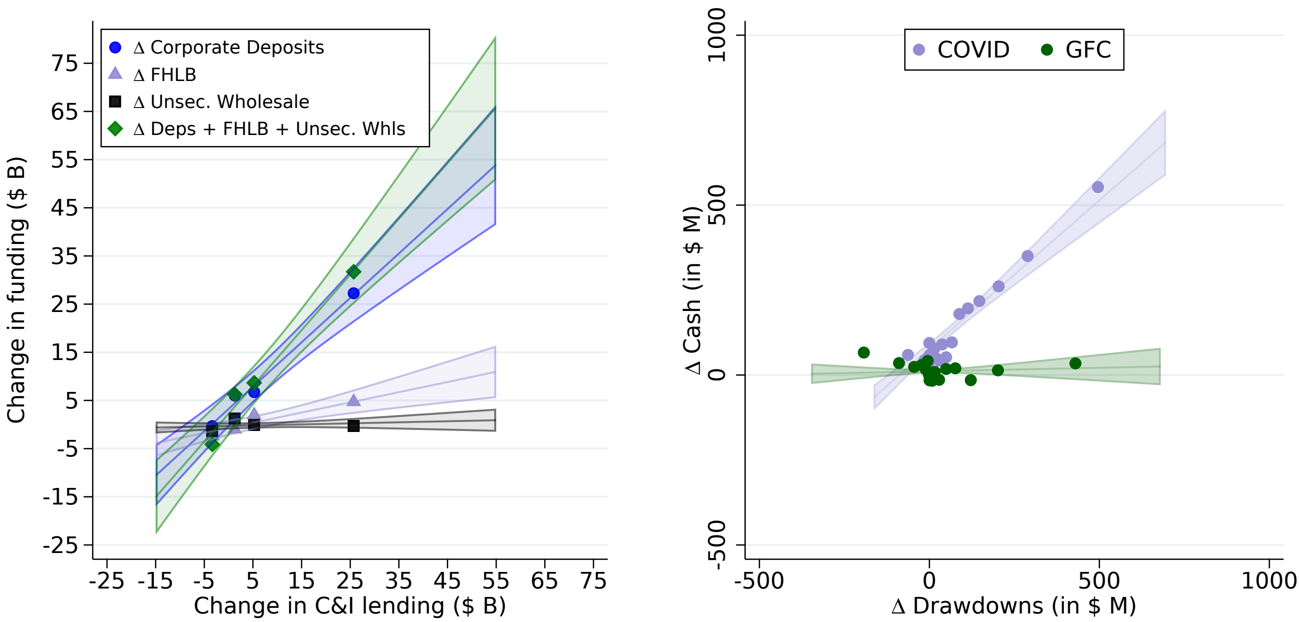
There is a strong correlation between an increase in C&I loans on the one hand and corporate deposits and FHLB advances on the other, with the slope being much higher for the former. Thus, our findings suggest that drawdowns in March and April 2020 were by and large for precautionary purposes, with corporates drawing their credit lines but leaving the drawn amounts in their deposit accounts. Firms plausibly chose to draw the cash on their lines before lenders might have invoked covenants that could have blocked them from doing so at a later stage. Further, to the extent that this drawing was not precautionary and the funds drawn were transferred to other banks, banks raised funds from relatively cheaper FHLB advances rather than tapping expensive unsecured wholesale funding.

We confirm this in the cross-section by estimating a model of the form:

$$\Delta y_{bt} = \tau_t + \gamma_b + \Delta \text{Drawdowns}_{bt} + \Delta \text{Drawdowns}_{bt} \times \text{COVID} + \epsilon_{bt}, \tag{7}$$

where, for bank b, $\Delta y_{bt} = y_{bt} - y_{b,t-1}$ and y_{bt} is the dollar amount of corporate deposits, FHLB advances, or unsecured wholesale funding in month t. Here, $\Delta \text{Drawdowns}_{bt}$ is the month-to-month dollar change in C&I loans. COVID is a dummy that takes the value one during March and April 2020. Finally, τ_t is a set of time fixed effects and γ_b a set of bank fixed effects.

Results are reported in Table 3. We find that each dollar of a corporate drawdown during the COVID recession is associated with an average increase in corporate deposits of 89 cents, supporting the notion



(a) Bank-level.

(b) Borrower-level.

Figure 4: **Drawdowns and Corporate Deposits.** Panel (a) shows a binned scatter plot using bank-level data from the FR 2052a, with 6 banks per bin, during the COVID pandemic showing a $1 change in C&I loans (drawdowns) on the x-axis against the corresponding dollar changes in funding sources on the y-axis. Panel (b) shows a binned scatter-plot of borrower-level data from Compustat, Capital IQ, and the FR Y-14Q with dollar drawdowns on the x-axis and change in cash on the y-axis, separately for the COVID pandemic and the GFC. Changes in both cash and drawdowns are trimmed at the 1% and 99%.

that drawdowns are precautionary and deposited at the *same* bank. (See Panel (a).) However, this was mostly driven by the largest US banks. At the large regional banks in Panel (b), only around 40% of drawdowns were deposited. The regional banks instead relied on advances from FHLBs,[31] which funded around 40% of additional draws.[32] Importantly, banks did not require additional unsecured wholesale funding to fund corporate draws, irrespective of their business model. In fact, the largest banks saw deposit growth significantly in excess of their drawdowns, as shown in column (5) of Panel (a).[33] This was driven by a growth in deposits at non-bank financial institutions, possibly because of Federal Reserve asset purchases and the concentration of reserve balances at larger banks. The

[31] The entirety of these advances was sourced from pre-pledged collateral at FHLBs, as we show in Table G.6.

[32] A potential explanation for the fact that regional banks had to raise relatively more funding from FHLBs is that drawdowns on syndicated facilities may not be deposited at the lending bank but rather at the main relationship bank of the borrower. See also Kiernan, Yankov, and Zikes (2021) for an analysis of liquidity co-insurance in syndicates. While we do not observe each borrower's relationship bank, there is a significant correlation between bank size and being agent on a syndicated facility (which is possibly correlated with being the main relationship bank. Our results also echo the findings of Glancy, Gross, and Ionescu (2020), that smaller banks saw a smaller portion of drawdowns deposited than did larger banks. However, we show that even among the largest US banks (those with over $ 100 billion in assets), there were differences in the fractions of deposited line draws.

[33] This increase in both total deposits and drawdowns during COVID is also consistent with a "flight to safety" during previous stress events (Gatev and Strahan, 2006), excluding the GFC when banks were at the center of the crisis (Acharya and Mora, 2015).

Table 3: **Drawdowns and Deposits in the Cross-Section: Monthly Data**.

Dependent variable	Δ Corp. Deposits	Δ FHLB	Δ Unsec. WSF	Δ Total Cols. (1-3)	Δ Total Deposits
Panel A: All Banks					
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns	0.01	-0.01	-0.00	0.00	-0.03
	(0.01)	(0.03)	(0.01)	(0.03)	(0.03)
Δ Drawdowns × COVID	0.89***	0.16	0.02	1.07***	1.79**
	(0.27)	(0.10)	(0.05)	(0.37)	(0.78)
N	1107	1107	1107	1107	1107
No. Banks	25	25	25	25	25
R^2	0.397	0.177	0.100	0.394	0.424
Panel B: Regional Banks Only					
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns	0.01*	-0.01	-0.00	-0.01	0.02
	(0.00)	(0.03)	(0.01)	(0.03)	(0.02)
Δ Drawdowns × COVID	0.42**	0.40***	-0.05	0.77***	0.37
	(0.20)	(0.14)	(0.06)	(0.23)	(0.46)
N	522	522	522	522	522
No. Banks	12	12	12	12	12
R^2	0.387	0.320	0.143	0.381	0.454

Notes: This table reports estimates from a bank-month-level panel regression of the form:

$$\Delta y_{bt} = \alpha + \Delta\text{Drawdowns}_{bt} + \Delta\text{Drawdowns}_{bt} \times \text{COVID} + \gamma_b + \eta_t + \epsilon_{bt}.$$

Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We exclude from our analysis the bank-month in which BB&T merged with SunTrust. We include bank and time fixed effects in all specifications. The dependent variable in column (3), unsecured wholesale funding (WSF), captures short-term wholesale funding categories: CP, CD, non-prime brokerage free credits, and other unsecured wholesale funding. The dependent variable in column (4) is the change in the sum of corporate deposits, FHLB advances, and unsecured wholesale funding. Data Source: FR2052a.

simultaneous increase in deposits and drawdowns is also consistent with the theoretical synergies of banks as liquidity providers through both deposits and committed credit lines (Kashyap, Rajan, and Stein, 2002).

Our bank-level analysis may be associated with endogeneity concerns. Namely, there can be factors that cause both corporate deposits to increase and lines to be drawn. For instance, a less balance-sheet constrained bank may be more willing to both provide credit and at the same time to attract new deposits. Hence, the findings regarding relationships between deposits and line drawing could be confounded, leaving the possibility that the increase in corporate deposit is not directly linked to credit-line draws. To tighten the empirical relationship of drawdowns and their fundings, we thus also estimate a dynamic difference-in-differences model in Appendix Section C, where we use details regarding each bank's loan portfolio in the Y-14 data to construct a bank-level measure that captures the extent to which a bank has committed lines to firms that are adversely affected by the COVID shock and able to draw their lines. We find that our results connecting drawdowns and deposit/FHLB funding hold, even after controlling for bank-level exposure to the COVID shock.

Borrower-level Evidence Our evidence thus far indicates that a substantial portion of drawdowns were re-deposited with banks during the COVID shock. However, our bank-level data do not include deposit-level information, so we cannot establish a direct link between drawdowns and precautionary deposit increases at the borrower level. To address this concern, we turn to granular borrower-level information from the FR Y-14Q, Compustat, and Capital IQ to examine the extent to which draws were associated with an increase in borrower cash—a proxy for corporate deposit holdings. We conduct this analysis for both COVID and the GFC to see how drawdown motives differed across the two stress events.

The right panel of Figure 4 shows the correlation between changes in borrower-level drawdowns and changes in cash holdings for both the GFC and COVID recession. The data indicate a strong correlation for the COVID recession, in line with the precautionary drawdown motives. This correlation is not present during the GFC, in line with firms not depositing drawdowns in the banking sector during this episode.

We next estimate cross-sectional regressions of the form:

$$\Delta \text{Cash}_i = \alpha + \beta_1 \Delta \text{Drawdowns}_i + X_i + \epsilon_i, \tag{8}$$

where ΔCash_i[34] is the change in the dollar amount of deposit holdings of borrower i and $\Delta\text{Drawdowns}_i$ is the change in the dollar-amount of drawdowns over the same time period.

Results can be found in Table 4. The estimation confirms the patterns from the right panel of Figure 4. We find that for this period, a one dollar increase in drawdowns is associated with an increase in cash holdings of 86 to 97 cents, roughly in line with our bank-level evidence reported earlier. In contrast, for the GFC, we find *no* statistically significant relationship between drawdowns and deposits (columns 5-7).[35] This indicates that drawdowns were not deposited in the banking system, but instead were deployed elsewhere – either via other investments or for firm expenditures, such as investment or compensation. Importantly, since these drawdowns were not precautionary,[36] banks would have

[34]For our analyses using Compustat, we use CHQ to measure cash. Importantly, cash does not include money market fund holdings or reverse repo transactions. For our analyses solely using the FR Y-14Q in columns 1 and 2 of Table 4, since the FR Y-14Q does not separate cash from cash equivalents, these analyses pool both cash and cash-like instruments.

[35]This is consistent with evidence from Ivashina and Scharfstein (2010) that drawdowns following Lehman's failure were of the form of a bank run on institutions with greater Lehman exposure. It is also in line with results from Berrospide and Meisenzahl (2021) that drawdowns during the GFC were not precautionary in nature and instead funded capital expenditures.

[36]For drawdowns to be precautionary, it is necessary for deposit holdings to increase in response to credit-line drawdowns.

Table 4: Precautionary Draws: COVID versus GFC

	COVID				GFC		
	Y-14		Y-14 / Compustat				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Util.	0.97***	0.97***	0.92***	0.86***	-0.01	0.04	-0.01
	(0.07)	(0.07)	(0.11)	(0.09)	(0.07)	(0.07)	(0.07)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year	No	Yes	No	Yes	No	Yes	Yes
Match Quality			No	No	No	No	Yes
Data	Y-14		Y-14 / Compustat		Compustat/CIQ		
R^2	.275	.275	.314	.303	.0791	.0859	.148
N	7130	7130	1635	1468	1317	1217	811

Notes: This table shows estimates from cross-sectional regressions of the form $\Delta\text{Cash}_i = \alpha + \beta_1 \Delta\text{Drawdowns}._i + X_i + \epsilon_i$ where the dependent variable is the change in cash for firm i before and after the shock, $\Delta\text{Drawdowns}_i$ is the change in credit-line utilization of firm i, and X_i are firm controls, such as industry fixed effects and other cash flows. Columns 1-2 use quarterly data from the FR Y-14Q (aggregated by borrower TIN) of borrowers who reported financials in either 2019q3 or 2019q4 *and also* in March 2020. Columns 3-4 merge Y-14 credit line usage to updated financials as reported in Compustat. Columns 5-7 conduct firm level analyses on annual data during the GFC using drawdowns from Capital IQ and financials from Compustat. In Columns 2, 4, 6, and 7, we restrict to borrowers whose financial statement "as-of" dates correspond to calendar year quarters (that is, March, not February). In Column 7, we restrict our sample to a sub-sample of firms where we match long-term debt between Compustat and Capital IQ within 10% on average. We trim both Δ cash and Δ draws at the 1% and 99% levels to attenuate the impact of outliers. Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. For robustness, we also run this table sourcing credit-line drawdowns from Capital IQ during the recent COVID recession. See Appendix Table G.7. We also include versions where we examine drawdowns during the GFC in a one-quarter and two-quarter window surrounding Lehman's failure. See Appendix Table G.8.

been required to fund them via other methods, which may have included costly unsecured wholesale funding.[37]

6 Calibrated Impacts of Reference Rates on Credit Supply

In this section, we quantify how the choice of a reference rate affects the equilibrium provision of revolving credit by large US banks. To do this, we parameterize and calibrate versions of the simple theoretical model presented in Section 3, based on the empirical analysis and insights of Section 5. We consider the implications for credit provision of heterogeneous banks and borrowers. Further, we analyze how ex-ante credit supply depends on the extent to which line draws are expected to be left on deposit at times of high bank funding stress. Finally, we show how the welfare-maximizing degree of credit sensitivity of a reference rate depends on the quality of the bank or the banking system.

Since we do not observe an increase in deposit holdings following drawdowns, we can conclude that drawdowns following Lehman's failure were not precautionary. This does not preclude reshuffling of corporate deposits among banks; however, that poses a different funding risk beyond the scope of this paper.

[37]Indeed, using borrower-level data, Ippolito, Peydró, Polo, and Sette (2016) found that Italian corporates drew *more* from banks subject to higher interbank stress in 2007, subjecting these banks to a "double bank run."

Consistent with the insights gained from our theoretical model, welfare-maximal reference rates are more credit sensitive for banking systems of lower credit quality, given their greater debt-overhang costs for funding line draws during crisis periods. A detailed guide to our calibration can be found in Appendix Section F.

Parametrization and Outcomes. We start by parameterizing a version of the model discussed in Section 3. The density of the spread W between LIBOR and the risk-free rate is plotted in the left side of Figure 5. The logarithm of W is modeled as a mixture of normals. With probability 0.96, $\log W$ has a mean and variance fit by maximum likelihood to daily LIBOR-OIS observations from January 2005 to April 2021. With a "crisis" probability of 0.04, however, W has log-normal distribution with a mean of 350 basis points, which is roughly the highest level reached by LIBOR-OIS during the GFC, with a variance of 40 basis points. Because our model has annual periods, we hence assume that a GFC-like event is expected to occur around once every quarter century.

Our representative bank is assumed to be of LIBOR quality, thus having an unsecured wholesale credit spread of W. Later, we consider the implications of the model for banks with wholesale funding costs that are higher or lower than LIBOR. The bank has a continuum of borrowers of total mass M. The deposited fraction φ of drawn funds is $\Phi(W)$, where $\Phi(\cdot)$ is the logistic function defined by

$$\Phi(x) = \frac{D}{1 + e^{-m(x-w_0)}}, \tag{9}$$

with $D = 0.2$, $m = 0.1$, and $w_0 = 130$ basis points. Thus, as shown in the righthand plot of Figure 5, when LIBOR is close to the risk-free rate, borrowers deploy most of their drawn funds into business operations and leave very little on deposit. However, in crisis states, when LIBOR-OIS is large, borrowers could potentially deposit a higher fraction of drawn funds, given the precautionary motives that may apply in a macro shock like COVID, as documented in Section 5.5. So, we have parameterized the deposited fraction $\Phi(x)$ of drawn funds so that it increases with x to a "crisis limit" of D.

Section 5.5 shows that even when LIBOR-OIS rose to over 300 basis points during the GFC, there was little depositing of drawn funds. What matters for credit line provision is the ex-ante expected average fraction of drawdowns left on deposit, conditional on LIBOR-OIS. Future shocks to LIBOR-OIS have some likelihood of reflect a banking crisis, such as the GFC, with very low depositing of drawn funds, whereas a macro shock like COVID could generate much higher depositing behavior. Our base-case choice of $D = 0.2$ is plausibly between the average GFC and COVID outcomes, but is nevertheless not

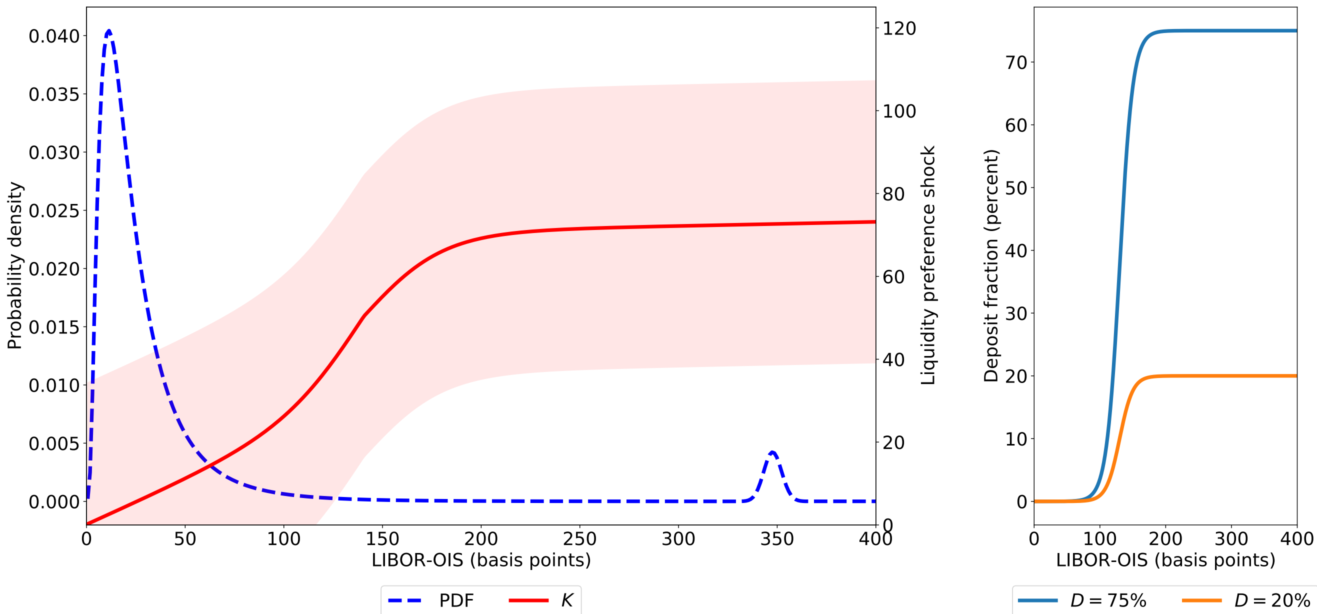


Figure 5: **The probability density of LIBOR-OIS, the borrowers' liquidity preference shock, and the deposited fraction of drawn credit.** The distribution of $\log W$ shown in the left figure is a mixture of normals: With probability 0.96, W has a mean of 27 basis points and a standard deviation of 24 basis points, fit by maximum likelihood estimation to daily LIBOR-OIS observations from January 2005 to April 2021. With probability 0.04, W has a crisis-conditional log-normal distribution with a mean of 350 basis points and variance of 40 basis points. The common component $K(W)$ of borrowers' liquidity shock, plotted in the left figure with a solid red line, is specified by $K(x) = \mathcal{C}_1 + \mathcal{C}_2 \min(x, x_0) + \mathcal{C}_3 (x - x_0)^+ + \mathcal{C}_4 / \left(1 + e^{-\mathcal{C}_5 (x - x_0)}\right)$, with coefficients $x_0 = 0.014$, $\mathcal{C}_1 = 0.08$, $\mathcal{C}_2 = 2140.8$, $\mathcal{C}_3 = 100$, $\mathcal{C}_4 = 40.41$, and $\mathcal{C}_5 = 497.9$, which were fit by least squares to drawdown data for our sample of 20 large banks, as detailed in Appendix Section F. The shaded region shows, at each potential outcome of $W =$ LIBOR-OIS, the inter-quartile range of the cross-sectional distribution among borrowers of the total liquidity shock $(K(W) + \epsilon)^+$, where ϵ is uniformly distributed on $(-\bar{\epsilon}, \bar{\epsilon})$, with a maximal idiosyncratic shock of $\bar{\epsilon} = 68.1$. The fraction $\Phi(x)$ of drawn credit that is deposited at a given level x of LIBOR-OIS, shown in the right-hand figure, is as specified by (9), with $D = 0.2$, $\theta = 1.0$, $m = 0.1$, and $w_0 = 130$ basis points.

well pinned down by data. Given the crucial role of this parameter, we will analyze the effect of varying D. We will also run experiments that vary D with the bank's expected unsecured wholesale funding costs, given the observed heterogeneity of depositing behavior across bank types that we uncovered in Section 5.5.

