Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

QE, Bank Liquidity Risk Management, and Non-Bank Funding: Evidence from U.S. Administrative Data

Darst, R. Matthew, Sotirios Kokas, Alexandros Kontonikas, Jose-Luis Peydro, and Alexandros P. Vardoulakis

2025-030

Please cite this paper as:
Darst, R. Matthew, Sotirios Kokas, Alexandros Kontonikas, Jose-Luis Peydro, and Alexandros P. Vardoulakis (2025). "QE, Bank Liquidity Risk Management, and Non-Bank Funding: Evidence from U.S. Administrative Data," Finance and Economics Discussion Series 2025-030. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2025.030.

QE, Bank Liquidity Risk Management, and Non-Bank Funding: Evidence from U.S. Administrative Data*

R. Matthew Darst
Federal Reserve Board

Sotirios Kokas
University of Essex

Alexandros Kontonikas
University of Essex

Jose-Luis Peydro
Imperial College London & CEPR

Alexandros P. Vardoulakis
Federal Reserve Board

April 21, 2025

Abstract

We show that the effectiveness of unconventional monetary policy is limited by how banks adjust credit supply and manage liquidity risk in response to fragile non-bank funding. For identification, we use granular U.S. administrative data on deposit accounts and loan-level commitments, matched with bank-firm supervisory balance sheets. Quantitative easing increases bank fragility by triggering a large inflow of uninsured deposits from non-bank financial institutions. In response, banks that are more exposed to this fragility actively manage their liquidity risk by offering better rates to insured deposits, while cutting uninsured rates. Doing so, they shift away from uninsured to insured deposits. Importantly, on the asset side, these banks also reduce the supply of contingent credit lines to corporate clients. This tightening of liquidity provision has real effects, as firms reliant on more exposed banks experience a reduction in liquidity insurance stemming from credit lines, leading to lower investment. Our analysis reveals that the fragility of deposit funding can disrupt the complementarity between deposit-taking and the provision of credit lines.

Keywords: Bank fragility, Liquidity risk, Liquidity Insurance, Deposits, Credit lines, Quantitative Easing, Quantitative Tightening, Non-banks

---

*We are grateful to Anil Kashyap, Beth Klee, Viral Acharya, and seminar participants at the Federal Reserve Board, King's College London, Loughborough University, Toulouse, and Virginia Tech. We thank Arazi Lubis for excellent analytical support. The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Board, or anyone in the Federal Reserve System. All errors are our responsibility. Emails: matt.darst@frb.gov; skokas@essex.ac.uk; a.kontonikas@essex.ac.uk; jose.peydro@gmail.com; alexandros.vardoulakis@frb.gov.

1 Introduction

Asset purchases by central banks via quantitative easing (QE) and their reversal via quantitative tightening (QT) have played an important role in the conduct of monetary policy operations since the Great Recession (Bernanke, 2022). Central banks fund these purchases by issuing central bank liabilities, known as reserves. The exchange of reserves for securities alters the portfolio composition of the private sector and the risk premium investors require to hold long-duration securities (Vayanos and Vila, 2021). Yet, the effects of quantitative policies on the financial system and the economy extend beyond the change in long-term yields and securities prices. Asset purchases can affect the size and composition of financial institutions' liabilities, resulting in an expansion of more fragile forms of funding for banks (Acharya and Rajan, 2024; Acharya, Chauhan, Rajan, and Steffen, 2023).

We show that the effectiveness of unconventional monetary policy is limited by how banks adjust credit supply and manage liquidity risk in response to fragile non-bank funding. Our main contribution shows that banks who are more exposed to QE-induced funding fragility actively, and simultaneously, manage their deposit liabilities and loan commitments to reduce liquidity risk. On the liabilities side, more exposed banks increase (decrease) the rates offered on insured (uninsured) deposits, which facilitates a shift from uninsured to insured deposits. On the asset side, they reduce the supply of contingent credit lines to firms. Importantly, the relatively lower liquidity insurance provided to firms via committed lines of credit has real effects and results in less firm investment. To that extent, our analysis uncovers novel results on the documented complementarity between deposit funding and bank-provided liquidity insurance, highlighting unintended consequences of quantitative policies. To support our empirical results, we extend the model of Kashyap, Rajan, and Stein (2002) by introducing runnable deposits akin to Diamond and Kashyap (2016) and show that deposit fragility can disrupt the complementarities between deposit-taking and credit-line issuance. To the best of our knowledge, this is the first evidence showing that the Kashyap et al. (2002)'s documented complementarity may break down when deposit inflows come from fragile funding, such as uninsured NBFI deposits.

We use two administrative datasets that provide confidential information on U.S. deposits and lending. First, we utilize data from the Complex Institution Liquidity Monitoring Report

(FR 2052a), a component of the Federal Reserve's supervisory surveillance program for liquidity risk management. FR 2052a data have unique advantages, in terms of granularity and frequency, compared to publicly available regulatory bank filings. The data are daily or monthly, provide information about deposit counterparty-types, including NBFIs, and indicate whether deposits are insured or uninsured as well as their maturity. Second, we use granular information about bank loan commitments from FR Y-14Q, quarterly collected by the Federal Reserve as part of the Comprehensive Capital Assessment and Review (CCAR) stress testing process. The data include the type of loan (term loan or credit line), total loan commitment and utilized amounts, pricing information as well as information about firms' investment, which allows us to examine the real effects of the QE-induced fragility. Importantly, our data covers both public and private firms. The deposits and lending datasets are supplemented with Call Reports information on bank characteristics and deposits rate data from RateWatch. The resulting rich granular dataset is combined with a multi-stage empirical approach to estimate the response of deposits and lending outcomes to funding fragility, stemming from unconventional monetary policy.

How does an increase in uninsured deposit funding influence bank strategies for managing assets and liabilities? Answering this question is challenging due to the endogenous links between bank assets and liabilities. Banks simultaneously originate loans and create uninsured demand deposits, particularly when loan sizes exceed deposit insurance limits. Moreover, when issuing credit lines, they generate contingent claims on liquidity. Our novel identification strategy exploits the fact that COVID-driven QE led to a surge in nonbank deposits, altering the funding composition of banks that were more exposed to nonbanks before the pandemic. This variation, exogenous to both COVID and the QE response, allows us to isolate the impact of an external funding shock. Crucially, these deposit inflows were not inherently related to banks' loan origination or liability management decisions, but stemmed from changes in non-bank liquidity holdings. This enables us to study how banks adjusted their balance sheets in response to an exogenous shock to funding fragility.

To ensure that our empirical strategy is not confounded by existing differences between banks with different levels of exposure to NBFI funding, we assess balance statistics comparability across key characteristics before the onset of QE (Roberts and Whited, 2013; Imbens and Wooldridge, 2009). Our analysis confirms that, apart from differences in total uninsured deposits and total

NBFI deposits, banks were otherwise similar in terms of size, capital levels, loan composition, and asset holdings. This comparability strengthens the validity of our approach, ensuring that the observed responses to QE-induced fragility reflect a systematic reaction to funding risk rather than pre-existing structural differences across banks. In addition, we control for different sets of fixed effects, taking advantage of the granularity in our data, to tackle unobserved heterogeneity.

We provide four key results. First, we show that the more exposed banks experience a higher inflow of uninsured NBFI deposits during QE. This result is robust to controlling for, among others, (i) bank size and the presence of Global Systemically Important Banks (GSIBs); (ii) for other policy interventions during this period, namely the relaxation and re-activation of the Supplementary Leverage Ratio (SLR); and (iii) for draw-downs of credit lines by NBFIs, which would mechanically push their deposits up. Moreover, we confirm there was no pre-trend difference in NBFI deposits between more and less exposed banks.

Second, we show that more exposed banks actively manage the liquidity risk of their deposit liabilities. Relative to less exposed banks, more exposed banks reduce both non-NBFI uninsured deposits and total uninsured deposits. Hence, they overcompensate for the influx of fragile NBFI funding by reducing other sources of fragile funding. In addition, more exposed banks increase their insured deposits more, making up for the decrease in uninsured deposits. Importantly, we show that the shift from uninsured to insured deposit constitute active liquidity risk management by the exposed banks. Results from the analysis of deposit rates suggest that more exposed banks increase the deposit rates offered for insured deposits, while decreasing the remuneration of uninsured deposits, consistent with an effort to reduce exposure to funding fragility. Thus, the active reshuffling and repricing of deposit liabilities suggest that banks strategically manage their funding structure, consistent with a bank-driven adjustment to mitigate liquidity risk.

Third, we show that the more exposed banks decrease the credit lines to firms relative to less exposed banks. Note that credit-line commitments increased for both types of banks during the QE and the inflow of reserves. However, our granular data and the novel identification of QE exposure allows us to capture the differential effect. By contrast, there is no significant difference in the term loans offered by more and less exposed banks. Zooming in the credit-line sub-components, the reduction is associated with the undrawn credit line amount, while there is no difference with respect to credit-line utilization between the more and less exposed banks.

Hence, the more exposed banks effectively manage the liquidity risk on their loan exposures by reducing the claims to future liquidity and, thus, decreasing the possibility of double runs whereby both depositors withdraw their deposits and firms draw down on their credit lines.[1]

This result is intuitive but may not appear to be in line with existing results on the complementarities between deposit taking and the issuance of credit lines. We corroborate our empirical findings by extending the theoretical model in Kashyap, Rajan, and Stein (2002) to introduce runnable deposits akin to Diamond and Kashyap (2016). The intuition is simple. Liquidity risk management with runnable deposits requires considering off-equilibrium withdrawals, not just withdrawals expected in equilibrium. Thus, a bank needs to guarantee it has enough liquidity also in off-equilibrium paths with more expensive non-deposit funding. Doing so may not be profitable under high deposit fragility resulting in a reduction in the issuance of credit lines.

Fourth, we show that the relative reduction in liquidity insurance offered by the more exposed banks has aggregate implications. Although firms' access to current credit is not affected, those firms that have more lending relationships before the Pandemic QE with exposed banks experience a reduction in the amount of liquidity insurance they enjoy against future shocks. This reduction results in relatively lower investment by exposed firms.[2]

Related literature. Our main contributions to the literature are (i) to demonstrate that limits in the effectiveness of unconventional monetary policy can arise due to an increase in deposit fragility and the associated liquidity risk management of (more exposed) banks both on their deposits and credit supply, and (ii) to show how the documented complementarity between deposit-taking and the provision of liquidity to firms may break down. Our paper relates to three main strands of the literature.

First, we show that bank liquidity risk management limits the effects of unconventional monetary policy. In addition to the aforementioned seminal paper by Kashyap et al. (2002), Hanson, Shleifer, Stein, and Vishny (2015) examine how funding fragility interacts with the holdings of liquid assets in financial institutions, focusing on the distinction between banks with insured deposits and non-banks with runnable liabilities.[3] Instead, we study the effect of

[1] See Ippolito, Peydró, Polo, and Sette (2016).

[2] See Holmström and Tirole (1998) for the link between liquidity insurance via credit lines and firm's investment.

[3] Empirical support for such complementarities comes from studies showing that during episodes of market stress, deposit inflows and credit line drawdowns are negatively correlated (Gatev and Strahan, 2006; Gatev,

bank deposit fragility on bank liquidity risk management and credit supply to firms.[4] Ippolito et al. (2016) study banks' liquidity risk management in the presence of double runs due to a joint withdrawal of interbank funding and credit-line draw-downs during the 2007 freeze in the European interbank market. They find that banks with higher interbank borrowing before the shock also extended fewer credit lines to firms. Acharya and Mora (2015) present similar dynamics when banks get run upon: banks with higher liquidity risk in the onset of the GFC experienced lower deposit growth and cut bank on new credit originations. We differ by studying how banks actively manage their assets and liabilities in response to a quasi-exogenous shock in their funding fragility. Moreover, our paper studies the interaction of quantitative monetary polices and bank fragility. Cooperman, Duffie, Luck, Wang, and Yang (2023) study how banks adjust their provision of credit lines when the effective cost of funding them goes up: banks are less willing to provide credit lines ex ante when the lending rate upon withdrawal is not also risk sensitive, which is an increase in effective funding costs. Our mechanism is different because we focus on the impact of funding fragility rather than effective funding cost. Moreover, we also examine how banks actively adjust their balance sheets to manage liquidity risk.[5]

Second, we relate to the literature on the effects of unconventional monetary policy. Acharya and Rajan (2024) and Acharya et al. (2023) link QE to persistent bank fragility via the creation of uninsured deposits, which is a stepping stone for our analysis (see also Joyce, Miles, Scott, and Vayanos, 2012). We show that the effects of unconventional monetary policy are limited through deposit risk management and the supply of new credit. We use granular administrative data to show how uninsured deposits—particularly from NBFIs—are heterogeneously injected in the banking system and how banks actively manage their deposit liabilities and loan commitments in response to this fragility; this is otherwise hard to tease out from more aggregated data due to

Schuermann, and Strahan, 2009).

[4]Our paper also analyzes credit supply and the associated real effects, hence contributing to the large literature on the real effects of credit supply. For example, Chodorow-Reich (2013) studies how an adverse shock in bank capital affects credit supply and subsequent real outcomes. We differ in two ways. First, we study the effects of the *ex ante build-up* in funding fragility rather than an *ex post shock* to capital. Second, we holistically explore how banks manage liquidity risk on both sides of their balance sheet.

[5]We also contribute to recent studies on the behavior of credit lines and deposits during the Pandemic. Li, Strahan, and Zhang (2020) and Acharya, Engle, Jager, and Steffen (2024) show that firms massively drew down on their lines of credit at the outbreak of the pandemic keeping the funds as deposits at banks, while Levine, Lin, Tai, and Xie (2021) suggest that the increase in deposits also accrued from a flight-to-safety motive. We complement this analysis by showing that the QE-induced fragility did not differentially affect the draw-downs of credit lines and total deposits across exposed banks, but rather affected the undrawn amounts and the mix between uninsured and insured deposits.

a simultaneous increase in deposits and credit lines across banks. Importantly, our data allows us to distinguish between utilized and undrawn credit-lines at the bank-firm level, which is not possible with publicly available regulatory data. This distinction allows us to control for credit demand and isolate the credit supply effect on bank provided (contingent) liquidity insurance.

Pre-Pandemic studies of QE focus on the asset swap channel—exchanging reserves for securities on the asset side of banks balance sheets—that do not involve creating fragile bank deposits. For example, Rodnyansky and Darmouni (2017) shows that banks with higher ex ante holdings of the QE-purchased securities increase lending relatively more after QE. Di Maggio, Kermani, and Palmer (2019) shows how QE facilitated the refinancing of mortgage debt by households, which reduced interest expenses and supported aggregate consumption.

We also relate to papers studying the unintended consequences of QE. Chakraborty, Goldstein, and MacKinlay (2020) demonstrate how banks may shift their portfolios towards securities purchased by central banks, such as mortgages, and away from C&I loans. This particular profit seeking mechanism is mitigated in our analysis by two facts: First, prior to QE, there is no significant difference in mortgage and C&I lending among banks that are more or less exposed to NBFI uninsured deposits. Second, most pandemic-QE purchases were Treasuries rather than mortgages. Diamond, Jiang, and Ma (2024) show that large injection of central bank reserves has the unintended consequence of crowding out bank loans, due to bank balance sheet costs.

