NBER WORKING PAPER SERIES

BANK FUNDING RISK, REFERENCE RATES, AND CREDIT SUPPLY

Harry R. Cooperman
Darrell Duffie
Stephan Luck
Zachry Z. Wang
Yilin Yang

Working Paper 30907
http://www.nber.org/papers/w30907

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
February 2023, revised December 2023

The authors thank discussants Anne Duquerroy, Dan Greenwald, David Glancy, Anil Kashyap, Elie Lewi, Jose-Luis Peydro, and Peter Zimmermann, and also thank Alena-Kang Landsberg for her excellent research assistance. The authors are also grateful for conversations with Gara Afonso, Yacov Amihud, Leif Andersen, Viral Acharya, Roc Armenter, Tom Baxter, Antje Berndt, Alastair Borthwick, Tim Bowler, Laurent Clerc, Natalie Cox, Tom Deas, Fulvia Fringuelotti, Jason Granet, Vivien Lévy-Garboua, Andrei Magasiner, John Marynowski, Bill Nelson, Peter Phelan, Michael Roberts, Richard Sandor, Gagan Singh, Jeremy Stein, Jonathan Wallen, and Nathaniel Wuerffel, as well as seminar and conference participants at FRBNY, Stanford University, NYU Stern, Wharton, Federal Reserve Bank of San Francisco, Financial Stability Conference at the Federal Reserve Bank of Cleveland, System Committee on Financial Institutions, Regulation, and Markets held at the Federal Reserve Bank of Kansas City, ES European Winter Meeting 2022, EFA 2022, AFA 2023 in New Orleans, Banque de France, Symposium on Private Firms at University of Chicago, and Summer Finance Symposium at London Business School. Duffie is an NBER Research Associate, CDI Research Fellow, and Resident Scholar at FRBNY. The views stated in this paper are those of the authors and are not necessarily those of the Federal Reserve Bank of New York, the Federal Reserve System, or the National Bureau of Economic Research.

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NBER Working Paper No. 30907
February 2023, revised December 2023
JEL No. E4,E43,G00,G01,G02,G20,G21

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 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 drawdowns are expected to be left on deposit at the same bank, which happened at some of the largest banks during the COVID recession.

Harry R. Cooperman
Maiden Lane
New York
hcoop18@stanford.edu

Darrell Duffie
Graduate School of Business
Stanford University
Stanford, CA 94305-7298
and NBER
duffie@stanford.edu

Stephan Luck
Federal Reserve Bank of New York
33 Liberty St
New York, NY 10045
stephan.luck@ny.frb.org

Zachry Z. Wang
Stanford University
zzwang28@stanford.edu

Yilin Yang
City University of Hong Kong
9-216, Lau Ming Wai Academic Building
83 Tat Chee Ave
Kowloon Tong
Hong Kong
yiliyang@cityu.edu.hk

1 Introduction

In the US, most bank lending to corporations 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 a borrowers' incentives to draw on committed credit lines when the cost to banks of funding these drawdowns is 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, 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 argued that the transition 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. When banks are forced to fund line draws by issuing new debt, their shareholders bear a disproportionate share of the interest expense, a form of debt overhang. This debt-overhang wedge is priced ex-ante into the terms of credit lines. We show that the resulting adverse impact on credit provision is in many cases mitigated by credit-sensitive reference rates that reduce borrowers' incentives to draw on their lines when bank funding spreads are high.

We show that the transition from LIBOR to SOFR will lead to heavier drawdowns on credit lines when bank credit spreads rise sharply. Our calibrated representative bank prices this behavior into the terms of newly originated lines, increasing the expected cost of drawn credit by about 15 basis points, reducing total line commitments by around 6%, and reducing the expected quantity of drawn credit by roughly 3%. The corresponding welfare loss is about 2.6%. The magnitudes of these results are sensitive to assumptions, especially a bank's prediction for how much of crisis line draws will simply be left on deposit at the bank, reducing the bank's marginal need for expensive

[1] We find that at the end of 2019, more than 70% of all US 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.

external funding. If most line draws are anticipated to be left on deposit, then a transition to risk-free reference rates could even *increase* the provision of credit lines.

Our analysis proceeds in three steps. First, we provide a simple equilibrium model of credit provision. We show that giving borrowers the option to draw funds at a pre-agreed fixed spread over a floating reference rate induces a debt-overhang cost to bank shareholders. This debt-overhang wedge inefficiently dampens banks' incentives to offer committed lines of credit. However, the adverse impact on credit supply is attenuated to the extent that: (1) reference rates are credit-sensitive and (2) when originally contracting the lines, the bank expects to have a low marginal cost of funding once the lines are eventually drawn. For example, the bank could anticipate that borrowers will leave much of the drawn credit on deposit, which we show occurred during the COVID pandemic. Or, the bank could anticipate that its marginal source of funding will be other source of deposits (Gatev and Strahan, 2006) or low-cost emergency liquidity from the central bank.

The second part of our analysis is an empirical evaluation of funding costs associated with the provision of revolving credit. We use confidential bank-level data from the Federal Reserve's FR2052a report and Y14Q data collection that allow us to pin down the composition and dynamics of bank funding costs for large US Bank Holding Companies (BHCs) in much more detail than was possible in prior work. As of 2019, for our main sample consisting of the 20 largest US BHCs, non-financial firms borrowed 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 BHCs 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 under stressed-market conditions when wholesale bank funding spreads are elevated.

Consistent with the premise of our theoretical model, we find that banks were indeed subject to substantial draws on credit lines during the GFC (Ivashina and Scharfstein, 2010) and the COVID recession (Acharya and Steffen, 2020; Greenwald, Krainer, and Paul, 2020). However, we find that banks funded line draws much differently across these two episodes. During the GFC, a large fraction of cash drawn on credit lines left the banking sector, forcing banks to fund drawdowns with other new borrowing, just when wholesale bank funding spreads were historically high (Acharya and Mora, 2015). In contrast, we show that during the COVID recession, drawdowns were generally of a "precautionary" nature. That is, on average across banks, firms kept most of the drawn funds in their corporate deposit accounts. Given the uncertainty of corporations 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. When COVID struck, we estimate that for every dollar drawn, an average of 94 cents was placed into low-interest-rate corporate deposit accounts at the same set of banks. Moreover, uninsured corporate deposit interest rates were not sensitive to LIBOR-OIS spreads. Thus, unlike the GFC, the high fraction of line draws that were left on deposit during COVID largely insulated bank shareholders from the costs of funding the draws. However, this was not the case for all banks. We also show that some large regional banks funded a substantial portion of COVID line draws with Federal Home Loan Bank (FHLB) advances, which were cheaper than wholesale unsecured funding but more expensive than deposits.

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 and estimate the impact on credit supply of the transition from the legacy credit-sensitive reference rate, LIBOR, to the new risk-free reference rate, SOFR. Borrowers will naturally exploit the opportunity to draw on SOFR-linked lines under stressed market conditions. In a scenario in which wholesale bank funding spreads reach GFC levels, we estimate that draws on SOFR lines will be roughly 60% higher than they would be on LIBOR lines. 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, when bank funding spreads are at normal low levels, borrowers will draw less credit on lines linked to SOFR than they would on lines that reference LIBOR. For our representative calibrated bank, a welfare-maximizing reference rate has about 72% of the credit sensitivity of LIBOR.

We find 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 to a higher expected fraction of line draws left in deposits, or both—are less affected by the transition, or may even increase overall credit provision. As we discuss in more detail in Section 5, low-debt-overhang banks may gain market share. In the aggregate, the impact on credit provision of transition from LIBOR to SOFR is thus likely to be more muted than would be suggested by our partial-equilibrium analysis, especially if borrowers have a low cost of switching their relationships to a new bank with relatively low funding spreads. A broader equilibrium analysis that incorporates the industrial organization of banking relationships is beyond the scope of this paper.

Consistent with our analysis, 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 we show are the most affected by this transition, wrote to bank regulators:

"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."

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. Since January 2022, supervisory guidance provided in interagency statements urged US banks to avoid referencing LIBOR in their loan contracts.[3] Banks now follow the guidance of the Fed and the Alternative Reference Rates Committee (ARRC) by almost always using SOFR as their loan reference rate, as shown in Appendix Figure C.2. The reporting of US dollar LIBOR ended on June 30, 2023.[4]

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. Our main empirical analysis, in Section 4, consists of mapping bank funding risk for large US BHCs and quantifying the importance of reference rates in mitigating funding shocks. In Section 5, we calibrate our theoretical model to key empirical moments and quantify the effects of the LIBOR-SOFR transition on credit-line supply and welfare-maximal reference rates. Section 6 provides a concluding discussion of our

[3]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.*"

[4]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.

findings and an overview on recent industry attempts to come up with alternative new credit sensitive reference rates.

2 Related Literature

Our paper is related to 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 (Kashyap, Rajan, and Stein, 2002; Gatev and Strahan, 2006).[5] 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). 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.

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). Drawdowns possibly resulted from concerns 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). These draws were accompanied by a large increase in deposits (Li et al., 2020; Levine et al., 2021).[6] Using the newly available FR 2052a data, we provide more detailed

[5]Empirical evidence from Brown, Gustafson, and Ivanov (2021) and Santos and Viswanathan (2020) suggests that credit lines indeed insure firms against liquidity shocks. 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). See also Acharya, Almeida, Ippolito, and Perez (2014), and Acharya, Almeida, Ippolito, and Orive (2020).

[6] See also Berrospide and Meisenzahl (2022), Acharya, Almeida, Ippolito, and Orive (2020), and Chodorow-Reich and Falato (2022) for evidence on drawdowns during the GFC. After the 1998 Russian default, banks also experienced both

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 thus emphasizes that most banks did not need to raise much costly external funding following the COVID shock.[7]

Second, our paper adds to recent research concerning the transition from LIBOR to risk-free reference rates.[8] 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. 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. 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. Risk aversion plays no role in our analysis. Credit-sensitive reference rates improve welfare in our model because they reduce the inefficiency associated with debt overhang.

credit-line drawdowns and transaction deposit inflows (Gatev, Schuermann, and Strahan, 2007).

[7] The fact that banks did not require costly external financing during COVID does not mean that they were not constrained. Credit line draws tighten bank capital constraints because drawn credit weighs more heavily on required capital than unfunded commitments. This can affect bank funding decisions. (Acharya, Engle, and Steffen, 2021; Greenwald, Krainer, and Paul, 2020; Kapan and Minoiu, 2021).

[8] In addition to the work we describe regarding the transition's impact on credit market, several researchers have examined the role of LIBOR and SOFR as reference rates. For instance, see Schrimpf and Sushko (2019); Abate (2020); Kuo, Skeie, and Vickery (2018); Bowman, Scotti, and Vojtech (2020).

3 A Model of Credit Line Provision

This section provides a simple equilibrium model of credit lines that shows the degree to which banks' incentives are affected by the choice of the floating reference rate. In Section 5, we calibrate this model using data on credit lines originated by large US banks to analyze the potential impact of reference rate transition.

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 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.

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 $r + S$.

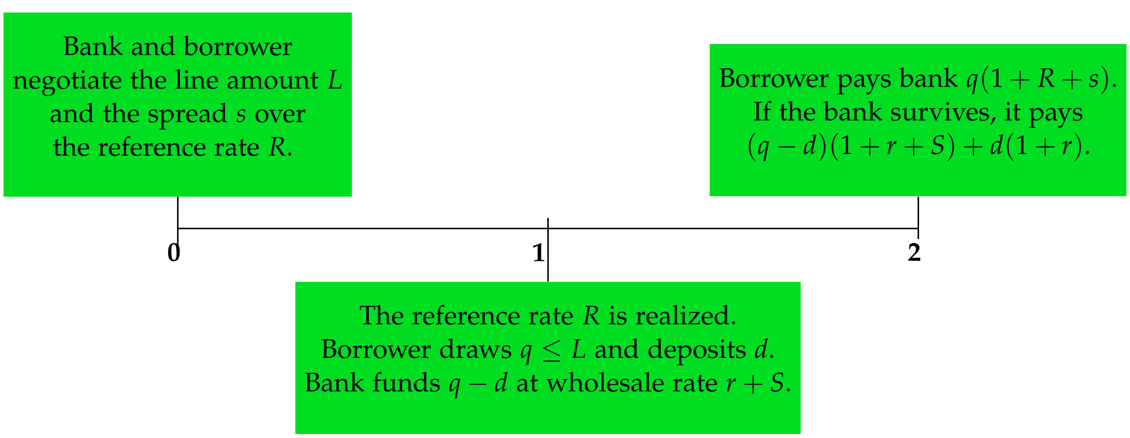


Figure 1: **Model timeline.** A credit-sensitive reference rate R such as LIBOR is of the form $r + W$, for some credit-spread benchmark W. With a risk-free reference rate, $R = r$.

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 $\varphi = d/q$ is set exogenously, but can be contingent on the state of the market at time 1. In Appendix D, 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.

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. In Section 4 we show that, empirically, the interest rate paid on corporate transaction deposits is indeed near the risk-free rate. For simplicity, we avoid modeling why corporate deposit interest rates are close to risk-free rates. This could be related to corporate-bank relationship frictions, depositor switching costs, holdup incentives of banks, and the operational benefits to corporate banking clients of being able to make and receive payments from and to their deposit accounts.

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 incremental funding 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. Borrower default risk plays no significant role in the debt-overhang channel that is central to our results. 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 access to x in cash[9] is $b(x, \psi)$, where ψ is a liquidity-preference shock 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.

At time 1, given the committed size L of the credit line and the borrower's observations of S, R, r, and ψ, 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. The net present value to the borrower of giving up $q\varphi$ in deposited cash at time 1 and receiving the corresponding cash payback $q\varphi(1 + r)$ at time 2 is $-q\varphi + \delta q\varphi(1 + r) = 0$, where $\delta = 1/(1 + r)$, so we can ignore cash

[9] 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).

deposit effects. The borrower's liquidity benefit $b(q,\psi)$, however, reflects the benefit of immediate access to both the deposited and undeposited cash amounts. State by state, $Q(L)$ thus solves

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

In the event that $b_x(0,\psi) \leq \delta(1+R+s(L))$, the optimal cash draw $Q(L)$ is zero. In the event that $b_x(L,\psi) \geq \delta(1+R+s(L))$, the optimal cash draw $Q(L)$ is L. Otherwise, from the 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 $f \geq 0$ is the proportional line fee.[10] 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.

We incorporate the impact of regulatory capital regulations associated with drawn credit by assuming that the bank is required to finance a fraction C of credit line draws with new equity, with the remaining fraction $1-C$ financed with debt.[11]

Because equity is assumed to be issued into a competitive market, new equity owners receive a claim at time 1 worth $CQ(L)$. Thus, the market value at time 1 of the equity claim of legacy bank shareholders for some quantity c of credit line customers is

$$V(c) = \delta E_1\left[(X+cY)^+\right] - cCQ(L),$$

[10]For notational simplicity, we vary from how revolver terms are stated in practice, with a proportional fee f on only the undrawn amount $L-Q(L)$ and a fixed spread $\bar{s}$ over the reference rate R on the drawn amount. These contractual terms are equivalent to those of our model, by taking $\bar{s} = s(L) - f$. The difference is purely notational. There are no implications for drawn rates, line size, drawn amounts, or any other substantive equilibrium quantities.

[11]Favara, Infante, and Rezende (2022) show how drawdowns during March 2020 reduced bank participation in Treasury markets. In practice, a bank would not obtain equity funding on a trade-by-trade basis. The bank would instead arrange in advance for enough excess regulatory equity capital to accommodate its likely potential trades. We do not model the more complicated impact of anticipatory funding.

where E_1 denotes conditional expectation at time 1, X is the payoff at time 2 of the bank's legacy assets net of its legacy liabilities, and

$$Y = \underbrace{Q(L)(1+R+s(L)) - \varphi Q(L)(1+r)}_{\text{net interest income from borrower}} - \underbrace{(1-\varphi-C)Q(L)(1+r+S)}_{\text{payback on external funding}} \tag{4}$$

is the cash flow at time 2 per unit of credit-line customers, net of the payback on the associated funding. For technical regularity, we assume that X and Y have finite expectations and that X has a probability density.[12] Following the approach of Andersen, Duffie, and Song (2019), the marginal benefit to bank shareholders of entering into credit lines with given terms $(L, s(L))$, is

$$G(L) = \frac{\partial_+ V(0)}{\partial c},$$

which is the right derivative of the market value $V(c)$ of the bank's legacy equity with respect to the incremental quantity c of customers contracting credit lines with the bank, evaluated at $c = 0$. The following calculation of $G(L)$ is demonstrated in Appendix B.

Proposition 1. *The marginal value of credit lines to legacy bank shareholders at time 1 is*

$$G(L) = p_1\Big(\delta Q(L)(1+R+s(L)) - Q(L)\Big) - p_1\delta(1-\varphi-C)Q(L)S - (1-p_1)CQ(L), \tag{5}$$

where $p_1 = P(X \geq 0)$ is the conditional probability[13] *at time 1 of bank solvency at time 2.*

The first term of (5) is is the bank's profit on lines multiplied by the solvency probability that equity survives to collect this profit. The second term is the debt-overhang cost to all shareholders of funding $(1-\varphi-C)Q(L)$ in new wholesale debt at the spread S. The third and last term of (5) is the debt overhang cost to legacy shareholders caused by equity issuance of $CQ(L)$.

For simplicity, the bank is assumed to Bertrand-compete against other banks of the same credit quality in the market for credit lines.[14] At time 0, the bank therefore offers the borrower, for any

[12] Rather than assuming a probability density, it suffices to assume that $P(X = 0) = 0$.

[13] 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 (5). 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.

[14] 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

line size L, a fixed spread $s(L)$ at which the bank's legacy shareholders break even on marginal new credit lines, implying that $E[G(L)] = 0$. From (5), this pins down the contractual spread

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

The borrower then solves (3) for the optimal line amount L^*.

Equation (6) conveys some key qualitative insights from our model. When credit lines are contracted at time 0, the expected debt overhang to shareholders incorporates the effect of any covariance between the bank's wholesale credit spread S and the quantity $Q(L)$ of line draws. Thus, the contractual spread is increasing in the covariance of S and $Q(L)$. Our model thus brings to light a funding-cost wedge that is not related to risk sharing,[15] namely 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 does not exist for term lending because the quantity of a term loan is fixed, thus eliminating the covariance component of expected bank funding costs.