A borrower's cash liquidity benefit is specified as

$$b(q, \psi) = \frac{\psi^{\alpha} q^{1-\alpha}}{1 - \alpha}, \tag{10}$$

for a positive constant α, where ψ is the borrower's liquidity-demand shock.[38] We set α at 0.025, so that the price elasticity of drawn credit is in the range suggested by the literature (for example, Diamond,

[38] This specification respects the natural restriction that, in equilibrium, the marginal value $b_q(Q(L), \psi)$ of drawn funds is at least 1 in every state.

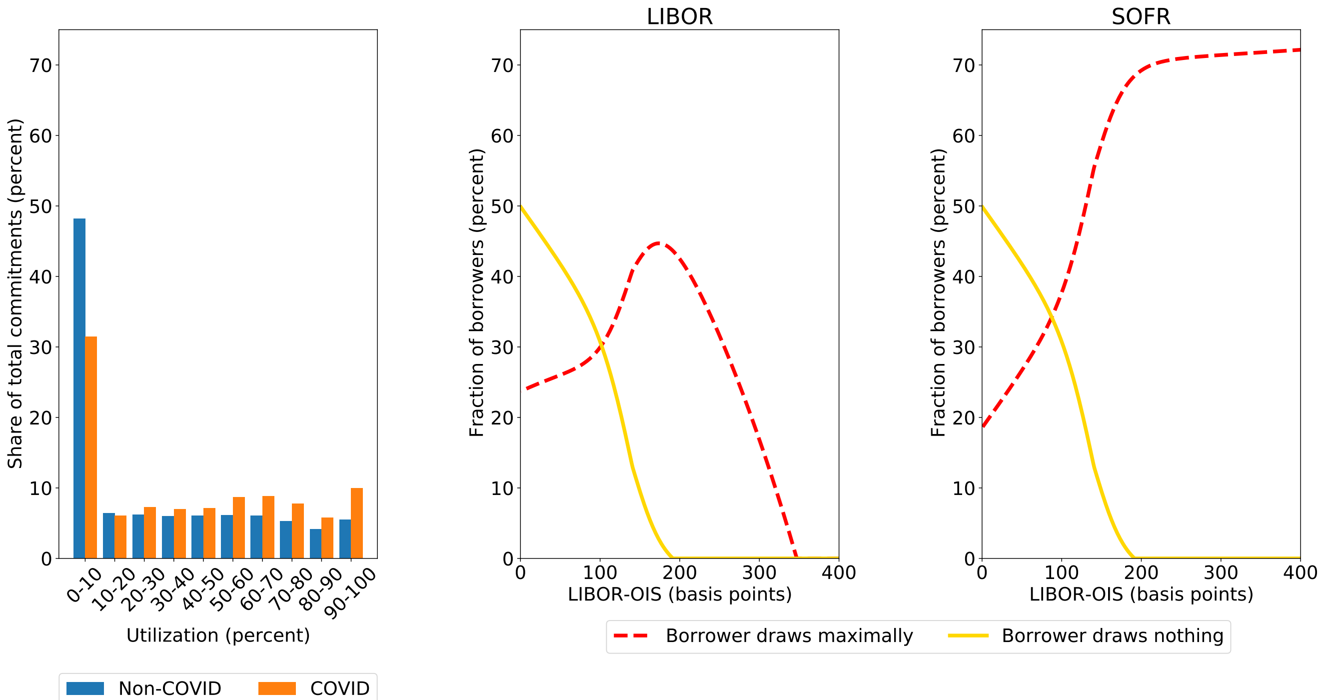


Figure 6: **The empirical cross-sectional distribution of credit line utilization and the modeled fraction of borrowers that utilize the entire or none of the credit line.** The data source for the left-hand figure is FRY14Q Schedule H. For the right-hand figure, the parameters determining K, Φ, and the probability distributions of W and ϵ are as specified in the caption of Figure 5. The other parameters determining the underlying equilibrium model: mass $M = 25.3$ of borrowers; capital ratio $C = 0.06$; risk-free rate $r = 0$; line fee $f = 20$ basis points; and credit demand elasticity parameter $\alpha = 0.025$.

Jiang, and Ma, 2021; Siani, 2021).[39]

We take the corporate borrower's liquidity shock ψ to be $(K(W) + \epsilon)^+$, with a common component $K(W)$ that is specified and calibrated as shown in Figure 5, and an idiosyncratic component ϵ that is independent of the common shock $K(W)$ and *iid* across borrowers. The probability distribution of ϵ is uniform on $(-\bar{\epsilon}, \bar{\epsilon})$, for some constant $\bar{\epsilon} > 0$.

The left panel of Figure 6 conveys a sense of the empirical cross-sectional heterogeneity of liquidity shocks in evidence through variation in line utilization over the period 2015-2021. The figure separates the COVID recession quarter from other quarters. In other non-crisis quarters, as shown, about 50% of lines are not drawn. For the remaining lines, utilization is roughly uniformly distributed. During the COVID recession, in contrast, only around 30% of all line commitments experienced low utilization and there is roughly a doubling of the normal fraction of lines that are utilized close to their limits. We will compare the empirical and theoretical cross sections of utilization after solving the equilibrium.

[39] Diamond, Jiang, and Ma (2021) estimate that an increase in the cost of credit of 10 basis points leads to a 16.1% decline in credit. Siani (2021) estimates that a 10-basis-point increase in the cost of credit leads to a 1.5% decrease in bond issuance for the average issuer. In our model, $\alpha = 0.025$ corresponds to an approximate theoretical decline in drawn credit of 4% in response to a 10-basis-point increase in credit costs, for a borrower not at its credit-line limit.

From Section 3, the modeled optimal quantity of credit drawn from a line of size L with a fixed spread s over the chosen reference rate R is

$$Q(L) = \min\left((K(W) + \epsilon)^+ (1 + R + s)^{-1/\alpha}, L \right). \tag{11}$$

For states in which the borrower is drawing more than zero and less than the line limit L, the optimal drawn amount $Q(L)$ is strictly decreasing in the drawn interest rate $R + s$ and strictly increasing in both the aggregate liquidity shock $K(W)$ and the idiosyncratic liquidity shock ϵ.

The calculations in Section 3 determine, for any candidate reference rate R, the bank's menu $\{(L, s(L)) : L \geq 0\}$ of offers of line size L and fixed interest rate spread $s(L)$ over the reference rate. In equilibrium, borrowers pick their optimal line size L from this menu. The exact law of large numbers implies that the aggregate amount of drawn credit is[40]

$$M \cdot E[Q(L) \mid W] = M \cdot E\left[\min\left((K(W) + \epsilon)^+ (1 + R + s)^{-1/\alpha}, L \right) \,\middle|\, W \right]. \tag{12}$$

Similarly, the fraction of borrowers that draw their lines to the limit is

$$P[Q(L) = L \mid W] = P\left[(K(W) + \epsilon)^+ (1 + R + s)^{-1/\alpha} \geq L \,\middle|\, W \right]. \tag{13}$$

For simplicity, we take the risk-free rate r to be zero and the loss given default (LGD) on the bank's unsecured funding to be 50%. The function $K(\,\cdot\,)$, the support of ϵ, and the quantity M of borrowers are jointly fit to our data bearing on the aggregate quantity of credit lines and the variation across borrowers and states of credit-line utilization, for our sample of historical experience for LIBOR-linked credit lines, for which the reference rate is $R = r + W$. Appendix Section F provides details on the fitting method. As Figure 5 shows, K is found to be an increasing function, implying that the cross-sectional average of line utilization increases with bank funding costs. The model parameters were calculated by minimizing the weighted sum of squares of *(i)* the expected loss to the borrower associated with suboptimal choice of L, which is zero with a perfect fit, *(ii)* the difference between the empirical average of the total dollar quantity of lines and its model-implied analogue $M \cdot L$, *(iii)* for each quarter, the difference between the actual quantity of line draws and the model-implied quantity of line draws given

[40] This equality holds with probability equal to one under measure-theoretic conditions on the space of borrowers and states of the world described by Sun (2006). The fraction of borrowers whose idiosyncratic liquidity shocks have an outcome in any given interval (a, b) is the same as $P(\epsilon \in (a, b))$. This implies (12) and (13), by integration over the probability distribution of ϵ.

by (12), and *(iv)* for each quarter, the difference between the actual fraction of lines drawn to their limits and the model-implied analogue given by (13).

With the resulting parameters calibrated to our sample of historical experience for LIBOR-linked credit lines, we are now in a position to consider the effects of varying the reference rate, bank quality, borrower deposit behavior, and other properties of the model.

The Effects of LIBOR-SOFR Transition on Credit Supply. We now present estimates of the impact of a transition from LIBOR to SOFR on the supply of credit lines by large US banks. Figure 7 plots, for each outcome of LIBOR-OIS, the equilibrium interest rate paid per unit of credit drawn (left panel) and the aggregate amount of line commitments and drawdowns (right panel). We find that transition from LIBOR to risk-free reference rates causes only a slight reduction, about 3.3%, in the line size L chosen by borrowers from our representative calibrated bank. However, we find that there is a substantial change in line utilization across different outcomes for LIBOR-OIS spreads. With SOFR as a reference rate, corporate borrowers draw their lines much more heavily during a bank credit crisis than they would with lines referencing LIBOR.

This equilibrium behavior reflects in part the bank's pricing of SOFR-linked credit lines. Under a SOFR-linked line, borrowers draw more credit when LIBOR-OIS is at the level it attained during the GFC, exploiting the fact that the drawn interest rate for SOFR-linked lines is around 300 basis points lower than that of LIBOR linked lines, as shown in the left side of Figure 7. Only those borrowers with a low outcome for the idiosyncratic shock ϵ would fail to heavily exploit this option. The equilibrium SOFR fixed spread must therefore be high enough to compensate bank shareholders for elevated total funding costs that will occur whenever LIBOR-OIS is high. As a consequence, in "normal times" (when LIBOR-OIS is near its sample average, the left vertical line in both panels of Figure 7), borrowers draw less credit on lines linked to SOFR than on lines linked to LIBOR. During those normal times, SOFR-linked lines are about 25 basis points more expensive than LIBOR-linked lines.

On the flipside, for the legacy case of LIBOR reference rates, however, when LIBOR-OIS is extremely low, the drawn interest rate on the credit line is also extremely low; so, typical borrowers take advantage of the relatively inexpensive credit by drawing on their lines. When LIBOR-OIS is high, however, borrowers are inhibited by the high cost of funds on LIBOR-linked lines, reducing the incentive to draw heavily, unless the borrower is hit by a sufficiently high combination of the common and idiosyncratic liquidity shocks.

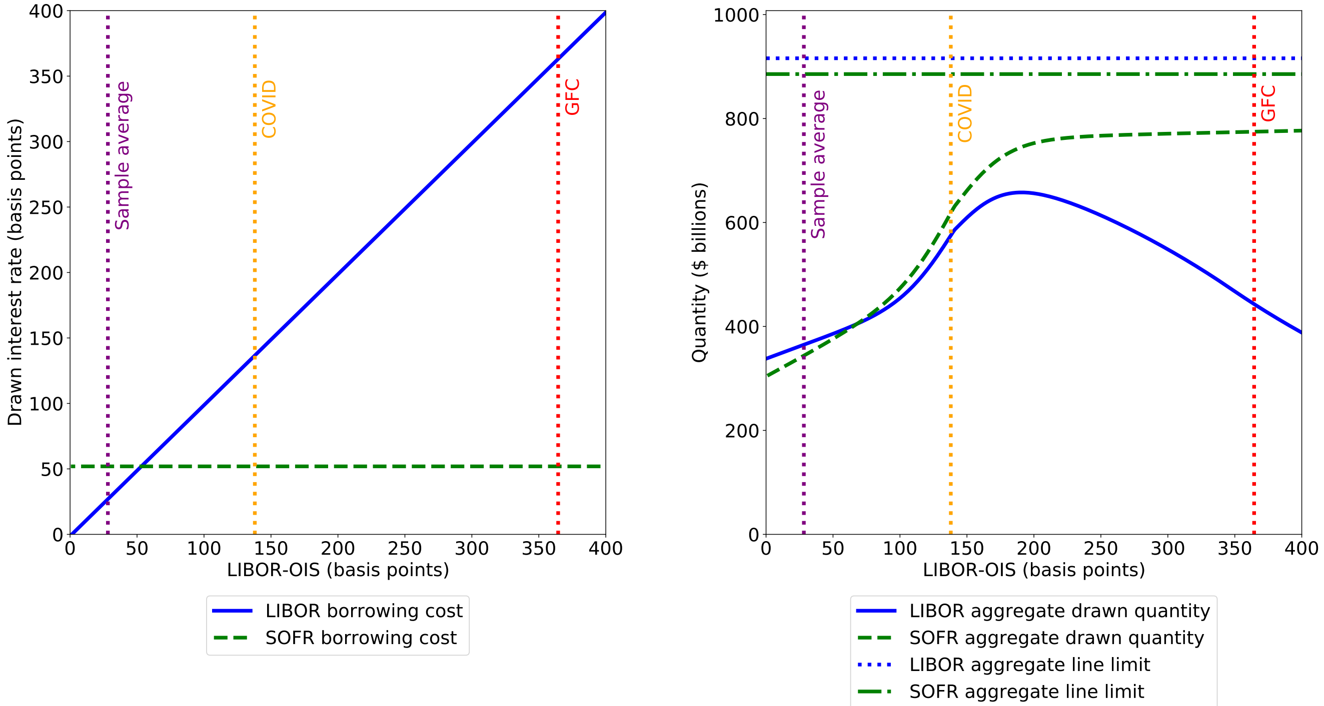


Figure 7: **The effect of the LIBOR-SOFR transition on credit line prices, aggregate drawn quantities, and aggregate quantities of credit lines.** All parameters are as specified in the captions of Figure 5 and Figure 6. The horizontal dashed-dotted lines in the right figure indicate the sizes of the credit lines. Vertical purple, orange, and red dotted lines are shown at the sample average of LIBOR-OIS (28 basis points), at the level of LIBOR-OIS reached in the COVID shock of March 2020 (140 basis points), and at the level of LIBOR-OIS reached during the GFC (360 basis points). The aggregate line limit is the product of the quantity M of borrower-bank pairs and the per capita credit line size L.

Additional implications of borrower heterogeneity are seen in the middle and right-hand panel of Figure 6, which shows the equilibrium fraction of borrowers that draw their lines to the limit L, at each outcome of LIBOR-OIS. In the event of very low levels of LIBOR-OIS, LIBOR-linked lines are relatively more attractive than SOFR-linked lines, and only borrowers with high outcomes for their idiosyncratic liquidity shock exhaust their credit limits. However, as LIBOR-OIS increases, the associated increase in the drawn cost of credit for LIBOR-linked lines eventually dominates the effect of the liquidity shocks of most borrowers, and LIBOR lines are relatively less likely to be drawn. In contrast, when LIBOR-OIS is high, the low drawn interest rate on SOFR-linked lines does not discourage borrowers from drawing, and most lines are drawn to the limit.

Our model is not rich enough to closely match the empirical fraction of borrowers that draw their lines to the maximum. The left panel of Figure 6 shows that, empirically, around 5% of borrowers were at or close to their line limits in normal quarters, and that this fraction doubles to around 10% during the COVID recession. In our calibrated model, however, as shown by the middle panel of the figure, around 20% of borrowers are at their line limits for lower realizations of LIBOR-OIS, and this modeled fraction increases to around 40% during the COVID recession. The primary objectives of our modeling, however, are implications for aggregate credit provision. The inability to match some cross-sectional moments for borrowing does not substantially change the thrust of our overall findings about aggregate credit provision.

Bank Heterogeneity. Section 5 provides evidence of substantial heterogeneity across banks in how drawdowns are funded during the COVID recession. We find that while banks, on average, received 90 cents of corporate deposits for each dollar drawn, some banks receive much higher deposit inflows than others. For instance, we find that regional banks (listed in Appendix Table A.1) received only about 40 cents in deposits per dollar drawn and had to raise the remaining funds with more expensive wholesale funding such as FHLB advances. There is also substantial heterogeneity across large banks in unsecured funding spreads (Berndt, Duffie, and Zhu, 2021). We therefore turn next to an analysis of how the implications of reference rate transition for credit provision vary with the type of bank.