Third, our work contributes to a growing strand of the literature that highlights the increasing interdependence between banks and NBFIs. Relative to banks, NBFIs have grown significantly since the GFC but remain lightly regulated (Acharya, Cetorelli, and Tuckman, 2024; Irani, Iyer, Meisenzahl, and Peydro, 2021). The connections between banks and NBFIs can operate through both assets and liabilities. From a lending perspective, several studies show that NBFIs act as shock absorbers, by filling the space left by banks during periods of monetary policy tightening (Elliott, Meisenzahl, and Peydró, 2024; Chen, Ren, and Zha, 2018). Our paper contributes to this strand of the literature by analyzing a different channel of interaction, focusing on the banks' funding dependency on NBFIs.

2 Data and Empirical Strategy

This section describes the datasets used in our analysis, provides background on the institutional context, and presents key descriptive statistics. In turn, we introduce our empirical strategy.

2.1 Datasets

Our analysis relies mainly on two administratively matched datasets. To document the effects of QE on NBFI uninsured deposits and bank funding fragility, we use granular data on deposit accounts at the counterparty-bank level for all large U.S. BHCs. We supplement this data with information on bank balance sheets. To investigate how deposit inflows affect bank lending, we use U.S. administrative bank-firm matched data at the loan-level containing firm-level balance sheet information. In sum, our deposit dataset comprises monthly observations of individual deposit accounts reported by 29 banks, covering January 2016 to February 2023.[6] Our credit dataset consists of quarterly observations of term loans and credit lines extended by the same 29 banks to 120,797 non-financial firms, spanning from 2016Q1 through 2022Q4.[7] For brevity, throughout the paper, we refer to bank holding companies (BHCs) simply as banks. This subsection describes each dataset and outlines the main sample selection criteria.

Deposit data. Our primary dataset for deposits is the *Complex Institution Liquidity Monitoring Report*, commonly referred to as the FR 2052a, which monitors the liquidity profiles of significant U.S. BHCs. The FR 2052a data collection began in December 2015, initially covering Global Systemically Important Banks (GSIBs) and foreign banking organizations (FBOs) with substantial U.S. broker-dealer operations. In July 2017, the dataset expanded to include a larger set of banks. This dataset offers two distinct advantages over publicly available regulatory filings such as the FR Y-9C. First, it provides granular breakdowns of banks' assets and liabilities by maturity, collateral, and depositor type (counterparty), allowing us to document previously unexplored aspects of U.S. banks' funding structures and depositor exposure. Second, it offers higher-frequency reporting: banks with $700 billion or more in total consolidated assets or $10

[6]Our sample period ends in February 2023 to exclude the potential distortions from the March 2023 banking turmoil in the United States.

[7]The complete details of the data cleaning procedure can be found in Appendix C.

trillion or more in assets under custody submit daily reports, whereas banks with assets between \$50 billion and \$700 billion report monthly. To ensure consistency across banks with different reporting frequencies, we harmonize the data by aggregating daily observations into monthly averages, aligning them with the reporting frequency of the remaining banks. In Appendix C, Table OA2 provides a detailed list of banks along with their respective reporting schedules. Additionally, FR 2052a explicitly identifies insured versus uninsured deposits, facilitating a precise analysis of liquidity risk stemming from banks' funding sources.[8]

We further supplement our deposit dataset with deposit rate information from Ratewatch–S&P Global, which provides detailed interest rates offered by banks across various deposit categories. This complementary dataset enables us to directly examine how banks adjust deposit pricing strategies in response to changing liquidity conditions.

Loan-Level Data Our analysis of bank lending utilizes detailed loan-level data from the Federal Reserve's FR Y-14Q H.1, collected quarterly as part of the Comprehensive Capital Analysis and Review (CCAR). FR Y-14Q collects detailed information on bank holding companies' (BHCs), savings and loan holding companies' (SLHCs), and U.S. intermediate holding companies' (IHCs) of foreign bank organizations (FBOs) on a quarterly basis.[9] We use the Corporate Loan H.1. Schedule comprising two sections: (1) the Loan and Obligor Description section, providing detailed characteristics of each loan and borrower; and (2) the Obligor Financial Data section, which includes borrowers' balance sheets and income statements. Facility-level data include, among much more, total committed and utilized amounts, pricing and spread details, origination and maturity dates, and collateral information.

2.2 Institutional Context

The Pandemic QE, which commenced in March 2020 and ended in March 2022, was the largest expansion in the Federal Reserve's history. Moreover, it led to significant changes in the balance sheet size and composition of both the Fed and the banking system. Our analysis starts with the observation that not all financial institutions can hold reserves, which has important implications

[8] Appendix B explains the selection rules we impose to avoid biases in our sample.

[9] Data are collected for BHCs, SLHCs and IHCs with at least \$50 billion (\$100 billion starting from 2019) in total assets. Banks that submit FR Y-14Q comprise over 85 percent of the total assets in the U.S. banking sector.

for the conduct of quantitative policies. Suppose first that the central bank purchases securities directly from banks that can hold reserves. Then, QE is purely an asset swap (reserves for securities). Now suppose that the central bank's counterparty is a non-bank financial institution (NBFI) that cannot hold reserves outright. In this case, the trade between the central bank and the NBFI is intermediated by banks. Banks source the securities from NBFIs to sell to the central bank, use the proceeds to credit NBFIs' deposit accounts, and receive reserves from the central bank. In practice, NBFIs exchange securities for bank deposits. Given the scale of QE, the resulting NBFI deposits are uninsured and hence more flighty.[10]

Figure 1A shows banks' and NBFIs' holdings of Treasury and Agency securities. A substantial portion of Treasuries and Agencies were held by NBFIs at the onset of the COVID-19 pandemic.[11] In response to the pandemic, the Federal Reserve expanded its balance sheet by about \$3 trillion from mid-March to early June 2020, while asset purchases stabilized at \$120 billion per month until the end of QE in March 2022. A large component of the securities purchased by the Federal Reserve were offloaded by NBFIs. As the figure shows, NBFIs' holdings declined during the Pandemic QE, while banks' holdings continued to increase. QT commenced in June 2022 with a balance sheet reduction of \$ 47.5 billion per month. Figure 1B uses administrative data for uninsured deposits held by NBFIs, which spike immediately after QE commenced, continued increasing, and finally stabilized at a higher level into the QT period.

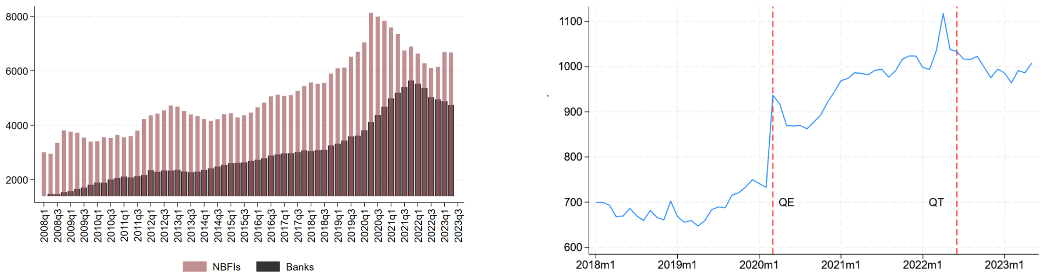
2.3 Descriptive statistics

Table 1 presents aggregate-level descriptive statistics across deposit categories and bank lending activities. Panel A reports statistics for banks' primary deposit categories across distinct monetary policy periods. Both uninsured NBFI and insured retail deposits expanded significantly during QE and continued to rise through QT, with the most pronounced changes occurring in QE. Specifically, uninsured NBFI deposits rose by approximately 40% from \$699.7 billion pre-

[10] See Joyce et al. (2012) and Leonard, Martin, and Potter (2017) for details about the accounting operations of QE in the presence of NBFIs. In the United States, commercial banks, government-sponsored enterprises, clearing houses, credit unions, and branches of foreign banking organizations are the main financial institutions with reserve accounts at the Federal Reserve. Certain other institutions may have access to Federal Reserve liabilities, other than reserves, such as the ON RRP facility. It is conceivable that those NBFIs withdraw the newly issued bank deposits to deposit directly at the central bank, but the scope of this operation is limited to eligible non-banks (see Afonso, Cipriani, and La Spada, 2022).

[11] Although the mechanism highlighted above is always operational, we focus on the pandemic QE for which we have detailed administrative data on bank deposits.

Figure 1: Security holdings and NBFI deposits



(A) Banks and NBFIs holdings of Treasury and Agency securities in billion USD

(B) NBFIs uninsured deposits in billion USD

Note: Panel (A) reports quarterly data from the Financial Accounts-Z.1. NBFIs include Insurance Companies, Pension Funds, Open- and Closed-ended Funds, REITs, ETFs, Money Market Funds, Broker Dealers, Hedge Funds, and other Financials. Panel (B) reports monthly administrative FR2052a data for the biggest banks.

QE to \$978.7 billion during QE. Similarly, insured retail deposits increased by roughly 27%, expanding from \$3.28 trillion pre-QE to \$4.16 trillion during QE. Notably, uninsured deposits consistently account for between 95% and 98% of total NBFI deposits, underscoring the inherently risky nature of banks' exposure to these institutions. Collectively, these patterns highlight meaningful shifts in banks' deposits composition driven by monetary policy adjustments.

Panel B documents substantial heterogeneity in banks' deposit composition based on their exposure to NBFI deposits over total deposit funding as of February 2020, prior to the pandemic QE. These NBFI deposit shares serve as key cross-sectional measures of bank exposure to NBFI deposits, which we discuss below in our empirical methodology section 2.4. Banks with high NBFI shares exhibit significantly greater reliance on uninsured NBFI deposits (22.84%) compared to banks with low NBFI exposure (2.12%). Likewise, the overall uninsured deposit ratio is considerably higher among banks with high NBFI shares (78.69%) compared to banks with lower NBFI exposure (40.63%). In contrast, banks with high NBFI shares hold significantly fewer insured retail deposits (17.66%) compared to banks with lower NBFI exposure (53.84%). These differences highlight substantial variation in banks' deposit structures linked to NBFI exposure, underscoring their distinct risk profiles and likely divergent liquidity management strategies.

Figure 2 further illustrates these differences by showing the evolution of uninsured NBFI deposits for banks with high and low exposure. Before QE, both groups exhibited relatively

Table 1: Descriptive statistics: Aggregate volumes

Panel A: Deposit categories

	Feb-20	Mar-20	Pre QE		QE		QT	
	Mean	Mean	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Uninsured NBFI	746.6	953.6	699.7	42.2	978.7	72.6	1051.1	93.2
Insured NBFI	19.3	19.4	23.3	2.3	17.6	4.5	49.3	21.2
Uninsured Retail	1,383.9	1,449.6	1,240.7	56.9	1,750.5	217.5	2,007.1	100.5
Insured Retail	3,573.0	3,738.5	3,281.2	119.5	4,162.5	214.8	4,575.1	159.3
Total Deposits	9,287.5	9,987.6	8,466.6	353.3	11,362.6	771.7	12,480.8	495.5

Panel B: Bank exposure to insured and uninsured Deposits

	Uninsured NBFI Ratio		Insured Retail Ratio		Total Uninsured Ratio	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Banks with low NBFI Share	2.12%	1.79%	53.84%	16.39%	40.63%	15.65%
Banks with high NBFI Share	22.84%	20.14%	17.66%	15.40%	78.69%	17.59%

Panel C: Statistics on loan-level data

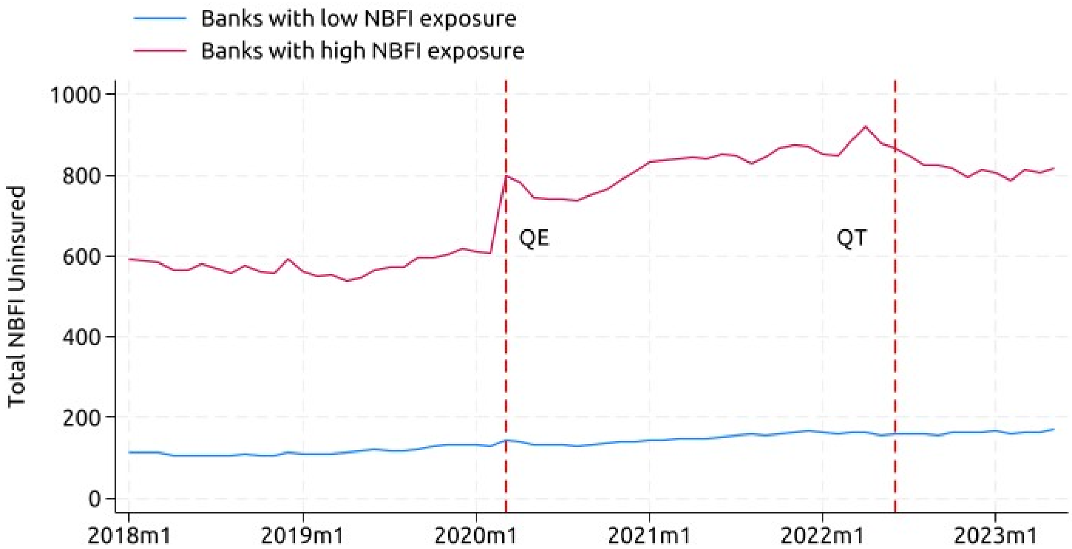
Period	Total Commitments	On-balance sheet Commitments	Undrawn Credit Lines	Utilized Credit Lines	Term Loans
2019q4	1,729	702	1,027	437	267
2020q1	1,762	866	896	580	286
Pre-QE	1,368	550	818	348	210
QE	1,764	658	1,095	397	255
QT	1,965	753	1,211	447	300

Note: Panel A reports the distribution of deposits by counterparty type across key monetary policy periods ($ billion), sourced from the FR 2052a (*Complex Institution Liquidity Monitoring Report Supervisory*). Panel B presents deposit ratios for banks with high and low NBFI deposit shares as of February 2020. Panel C summarizes loan-level data ($ billion) from the FR Y-14Q (*Capital Assessments and Stress Testing*). Variable definitions and data sources are provided in Appendix C.

stable trends in uninsured NBFI deposits. However, following QE, banks with high exposure experienced a sharp and persistent increase in uninsured NBFI deposits, whereas those with lower exposure saw only modest changes. This divergence persists through QT, underscoring the structural differences in banks' reliance on NBFI funding. These patterns suggest that pre-QE exposure may have played a key role in shaping banks' funding responses to monetary policy interventions, something that we will explore in our empirical methodology.