Importantly, the funding cost wedge depends on both the reference rate and the fraction of line draws anticipated to be left on deposit. Consider first the degree of credit sensitivity of the reference rate R. If R is credit-sensitive, of the form $R = r + S$, then the covariance between wholesale funding spread S and the quantity $Q(L)$ is smaller as drawdowns become less attractive when bank funding costs are high. Next consider the fraction φ of line draws that is anticipated to be left on deposit. As φ increases, the bank needs to raise less funds externally and thus faces a lower debt-overhang wedge. In Section 4, we therefore study the extent to which banks require wholesale funding under stress by examining their marginal funding sources. We also quantify the important importance of R and φ in Section 5.

4 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 several facts about the composition of bank funding and the sensitivity

choice on incentives for loan provision. This is so because the rents associated with imperfect competition are likely to be about the same for LIBOR-linked lines as for SOFR-linked lines.

[15] 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.

of funding costs to macro shocks such as the COVID recession and the GFC. Second, we investigate the extent to which revolving credit can pose bank funding risk by studying how banks fund credit line drawdowns during the same time periods.

4.1 Data

Our primary source of data on bank funding and the dynamics of bank balance sheets is the FR2052a report, 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. The FR 2052a data are more granular than publicly available regulatory bank filings such as the FR Y-9C 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. The data are collected at a monthly frequency for firms with more than $50 billion in assets, and daily for firms with $700 billion or more in assets. The high frequency of reported data allows 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 FRY-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 commericial and industrial (C&I) and commercial real estate (CRE) lending.

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 20 of the largest US banks that report each month from July 2017 onwards. 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.

We further exclude trust banks that are not active in the market for C&I lending.[16]

We complement our main analysis by using various other data sets. We use confidential microdata from the FR2416 to study cross-sectional variation in bank lending and bank funding during the GFC. The FR2416 provide basic weekly data from large US commercial banks on broadly categorized balance sheet line items such as total C&I lending, total deposit funding, and borrowing. These data are an unbalanced panel that consists of a random stratified sample and cover only the domestic offices of the reporting banks.

We also construct measures of bank funding rates using various sources. First, we use the FR2420 to construct these measures for corporate deposits, interbank deposits, and other deposit and wholesale funding rates. The FR2420 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 to financial versus non-financial counterparties. The reporting panel comprises US commercial banks and thrifts that have $18 billion or more in total assets. Additional information on bank funding costs is sourced from FRED, Bloomberg, and the FHLB of Des Moines historical fixed rate advance file. A more detailed documentation of the data can be found in Appendix A.

4.2 The Composition of Bank Deposit and Wholesale Funding

Table 1 summarizes key evidence on the composition of bank funding, as reported in the FR 2052a. Panel A of Table 1 shows deposits by counterparty as of December 2019. The far right column reports the share of each type of deposit as a share of total deposits. As of December 2019, total deposits are 54% of total bank assets.[17] The largest fraction of bank deposits is retail, constituting around 52% of deposit funding. The second most important source of deposit funding is non-financial corporate deposits (25%), followed by deposits from financial institutions (11%) and small businesses (7%). Most financial deposits, around 8% of total deposits, are held by non-bank financial institutions

[16] 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. For our main analysis, we include four different bank types: "universal" banks, "regional" banks, credit-card firms, and investment banks. We exclude the Trust banks due to their non-traditional high-deposit, low-lending business model. These banks, State Street, Bank of New York Mellon, Charles Schwab and Northern Trust have significant volumes of corporate deposits but do not engage in commensurate levels of corporate lending. We later discuss the robustness of our finding to including these banks.

[17] This number is considerably smaller for our sample compared to the average commercial bank in the U.S. due to the nature of large BHC business lines. The large BHCs in our sample have significant non-core banking activities, including market making in their broker-dealer subsidiaries. Their balance sheets contain significantly more trading assets and liabilities and repurchase agreements than the average commercial bank.

(NBFIs).

We distinguish deposits by three additional properties: maturity, whether deposits are covered by deposit insurance or not, and whether the associated deposit account is classified as a relationship account or not. Across all counterparty types, more than 91% of deposits are available on demand — referred to in Table 1 as "open." Time deposits are uncommon. Retail and small-business deposits are mostly FDIC insured, in contrast to deposits from all other counterparties, which are almost entirely uninsured. Further, most deposits – around 64% – are considered stable, labeled as "relationship" accounts in Table 1, and are thus less likely to cause an increase in banks' funding costs under stressed market conditions.[18] Relationship accounts tend to be more common among retail and small business deposits and less common among financial and corporate deposits.

We turn next to the composition of wholesale funding in Panel (B) of Table 1. Around 15% of bank assets are financed by wholesale debt. Reflecting regulatory reforms after the GFC, the majority of wholesale debt is longer term. As of December 2019, less than one-third of outstanding wholesale funding was expected to mature within 12 months and only 11% 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 more than 70% of total wholesale funding and are mostly at fixed interest rates.[19]

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.

There is relatively little reliance on other forms of credit-sensitive wholesale funding, such as

[18] 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. Relationship deposits are typically stickier in times of stress (Martin, Puri, and Ufier, 2022), although there is potential regulatory arbitrage in the classification of operational deposits.

[19] 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 refer to 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). 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 11% reference LIBOR, see Online Appendix Table C.2.

wholesale certificates of deposits (2.4%) and commercial paper (1.1%). Banks also use some secured funding provided by conduits (such as asset-backed commercial paper), which constitute around 6% of wholesale funding. Free credits (deposits placed at broker-dealers) account for around 4% of wholesale funding, most of which come from prime-brokerage clients.

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

Panel A: Deposit Funding by Counterparty (percent)

Counterparty	Maturity			Uninsured	Relationship	% of Total
	Open	1 Day-1 Year	1 Year+			Deposits
Retail	86.9	8.9	4.2	28.5	71.6	51.9
Non-Financial Corporate	96.5	3.4	0.1	97.2	46.5	24.5
NBFI	92.0	5.4	2.6	96.8	60.3	7.7
Small Business	98.0	1.9	0.1	45.8	81.4	7.1
Bank	96.2	3.2	0.5	99.6	65.2	3.8
Public Sector Entity	96.0	3.8	0.2	97.3	50.2	2.6
Other Counterparty	88.3	10.5	1.2	94.8	53.0	2.3
All Counterparties	91.1	6.5	2.5	57.9	64.0	

Panel B: Wholesale Funding by Type (percent)

Product	Maturity				Collateralized	% of Wholesale
	Open-30 Days	1-6 Months	6 Months-1-Year	Long-Term		Funding
Unstructured LTD	1.1	4.5	5.1	89.3	0.0	60.1
Structured LTD	3.1	8.4	9.3	79.2	0.0	13.2
FHLB	21.9	30.9	13.5	33.7	100.0	8.3
Conduit and SPV	14.9	23.4	8.2	53.4	100.0	6.4
Free Credits	100.0	0.0	0.0	0.0	0.0	4.3
Other Wholesale Funding	54.8	31.3	10.7	3.2	0.0	4.1
Wholesale CDs	16.8	56.2	23.0	4.0	0.0	2.4
CP	16.1	75.4	8.5	0.0	0.0	1.1
All Products	11.0	11.4	7.1	70.5	14.7	

Data Sources: FR2052a, FR Y-9C. Notes: Table contains the distribution of deposits by counterparty type (Panel A) and of wholesale funding by product type (Panel B) for the aggregate of 20 banks in our monthly FR 2052a panel as of Dec. 31, 2019. Counterparty types and funding products are sorted from most material to least material, measured as a percentage of total deposits and total wholesale funding, respectively. Maturity breakdowns reflect remaining maturity of funding source. For more details on counterparty/product breakdowns, see Appendix Section A. Abbreviations: NBFI: non-bank financial institution; FHLB: Federal Home Loan Bank; LTD: long-term debt; SPV: special purpose vehicle; CD: certificate of deposit; CP: commercial paper.

There is also additional heterogeneity across banks in their funding composition. Appendix Table E.1 shows the cross-bank distribution of funding sources. For instance, regional banks rely more on FHLB advances, which made up around 30% of their wholesale funding as of December 31, 2019. They also rely relatively more on deposit funding than the average bank in our sample, as 76% of all assets are financed by deposits and only around 11% by wholesale funding.[20]

[20]The US operations of FBOs also have a substantially different funding profile than the domestic U.S. banks, as documented in Online Appendix Table E.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

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

To understand which types of funding sources are relatively more expensive, we next study the rate sensitivity of different funding instruments to changes in banking sector funding conditions, which we measure by the LIBOR-OIS, which is 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.

Figure 2 shows 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 100 basis points. After the failure of Lehman Brothers, LIBOR-OIS then sky-rocketed to a peak of 350 basis points in early October 2008. Moreover, reported LIBOR rates were significantly downward biased measures of actual large bank funding costs during the GFC because of manipulative reporting (Duffie and Stein, 2015).

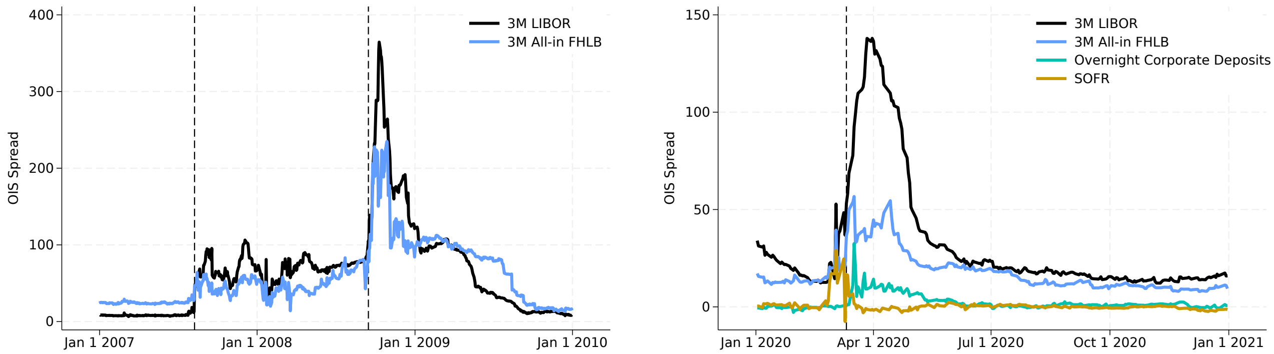
LIBOR is a measure of unsecured wholesale funding. In contrast, FHLB advances are secured. Nevertheless, spreads on FHLB advances increased as LIBOR-OIS ticked up in summer 2007 and peaked at the same time of LIBOR-OIS, at levels above 200 basis points. While expensive compared to deposit funding, FHLB advances are substantially cheaper than unsecured funding in periods of bank stress.[21]

A similar pattern holds for the COVID recession, as shown in Panel (b) of Figure 2. LIBOR-OIS increased throughout March, especially after the World Health Organization announced on March 11 that COVID-19 had become a global pandemic. In line with patterns observed during the GFC, "all-in" FHLB spreads also rose, but peaked at less than 40% of LIBOR-OIS. Notably, both LIBOR-OIS and spreads on FHLB advances reached much lower peaks than they had during the GFC.

For the COVID recession, our data allow us to also proxy for the dynamics of corporate deposit rates. These rates, unlike retail deposit rates, are sensitive to the effective fed funds rate. However,

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.

[21] While there are 11 regional FHLBs, we rely primarily on a proxy, the historical fixed rate advances published by the FHLB Des Moines. The Government Accountability Office (GAO) has found substantial variation in interest rates charged by the different regional banks—as much as 34 basis points—as well as the common use of *discounts* on published rates provided to the largest FHLB members (see GAO Report 03-973, "Federal Home Loan Bank System - Key Loan Pricing Terms Can Differ Significantly"). Nonetheless, that fact that the the published FHLB rates we observed during the COVID pandemic and the GFC were below LIBOR but above the risk-free rate suggests that FHLB advances are cheaper than unsecured funding but more expensive than deposit funding.



(a) Global Financial Crisis

(b) COVID-19 Recession

Figure 2: **Bank funding rates during financial distress.** Funding spreads during the GFC (Panel (a)), and COVID pandemic (Panel (b)). Data Sources: FR2420, FRED, 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. Overnight ("O/N") Corporate deposit rates are calculated from bank-level transactions in the FR 2420 report, and spread to the effective federal funds rate of the same date. Appendix A provides details on how these series are constructed.

spreads of corporate deposit rates over the effective federal funds rate are relatively insensitive to LIBOR-OIS during the COVID episode and instead closely track the risk-free rate. We find that an increase in LIBOR-OIS of 100 basis points is associated with a mere 9-basis-point increase in overnight corporate deposit spreads, as illustrated in Appendix Table C.1. Corporate wholesale certificates of deposits, in contrast, track LIBOR-OIS closely, but this form of funding is rarely used.

Our analysis of funding rate sensitivity shows that deposits are a cheap source of funding for banks. While this is less surprising for retail deposits,[22] this also applies to overnight corporate and financial deposits whose spreads to risk-free rates are only mildly sensitivity to LIBOR-OIS. There are several plausible explanations. For example, like retail deposits, uninsured corporate deposits may generate non-pecuniary liquidity benefits. In addition, banks may exploit their market power. Further, uninsured deposits are rarely subject to losses in case of bank failures because failing banks are typically acquired by other banks, which hope to preserve deposit relationships (Martin et al., 2022; Federal Deposit Insurance Corporation, 2023).[23]

Altogether, our analysis in Section 4.2 suggests that, in normal times, most large banks make relatively little use of credit-sensitive forms of funding. However, the composition of marginal

[22] Rates for retail deposits were insensitive to movements in LIBOR-OIS spreads during the GFC. 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). 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.

[23] For instance, from 2008 through 2022, uninsured deposits only were subject to losses in 6% of bank failures (see Federal Deposit Insurance Corporation, 2023).

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	1560.43	3504.66	44.52	20
Credit Line	541.46	1850.15	29.27	20
Term Loan	304.64	369.26	82.50	20
Other C&I	133.11	537.88	24.75	20
Commercial Real Estate	581.21	747.38	77.77	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. Trusts and 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."

funding sources can shift in times of funding stress towards more expensive sources. We next show that credit line commitments—to the extent that line draws may need to be funded at wholesale rates—pose a significant funding risk.

4.4 Undrawn Commitments

Our theoretical analysis in Section 3 emphasizes that large banks expose themselves to funding risk when providing revolving credit. Table 2 shows that this risk is economically large. For the 20 largest BHCs, 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. The BHCs in our sample alone had around $1.3 trillion of undrawn credit-line commitments, more than the total amount of utilized credit from term lending and revolving credit combined.

These unfunded commitments represent a substantial funding risk to banks. Unfunded commitments may be drawn when bank credit spreads are elevated, possibly requiring banks to fund the additional drawdowns via unsecured wholesale funding. Linking lines to credit-sensitive reference rates has historically mitigated this funding risk. Approximately 70% of these loans were until recently indexed to LIBOR (see Appendix Table C.3). Our analysis implies that the funding risk associated with credit lines has become higher now that LIBOR has been replaced with risk-free reference rates like SOFR.

4.5 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 periods of market stress? Is the covariance between drawdowns and bank funding spreads—a key determinant of credit supply according to our theory in Section 3—positive and large? How are drawdowns actually funded? And, how are macro shocks to funding costs mapped to actual bank funding costs?

Table 3 shows cumulative changes in various categories of bank assets and liabilities at large banks during both the COVID recession and the GFC. To make changes comparable across both periods, we normalize by total assets at the beginning of each period (November 2019 for the COVID recession, and June 2008 for the Lehman period).

Table 3: **Changes in aggregate assets and liabilities during the COVID recession and the GFC**

Panel A: COVID recession								
Cumulative changes in assets as a fraction of initial total assets in November 2019 (percent)								
	12/2019	01/2020	02/2020	**03/2020**	**04/2020**	05/2020	06/2020	07/2020
C&I Loans	−0.07	0.13	0.29	2.20	2.38	0.97	1.02	0.79
Reserves	0.09	0.02	0.04	1.89	4.49	6.16	4.75	4.54
Cumulative changes in liabilities as a fraction of initial total assets in November 2019 (percent)								
Corporate Deposits	0.08	−0.28	−0.23	1.80	2.52	2.82	3.06	2.81
Retail Deposits	0.28	0.43	0.87	1.93	2.92	3.67	3.97	4.17
Financial Deposits	−0.21	−0.01	−0.10	0.90	0.62	0.58	0.67	0.82
Small Business	−0.10	−0.10	−0.07	−0.02	0.12	0.39	0.55	0.56
FHLB Advances	0.07	−0.07	−0.10	0.58	0.21	−0.14	−0.37	−0.42
Long Term Debt	–0.11	–0.12	–0.11	0.05	0.30	0.33	0.32	0.33
Other Wholesale	–0.06	–0.03	–0.10	–0.18	–0.23	–0.29	–0.36	–0.44
Panel B: Global Financial Crisis								
Cumulative changes in assets as a fraction of initial total assets in June 2008 (percent)								
	07/2008	08/2008	**09/2008**	**10/2008**	**11/2008**	12/2008	01/2009	02/2009
C&I Loans	0.00	0.02	0.23	0.39	0.35	0.06	0.02	–0.04
Reserves	0.08	0.02	0.59	2.37	2.57	3.12	2.54	2.62
Cumulative changes in liabilities as a fraction of initial total assets in June 2008 (percent)								
Deposits	0.31	0.10	2.32	2.67	2.92	3.42	2.41	2.74
Other Borrowing	0.08	0.08	0.76	1.35	0.84	–0.00	–0.15	–0.21
Interbank Borrowing	–0.09	0.00	–0.04	–0.13	–0.37	–0.17	–0.02	–0.05

Notes: Values shown are cumulative dollar changes from the indicated starting month normalized by starting-month assets. Data in Panel A are sourced from the FR2052a, aggregating a panel of 20 BHCs (excluding Trust banks). Data in Panel B are sourced from the FRED series for large domestically chartered banks, adjusted for large mergers and acquisitions based on public notes to the H8 series.