We first consider the effect of varying bank funding costs by taking the external funding spread of the modeled bank to be $S = \theta W$, for some constant θ that we allow to vary parametrically.[41] For our base-case calibration, we took $\theta = 1$, corresponding to a LIBOR-quality bank. For instance, with $\theta = 1.5$, the credit spread of the modeled bank is 50% higher than that of an average LIBOR-quality bank, state by state. The left panel of Figure 8 illustrates how the equilibrium quantity of credit lines depends on proportional increases in the bank's uncertain future unsecured funding spreads. As θ increases, the bank offers more expensive line terms. This in turn both reduces the equilibrium line size L chosen by the borrower and also increases the borrower's contractual spread $s(L)$ over LIBOR. The underlying logic is simple: As shown in Section 3, to the extent that borrower credit demand is correlated with bank funding spreads, debt overhang reduces the incentives for a bank to provide revolving credit. An increase in θ raises the severity of the debt overhang and reduces the supply of credit lines. Our calibrated pool of borrowers take about 6% more in LIBOR-linked credit lines from a LIBOR-quality bank than from a bank that obtains external funding at 50% higher credit spreads, all else equal. As shown, the impact of deteriorating bank quality on credit-line provision is more severe for SOFR-linked lines, consistent with the key debt-overhang channel of our model, which is aggravated for credit lines

[41] From the results of Section 3, for a given θ, the contractual spread $s(L)$ over LIBOR, with an LGD of 50%, is

$$s(L) = \frac{E[2\theta W Q(L)(1 - \delta(1 + R - (1 + C)(1 - Phi(W))\theta W))]}{E[\delta 2\theta W Q(L)]}.$$

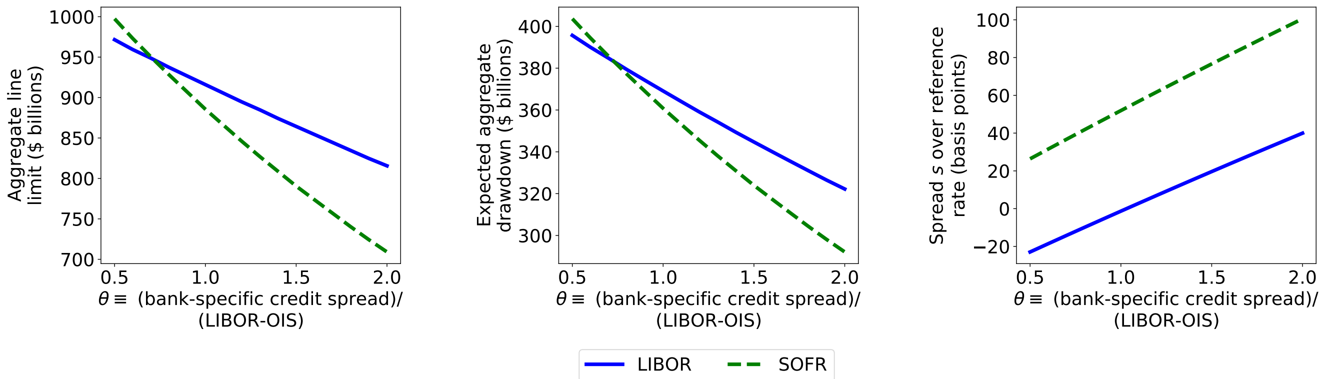


Figure 8: **Bank pricing of credit lines as a function of bank quality.** All parameters are as specified in the caption of Figure 6, except for variation in the bank-quality parameter θ. The bank's funding spread when lines are drawn is the product of θ and LIBOR-OIS. The left panel shows the associated impact on the aggregate line limit, $M \cdot L$. The right panel shows the impact on the aggregate amount of drawn credit, $ME(Q(L))$.

by SOFR reference rates.

We also consider the impact on the provision of credit lines of varying the fraction of drawn funds that is anticipated to be left on deposit. Consistent with the empirical evidence presented earlier, we assume that this fraction rises monotonically with LIBOR-OIS to a crisis limit of D, which we allow to vary parametrically. Figure 9 shows that the equilibrium provision of credit rises with D, for the obvious reason that the debt-overhang cost associated with expensive external funding does not apply to deposit funding. As shown, this effect is steeper for SOFR lines than for LIBOR lines, because SOFR lines are more heavily drawn when LIBOR-OIS is high, which is precisely when deposit-based funding is more valuable as a substitute for external funding.

If the limit deposit fraction D is high enough, the transition to risk-free reference rates actually *increases* the equilibrium provision of credit lines, as shown in Figure 9. For instance, with $D = 75\%$ of drawdowns the transition to risk-free reference rates induces a 5.5% increase in line limits and a 4.1% increase in expected drawn credit.

In summary, the impact of the transition to risk-free reference rates on the provision of credit lines will be more severe for banks with higher debt-overhang costs, whether arising from higher external funding spreads or from lower anticipated depositing of drawn lines. These two drivers of debt overhang are likely to be correlated, because a banking crisis will probably cause borrowers to deposit a smaller fraction of their drawn funds at weaker banks. (This issue is briefly explored in Appendix Section E.) Our analysis thus suggests that low-debt-overhang banks (generally, those with higher capital and liquidity) may gain a greater share of the market for credit lines. The aggregate impact on credit provision of the transition from LIBOR to SOFR is thus likely to be more muted than would be

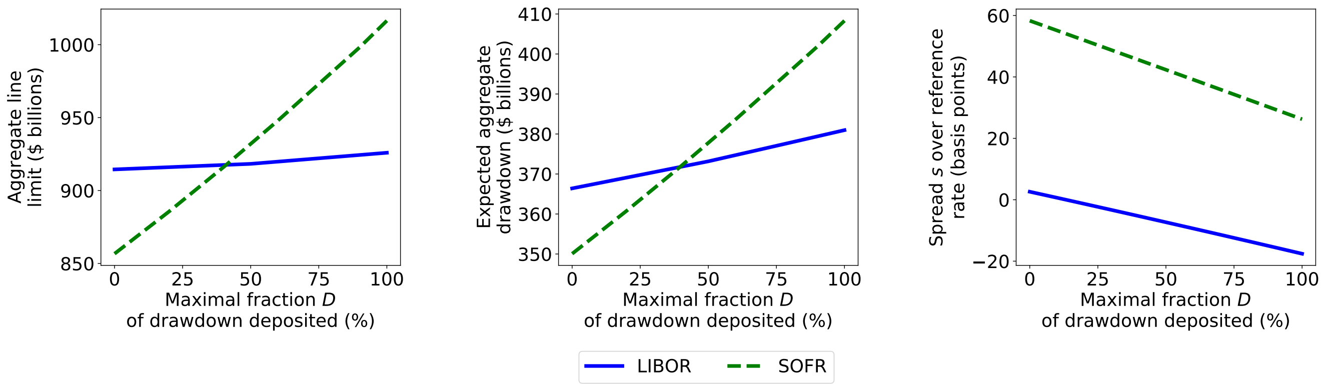


Figure 9: **The effect of increasing the maximal fraction of drawdown deposited** All parameters are as specified in the caption of Figure 6, except for parametric variation of the maximal deposited fraction D of drawn funding. The aggregate line limit is the product of the quantity M of borrower-bank pairs and the per capita credit line size L. The expected aggregate drawdown is defined similarly.

suggested by our partial-equilibrium analysis, especially if the cost of switching a borrower's banking relationship to a new bank is low. A broader equilibrium analysis that incorporates the industrial organization of banking relationships is beyond the scope of this paper.

Welfare-Maximizing Reference Rates We have focused on the quantity of credit provision, but our model reflects the fact that a dollar of funding in stressed states of the world is more valuable to borrowers than a dollar of funding in normal states. One can view a credit line as a form of insurance against liquidity shocks. Thus, the welfare-maximal reference rate could in principle be quite different than the reference rate that maximizes the expected quantity of credit granted. We now consider the welfare-maximizing degree of sensitivity of the reference rate, taking as our welfare measure the expected liquidity benefit to borrowers, which is $E[b(Q(L), \psi)]$. All other costs and benefits in our model are merely transfers. Figure 10 show how total welfare in our model depends on the degree λ of credit sensitivity of the reference rate. The risk-free reference rate, SOFR, corresponds to $\lambda = 0$. LIBOR corresponds to $\lambda = 1$. A point λ on the horizontal axis corresponds to a reference rate that is the linear combination $\lambda \times$ LIBOR $+ (1-\lambda)\times$ SOFR.

The vertical dotted line in the left-hand figure indicates the convex combination of LIBOR and SOFR defining the reference rate that maximizes the welfare gain of a new credit line. As shown, our analysis suggests that the welfare-optimal reference rate for our modeled LIBOR-quality bank has about 72% of the credit sensitivity of LIBOR. The right-hand panel of the figure shows that the reference rate that maximizes the provision of credit lines is slightly more credit sensitive.

Our marginal analysis of credit-line provision, however, ignores the impact of reference-rate design

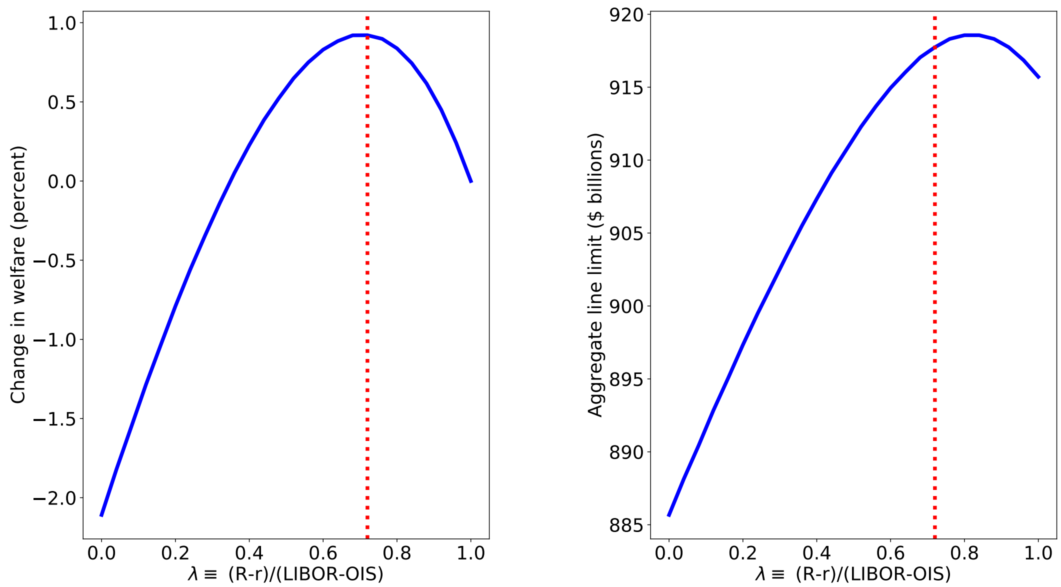


Figure 10: **How welfare and aggregate quantity of lines depend on the credit sensitivity of the reference rate.** All parameters are as specified in the caption of Figure 6. The vertical dotted line indicates the convex combination of LIBOR and SOFR defining the reference rate that maximizes the welfare gain of incremental credit lines.

on bank distress costs. Because there can be non-zero bank distress costs associated with heavier drawing of lines in stressed states, our marginal analysis understates the credit sensitivity of welfare-optimal reference rates that would apply in a full general-equilibrium setting.

The welfare-maximizing reference rate varies with the type of bank or banking system. Figure 10 corresponds to our base case of a LIBOR-quality bank ($\theta = 1$) and a maximal anticipated deposited fraction $D = 0.2$ of drawn funds. Figure 11 shows how welfare is affected by the credit sensitivity of the reference rate for a "low-debt-overhang bank," whose credit spread is only $\theta = 75\%$ of LIBOR-OIS, and for a "high-debt-overhang bank," whose credit spread is assumed to be 50% higher than LIBOR-OIS. Whereas the low-debt-overhang bank is assumed to receive in deposits a maximum of $D = 75\%$ of drawn funds, the high-debt-overhang bank is assumed to receive a maximum of only $D = 20\%$ in deposits. A negative relationship between bank funding spreads and the fraction of deposited line draws is natural, as we discuss in Appendix Section E.

Figure 11 shows that the welfare associated with credit-line provision by high-debt-overhang banks is maximized by a reference rate whose credit sensitivity is close to that of LIBOR. Low-debt-overhang banks, however, offer better credit provision, in the sense of this experiment, with a reference rate that is much closer to the risk-free rate.

This analysis may help explain why regional US banks have dominated the collection of banks arguing that the transition to risk-free reference exacerbates the impact of bank funding shocks and

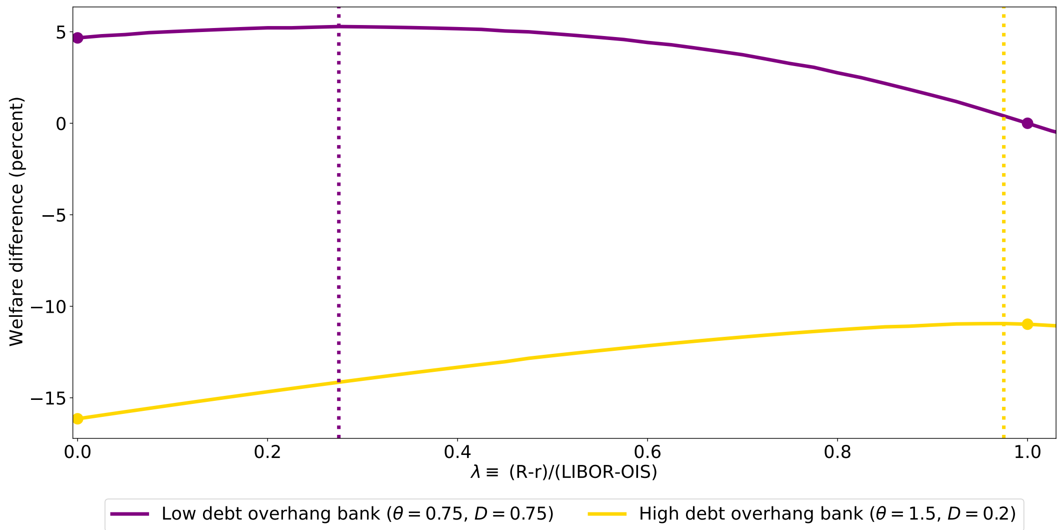


Figure 11: **Welfare-maximizing reference rate by bank type.** Welfare differences are with respect to a low-debt-overhang bank under LIBOR. Dots indicate welfare differences for LIBOR ($\lambda = 1$) and SOFR ($\lambda = 0$). For high-debt-overhang banks, we set $\theta = 1.5$ and $D = 0.2$. For low-debt-overhang banks, we set $\theta = 0.75$ and $D = 0.75$. All other parameters are as specified in the caption of Figure 6. The vertical dotted lines indicate the convex combination of LIBOR and SOFR defining the reference rate that maximizes welfare.

reduces incentives for credit provision. Their joint letter to the heads of the US banking authorities[42] emphasized that "borrowers may find the availability of low cost credit in the form of SOFR-linked credit lines committed prior to the market stress very attractive and borrowers may draw-down those lines to 'hoard' liquidity. The natural consequence of these forces will either be a reduction in the willingness of lenders to provide credit in a SOFR-only environment, particularly during periods of economic stress, and/or an increase in credit pricing through the cycle." Our analysis in Appendix Section B shows that the wholesale unsecured funding spreads of regional banks are only slightly higher than those of the largest US bank holding companies,[43] an estimated average of 22 basis points higher post-GFC, and about 10 basis points higher from 2015-2021, controlling for maturity and time fixed effects. That reference rate transition may have a higher impact on the provision of revolvers by regional banks is also suggested by our finding in Section 5 that regional banks experienced a much lower extent of depositing of drawn lines during the Covid shock of 2020 than did the largest banks in our sample.

[42]See the letter of September 23, 2019 from Credit Sensitivity Group to Randall Quarles, vice-chair of supervision of the Board of Governors of the Federal Reserve System, Joseph Otting, Comptroller of the Currency, and Jelena McWilliams, chair of the Federal Deposit Insurance Corporation.

[43]These estimates arises from fitting the model $Y_{it} = \beta_0 + \beta_1 M_{it} + \beta_2 D_{it} + \delta_t + \epsilon_{it}$, where Y_{it} is the average secondary-market yield spread of debt instrument i during month t, M_{it} is its remaining maturity, D_{it} is an indicator for regional banks (1 if regional, 0 otherwise), δ_t is a month fixed effect, and ϵ_{it} is a noise term. We fit by weighted least squares, with weights proportional to traded volumes, corresponding to best linear unbiased estimation under the assumption that the model is correctly specified with noise terms that are uncorrelated and have variances proportional to the reciprocals of trade volumes.

7 Discussion

Bank shareholders do not break even when banks raise cash to invest in assets unless the bank extracts a profit margin from its counterparties that offsets the credit-spread component of the bank's funding cost. In market practice, this wedge is called a "funding value adjustment" (Andersen, Duffie, and Song, 2019). We find that the transition from credit-sensitive reference rates like LIBOR and EURIBOR to risk-free reference rates such as SOFR or ESTR increases this wedge by inciting borrowers to draw on their lines even more heavily during periods of market stress, because the cost of drawing on a line referencing a risk-free rate is typically very cheap when credit markets are stressed. When a SOFR-linked line is originally contracted, the higher expected future funding cost wedge will be priced into the terms of credit facilities, leading to an equilibrium reduction in revolving credit for our representative calibrated bank. We show that this impact is smaller for banks with lower funding spreads, or even reversed if it is anticipated that borrowers will leave the majority of their future line draws on deposit at the same bank. Empirically, we find that the extent to which line draws induced by the COVID pandemic shock were left on deposit was much lower at regional US banks than at the largest US banks. Because of this, reference rate transition is likely to impact the provision of credit lines more for regional US banks than for the largest US banks.

As opposed to prior work offering a risk-sharing rationale for credit-sensitive reference rates, our finding that credit-sensitive reference rates improve credit provision is not driven by hedging or risk aversion, and does not apply to term loans, which do not give borrowers the option to increase the loan size when market stress increases.

Our paper also identifies a new channel of synergy between deposit-taking and credit-line provision. Kashyap, Rajan, and Stein (2002) emphasize the synergy associated with a bank's ability to draw on a common pool of liquid assets, whether to meet line draws or for other funding needs. We show that there is also a synergy between these two business lines, revolvers and deposit taking, via a complementary channel, namely the associated reduction in debt-overhang costs to bank shareholders. This synergy is stronger for risk-free reference rates than for credit-sensitive reference rates because, when markets are stressed and bank funding costs rise, borrowers are expected to draw more heavily on lines linked to risk-free reference rates. However, we emphasize that this effect is not uniform across the banking sector.

Based on our results, it may be predicted that reference rate transition will cause some degree of substitution of credit-line provision away from banks with high funding costs toward banks with lower funding costs. What matters here is the blended average spread on the marginal sources of funding of credit-line draws, which is a combination of the spreads on wholesale external funding and on corporate deposits, to the extent that line draws are left on deposit. However, relationships between banks and corporate borrowers are somewhat sticky; otherwise credit lines would already have been highly concentrated at banks with the lowest funding costs, well before LIBOR transition. This is clearly not the case. Corporate borrowers are paired with banks in somewhat stable relationships, whether because of monitoring costs, geography, or other reasons (Chodorow-Reich, 2013; Schwert, 2018). However, it is beyond the scope of our work to analyze the degree to which the stability of banking relationships could be disrupted by reference rate transition.

Further, one might predict that the impact on credit-line provision associated with the transition away from credit-sensitive reference rates would be mitigated by borrowers' ability to substitute some of their credit lines with term loans, given the negligible impact of reference rate transition on the pricing of term loans. In additional analysis, however, we find relatively little substitution into term loans. In our calibrated model, the demands for term loans and credit lines are relatively separable; one is not a significant substitute for the other. At least in our calibrated model setting, credit lines are only useful as insurance against unanticipated liquidity shocks, whereas term loans are useful for meeting known funding requirements.