Panel C in Table 1 provides summary statistics on banks' lending activities. On-balance sheet commitments (defined as the sum of utilized credit lines and term loans) rose significantly in 2020Q1, a rise of $164 billion relative to 2019Q4. Utilized credit lines increased from $437 billion to $580 trillion between 2019Q4 and 2020Q1. This development reflects the heavy utilisation

Figure 2: Total uninsured deposits from NBFIs



Note: This figure presents the total uninsured deposits from NBFIs, expressed in $ billion.

of credit lines by firms in the last three weeks of March 2020. We also note that total loan commitments increased from $1.37 trillion pre-QE to $1.76 trillion during QE, primarily driven by the rise in undrawn credit lines from $818 billion to $1.10 trillion. This growth in undrawn credit lines suggests increased provision of contingent liquidity to firms, thus potentially elevating banks' exposure to liquidity risk associated with future credit-line draw-downs. In contrast, the increase in utilized credit lines and term loans was comparatively modest. These lending patterns indicate that banks adjusted their credit provision primarily through contingent liquidity, highlighting the importance of liquidity management considerations arising from monetary policy-driven shifts in banks' deposit structures. At the same time, we will show that these are aggregate developments and the overall change in undrawn credit lines are heterogeneously distributed across banks.

2.4 Empirical methodology

As discussed above, QE operations can lead to a surge in NBFI deposits at banks. These deposits are highly sensitive to market conditions and prone to rapid withdrawals.[12] Although

[12] See, for example, Franceschi, Grodzicki, Kagerer, Kaufmann, Lenoci, Mingarelli, Pancaro, and Senner (2023).

banks receive reserves at the same time when crediting NBFI deposit accounts, their overall funding fragility can still increase. To illustrate this, consider a bank that aims to maintain a level of high-quality liquid assets that create a buffer over the estimated deposit outflows over a given period. When uninsured NBFI deposits increase, the expected outflow rate rises—not only because total deposits grow but also because these deposits are more volatile. Hence, the additional liquid assets required to preserve the same liquidity buffer exceed the proportional increase in deposits. In other words, despite the mechanical rise in reserves, a bank's funding stability may deteriorate.

Using the deposit dataset, we construct a measure for the ex ante exposure of each bank to such QE-induced fragility. In particularly, we calculate the shares of NBFI uninsured deposits relative to total deposits as of February 2020, prior to the onset of pandemic QE. This measure proxies for the degree that a bank interacts with NBFIs prior to the pandemic. Intuitively, a higher share of NBFI funding suggests that a bank is having more relationships and doing more business with NBFIs, providing a crucial gauge of the bank's exposure to the creation of NBFI deposits from the QE operations.

Prior to QE, the cross-sectional variation in this measure remained stable over time, suggesting that differences in banks' exposure to uninsured NBFI deposits were persistent rather than driven by transitory factors (see Figure 2). The stability in the aforementioned pattern indicates that, ex-ante, banks' exposure to uninsured NBFI deposits was not expected to be systematically affected by the COVID-19 shock, reinforcing the exogeneity of the pandemic to this funding source. Moreover, the banks in our sample were well capitalized and in strong financial condition at the outbreak of pandemic, mitigating concerns that NBFIs would shift their relationships to other banks. As a result, the pre-QE uninsured NBFI share serves as a meaningful and persistent indicator of banks' exposure to the QE-induced fragility, rather than reflecting a short-term adjustment to pandemic-related disruptions.

Our empirical strategy exploits the cross-sectional variation in banks' pre-QE shares of NBFI funding and implements a continuous treatment approach to analyze how banks with different NBFI shares responded to the QE-induced fragility. Specifically, we examine two key dimensions: (i) banks' adjustments in deposit composition, particularly shifts between insured and uninsured deposits, and (ii) changes in credit allocation, focusing on loan commitments.

Table 2: Identifying exposed banks: Balancing test

	Low NBFI Exposure		High NBFI Exposure		Difference
	Mean	SD	Mean	SD	Std. Diff.
NBFI Deposits	4.9	8.3	36.8	45.1	-0.98
Uninsured Deposits	101	169.1	183.8	250.8	-0.39
Total Deposits	242	341.5	279.4	400.4	-0.10
Total Assets	522.9	657.3	540.9	757.3	-0.03
Tier 1 Capital Ratio	0.14	0.04	0.15	0.05	-0.03
C&I Loans	43.5	58.1	43.4	49.4	0.003
Treasury + Agency Securities	54.1	103.4	56.7	79.7	-0.03

Note: This table reports standardized differences in bank characteristics between banks with low and high NBFI exposure in 2019Q4. Low NBFI-exposed banks have below-median uninsured NBFI shares in their total deposits, while high NBFI-exposed banks have above-median shares. Following Imbens and Wooldridge (2009), a standardized difference above 0.25 in absolute value indicates a substantial imbalance between the two groups. All values are in $ billion, except for the capital ratio. Appendix C provides variable definitions and data sources.

Although our identification strategy does not strictly require banks with low and high exposure to uninsured NBFI deposits to be identical, ensuring comparability strengthens the internal validity of our estimates and mitigates concerns about potential omitted variable bias (Roberts and Whited, 2013). Following Imbens and Wooldridge (2009), we assess the balance across key bank characteristics in 2019Q4 using standardized differences, where absolute values below 0.25 indicate sufficient comparability.

Table 2 reports mean and standard deviation values for key balance sheet characteristics across banks with high and low exposure. We compare banks along several dimensions, including (1) NBFI Deposits, (2) Uninsured Deposits, (3) Total Deposits, (4) Total Assets, (5) Tier 1 Capital Ratio, (6) Total C&I Loans, and (7) Treasury and Agency Securities. All standardized differences remain far below the 0.25 threshold, except for NBFI Deposits and Uninsured Deposits, which naturally differ between the two groups by construction. The similarity across other balance sheet fundamentals suggests that differences in outcomes are unlikely to be driven by pre-existing structural differences between the two groups.

3 NBFI deposits and QE-induced fragility

This section establishes how uninsured NBFI deposits evolved based on banks' ex-ante heterogeneous exposure to the QE-induced fragility. To do so, we estimate a panel regression over the period from January 2016 to February 2023:

$$\log(Un.\ NBFI_{i,t}) = \lambda \cdot (QE_t \cdot Shares_i) + \beta \cdot Controls_{i,t} + a_i + a_t + \varepsilon_{i,t}\ . \tag{1}$$

The dependent variable, $\log(Un.\ NBFI_{i,t})$, represents the logarithm of uninsured NBFI deposits held by bank i in month t. The variables QE_t is dummy variable equal to one during the QE period (March 2020–March 2022). $Shares_i$ measures the share of uninsured NBFI deposits relative to total deposits in February 2020, providing a measure of banks' pre-pandemic reliance on NBFI funding. We include bank fixed effects (a_i) to account for time-invariant heterogeneity across banks and month (time) fixed effects (a_t) to control for common macroeconomic shocks. $Controls_{i,t}$ is a vector of controls to account for other time-varying confounding factors. Finally, we cluster standard errors at the month level to address potential autocorrelation in residuals.

Table 3 reports the results from estimating equation (1). In Column 1, we begin with a parsimonious specification that includes the QE interaction term ($QE \cdot Shares$), as well as bank and month fixed effects. The coefficient on the interaction term is positive and statistically significant, suggesting that banks with a higher share of uninsured NBFI deposits prior to the pandemic saw these deposits increase substantially during QE. Economically, the estimate in Column 1 indicates that a one standard deviation increase in exposure to NBFI deposits is associated with a 3.2% increase in uninsured NBFI deposits during QE.

In Columns 2, 3 and 4, we sequentially add bank size, the QT interaction term ($QT \cdot Shares$), and an interaction term that account for differences in deposits between GSIBs and other banks during QE. These extensions allow us to account for characteristics beyond those captured by bank fixed effects. Bank size, measured as the logarithm of total assets, accounts for time-varying banks' ability to absorb inflows from NBFIs. The QT interaction term allows us to distinguish the effects of QT from those of QE. Moreover, QE interacted with the GSIB indicator captures the distinct role of systemically important banks in deposit flows. The coefficient on

Table 3: NBFI uninsured deposits

	1	2	3	4	5	6
Dependent variable:	Log(Uninsured NBFI deposits)					
QE * Shares	0.286***	0.288***	0.272***	0.268***		0.263***
	(5.258)	(5.436)	(4.655)	(4.813)		(4.469)
QT * Shares			-0.099			
			(-1.196)			
Bank size		0.353***	0.347***	0.342***	0.354***	0.738***
		(3.503)	(3.365)	(3.446)	(3.507)	(7.509)
QE * GSIBS				0.047**		
				(2.340)		
QE (SLR rel.)* Shares					0.209***	
					(3.137)	
QE (SLR act.)* Shares					0.362***	
					(7.279)	
NBFI credit						0.046***
						(3.008)
Month FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Observations	2,079	2,077	2,077	2,077	2,077	2,066
R-squared	0.968	0.968	0.969	0.968	0.968	0.970

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(\mathit{Un.\ NBFI}_{i,t}) = \lambda \cdot (QE_t \cdot \mathit{Shares}_i) + \beta \cdot \mathit{Controls}_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $\log(\mathit{Un.\ NBFI}_{i,t})$ is the logarithm of uninsured NBFI deposits held by bank i in month t. QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. Shares_i indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. $\mathit{Bank\ Size}_{i,t}$ is the logarithm of total assets. *GSIBS* is a dummy equal to one for Global Systemically Important Banks. *QE (SLR rel.)* refers to SLR relaxation and the exclusion of securities and reserves from SLR calculations between April 1, 2020, and April 1, 2021, while *QE (SLR act.)* marks the re-activation of SLR criteria. *NBFI Credit* is the logarithm of total outstanding credit, including credit lines and term loans, that NBFIs received. The terms a_i and a_t represent bank and month fixed effects, respectively. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

$QE \cdot Shares$ remains positive and statistically significant under all controls, confirming that banks with a higher pre-pandemic share of uninsured NBFI deposits experienced a substantial increase in these deposits during QE. Interestingly, the coefficient of $QT \cdot Shares$ is statistically insignificant, suggesting that QT did not have a persistent effect on uninsured NBFI deposits after accounting for bank-specific attributes and time effects. These findings underscore that QE-induced inflows of uninsured NBFI deposits were a dominant driver of bank funding dynamics, while any potential reversal during QT appears to be more muted.[13]

In Column 5 of Table 3, we explore the impact of the Supplementary Leverage Ratio (SLR) adjustments during the pandemic-related QE.[14] Shortly after the initiation of QE, the Federal Reserve Board (FRB) announced that the calculation of the SLR would be temporarily modified. The modification excluded U.S. Treasury securities and bank reserves from the calculation of the SLR for bank holding companies. This adjustment aimed to alleviate balance sheet constraints and encourage liquidity provision.[15] The FRB specified that the change would be in effect until March 31, 2021 (Federal Reserve Board, 2021). The results in Column 5 subdivide the QE period into the SLR relaxation and re-activation phases and interact them with the NBFI shares. The QE sub-periods are defined using dummy variables corresponding to each SLR phase. Results highlight that the rise in uninsured NBFI deposits of exposed banks during QE spans both phases of the SLR change and is not driven solely by the relaxation phase.

In Column 6, we account for the mechanical link between bank lending and deposits by controlling for asset-side exposures to NBFIs. Specifically, we include the log of total outstanding credit that NBFIs received, recognizing that loans can mechanically influence deposit balances. The results show that our main findings remain unchanged. To gain further insight into the role of different types of NBFI deposits, in Appendix C, Table OA4 focuses exclusively on demandable uninsured NBFI deposits, which can be withdrawn without prior notice and even more prone to

[13] In Appendix C, Table OA3 further explores the heterogeneity in uninsured NBFI deposit dynamics by differentiating between supervised and non-supervised NBFIs. The results show that the effect of $QE \cdot Shares$ on uninsured NBFI deposits is primarily driven by supervised NBFIs.

[14] The SLR was established in 2014 as part of the Basel III regulatory framework. The SLR applies only to large, complex financial institutions with \$250 billion or more in total consolidated assets or \$10 billion in on-balance-sheet foreign exposures. Banks must report their SLR since 2015 and must comply with the SLR requirement since January 1, 2018 (binding period). Bank holding companies generally must maintain an SLR of at least 3 percent, and GSIB holding companies in the U.S. must maintain an enhanced SLR (eSLR) of 5 percent. The SLR is calculated as the ratio of Tier 1 capital (essentially common equity plus preferred stock) to total leverage exposure (assets plus certain off-balance-sheet items, such as OTC derivatives).

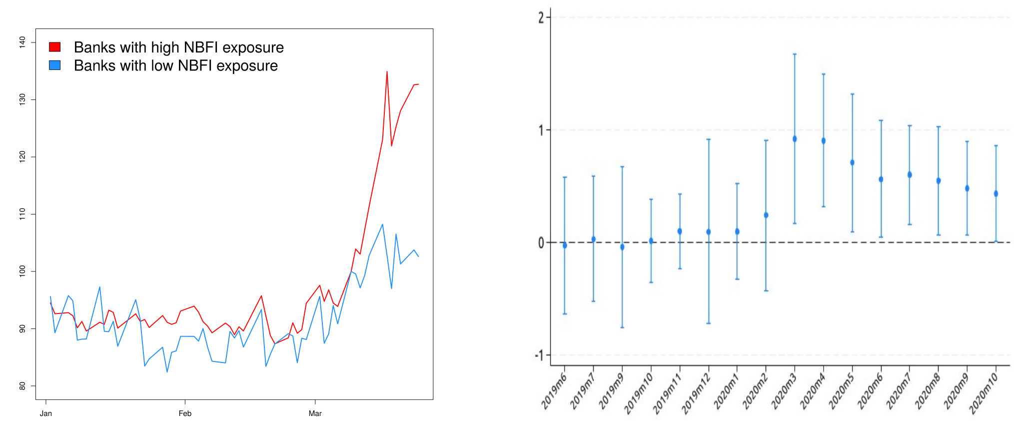
[15] See Duffie (2020) and Favara, Infante, and Rezende (2024).

runs. The results indicate that the observed effects are particularly pronounced for NBFIs with demandable deposits, reinforcing the view that inflows of uninsured NBFI deposits are associated with heightened liquidity risk.

Finally, a potential alternative driver for the observed increase in uninsured NBFI deposits could be the fiscal transfers to households and firms during the pandemic. Several pieces of evidence suggest that these transfers do not explain our findings. Our empirical design mitigates this concern by including month fixed effects, which absorb aggregate liquidity injections, including fiscal transfers, ensuring that our estimates isolate the effect of banks' pre-QE exposure to uninsured NBFI deposits from broader system-wide liquidity dynamics. Additionally, in Appendix C, Table OA5, we estimate equation (1) using as the dependent variable the total retail insured deposits (Columns 1–2) and corporate insured deposits (Columns 3–4). Across all specifications, the interaction term $QE \cdot Shares$ is statistically insignificant, indicating that banks with higher pre-QE exposure to uninsured NBFI deposits did not experience a differential increase in insured deposits during QE relative to less exposed banks. This finding suggests that fiscal transfers, which primarily flowed into insured retail and corporate deposits, do not explain the observed patterns in uninsured NBFI deposits. Moreover, fiscal transfers began in mid-April 2020, after \$1.3 trillion in QE operations had already been conducted, accounting for approximately 40% of the total cumulative increase in reserves during the Pandemic-QE period. Finally, in unreported results, we find that the effect of QE is strongest in March 2020, reinforcing the view that monetary policy, not fiscal transfers, drove deposit inflows at exposed banks.