Table 3 shows that during the COVID recession, C&I loans increase by around 2% as a share of total assets in March 2020—an increase of almost 20% in total C&I lending (Li, Strahan, and Zhang, 2020; Acharya and Steffen, 2020). Most of these draws were from LIBOR-linked facilities.[24] The increase in drawdowns in March 2020 was accompanied by large increases in corporate deposits (1.8% of total assets) and FHLB advances (0.6% of total assets). Financial and retail deposits also increased significantly. By April 2020, reserves had increased by 4.49%, presumably as a liquidity buffer against

[24] See Panel (a) of Figure C.1 in the Appendix.

these increases in short-term liabilities. Unsecured wholesale funding decreased beginning in March 2020.[25]

A similar pattern emerges for the GFC. C&I lending increased following Lehman's failure, but only around 0.39% of total assets by October 2008, which is broadly in line with the fact that the spike in LIBOR-OIS made draws relatively expensive for borrowers. At the same time, banks experienced large deposit inflows and increases in wholesale funding (labeled "other borrowing"), including FHLB advances.[26] Deposits increased by around 2% of total assets and wholesale funding by around 1.35% of assets at the peak of the GFC, immediately following Lehman's failure.

While both of these episodes saw significant credit line drawdowns, the composition of aggregate bank funding tilts toward more expensive sources during the GFC than during the COVID recession (see, e.g. Ivashina and Scharfstein, 2010; Acharya and Mora, 2015). During the COVID recession, cheap deposit funding increased and relatively expensive wholesale funding decreased. In contrast, there was a significant increase in wholesale funding during the GFC.

4.6 How Credit-Line Drawdowns Are Funded

We next address how individual banks finance drawdowns in stress. We use bank-level data to study how balance sheets respond to stress during both the COVID recession and the GFC.

The funding of drawdowns during the COVID recession

Using the monthly FR2052 data, we examine how banks fund drawdowns during COVID by estimating a regression of the form:

$$\Delta y_{bt} = \tau_t + \gamma_b + \beta_1 \Delta \text{Drawdowns}_{bt} + \beta_2 \Delta \text{Drawdowns}_{bt} \times \text{COVID}_t + \epsilon_{bt}, \tag{7}$$

where, for bank b, Δy_{bt} is the change of one of the following balance-sheet line items: corporate deposits, FHLB advances, unsecured wholesale funding, and total deposits. Here, $\Delta\text{Drawdowns}_{bt}$

[25] There has been significant and notable work documenting the evolution of banks' balance sheets during the Covid pandemic, including Li et al. (2020); Acharya et al. (2021). Greenwald, Krainer, and Paul (2020); Chodorow-Reich, Darmouni, Luck, and Plosser (2021) find that drawdowns went to the largest firms, and Darmouni and Siani (2022) find that line draws were repaid quickly after bond markets started to recover, consistent with the presumption that firms drew on lines to weather temporary turmoil. The increase in small business loans and retail deposits can be explained by the Paycheck Protection Program (Granja, Makridis, Yannelis, and Zwick, 2022) and government stimulus checks/precautionary savings (Cox, Ganong, Noel, Vavra, Wong, Farrell, Greig, and Deadman, 2020), respectively.

[26] Ashcraft et al. (2010) show that part of the wholesale funding increase was due to borrowings from FHLBs, although the collapse of the interbank market required some banks to raise additional wholesale funds to replace lost interbank funding (Afonso, Kovner, and Schoar, 2011).

denotes the month-to-month change in C&I drawdowns. We consider both changes in dollar amounts and changes in dollar amounts normalized by lagged total assets. COVID_t 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 is a set of bank fixed effects. We estimate (7) using our sample of the largest 20 BHCs from July 2017 through April 2022.[27]

The results are reported in Table 4. We find that each dollar of corporate drawdowns during the COVID recession is associated with an average increase in corporate deposits of 94 cents (Panel A). This suggests that drawdowns are precautionary and deposited at the *same* bank. Given that deposit funding tends to be at or below the risk-free rate, the funding cost to shareholders was minimal during COVID. However, this average response of deposits is driven by the largest banks in our sample, which experienced both the largest drawdowns and largest deposit inflows, in dollar terms. When we normalize by assets, we find in Panel B that only 52% of the drawdowns generate corporate deposits. For the large regional banks, each dollar of draws generated between 28 cents and 41 cents of deposits.[28] The large regional banks also relied heavily on FHLB funding, which covered 49% to 59% of their drawdowns.[29] Importantly, the banks in our sample did not require additional unsecured wholesale funding to fund corporate draws, irrespective of their business model. In fact, the largest banks experienced deposit growth significantly in excess of their drawdowns, as shown in column (5) of Panel A.[30]

The funding of drawdowns during the GFC

To examine how banks funded drawdowns during the GFC, we use FR2416 data to estimate a regression model similar to Equation (7). These data are weekly and thus at a higher frequency.

[27] Results when including the Trust banks are in Appendix Table E.5. The "levels" regressions (in dollars) are quantitatively similar to the ones in our main text, Table 4. The "normalized" regressions (dividing by assets) differ due to unique nature of these banks' business models.

[28] See Appendix Table E.4 for these regressions restricted to our sample of large, regional banks.

[29] 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.

[30] 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). The 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).

Table 4: **Monthly Changes in Drawdowns, Deposits, FHLB Advances, and Wholesale Funding during the COVID recession.**

Panel A: dollar changes					
Dependent variable	Δ Corp. Deposits	Δ FHLB	Δ Unsec. WSF	Δ Total Cols. (1-3)	Δ Total Deposits
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns	0.07*	0.00	0.00	0.07	0.19
	(0.04)	(0.01)	(0.01)	(0.05)	(0.12)
Δ Drawdowns $\times$ COVID	0.94**	0.11	-0.01	1.04**	2.31**
	(0.34)	(0.13)	(0.06)	(0.49)	(1.01)
Bank fixed effects	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓
N	1111	1111	1111	1111	1111
Number of Banks	20	20	20	20	20
R^2	0.353	0.204	0.087	0.341	0.401

Panel B: dollar changes normalized by assets					
Dependent variable	Δ Corp./ Assets	Δ FHLB/ Assets	Δ Unsec. WSF/ Assets	Δ Total/ Assets	Δ Total Deposits/ Assets
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns/Assets	0.03	0.00	-0.00	0.03	0.16*
	(0.03)	(0.01)	(0.00)	(0.04)	(0.09)
Δ Drawdowns/Assets $\times$ COVID	0.52***	0.47***	0.02	1.00***	0.20
	(0.14)	(0.13)	(0.02)	(0.18)	(0.25)
Bank fixed effects	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓
N	1090	1090	1090	1090	1090
Number of Banks	20	20	20	20	20
R^2	0.241	0.162	0.063	0.233	0.252

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

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

where COVID_t is a dummy that is one during the COVID recession in March and April 2020 and zero otherwise. In Panel B we report results from the following regression:

$$\Delta y_{bt}/\text{Assets}_{bt-1} = \alpha + \Delta\text{Drawdowns}_{bt}/\text{Assets}_{bt-1} + \Delta\text{Drawdowns}_{bt}/\text{Assets}_{bt-1} \times \text{COVID}_t + \gamma_b + \eta_t + \epsilon_{bt}.$$

The dependent variable in column (3) of Panel A (labeled unsecured wholesale funding (WSF)) pools various short-term wholesale funding categories: CP, CD, non-prime brokerage free credits, and other unsecured wholesale funding. The dependent variable in column (4) of Panel A is the change in the sum of corporate deposits, FHLB advances, and unsecured wholesale funding. The dependent variable in column (5) is total deposits, pooling across all counterparties listed in Table 1. In Panel B we use the same the dependent variables as in Panel A and normalize lagged total assets. Monthly data from July 2017 through April 2022 for our sample of large banks excluding Trusts. Table E.4 shows results when restricting the sample to regional banks. Table E.5 shows result when including Trust banks. Data Source: FR2052a. Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

However, the reported line items are less granular than those of the FR2052a. We can only proxy for drawdowns using the change in C&I balances. Moreover, we cannot distinguish corporate deposits; we only observe total deposits. To get a broad sense of how drawdowns were funded, we estimate the model

$$y_{bt} = \tau_t + \gamma_b + \beta_1 \Delta\text{C\&I Loans}_{bt} + \beta_2 \times \Delta\text{C\&I Loans}_{bt} \times \text{Lehman}_t + \epsilon_{bt}, \tag{8}$$

where y_{bt} is either the weekly change in total deposits or the weekly change in wholesale funding (borrowings from banks and other borrowings),[31] ΔC&I Loans is the monthly weekly change in C&I lending, and Lehman$_t$ is a dummy that takes the value one on dates after the failure of Lehman, specifically from the week starting in September 15, 2008 through end of December 2008. Again, we also estimate a variant in which we normalize variables by a bank's total assets.

Table 5 shows the results. Banks that experienced relatively larger increases in C&I lending also had an increase in wholesale funding, but not an increase in deposits. Thus, unlike during the COVID recession, increases in C&I lending during the GFC are likely to have required raising significant external wholesale funds. Our estimates suggest that a bank that received a \$1 increase in C&I lending also raised almost \$4 in wholesale funding, So, banks subject to heavy drawdowns were typically hit by funding pressures. Further, when we normalize the change by initial assets, we find that loan growth is correlated with both deposit funding and wholesale funding in normal times. However, during the turmoil immediately after the failure of Lehman, those banks subject to greater drawdowns experienced relatively less deposit inflows, and raised relatively more funding from wholesale external sources. Altogether, these patterns are in line with Ivashina and Scharfstein (2010). This could have been due to the fear by borrowers of a future inability to access funding from their banks. Bearing in mind our earlier caveats about data granularity, we find this evidence supportive of the notion that during the GFC banks were forced to fund drawdowns by raising wholesale external funding. We also use borrower-level data to confirm our bank-level findings on the depositing of line draws, which we discuss in Appendix Section G.

5 Calibrated Impacts of Reference Rates on Credit Supply

In order to quantify how the choice of loan reference rate affects the equilibrium provision of revolving credit by large US banks, we now calibrate the theoretical model of Section 3 based on the

[31] Other borrowing is a highly aggregated category of balance sheet funding. In additional to short-term wholesale funding, this line item includes advances from FHLBs as well as emergency lending facilities from the Federal Reserve System

Table 5: **Weekly Changes in C&I Loans, Deposits, and Other Borrowed Money During the GFC.**

Dependent Variable	Δ Deposits	Δ Deposits/Assets	Δ Wholesale Fund.	Δ Wholesale Fund./Assets
	(1)	(2)	(3)	(4)
Δ C&I loans	0.75		0.26	
	(0.71)		(0.26)	
Δ C&I loans × Lehman	1.23		4.33***	
	(1.10)		(0.41)	
Δ C&I Loans/Assets		2.03***		0.89***
		(0.26)		(0.15)
Δ C&I Loans/Assets × Lehman		-1.51***		0.90*
		(0.46)		(0.47)
Observations	1765	1765	1765	1765
No. Banks	30	30	30	30
R^2	0.19	0.24	0.32	0.17
Month FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓

Notes: This table shows results from estimating a model of the following form:

$$y_{bt} = \tau_t + \gamma_b + \beta_1 \Delta\text{C\&I Loans}_{bt} + \beta_2 \times \Delta\text{C\&I Loans}_{bt} \times \text{Lehman}_t + \epsilon_{bt},$$

where Lehman_t is a dummy that takes the value one on dates after the failure of Lehman, specifically from the week starting in September 15, 2008 through end of December 2008. The "deposit" line-item pools all deposit types irrespective of maturity and counterparty. "Borrowing" pools various sources of bank wholesale funding, such as advances from Federal Home Loan Banks (FHLBs), other types of wholesale borrowings in the private market, and credit extended by the Federal Reserve. In columns (1) and (3), the dependent variable is a \$-change. In columns (2) and (4) we normalize the \$-change by lagged total assets. Data: FR2416. The sample consits of weekly reporting commercial banks from December 2007 through May 2009 and banks with more than \$50 billion in assets. Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

empirical analysis in Section 4. We then analyze how the equilibrium supply of credit lines depends on the extent to which line draws are expected to be left on deposit at times of high bank funding stress. Further, we show that welfare-maximizing reference rates are more credit sensitive for banks (or banking systems) with greater debt overhang.

Parameters of the Calibrated Baseline Model

Among the key model parameters are the likelihood of a future crisis and borrower liquidity preferences, which determine the extent of line draws during a crisis and the degree to which line draws are left on deposit.

Expected discounted cash flows are computed with risk-neutral probabilities in order to incorporate the effect of risk premia on bank equity market values. In particular, the risk-neutral probability of a crisis is naturally much higher than its empirical counterpart. Conditional on the absence of a crisis, the risk-neutral distribution of the LIBOR-OIS spread W is modeled as log normal and fit by maximum likelihood to daily LIBOR-OIS observations from January 2005 to April 2021. That is, conditional on no crisis, we ignore premia for LIBOR-OIS risk. Conditional on a crisis, the risk-neutral probability distribution of W is modeled as log-normal with a mean of 350 basis points, which is roughly the highest level reached by LIBOR-OIS during the GFC, and with a standard deviation of 40 basis points. In our baseline model, the risk-neutral probability of a crisis is taken to be 4%. Because our model has annual time periods, a GFC-like event is risk-neutrally expected to occur once every quarter century. The corresponding actual mean frequency would be much lower.[32] The resulting risk-neutral probability density of one-year-ahead LIBOR-OIS credit spreads is plotted in the left panel of Figure 3. We later quantify the sensitivity of our results to varying the risk-neutral likelihood of a crisis, among other key parameters.

The bank has a continuum of borrowers of total mass M. A borrower's cash liquidity benefit is specified as

$$b(q, \psi) = \frac{\psi^{\alpha} q^{1-\alpha}}{1-\alpha}, \tag{9}$$

for a positive constant α, where ψ is the borrower's liquidity preference shock.[33] The price elasticity of drawn credit is $1/\alpha$ at any line utilization strictly between 0 and 1. We take a baseline assumption of $\alpha = 1/25$, implying an elasticity of 25 that is in the range suggested by prior empirical work.[34] This corresponds to a decline in drawn credit of approximately 2.5% in response to a 10-basis-point increase in the drawn interest rate.[35] We take the corporate borrower's liquidity shock ψ to be $(K(W) + \epsilon)^+$, which includes a component $K(W)$ common to all borrowers and an idiosyncratic component ϵ that is independent of the common shock $K(W)$ and *iid* across borrowers. The parameters of the function K and the probability distribution of ϵ are calibrated to empirical line draw behavior using a nonlinear-least-squares approach described in Appendix H. The parameters are shown in the caption of Figure 3.

The left panel of Figure 4 conveys a sense of the empirical cross-sectional heterogeneity of liquidity shocks implied by line utilization over the period 2015-2021. The figure separates the COVID recession from all other quarters. Outside of the COVID recession, as shown, about 50% of lines are not drawn. For the remaining lines, utilization is roughly uniformly distributed. During the

[32] For example, Berndt et al. (2018) estimate that risk-neutral probabilities of default of investment-grade firms are two to five times their actual-probability counterparts. The common component of large-bank default risk premia is likely to be substantially higher. Because we calibrate to quarterly LIBOR-OIS and our model has a single annual period of drawing, we are effectively assuming that drawn loans are rolled over quarterly for one year.

[33] 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.

[34] For example, 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.

[35] This assumes line utilization is strictly between 2.5% and 100%.

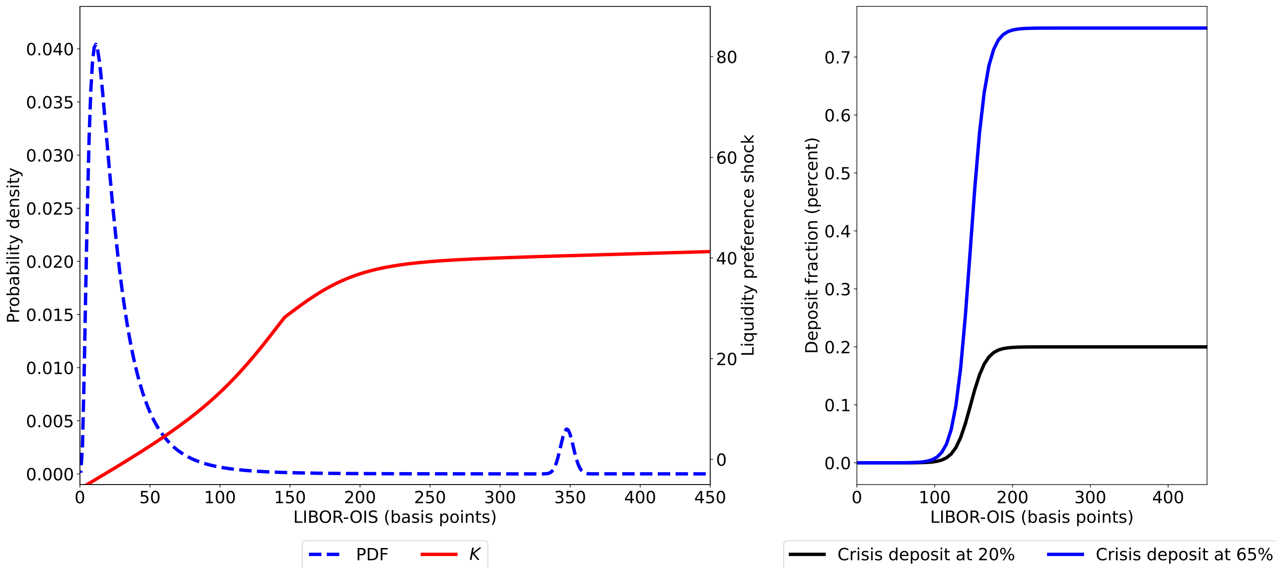


Figure 3: **The risk-neutral probability density of LIBOR-OIS, the borrowers' liquidity preference shock, and the deposited fraction of drawn credit.** The baseline probability density of W shown in the left figure is a mixture of two parametric distributions: With probability $p = 0.04$, W has a conditional normal distribution with a GFC-like mean of 350 basis points and standard deviation of 40 basis points. With probability $1 - p = 0.96$, W has a conditional log-normal distribution with a mean of 27 basis points and a standard deviation of 24 basis points, fitted by maximum likelihood estimation to daily LIBOR-OIS observations from January 2005 to April 2021. The common component $K(W)$ of borrowers' liquidity shock ψ, 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 $x_0 = 146.1$ basis points, $\mathcal{C}_1 = -5.9$, $\mathcal{C}_2 = 1608.8$, $\mathcal{C}_3 = 80.0$, $\mathcal{C}_4 = 21.3$, and $\mathcal{C}_5 = 380.3$, which were fit by least squares to line utilization data for our sample of 20 large banks, as detailed in Appendix H. At each potential outcome of $W =$ LIBOR-OIS, the inter-quartile range of the cross-sectional distribution among borrowers of the total liquidity shock $\psi = (K(W) + \epsilon)^+$, where ϵ has a probability $v = 0.050$ of a "rare-disaster" outcome of $\epsilon^d = 157.6$ and a probability $1 - v$ of being conditionally uniformly distributed on $(-\bar{\epsilon}, \bar{\epsilon})$, with $\bar{\epsilon} = 62.6$. 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 (10), with $D = 0.2$, $\theta = 1.0$, $m = 0.1$, and $w_0 = 146.1$ basis points. For comparison with the baseline model, we also provide results for an alternative "high-deposit" specification for Φ, with $D = 0.75$, as shown in the right panel.