Finally, our findings should not be interpreted as suggesting that a transition away from LIBOR has negative overall benefits. It is well documented that LIBOR is not a trustworthy benchmark, given the extent of its past manipulation and the paucity of underlying transaction data needed to determine LIBOR, especially under stressed market conditions.[44] Our analysis, however, does suggest that when debt overhang is high, alternative credit-sensitive reference rates can have beneficial effects in the market for C&I lending.

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[44]See Vaughan (2017); Bailey (2017); Duffie and Stein (2015); Kuo, Skeie, and Vickery (2018).

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APPENDIX

- Appendix A: Data.
- Appendix B: Heterogeneity in Bank Funding Costs.
- Appendix C: Drawdowns and Deposit Inflows.
- Appendix D: Counterfactual Assumptions and Additional Results.
- Appendix E: Incitements to Draw Early or to Run.
- Appendix F: Details on Calibration.
- Appendix G: Additional Tables and Figures.

A Data

We make use of several confidential and public data sources to reconstruct bank balance sheets, lending terms, funding costs, and exposure to LIBOR.

We source daily and monthly bank balance-sheet information from the FR 2052a. This confidential regulatory report collects quantitative information on selected assets, liabilities, funding activities, and contingent liabilities on a consolidated basis and by material entity subsidiary. Banks' outstanding balances are reported at a granular level, including by counterparty type, maturity bucket, product type, and collateral category. U.S. bank holding companies designated as global systemically important banks (G-SIBs) and foreign banking organizations (FBOs) with US assets greater than $100 billion are required to report.

For our analysis, we only include line items reported for the consolidated holding company level (that is, the highest holder). We also exclude all FBO reporting banks, as we do not observe the full asset and liability profile for these institutions (only that of their U.S. operations). Additionally, as the reporting frequency varies by the size and risk profile of the institution,[45] we create two balanced panels of banks for our analysis. The first of these is a daily panel of the eight largest banks in the U.S, for which we include observations between Dec. 30, 2015, and May 21, 2021. The second is a monthly panel of 24 large U.S. banks, for which we include observations between Sept. 30, 2017, and April 30, 2021. A list of banks in each sample is included in Table A.1.[46]

We rely primarily on a few select schedules within the FR 2052a. For bank liabilities (and contingent liabilities), we focus on the Deposits-Outflow Schedule, the Wholesale-Outflow Schedule, FHLB Advances and Exceptional Central Bank Operations from the Secured-Outflow Schedule, and unfunded commitments on credit and liquidity facilities from the Outflows-Other Schedule. We exclude other secured funding and contingent liabilities from our analysis.[47] For bank assets, we restrict our attention primarily to bank loan balances—which we source from the Inflows-Unsecured Schedule (Outstanding Draws on Revolving Credit Facilities and Other Loans) and the Inflows-Secured Schedule (Margin Loans and Other Secured Loans)—and central bank reserves—which we source from the Inflows-Assets

[45]The largest institutions, which are those designated by the Federal Reserve as part of the Large Institution Supervision Coordinating Committee (LISCC) portfolio or have more than $700 billion in assets, report the FR 2052a on a daily basis with a T+2 day lag, while smaller institutions report monthly with a T+10 day lag.

[46]For some of the analyses that we include in our appendix, we also consider a third balanced panel. This panel consists of the consolidated US branches of 14 foreign banking organizations (FBOs): BARC, BNPP, TD, SOGN, DB, UBS, BMO, BBVA, KN, CS, MUFG, SMBC, MFG, and RY. These banks are not included in our main analyses, as we do not observe the full asset and liability profile of these institutions, only that of their US operations.

[47]This primarily includes non-balance-sheet funding, such as collateral swaps and dollar rolls, as well as certain balance sheet funding, namely repo.

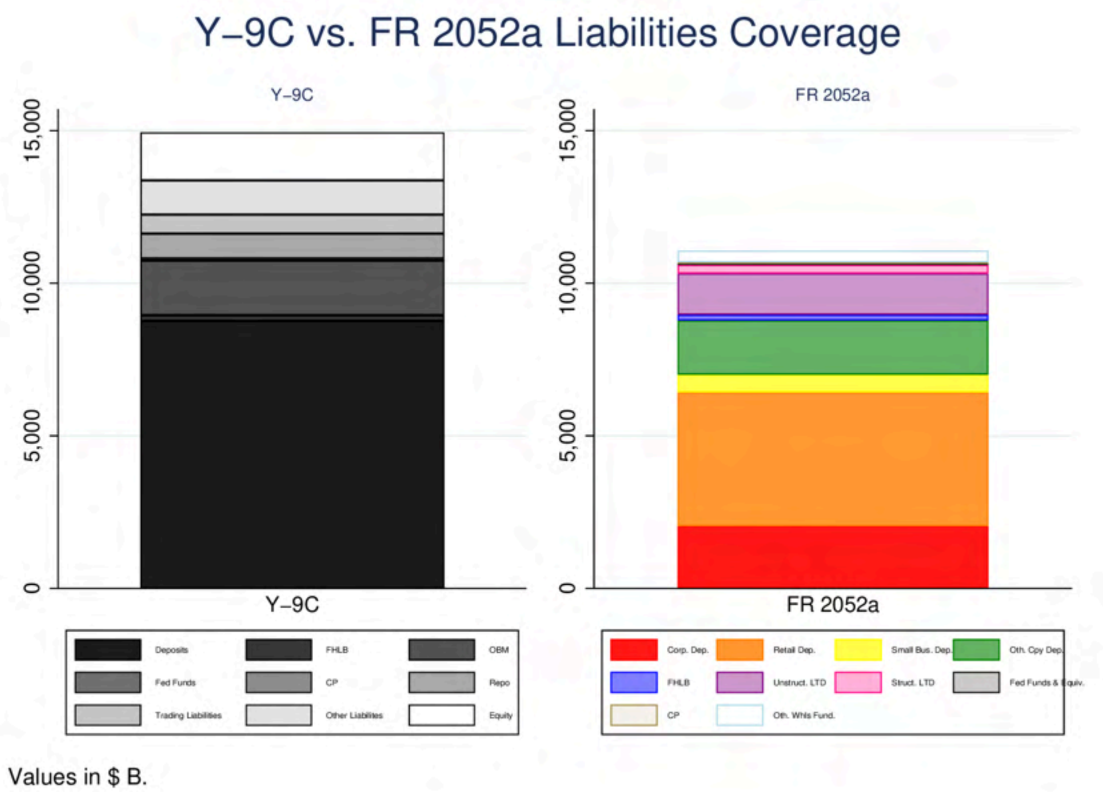


Figure A.1: **Y-9C vs. FR 2052a Total Liabilities Coverage.** Data Source: FR 2052a and FR Y-9C for banks in the FR 2052a monthly panel.

Schedule (Restricted and Unrestricted Reserve Balances). We reconcile the liabilities that we collect from the FR 2052a to total liabilities reported in the FR Y-9C for the same bank and find that we cover most of our sample banks' balance sheets with these schedules. We note only one institution with a deviation of more than 10% between the two reports in any quarter.[48] Importantly, we do not try to reconcile loans reported in the FR Y-9C with those reported in the FR 2052a, as this requires banks to report the lifetime cash flows from a loan, which includes both its principal and interest payments. This is in contrast to the FR Y-9C, which reports the book (or market) value of bank loans.

We also make use of the FR Y-14Q, a confidential supervisory data set maintained by the Federal Reserve to assess capital adequacy and to support stress testing. The FR Y-14Q data contain detailed quarterly data on: various asset classes, capital components, and categories of pre-provision net revenue. These data are for US bank holding companies, intermediate holding companies of foreign banking organizations, and savings and loan holding companies with more than $100 billion in total consolidated assets.[49]

[48]Specifically, we compare total deposits and wholesale funding that we source from the FR 2052a to Total Liabilities less Other Liabilities less Trading Liabilities less Repo in the FR Y-9C to construct a like-for-like comparison. We also compare component balances to the extent possible. For deposits specifically, we note only a single bank-quarter observation with a > 5% deviation between the FR 2052a and the FR Y-9C. The remaining deviations are expected, as values reported in the FR 2052a reflect contractual cash flows, while values in the FR Y-9C reflect balance sheet book values, which can be adjusted for various accounting reasons, such as securities recorded at fair value.

[49]The size cutoff is based on: "(i) the average of the firm's total consolidated assets in the four most recent quarters as reported quarterly on the firm's Consolidated Financial Statements for Holding Companies (FR Y-9C); or (ii) if the firm has not filed an FR Y-9C for each of the most recent four quarters, then the average of the firm's total consolidated assets in the most recent consecutive quarters as reported quarterly on the firm's FR Y-9Cs." Prior to 2020Q2, the respondent panel was composed of any top-tier BHC or IHC with $50 billion or more in total consolidated assets.

We primarily make use of the FR Y-14Q corporate loan and commercial real estate schedules to analyze loan terms to C&I and CRE borrowers. For this purpose, the FR Y-14Q covers approximately two-thirds of the bank C&I lending market (Chodorow-Reich et al., 2021). It includes key information on loan-terms, including the utilized and committed amount each quarter, interest rate, interest rate index (for floating rate loans), and interest rate floors and ceilings, if they exist. For some of our analyses, we restrict our sample to a sub-sample of Y-14 loans. For our accounting counterfactal analysis, we restrict our sample to domestic C&I and CRE loans so we can compare estimated Y-14 revenues to Y-9C call report income for the same line item. In most of our analyses, we include loans secured by owner-occupied real estate (which are reported on the Y-14Q C&I schedule) with other loans secured by real estate (loans reported on the Y-14Q CRE schedule) to align with the Y-9C reporting aggregation.

We also use the FR 2420 data collection to analyze bank funding costs prior to and at the onset of the COVID pandemic. This confidential report is filed daily by US banks with greater than $18 billion in assets, and contains transaction-level information for bank wholesale Certificate of Deposit (CD) and time deposit issuances of greater than $1 million, including interest rate, maturity term, and counterparty type. It also includes transaction-level information for selected deposits of greater than $1 million and with a maturity between 1 and 7 days. In our analyses of interest rates at the onset of the COVID pandemic, we compute period-specific interest rates as volume-weighted means or medians among banks that reported transactions during that period. For overnight deposit rates, we include all transactions with the relevant counterparty (for example, bank, NBFI, or non-financial corporate) that have a term of 1-day. For 3-month wholesale deposit rates, we include all transactions with the specified counterparty that have terms between 89- and 92-days. This includes transactions from banks that are both within and outside our main sample from the FR 2052a and FR Y-14 bank-level results.

For publicly available interest rates, including LIBOR and SOFR, we source data from FRED. We source OIS, BSBY, and term SOFR rates via Bloomberg. Interest rates for Federal Home Loan Banks (FHLBs) are not publicly available for all 11 FHLBs. We rely primarily on the publicly available FHLB Des Moines historical rate file. However, we compared these rates to other publicly available FHLB rates for the first six months of 2020 (FHLB Boston and FHLB Pittsburgh) and note that these rates follow similar trends during the pandemic, after adjusting for required investment in FHLB activity-based capital and dividends that FHLBs pay on those investments.

We adjust for FHLB dividends and for the cost of holding FHLB activity-based capital stock in a way similar to Ashcraft, Bech, and Frame (2010),[50] using the formula:

$$\begin{aligned}\text{Adjusted Rate}_t = {} & r_t \times (1-h) + (h \times \text{LIBOR}_t) - (c * (1-h) * d) \\ & + (c * (1-h) * (1 - \text{CET1} * rw) * \text{LIBOR}_t) + (c * (1-h) * \text{CET1} * rw * \text{ROE}),\end{aligned}$$

where Adjusted Rate$_t$ is the all-in FHLB rate, r_t is the notional FHLB rate for a given term t, h is the collateral haircut, LIBOR$_t$ is the LIBOR rate for term t, c is the FHLB's activity-based capital requirement, CET1 is a bank's minimum CET1 ratio target, rw is the risk weight that banks must apply to FHLB stock, and ROE is the bank's cost of equity (the ROE target). In essence, this formula captures the all-in interest rate for funding a dollar of collateral via the FHLB. We assume that the collateralized portion of the advance is funded at the FHLB notional rate (first term) and that the un-collateralized portion of the FHLB advance is funded via LIBOR (second term). We also account for the bank's requirement to purchase additional FHLB activity-based capital that is partially funded by unsecured funding at LIBOR (fourth term) and partially funded by equity at the bank's ROE target (fifth term). We also reduce the rate by the value of expected dividends that the bank receives from the FHLB for its activity-based capital purchase (third term).

Details on our assumptions vary between the GFC and COVID period because collateral haircuts, activity-based capital requirements, and dividend expectations have changed since the GFC. To account

[50]We build on this adjustment by also including factors to adjust for the cost of capital for holding FHLB activity-based capital.

for these time-varying parameters, we leverage the FHLB Des Moines historical dividend file, which reports quarterly dividends on activity-based capital since 2000. We use the prior quarter's dividend rate in our calculations for the current quarter's "All-in" rate. We also assume the existence of a 4.45% activity-based stock purchase requirement until 2013, when SEC filings show that the requirement decreased to 4%. For both periods, we assume a static 19% collateral haircut. We also account for the incremental cost of capital to purchase FHLB stock using static adjustment parameters: 15% minimum bank CET1 ratio, 20% FHLB stock risk weight, and 15% ROE target.[51]

We source additional bank-level information from the FR Y-9C and bank call reports, which are public and reported quarterly. These reports include information on bank assets, capital ratios, and quarterly interest income and expenses. For certain fields reported only in the call reports, for instance small business loans, FHLB advances, and interest income on C&I loans, we aggregate across all bank subsidiaries to estimate exposure at the holding company-level.

We obtain aggregate time series from FRED on bank assets and liabilities during the GFC. We focus primarily on asset and liability series for large domestically chartered banks, and adjust these for large non-bank mergers based on public notes on the Fed's H8 series.

We also use data from S&P Compustat and Capital IQ to conduct firm-level analysis of drawdowns during the COVID recession and the GFC. We source standard financial statement variables, including cash (CHQ), cash and equivalents (CHEQ), annual operating cash flow (OANCFY), annual cash dividends paid (DVY), and annual long-term debt issuance (DLTISY) from Compustat. We source credit lines outstanding (IQ_RC) from Capital IQ. As credit lines outstanding are only reported on an annual basis for most firms during the GFC, our main cross-sectional GFC analysis is conducted at an annual frequency. In some analyses (for example, Table 4), we also filter, based on data quality in Capital IQ, by restricting our sample to a sub-sample of firms for which we are able to match long-term debt between Compustat (DLTTQ) and Capital IQ (IQ_TOTAL_DEBT - IQ_ST_DEBT) within 10%, on average.

[51] For comparison, in December 2019 the median call report bank had a 15% CET1 ratio and 10% ROE.

Table A.1: **Banks in FR 2052a and FR Y-14 Samples**

Bank Name	Bank Type	Assets	% Committed C&I / Assets	FR 2052a Monthly	FR 2052a Daily	Y-14
JPMORGAN CHASE & CO	Universal	2687.8	0.16	Yes	Yes	Yes
BANK OF AMER CORP	Universal	2434.1	0.25	Yes	Yes	Yes
CITIGROUP	Universal	1951.2	0.19	Yes	Yes	Yes
WELLS FARGO & CO	Universal	1927.6	0.20	Yes	Yes	Yes
GOLDMAN SACHS GROUP THE	IB	993.0	0.14	Yes	Yes	Yes
MORGAN STANLEY	IB	895.4	0.11	Yes	Yes	Yes
U S BC	Regionals	495.4	0.35	Yes	No	Yes
TRUIST FC	Regionals	473.1	0.34	Yes	No	Yes
PNC FNCL SVC GROUP	Regionals	410.4	0.43	Yes	No	Yes
TD GRP US HOLDS LLC	Other	408.6	0.16	No	No	Yes
CAPITAL ONE FC	Cards	390.4	0.14	Yes	No	Yes
BANK OF NY MELLON CORP	Trust	381.5	0.03	Yes	Yes	Yes
CHARLES SCHWAB CORP	Trust	294.0	0.01	Yes	No	Yes
HSBC N AMER HOLDS	Other	249.1	0.37	No	No	Yes
STATE STREET CORP	Trust	245.6	0.02	Yes	Yes	Yes
AMERICAN EXPRESS CO	Cards	198.3	0.26	Yes	No	No
ALLY FNCL	Regionals	180.6	0.32	Yes	No	Yes
BMO FNCL CORP	Other	172.9	0.40	No	No	Yes
MUFG AMERS HOLDS CORP	Other	170.8	0.22	No	No	Yes
FIFTH THIRD BC	Regionals	169.4	0.50	Yes	No	Yes
CITIZENS FNCL GRP	Regionals	166.1	0.42	Yes	No	Yes
SANTANDER HOLDS USA	Other	149.5	0.19	No	No	Yes
KEYCORP	Regionals	145.6	0.49	Yes	No	Yes
RBC US GRP HOLDS LLC	Other	139.7	0.09	No	No	Yes
NORTHERN TR CORP	Trust	136.8	0.13	Yes	No	Yes
REGIONS FC	Regionals	126.6	0.37	Yes	No	Yes
BNP PARIBAS USA	Other	125.3	0.21	No	No	Yes
M&T BK CORP	Regionals	119.9	0.24	Yes	No	Yes
DISCOVER FS	Cards	114.0	0.00	Yes	No	No
DB USA CORP	Other	109.4	0.03	No	No	Yes
HUNTINGTON BSHRS	Regionals	109.0	0.36	Yes	No	Yes
SYNCHRONY FNCL	Cards	104.8	0.01	Yes	No	No
BBVA USA BSHRS	Other	93.6	0.33	No	No	Yes

Note: The table captures bank holding companies (BHCs) and intermediate holding companies (IHCs) of foreign banks operating in the US that are present in our final balanced panel samples. As part of our data cleaning process, we drop certain banks from the FR 2052a and FR Y-14 samples even though they file the respective schedules. We exclude IHCs of FBOs from our FR 2052a panels. We also exclude some banks from the Y-14 panel due to the data checks we apply. Assets and C&I values are sourced from the FR Y-9C as of December 31, 2019. Committed C&I is calculated as the sum of C&I loans (BHCK1763 & BHCK1764) and unfunded C&I commitments (BHCKJ457).

One additional bank included in our FR 2052a monthly balanced panel and Y-14 panel but not listed above is Suntrust; in December 2019, Suntrust merged with BB&T to form Truist (which is included). Given that we fully observe both the predecessor and successor entities for this merger, we do not drop Suntrust from our sample prior to the merger. In regressions, we often exclude the bank-month in which the Truist merger occurred.

B Heterogeneity in Bank Funding Costs

This section provides further details on the calculation of heterogeneity in bank funding costs, with a focus on the incremental funding costs of regional banks.

To estimate the heterogeneity in bank short-term funding costs, we use secondary market transaction data from TRACE and FISD/Mergent between July 2002 and July 2021 for our sample of large banks. We source these data via WRDS, using a cleaned version of merged TRACE/Mergent data, aggregated to the monthly level at the instrument-level. The WRDS-cleaned version of this data set has several advantages over the raw data, including the de-duplication of trades that are reported by both buyer and seller, and the removal of canceled trades and variable-rate securities. We further restrict our sample of transactions by dropping securities that are subordinated or convertible. We restrict our focus to instruments with a remaining maturity of between 3 months and 3 years.