Parallel trends. A key assumption underlying our identification strategy is that, in the absence of QE, banks with different levels of exposure to uninsured NBFI deposits would have followed similar trends in deposit accumulation. While this parallel trends assumption cannot be directly tested, we assess its plausibility by examining pre-QE deposit trends. Figure 3A presents the daily growth rates of uninsured NBFI deposits for high- and low-exposure banks from January to March 2020. The x-axis is normalized to 100 on March 9 for comparability. The figure shows that in the months leading up to QE, both groups followed largely similar trends, with no systematic differences in growth rates. However, starting in March 2020, a sharp divergence emerges, with banks that had higher pre-QE NBFI exposure experiencing a significantly

Figure 3: Security holdings and NBFI deposits



(A) Daily growth in uninsured NBFI deposits

(B) Parallel trends

Note: Panel (A) shows the daily growth of NBFI deposits from January to March 2020. Panel (B) presents the estimated monthly coefficients for the pre- and post-QE period: $Log(Un.\ NBFI_{i,t}) = \sum_{t=1}^{T} \lambda_t (Month_t \cdot Shares_i) + \beta \cdot Bank\ Size_{i,t} + a_i + a_t + \varepsilon_{i,t}$. $Y_{i,t}$ denotes uninsured NBFI deposits at bank i in month t; $Month_t$ are month dummies; $Shares_i$ is the share of uninsured NBFI deposits in total deposits as of February 2020; $Bank\ Size_{i,t}$ is the logarithm of total assets; a_i, a_t are bank and month fixed effects. Observations are monthly, except for total assets, which are quarterly. Standard errors clustered at the month level.

larger increase in uninsured NBFI deposit inflows. This pattern supports our empirical design, suggesting that the differential post-QE response is not driven by pre-existing differences but rather by monetary policy-induced liquidity shocks.

To formally assess this assumption, we estimate the following dynamic specification:

$$\log(Un.\ NBFI_{i,t}) = \sum_{t=1}^{T} \lambda_t (Month_t \cdot Shares_i) + \beta \cdot Bank\ Size_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}$$

where $\log(Un.\ NBFI_{i,t})$ represents uninsured NBFI deposits for bank i at time t, $Month_t$ denotes month dummies, $Shares_i$ captures a bank's exposure to uninsured NBFI deposits as of February 2020, $Bank\ Size_{i,t}$ controls for bank size, and α_i and α_t are bank and time fixed effects. Standard errors are clustered at the month level. Figure 3B presents the estimated λ_t coefficients for the months preceding and following QE. The results indicate that pre-QE trends in uninsured NBFI deposits were statistically indistinguishable between high- and low-exposure banks, with estimated coefficients ranging around zero. However, following QE (March 2020), we observe a sharp divergence, as banks with greater exposure experience a disproportionate increase in uninsured NBFI deposits relative to less exposed banks. This provides empirical support for our identification assumption, validating the credibility of our research design.

The next sections assess how banks responded to the QE-induced fragility, first by examining adjustments in deposit composition and subsequently by analyzing changes in credit allocation.

4 Liquidity risk management: Deposit liabilities

We begin by analyzing banks' responses on the liability side, focusing on how exposed banks adjusted their total deposits and the composition of deposit categories. In Column 1 of Table 4, we examine total deposits. The coefficient on $QE \cdot Shares$ is statistically insignificant, indicating that, on average, banks with higher pre-pandemic exposure to NBFI uninsured deposits did not experience a significant change in their total deposits during QE. This suggests that any funding adjustments occurred primarily through shifts in deposit composition rather than overall deposit growth. To explore these shifts, we turn to Columns 2 through 5. Column 2 reports the increase in NBFI uninsured deposits for more exposed banks and is included here to maintain comparability and the complete set of deposit categories. Banks manage their liability structures by reducing their exposure to total uninsured deposits, as evidenced by the negative coefficient during the QE period (Column 3). This adjustment is even more pronounced when excluding NBFI deposits (Column 4), suggesting a strategic contraction in uninsured liabilities where NBFI exposures are not a factor. At the same time, banks with higher NBFI exposure increased their insured deposit holdings, as shown by the positive and highly significant coefficient in Column 5. This shift reflects a deliberate effort to strengthen liquidity buffers and reduce reliance on volatile funding sources during QE. This dual strategy highlights how banks not only respond to immediate financial stresses but also proactively adjust their balance sheets in anticipation of potential liquidity needs.[16]

The banks in our analysis are subject to Liquidity Coverage Ratio (LCR) regulation, which

[16] In unreported results (available upon request), we re-estimate Table 4 while controlling for interactions between QE with the GSIB indicator to account for the distinct role of systemically important banks. The results remain unchanged when we control for the role of GSIBs.

requires them to hold high-quality liquid assets sufficient to cover estimated net cash outflows over a 30-day stress period. Most banks in our sample maintain an LCR above one, meaning they hold liquidity buffers exceeding the regulatory minimum (see Table OA2 in the Appendix).[17] Importantly, the LCR assigns a 100% run-off factor to NBFI deposits, recognizing their flighty nature and the elevated risk of withdrawal under stress. The influx of uninsured NBFI deposits therefore increases expected cash outflows, tightening banks' LCRs and bringing them closer to the regulatory threshold. Therefore, we need to address the potential concern that more exposed banks to QE-induced fragility may also have had smaller liquidity buffers relative to expected funding outflows, as measured by their LCR. Hence, the relative shift from uninsured to insured deposits for more exposed banks could stem from broader precautionary motives to preserve their liquidity buffers rather than being a direct response to the influx of uninsured NBFI deposits. To address this concern, we re-estimate Table 4 while controlling for interactions between QE with the bank's LCR in 2019Q4, i.e., before the pandemic. Table OA6 in the Appendix shows that our key results remain robust. More exposed banks continue to actively manage the liquidity risk of their deposit liabilities in response to QE-induced funding fragility.[18]

Deposit rates. The findings suggest that banks with higher pre-pandemic exposure to NBFI deposits not only experienced a surge in uninsured NBFI deposits during QE, but also actively reshaped their deposit mix in response. This underscores the role of liquidity risk management in mitigating funding instability. A key mechanism through which banks manage liquidity risk is deposit pricing. By adjusting deposit rates, banks influence the volume and composition of their funding sources, either attracting or disincentivizing certain types of deposits. In Table 5, we explore this mechanism by examining how exposed banks adjust deposit rates between insured (Columns 1-3) and uninsured (Columns 4-6) deposits. The coefficient on $QE \cdot Shares$ is positive and statistically significant for insured deposits, indicating that banks with greater NBFI exposure raise interest rates on insured deposits during QE. Economically, a one standard deviation increase in NBFI exposure is associated with an increase in insured deposit rates by approximately 5.8-7.6 basis points. This suggests that these banks actively sought to attract

[17] Some banks, however, are subject to reduced LCR requirements.

[18] See also Kiernan, Yankov, and Zikes (2021) who show that the large liquidity buffers that the largest banks accumulated after the Global Financial Crisis would enable them to provide liquidity to firms even in the most extreme draw-down scenarios without violating their LCR.

Table 4: Other deposit categories

	1	2	3	4	5
Dependent variable:	Log(Total deposits)	Log(Uninsured NBFI deposits)	Log(Total uninsured deposits)	Log(Total uninsured deposits exc. NBFI)	Log(Total insured deposits)
QE * Shares	-0.049	0.272***	-0.253***	-0.398***	1.711***
	(-1.374)	(4.655)	(-6.469)	(-8.444)	(14.754)
Bank control	Y	Y	Y	Y	Y
QT control	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Observations	2,145	2,077	2,145	2,145	2,000
R-squared	0.988	0.969	0.981	0.980	0.957

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,t}) = \lambda \cdot (QE_t \cdot Shares_i) + \beta \cdot Controls_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $Y_{i,t}$ is the dependent variable labelled in each column for bank i in month t. QE_t is a dummy equal to one from March 2020 to March 2022. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. The *Bank control* indicates whether we control for time-varying bank size (logarithm of total assets), and the *QT control* indicates whether the interaction term $QT_t \cdot Shares_i$ is included. The terms a_i and a_t represent bank and month fixed effects, respectively. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

more stable funding sources in response to the influx of NBFI uninsured deposits.

In contrast, the coefficient on $QE \cdot Shares$ is negative and highly significant for uninsured deposits, indicating that the more exposed banks reduced rates on these deposits during QE. A one standard deviation increase in NBFI exposure is associated with a 5.5-6.6 basis point decline in uninsured deposit rates, further reinforcing the shift toward more stable funding sources. Taken together, these findings highlight that banks proactively manage liquidity risk by reshaping their liability structures in response to the influx of fragile NBFI deposits. This behavior is consistent with the fact that exposed banks typically have less (more) insured (uninsured) deposits, as previously discussed, hence the incentive to protect liquidity is even stronger.

5 Liquidity risk management: Lending effects

In the previous section, we established how more exposed banks adjust their deposit composition by shifting towards more insured deposits while keeping the total deposit base the same, relative to less exposed banks. We argued that this response signals a desire to reduce fragility on the liabilities resulting from the QE-induced increase in NBFI uninsured deposits. In this section, we examine how the QE-induced fragility translates into adjustments on the asset side of banks'

Table 5: Deposit rates

	1	2	3	4	5	6
Dependent variable:	Rates on Insured Deposits			Rates on Uninsured Deposits		
QE * Shares	0.529***	0.660***	0.690***	-0.496***	-0.592***	-0.597***
	(6.049)	(9.864)	(10.257)	(-6.074)	(-5.715)	(-5.733)
Bank control			Y			Y
QT control		Y	Y		Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Observations	1,224	1,224	1,224	659	659	659
R-squared	0.722	0.724	0.724	0.516	0.519	0.518

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $Deposit\ rate_{i,t} = \lambda \cdot (QE_t \cdot Shares_i) + \beta \cdot Controls_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $Deposit\ rate_{i,t}$ is the deposit rate for bank i in month t. The table analyzes two types of rates: rates on insured deposits (columns 1 to 3) and rates on uninsured deposits (columns 4 to 6). QE_t is a dummy equal to one from March 2020 to March 2022. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. The *Bank control* indicates whether we control for time-varying bank size (logarithm of total assets), and the *QT control* indicates whether the interaction term $QT_t \cdot Shares_i$ is included. The terms a_i and a_t represent bank and month fixed effects, respectively. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

balance sheets, focusing on lending outcomes. Our results capture the *relative* effects on lending by more exposed banks compared to their less exposed counterparts.[19]

In particular, we analyze the effect on loan commitments offered to firms by the same set of 29 banks studied in the previous section. We aggregate loans at the bank-firm-quarter level. The richness of our data enables us to account for time-varying firm characteristics, including a firm's demand for credit, and unobservable relationships between banks and firms. Section

[19] An important question is whether banks with a higher pre-QE reliance on uninsured NBFI deposits already exhibited distinct risk profiles in the pre-QE period. To investigate this, we estimate cross-sectional regressions examining differences in credit risk between high- and low-exposure banks before QE. Specifically, we regress net charge-offs (NCOs) across different loan categories on an indicator for banks with above-median uninsured NBFI deposits, controlling for time fixed effects. The results, reported in Appendix C, Table OA7, suggest that high-exposure banks had significantly lower charge-offs on commercial and industrial (C&I) loans and consumer loans before QE. This finding supports the view that these banks were already managing risk conservatively and sought to maintain a strong liquidity buffer post-QE rather than responding to a deterioration in asset quality. Consistent with this, high-exposure banks also exhibited higher LCRs pre-QE, reinforcing the interpretation that these banks were structurally more conservative in their liquidity and risk management.

5.1 examines the relative effect on general lending outcomes. Section 5.2 focuses on credit lines, providing additional evidence and intuition for our key finding that more exposed banks reduce the liquidity insurance they extend to firms relative to less exposed banks.

5.1 General lending effects

We estimate the following panel regression from 2016Q1 to 2022Q4:

$$\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot Shares_i) + \lambda_2(QT_t \cdot Shares_i) + \beta X_{i,t} + \alpha_{i,f} + \alpha_{f,t} + \epsilon_{i,f,t} \quad (2)$$

The dependent variable, $\log(Y_{i,f,t})$, represents the logarithm of three lending measures: committed credit lines, term loans, and total commitments (the sum of the two) for bank i, firm f, and time period t. QE_t, QT_t, and $Shares_i$ are the same variables used in the previous section indicating, respectively, the periods of quantitative easing and tightening, and the level of bank i's exposure to the QE-induced fragility. $X_{i,t}$ includes a set of time-varying bank controls, including bank size, deposit liabilities, and liquid assets. As shown in the previous section, while total deposits do not differ significantly between more and less exposed banks, there is a notable compositional shift: more exposed banks shift from uninsured to insured deposits relative to less exposed banks. To account for this dynamic, we separately control for insured and uninsured deposits in the lending regressions. Additionally, we control for the level of reserves and other high-quality liquid assets, namely treasuries and agencies, to account for their potential imperfect substitutability and the possibility that QE affects them differently.

To account for unobserved heterogeneity, we include bank-firm ($\alpha_{i,f}$) fixed effects and either industry-location-size-time (ILST) or firm-time ($\alpha_{f,t}$) fixed effects. The former allows us to control for persistent bank-firm relationships, while the latter absorbs time-varying firm-level credit demand. Specifically, bank-firm fixed effects control for potential non-random matching between firms and banks, capturing all time-invariant factors that may influence credit within a given bank-firm pair, such as relational banking. Firm-time fixed effects ensure that our estimates capture the supply-side effects of bank lending behavior by absorbing all firm-level demand factors. However, their use results in the exclusion of firms that borrow from only one bank, which is a substantial share of our sample. Given that many smaller firms rely on a single bank, estimates based on firm-time fixed effects may not fully represent broader firm-level credit dynamics. To address this concern, we also consider an alternative specification that replaces firm-time fixed effects with industry-location-size-time fixed effects, which retains both single- and multi-bank firms, following Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019). Finally, we cluster standard errors at the bank-time and firm levels.

Table 6 presents the results from estimating equation (2) for credit lines (columns 1-2), term loans (columns 3-4), and total loan commitments (columns 5-6). Across all specifications, we include the full set of time-varying bank controls as discussed above.[20] The key difference between columns 1 and 2 (and subsequently between columns 3-4 and 5-6) lies in the choice of fixed effects. Specifically, in columns 1, 3, and 5, we include bank-firm FE alongside ILST FE, while in columns 2, 4, and 6, we replace the ILST FE with firm-time FE. The latter provide a stricter control for firm-level credit demand but reduce the sample size considerably, as firms borrowing from only one bank do not contribute to the estimation.