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. The middle and right panels of Figure 4 show the calibrated theoretical counterparts, which we discuss below.

Our baseline representative bank is assumed to be of "LIBOR quality," thus having an unsecured wholesale credit spread S equal to the spread W between LIBOR and OIS. Below, we also consider banks with wholesale funding costs that are higher or lower than LIBOR.

Banks fund drawdowns with a mix of both deposit and wholesale funding. Further below, we also discuss the implications of access to secured wholesale funding or central bank emergency

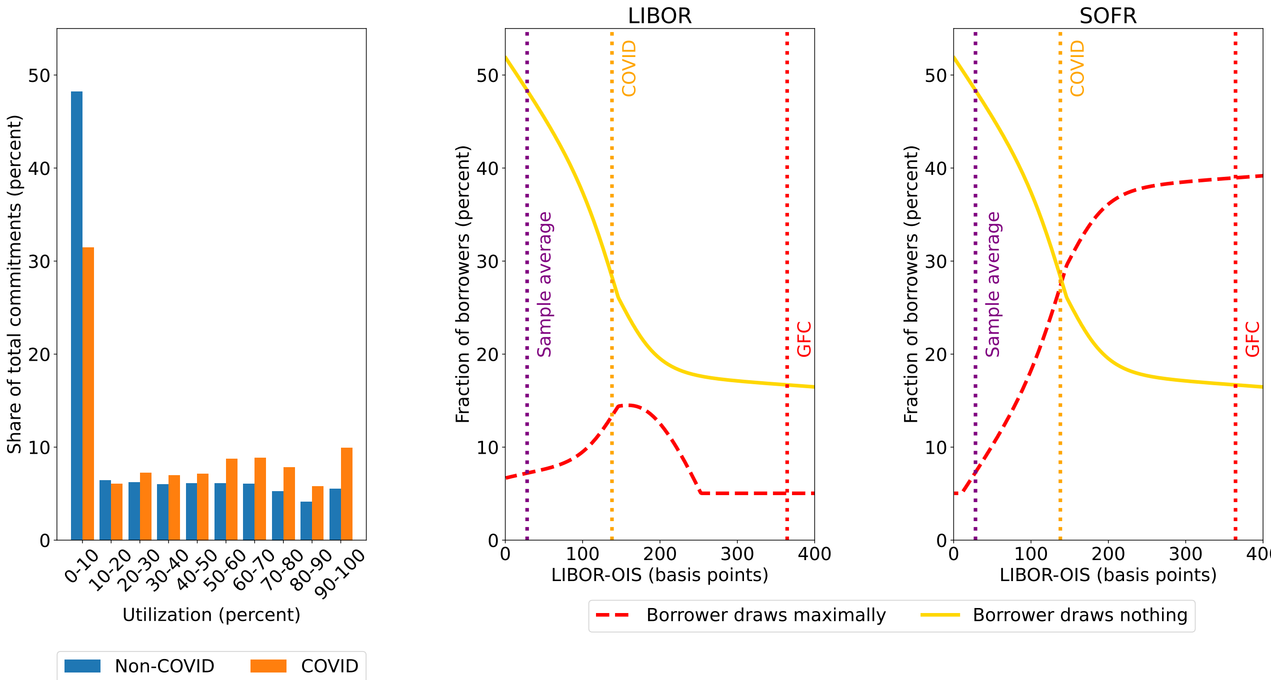


Figure 4: **The empirical cross-sectional distribution of credit line utilization and the modeled fraction of borrowers that utilize the entire or none of the credit line.** The data source for the left-hand figure is FRY14Q Schedule H. For the middle and right-hand figures, the parameters determining K, Φ, and the probability distributions of W and ϵ are as specified in the caption of Figure 3. The other parameters determining the underlying equilibrium model are: mass $M = 26.79$ of borrowers; required capital ratio $C = 0.06$; risk-free rate $r = 0$; line fee $f = 20$ basis points; and credit demand elasticity parameter $\alpha = 1/25$.

funding. The blended funding spread to cover marginal line draws is thus $(1 - \varphi)S$, because φ of the draws are funded at the deposit-rate spread, which is zero, and the remainder are funded at the unsecured wholesale credit spread S.

The deposited fraction φ of drawn funds is specified as $\Phi(W)$, where $\Phi(\,\cdot\,)$ is the logistic

$$\Phi(x) = \frac{D}{1 + e^{-m(x - w_0)}}, \tag{10}$$

with base-case parameters $D = 0.2$, $m = 0.1$, and $w_0 = 146.1$ basis points. Thus, as shown in the righthand plot of Figure 3, we assume that when LIBOR is close to the risk-free rate, borrowers deploy most of their drawn funds into business operations, leaving little on deposit. However, in crisis states, when LIBOR-OIS is large, borrowers could potentially leave a higher fraction of drawn funds on deposit, given the precautionary motives that may apply in a macro shock like COVID, as documented in Section 4.6. The deposited fraction $\Phi(W)$ of drawn funds increases with LIBOR-OIS to a "crisis limit" of D.

Section 4.6 indicates that when LIBOR-OIS rose to over 300 basis points during the GFC, there was little depositing of drawn funds. Future shocks to LIBOR-OIS could result in low depositing of drawn funds, as with GFC, or much higher depositing behavior, as with COVID. Our base-case choice of $D = 0.2$ is plausibly between the average GFC and COVID outcomes, but merely represents an assumption rather than an empirically identified parameter. Given the crucial role of this parameter, we will later analyze the effect of varying D. In Appendix J, we explore the implications of a richer specification of the functional form of Φ, and find roughly similar equilibrium quantities of aggregate credit lines and expected drawn credit.

Our model allows for the possibility that banks may receive *additional* unrelated deposit inflows (Gatev and Strahan, 2006), with total deposit inflows possibly exceeding line draws in some states. What matters for a bank's pricing of credit lines, however, is the anticipated *marginal* source of funding in each state. If total deposit inflows exceed all cash uses, then the marginal source of funds to the bank is deposits. If the bank is ex-ante assured of excess deposit funding across all state, in this sense, then there is no cost wedge in our model and credit lines will be supplied abundantly. In practice, as explained in our introduction, regional banks are known to be especially concerned that, under stress and especially with SOFR-linked credit lines, heavy line draws could cause them to seek expensive external funding. Our analysis in Section 4 shows that during both the GFC and the COVID recession at least some banks were forced to seek expensive external funding to fund drawdowns.

From Section 3, the 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 macro 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 equilibrium menu $\{(L, s(L)) : L \geq 0\}$ of offers of the line size L and the 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[36]

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

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 proportional line fee[37] f is assumed to be 20 basis points. Appendix H shows how the quantity M of borrowers and the parameters of K and ϵ that determine the distribution of borrower liquidity preferences are jointly calibrated by non-linear least squares to 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. Aside from some parameters that are chosen to match specific empirical counterparts, these parameters are chosen to minimize the weighted sum of squares of *(i)* the difference between the empirical average of the total dollar quantity of lines and its model-implied analogue $M \cdot L$, *(ii)* for each quarter, the difference between the actual quantity of line draws and the model-implied quantity of line draws given by (12), and *(iii)* 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 next consider the effects of varying the chosen reference rate, bank quality, borrower deposit behavior, and other properties of the model.

The Baseline Impact of LIBOR-SOFR Transition on Credit Supply

The modeled impact of a transition from LIBOR to SOFR on credit provision through revolvers by large US banks is shown in Figure 5. This figure displays, for each outcome of LIBOR-OIS, the equilibrium interest rate paid on drawn credit (left panel) and the aggregate amount of line

[36]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.

[37]Based on an informal communication, we observed that a large non-bank borrower had line fees for its two revolvers of 15 basis points and 25 basis points. This is also consistent with the mean facility fee reported in Berg et al. (2016) of 16.16 basis points.

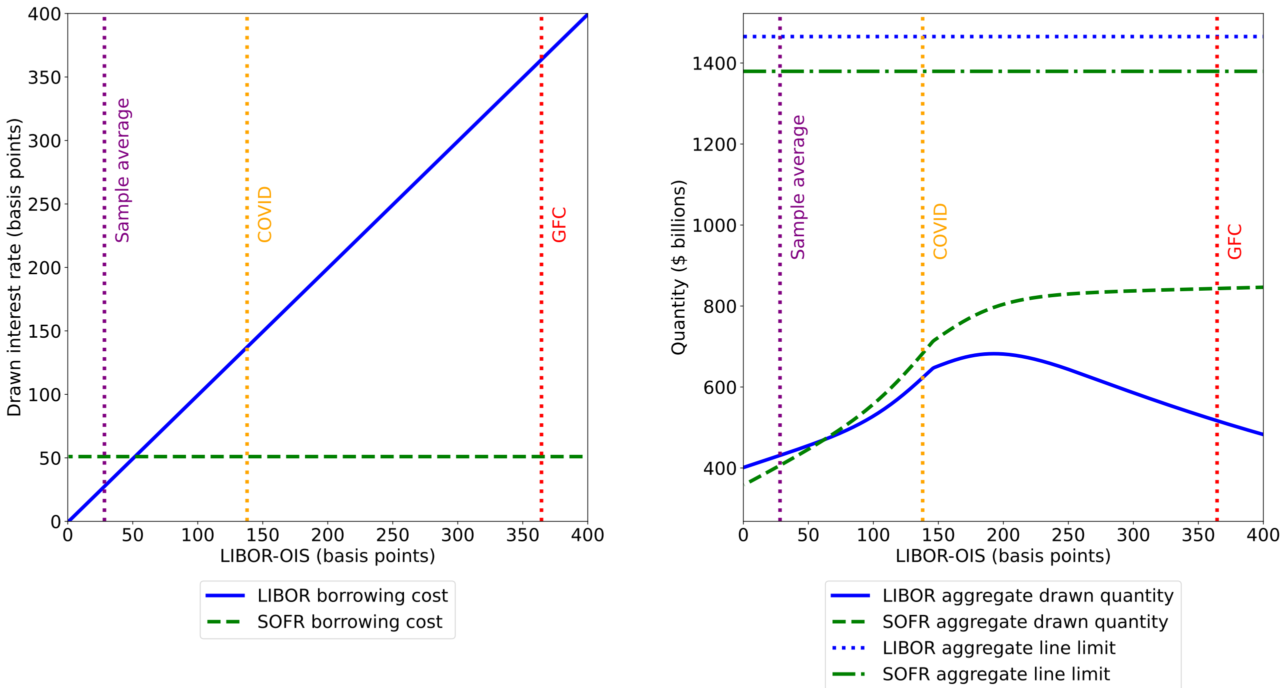


Figure 5: **The effect of the LIBOR-SOFR transition on credit line prices, aggregate drawn quantities, and aggregate quantities of credit lines.** All parameters are as specified in the captions of Figure 3 and Figure 4. The horizontal dashed-dotted lines in the right figure indicate the sizes of the 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.

commitments and drawn credit (right panel). For the baseline calibrated bank, transition from LIBOR to risk-free reference rates reduces equilibrium credit line sizes by about 5.9%, reduces the expected quantity of drawn credit by around 2.8%, and causes a substantial shift in line utilization across different outcomes for LIBOR-OIS. Under SOFR, our baseline calibration implies that corporate borrowers will draw about 63% more credit during a GFC-like banking crisis than they would with lines referencing LIBOR. The equilibrium SOFR fixed spread must therefore be high enough to compensate bank shareholders for the elevation of shareholder-borne funding costs that will occur whenever LIBOR-OIS is high. As a consequence, when LIBOR-OIS is near its sample average, shown by the left vertical line in both panels of Figure 5, borrowers draw less credit on lines linked to SOFR than on lines linked to LIBOR. During those "normal" times, SOFR-linked lines are about 24 basis points more expensive than LIBOR-linked lines.

Further implications of borrower heterogeneity are seen in the middle and right-hand panels of Figure 4, which show the equilibrium fraction of borrowers that draw their lines to the limit at each outcome of LIBOR-OIS. At low outcomes of LIBOR-OIS, only borrowers with high idiosyncratic liquidity shocks exhaust their line limits. However, as LIBOR-OIS increases, the associated increase in the drawn interest rate on LIBOR-linked lines eventually dominates the liquidity preference shocks of most borrowers, and LIBOR lines are less heavily drawn than SOFR lines.

Our model is calibrated, in part, to approximate the empirical fraction of borrowers that draw their lines to the maximum in normal times. The left panel of Figure 4 shows that, empirically, around 5.5% of borrowers were at or close to their line limits in normal times, and shows that this fraction doubles to around 9.9% during the COVID recession. In our calibrated model, as shown by the middle panel of the figure, around 7% of borrowers are at their line limits during normal times, and this modeled fraction increases to around 14% during the COVID recession. For SOFR-linked lines, in contrast, while around 7% of borrowers draw the maximum amount during normal times, around 29% of borrowers would have been at the line limit during the COVID recession and a striking 39% of borrowers are predicted by the model to be drawing revolvers to their limits if LIBOR-OIS reaches its GFC level.

These results are sensitive to the parameter choices. For instance, the negative effect of the transition to SOFR would be weaker if crises are less likely or if credit demand is less elastic. The sensitivities of our results to the price elasticity $1/\alpha$ of borrower demand for credit and to the probability p of a GFC-like increase in LIBOR-OIS are discussed in detail in Appendix I.

We assume that drawdowns are funded, at the margin, with both corporate deposits and wholesale funding. In practice, banks could also take advantage of other funding sources. For instance, if cheap central-bank funding is abundant in those states of the world in which bank funding spreads are high, then the bank's marginal cost of funding might be only slightly above the risk-free rate. Because rates on central bank and FHLB funding are between the risk-free rate and the bank's wholesale unsecured funding rate, use of these alternative sources can be captured in the model by increasing the assumed fraction of line draws that are left on deposit. Qualitatively, the anticipated availability of cheap central bank funding is thus comparable to draws left of deposits.

Unfortunately, the available data do not lead to a clear prediction of the fraction of line draws that borrowers will leave on deposit in a future credit crisis. Effectively, there are two meaningful data points, the GFC and COVID, across which average credit-line depositing behavior differed markedly. Moreover, Section 4 shows substantial heterogeneity across banks regarding how drawdowns were

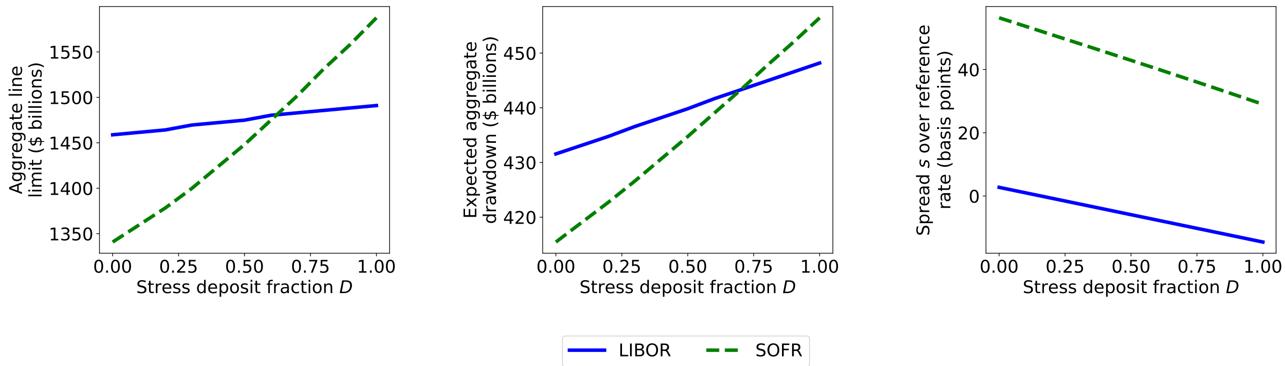


Figure 6: **The effect of increasing the maximal fraction of drawdown deposited** All parameters are as specified in the caption of Figure 4, except for parametric variation of the maximal deposited fraction D of drawn funding. The aggregate line limit is the product of the quantity M of borrower-bank pairs and the per capita credit line size L. The expected aggregate drawdown is defined similarly.

funded during the COVID recession. Given this uncertainty around the true expectations regarding extent to which line draw are anticipated to be left on deposit or other cheap sources of funding become available, we estimate the effect of the LIBOR-SOFR transition for a range of alternative parameters for line-draw depositing. Appendix J goes further by considering alternative functional dependence of depositing on LIBOR-OIS. Figure 6 shows that equilibrium provision of credit rises with the maximal-deposit-fraction parameter D. This follows from the fact 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 can even *increase* the equilibrium provision of credit lines, as shown in Figure 6. For instance, with $D = 75\%$, the transition to risk-free reference rates induces a 6.6% increase in the total dollar amount of credit lines.

Bank Heterogeneity

Thus far, we have considered a representative bank whose wholesale unsecured funding rate is LIBOR. In practice, there is substantial heterogeneity across large banks in unsecured funding spreads (see Berndt, Duffie, and Zhu (2021) and Appendix Section F). There is also significant variation across banks in the extent to which they rely on deposits for marginal external funding under stress, as documented in Section 4. We therefore now consider how our results may vary across banks, in both of these respects.

Consider first variation in a bank's credit quality, keeping fixed the fraction of drawdowns left on deposits. The external funding spread of the bank is modeled as some multiple θ of the LIBOR-OIS spread.[38] For our baseline calibration, we took $\theta = 1$, corresponding to a LIBOR-quality bank. With $\theta = 1.5$, for example, the wholesale unsecured spread of the modeled bank is 50% higher than that of an average LIBOR-quality bank, state by state.