We calculate instrument-level yield spreads as the difference between the trade-weighted yield on the instrument and the maturity-matched constant-maturity US Treasury yield.[52] We then estimate the following equation via weighted least squares:

$$Y_{ibt} = \beta_0 + \beta_1 M_{ibt} + \beta_2 D_b + \delta_t + \epsilon_{ibt}, \tag{14}$$

where $Y_{i,b,t}$ is the yield spread on instrument i issued by bank b trading at time t, M_{ibt} is the remaining maturity on that instrument in month t, D_b is an indicator variable bank set to 1 if and only if bank b is listed in Table A.1 as a regional bank, and δ_t is a month fixed effect. A summary of the results of this regression are in Table B.1, for three different sample periods. The results suggest that the unsecured wholesale funding costs of regional banks are about 22 basis points higher than those of the largest banks in our sample, post-GFC (Column 2), and about 10 basis points higher since 2015 (Column 3).

These results are based on weighted-least-squares (WLS) estimation, with a weight on the squared residual ϵ^2_{ibt} that is proportional to the total trade volume T_{ibt} of instrument i during month t. This is the optimal linear unbiased estimator (generalized least squares) under the assumption that the noise terms $\{\epsilon_{ibt}\}$ are uncorrelated and that the variance of ϵ_{ibt} is proportional to the inverse of the trade volume of instrument i in month t. Ordinary least squares (OLS) estimation generated a much poorer fit, a much higher p-value, and a counter-intuitive negative sign for the estimated coefficient β_1, the slope of the term structure of yield spreads.

Table B.1: **Heterogeneity in Bank Funding Costs.**

Variable	(1)	(2)	(3)
Remaining Maturity	0.2137	0.2486	0.146
	[0.0002]	[0.0]	[0.0]
Regional Indicator	0.015	0.2227	0.1053
	[0.79]	[0.00]	[0.00]
Sample	Full	Post-GFC	Recent
Reg Type	WLS	WLS	WLS
R^2	0.0014	0.0796	0.1432
N	39279	24560	12773

Notes: The table summarizes estimates of model (14) obtained by weighted-least-squares (WLS), with a weight on the squared residual ϵ^2_{ibt} that is proportional to the total trade volume T_{ibt} of instrument i during month t. The R^2 shown corresponds to the weighted sum of squares. The p-values shown are rounded to two significant figures and estimated with heteroskedastic robust standard errors, and reported in brackets. The "Full" sample period (Column 1) is July 2002 to July 2021. The Post-GFC period (Column 2) is January 2010 to July 2021. The "Recent" sample period is January 2015 to July 2021.

[52] We interpolate between the yield on 3-month and 3-year US Treasuries, based on the remaining maturity of the bank debt instrument. For instance, a bank note with remaining maturity of 6 months would be spread against a rate that is $\frac{10}{11}$ the 3-month US Treasury rate and $\frac{1}{11}$ the 3-year US Treasury rate.

C Drawdowns and Deposit Inflows

To tighten the empirical relationship between drawdowns and their funding, we thus also estimate a dynamic difference-in-differences model. We use detailed information on each bank's loan portfolio, provided in Y-14 data, to construct a bank-level drawdown exposure measure that captures the extent to which a bank has committed lines to firms that are adversely affected by the COVID shock and able to draw their lines (Chodorow-Reich et al., 2021).

The exposure measure is constructed as

$$\text{COVID Exposure}_b = \frac{\sum_i^N \mathbb{I}[\text{Firm Size}_i > 1\$ \text{ bil}] \times \text{Industry Exposure}_i \times \text{Committed Credit Lines}_i}{\text{Total Committed Credit Lines}_b},$$

where $\mathbb{I}[\text{Firm Size}_i > 1\$ \text{ bil}]$ is an indicator that is one if firm i is larger than \$1 billion in assets. Industry Exposure_b is constructed as follows. We compute the percent change in national employment in firm i's three digit industry between 2019Q2 and 2020Q2, using data from the Bureau of Labor Statistics Current Employment Statistics. We use the resulting change as a proxy for the demand shock to a firm (as in Chodorow-Reich et al. (2021)). We then determine the decile of the percent change of the industry of firm i. We normalize Industry Exposure_b to be between 0 and 1.

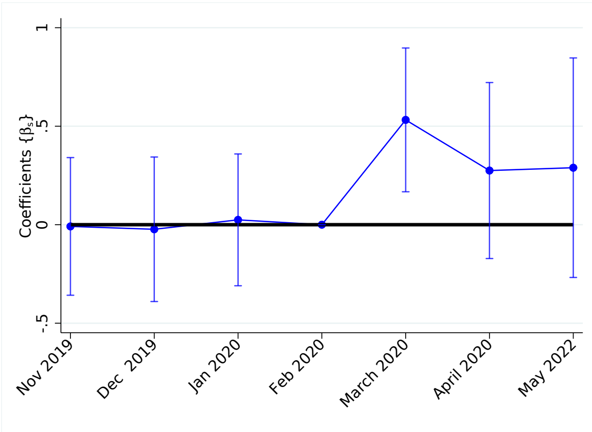
Thus, COVID Exposure_b is the share of credit line commitment that bank b has to large firms—those that tend to draw their lines—that are exposed to COVID. Given the unexpected nature of COVID and that the lending decisions were made before the COVID recession, any cross-sectional variation across more or less exposed banks results from bank borrower demand shocks. Ideally, one would like to instrument drawdowns with the exposure measure and then explain the different funding types in the next step. However, even though the exposure measure correlated strongly with drawdowns, our sample is too small, making the instrument weak.

We then estimate a model of the form

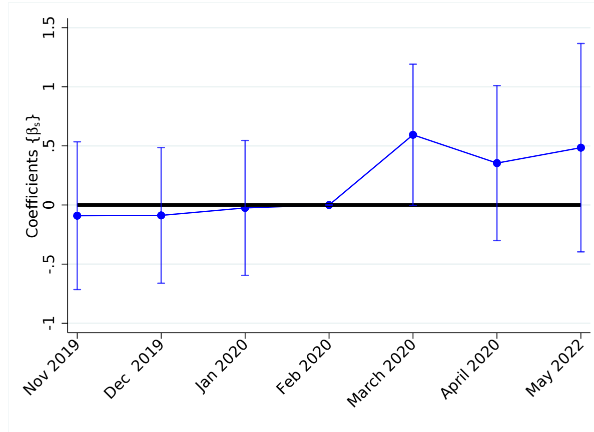
$$\ln y_{bt} = \gamma_b + \gamma_{\theta t} + \sum_{s \neq \text{Feb 2020}} \beta_s \times \mathbb{I}[s = t] \times \text{COVID Exposure}_b + \epsilon_{bt}, \tag{15}$$

where, for bank b, $\ln y_{bt}$ is the natural logarithm of one of the following: corporate deposits, deposits, FHLB advances, and unsecured wholesale funding. We are interested in the sequence of $\{\beta_s\}$, which allows us to understand how the respective balance-sheet items evolved at relatively more exposed banks compared to less exposed banks.

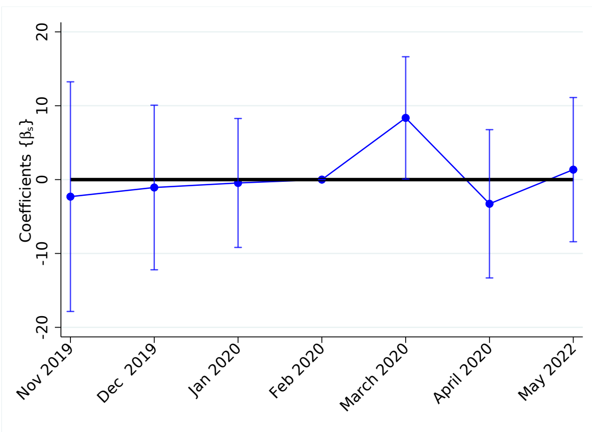
Figure C.1 shows the results. The coefficients plotted in Panel (a) show that banks with more exposed C&I portfolios are subject to larger drawdowns, confirming the findings of Chodorow-Reich et al. (2021). Panels (b) and (c) show that these banks have a higher increase in corporate deposits and FHLB advances. We note that corporate deposits increase in March together with drawdowns and then return to a lower level—although not exactly to the pre-pandemic level. In contrast, the relative differences in FHLB advances only increase in March and then return to pre-pandemic levels, indicating that banks use FHLB advances to fund the marginal drawdowns at the onset of the pandemic. Finally, in line with the presumption that unsecured wholesale funding played no role in funding the drawdowns, there is no variation in unsecured wholesale funding.



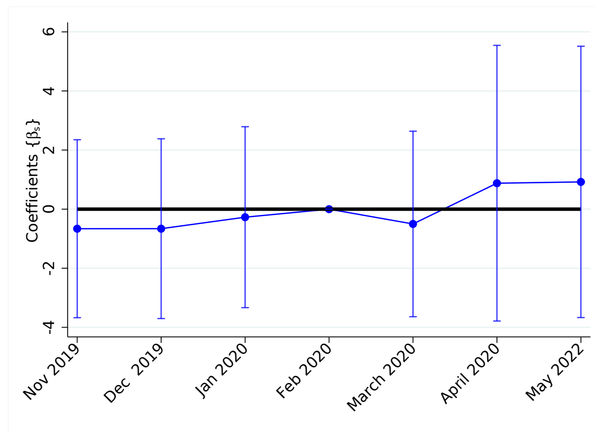
(a) C&I Loans



(b) Corporate Deposits



(c) FHLB Advances



(d) Unsecured Wholesale Funding

Figure C.1: **Loans, Deposits, FHLB and Wholesale Funding during COVID by Bank Exposure.** This figure shows the fitted sequence $\{\beta_s\}$ for the regression (15). Data are sourced from our monthly FR 2052a balanced panel between September 2017 and April 2021. COVID exposures are calculated from the FR Y-14Q Schedule H1.

D Accounting Counterfactual Assumptions & Additional Results

Here, we construct an "accounting" counterfactual[53] for bank loan revenues and interest expenses during the COVID recession and the global financial crisis. This allows us to answer the following questions: Keeping all other outcomes fixed, how much income would banks have lost if credit lines had not been linked to LIBOR but instead were linked to a risk-free rate such as SOFR? And, what would bank interest expenses have been if drawdowns had not been pre-cautionary, causing these draws to be financed at prevailing market rates for unsecured wholesale funding? '

To construct these counterfactuals, we require a series of assumptions regarding how bank revenues and expenses evolve over this period. For this analysis, we define the COVID shock to have occurred between January 2020 and June 2020. We define the GFC to have been between July 2007 and June 2009.

These counterfactuals do not incorporate the impact of loan revenues and funding costs caused by incremental equilibrium shifts in line draws that would be triggered by transition from LIBOR to SOFR.

[53]We refer to this exercise as an "accounting" counterfactual, since our calculations do not take into account how agents would have adjusted as a response to changes in the reference rates. We assume that balances are unchanged regardless of the underlying loan reference rate. Our model suggests that draws would comparatively increase for SOFR-linked credit lines vs. LIBOR-linked lines in periods of stress, but would decrease vs. LIBOR-linked loans in periods without stress.

Those effects can be gauged from the calibrated model results shown in Section 6.

D.1 COVID Counterfactual

For our COVID counterfactual, we use the FR Y-14 to model bank-level loan revenues and we use the FR 2052a to model bank-level interest expenses. Our bank sample for this counterfactual excludes all IHCs, as well as all banks that do not file the FR Y-14Q Schedule H1.

On the loan side, we leverage the granularity of the FR Y-14Q to recalculate interest income at the loan-level for all C&I loans held by each bank. Specifically, we calculate:

$$\text{LIBOR Revenue}_{i,t} = (\text{LIBOR}_t + \text{Interest Rate Spread}_{i,t}) * \text{Utilized}_{i,t},$$

where LIBOR_t is the value of LIBOR reported at the end of the prior quarter, $\text{Interest Rate Spread}_{i,t}$) is the interest rate spread reported for loan i at time t, and $\text{Utilized}_{i,t}$ is the utilization of loan i at time t. For loans that report LIBOR as the underlying base rate, we also run a SOFR counterfactual scenario, where we calculate:

$$\text{SOFR Revenue}_{i,t} = (\text{SOFR}_t + \text{Interest Rate Spread}_{i,t} + \text{ISDA Spread Adjustment}) * \text{Utilized}_{i,t},$$

where SOFR_t is the value of term SOFR reported at the end of the prior quarter, and ISDA Spread Adjustment is ISDA- and ARRC-recommended credit spread adjustment for loans.[54] For fixed rate loans and floating rate loans not linked to LIBOR, we do not vary our calculations between scenarios. To estimate interest income from these loans, we calculate

$$\text{Loan Revenue}_{i,t} = \text{Interest Rate}_{i,t} * \text{Utilized}_{i,t},$$

where Interest Rate_t is the interest rate reported on loan i at time t.

For these scenarios, we restrict our attention to domestic C&I and CRE loans only, as this allows us to reconcile our estimated bank-level loan-revenues to the domestic C&I and CRE loan revenues reported in bank call reports.[55] We apply minor data cleaning to reported interest rates and interest rate spreads, which affect less than 0.1% of observations. We also apply additional adjustments, which affect a small portion of loans. We apply loan-level interest rate floors and ceilings if the interest rate falls below or above the respective value reported for the loan. We also assume no interest income in all periods for which a loan is flagged as non-accrual. As the Y-14 data are reported quarterly, but our analysis is conducted monthly, we assume that loan balances increase or decrease linearly between quarter ends (that is, we linearly interpolate between quarter-end balances at the loan-level). Additionally, as we do not observe to which term LIBOR a loan is linked, we run two simulations: a 1M and a 3M scenario. We further restrict our recent loan-revenue analysis to start in 2019, since that is when term SOFR rates began publication.

On the liabilities side, we calculate three alternative scenarios based on our monthly panel in the FR 2052a. These scenarios are intended to analyze the incremental cost required to fund large drawdowns in March 2020. In the first scenario, we assume that all bank-level corporate drawdowns were funded entirely by wholesale funding at the relevant term LIBOR. This provides an upper bound for the interest expense required to fund these drawdowns.

In the second scenario, we estimate actual funding costs for corporate drawdowns based on how each bank actually funded them. To do so, we assume a waterfall of funding sources, aligned with

[54]These values are 26.161 basis points for a 3-month term and 11.448 basis points for a 1-month term.

[55]These account for between 70% and 80% of domestic C&I and CRE loans at the banks in our sample. We do not fully capture C&I or CRE loan revenues or balances because the Y-14 only contains a subset of these loans. We do not observe small business loans or Paycheck Protection Program loans. Additionally, with respect to income, we do not observe any portfolio or loan-level hedges that would affect interest income.

our results from Section 5.4 on how drawdowns were funded in the cross-section. We assume that corporate deposits paid the average fed funds rate over the month. To the extent that banks took out FHLB advances to fund these draws, we apply the average FHLB Des Moines fixed rate advance rate for that portion of the funding. Finally, all remaining funding is assumed to be funded at term LIBOR. This scenario is intended to illustrate the actual incremental cost of borrower drawdowns between March and June 2020.

In our third scenario, we estimate the funding costs for corporate drawdowns, assuming that they were entirely precautionary (meaning that they were all deposited at the banks from which they were drawn). Again, we assume that those deposits paid the average fed funds rate during the month. This scenario provides a lower bound on the incremental interest expense that banks would have had to pay.

D.2 GFC Counterfactual

For our GFC counterfactual, we do not have data at the bank-loan level to calculate counterfactual interest income by replacing LIBOR with SOFR. As a result, we estimate our counterfactual using the FR Y-9C for the subset of our main sample banks that reported the Y-9C in all quarters between July 2007 and June 2009. We also must make assumptions about the balance-sheet composition of the banks in our sample. We assume that 70.21% of domestic C&I loans are LIBOR-linked, which represents the percentage of domestic C&I LIBOR-linked loans as of December 2019 (see Table G.9). Given that term SOFR did not exist during the GFC, we proxy for it using the relevant term OIS, as in Jermann (2021). We leverage BHC subsidiary data on interest income on C&I loans to calculate base C&I loan revenues. We estimate the portion of C&I loan revenues linked to LIBOR as

$$\text{LIBOR Revenue}_t = \%\ \text{LIBOR} \times \text{C\&I Loans}_t \times (\text{3M LIBOR}_{t-1} + \text{C\&I Spread}_t),$$

where 3M LIBOR_{t-1} is the end-of quarter 3M LIBOR from the prior quarter and C&I Spread_t represents the difference between industry reported C&I rate and average 3M LIBOR in a given quarter. When calculating SOFR revenues, we estimate

$$\text{SOFR Revenue}_t = \%\ \text{LIBOR} \times \text{C\&I Loans}_t \times (\text{3M OIS}_{t-1} + \text{ISDA Spread Adj.} + \text{C\&I Spread}_t),$$

where the additional ISDA spread adjustment term is added to account for the impact of the transition.

On the liability side, we apply the same logic as we do for the COVID counterfactual to estimate incremental funding costs under three scenarios: (1) entirely wholesale funding; (2) 85% deposits and 15% FHLB; and (3) entirely deposit funding.

D.3 Results

Table D.1 shows the results of this analysis, assuming that all LIBOR-linked loans are 3M tenor and transitioned to a 3M SOFR term. Overall, we estimate that banks would have lost about $1.6 billion (or 9%) of interest income on domestic C&I loans in the first two quarters of 2020 if loans had referenced SOFR instead of LIBOR.[56] Further, if we expect that banks fund these additional drawdowns entirely with wholesale unsecured market sources (at LIBOR rates), we estimate that industry interest expenses would have been $430 million above their actual estimated funding costs (or 2.4% of domestic C&I loan income over the period). Again, this is holding constant the amount of drawdowns, rather than accounting for the increased incentive to draw on SOFR-linked lines relative to LIBOR-linked lines during a stressed-market period.

[56] The results are consistent but smaller for a 1M term. Additionally, we conduct a similar counterfactual for CRE loans during COVID using the FR Y-14Q. In Table D.2, we estimate that banks would have lost an additional $320 million in domestic CRE loans.

Table D.1: **Counterfactual Estimated Impacts of Replacing LIBOR with SOFR During GFC and COVID ($B).**

Period	C&I Loans		Interest Income			Interest Expense on Draws		
	Start	Max	LIBOR	SOFR	Diff.	All WSF	COVID Dist.	All Precaution
GFC	498.1	752.4	71.17	64.69	-6.48	7.86	5.09	4.72
COVID	985.2	1234.0	17.60	16.01	-1.59	0.68	0.25	0.19

Notes: This table displays results from a counterfactual exercise to understand the impact of the LIBOR-SOFR replacement on banking income and expenses. All values are in $ billion. For this analysis, we define the GFC to be between July 2007 and June 2009 and COVID to be between Jan. 2020 and June 2020. We assume all LIBOR and SOFR revenues and expenses are indexed to a 3M tenor. Given the lack of data availability during the GFC, we proxy for 3M term SOFR during the GFC using 3M OIS. Interest income reflects the estimated total interest income on C&I loans, both term loans and credit lines. We assume floating rate loans reprice quarterly based on the prior month-end index rate. Interest expenses for both COVID and GFC reflect the incremental interest expenses required to finance loan drawdowns during the relevant shock period. We assume interest expenses are based on average monthly (COVID) or quarterly (GFC) rates. We restrict our sample to a balanced panel of large banks in both periods.

By contrast, in the GFC we find that banks would have lost significantly more revenue on their C&I loan books. Given the prolonged period of stress, we calculate a decrease in interest income of $6.5 billion (or 9.1%) between July 2007 and June 2009 for the C&I loan portfolios of the largest banks. This is less than the headline impact in Jermann (2021) due to differences in the portfolios that we study; our results are generally aligned for the same sub-portfolios.[57] On the liability side, we find that funding these drawdowns at 100% LIBOR throughout the entire period would have increased interest expense by $3.1 billion (or 4.4% of C&I loan revenue), compared to an entirely precautionary-draw scenario. If industry drawdowns were funded by a liability composition similar to that of the COVID pandemic – 85% deposits and 15% FHLB advances – incremental expenses would have been $5 billion over the period, $2.8 billion lower than if they were entirely funded via wholesale markets.