Our coefficient of interest is the interaction term, $QE \cdot Shares$. With respect to credit lines, this coefficient is negative and significant in all specifications, suggesting that banks with higher exposure to the QE-induced fragility had fewer credit-line commitments to firms after QE, relative to less exposed banks. Economically, the estimates in columns 1-2 indicate that a one percentage point increase in the exposed banks is associated with a 0.08-0.13 percentage point decrease in credit-line commitments during the QE period. Section 5.2 further dissects this result by examining the sub-components of credit-line commitments and the implications for banks' liquidity management. Note that this result concerns the differential effect on credit-line extension between more and less exposed banks. Credit-line commitments kept increasing for both types of banks throughout QE. However, our granular data and the novel identification of QE exposure via the inflow of NBFI deposits, allows to capture this differential effect.

With respect to term loans, we find no significant difference between more exposed and less exposed banks after the QE. This result may not be surprising given that total deposits did not evolve differently for more exposed and less exposed banks. Finally, the results in columns 5-6

[20]Including bank-level controls helps to account for potential differences in banks' balance sheet characteristics. However, controlling for them may absorb part of the variation through which QE-induced fragility influences lending, potentially underestimating the full effect. To ensure that our findings are not driven by selection bias, we present results both with and without these controls as suggested by Gormley and Matsa (2011). The results remain unchanged when bank controls are excluded. See Table OA8 in the Appendix.

Table 6: Credit lines, Term loans, and Total Loan Commitments

	1	2	3	4	5	6
Dependent variable:	Log(Credit lines)		Log(Term loans)		Log(Total commitments)	
QE*Shares	-0.095**	-0.076*	0.065	0.110	-0.142***	-0.153***
	(-2.063)	(-1.783)	(0.752)	(1.394)	(-3.212)	(-3.603)
QT*Shares	-0.271***	-0.235***	-0.013	-0.028	-0.314***	-0.338***
	(-3.761)	(-4.045)	(-0.086)	(-0.211)	(-4.278)	(-5.124)
Bank size	0.047	0.051	0.085	0.086	0.086***	0.113***
	(1.347)	(1.408)	(1.259)	(1.141)	(2.659)	(3.127)
Bank reserves	0.016***	0.028***	0.003	0.003	-0.004	0.000
	(2.751)	(4.273)	(0.386)	(0.415)	(-1.133)	(0.052)
Bank treasuries & agencies	-0.019**	-0.009	-0.017	-0.006	-0.025***	-0.019**
	(-2.390)	(-0.981)	(-1.434)	(-0.426)	(-3.509)	(-2.087)
Bank insured deposits	-0.061***	-0.075***	-0.052	-0.067*	-0.050***	-0.063***
	(-2.833)	(-3.723)	(-1.378)	(-1.757)	(-2.715)	(-3.429)
Bank uninsured deposits	0.094***	0.112***	-0.073	-0.042	0.028	0.032
	(3.625)	(4.197)	(-1.366)	(-0.697)	(1.198)	(1.279)
Bank*Firm FE	Y	Y	Y	Y	Y	Y
ILST FE	Y		Y		Y	
Firm*Time FE		Y		Y		Y
Observations	632,635	317,776	236,988	95,199	919,369	391,659
R-squared	0.966	0.944	0.953	0.918	0.962	0.935

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot Shares_i) + \lambda_2(QT_t \cdot Shares_i) + \beta X_{i,t} + a_i + a_{f,t} + \varepsilon_{i,f,t}$. The dependent variable for each bank i, firm f, and time period t is the logarithm of credit lines (columns 1 to 2), the logarithm of term loans (columns 3 to 4), and the logarithm of total (loan) commitments, which is the sum of the two (columns 5-6). QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. *Bank size*$_{i,t}$ is the logarithm of total assets, *Bank reserves* is the logarithm of reserves, and *Bank treasuries & agencies* is the logarithm of the treasuries and agencies a bank holds. The variables *Bank insured deposits* and *Bank uninsured deposits* represent the logarithm of insured and uninsured deposits, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Observations are at the bank-firm-time level and are reported quarterly. Standard errors are clustered at the bank-quarter and firm levels. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

show that total loan commitments are lower for more exposed banks after the QE relative to less exposed banks.[21] In Section 6, we further examine the aggregate implications for firms' access to credit and real economic outcomes. Taken together, these results indicate that more exposed banks did not expand their credit-line commitments following QE, leading to a relative decline compared to less exposed banks. At the same time, their term loan commitments remained unchanged, resulting in an overall reduction in total loan commitments.

5.2 Credit lines and Liquidity Insurance

We now examine in more detail the underlying forces that drive down credit-line commitments for more exposed banks relative to less exposed ones. Credit-line commitments consist of two components: utilized credit lines and undrawn credit lines. When a bank issues a credit line, it does not immediately extend a loan on its balance sheet. Instead, it provides a commitment that allows the firm to draw funds when needed. Once a firm withdraws from a committed credit line, the utilized portion (known as draw-down) appears as a credit-line loan on the bank's balance sheet, while the remaining amount represents undrawn credit, which firms can access in the future. Undrawn credit lines are a key measure of liquidity insurance, as they reflect the funding available to firms for future needs. However, from a bank's perspective, these undrawn commitments pose liquidity risk, as they represent off-balance-sheet obligations that could be drawn unpredictably (Ippolito et al., 2016; Acharya et al., 2024). Unlike publicly available call reports, which only capture utilized credit lines, our dataset allows us to separately analyze utilized and undrawn credit lines, providing a more precise view of how QE-induced fragility affects banks' provision of contingent liquidity.

Table 7 reports the results from estimating equation (2) for utilized credit lines (columns 1-2) and undrawn credit lines (columns 3-4).[22] Our coefficient of interest is the interaction term, $QE \cdot Shares$. Focusing on utilized credit lines, we find no significant difference between more exposed and less exposed banks after the QE. This result is intuitive: the decision to utilize a

[21] To ensure that our lending results are not sensitive to the log transformation of loan variables, we re-estimate all lending regressions using Poisson pseudo-maximum likelihood (PPML). This method is well-suited for handling skewed data and cases where some loan commitments are zero (Cohn, Liu, and Wardlaw, 2022). The results remain robust and aligned with our main findings. Unreported estimates are available upon request.

[22] The results do not change if we exclude bank controls. See Table OA9 in the Appendix. Additionally, in unreported results (available upon request), we control for interactions between QE and QT with the LCR-indicator described above to account for general precautionary liquidity motives. All results remain robust.

Table 7: Utilized & Undrawn Credit Lines

	1	2	3	4
Dependent variable:	Log(Utilized credit lines)		Log(Undrawn credit lines)	
QE*Shares	-0.005	-0.058	-0.291***	-0.182***
	(-0.041)	(-0.566)	(-4.855)	(-4.021)
QT*Shares	-0.160	-0.072	-0.420***	-0.326***
	(-0.837)	(-0.450)	(-4.987)	(-5.324)
Bank size	-0.144*	0.119*	0.119**	0.071**
	(-1.789)	(1.962)	(2.577)	(2.143)
Bank reserves	0.002	0.022**	-0.017**	-0.005
	(0.206)	(2.440)	(-2.322)	(-0.983)
Bank treasuries & agencies	-0.068***	-0.025	-0.014	-0.019**
	(-4.057)	(-1.348)	(-1.125)	(-2.166)
Bank insured deposits	-0.057	-0.064	-0.044*	-0.027
	(-1.109)	(-1.389)	(-1.704)	(-1.460)
Bank uninsured deposits	0.269***	0.093*	0.005	0.022
	(4.477)	(1.866)	(0.156)	(0.883)
Bank*Firm FE	Y	Y	Y	Y
ILST FE	Y		Y	
Firm*Time FE		Y		Y
Observations	408,805	184,557	550,076	300,783
R-squared	0.860	0.874	0.897	0.942

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot Shares_i) + \lambda_2(QT_t \cdot Shares_i) + \beta X_{i,t} + a_i + a_{f,t} + \varepsilon_{i,f,t}$. The dependent variable for each bank i, firm f, and time period t is the logarithm of utilized credit lines (Columns 1–2) or the logarithm of undrawn credit lines (Columns 3–4). QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. *Bank size*$_{i,t}$ is the logarithm of total assets, *Bank reserves* is the logarithm of reserves, and *Bank treasuries & agencies* is the logarithm of the treasuries and agencies a bank holds. The variables *Bank insured deposits* and *Bank uninsured deposits* represent the logarithm of insured and uninsured deposits, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Observations are at the bank-firm-time level and are reported quarterly. Standard errors are clustered at the bank-quarter and firm levels. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

credit line is primarily driven by firms, and after controlling form firm demand, there is no clear reason why firms would systematically treat more exposed and less exposed banks differently when drawing down their credit lines.[23] Turning to the undrawn credit lines, we observe a different pattern. There is a significant difference between more exposed and less exposed banks, with more exposed banks offering relatively less liquidity insurance to firms after the QE, as measured by the undrawn credit lines. This reduction in undrawn credit lines is also what drives the decline in total loan commitments for more exposed banks relative to less exposed ones, as described above.

Liquidity management. These results indicate that the more exposed banks limit or do not top up the undrawn amount in firms' credit lines relative to less exposed banks. This adjustment primarily occurs through quantities rather than pricing, as there is no significant difference in interest rate setting on credit lines between more and less exposed banks after QE (see columns 1-4 in Table OA10 in the Appendix). Furthermore, the effect is not driven by newly issued credit lines, where we do not find a significant difference between more and less exposed banks (see columns 5-8 in Table OA10 in the Appendix). Instead, more exposed banks reduce the liquidity insurance they provide to firms, likely as a precautionary measure to mitigate the liquidity risk stemming from QE-induced funding fragility and to lower the probability of a "double run" scenario, in which both depositors withdraw their funds and firms draw down their credit lines (Ippolito et al., 2016). We next examine the underlying mechanism driving this adjustment and investigate the aggregate effects for firms' access to liquidity in Section 6. But, before that, we present additional evidence that more exposed banks indeed try to reduce the liquidity risk from future credit-line draw-downs.

We examine whether more exposed banks disproportionately reduced their undrawn credit-line exposures to firms mostly vulnerable to liquidity strains after the pandemic shock. To identify such firms, we focus on industries more affected by Covid-19 and, within those industries, on firms with a higher anticipated need for liquidity. We approximate liquidity needs using the ratio of firms' sales to account receivables, which serves as a proxy for working capital or bridge liquidity that firms may need. To test this, we extend regression (2) by including a quadruple

[23] Recall that our sample consists of the biggest bank in the United States, which were adequately capitalized and served as a source of strength during the pandemic.

interaction term $QE \cdot Shares \cdot Covid \cdot Liquidity$, where $Covid$ is a dummy indicating whether firm f operates to a more Covid-affected industry and $Liquidity$ is a dummy equal to one if the firm's sales-to-accounts-receivable ratio in 2019Q4 is above the median. Table OA11 reports the results from our strictest specification that accounts for all variation at the firm-time level. Our key coefficient of interest, $QE \cdot Shares$, remains negative and significant. Additionally, the coefficient on the quadruple interaction term is also negative and significant, indicating that more exposed banks not only reduce their undrawn credit lines relative to less exposed banks, but they may do so even more for firms most vulnerable to liquidity strains in the post-QE environment.

Economic mechanism. In an influential paper, Kashyap et al. (2002) demonstrate strong complementarities between deposit taking and the provision of liquidity insurance to firms via the extension of credit-line commitments. The underlying idea is straightforward: banks must hold liquid assets to meet deposit withdrawals and credit-line drawdowns, but doing so entails an opportunity cost. When deposit-withdrawals and credit-line-utilization are imperfectly correlated, synergies arise, giving banks a comparative advantage in providing both services. The authors show that credit-line commitments are increasing with deposit-taking. In contrast we showed above that more exposed banks, those receiving larger inflows of uninsured NBFI deposits, reduce their credit-line commitment relative to less exposed banks.

To reconcile our results with Kashyap et al. (2002), we extend their model to explicitly incorporate runnable uninsured deposits akin to Diamond and Kashyap (2016) (see the Appendix A for the full exposition of the model). We show that this small modification is sufficient to reverse their original result, aligning with our empirical findings. The intuition is straightforward once one accounts for out-of-equilibrium considerations, which are crucial when studying runnable deposits. Managing liquidity in the presence of runnable deposits requires banks to prepare for self-fulfilling withdrawals—not just those expected in equilibrium. In particular, a bank must assess its solvency even in a worst-case scenario where all depositors withdraw and the bank resorts to more expensive wholesale funding. When the share of runnable deposits becomes sufficiently large, insuring against all potential out-of-equilibrium withdrawals becomes prohibitively expensive, prompting banks to reduce their lines of credit despite the inflow of runnable deposit funding. Notably, this mechanism does not arise if deposits are insured and therefore not runnable, or if the bank remains solvent under all potential withdrawal scenarios—an assumption maintained in the numerical example of Kashyap et al. (2002).

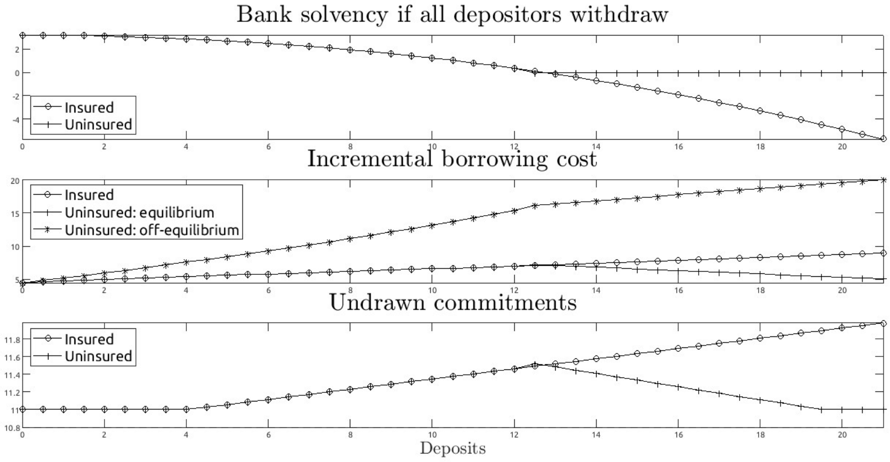
Figure 4 outlines the mechanism through which runnable deposits may reverse the result of Kashyap et al. (2002), using a calibration similar to theirs (see the Appendix A for analytical results and calibration details).[24] Similar to Kashyap et al. (2002), we consider an exogenous increase in deposits, but we analyze two cases: (i) insured and non-runnable deposits, and (ii) uninsured and runnable deposits. If depositors withdraw, then the bank must rely on more expensive funding. The key variable to track is the bank profits under an out-of-equilibrium scenario in which all depositors withdraw (top chart). As deposits increase, the bank approaches a threshold beyond which it can no longer remain solvent if all depositors withdraw simultaneously. If all deposits are insured, then the bank can theoretically violate its solvency constraint in out-of-equilibrium paths, as insured depositors have no incentives to run in equilibrium. However, when deposits are uninsured and runnable, the solvency constraint becomes binding once deposits reach a critical level; otherwise, uninsured depositors would decide to run in equilibrium fearing that others may do the same.[25]

The middle chart of Figure 4 shows the incremental costs of wholesale borrowing to meet deposit withdrawals. As deposits increase, the incremental costs rise in equilibrium for both insured and uninsured deposits at a similar rate. However, the cost of serving withdrawals in all out-of-equilibrium paths escalates much more rapidly for uninsured, runnable deposits. Consequently, banks initially expand their credit-line commitments as deposits grow, regardless of whether these deposits are insured or uninsured. However, once uninsured deposits exceed a critical threshold, the rising liquidity risk and associated costs become too severe. At this point, banks actively adjust their exposure by reducing credit-line commitments (bottom panel). These dynamics suggest that beyond a certain level of uninsured deposits, the strong complementarity between deposit-taking and the provision of liquidity insurance via credit-line commitments—emphasized by Kashyap et al. (2002)—breaks down.