The left panel of Figure 7 shows that as θ increases, the bank offers more expensive line terms. This in turn reduces the equilibrium line size L chosen by the borrower and 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 co-varies with bank funding spreads, debt overhang reduces the incentives for a bank to provide revolving credit. This covariance is proportional to θ, holding drawing behavior constant, thus increasing the severity of debt overhang and reducing the equilibrium supply of credit lines.

Our calibrated borrowers are expected to take about 4.9% 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. Borrowers take about 6.7% more in SOFR-linked credit lines from a LIBOR-quality bank than from a bank that obtains external funding at 50% higher credit spreads, all else equal. Variation across banks in wholesale unsecured credit spreads is primarily a reflection of the relative strength of bank capitalization. Our analysis here shows that the impact of reference rate transition on credit supply is stronger for less-well capitalized banks. Likewise, higher regulatory capital requirements would lessen the impacts of reference-rate transition.

Next, we consider bank heterogeneity with respect to *both* external funding spread and the fraction of drawdowns expected to be left on deposit. Intuitively, these two drivers of debt overhang are likely to be correlated, because a banking crisis will probably cause borrowers to deposit a larger fraction of their drawn funds at more highly capitalized banks. This issue is briefly explored in more depth in Appendix D. In addition to our baseline model of a bank, we consider two types of banks: a

[38] As deduced from the results in Section 3, for a given θ, the contractual spread $s(L)$ over LIBOR, assuming a 50% Loss Given Default (LGD), is given by

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

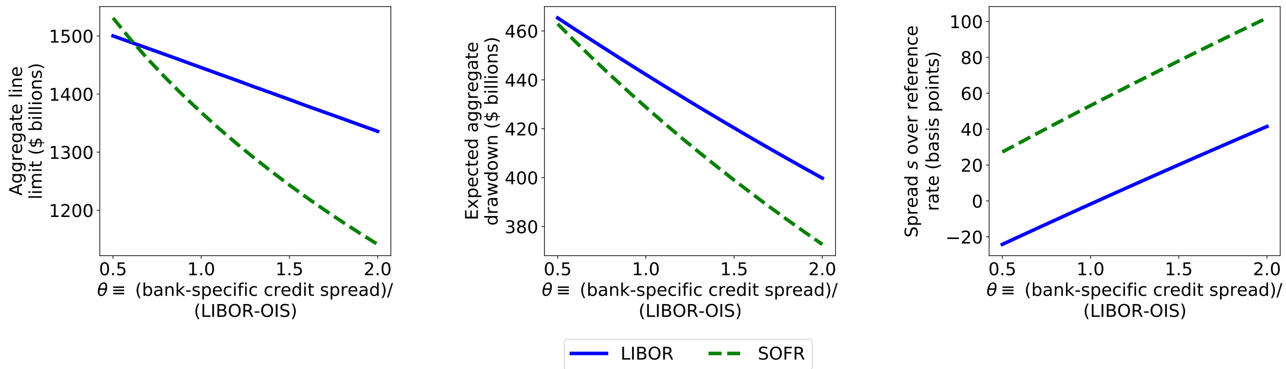


Figure 7: **Bank pricing of credit lines as a function of bank quality.** All parameters are as specified in the caption of Figure 4, except for variation in the bank-quality parameter θ. The bank's funding spread when lines are drawn is the product of θ and LIBOR-OIS. The left panel shows the associated impact on the aggregate line limit, $M \cdot L$. The right panel shows the impact on the aggregate amount of drawn credit, $ME(Q(L))$.

"high-debt-overhang bank" that is characterized by high funding spreads ($\theta = 1.5$) and a low fraction of drawdowns left on deposit ($D = 0.1$); and a "low-debt-overhang bank," which has a low funding spread ($\theta = 0.5$) and a large fraction of drawdowns financed by deposits ($D = 0.75$). As shown in Table 6, LIBOR-SOFR transition is predicted to reduce aggregate line limits by about 11% for high debt-overhang banks, relative to our baseline reduction of 5.9%. In contrast, for high-quality banks, transition to risk-free rates *increases* aggregate line limits by 4.6%. Our analysis thus suggests that low-debt-overhang banks — generally those with higher capital and better sources of 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 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

We next turn to welfare analysis. Our model implies that the total welfare for borrowers and banks is captured by the expected liquidity benefit to borrowers, which is $E[b(Q(L), \psi)]$, because all other costs and benefits in our model are merely transfers. Table 6 shows that LIBOR-SOFR transition would cause a total welfare reduction of about 2.6% for a baseline bank, with a bigger impact for high-debt-overhang banks, and a predicted *improvement* in welfare for low-debt-overhang banks.

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

Table 6: **Implications of reference rate transition across heterogeneous banks.**

	Baseline $\theta = 1.0$, D=0.2	Low debt overhang $\theta = 0.5$, $D = 0.75$	High debt overhang $\theta = 1.5$, $D = 0.1$
Change in drawn spread s^* (bps)	51.7	45.1	56.2
Change in credit line limit	−5.87%	4.64%	−11.36%
Change in expected drawn credit	−2.77%	1.12%	−5.20%
Change in welfare	−2.62%	1.16%	−4.98%
Optimal rate credit-sensitivity λ^*	0.72	0.32	1.0

Notes: The table shows changes in equilibrium quantities (in percentage) and spreads (in basis points) caused by a transition from LIBOR to SOFR. Transition to a risk-free reference rate automatically elevates the contractual spread s^* to the reference rate, because LIBOR is above the risk-free rate. The first row of the table shows how this increase in s^* depends on bank type. The percentage changes shown are the ratio of the change of the indicated quantity from the case of LIBOR to the case of SOFR, divided by the quantity for the case of LIBOR. The welfare optimal credit-sensitivity λ^* of the reference rate is the sensitivity of the welfare-optimal reference rate R^* to LIBOR-OIS, in that $R^* = r + \lambda^*(\text{LIBOR} - \text{OIS})$.

incentives for credit provision. Wholesale unsecured funding spreads of regional banks are slightly higher than those of the largest US bank holding companies, see Section F. Moreover, our analysis in Section 4 suggests that regional banks experienced a much lower extent of depositing of drawn lines during the COVID recession than did the largest banks in our sample. Given this mix of relatively higher funding spreads and possibly lower drawdowns left on deposit, the reference-rate transition may have a higher impact on the provision of revolvers by these regional banks.

We also consider the welfare-maximizing degree of credit sensitivity of the reference rate. Here, λ denotes the degree of credit sensitivity of the chosen reference rate, $R = r + \lambda(\text{LIBOR} - \text{OIS})$. The risk-free reference rate, SOFR, corresponds to $\lambda = 0$. LIBOR corresponds to $\lambda = 1$. As shown in Table 6, as the effect of bank debt overhang rises, the credit sensitivity of the welfare-optimal reference rate rises.[39]

6 Discussion

We find that the transition from credit-sensitive reference rates like LIBOR and EURIBOR to risk-free reference rates such as SOFR and ESTR increases borrower incentives to draw on credit lines more

[39] Appendix Figure K.2 shows how total welfare in our model depends on the degree λ of credit sensitivity of the reference rate. 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 80% 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.

heavily during periods of stress. This is so because a line referencing a risk-free rate is typically a very cheap source of firm credit when financial markets are stressed. When a SOFR-linked line is originally contracted, the higher expected future funding cost wedge is priced into the terms of credit facilities, which reduces equilibrium credit supply for our representative bank. We show that this impact is smaller for banks with lower funding costs, or even reversed if it is anticipated that borrowers will leave the majority of their future line draws on deposit at the same bank.

Our results suggest that reference-rate transition may cause some credit-line provision to move away from banks with high funding costs toward banks with lower funding costs. 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). 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.

Our paper 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 a complementary source of synergy between these two business lines – revolvers and deposit taking – via a 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, making the inflow of cheap deposits especially valuable. The synergy between revolvers and deposit taking is arguably weaker for syndicated loans, because the associated deposit inflows tend to be more concentrated among the syndicate of banks, especially at the lead arranger. Given that deposit inflows are relatively more valuable under risk-free reference rates, we speculate that the transition away from credit-sensitive rates may create incentives to change loan pricing terms across a syndicate or even lead to a reduction in loan syndication.

Adverse impacts of reference-rate transition on credit-line provision could seemingly be mitigated by the ability of borrowers 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 (unreported) theoretical 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 primarily a form of insurance against unanticipated liquidity shocks, whereas term loans are cost effective for meeting known funding requirements.

There is, however, a different channel, explored by Greenwald, Krainer, and Paul (2020) and Acharya, Engle, and Steffen (2021), by which term-loan origination during periods of stress could be affected by the transition to risk-free reference rates. We have shown that, relative to LIBOR-linked lines, revolvers linked to risk-free rates like SOFR are much more heavily utilized in stressed market conditions. These additional drawdowns could make banks become more capital-constrained in periods of stress, which could crowd out new term-loan origination.

For the same reason, the supervisory stress tests conducted by regulators—a form forward-looking capital requirements—could reasonably be adapted to incorporate the impact on bank balance sheets of line draws in a stress scenario, especially given the much larger line draws under stress that our modeling suggests for SOFR-linked lines, relative to LIBOR-linked lines. Banks would then consider, when pricing revolvers, the additional debt-overhang costs to their shareholders of having sufficient capital to pass the associated stress test. SOFR-linked lines could in that case become even more expensive, relative to LIBOR-linked lines, than suggested by our model.

We have shown that the impact of reference-rate transition on credit line provision is exacerbated by more costly external bank funding. In our model, banks get wholesale external financing in a competitive frictionless market. If, in addition, wholesale bank creditors suffer from adverse selection about the bank's credit quality, this would magnify the increase in cost to bank shareholders of providing credit lines, under the natural assumption that the adverse selection impact on external financing costs to the bank are positively correlated with LIBOR-OIS spreads.

In response to concerns expressed by some large US banks to regulators about access to a credit sensitive reference rate, the New York Fed convened a collection of these banks, the Credit Sensitivity Group, to meet at the New York Fed to discuss this issue and to consider the potential for a "credit sensitive rate/spread that could be added to SOFR."[40] Regulators, however, have discouraged the use of two such alternatives, BSBY and Ameribor, especially after a 2023 IOSCO review found that

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

BSBY and Ameribor "exhibit some of the same inherent 'inverted pyramid' weaknesses as LIBOR ... [and] their use may threaten market integrity and financial stability." U.S. banking agencies issued supervisory guidance that cautioned banks against using reference rates that have the weaknesses identified in IOSCO's review. Subsequently, BSBY was withdrawn by Bloomberg and the use of Ameribor is extremely limited. Berndt, Duffie, and Zhu (2023) proposed a different approach: a reference credit spread, AXI, that is an average of wholesale unsecured bank credit spreads at all maturities out to five years. Although AXI has since been commercialized,[41] the official sector has not yet reacted to it. While EURIBOR, a European analogue of LIBOR, remains active in the European Union, there are currently no credit sensitive benchmark rates in active use in the US and UK.[42]

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 robustly, especially under stressed market conditions.[43] Our analysis does suggest, however, that when debt overhang is high, alternative credit-sensitive reference rates can have beneficial effects in the market for C&I lending.

[41] AXI and a broader corporate spread index, FXI, are available through Invesco. Of the authors Berndt, Duffie, and Zhu (2023) who proposed AXI, Duffie is also an author of this paper but is not involved in the commercialization of AXI and has no related compensation.

[42] A bank could in principle use *its own* wholesale funding costs as the interest rate index in a loan contract. However, this may not be effective in practice due to lack of commonality and transparency to borrowers (Duffie, Dworczak, and Zhu, 2019). Moreover, the majority of credit line commitments are syndicated and involve multiple bank lenders, so a loan syndicate must agree on a common reference rate. This could cause incentive issues if the rate is linked to the wholesale funding costs of a single bank in the syndicate. This implies that there are benefits of a common public benchmark reference rate, as opposed to a private, idiosyncratic interest rate, for credit lines.

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

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APPENDIX

- Appendix A: Data.
- Appendix B: Proofs
- Appendix C: Bank Reference Rate Exposures.

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.

FR 2052a: 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,[44] we create two balanced panels of banks for our analysis. The first panel comprises the eight largest banks in the U.S. We include daily observations from Dec. 30, 2015, to May 21, 2021. The second is a monthly panel of 20 large U.S. banks, for which we include observations between Sept. 30, 2017, and April 30, 2021. We exclude the four trust banks from our main sample, due to their unique business model (focused on deposit-taking and not corporate lending). A list of banks in each sample is included in Table A.1.[45]

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.[46] 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 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

[44] 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.

[45] For some of analyses in the Online 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.

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

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

Bank Name	Bank Type	Assets	% Committed	FR 2052a		Y-14
			C&I / Assets	Monthly	Daily	
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. Additionally, 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.

quarter.[47] 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.

In several tables using the FR 2052a, for instance Table 1, we aggregate across various counterparty and product types. 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. 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. 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.

FR Y-14Q: 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 information 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.[48]

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.

FR 2416: In our analysis of redepositing during the GFC, we use confidential microdata from the FR 2416, which are used to construct the Federal Reserve's weekly H8 series. The FR 2416 was a survey of depository institutions that required confidential treatment of institution-level data and any information that identifies the individual institutions that reported the data. The FR 2416 was sunset on June 24, 2009 and replaced with the FR 2644. Both series report on a weekly basis a key subset of line items on bank call reports, including total assets, loans to C&I borrowers, and certain categories of liabilities.

Other Data Sources: We also use the FR 2420 data collection to analyze bank funding costs prior

[47] 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.

[48] 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.

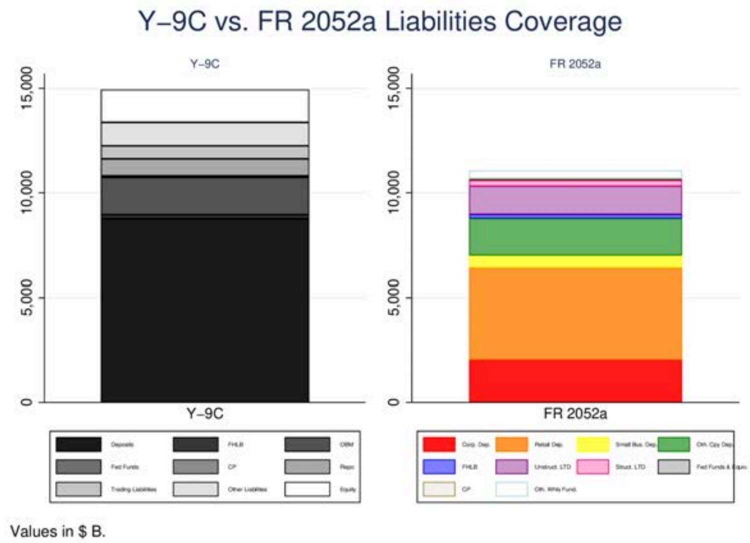


Figure A.1: **Y-9C vs. FR 2052a Total Liabilities Coverage.** Data Source: FR 2052a and FR Y-9C for banks in the FR 2052a monthly panel.

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),[49] 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

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

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 G.1), 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.

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

B Proof of Proposition 1

This appendix provides a proof of Proposition 1. First, we show that

$$G(L) = \delta p_1 Y - CQ(L). \tag{14}$$

We have

$$\begin{aligned}
G(L) &= \frac{\partial_+ V(0)}{\partial c} \\
&= \frac{\partial_+ \delta E_1\left[(X+cY)^+\right]}{\partial c}\bigg|_{c=0} - CQ(L) \\
&= \delta \lim_{c\downarrow 0} \frac{E_1\left[(X+cY)1_{\{X+cY\geq 0\}}\right] - E_1\left[X1_{\{X\geq 0\}}\right]}{c} - CQ(L) \\
&= \delta \lim_{c\downarrow 0} \frac{E_1\left[(X+cY)1_{\{X+cY\geq 0\}}\right] - E_1\left[X1_{\{X\geq 0\}}\right]}{c} - CQ(L) \\
&= \delta \lim_{c\downarrow 0} \frac{E_1\left[cY1_{\{X+cY\geq 0\}}\right] + E_1\left[X(1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}})\right]}{c} - CQ(L) \\
&= \delta \lim_{c\downarrow 0} E_1\left[Y1_{\{X+cY\geq 0\}}\right] + \delta \lim_{c\downarrow 0} \frac{E_1\left[X(1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}})\right]}{c} - CQ(L).
\end{aligned}$$

Because and X and Y are integrable and $P(X=0)=0$, dominated convergence implies that

$$\delta \lim_{c\downarrow 0} E_1\left[Y1_{\{X+cY\geq 0\}}\right] = \delta E_1\left[\lim_{c\downarrow 0} Y1_{\{X+cY\geq 0\}}\right] = \delta E_1\left[Y1_{\{X\geq 0\}}\right].$$

Further,

$$1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}} = 1_{\{X+cY\geq 0 \text{ and } X<0\}} - 1_{\{X\geq 0 \text{ and } X+cY<0\}}.$$

On the event $\{X \geq 0 \text{ and } X+cY<0\}$ or $\{X+cY\geq 0 \text{ and } X<0\}$, we have $|X| \leq |cY|$. Therefore,

$$\begin{aligned}
\delta \lim_{c\downarrow 0} \left| \frac{E_1\left[X(1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}})\right]}{c} \right| &\leq \delta \lim_{c\downarrow 0} \frac{E_1\left[|cY||1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}}|\right]}{c} \\
&= \delta \lim_{c\downarrow 0} E_1\left[|Y||1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}}|\right].
\end{aligned}$$

Using dominated convergence again,

$$\delta \lim_{c\downarrow 0} E_1\left[|Y||1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}}|\right] = \delta E_1\left[\lim_{c\downarrow 0} |Y||1_{\{X+cY\geq 0\}} - 1_{\{X\geq 0\}}|\right] = 0.$$

This leaves

$$G(L) = \delta E_1\left[Y1_{\{X\geq 0\}}\right] - CQ(L).$$

Finally, the fact that Y is observable at time 1 implies the result (14).