The results of these counterfactual exercises highlight how LIBOR can mitigate a bank's funding costs in periods of stress. Comparing the incremental revenue from LIBOR versus SOFR loans ($1.6 billion in COVID, $6.5 billion in the GFC) to the "worst" case incremental interest expenses from draws ($0.68 billion in COVID, $7.9 billion in the GFC), we see that incremental LIBOR-based revenues fully or almost fully cover the incremental expenses associated with drawdowns.

E Incitements to Draw Early or to Run

The following extension addresses a borrower's incentives to draw on its credit lines even before they are needed, and when drawing to deposit the resulting funds at the same bank. These incentives are influenced by the combined effects of potential future deteriorations in the credit qualities of the bank or the borrower. Ideally, we want to capture the following incentives:

1. There is a relationship benefit or convenience to keeping drawn funds on deposit in the same bank.

2. If the bank's credit quality is at risk of worsening significantly, the borrower has an incentive to maintain liquidity by drawing early and placing the funds in another cash instrument, such as

[57] Jermann (2021) found that using term SOFR during the financial crisis would have reduced overall bank loan revenues by about $26 billion. The key difference between our analysis is that we restrict our focus to large bank C&I lending, to: (1) allow for greater comparability between our COVID and GFC samples; and (2) allow for a greater focus on the impact of credit lines. Restricting his sample to the same sub-sample of loans that we consider (in Jermann (2021), "syndicated loans" and "corporate business loans"), Jermann (2021) finds a $11.7 billion impact on $930 billion of LIBOR-linked notional, which is comparable to our $6.5 billion impact on $528 billion of LIBOR-linked notional (at peak draws).

Table D.2: **Counterfactual COVID impacts of replacing LIBOR with SOFR on bank revenues for Y-14 banks.**

Period	Bank	Y-14 Coverage		3M Term			1M Term		
	Loans	% Balances	% Income	LIBOR	SOFR	Diff	LIBOR	SOFR	Diff
Panel A: C&I Loan Portfolio									
Pre-COVID	1129.11	82.79	69.78	38.96	39.09	0.14	38.30	38.66	0.36
COVID	1320.93	81.26	59.12	17.60	16.01	-1.59	16.71	15.56	-1.15
Post-COVID	1118.78	75.40	47.43	22.25	22.54	0.29	21.86	21.98	0.12
Panel B: CRE Loan Portfolio									
Pre-COVID	789.08	72.80	81.90	25.81	25.89	0.07	25.47	25.66	0.19
COVID	809.92	74.10	74.56	11.63	10.86	-0.77	11.22	10.65	-0.58
Post-COVID	806.81	75.01	76.10	20.80	20.94	0.14	20.61	20.67	0.06

Notes: This table displays the impact, by time period, to industry loan revenues by switching from a LIBOR-based index to a SOFR-based index. Data are restricted to 2019q1 through 2021q2: Pre-COVID is 2019, COVID is 2020q1 and 2020q2, and Post-COVID is 2020q3 and beyond. Within the Y-14Q, we restrict to domestic C&I loans (Panel A) and domestic CRE loans (Panel B) to ensure comparability with the Y-9C. From left to right, columns represent: (1) Time period; (2) Average quarterly value of outstanding loans; (3) Coverage of loan balances by the FR Y-14Q; (4) Coverage of loan revenues by the FR Y-14Q; (5) Total loan revenues in $ billion, assuming 3M LIBOR index using the Y-14 over the relevant period; (6) Total loan revenues, assuming 3M term SOFR plus ISDA spread adjustment; (7) Difference between LIBOR and SOFR for 3M term; (8) Total loan revenues in $ billion, assuming 1M LIBOR index using the Y-14 over the relevant period; (9) Total loan revenues, assuming 1M term SOFR plus ISDA spread adjustment; (10) Difference between LIBOR and SOFR for 1M term. Of note: Y-14 and Y-9C do not fully reconcile due to unobserved balances and income in the Y-14. Data sources: FR Y-14Q Schedules H1 and H2, FR Y-9C, Bloomberg, FRED.

deposits in a different bank. This could be part of a run on the bank.

3. If the borrower's or the bank's credit quality is at risk of worsening significantly, the borrower has an incentive to draw on the line early, before the bank blocks the borrower from doing so by claiming that the borrower has not met the necessary covenants. If the bank's credit quality were to deteriorate significantly, then the bank has an incentive to block the drawing on lines to preserve its liquidity, even if the borrower's quality has not deteriorated, in which case there is an associated relationship cost to the bank.

First, however, we ignore for simplicity the borrower's credit risk, which makes the problem complicated.

Lines are contracted at time 0, giving the borrower the option to draw on the line at time 1 or at time a at an interest rate equal to a fixed contractual spread s over the reference rate. We analyze cases in which the reference rate is either a credit-sensitive rate like LIBOR or a risk-free rate r like SOFR. Purely for notational simplicity, given the increased model complexity, we assume that the risk-free rate r is always zero. The reference rate is R_1 for loans taken at time 1 and maturing at time a, and R_a for loans taken at time a and maturing at time 2. We ignore risk aversion throughout. For the case of credit-sensitive reference rates, we take R_1 and R_a to be positively correlated with the unsecured borrowing rates of the bank, $r + S_1$ at time 1 and $r + S_a$ at time a.

The borrower will be blocked from drawing at time a if $S_a \geq \hat{S}$, for some threshold $\hat{S}$. Because we are conducting a marginal analysis, we take $\hat{S}$ as given, although it may depend on the borrower type. The spreads S_1 and S_a are affiliated, so the conditional probability at time 1 that the borrower is blocked from drawing at time a is increasing in S_1. The borrower will endogenously choose whether to deposit any funds drawn at time 1. Any drawn funds outstanding at time a are for uses by the borrower at that time, and are not left on deposit. If the borrower does not need cash at time a, any previously drawn funds are repaid.

At time 0, the bank offers the borrower a menu $\{(L, s) : L \geq 0\}$ of credit line terms distinguished by the size L of the line and the associated fixed spread s over the variable loan benchmark rate R. At time

1, information reveals the credit spread S_1 of the bank for unsecured wholesale funding maturing at time a. Likewise, at time a, the credit spread S_a of the bank for loans maturing at time 2 is observed. Information is symmetric throughout.

The borrower will use the drawn funds only at time a, if at all. At time a, the benefit to the borrower of having access to x in cash is $b(x, \psi)$, where ψ is a liquidity-preference variable that is revealed at time 1 and b is a function with the same properties assumed in the basic model. At time 1, given the committed size L of the credit line, the borrower chooses the amounts q_1 to borrow at time 1. At time a, the borrower chooses the incremental amount q_a to borrow, if not blocked by the bank, so as to maximize the benefit of access to the cash, net of the present value of the loan repayment. We allow q_a to be negative, subject to $q_1 + q_a \geq 0$, with the idea that by time a, the borrower will either have used the drawn funds or paid back funds drawn at time 1. At time 2, the total assets and total liabilities of the bank are revealed and the bank is either solvent or not. For simplicity, the bank will not default before time a, for example because the bank has no liabilities maturing before time 2. If solvent at time 2, the bank pays back $q_1(1 + S_1)(1 + S_a) + q_a(1 + S_a)$. The corporate borrower repays the outstanding loan amount, $q_1 + q_a$, whether or not the bank is solvent at time 2. The proportional reputational or convenience cost to the borrower of not leaving the drawn funds on deposit at the same bank is ϵ. For simplicity, we assume that the borrower will not default on the credit line and take $R_1 = r + S_1$. We don't take $R_a = r + S_a$, because we want to allow for the risk that the bank will become much worse at time a than "LIBOR quality," which as a result could prevent the borrower from drawing or even make the bank unable to fund the draw request.

State by state, the borrower thus solves

$$V(L) = \sup_{0 \leq q_1 + q_a \leq L,\, W} E\left[b(Q + q_a, \psi) - Wq_1\epsilon - Q(1 + R_1 + s)(1 + R_a + s) - q_a(1 + R_a + s) \,|\, S_1, \psi\right], \tag{16}$$

where q_a is constrained to be non-positive on the event $\{S_a \geq \hat{S}\}$, where

$$Q = q_1(H + (1 - H)W),$$

and where H is the indicator of the event that the bank honors its deposit obligation at time a. We take $P(H \,|\, S_1)$ to be a simple given function, for example linear, assuming that S_1 has a sufficiently bounded range. Or, for another example, we can take $H = 1_{\{S_a < S^*\}}$, where S^* is a threshold above $\hat{S}$. As reflected in (16), if the borrower loses its deposits at time a, then of course it is not obligated to pay back the loan.

The problem can be solved inductively as follows. At time a, for each given amount q_1 of funding obtained at time 1, the optimal incremental borrowing amount q_a is the solution of the associated Kuhn-Tucker conditions, which have an explicit first-order interior condition whenever the solution is interior. We can thus treat q_a as an explicit function of variables observable at time a. We ignore for now cases in which the fraction W of withdrawn cash may interior, and take W to be chosen as zero or 1 for simplicity. Then, given S_1 and ψ, the optimal amount q_1 of funding at time 1 can be solved by a line search for each of two cases, $W = 0$ and $W = 1$. The better of these two cases determines W and q_1, state by state, and from these, q_a.

The marginal increase at time 1 in the equity value of the bank associated with given contractual credit line terms (L, s) is

$$g_{L,s} = E\left(1_A[q_1[(1 + R_1 + s)(1 + R_a + s) - 1] + q_a(R_a + s) - q_1((1 + S_1W)(1 + S_a) - 1) - q_aS_a]\right). \tag{17}$$

where 1_A is the event of bank solvency at time 2. The first two terms inside the expectation of (17) are the bank's profit markups. The third and fourth terms are debt overhang costs to shareholders. For each line size L, the bank offers a competitive spread s at which the bank's shareholders break even on marginal new credit lines, meaning that $g_{L,s} = 0$. Given the resulting menu of feasible line terms, the borrower solves (16) for the optimal line amount L^*.

F Model Calibration Details

This appendix section provides additional details on the calibration of the theoretical model. The main goal of the calibration is to match the aggregate quarterly credit line drawing behavior from the first quarter of 2015 to the second quarter of 2021. We first provide some properties of the model used in the calibration. In the following, we let $\underline{\epsilon} = -\overline{\epsilon}$.

Theorem 1. *For a given credit line limit L, the optimal quantity $Q(L)$ of drawn credit has the following properties.*

1. *On the event $\{K(W) + \overline{\epsilon} > 0,\, K(W) + \underline{\epsilon} < L((1+R+s)^{\frac{1}{\alpha}}\}$,*

$$E[Q(L) \mid W] = \quad \frac{L(K(W) + \overline{\epsilon} - L(((1+R+s)^{\frac{1}{\alpha}}))^{+}}{(\overline{\epsilon} - \underline{\epsilon})} + \frac{-\max(0, \frac{(K(W)+\underline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}})^2 + \min(L, \frac{(K(W)+\overline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}})^2}{\frac{2(\overline{\epsilon}-\underline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}}}.$$

2. *On the event $\{K(W) + \overline{\epsilon} \leq 0\}$, we have $E[Q(L) \mid W] = 0$.*

3. *On the event $\{K(W) + \underline{\epsilon} \geq L(1+R+s)^{\frac{1}{\alpha}}\}$, we have $E[Q(L) \mid W] = L$.*

Theorem 2. *For a given credit line limit L, the cumulative distribution function F of the cross-sectional distribution of credit line utilization has the properties*

$$F(0) = P(Q(L) = 0 \mid W) = \begin{cases} 1 & \textit{on the event } \; K(W) + \overline{\epsilon} \leq 0 \\ 0 & \textit{on the event } \; \frac{(K(W)+\underline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}} \geq 0 \\ -\frac{(K(W)+\underline{\epsilon})}{\overline{\epsilon}-\underline{\epsilon}} & \text{otherwise,} \end{cases}$$

and

$$F(L) = P(Q(L) = L \mid W) = \begin{cases} 1 & \textit{on the event } \; \frac{(K(W)+\underline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}} \geq L \\ 0 & \textit{on the event } \; \frac{(K(W)+\overline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}} \leq L \\ \frac{\overline{\epsilon}-L((1+R+s)^{\frac{1}{\alpha}}+K(W)}{-\underline{\epsilon}+\overline{\epsilon}} & \textit{otherwise.} \end{cases}$$

The density $f(x) = F'(x)$ of the cross-sectional distribution of credit line utilization at any interior support point $x \in (0, L)$ is

$$f(x) = P(Q(L) \in dx \mid W) = \frac{((1 + \frac{R-r+s}{1+r})^{\frac{1}{\alpha}}}{(\overline{\epsilon} - \underline{\epsilon})}.$$

Motivated by aggregate utilization of credit lines observed in our sample, we assume the following functional form for the function $K(\cdot)$ determining the aggregate component $K(W)$ of borrowers' liquidity shocks:

$$K(x) = \mathcal{C}_1 + \mathcal{C}_2 \min(x, x_0) + \mathcal{C}_3(x - x_0)^{+} + \frac{\mathcal{C}_4}{1 + e^{-\mathcal{C}_5(x-x_0)}}, \tag{18}$$

for some constants $x_0, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4$, and $\mathcal{C}_5$ to be calibrated. This functional form captures the features of the data that borrowers sharply increased their total draw-down quantity during COVID shock when LIBOR-OIS rose to around $x_0 = 140$ basis points, the level at which drawing sharply increases for the median borrower. The sensitivity to LIBOR of this increase is captured by the parameter $\mathcal{C}_5$.

We let the data speak by calibrating the values of $\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5$, $\overline{\epsilon}$ and x_0 with the following steps.

1. For any parameter choices $\mathcal{P} = (M, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5, x_0, L, \bar{\epsilon})$, we can calculate the bank's marginal improvement in equity value per credit line when the equilibrium spread is s as,

$$\Pi(\mathcal{P}, s) = E[(1 - 2W)\delta E[Q(L) \mid W](s + W - \kappa(W)W)],$$

   by numerical integration with respect to the probability density of W.

2. Fixing $\mathcal{P}$, we solve $s(L)$ with a numerical binary search for the solution to

$$\Pi(\mathcal{P}, s(L)) = 0$$

   .

3. Let $\mathcal{P}^{shock+} = (M, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5, x_0, 1.1L, \bar{\epsilon})$ and $\mathcal{P}^{shock-} = (M, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5, x_0, 0.9L, \bar{\epsilon})$. We solve $s(1.1L)$ and $s(0.9L)$ such that

$$\Pi(\mathcal{P}^{shock+}, s(1.1L)) = 0$$

   and

$$\Pi(\mathcal{P}^{shock-}, s(0.9L)) = 0.$$

4. We fix a credit line fee f of 20 basis points. We solve for the line size L that maximizes a borrower's expected net benefit, using numerical integration. This expected benefit, for each of three parameter choices, is

$$U(\mathcal{P}, L, s(L)) = E\left[\frac{(K(W)+\epsilon)^{\alpha}}{1-\alpha} Q(L)^{1-\alpha}) - Q(L)\delta(1 + R + s(L))\right] - fL$$

$$U(\mathcal{P}^{shock+}, 1.1L, s(1.1L)) = E\left[\frac{(K(W)+\epsilon)^{\alpha}}{1-\alpha} Q(1.1L)^{1-\alpha}) - Q(1.1L)\delta(1 + R + s(1.1L))\right] - 1.1fL$$

$$U(\mathcal{P}^{shock-}, 0.9L, s(0.9L)) = E\left[\frac{(K(W)+\epsilon)^{\alpha}}{1-\alpha} Q(0.9L)^{1-\alpha}) - Q(0.9L)\delta(1 + R + s(0.9L))\right] - 0.9fL.$$

   In equilibrium, borrowers choose a line size L with the property that $\Xi(\mathcal{P}) = 0$ where

$$\Xi(\mathcal{P}) = \max(U(\mathcal{P}^{shock-}, 0.9L, s(0.9L)), U(\mathcal{P}^{shock+}, 1.1L, s(1.1L)), U(\mathcal{P}, L, s(L))) - U(\mathcal{P}, L, s(L)).$$

5. For the realization w_i of LIBOR-OIS observed in the data in quarter i, we solve the equilibrium assuming that the equilibrium s and L are the actual spread and credit limit observed in the historical data. From this, we calculate the modeled aggregate amount drawn,[58] $Q_i^*(\mathcal{P}) = M \cdot E[Q(L) \mid W = w_i]$. The empirical analogue is the actual aggregate quantity Q_i drawn in quarter i. Likewise, we compute the modeled fraction of borrowers utilizing their entire credit line, which is $Z_i^*(\mathcal{P}) = P(Q(L) = L \mid W = w_i)$. As an approximation of the precise empirical analogue to Z_i^*, we take the empirical analogue to be the fraction Z_i of lines that were drawn in quarter i to within 95% of their line limits. We also calculate the average across sample periods of the total across borrowers of credit line sizes in the data. This average is denoted $\overline{L^{sum}}$.

[58] Here, we abuse the conditional-expectation notation by using a regular version $w \mapsto E[Q(L) \mid W = w]$ of the conditional expectation, a function that exists under a mild technical integrability condition.

6. As a first step in calibrating the model, we choose the model parameters $\mathcal{P}_1$ that minimize the sum of squared model errors, defined by

$$O_1(\mathcal{P}) = \Xi(\mathcal{P})^2 + (\overline{L^{sum}} - M \cdot L)^2 + \sum_{i=1}^{N}(Q_i^*(\mathcal{P}) - Q_i)^2 + \sum_{i=1}^{N}(Z_i^*(\mathcal{P}) - Z_i)^2,$$

   where the summation over i is across all N quarters in our 2015-2021 sample period.

7. Minimizing the unweighted sum $O_1(\mathcal{P})$ does not account for the quite different magnitudes of the different types of terms in the sum. This could result in heavily overweighting some types of model errors over other types. So, we perform a second calibration step by using the first-step parameters $\mathcal{P}_1$ to estimate the error moments

$$\begin{aligned}
\mathcal{E}_1 &\equiv |\Xi(\mathcal{P}_1)| \\
\mathcal{E}_2 &\equiv |\overline{L^{sum}} - M_1 \cdot L| \\
\mathcal{E}_3 &\equiv \sqrt{N^{-1} \sum_i (Q_i^*(\mathcal{P}_1) - Q_i)^2} \\
\mathcal{E}_4 &\equiv \sqrt{N^{-1} \sum_i (Z_i^*(\mathcal{P}_1) - Z_i)^2},
\end{aligned}$$

   where M_1 denotes the quantity of borrowers associated with $\mathcal{P}_1$.

8. Our final model parameters $\mathcal{P}^*$ are those minimizing the weighted sum of squared model errors,

$$O_2(\mathcal{P}) = \frac{1}{\mathcal{E}_1}\Xi(\mathcal{P})^2 + \frac{1}{\mathcal{E}_2}(\overline{L^{sum}} - M \cdot L)^2 + \frac{1}{\mathcal{E}_3}\sum_{i=1}^{N}(Q_i^*(\mathcal{P}) - Q_i)^2 + \frac{1}{\mathcal{E}_4}\sum_{i=1}^{N}(Z_i^*(\mathcal{P}) - Z_i)^2.$$

9. It turns out that $\mathcal{C}_3$ is not well identified in our sample, because LIBOR-OIS spreads vary within our sample by no more than 150 basis points, but x_0 is 140.6 basis points. We ultimately chose $\mathcal{C}_3 = 100$ so that the modeled line utilization during the GFC is roughly equal to the maximum sample utilization in non-crisis sample periods for which LIBOR-OIS is 80 basis points or less. We experimented with a wide choices of $\mathcal{C}_3$ and found that our main results are quite robust to this choice.