[24] The key difference is that we introduce the impatient/patient depositors akin to Diamond and Dybvig (1983), to explicitly model self-fulfilling runs and highlight the importance of runnable deposits.

[25] For simplicity and without loss of generality, we follow Diamond and Kashyap (2016) in assuming that banks aim to avoid failure in any out-of-equilibrium paths, which is justified by the assumtpion that depositors are very risk averse and only accept riskless deposits. Our argument does not rely strictly on such run-proof contracts and could be extended to cases that run risk is positive in equilibrium as in Kashyap, Tsomocos, and Vardoulakis (2024). We leave this extension to future research.

Figure 4: Model Simulation. Runnable deposits & Credit-line commitments



Note: The Figure plots the equilibrium outcomes from simulating the model outlined in the Appendix for different level of deposits. We consider two cases: (i) deposits are insured and not runnable, and (ii) deposits are uninsured and runnable. The top chart reports bank's solvency constraint in the out-of-equilibrium paths that all depositors withdraw. The middle chart reports the incremental cost of serving deposits withdrawal in- and out-of-equilibrium. The bottom chart shows the equilibrium level of (undrawn) credit-line commitments.

6 Aggregate Lending and Real Effects

In the previous section, we showed that banks more exposed to the QE-induced fragility actively managed their liquidity risk by adjusting their loan commitments, primarily by reducing undrawn credit lines. This response may have constrained firms' access to contingent liquidity, even as total deposits remained stable but shifted toward a composition with more uninsured and runnable deposits. While these results suggest that exposed banks took steps to reduce their liquidity risk, a key question remains: Did this shift in exposed banks have broader firm-level consequences? In principle, firms affected by the contraction in credit-line commitments could have offset the impact by switching to less exposed banks. If they were able to do so, the decline in bank-level liquidity provision may not have necessarily led to a contraction in firm borrowing or investment. To examine this, we aggregate quarterly loan commitments at the firm level and estimate the following panel regression from 2016Q1 to 2022Q4:

$$\log(Y_{f,t}) = \lambda_1(QE_t \cdot Exposure_f) + \lambda_2(QT_t \cdot Exposure_f) + \alpha_{ILST} + \alpha_f + \epsilon_{f,t} \quad (3)$$

The dependent variable, $log(Y_{f,t})$, represents the logarithm of (i) the following types of lending: utilized credit lines, undrawn credit lines, term loans, and total loan commitments, and (ii) firm investment as measured by the change in fixed assets, for each firm f and time period t. QE_t and QT_t are the same variables used in the previous sections, indicating the periods of quantitative easing and tightening. $Exposure_f$ captures how exposed a firm is to the QE-induced fragility through its loan relationships with exposed banks. We construct three measures to capture different dimensions of firm reliance on more exposed banks. The first measure (*Unweighted Shares Exposure*) is the average share S_i of uninsured NBFI deposits among the banks with which firm f has loan relationships as of 2019Q4. The second (*Weighted Shares Exposure*) is a weighted version of the same measure, where the weights corresponds to the shares of firm f total loan commitments held with each bank i. The third measure (*Relationships Dummy*) is a dummy equal to one for firms that have more than 50% of their lending relationships with more exposed banks. These measures capture different dimensions of firm exposure, ensuring a broad and consistent pattern across different ways firms interact with exposed banks. To control for firm characteristics and credit demand, we saturate the specification with industry-location-size-time fixed effects and firm fixed effects. Standard errors are clustered at the firm level.

Table 8 reports the results for lending (columns 1-4) and real effects (column 5) for the first exposure measure. The findings are consistent for the other two measures, reported in Table OA12 in the Appendix. At the firm level, we confirm that more affected firms experience a decline in liquidity insurance, as reflected in lower undrawn credit lines, but show no significant differences from less affected firms in terms of credit-line utilization or term loans received. Hence, the total impact on credit availability, measured by total loan commitments (column 4), is largely insignificant. These results indicate that the decline in undrawn credit lines observed at the bank-firm level extends to the firm level, i.e., affected firms face reduced access to contingent liquidity. In response, firms reduce investment (column 5), likely as a precautionary measure to preserve liquidity and flexibility amid a diminished ability to hedge future liquidity shocks.[26] Overall, the QE-induced fragility can have aggregate effects by reducing liquidity insurance to firms and affecting real economic outcomes. We believe that our analysis is shedding light on

[26]This aligns with previous studies that highlight the importance of credit lines for firms' investment, for example, Chang, Chen, and Masulis (2023).

these important unintended consequences of quantitative easing.

Table 8: Aggregate effects at firm level

	1	2	3	4	5
Dependent variable: Dependent variable:	Log(Utilized credit lines)	Log(Undrawn credit lines)	Log(Term loans)	Log(Total commitments)	Log(Investment)
QE *Unweighted Shares Exposure	0.201	-0.354*	0.157	-0.063	-2.391**
	(1.122)	(-1.945)	(1.063)	(-0.959)	(-2.638)
QT *Unweighted Shares Exposure	0.219	-0.595**	0.212	-0.230**	-1.718
	(0.776)	(-2.729)	(0.867)	(-2.158)	(-1.675)
Observations	223,976	256,001	122,718	497,200	43,199
R-squared	0.820	0.798	0.929	0.951	0.817
ILST FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{f,t}) = \lambda_1(QE_t \cdot Exposure_f) + \lambda_2(QT_t \cdot Exposure_f) + a_{ILST} + a_f + \varepsilon_{f,t}$, where the dependent variable for each firm f in time period t is the sum of credit the firm received. The dependent variables are: the logarithm of utilized credit lines (column 1), the logarithm of undrawn credit lines (column 2), the logarithm of term loans (column 3), the logarithm of total commitments (column 4) and the logarithm of investments (column 5). $Exposure_f$ is a measure of how exposed a firm is to the QE-induced fragility via the loan relationships that firm has with exposed banks. Table reports results for $Exposure_f = \{Unweighted\ Shares\ Exposure_f\}$, which is the average share S_i among those banks with which a firm f has loan relationships at 2019Q4. The regression includes industry-location-size-time (a_{ILST}) and firm (a_f) fixed effects. Standard errors are clustered at the firm level. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

7 Conclusions

Our findings highlight the critical role of bank liquidity management in response to central bank quantitative policies such as QE and QT. We show that banks with greater exposure to uninsured NBFI deposits during the Pandemic QE adjusted their liability structures by shifting their composition of deposits from insured to uninsured. On the asset side, we find that exposed banks cut back on credit line commitments while maintaining term loan issuance, thereby limiting firms' access to contingent liquidity. This active liquidity management on both sides of the balance sheet reflects banks' efforts to mitigate funding fragility induced by the large influx of flighty NBFI deposits as an outcome of the QE operations. This suggests that while QE injected substantial liquidity into the banking system, it also led to unintended consequences for corporate liquidity insurance, reducing firms' ability to manage future liquidity shocks.

Our results carry important implications for monetary policy transmission and financial stability. While QE aims to ease financial conditions and stimulate lending, our findings suggest that its impact is nuanced, as shifts in bank funding composition can lead to constraints on liquidity provision. The persistence of uninsured NBFI deposits post-QE, despite the initiation of QT, underscores the long-term structural changes in bank balance sheets driven by central bank interventions. Future research could explore whether similar patterns emerge in different regulatory environments or during periods of financial stress, shedding further light on the evolving interactions between monetary policy, banks and NBFIs.

References

Acharya, V. V., N. Cetorelli, and B. Tuckman (2024). Where do banks end and nbfis begin? Technical report, National Bureau of Economic Research.

Acharya, V. V., R. S. Chauhan, R. Rajan, and S. Steffen (2023). Liquidity dependence and the waxing and waning of central bank balance sheets. Technical report, National Bureau of Economic Research.

Acharya, V. V., R. Engle, M. Jager, and S. Steffen (2024). Why did bank stocks crash during covid-19? *The Review of Financial Studies 37*(9), 2627–2684.

Acharya, V. V. and N. Mora (2015). A crisis of banks as liquidity providers. *The Journal of Finance 70*(1), 1–43.

Acharya, V. V. and R. Rajan (2024). Liquidity, liquidity everywhere, not a drop to use: Why flooding banks with central bank reserves may not expand liquidity. *The Journal of Finance 79*(5), 2943–2991.

Afonso, G., M. Cipriani, and G. La Spada (2022). Banks' balance-sheet costs, monetary policy, and the on rrp. *FRB of New York Staff Report* (1041).

Bernanke, B. S. (2022). *21st century monetary policy: The Federal Reserve from the great inflation to COVID-19.* WW Norton & Company.

Chakraborty, I., I. Goldstein, and A. MacKinlay (2020). Monetary stimulus and bank lending. *Journal of Financial Economics*.

Chang, X., Y. Chen, and R. W. Masulis (2023). Bank lines of credit as a source of long-term finance. *Journal of Financial and Quantitative Analysis 58*(4), 1701–1733.

Chen, K., J. Ren, and T. Zha (2018). The nexus of monetary policy and shadow banking in china. *American Economic Review 108*(12), 3891–3936.

Chodorow-Reich, G. (2013, 10). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146*(2), 529–551.

Cooperman, H. R., D. Duffie, S. Luck, Z. Wang, and Y. Yang (2023). Bank funding risk, reference rates, and credit supply. Technical report, National Bureau of Economic Research.

Degryse, H., O. De Jonghe, S. Jakovljević, K. Mulier, and G. Schepens (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation 40*, 100813.

Di Maggio, M., A. Kermani, and C. J. Palmer (2019, 12). How quantitative easing works: Evidence on the refinancing channel. *The Review of Economic Studies 87*(3), 1498–1528.

Diamond, D. and A. Kashyap (2016). Liquidity requirements, liquidity choice, and financial stability. Volume 2 of *Handbook of Macroeconomics*, pp. 2263–2303. Elsevier.

Diamond, D. W. and P. H. Dybvig (1983). Bank runs, deposit insurance, and liquidity. *Journal of political economy 91*(3), 401–419.

Diamond, W., Z. Jiang, and Y. Ma (2024). The reserve supply channel of unconventional monetary policy. *Journal of Financial Economics 159*, 103887.

Duffie, D. (2020). Still the world's safe haven? – redesigning the us treasury market after the covid-19 crisis. *Hutchins Center Working Paper 62, Brookings Institution*.

Elliott, D., R. R. Meisenzahl, and J.-L. Peydró (2024). Nonbank lenders as global shock absorbers: evidence from us monetary policy spillovers. *Journal of International Economics*, 103908.

Favara, G., S. Infante, and M. Rezende (2024). Leverage regulations and treasury market participation: Evidence from credit line drawdowns. *working paper*.

Federal Reserve Board (2021, March). Press release. https://www.federalreserve.gov/newsevents/pressreleases/bcreg20210319a.htm. Accessed: 2024-07-10.

Franceschi, E., M. Grodzicki, B. Kagerer, C. Kaufmann, F. Lenoci, L. Mingarelli, C. Pancaro, and R. Senner (2023). Key linkages between banks and the non-bank financial sector. *Financial Stability Review 1*.

Gatev, E., T. Schuermann, and P. E. Strahan (2009). Managing bank liquidity risk: How deposit-loan synergies vary with market conditions. *The Review of Financial Studies 22*(3), 995–1020.

Gatev, E. and P. E. Strahan (2006). Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market. *The Journal of Finance 61*(2), 867–892.

Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez (2017). Capital Allocation and Productivity in South Europe. *The Quarterly Journal of Economics 132*(4), 1915–1967.

Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? corporate responses to liability risk. *The Review of Financial Studies 24*(8), 2781–2821.

Hanson, S. G., A. Shleifer, J. C. Stein, and R. W. Vishny (2015). Banks as patient fixed-income investors. *Journal of Financial Economics 117*(3), 449–469.

Holmström, B. and J. Tirole (1998). Private and public supply of liquidity. *Journal of Political Economy 106*(1), 1–40.

Imbens, G. W. and J. M. Wooldridge (2009). Recent developments in the econometrics of program evaluation. *Journal of economic literature 47*(1), 5–86.

Ippolito, F., J.-L. Peydró, A. Polo, and E. Sette (2016). Double bank runs and liquidity risk management. *Journal of Financial Economics 122*(1), 135–154.

Irani, R. M., R. Iyer, R. R. Meisenzahl, and J.-L. Peydro (2021). The rise of shadow banking: Evidence from capital regulation. *The Review of Financial Studies 34*(5), 2181–2235.

Joyce, M., D. Miles, A. Scott, and D. Vayanos (2012). Quantitative easing and unconventional monetary policy–an introduction. *The Economic Journal 122*(564), F271–F288.

Kashyap, A. K., R. Rajan, and J. C. Stein (2002). Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking. *The Journal of Finance 57*(1), 33–73.

Kashyap, A. K., D. P. Tsomocos, and A. P. Vardoulakis (2024). Optimal bank regulation in the presence of credit and run risk. *Journal of Political Economy 132*(3), 772–823.

Kiernan, K. F., V. Yankov, and F. Zikes (2021). Liquidity provision and co-insurance in bank syndicates. *FEDS WP 2021-060*.

Leonard, D., A. Martin, and S. M. Potter (2017). How the fed changes the size of its balance sheet. Technical report, Federal Reserve Bank of New York.

Levine, R., C. Lin, M. Tai, and W. Xie (2021). How did depositors respond to covid-19? *The Review of Financial Studies 34*(11), 5438–5473.

Li, L., P. E. Strahan, and S. Zhang (2020). Banks as lenders of first resort: Evidence from the covid-19 crisis. *The Review of Corporate Finance Studies 9*(3), 472–500.

Roberts, M. R. and T. M. Whited (2013). Endogeneity in empirical corporate finance1. In *Handbook of the Economics of Finance*, Volume 2, pp. 493–572. Elsevier.

Rodnyansky, A. and O. M. Darmouni (2017). The effects of quantitative easing on bank lending behavior. *The Review of Financial Studies 30*(11), 3858–3887.

Vayanos, D. and J.-L. Vila (2021). A preferred-habitat model of the term structure of interest rates. *Econometrica 89*(1), 77–112.

Appendix

“QE, Bank Liquidity Management, and Non-Bank Funding:

Evidence from Administrative Data”

This appendix provides supplementary information and results to support the main paper. The content is organized as follows:

Appendix A presents the theoretical model.

Appendix B details the filters applied to construct the final dataset.

Appendix C provides additional tables that supplement the main results.