Recalling (4), we can express Y as

$$Y = Q(L)(1+R+s(L)) - \varphi Q(L)(1+r) - (1-\varphi)Q(L)(1+r+S) + CQ(L)(1+r+S).$$

Plugging this expression into (14) and using the definition $\delta = 1/(1+r)$, we have

$$
\begin{aligned}
G(L) = &\delta p_1 \Big(Q(L)(1+R+s(L)) - \varphi Q(L)(1+r) - (1-\varphi)Q(L)(1+r+S) + CQ(L)(1+r+S) \Big) \\
&\quad - CQ(L) \\
= &\delta p_1 \Big(Q(L)(1+R+s(L)) - \varphi Q(L)(1+r) - (1-\varphi)Q(L)(1+r+S) \Big) \\
&\quad + (\delta p_1(1+r+S) - 1)CQ(L) \\
= &p_1 \Big(\delta Q(L)(1+R+s(L)) - Q(L) - \delta(1-\varphi)Q(L)S \Big) + (p_1 + p_1\delta S - 1)CQ(L) \\
= &p_1 \Big(\delta Q(L)(1+R+s(L)) - Q(L) \Big) - p_1\delta(1-\varphi)Q(L)S + (p_1 - 1)CQ(L) + p_1\delta SCQ(L) \\
= &p_1 \Big(\delta Q(L)(1+R+s(L)) - Q(L) \Big) + (p_1 - 1)CQ(L) + (C + \varphi - 1)p_1\delta Q(L)S \\
= &p_1 \Big(\delta Q(L)(1+R+s(L)) - Q(L) \Big) - (1 - C - \varphi)p_1\delta Q(L)S - (1-p_1)CQ(L),
\end{aligned}
$$

which is the claimed result.

C Bank Reference Rate Exposures

This appendix provides more details on banks' exposures to various reference rates. Table C.1 provides details on how sensitive different categories of bank liabilities are to bank funding risk. Table C.2 shows that most long-term bank debt is fixed rate, and that only a limited portion of floating rate debt is LIBOR-based. Figure C.1 shows the outstanding balance of C&I loans by underlying reference rate, including that the credit line draws during the COVID pandemic occurred predominantly in LIBOR-linked facilities. Table C.3 provides details on how reference rates are used by different banks across loan products. Figure C.2 provides detail on reference rate use in new credit line originations, following the LIBOR transition.

Table C.1: **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

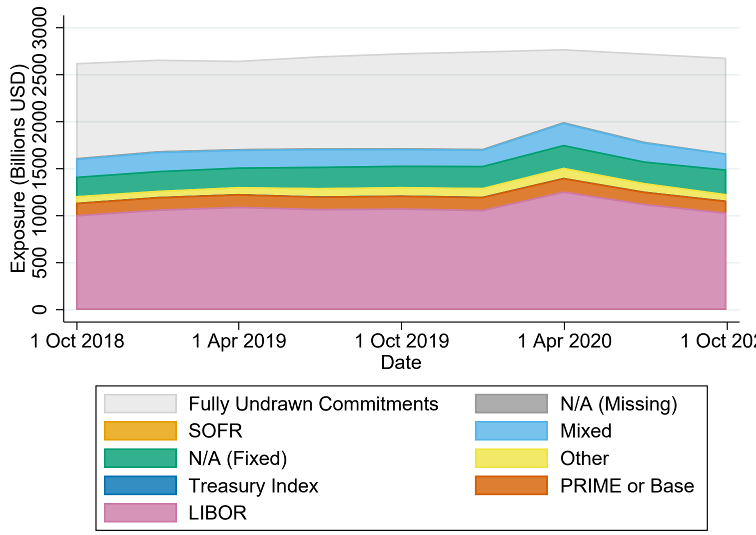
$$Y_t = \alpha + \beta \times \text{LIBOR-OIS}_t + \epsilon_t$$

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 C.2: **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).



(a) Aggregate C&I Loans by Reference Rate

Figure C.1: **Corporate Loans by Reference Rate.** Data Source: FR Y-14Q. This figures displays outstanding corporate loan balances by underlying reference rate over time. Panel (a) displays C&I loans by underlying reference rate, using the FR Y-14Q Schedule H1.

Table C.3: **Floating Rate Loans at Large US BHCs (as of December 31, 2019)**

(in %)	Industry	Bank Holding Company			No. of
		25th	Median	75th	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.

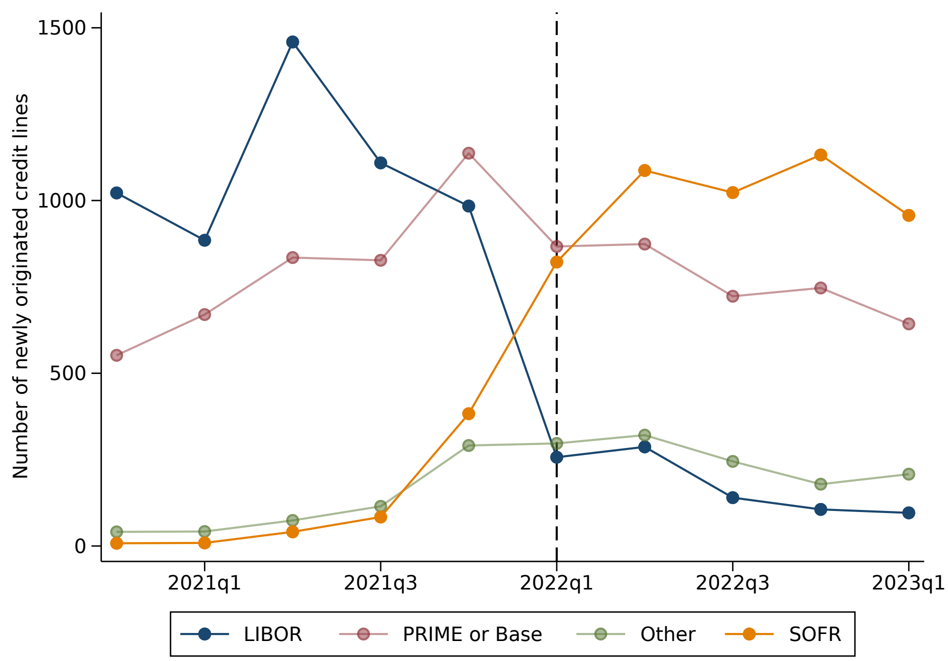


Figure C.2: **Credit line originations by underlying reference rate.** Data Source: FR Y-14Q. This figure represents the number of new credit line originations each quarter by the loan's underlying reference rate. The vertical line on Jan. 1, 2022 represents the first date on which banks were prohibited from originating new loans that reference LIBOR as the underlying rate. Observed LIBOR-linked issuance post-2022 likely reflects misreporting errors in the FR Y-14Q.

Internet APPENDIX [FOR ONLINE PUBLICATION ONLY]

- Internet Appendix D: Incitements to Draw Early or to Run.
- Internet Appendix E: Heterogeneity in Bank Funding Composition.
- Internet Appendix F: Heterogeneity in Bank Funding Costs.
- Internet Appendix G: Borrower-Level Evidence on Draws
- Internet Appendix H: Calibration Methodology.
- Internet Appendix I: Calibration: Model Sensitivity.
- Internet Appendix J: Calibration: Impacts of Different Deposit Functions.
- Internet Appendix K: Calibration: Additional Welfare Analyses

D 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 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

$$V(L) = \sup_{0 \leq q_1 + q_a \leq L,\, W} E\left[b(Q+q_a,\psi) - Wq_1\epsilon - Q(1+R_1+s)(1+R_a+s) - q_a(1+R_a+s)\,|\,S_1,\psi\right], \tag{15}$$

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 (15), 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

$$g_{L,s} = E\left(1_A[q_1[(1 + R_1 + s)(1 + R_a + s) - 1] + q_a(R_a + s) - q_1((1 + S_1 W)(1 + S_a) - 1) - q_a S_a]\right). \tag{16}$$

where 1_A is the event of bank solvency at time 2. The first two terms inside the expectation of (16) 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 (15) for the optimal line amount L^*.

E Heterogeneity in Bank Funding Composition

This section provides additional details on heterogeneity in funding composition of the largest U.S. Bank Holding Companies (BHCs).

Among the 20 banks in our main sample, there is significant heterogeneity in the composition of both deposit liabilities and wholesale funding. For instance, Table E.1 shows that while 50% of deposits are uninsured at the average large bank, reliance on uninsured deposits varies significantly, with an interquartile range of 34% to 61% of total deposits. Table E.2 shows that regional banks also rely more heavily on FHLB advances than the largest banks in our sample, accounting for around 29% of their total wholesale funding (compared to the full sample, where FHLBs provide only 8% of wholesale funding).

Table E.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 our 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.

The funding composition of large U.S. BHCs also differs significantly from the U.S. Operations of Foreign Banking Organizations (FBOs). As documented in Table E.3 and in contrast to U.S. BHCs, most funding for U.S. branches of FBOs is sourced via wholesale funding markets instead of via deposits, accounting for 77% of third-party assets.[51] Within wholesale funding, a majority (54%) comes from internal capital markets. Also, in contrast to U.S. BHCs, nearly all FBO branch deposits are uninsured and there is significant reliance on Wholesale CDs.

[51] We primarily normalize by third-party assets when discussing FBOs, since branches of FBOs may engage in both intercompany lending and borrowing. Intercompany loans are recorded as assets for the unconsolidated branch but net out in parent company consolidated financial reporting. The FR 2052a only reports obligations of the U.S. Operations of FBOs.

Table E.2: **Deposit and Wholesale Funding Breakdown as of December 31, 2019 (Regional Banks Only)**

Panel A: Deposit Funding by Counterparty (percent)

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

Panel B: Wholesale Funding by Type (percent)

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

Data Sources: FR2052a, FR Y-9C. Notes: Table contains the industry-level distribution of deposits by counterparty type (Panel A) and of wholesale funding by product type (Panel B). Industry-level statistics calculated from the 10 regional banks in our monthly FR 2052a panel as of Dec. 31, 2019. Counterparty types and funding products are sorted from most material to least material, measured as a percentage of total deposits and total wholesale funding, respectively. Maturity breakdowns reflect *remaining* maturity of funding sources and not maturities *at origination.*

Given the heterogeneity in bank funding composition in normal times, it is no surprise that we observe how the largest banks responded to funding needs during the COVID pandemic. Table E.4 shows that for regional banks, only between 28% and 41% of drawdowns were re-deposited at regional banks, in contrast to the redepositing of between 52% and 94% in the full sample, excluding trust banks.[52] Regional banks also did not benefit from "flight to safety" deposit inflows, as the increase in total deposits was not statistically significant for this subsample of banks.

[52]Note that Table E.5 shows the inclusion of trust banks in our regression sample significantly reduces the coefficient estimate on ΔDrawdowns / Assets × COVID. These banks experienced significant deposit inflows during the COVID pandemic but did not experience commensurate drawdowns, since credit lines are a less significant portion of their business model.

Table E.3: **Deposit and Wholesale Funding Breakdown as of December 31, 2019 (Consolidated U.S. Branches of FBOs)**

Panel A: Deposit Funding by Counterparty (percent)

Counterparty	Maturity: Open	Maturity: 1 Day-30 Days	Maturity: 30 Days-1 Year	Maturity: 1 Year+	Uninsured	% of Total Claims
Non-Financial Corp.	44.5	35.0	19.1	1.5	99.9	12.8
Bank	19.9	16.2	14.1	49.7	72.7	8.3
NBFI	28.9	52.2	17.8	1.1	99.3	4.7
Other Counterparty	10.3	40.8	42.2	6.8	100.0	1.8
Retail	42.4	52.9	4.7	0.0	100.0	0.9
Public Sector Entity	2.7	91.5	0.0	5.8	100.0	0.1
Small Business	60.4	30.7	8.6	0.3	99.9	0.0
All Counterparties	32.5	33.4	18.3	15.8	91.9	

Panel B: Wholesale Funding by Type (percent)

Product	Maturity: Open-30 Days	Maturity: 1-6 Months	Maturity: 6 Months-1-Year	Maturity: Long-Term	Internal	% of Total Claims
Offshore Borrowing	35.5	10.7	10.6	43.1	98.7	35.7
Wholesale CDs	12.1	58.6	27.7	1.7	0.0	25.3
Unstructured LTD	1.5	2.8	5.8	89.8	52.2	7.7
CP	22.3	68.7	9.0	0.0	0.0	4.7
Other Wholesale Funding	81.2	9.7	5.8	3.3	96.2	2.2
Onshore Borrowing	51.9	14.3	9.4	24.5	40.8	1.0
Free Credits	34.5	65.5	0.0	0.0	0.0	0.3
Conduit and SPV	27.4	71.0	0.0	1.6	0.0	0.3
All Products	25.1	29.6	15.4	29.8	54.1	

Data Sources: FR2052a, FFIEC 002. Notes: Table contains the industry-level distribution of deposits by counterparty type (Panel A) and of wholesale funding by product type (Panel B). Industry-level statistics calculated from the Consolidated U.S. Branches of 14 Foreign Banking Organizations (FBOs) that reported the FR 2052a as of Dec. 31, 2019. These 14 FBOs include: BARC, BNPP, TD, SOGN, DB, UBS, BMO, BBVA, KN, CS, MUFG, SMBC, MFG, and RY. Counterparty types and funding products are sorted from most material to least material, measured as a percentage of total third-party claims. Maturity breakdowns reflect *remaining* maturity of funding sources and not maturities *at origination*.

Table E.4: **Drawdowns and Deposits in the Cross-Section: Monthly Changes. (Regional banks only.)**

Panel A: $-changes					
Dependent variable	Δ Corp. Deposits	Δ FHLB	Δ Unsec. WSF	Δ Total Cols. (1-3)	Δ Total Deposits
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns	0.06	-0.00	-0.00	0.06	0.23*
	(0.04)	(0.02)	(0.00)	(0.06)	(0.13)
Δ Drawdowns × COVID	0.41*	0.59***	0.00	1.00***	0.43
	(0.21)	(0.12)	(0.01)	(0.30)	(0.38)
Bank FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
N	598	598	598	598	598
No. Banks	11	11	11	11	11
R^2	0.329	0.316	0.121	0.338	0.269

Panel B: $-changes normalized by assets					
Dependent variable	Δ Corp./ Assets	Δ FHLB/ Assets	Δ Unsec. WSF/ Assets	Δ Total/ Assets	Δ Total Deposits/ Assets
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns/Assets	0.03	0.01	-0.00	0.03	0.16
	(0.03)	(0.02)	(0.00)	(0.03)	(0.09)
Δ Drawdowns/Assets × COVID	0.28***	0.49***	0.01	0.78***	0.12
	(0.07)	(0.12)	(0.01)	(0.15)	(0.34)
Bank FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
N	586	586	586	586	586
No. Banks	11	11	11	11	11
R^2	0.337	0.233	0.098	0.300	0.326

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

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

where COVID_t is a dummy that is one during the COVID recession in March and April 2020 and zero otherwise. In Panel B we report results from the following regression:

$$\Delta y_{bt}/\text{Assets}_{bt-1} = \alpha + \Delta\text{Drawdowns}_{bt}/\text{Assets}_{bt-1} + \Delta\text{Drawdowns}_{bt}/\text{Assets}_{bt-1} \times \text{COVID}_t + \gamma_b + \eta_t + \epsilon_{bt}.$$

The dependent variable in column (3) of Panel A (labeled unsecured wholesale funding (WSF)) pools various short-term wholesale funding categories: CP, CD, non-prime brokerage free credits, and other unsecured wholesale funding. The dependent variable in column (4) of Panel A is the change in the sum of corporate deposits, FHLB advances, and unsecured wholesale funding. The dependent variable in column (5) is total deposits, pooling across all counterparties listed in Table 1. In Panel B we use the same the dependent variables as in Panel A and normalize lagged total assets. Monthly data from July 2017 through April 2022 for our sample regional banks. See Table A.1 for a list of banks and their type. Data Source: FR2052a. Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table E.5: **Drawdowns and Deposits in the Cross-Section: Monthly Changes. (All banks.)**.

Panel A: \$-changes					
Dependent variable	Δ Corp. Deposits	Δ FHLB	Δ Unsec. WSF	Δ Total Cols. (1-3)	Δ Total Deposits
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns	0.06***	0.00	0.00	0.07***	0.18***
	(0.02)	(0.01)	(0.01)	(0.02)	(0.04)
Δ Drawdowns × COVID	0.88***	0.16	-0.03	1.01***	1.78***
	(0.08)	(0.13)	(0.03)	(0.09)	(0.17)
Bank FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
N	1339	1339	1339	1339	1339
No. Banks	24	24	24	24	24
R^2	0.323	0.169	0.095	0.310	0.353

Panel B: \$-changes normalized by assets					
Dependent variable	Δ Corp./ Assets	Δ FHLB/ Assets	Δ Unsec. WSF/ Assets	Δ Total/ Assets	Δ Total Deposits/ Assets
	(1)	(2)	(3)	(4)	(5)
Δ Drawdowns/Assets	0.03	0.00	0.00	0.03	0.16*
	(0.03)	(0.01)	(0.00)	(0.04)	(0.08)
Δ Drawdowns/Assets × COVID	0.27	0.56***	-0.07	0.77**	0.20
	(0.19)	(0.10)	(0.07)	(0.28)	(0.24)
Bank FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
N	1314	1314	1314	1314	1310
No. Banks	24	24	24	24	24
R^2	0.209	0.132	0.100	0.200	0.181

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

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

where COVID_t is a dummy that is one during the COVID recession in March and April 2020 and zero otherwise. In Panel B we report results from the following regression:

$$\Delta y_{bt}/\text{Assets}_{bt-1} = \alpha + \Delta \text{Drawdowns}_{bt}/\text{Assets}_{bt-1} + \Delta \text{Drawdowns}_{bt}/\text{Assets}_{bt-1} \times \text{COVID}_t + \gamma_b + \eta_t + \epsilon_{bt}.$$

The dependent variable in column (3) of Panel A (labeled unsecured wholesale funding (WSF)) pools various short-term wholesale funding categories: CP, CD, non-prime brokerage free credits, and other unsecured wholesale funding. The dependent variable in column (4) of Panel A is the change in the sum of corporate deposits, FHLB advances, and unsecured wholesale funding. The dependent variable in column (5) is total deposits, pooling across all counterparties listed in Table 1. In Panel B we use the same the dependent variables as in Panel A and normalize lagged total assets. Monthly data from July 2017 through April 2022 for our sample of 24 large banks including Trusts. Data Source: FR2052a. Robust standard errors in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

F 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 the Wharton Research Data Services (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.[53] We then estimate the following equation via weighted least squares:

$$Y_{ibt} = \beta_0 + \beta_1 M_{ibt} + \beta_2 D_b + \delta_t + \epsilon_{ibt}, \tag{17}$$

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 F.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_{ibt}^2 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.