G Additional Tables and Figures

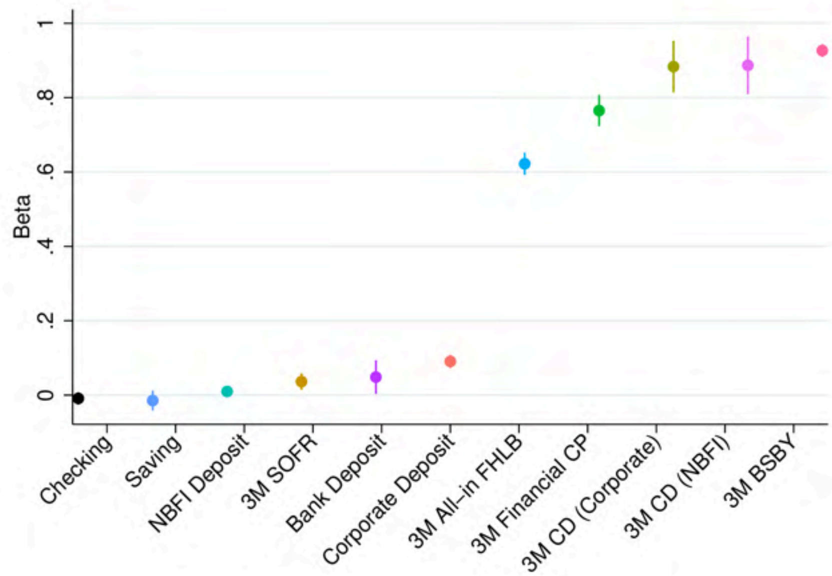


Figure G.1: **Bank Funding Rates and LIBOR.** Notes: This table displays the coefficient on 3M LIBOR-OIS in a regression of the form $y_t = \beta \times [\text{LIBOR}_t - \text{OIS}_t] + \epsilon_t$, where y_t is the interest rate or OIS spread on date t. Table G.5 in the Appendix also shows the corresponding detailed regression output. Confidence intervals calculated from robust standard errors. Series represent different maturities and different start dates, which are further detailed in Table G.5. Checking and Saving series represent demand deposit rates. NBFI, Bank and Corporate Deposit are spreads over the effective fed funds rate. 3M SOFR, 3M "All-in" FHLB Advance, 3M CD (corporate), 3M CD (NBFI), and 3M BSBY represent spreads over 3M OIS.

Table G.1: **Bank-Level Distribution of Deposits and Wholesale Funding (percent), Dec. 31, 2019.**

Metric	25^{th} %-tile	Median	Mean	75^{th} %-tile
Panel A: Deposits				
Open	82.2	93.2	85.4	95.9
1 Day-1 Year	2.4	5.5	10.0	11.1
> 1 Year	0.0	1.3	4.6	6.4
Uninsured	33.5	51.7	50.5	61.3
Brokered	0.6	2.1	6.0	9.3
Relationship	49.9	63.8	53.6	72.4
Counterparty Breakdown				
Corporate	9.9	19.0	17.5	25.4
Retail	43.3	54.1	56.9	79.5
Small Business	0.6	4.9	5.5	10.2
NBFI	1.7	4.1	13.3	12.1
Other Cpy	1.5	5.7	6.8	11.1
Panel B: Wholesale Funding				
Very Short Term (Open-30 Days)	6.5	10.8	16.1	20.2
Short Term (1-6 Months)	8.2	11.8	11.9	16.0
Medium Term (1-6 Months)	5.3	6.8	8.2	9.5
Long Term (1+ Year)	58.2	67.3	63.8	75.4
Collateralized	0.8	17.5	23.6	40.6
Prime Brokerage	0.0	0.0	1.1	0.1
Product Breakdown				
Unstructured LT Debt	49.2	60.1	59.4	67.1
Structured LT Debt	0.0	0.0	4.2	3.4
FHLB Loans	0.1	5.5	14.0	28.5
Free Credits	0.0	0.0	6.1	3.3
Other Product	5.0	11.1	16.3	24.4

Notes: Data Source: FR2052a. The table represents the percentage distribution of deposit and wholesale funding characteristics by bank across 24 banks in a monthly FR 2052a panel, as of December 31, 2019. Metrics are aggregated at the bank level, and statistics are calculated across banks. Maturity information reflects remaining maturity as of Dec. 31, 2019, and not maturity at origination. NBFI reflects non-bank financial institutions and includes Supervised Non-Bank Financial Institutions and Other Financial Instiutions (as reported on the FR 2052a). Panel A reflects distributional information for deposits, while Panel B reflects information for wholesale funding.

Table G.2: **Regional Bank Funding Breakdown (percent), Dec. 31, 2019.**

Counterparty	Open	1 Day-1 Year	1 Year+	Uninsured	Brokered	Relation-ship	Total Deposits	Total Assets
Retail	82.4	12.7	4.8	21.5	81.5	3.0	54.0	39.3
Non-Financial Corp.	96.5	3.2	0.2	96.2	46.5	0.5	24.6	17.9
Small Business	98.1	1.6	0.3	47.5	93.8	0.0	9.5	6.9
NBFI	85.3	14.7	0.0	98.2	47.8	0.0	5.4	3.9
Public Sector Entity	93.6	5.9	0.5	97.9	37.1	0.5	5.2	3.8
Bank	87.2	12.6	0.2	99.3	26.7	0.6	1.0	0.7
Other Counterparty	98.2	1.8	0.0	98.0	76.2	0.3	0.4	0.3
All Counterparties	88.2	9.0	2.7	51.5	69.4	1.8		

Product	Open-30 Days	1-6 Months	6 Months-1-Year	Long-Term	Collateral-ized	Prime Brokerage	Wholesale Funding	Total Assets
Unstructured LTD	0.5	7.4	8.8	83.4	0.0	0.0	59.8	6.6
FHLB	36.6	19.6	11.4	32.4	100.0	0.0	28.5	3.1
Conduit and SPV	23.6	12.1	12.8	51.5	100.0	0.0	5.1	0.6
Other Wholesale	95.0	5.0	0.0	0.0	0.0	0.0	5.1	0.6
Wholesale CDs	67.7	32.3	0.0	0.0	0.0	0.0	1.2	0.1
Structured LTD	0.0	0.0	0.0	100.0	0.0	0.0	0.2	0.0
CP	85.2	14.8	0.0	0.0	0.0	0.0	0.1	0.0
Free Credits	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
All Products	17.7	11.3	9.1	61.9	33.6	0.0		

Notes: Table represents the distribution of deposit and wholesale funding characteristics across regional banks in monthly FR 2052a panel. For deposits: Other Counterparty includes Central Banks, Debt Issuing SPEs, GSEs, Multilateral Development Banks, Sovereigns, Other Supranationals, counterparties categorized as "Other" and deposits with missing counterparty type information. Maturity information reflects remaining maturity as of Dec. 31, 2019, and not maturity at origination. Relationship deposits include: (1) transactional and non-transactional relationship accounts for retail and small business customers; (2) operational deposits, for all other counterparty types.
For wholesale funding:Conduit and SPV financing includes asset-backed commercial paper, other asset-backed securities, collateralized CP, covered bonds, and tender option bonds. Other Wholesale Funding includes banks' draws on committed lines, government supported debt, onshore and offshore borrowing (e.g. fed funds), structured notes, and unsecured notes.

Table G.3: **FBO Bank Funding Breakdown (percent), Dec. 31, 2019.**

Panel A: Deposit Funding by Counterparty								
Counterparty	Open	1 Day-30 Days	30 Days-1 Year	1 Year+	Uninsured	Relation-ship	Total Deposits	Total Claims
Non-Financial Corp.	44.5	35.0	19.1	1.5	99.9	5.9	44.7	12.8
Bank	19.9	16.2	14.1	49.7	72.7	1.0	29.1	8.3
NBFI	28.9	52.2	17.8	1.1	99.3	5.7	16.3	4.7
Other Counterparty	10.3	40.8	42.2	6.8	100.0	3.0	6.1	1.8
Retail	42.4	52.9	4.7	0.0	100.0	16.5	3.3	0.9
Public Sector Entity	2.7	91.5	0.0	5.8	100.0	0.8	0.3	0.1
Small Business	60.4	30.7	8.6	0.3	99.9	87.6	0.1	0.0
All Counterparties	32.5	33.4	18.3	15.8	91.9	4.7		
Panel B: Wholesale Funding by Type								
Product	Open-30 Days	1-6 Months	6 Months-1-Year	Long-Term	Internal Debt	Collateral-ized	Wholesale Funding	Total Claims
Offshore Borrowing	35.5	10.7	10.6	43.1	98.7	0.0	46.2	35.7
Wholesale CDs	12.1	58.6	27.7	1.7	0.0	0.0	32.8	25.3
Unstructured LTD	1.5	2.8	5.8	89.8	52.2	0.0	9.9	7.7
CP	22.3	68.7	9.0	0.0	0.0	0.0	6.0	4.7
Other Wholesale Funding	81.2	9.7	5.8	3.3	96.2	0.0	2.9	2.2
Onshore Borrowing	51.9	14.3	9.4	24.5	40.8	0.0	1.3	1.0
Free Credits	34.5	65.5	0.0	0.0	0.0	0.0	0.4	0.3
Conduit and SPV	27.4	71.0	0.0	1.6	0.0	100.0	0.4	0.3
All Products	25.1	29.6	15.4	29.8	54.1	0.4		

Data Source: FR2052a. Table represents the distribution of deposit and wholesale funding characteristics across consolidated US branches of foreign banking organizations (FBOs) in a monthly balanced FR 2052a panel of 14 FBOs: BARC, BNPP, TD, SOGN, DB, UBS, BMO, BBVA, KN, CS, MUFG, SMBC, MFG, and RY.

For deposits: Other Counterparty includes Central Banks, Debt Issuing SPEs, GSEs, Multilateral Development Banks, Sovereigns, Other Supranationals, counterparties categorized as "Other" and deposits with missing counterparty type information. Maturity information reflects remaining maturity as of Dec. 31, 2019, and not maturity at origination. Relationship deposits include: (1) transactional and non-transactional relationship accounts for retail and small business customers; (2) operational deposits, for all other counterparty types.

For wholesale funding: Conduit and SPV financing includes asset-backed commercial paper, other asset-backed securities, collateralized CP, covered bonds, and tender option bonds. Other Wholesale Funding includes banks' draws on committed lines, government supported debt, onshore and offshore borrowing (e.g. fed funds), structured notes, and unsecured notes.

The final column (far right) reflects each measure as a % of total claims on non-related parties across all U.S. branches of FBOs in our sample. We use this measure instead of assets since FBO branches may have intercompany loans that overstate total third-party assets.

Table G.4: **Bank-Level Distribution of Floating Rate Long-Term Debt**

in %	Industry	Mean	25^{th} %	Median %	75^{th} %	No. Banks
Fixed	69.93	78.24	69.70	78.56	88.73	14
Floating	29.02	21.51	11.27	21.34	30.30	14
LIBOR	11.36	11.94	8.97	10.82	18.67	14
SOFR	11.34	5.70	0.00	0.00	9.67	14

This table displays statistics from the cross-sectional distribution of banks for which we were able to "confidently" source long-term debt issuance terms via Bloomberg. Data are as of June 30, 2021. We define our "confidence" by measuring the bank-level difference between outstanding amounts as reported in Bloomberg and borrowings as reported in the FR Y-9C. Borrowing in the FR Y-9C is defined as other borrowed money plus subordinated debt less advances from FHLBs. "Confidence" is defined as matching Y-9C within 10% or matching non-deposit liabilities within 5%. Floating rate debt includes both current floating rate notes, as well as variable notes (which start paying fixed and convert to floating at a future date).

Table G.5: **Interest Rate Correlations with LIBOR-OIS**

	Deposit & Risk-Free Rates					
	Checking	Saving	ON Corp	ON NBFI	ON Bank	SOFR
LIBOR-OIS	-0.01	-0.01	0.09***	0.01	0.05***	0.04***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
N	447	447	696	696	693	615
Start Date	14 May 2009	14 May 2009	01 Oct 2018	01 Oct 2018	04 Oct 2018	03 Jan 2019
	Wholesale Rates					
	FHLB	FHLB Adj.	Fin. CP	Corp.	NBFI	BSBY
LIBOR-OIS	0.51***	0.62***	0.77***	0.88***	0.89***	0.93***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)
N	4875	4875	4639	1340	1385	1351
Start Date	04 Dec 2001	04 Dec 2001	04 Dec 2001	15 Jan 2016	11 Jan 2016	06 Jan 2016

This table displays the coefficient on LIBOR-OIS in regressions of the form

$$Y_t = \alpha + \beta \times \text{LIBOR-OIS}_t + \epsilon_t$$

where Y_t is the interest rate or OIS spread on date t. The rates displayed in this table are: Interest and Savings Rate, sourced from FDIC calculations using RateWatch Data; overnight corporate, non-bank financial, and bank deposit spread vs. effective fed funds, where O/N rates are calculated by counterparty type from FR 2420 data; 3M term SOFR and 3M BSBY spreads to 3M OIS, sourced from Bloomberg; 3M Financial CP-OIS spread, sourced from FRED; the 3M FHLB Des Moines rate on fixed rate advances spread to 3M OIS; and the average 3M non-financial corporate CD and non-bank financial CD rates, calculated from the FR 2420, spread to 3M OIS. Regression coefficients can be interpreted as the average relationship between LIBOR-OIS and the corresponding rate or spread. Note: The relatively low observation count for savings and checking deposit rates is due to the weekly nature of the data series, compared to other series, which are reported daily.

Table G.6: **FHLB Drawdowns as a Function of Pre-Positioned FHLB Capacity**

	Δ FHLB Capacity		Δ FHLB Capacity / Lagged Assets	
	(1)	(2)	(3)	(4)
Δ FHLB Funding	-0.65***	-0.66***		
	(0.09)	(0.09)		
Δ FHLB Funding × COVID	-0.34***	-0.33***		
	(0.09)	(0.10)		
Δ FHLB Funding / Lag Assets			-0.61***	-0.58***
			(0.15)	(0.14)
Δ FHLB Funding / Lag Assets × COVID			-0.38*	-0.42*
			(0.20)	(0.20)
No. Banks	22	22	22	22
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
N	973	973	971	971
R^2	0.267	0.299	0.287	0.324

Note: Table reflects regressions of Federal Home Loan Bank (FHLB) capacity (by bank) on FHLB drawdowns. Regressions of the form:

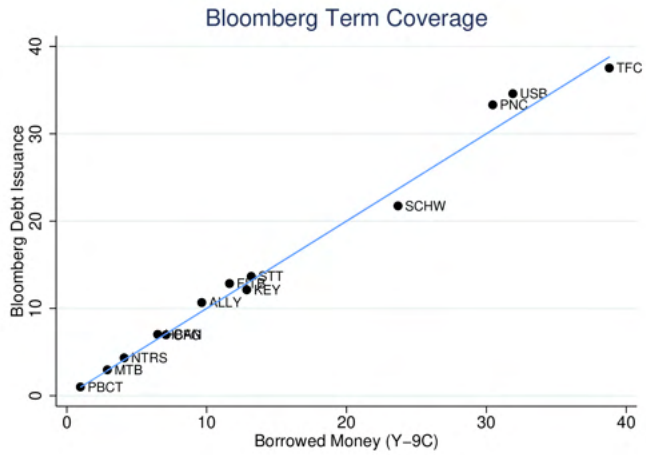
$$\Delta y_{i,t} = \alpha + \beta_1 \mathbb{I}\{\text{COVID}\} + \beta_2 \Delta x_{i,t} + \beta_3 \Delta x_{i,t} \times \mathbb{I}\{\text{COVID}\} + \tau_t + b_i + \epsilon_{i,t}$$

where $\Delta y_{i,t}$ is the change in FHLB capacity (in dollars or over assets), $\Delta x_{i,t}$ is the change in FHLB advances (in dollars or over assets), τ_t reflect time fixed-effects that could affect FHLB capacity, and b_i are bank fixed-effects. FHLB capacity is based on the lendable value of collateral that banks have pre-positioned with the FHLBs. Bank sample restricted to monthly panel of banks in FR 2052a that have ever received FHLB funding. In this table, we define COVID to be March 2020, which is when FHLB draws primarily occurred. Robust standard errors are clustered at the bank level in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

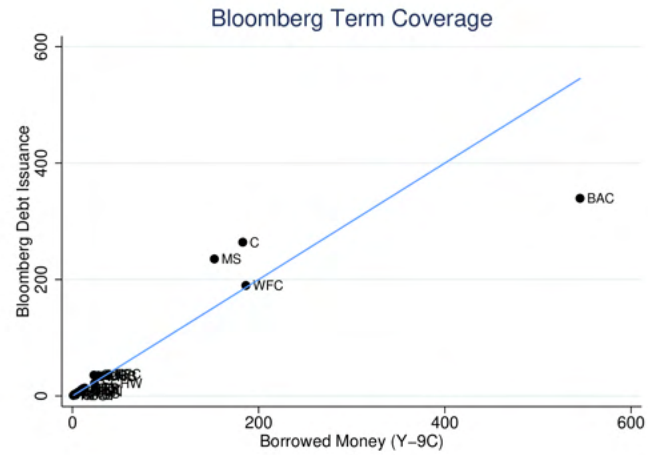
Table G.7: **Precautionary Draws: COVID vs. GFC**

	COVID					GFC		
	Y-14		CIQ / Compustat					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Util.	0.97***	0.97***	0.58***	0.53***	0.45***	-0.01	0.04	-0.01
	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.07)	(0.07)	(0.07)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year	No	Yes	No	Yes	Yes	No	Yes	Yes
Match Quality			No	No	Yes	No	No	Yes
R^2	.275	.275	.281	.29	.379	.0791	.0859	.148
N	7130	7130	1683	1536	1020	1317	1217	811

Notes: This table provides cross-sectional evidence on drawdowns and re-depositing during the COVID pandemic (before and after March 11, 2020) and the GFC (before and after Lehman's failure in September 2008). It estimates cross-sectional regressions of the form $\Delta \text{Cash}_i = \alpha + \beta_1 \Delta \text{Drawdowns}._i + X_i + \epsilon_i$ where the dependent variable is change in cash for firm i before and after the shock, $\Delta\text{Drawdowns}_i$ is the change in credit line utilization for firm i, and X_i are firm controls. Firm controls include industry fixed effects (NAICS 2-digit codes) and cash flow controls. For COVID analysis using the Y-14, cash flow controls include EBITDA and Δ Total Debt less drawdowns. For COVID and GFC analyses using Compustat & Capital IQ (CIQ), cash flow controls include cash dividends paid (DVY), operating cash flow (OANCFY), and long-term debt issuance (DLTISY). Columns 1-2 conduct firm level analyses on quarterly data using the FR Y-14Q (aggregated by borrower TIN) using borrowers who reported financials in either 2019q3 or 2019q4 AND also in March 2020. Columns 3-5 conduct firm level analyses on quarterly data during COVID using drawdowns from Capital IQ (Δ IQ_RC) matched to financials as reported in Compustat. Columns 6-8 conduct firm-level analyses on annual data during the GFC using drawdowns from Capital IQ and financials from Compustat. In Columns 2, 4, 5, 7, and 8, we restrict our sample to borrowers whose financial statement "as-of" dates correspond to calendar year quarters (i.e. March, not February). In Columns 5 and 8, we restrict our sample to a sub-sample of firms where we match long-term debt between Compustat (DLTTQ) and CIQ (IQ_TOTAL_DEBT - IQ_ST_DEBT) within 10% on average. We conduct annual analysis during the GFC, since credit line drawdowns appear most predominantly reported on an annual basis at this time. The dependent variable in Columns 1-2 is the change in cash *and cash equivalents*, since the Y-14 does not segregate cash from equivalents. By contrast, the dependent variable in Columns 3-8 are the change in cash *excluding cash equivalents*. In all cases, we trim both Δ cash and Δ draws at 1% and 99% to attenuate the impact of outliers. Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