A Theory

We extend Kashyap et al. (2002) to examine how an increase in uninsured, runnable, deposits affects a bank's choice to offer credit-line commitments to firms. We maintain the whole structure of their model and only make two modifications. First, we consider that depositors are homogeneous ex ante but receive ex post an idiosyncratic, uninsurable, preference shock to consume early or late. This ex post heterogeneity between impatient and patient depositors allow us to study the incidence of self-fulfilling runs as in Diamond and Dybvig (1983). Second, we consider two types of deposits: insured (non-runnable) deposits and uninsured (runnable) deposits. The former correspond to Kashyap et al. (2002), where only the solvency and liquidity of the bank on the equilibrium path matter. The latter corresponds to the case that runs are possible. To eliminate such runs depositors need to be certain about the solvency and liquidity of the bank not only on the equilibrium path, but also for all out-of-equilibrium paths, or in other words for the worst-case scenario as in Diamond and Kashyap (2016).

We briefly describe the Kashyap et al. (2002) environment and refer the reader to their paper for all details. There are three time periods $t = 0, 1, 2$ and four types of agents: depositors, firms, financiers, and a bank. The per-period net interest rate is set to $i > 0$. At $t = 0$ depositors invest all their endowment in deposits and, hence, the amount of deposits, D, in the bank is exogenously determined. Depositors are very risk averse and only accept deposit contracts that carry zero risk. In return, they are willing to accept a zero deposit rate, generating a deposit franchise for the bank. Depositors receive an uninsurable idiosyncratic preference shock at $t = 1$, urging $\tilde{\delta}$ of them to withdraw early; $\tilde{\delta} = \delta \in (0, 1)$ and $\tilde{\delta} = 0$ with equal probability. This is the first modification we make on Kashyap et al. (2002) that consider $\delta = 1$, i.e., either all depositors or none withdraw.

The bank has also access to funding markets both at $t = 0$ and $t = 1$ were financiers invest in the bank in the form of wholesale funding or equity injections. Denote by e_0 and e_1 the external financing at $t = 0$ and $t = 1$, respectively. Financiers demand the market interest rate i but also require an additional premium for period-1 financing equal to $\alpha/2e_1^2$, with $\alpha > 0$. This incremental cost of external financing will play an important role in the bank's liquidity management. Finally, for simplicity, all interest payments accrue at $t = 2$.

The bank uses the period-0 deposits and external funds to extend term loans and also invest in liquid assets, denoted by L and S_0. Term loans mature at $t = 2$ yielding a net loan rate r. Liquid assets mature after one period and pay net interest $i - \tau$, with $\tau > 0$ to account for the fact that hoarding liquidity is costly for the bank. The bank can also extend credit-line commitments to firms at $t = 0$, denoted by C. These lines of credit constitute a promise to extend loans up to C at $t = 1$ if the firms decides to draw-down the line of credit. Utilized credit lines carry an net interest i, but firms also pay a fee fC, with $dfC/dC > 0$ and $d^2fC/dC^2 < 0$, to have access to such lines of credit irrespective if they end up using or not. But, credit lines do not take balance-sheet capacity unless drawn and, thus, the balance sheet of the bank at $t = 0$ is $L + S_0 = D + e_0$. At $t = 1$ firms receive a shock urging them to utilize $\tilde{z}$ portion of the credit lines; $\tilde{z} = 1$ and $\tilde{z} = 0$ with equal probability. Importantly, $\tilde{z}$ and $\tilde{\delta}$ may be imperfectly correlated with correlation $\rho \leq 1$.

Next, we examine the balance sheet constraint at $t = 1$ and bank solvency at $t = 2$ when λ depositors decide to withdraw. Given that self-fulfilling runs are possible under uninsured deposits, we study the general case the $\lambda \in (\tilde{\delta}, 1)$. This is the second modification we make on Kashyap et al. (2002) that consider only the equilibrium level of (impatient) withdrawals $\lambda = \tilde{\delta}$. The balance sheet constraint at $t = 1$ is, then, $\tilde{z}C + \lambda D = S_0 + e_1$ if $\tilde{z}C + \lambda D - S_0 > 0$ and $\tilde{z}C + \lambda D + S_1 = S_0$ otherwise. In other words, the bank resorts to external financing, e_1, at $t = 1$ only if their liquidity outflows cannot be met by the liquidity they carried over from the previous period; otherwise, the bank rolls over any remaining liquidity, S_1, to $t = 2$. We focus on the case that $S_0 < \min(\delta D, C)$, i.e., the bank requires external financing at $t = 1$ apart from the cases that $\tilde{\delta} = \tilde{z} = 0$. This is the interesting case in Kashyap et al. (2002) that gives rise to the mechanism they highlight, but we also show the other cases in the numerical solution.

We examine the solvency of the bank at $t = 2$ when it faces a liquidity shortfall $\tilde{z}C+\lambda D-S_0 > 0$ at $t = 1$ and needs to borrow at more expensive rates. Given a λ, the highest shortfall is for $\tilde{z} = 1$, so if a bank can survive that state, it is solvent for $\tilde{z} = 0$ as well. The profits for deposit withdrawals λD and credit-line draw-downs for $z = 1$ C are given by:

$$\begin{aligned}\Pi(\lambda) &= (1+r)L + fC + S_0(i-\tau) + (1+i)C - (1+2i)e_0 - (1+i)e_1 - \alpha/2e_1^2 - (1-\lambda)D \\ &= rL - 2iL + fC - \tau S_0 - \alpha/2(C + \lambda D - S_0)^2 + (2-\lambda)Di, \end{aligned} \tag{4}$$

using the expressions for e_0 and e_1 from the balance-sheet constraints. $\Pi(\lambda)$ is decreasing in λ. Thus, as long as it it positive for the highest possible λ given the deposit contract, then the bank is always solvent. In the case of insured deposits, only impatient depositors would withdraw early, and hence the highest possible λ is equal to δ. It suffices then that the equilibrium profits $\Pi(\delta)$ for $\tilde{\delta} = \delta$ and $\tilde{z} = 1$ are positive, which is always true from optimality; otherwise deposits would be risky and depositors would not deposit in the bank. In the case of uninsured depositors, the stricter condition $\Pi(1) \geq 0$ is needed to eliminate all fears about potential runs, i.e., the bank needs to remain solvent in all out-of-equilibrium paths for potential withdrawals, which is true is profits are positive for $\lambda = 1$ and $\tilde{z} = 1$. Note that if this condition is satisfied, then only impatient depositors withdraw in equilibrium, i.e., $\lambda = \tilde{\delta}$. But the bank may need to make adjustments to eliminate out-of-equilibrium fears. In fact, $\Pi(1) \geq 0$ can be regarded as an incentive compatibility constraint for the bank, since the slightest probability of a run would make deposits risky and push the very risk-averse depositors away. [27]

Then, the bank chooses L, C, S_0 to maximize

$$\begin{aligned} &\rho/2 \cdot \left[rL - 2iL + fC - \tau S_0 - \alpha/2(C + \delta D - S_0)^2 + (2-\delta)Di\right] \\ &+(1-\rho)/2 \cdot \left[rL - 2iL + fC - \tau S_0 - \alpha/2(C - S_0)^2\right] + 2iD\right] \\ &+(1-\rho)/2 \cdot \left[rL - 2iL + fC - \tau S_0 - \alpha/2(\delta D - S_0)^2\right] + (2-\delta)Di\right] \\ &+\rho/2 \cdot \left[rL - 2iL + fC - \tau S_0 + 2iD\right], \end{aligned} \tag{5}$$

subject to

$$\Pi(1) = rL - 2iL + fC - \tau S_0 - \alpha/2(C + D - S_0)^2 + Di \geq 0 \quad (\mu), \tag{6}$$

[27] Our arguments should carry through for at least certain cases with positive run risk in equilibrium akin to Kashyap et al. (2024), who microfound the probability of a run using a global game and derive the optimal capital and liquidity regulation.. We leave this extension to future work.

where μ is the Lagrange multiplier on the out-of-equilibrium solvency constraint (6).

The first-order conditions with respect to L, C, and S_0 are:

$$L: \qquad (r_L L + r - 2i)(1+\mu) = 0, \tag{7}$$

$$C: \qquad dfC/dC - \frac{\alpha}{2}(\rho\delta D + C - S_0) + \mu\,(dfC/dC - \alpha(C + D - S_0)) = 0, \tag{8}$$

$$S_0: \qquad -\tau + \frac{\alpha}{2}(\delta D + C - S_0(2-\rho)) + \mu(\alpha(C + D - S_0) - \tau) = 0, \tag{9}$$

where $r_L < 0$ is the derivative of the loan rate with respect to loan amount along loan demand. Recall that the bank is internalizing the loan demand schedule. L is determined by exogenous parameters similar to Kashyap et al. (2002). C and S_0 depend on whether the solvency constraint binds, i.e., on μ.

Suppose first that $\mu = 0$. Then, substituting (9) in (8) and totally differentiating with respect , we obtain the same result as in Kashyap et al. (2002):

$$\frac{dC}{dD} = \frac{-\frac{\alpha\delta(1-\rho)^2}{4-\rho}}{\frac{d^2 fC}{dC^2} - \frac{\alpha(1-\rho)}{4-2\rho}} > 0 \quad \text{for} \quad \rho < 1. \tag{10}$$

Hence, an exogenous increase in deposits D results in higher credit lines commitment C, as long as deposit withdrawals and credit line draw-downs are not perfectly correlated, i.e., $\rho < 1$, and the out-of-equilibrium solvency constraint does not bind, i.e., $\mu = 0$. In the numerical exercise in section 5.2 of the paper, we show that this result can revert once the solvency constraint binds as the level of deposit increases.[28]

Below we provide an analytical proof for this reversal. Proposition 1 shows that $\Pi(1)$ is decreasing in the level of deposit funding and, hence, the out-of-equilibrium solvency constraint (6) will start binding after a level of deposits. It follows that the complementarity between deposit-funding and credit-line issuance ceases to exist when (6) binds and, instead banks reduce the issuance of credit lines when uninsured deposit funding increases.

Proposition 1. *For low enough α and i: $\Pi(1) \geq 0$ for $D \leq \bar{D}$, $\Pi(1) < 0$ for $D > \bar{D}$, and*

[28]We employ the following parameterization, which is similar to Kashyap et al. (2002): The loan rate derived from firm's loan demand is $r = A \cdot \gamma \cdot L^{\gamma-1}$, with $A = 2$, $\alpha = 0.09$ and $\gamma = 0.9$; $fC = C - 0.0.25C^2$; $i = 0.8$, $\tau = 0.45$, $\delta = 0.5$, and $\rho = 0.5$.

$d\Pi(1)/dD < 0$. *Then,* $C(D) < C(\bar{D})$ *for* $D > \bar{D}$

Proof. Recall that we are interested in the region that $S_0 < \min(\delta D, C)$, where the complementarity between deposit-funding and credit-line issuance exists in Kashyap et al. (2002). Consider such an equilibrium. Then, evaluate $\Pi(1)$ at a level of deposits $D' \to S_0/\delta$:

$$\lim_{D' \to S_0/\delta} \Pi(1) = rL - 2iL + fC + S_0(i/\delta - \tau) - \frac{\alpha}{2}\left(C + S_0\frac{1-\delta}{\delta}\right)^2,$$

which is strictly positive for

$$\alpha < \hat{\alpha} \equiv 2\frac{rL - 2iL + fC + S_0(i/\delta - \tau)}{\left(C + S_0\frac{1-\delta}{\delta}\right)^2} > 0,$$

since $rL - 2iL = -r_L L^2 > 0$ and $i > \tau$. Thus, by continuity, $\Pi(1)$ can be slack in an equilibrium with $D > S_0/\delta$ in the neighborhood of D' as along as α is sufficiently low.

Next take the derivative of $\Pi(1)$ with respect to D:

$$\frac{d\Pi(1)}{dD} = \frac{dfC}{dC}\frac{dC}{dD} - \tau\frac{dS_0}{dD} - \alpha(C + D - S_0)\left(\frac{dC}{dD} + 1 - \frac{dS_0}{dD}\right) + i. \tag{11}$$

Totally differentiating (9), for $\mu = 0$, we get that

$$\frac{dS_0}{dD} = \frac{\delta + dC/dD}{2-\rho}. \tag{12}$$

Substituting (8) and (9) for $\mu = 0$, as well as (12) in (11), after some algebra, we get

$$\begin{aligned}\frac{d\Pi(1)}{dD} = &-\frac{dC}{dD}\frac{\alpha}{4-2\rho}\left[(1-\rho)^2\delta D + (1-\rho)(C + D - S_0) + (1-\rho)(D - S_0)\right] \\ &-\frac{\tau\delta}{2-\rho} - \alpha(C + D - S_0)\frac{2-\rho-\delta}{2-\rho} + i < 0,\end{aligned} \tag{13}$$

for sufficiently low i since $dC/dD > 0$ for $\mu = 0$ from 10. Given that for $D \to \infty$ we have that $\Pi(1) \to -\infty$, there exists a level of deposits $\bar{D}$ that the constraint becomes binding.

Finally, totally differentiating $\Pi(1) = 0$ requires that $d\Pi(1)/dD = 0$. Evaluating this condition at $D = \bar{D}$, at which point $\mu \to 0$, implies that $dC/dD < 0$ from (13). Hence, the complementarity between deposit-funding and credit-line issuance breaks down when the out-of-equilibrium solvency constraint starts binding. It follows that for all $D > \bar{D}$, the level of C is below its level before the solvency constraint starts binding; otherwise the bank would need to fund these higher commitments with more expensive funding given that it would need to, inefficiently, hold excess liquid assets to cover all out-of-equilibrium deposit withdrawals. $\square$

B Data

We make use of several confidential and public data sources to reconstruct bank balance sheets and lending terms. This appendix outlines the filtering criteria applied to construct the final dataset used in the analysis. We implement a series of selection rules to ensure data consistency and mitigate potential biases.

FR 2052a. The unit of analysis from the FR 2052a is the consolidated Bank Holding Company. Our analysis focuses on Product Instruction O.D which reports bank deposits by type (operational (O.D.4), non-operational (O.D.6), transactional, etc), where each product instruction sub-category reports on the status of deposit insurance (FDIC insured or not), maturity (open or dates to maturity), currency (USD, EUR, etc), and counterparty (retail, corporate, government, financial institution, etc). In our analysis we consider USD-denominated deposits and aggregate over all deposit types. We mainly differentiate along the deposit insurance status and counterparty-type, focusing in particular on NBFIs. Daily data are then aggregated to monthly averages for each bank-year.

There is a reporting transition for FR2052a in April 2022 that expanded the set of NBFI counterparty categories. Before the reporting change there were three broad categories of NBFIs: Supervised Non-Bank Financial Entities (SNBFEs), Debt Issuing Special Purpose Entities (DISPEs), and Other Financial Entities (OFEs). SNBFEs include supervised institutions such as investment advisors, (certain) investment companies, brokers/dealers, and insurance companies. DISPEs issue (or have issued) commercial paper or securities to finance their purchases or operations. OFEs comprise institutions such as (certain) investment companies as well as hedge funds or private equity funds. Our main NBFI deposits series aggregates all these three categories.