[53] 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.

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

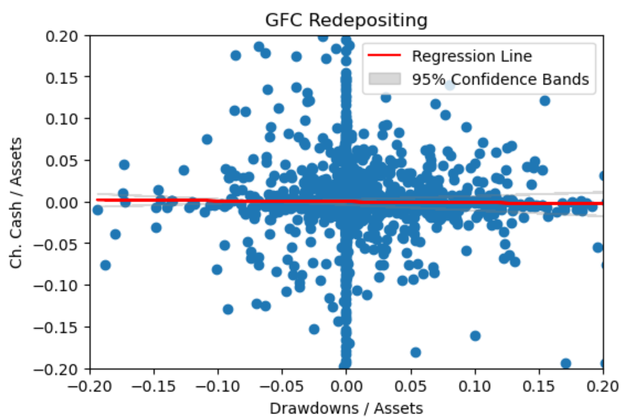
Variable	(1)	(2)	(3)
Remaining Maturity	0.2137	0.2486	0.146
	[0.0002]	[0.0]	[0.0]
Regional Indicator	0.015	0.2227	0.1053
	[0.79]	[0.00]	[0.00]
Sample	Full	Post-GFC	Recent
Reg Type	WLS	WLS	WLS
R^2	0.0014	0.0796	0.1432
N	39279	24560	12773

Notes: The table summarizes estimates of model (17) obtained by weighted-least-squares (WLS), with a weight on the squared residual ϵ_{ibt}^2 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.

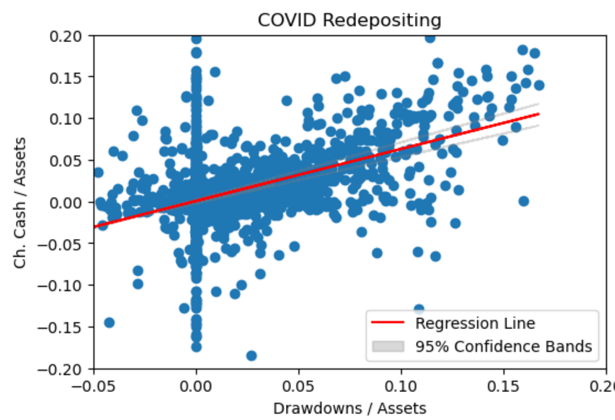
G Borrower Level Evidence on Drawdowns in Stress

In Section 4.6, we present evidence using bank-level panel data that credit line behavior varied significantly between the Covid pandemic and the GFC. During the Covid pandemic, borrowers drew down on lines and largely re-deposited those lines at the same bank. Wholesale funding did not increase. By contrast, during the GFC, banks required significantly more wholesale funding in response to drawdowns.

In this section, we confirm these findings using borrower-level financials. We leverage data from the FR Y-14Q, Compustat and Capital IQ to examine the extent to which draws were associated with an increase in borrower cash – which we use as a proxy for corporate deposit holdings in the banking system.[54]



(a) GFC



(b) Covid

Figure G.1: **Drawdowns and Corporate Deposits.** This figure shows a scatter plot of borrower-level data from Compustat and Capital IQ during the GFC (Panel A) and COVID (Panel B). The y-axis shows the change in cash / firm assets and the x-axis shows the borrower's drawdowns / firm assets. Changes in both cash and drawdowns are trimmed at the 1% and 99% level over the two years prior to our quarters of interest. GFC figure represents changes over four-quarters (2008q4 vs. 2007q4) while COVID panel represents changes over one-quarter (2020q1 vs. 2019q4), due to differences in data reporting timeliness.

Figure G.1 shows the correlation between changes in borrower-level drawdowns and changes in cash holdings for both the GFC and COVID recession, using data from Compustat and Capital-IQ. The x-axis displays firm-level drawdowns (normalized by firm size) and the y-axis displays the change in firm-level cash (normalized by firm size). The data indicate a strong correlation for the COVID recession, in line with 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:

$$\Delta \text{Cash}_i = \alpha + \beta_1 \Delta \text{Drawdowns}_i + X_i + \epsilon_i, \tag{18}$$

where ΔCash_i 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, and X_i are control

[54] Importantly, Compustat allows us to disentangle cash (CHQ) from cash and equivalent instruments (CHEQ). Thus, our response variable does not include instruments such as money market fund holdings or reverse repo transactions. For our analyses solely using the FR Y-14Q in columns 1 and 2 of Table G.1, since the FR Y-14Q does not separate cash from cash equivalents, these analyses pool both cash and cash-like instruments.

variables. Results can be found in Table G.1.

Table G.1: 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 (2008q4 vs. 2007q4) 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.

Our regressions confirm the patterns of Figure G.1. We find during Covid (columns 1-4), a one dollar increase in drawdowns is associated with an 86-97% increase in re-depositing, roughly in line with our aggregate bank-level evidence. In contrast, for the GFC, we find *no* statistically significant relationship between drawdowns and deposits (columns 1-2). 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. 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 apparently not merely left in deposit accounts, banks would have been required to fund them via other methods, which may have included costly unsecured wholesale funding. For drawdowns to be precautionary, it is necessary for deposit holdings to increase in response to credit-line drawdowns. 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.

In unreported results, we estimate the same regression during COVID using the Compustat and Capital IQ data (instead of the FR Y-14Q), and in specifications where we normalize our response and control variables by firm size. The normalized results are consistent with the results we report in Table G.1. The coefficient estimates during the COVID period are slightly smaller than the Y-14Q results – a one dollar increase in drawdowns is associated with 50-63% increase in re-depositing, in line with the bank-level evidence for regional banks – since the Y-14Q measures loan-level draws while Capital IQ measures firm-level borrowing.

H Model Calibration Details

This section of the appendix 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 $\underline{\epsilon} = -\bar{\epsilon}$.

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 $\{K(W) + \bar{\epsilon} > 0,\, K(W) + \underline{\epsilon} < L((1 + R + s)^{\frac{1}{\alpha}}\}$,*

$$
\begin{aligned}
E[Q(L)\,|\,W] = v \quad & \frac{L(K(W) + \bar{\epsilon} - L(((1 + R + s)^{\frac{1}{\alpha}}))^{+}}{(\bar{\epsilon} - \underline{\epsilon})} \\
+ v \quad & \frac{-\max(0, \frac{(K(W)+\underline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}})^2 + \min(L, \frac{(K(W)+\bar{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}})^2}{\frac{2(\bar{\epsilon}-\underline{\epsilon})}{(1+R+s)^{\frac{1}{\alpha}}}} \\
+ (1 - v)\, & \min\left(L, \frac{(K(W) + \epsilon^{d})}{(1 + R + s)^{\frac{1}{\alpha}}}\right)^{+}.
\end{aligned}
$$

2. *On the event $\{K(W) + \epsilon^d \leq 0\}$, we have $E[Q(L)\,|\,W] = 0$.*
3. *On the event $\{K(W) + \bar{\epsilon} \leq 0\}$ and $\{K(W) + \epsilon^d > 0\}$, we have $E[Q(L)\,|\,W] = (1 - v)\min(L, \frac{(K(W)+\epsilon^d)}{(1+R+s)^{\frac{1}{\alpha}}})$.*
4. *On the event $\{K(W) + \underline{\epsilon} \geq L(1 + R + s)^{\frac{1}{\alpha}}\}$, we have $E[Q(L)\,|\,W] = L$.*

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*

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

and

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

Motivated by calibrating the model so as to match the aggregate utilization of credit lines observed in our sample, we assume the following functional form for the function $K(\cdot)$ that determines the macro component $K(W)$ of borrowers' liquidity shocks:

$$
K(x) = \mathcal{C}_1 + \mathcal{C}_2 \min(x, x_0) + \mathcal{C}_3 (x - x_0)^{+} + \frac{\mathcal{C}_4}{1 + e^{-\mathcal{C}_5 (x - x_0)}}, \tag{19}
$$

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 the 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 calibrate the model in the following steps

1. For any parameter choices $\mathcal{P} = (M, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5, x_0, L, \bar{\epsilon}, \epsilon^d, v)$, 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
$$\mathcal{P}^{shock+} = (M, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5, x_0, 1.1L, \bar{\epsilon}, \epsilon^d, v)$$
and
$$\mathcal{P}^{shock-} = (M, \mathcal{C}_0, \mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \mathcal{C}_4, \mathcal{C}_5, x_0, 0.9L, \bar{\epsilon}, \epsilon^d, v).$$
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 would 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,[55] $Q_i^*(\mathcal{P}) = M \cdot E[Q(L) \mid W = w_i]$. 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 credit line sizes across borrowers in the data. This average is denoted $\overline{L^{sum}}$.

6. Because ϵ is conditionally uniformly distributed with probability v, we know that for any ι and ι' in $\{0, 1, 2, 3, 4, 5, 6, 7, 8\}$,

$$Z_i^{m,*}(\mathcal{P}) \equiv P\left(Q(L) \in \left(\frac{\iota L}{9}, \frac{(\iota+1)L}{9}\right) \;\middle|\; W = w_i\right) = P\left(Q(L) \in \left(\frac{\iota' L}{9}, \frac{(\iota'+1)L}{9}\right) \;\middle|\; W = w_i\right).$$

In the data, we observe the fraction of borrowers with line utilization between $(10 + \frac{80l}{9})\%$ and $(10 + \frac{80(l+1)}{9})\%$ for each $l \in \{1, 2, 3, 4, 5, 6, 7, 8\}$. These empirical fractions are roughly the same across these "interior" deciles. For each quarter, we calculate the average of these interior fractions, denoted $\overline{Z_i^m}$.

7. 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

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

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

8. 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

$$\begin{aligned}
\mathcal{E}_1 &\equiv |\Xi(\mathcal{P}_1)| \\
\mathcal{E}_2 &\equiv |\overline{L^{sum}} - M_1 \cdot L| \\
\mathcal{E}_3 &\equiv \sqrt{N^{-1}\sum_i (Q_i^*(\mathcal{P}_1) - Q_i)^2} \\
\mathcal{E}_4 &\equiv \sqrt{N^{-1}\sum_i (Z_i^*(\mathcal{P}_1) - Z_i)^2} \\
\mathcal{E}_5 &\equiv \sqrt{N^{-1}\sum_i (Z_i^{m,*}(\mathcal{P}_1) - \overline{Z_i^m})^2},
\end{aligned}$$

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

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

[55] 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.

errors,

$$O_2(\mathcal{P}) = \frac{1}{\mathcal{E}_1}\Xi(\mathcal{P})^2 + \frac{1}{\mathcal{E}_2}(\overline{L^{sum}} - M \cdot L)^2 + \frac{1}{\mathcal{E}_3}\sum_{i=1}^{N}(Q_i^*(\mathcal{P}) - Q_i)^2 + \frac{1}{\mathcal{E}_4}\sum_{i=1}^{N}(Z_i^*(\mathcal{P}) - Z_i)^2$$
$$+ \frac{1}{\mathcal{E}_5}\sum_{i=1}^{N}(Z_i^{m,*}(\mathcal{P}) - \overline{Z_i^m})^2.$$

At the fitted parameters, the first term is zero, so in fact plays no role in determining the fitted model.

10. 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 $\mathcal{C}_3 = 80$ so that the modeled line utilization during the GFC is roughly 7% more than the maximum sample utilization in non-crisis sample periods for which LIBOR-OIS is 80 basis points or less. We experimented with a wide choice of $\mathcal{C}_3$ and found that our main results are quite robust to this choice.

I Model sensitivity.

Table I.1 shows a sensitivity analysis of some of the main results with respect to two key parameters: the price elasticity $1/\alpha$ of borrower demand for credit and the probability p of a GFC-like increase in LIBOR-OIS. For example, reducing the assumed price elasticity of credit demand from 25 to 24 (by 4%) causes the model-implied impact of LIBOR-to-SOFR reference-rate transition on the aggregate dollar amount of lines to change from a 5.9% reduction at baseline to a 4.3% reduction after re-calibrating other parameters following the procedure described in Appendix H. Because of the resulting adjustment of other parameters, this is a check on model robustness, and *not* a comparative-static analysis of the effect of price elasticity on credit demand.

A higher probability of distressed funding markets implies relatively higher expected debt-overhang costs to banks for offering SOFR lines. Therefore, increasing the likelihood of a GFC shock almost monotonically increases the cost of credit line during average times, as the equilibrium funding spread s^* becomes larger under SOFR. This also monotonically drives down the average drawn credit during average times (i.e. when LIBOR-OIS is at 28 basis points).

We emphasize that most observations in our sample occur at low LIBOR-OIS states, so our calibrated model less accurately captures borrowers' liquidity preferences under states like GFC. Hence, the effects of the changing likelihood of a GFC shock on equilibrium outcomes at very high LIBOR-OIS states are more ambiguous. Overall, it is important to caveat that, while our findings are qualitatively robust, the magnitudes of transition impacts are uncertain due to model sensitivity

Table I.1: Sensitivity of modeled transition impacts to demand elasticity and crisis probability

	Total credit lines ($ billions)			Impact on drawn rate (bps)		Impact on drawn credit	
Assumed parameters	(1) LIBOR-linked	(2) SOFR-linked	(3) Impact	(4) LIBOR-OIS at 28 bps	(5) LIBOR-OIS at GFC level	(6) LIBOR-OIS at 28 bps	(7) LIBOR-OIS at GFC level
$1/\alpha = 25$, $p = 1\%$	1446.0	1437.0	−0.6%	11.3	−324.7	−2.27%	-0.4%
$1/\alpha = 25$, $p = 2\%$	1,470	1,418	−3.5%	19.8	−316.2	−4.0%	26.3%
$1/\alpha = 25$, $p = 3\%$	1,445	1,377	−4.7%	18.1	−317.9	−4.5%	66.9%
$1/\alpha = 25$, $p = 4\%$	1,465	1,379	−5.9%	23.5	−312.5	−5.7%	63.1%
$1/\alpha = 25$, $p = 5\%$	1,405	1,328	−5.4%	44.4	−291.6	−9.1%	23.6%
$1/\alpha = 24$, $p = 4\%$	1,446	1,384	−4.3%	37.9	−298.1	− 7.7%	18.9%

Notes: Row 1 of the table corresponds to the baseline model, which assumes an unconstrained price elasticity of credit demand of 25 ($\alpha = 0.04$) and assumes a mixed probability of $p = 4\%$ for a GFC-like conditional distribution of LIBOR-OIS. Row 2 corresponds to the model that is re-calibrated to empirical data based on an assumed price elasticity of 24 ($\alpha = 0.04167$) and $p = 4\%$. Row 3 corresponds to the model that is re-calibrated to empirical data based on an assumed price elasticity of 25 and $p = 5\%$. Column 1 is the modeled aggregate quantity of credit lines if LIBOR is the reference rate. Column 2 is the aggregate quantity of credit lines if SOFR is the reference rate. Column 3 is the percentage difference between the quantities of SOFR-linked lines and LIBOR-linked lines, relative to LIBOR-linked lines. . Column 4 is the difference between the drawn interest rates on SOFR-linked lines and LIBOR-linked lines when LIBOR-OIS is at its sample average of 28 basis points. Column 5 is the difference between the drawn interest rates on SOFR-linked lines and LIBOR-linked lines when LIBOR-OIS is at the GFC level of 360 basis points. Column 6 is the percentage difference in the drawn amounts of credit on SOFR-linked lines and LIBOR-linked lines when LIBOR-OIS is at its sample average of 28 basis points, relative to LIBOR-linked lines. Column 7 is the percentage difference in the drawn amounts of credit on SOFR-linked lines and LIBOR-linked lines when LIBOR-OIS is at the GFC level of 360 basis points, relative to LIBOR-linked lines..

J An Alternative Linedraw Deposit Function

In this appendix, we explore the implications for our calibration results of an alternative to the deposit function Φ used in the main body of the paper, defined by

$$\Phi(x) = \frac{D^*}{1 + e^{-m^*(x - w_0^*)}}.$$

The alternative deposit function Φ^* considered in this appendix is a mixture of two piece-wise (scaled and shifted) normal density functions defined by

$$\Phi^*(x) = D_{COVID} \left(\frac{e^{-\frac{(x-w_0)^2}{2m^2}} - e^{-\frac{w_0^2}{2m^2}}}{1 - e^{-\frac{w_0^2}{2m^2}}} \, 1_{0 \leq x \leq w_0} + \frac{e^{-\frac{\overline{m}(x-w_0)^2}{2m^2}} - e^{-\frac{w_0^2}{2m^2}}}{1 - e^{-\frac{w_0^2}{2m^2}}} 1_{w_0 \leq x \leq 350} \right) + D_{GFC} \, 1_{350 < x}, \quad (20)$$

where

$$\overline{m} = \frac{-2m^2}{(350 - w_0)^2} \log \left(\frac{D_{GFC}}{D_{COVID}} \left(1 - e^{-\frac{w_0^2}{2m^2}} \right) + e^{-\frac{w_0^2}{2m^2}} \right).$$

We specifically design the functional form of Φ^* such that

1. $\Phi^*(0) = 0$ and $\Phi^*(W)$ monotonically increases for $W \leq w_0$ to D_{COVID}. Then $\Phi^*(W)$ monotonically decreases for $w_0 \leq W \leq 350$ (basis points) to D_{GFC} and stays constant for $W \geq 350$ (basis points).

2. Under Φ^*, D_{GFC}, determines the final deposit fraction when the LIBOR-OIS spread, W, exceeds 350 basis points, a scenario that corresponds to "crisis states" in our model. Consistent with our baseline analysis, we set the terminal deposit fraction $D_{GFC} = D = 0.2$.

3. The other parameter D_{COVID} determines the largest deposit fraction across all states. We set $D_{COVID} = 0.9$ to capture the empirical observation that 90% of draw down credit are deposited with the same large banks during COVID recession.

Although Φ^* has a more complicated functional form, it is motivated by the available empirical evidence. Additionally, because $\Phi^*(x) \geq \Phi(x)$ for any LIBOR-OIS outcome x, our model's quantitative prediction of the impact of transition from LIBOR to SOFR under Φ^* is always more *conservative* than that under Φ. Figure J.1 illustrates the shape of these two deposit functions.