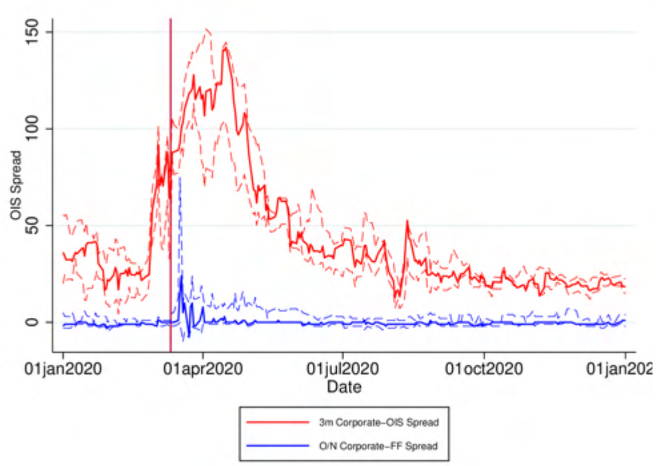


(a) “Confident” Banks Only

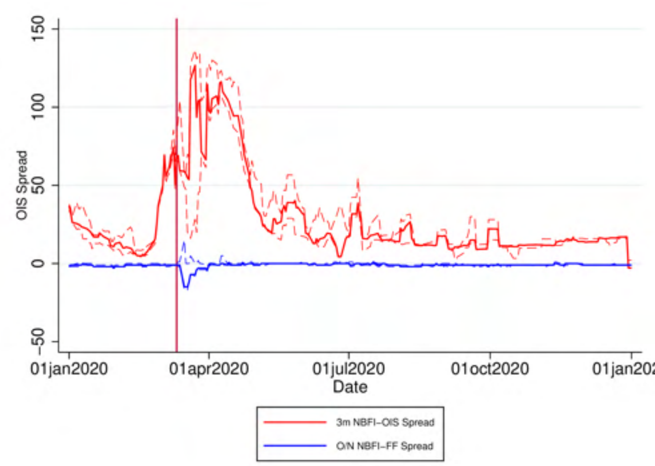


(b) All Banks

Figure G.2: **Bloomberg Coverage of Y-9C Bank Borrowings.** Data source: Bloomberg and FR Y-9C. These figures show our coverage of bank borrowings, as defined in the FR Y-9C, from debt issuances sourced from Bloomberg. Panel (a) shows the non-GSIBs for which we can confidently match total borrowings; Panel (b) shows our match for all banks. In addition to the banks in Panel (a), we also “confidently” match other borrowed money for WFC.

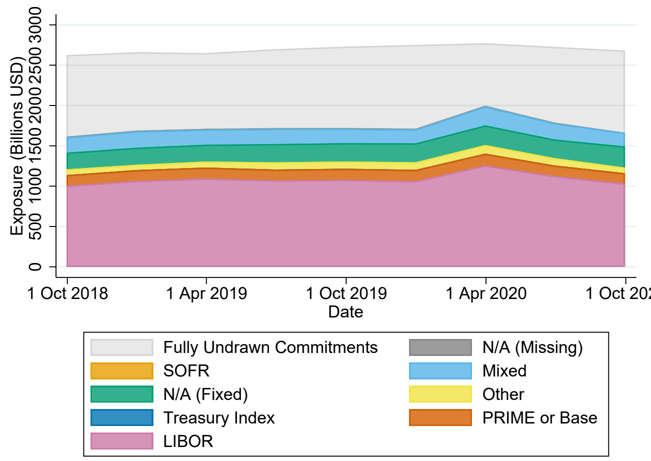


(a) Corporate Deposits

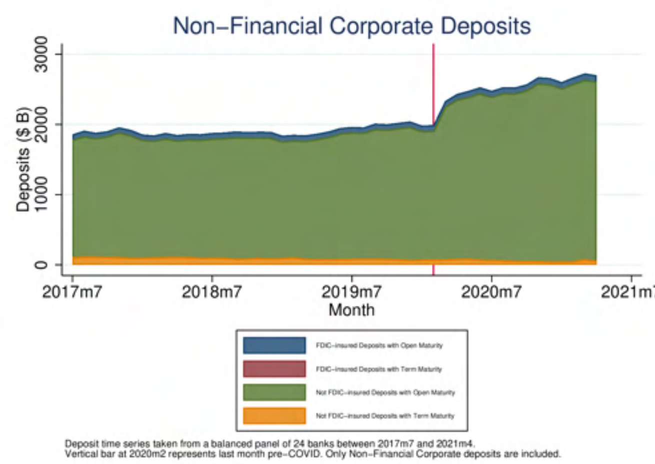


(b) NBFI Deposits

Figure G.3: **3-Month Wholesale CD and O/N Deposit Rate Distribution During COVID.** Data are sourced from FR 2420 daily trade-level reporting. Interest rates are set to missing on days we observe fewer than 10 trades. 3-Month Wholesale CD statistics are calculated by date and dollar-weighted; we include trades with original maturity between 89 and 92 days. 5-day rolling averages are then calculated after daily aggregation. Overnight deposit rates are calculated using 1-day maturities. Dotted lines represent smoothed 25^{th}% and 75^{th}% of trade distributions, respectively. In Panel (a), we restric our sample to non-financial corporate counterparties. In Panel (b), we restrict our sample to non-bank finanical counterparties.



(a) Aggregate C&I Loans by Reference Rate



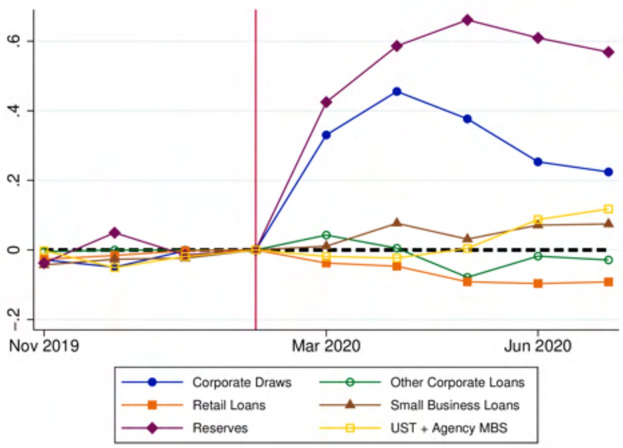
(b) Non-Financial Corporate Deposit Funding in $

Figure G.4: **Corporate Loans & Deposits.** Data Source: FR Y-14Q, FR2052aThese figures display corporate loans and deposits over time. Panel (a) displays C&I loans by underlying reference rate, using the FR Y-14Q Schedule H1. Panel (b) displays corporate deposits by insurance-type and maturity (open or term), using data from our monthly balanced FR 2052a panel.

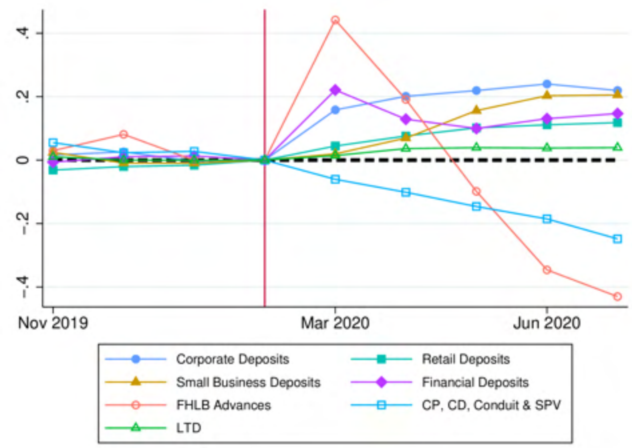
Table G.8: **Precautionary Draws: GFC Robustness**

	2Q Δ Cash			1Q Δ Cash		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Util.	-0.00	-0.00	0.02	0.10	-0.07	-0.10
	(0.08)	(0.08)	(0.11)	(0.14)	(0.15)	(0.19)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year	No	Yes	Yes	No	Yes	Yes
Match Quality	No	No	Yes	No	No	Yes
R^2	.0985	.0985	.167	.225	.228	.329
N	283	283	177	267	206	128

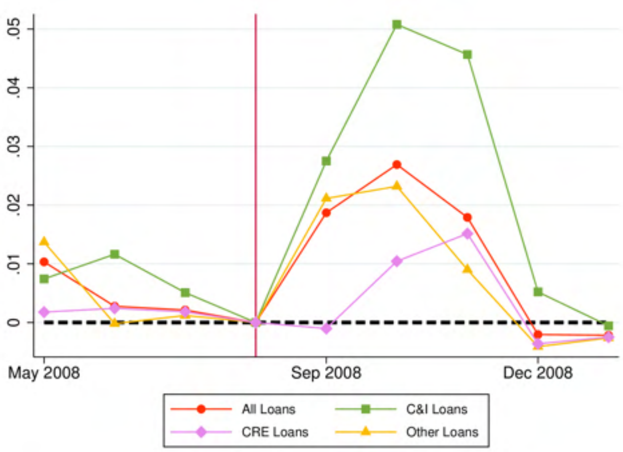
Notes: This table provides cross-sectional evidence on drawdowns and re-depositing during the GFC (before and after Lehman's failure in September 2008). It estimates cross-sectional regressions of the form $\Delta \text{Cash}_i = \alpha + \beta_1 \Delta \text{Util.}_i + \gamma_i + \epsilon_i$ where the dependent variable is the change in cash for firm i before and after the shock, $\Delta \text{Util.}_i$ is the change in credit line utilization for firm i, and γ_i are firm controls. Credit line data are sourced from Capital IQ (CIQ) and firm financials are sourced from Compustat. Firm controls include industry fixed effects (NAICS 2-digit), cash dividends paid (DVY), operating cash flow (OANCFY), long-term debt issuance (DLTISY), and the change in non-cash equivalents, such as monetization of U.S. Treasuries (Δ (CHEQ - CHQ)). The dependent variable is the change in cash (CHQ), which notably *excludes cash equivalents* and thus serves as a strong proxy for deposits. Firm-level analyses analyze the change between the pre-Lehman credit draws and either two (Columns 1-3) or one (Columns 4-6) subsequent quarters. In Columns 2-3 and 5-6, we require fiscal quarters be aligned to calendar quarters (i.e., we exclude companies with quarter-end in October 2008, rather than September 2008). In Columns 3 and 6, we further restrict our sample to a set of firms where long-term debt matches between CIQ and Compustat within 10% on average. For all these analyses, we restrict our sample to the subset of firms that drew on credit lines. Further, since most borrowers that reported credit lines in Capital IQ (CIQ) during the GFC appeared to do so on an annual basis, we restrict our sample further to borrowers who report outstanding credit lines on a quarterly basis. In all cases, we trim both Δ cash and Δ draws at 1% and 99% to attenuate the impact of outliers.



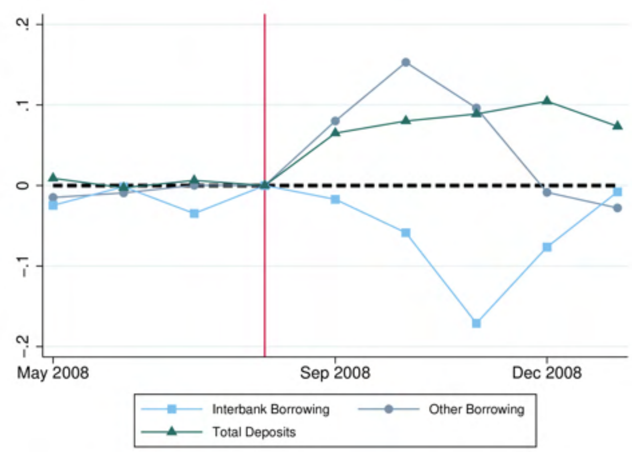
(a) Loans During COVID Recession



(b) Funding During COVID Recession



(c) Loans Around the Lehman Failure



(d) Funding Around the Lehman Failure

Figure G.5: **Industry Assets & Liabilities in Periods of Distress.** This figure shows the evolution of aggregate assets and liabilities during the GFC (following Lehman's collapse) and during the COVID pandemic (following the declaration of the global pandemic in March 2020). Values are normalized to 0 in the month prior to the shock, and represent the log difference compared to the base month. Data from the GFC are sourced from the FRED series for large domestically chartered banks, adjusted for large M&A based on public notes to the H8 series. Data from COVID are sourced from the FR 2052a monthly balanced panel of 24 banks. Due to balance reclassifications between business segments in the FR 2052a, we exclude some banks (in all cases, fewer than three) from our aggregate series for: small business loans, small business deposits, corporate draws, and other corporate loans.

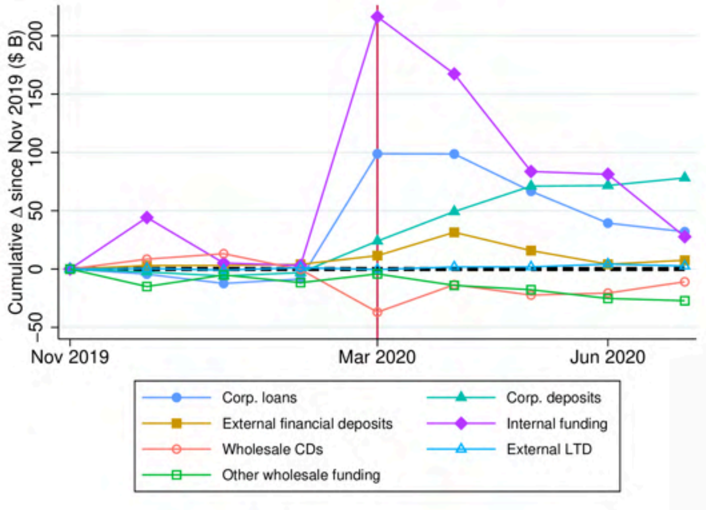
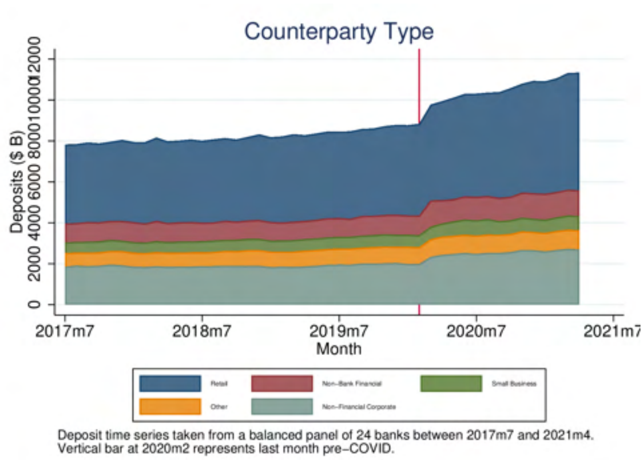
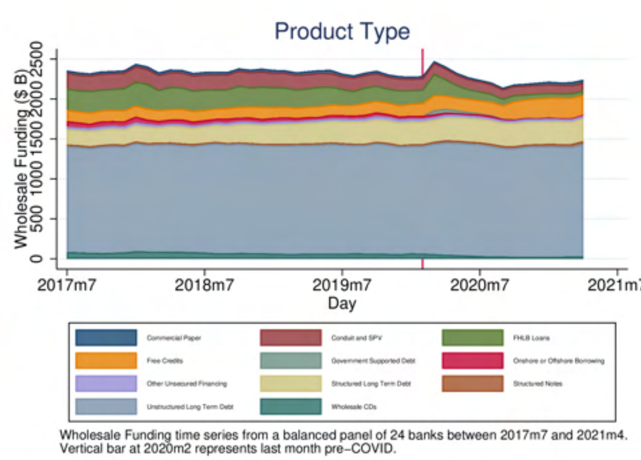


Figure G.6: **Corporate Drawdowns and Funding Sources: U.S. Operations of Foreign Banking Organizations (FBOs).** Data Source: FR 2052a. This figure shows the evoluation of aggregate assets and liabilities during the COVID pandemic for the consolidated US branches of a balanced panel of 14 FBOs: BARC, BNPP, TD, SOGN, DB, UBS, BMO, BBVA, KN, CS, MUFG, SMBC, MFG, and RY. Values represent cumulative growth/decreases compared to the starting month in $ billion.



(a) Deposits by Counterparty in $



(b) Wholesale Funding by Type in $

Figure G.7: **Deposits and Wholesale Funding During COVID.** Data are sourced from our monthly FR 2052a balanced panel between September 2017 and April 2021. Data Source: FR2052a.

Table G.9: **Floating Rate Loans at Large US BHCs (as of December 31, 2019)**

(in %)	Industry	Bank Holding Company 25th	Bank Holding Company Median	Bank Holding Company 75th	No. of Banks
Panel A: Credit Lines					
% LIBOR	70.51	53.75	74.95	84.79	20
% Prime	6.92	2.51	5.07	9.22	20
% Fixed	6.22	0.52	2.52	6.75	20
% Other	16.36	9.36	13.82	32.14	20
Panel B: Term Loans					
% LIBOR	72.80	51.73	84.01	89.88	20
% Prime	4.15	0.10	0.83	1.64	20
% Fixed	14.99	4.74	12.65	17.84	20
% Other	8.05	0.58	1.60	5.57	20
Panel C: Commercial Real Estate					
% LIBOR	65.61	54.82	75.06	83.27	20
% Prime	3.58	0.08	0.98	2.78	20
% Fixed	28.38	9.89	18.80	29.77	20
% Other	2.43	0.45	1.32	2.69	20
Panel D: C&I and CRE Loans					
% LIBOR	68.49	62.21	75.37	80.75	21
% Prime	5.08	0.61	2.49	4.90	21
% Fixed	17.18	8.18	12.71	15.69	21
% Other	9.25	4.21	7.85	10.49	21
LIBOR Util. / Assets	7.39	1.99	10.81	20.38	21
LIBOR Util. / STWF	129.73	34.13	171.79	287.65	21

This table displays the distribution of floating rate loan terms across banks that file the FR Y-14Q Schedule H1 B (corporate loans) and FR Y-14Q Schedule H2 (commercial real estate). In Panels A and B, we restrict our sample to domestic C&I loans only. In Panel C, we restrict our sample to domestic loans secured by real estate. In Panel D, we pool loans across C&I and CRE schedules. We also exclude all holding companies that are owned by foreign (non-U.S.) banks. Data are as of December 31, 2019 and reflect utilized loans (and not unfunded commitments). We define short-term wholesale funding (STWF) similarly to Bowman et al. (2020), as the sum of commercial paper, fed funds purchased, and large time deposits with remaining maturity less than one year, as reported in the FR Y-9C. We add to their definition other borrowed money maturing in one year or less.