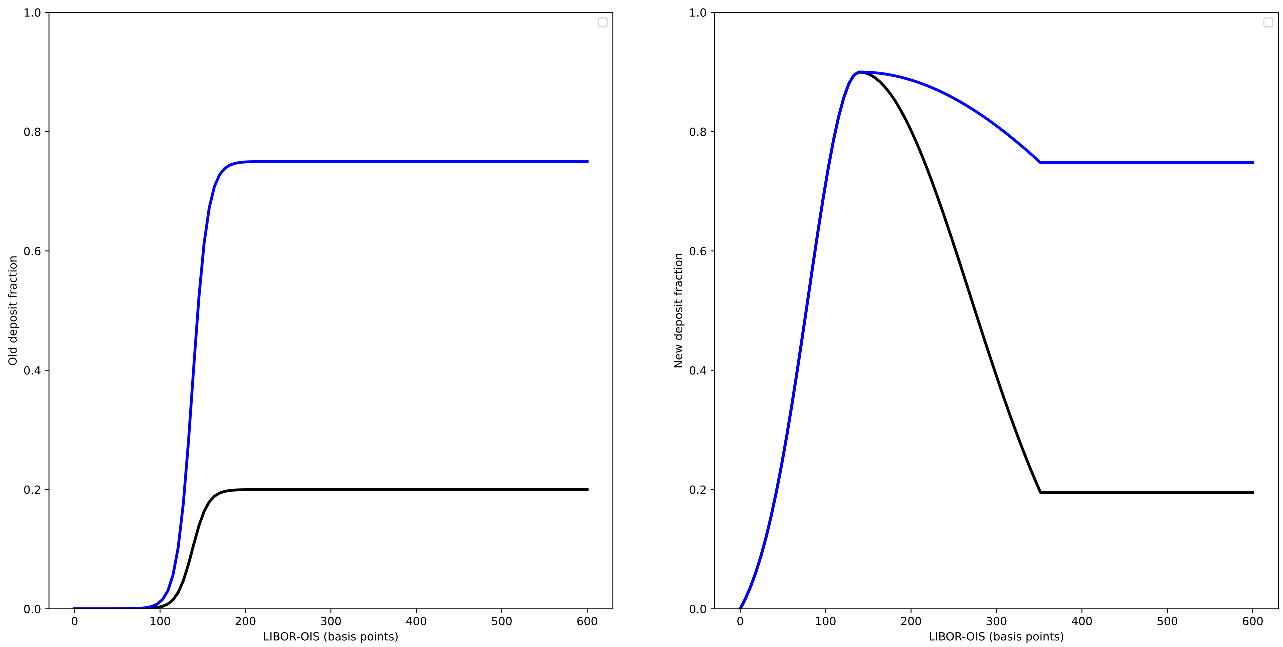


Figure J.1: Deposit functions. The left panel illustrates $\Phi^*(W)$ and the right panel depicts $\Phi(W)$. Blue curves correspond to $D = D_{GFC} = 75\%$ and black curves correspond to $D = D_{GFC} = 20\%$. Our baseline analysis follows the assumption that $D = D_{GFC} = 20\%$.

Our calibration analysis is based on the same approach taken in the main text. The calibration results are illustrated by Figure J.2.

Figure J.3 shows that this calibration predicts that LIBOR-SOFR transition causes an increase in the credit line spread by approximately 22 basis points, a reduction in the aggregate credit line limits by roughly 5%, and a decrease in the expected drawdown quantities by about 2.2%. Figure J.4 shows that the associated welfare loss is approximately 2%. Table J.1 includes the details of the equilibrium outcomes under Φ^*, as well as the model sensitivity analysis with respect to assumptions on paprameters.

Overall, these results align closely with the findings in the main body of our paper (driven by the fact that the states of the world in which drawdowns tend to be redeposited are relatively unlikely). The similarity betwen our baseline analysis and the results discussed in this section is quite remarkable, suggesting that the qualitative conclusions drawn from our model remain robust even when facing variations in deposit fractions during non-crisis periods.

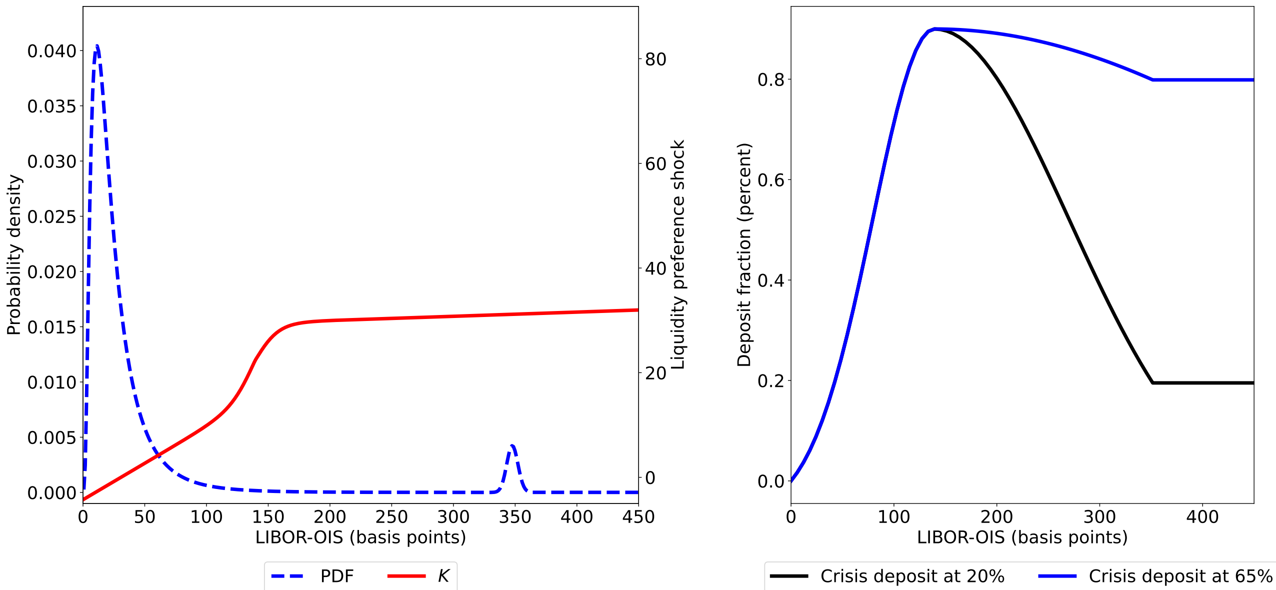


Figure J.2: **The probability density of LIBOR-OIS, the borrowers' liquidity preference shock, and the deposited fraction of drawn credit.** The baseline probability density of W shown in the left figure is a mixture of normals: With probability $p = 0.04$, W has a conditional normal distribution with a GFC-like mean of 350 basis points and standard deviation of 40 basis points. With probability $1 - p = 0.96$, W has a conditional log-normal distribution with a mean of 27 basis points and a standard deviation of 24 basis points, fitted by maximum likelihood estimation to daily LIBOR-OIS observations from January 2005 to April 2021. The common component $K(W)$ of borrowers' liquidity shock ψ, plotted in the left figure with a solid red line, is specified by $K(x) = C_1 + C_2 \min(x, x_0) + C_3(x - x_0)^+ + C_4/\left(1 + e^{-C_5(x-x_0)}\right)$, with coefficients $x_0 = 139.3$ basis points, $C_1 = -4.2$, $C_2 = 1392.4$, $C_3 = 80.0$, $C_4 = 14.4$, and $C_5 = 1038.3$, which were fit by least squares to line utilization data for our sample of 20 large banks, as detailed in Appendix Section H. At each potential outcome of $W =$ LIBOR-OIS, each borrower has a total liquidity shock $\psi = (K(W) + \epsilon)^+$, where ϵ has a probability $v = 0.05$ of a "rare-disaster" outcome of $\epsilon^d = 132.1$ and a probability $1 - v$ of being conditionally uniformly distributed on $(-\bar{\epsilon}, \bar{\epsilon})$, with $\bar{\epsilon} = 51.8$. The mass of the borrower M is 31.47. 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 Φ^*, with $w_0 = 139.3$ basis points. For comparison with the baseline model, we also provide results for an alternative "high-deposit" specification for Φ, with $D_{GFC} = 0.75$, as shown in the right panel.

Table J.1: Sensitivity of model calibration to demand elasticity and crisis probability

	Total credit lines ($ billions)			Impact on drawn rate (bps)		Impact on drawn credit	
Assumed parameters	(1) LIBOR-linked	(2) SOFR-linked	(3) Impact	(4) LIBOR-OIS at 28 bps	(5) LIBOR-OIS at GFC level	(6) LIBOR-OIS at 28 bps	(7) LIBOR-OIS at GFC level
$1/\alpha = 25, \quad p = 4\%$ (Baseline)	1,462	1,389	-4.96%	21.91	-314.09	-5.23%	67.13%
$1/\alpha = 25, \quad p = 1\%$	1,444	1,430	-0.96%	5.53	-330.47	-1.26%	74.43%
$1/\alpha = 25, \quad p = 2\%$	1,442	1,408	-2.33%	11.54	-324.46	-2.7%	69.32%
$1/\alpha = 25, \quad p = 3\%$	1,412	1,365	-3.37%	27.12	-308.88	-5.69%	28.01%
$1/\alpha = 25, \quad p = 5\%$	1,444	1,366	-5.41%	36.57	-299.43	-7.93%	44.88%
$1/\alpha = 24, \quad p = 4\%$	1,444	1,379	-4.5%	23.15	-312.85	-5.16%	60.86%

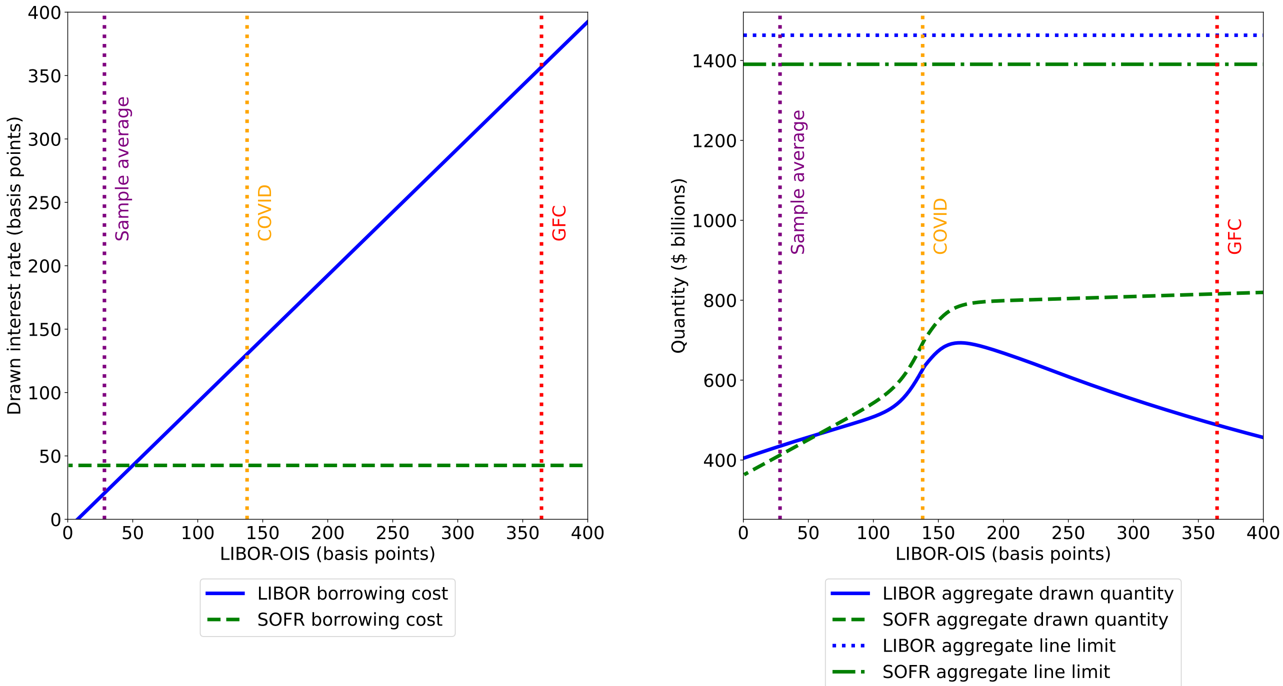


Figure J.3: **The effect of the LIBOR-SOFR transition on credit line prices, aggregate drawn quantities, and aggregate quantities of credit lines.** All parameters are as specified in the captions of Figure J.2 The horizontal dashed-dotted lines in the right figure indicate the sizes of the credit lines. 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.

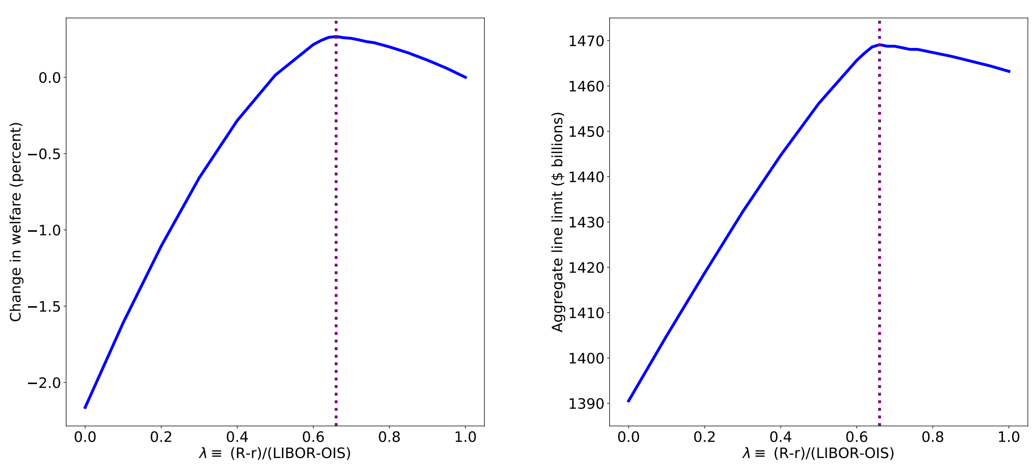


Figure J.4: **How welfare and aggregate quantity of lines depend on the credit sensitivity of the reference rate.** All parameters are as specified in the caption of Figure J.2. The vertical dotted line indicates the convex combination of LIBOR and SOFR defining the reference rate that maximizes the welfare gain of incremental credit lines.

K Calibration: Additional Welfare Analyses

This section provides additional welfare analysis related to our baseline calibration in Section 5. Figure K.1 plots the welfare impacts for various levels of credit sensitivity in reference rates. Impacts for three types of banks are plotted: low-debt overhang (purple); high-debt overhang (yellow); and baseline (red). Figure K.2 plots the impact on welfare and equilibrium line limits in our baseline model.

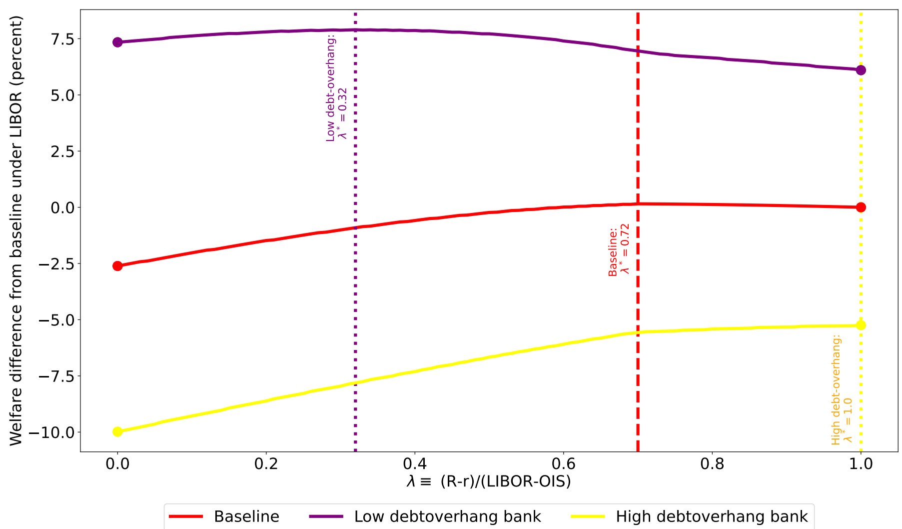


Figure K.1: **Welfare-maximizing reference rate by bank type.** Welfare differences are with respect to a low-debt-overhang bank under LIBOR. Dots indicate welfare differences for LIBOR ($\lambda = 1$) and SOFR ($\lambda = 0$). For high-debt-overhang banks, we set $\theta = 1.5$ and $D = 0.2$. For low-debt-overhang banks, we set $\theta = 0.75$ and $D = 0.75$. All other parameters are as specified in the caption of Figure 4. The vertical dotted lines indicate the convex combination of LIBOR and SOFR defining the reference rate that maximizes welfare.

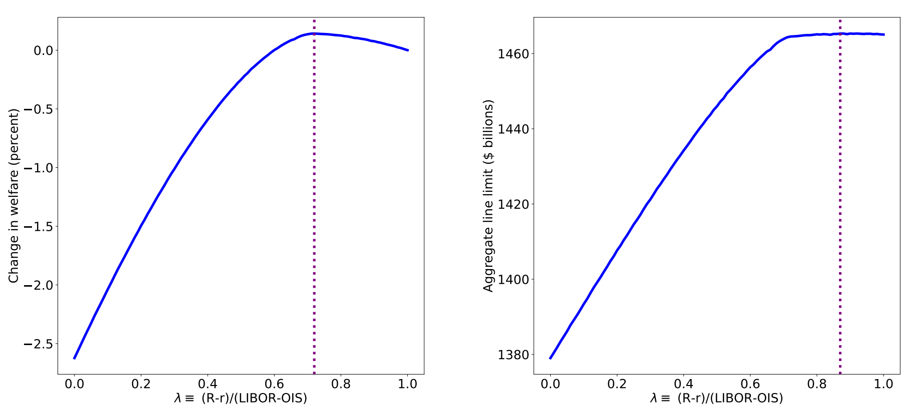


Figure K.2: **How welfare and aggregate quantity of lines depend on the credit sensitivity of the reference rate.** All parameters are as specified in the caption of Figure 4. The vertical dotted line indicates the convex combination of LIBOR and SOFR defining the reference rate that maximizes the welfare gain of incremental credit lines.