The change introduced additional granularity in NBFI types which further included Broker Dealers, Non-regulated Funds, Debt Issuing Special Purpose Entities, Pension Funds, Other Supervised Non-Bank Financial Entities, Financial Market Utilities, and Investment Companies. Our main NBFI series aggregates all these new categories after the change. Note that from the three NBFI categories before the change only Debt Issuing Special Purpose Entities continued to be reported the same way after the change, while the information in the other was disaggregated in way that they cannot be unambiguously reconstructed.

To avoid discontinuities and/or double reporting during the first several months of the transition, we hand-checked, bank-by-bank, the NBFI aggregate series and, separately, each subseries was reported the same way before and after the change. We interpolated the data at the daily level for each series when the reporting transition led to a big discontinuity in reported values and then aggregate our series to the monthly level.

Deposit rates. We utilize two different Ratewatch datasets, one with retail rates and the other with business rates. We leveraged a Ratewatch retail rate database that included information on different deposit products and associate rate information that was aggregated to the BHC level and filtered out for Y-14 reporting banks. After merging monthly raw business rate files together with raw institutional detail data, and appending each monthly file together, the business rate data was in a similar state to the cleaned retail data. From here, were able to roll up and subset the business rate data in a similar way. Then we create some dummy variables, one which denotes if a product is for amounts greater than $250k, and another if the rate is retail. From here, we append the retail and business rate data together.

Banks balance sheet. Bank balance sheet data are collected from the Y9-C using bank holding company RSSDs, which accounts for any bank mergers. For the second stage of analysis (Stage 2) on credit commitments, we convert the monthly data to quarterly averages for every column in FR2052a to merge with FRY-14Q.

Y-14Q. The FR Y-14Q dataset covers bank holding companies (BHCs), savings and loan holding companies (SLHCs), and U.S. intermediate holding companies (IHCs) of foreign banking organizations (FBOs). It includes quarterly loan-level data collected as part of the Federal

Reserve's Comprehensive Capital Analysis and Review (CCAR). Institutions covered have consolidated assets exceeding $50 billion (increased to $100 billion from 2019 onward), capturing more than 85 percent of the U.S. banking sector assets.

The population of loans in the FR Y-14Q is reported at the credit facility (loan) level and is restricted to commercial and industrial loans with a committed balance of at least $1 million. Each facility is reported separately, even if a borrower has multiple facilities with the same bank. Facility-level details include total committed and utilized amounts, pricing and spread information, origination and maturity dates, and collateral information. Loans are categorized primarily as held-for-investment (HFI), representing approximately 98 percent of total loan amounts. The total committed amount reported on the FR Y-14Q as of 2019Q4 is approximately $3.3 trillion, accounting for around 70 percent of U.S. commercial and industrial lending relative to FR Y-9C reports.[29]

The FR Y-14Q also provides comprehensive financial information (balance sheets and income statements) on borrowing firms, which is particularly valuable for privately held U.S. firms that are typically not covered in other datasets. Borrower identifiers, such as tax identification numbers, CUSIPs, and company names and addresses, enable matching with external sources to distinguish borrower types (e.g., public versus private firms, SMEs versus large firms, syndicated versus non-syndicated loans). For public companies we merge FR Y-14 with Compustat by firm EIN to obtain their balance sheet information. Finally, we merge in geographic census data information to get MSAs for each firms in our sample.

Data Cleaning and Sample Construction. This section describes the intensive data cleaning process needed to use the FR Y14 data for our purposes.

1. Remove from the raw loan-level data loans issued to "Individuals" and loans to foreign addresses.

2. Remove any loans to financial firms (NAICS 52); real estate REITS (NAICS 513); educational servies (NAICS 611); religious, grantmaking, and civil and professional organizations (NAICS 813); and private household (NAICS 814).

[29] We keep loans identified on the FR Y-9C as C&I loans domiciled in the U.S. (item 4(a)), loans to finance agricultural production (item 3), loans secured by owner-occupied real estate domiciled in the U.S. (item 1(e)(1)), and other leases (item 10(b)).

3. Drop all observations for which there is no financial data reported and when total firm assets are missing or equal to 0.

4. Drop all facilities where the total value of commitments is less than $1 million (probable errors given reporting threshold).

5. To consistently identify firms across banks with missing or different tax ids, we first apply a name cleaning algorithm to make a consistent names for firms that are the same based on string matches, zipcode, and city. For example Firm A LLC, 20002 Washington D.C, Firm A Limited Liability Corporation 20002 Washington D.C., and Firm a LLC, 20002 Washington D.C. are all treated as the same firm, etc.

6. Once we have a clean and uniform set of firm names, we can fill in missing tax ids. For observations loans where firm tax id is missing, we fill in missing observations if the bank reports a consistent tax id through any portion of the loan; for multi-bank borrowers for which one bank does not report the tax id, we use a consistent tax id reported by other banks.

7. To ensure that firm income statement and balance sheet variables are reasonable and reported in consistent units, we apply a cleaning algorithm that searches for large reporting discrepancies within and across banks over time for the same firm. We set threshold for potential misreported to be a difference in a variable either by the same bank or across different banks of either 10^3, 10^6, 10^9 since these are most common unit differences reported in the data. We also note that when there is miss reporting, all variables appear to be consistently miss reported in the same units, so financial ratios are correct.

Internal Consistency of Balance Sheet Information. We follow Gopinath, Kalemli-Ozcan, Karabarbounis, and Villegas-Sanchez (2017) to check the sensibility of our cleaning procedure by comparing the sum of variables belonging to some aggregate of their respective category:

1. The sum of tangible fixed assets, intangible fixed assets, and other fixed assets as a ratio of total fixed assets.

2. The sum of fixed assets and current assets as a ratio of total assets

3. The sum of long-term debt and other non-current liabilities as a ratio of total non-current liabilities
4. The sum of cash and securities, inventory, and accounts receivable as a ratio of current assets
5. The sum of current assets and tangible assets as a ratio of total assets
6. The sum of accounts payable, short-term debt, and current maturity long-term debt as a ratio of current liabilities
7. The sum of current liabilities, long-term debt and minority interest as a ratio of total liabilities
8. The sum of total liabilities, retained earnings, and capital expenditure as a ratio of total assets.

C Additional tables

Table OA1: Variable definitions and sources

Name	Description	Source
Policy Variables:		
QE	A dummy equal to one from March 2020 to March 2022, indicating the quantitative easing period.	Own calculations
QT	A dummy equal to one from June 2022 onwards, indicating the quantitative tightening period.	Own calculations
Deposits and Shares:		
Shares	The share of uninsured NBFI deposits in total deposits as of February 2020.	FR 2052a
Average shares	A dummy equal to one for firms with more than 50% of their lending relationships with exposed banks.	FR 2052a, FR Y-14Q
Total uninsured deposits exc. NBFI	The total amount of deposits that are not covered by deposit insurance excluding non-bank financial institution (NBFI) deposits.	FR 2052a
Total uninsured deposits	The total amount of deposits that are not covered by deposit insurance.	FR 2052a
Total insured deposits	The total amount of deposits that are covered by deposit insurance.	FR 2052a
Uninsured NBFI	The amount of (uninsured) deposits from NBFIs that are not covered by deposit insurance.	FR 2052a
Insured NBFI	The amount of (insured) deposits from NBFIs that are covered by deposit insurance.	FR 2052a
Uninsured retail	The amount of (uninsured) deposits from retail customers that are not covered by deposit insurance.	FR 2052a
Insured retail	The amount of (insured) deposits from retail customers that are covered by deposit insurance.	FR 2052a
Total deposits	The total amount of total deposits, including both insured and uninsured deposits.	FR 2052a
Rates on insured deposits	The interest rate paid on insured deposits.	RateWatch
Rates on uninsured deposits	The interest rate paid on uninsured deposits.	RateWatch
NBFI Variables:		
NBFI credit	The total amount of credit extended to NBFIs.	FR 2052a, FR Y-14Q
Supervised NBFI	NBFI deposits from supervised entities, including investment advisors, insurance companies, and broker-dealers.	FR 2052a
Non-supervised NBFI	NBFI deposits from non-supervised entities, including hedge funds, private equity funds, investment companies, and REITs.	FR 2052a
Loan-Level Variables:		

Continued on next page

Table OA1 – continued from previous page

Name	Description	Source
Total commitments	The total amount committed across all credit lines and term loans, including both utilized and undrawn amounts.	FR Y-14Q
On-balance sheet commitments	The sum of utilized credit lines and term loans.	FR Y-14Q
Utilized & drawn credit	The combined total of drawn credit lines and utilized term loans.	FR Y-14Q
Undrawn credit Lines	The amount of credit lines that has been committed but not yet drawn.	FR Y-14Q
Utilized credit lines	The amount drawn and used from the available credit line.	FR Y-14Q
Term loans	The amount of term loans.	FR Y-14Q
Rate on credit lines	The interest rate charged on utilized credit lines.	FR Y-14Q
Rate on term loans	The interest rate charged on term loans.	FR Y-14Q
Bank Characteristics:		
Bank size	The logarithm of total bank assets.	FR Y-9C
GSIBS	A dummy equal to one for Global Systemically Important Banks.	Own calculations
Tier 1 capital ratio	The ratio of Tier 1 capital to total assets.	FR Y-9C
C&I loans	The total amount of commercial and industrial loans.	FR Y-9C
Treasury & agency securities	The total amount of Treasury and agency securities held by the bank.	FR Y-9C

Table OA2: List of banks in FR 2052a and FR Y-14 samples

Bank Name	Total assets ($ bn)	Total deposits ($ bn)	C&I/TA	CR	LCR
JPMORGAN CHASE & CO$^+$	2688	1563	0.05	0.14	1.16
BANK OF AMER CORP$^+$	2434	1435	0.10	0.13	1.16
CITIGROUP$^+$	1951	1071	0.04	0.13	1.15
WELLS FARGO & CO$^+$	1928	1323	0.09	0.13	1.20
GOLDMAN SACHS GROUP THE$^+$	993	190	0.02	0.15	1.27
MORGAN STANLEY$^+$	895	190	0.02	0.19	1.34
U S BC	495	362	0.16	0.11	1.07
PNC FNCL SVC GROUP	410	289	0.22	0.11	1.07
TD GRP US HOLDS LLC	409	285	0.08	0.16	1.06
CAPITAL ONE FC	390	263	0.10	0.14	1.41
BANK OF NY MELLON CORP$^+$	382	260	0.00	0.14	1.20
HSBC N AMER HOLDS	249	116	0.11	0.14	1.14
STATE STREET CORP$^+$	246	182	0.01	0.15	1.10
ALLY FNCL	181	121	0.22	0.11	1.24
BMO FNCL CORP	173	104	0.23	0.12	1.49
MUFG AMERS HOLDS CORP	171	96	0.10	0.14	1.52*
FIFTH THIRD BC	169	127	0.27	0.11	1.15
CITIZENS FNCL GRP	166	126	0.23	0.11	1.15*
SANTANDER HOLDS USA	149	67	0.12	0.16	1.44*
KEYCORP	146	112	0.27	0.11	1.45
RBC US GRP HOLDS LLC	140	53	0.06	0.17	1.28
UBS	139	56	0.04	0.28	1.34*
NORTHERN TR CORP	137	109	0.03	0.14	1.10
REGIONS FC	127	98	0.19	0.11	1.10
BNP PARIBAS	125	67	0.11	0.16	1.25*
M&T BK CORP	120	95	0.16	0.11	1.21
DEUTSCHE BANK	109	19	0.02	0.38	1.75
HUNTINGTON BSHRS	109	82	0.21	0.11	1.49
BBVA USA BSHRS	94	75	0.18	0.13	1.28*

Note: The table lists the banks in our final sample, which report both FR 2052a and FR Y-14 data. $^+$ indicates daily FR2052a filers. Total assets and total deposits are in $ billion in 2019Q4. C&I/TA is the share of C&I loans in total assets in 2019Q4. CR and LCR are the Tier-1 capital ratio and the Liquidity Coverage Ratio in 2019Q3 or 2019Q4. Sources for balance sheet data: FR Y-9C and public disclosures. (*) indicates the global LCR.

Table OA3: NBFI uninsured deposits: Supervised and non-supervised NBFIs

	1	2	3	4
Dependent variable:	Log(uninsured NBFI deposits)			
Group	Supervised NBFI		Non-supervised NBFI	
QE * Shares	2.615***	2.735***	0.064	0.061
	(3.556)	(4.106)	(1.045)	(0.977)
Bank control		Y		Y
Month FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Observations	1,736	1,734	1,625	1,623
R-squared	0.877	0.877	0.952	0.952

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(\mathit{Un.\ NBFI}_{i,t}) = \lambda \cdot (QE_t \cdot \mathit{Shares}_i) + \beta \cdot \mathit{Bank\ Size}_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $\log(\mathit{Un.\ NBFI}_{i,t})$ is the logarithm of uninsured NBFI deposits held by bank i in month t. QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. Shares_i indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. The *Bank control* indicates whether we control for time-varying bank size (logarithm of total assets). The terms a_i and a_t represent bank and month fixed effects, respectively. Columns (1)-(2) examine uninsured deposits from Supervised Non-Bank Financial Entities, which include regulated institutions such as investment advisors, brokers/dealers, and insurance companies. Columns (3)-(4) analyze uninsured deposits from Non-Supervized Non-Bank Financial Entities, comprising institutions registered with the SEC under the Investment Company Act of 1940, as well as hedge funds and private equity funds. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA4: Demandable NBFI uninsured deposits

	1	2	3	4	5	6
Dependent variable:	Log(Demandable uninsured NBFI deposits)					
QE * Shares	0.423***	0.410***	0.350***	0.435****		0.344***
	(4.153)	(4.063)	(2.994)	(3.824)		(2.971)
QT * Shares			-0.351**			
			(-2.578)			
Bank size		-0.207	-0.227	-0.195	-0.207	-0.142
		(-1.283)	(-1.411)	(-1.227)	(-1.285)	(-0.516)
QE * GSIBS				-0.055		
				(-1.158)		
QE (SLR rel.)* Shares					0.444***	
					(4.302)	
QE (SLR act.)* Shares					0.377***	
					(3.618)	
NBFI credit						0.117***
						(3.031)
Month FE	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Observations	2,028	2,026	2,026	2,026	2,026	2,015
R-squared	0.907	0.906	0.906	0.906	0.906	0.907

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(\textit{Un. NBFI}_{i,t}) = \lambda \cdot (QE_t \cdot \textit{Shares}_i) + \beta \cdot \textit{Controls}_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $\log(\textit{Un. NBFI}_{i,t})$ is the logarithm of demandable uninsured NBFI deposits held by bank i in month t. QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. $\textit{Shares}_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. $\textit{Bank Size}_{i,t}$ is the logarithm of total assets. *GSIBS* is a dummy equal to one for Global Systemically Important Banks. *QE (SLR rel.)* refers to the SLR relaxation and exclusion of securities and reserves from SLR calculations between April 1, 2020, and April 1, 2021, while *QE (SLR act.)* marks the re-activation of SLR criteria. *NBFI Credit* is the logarithm of total outstanding credit, including credit lines and term loans, that NBFIs received. The terms a_i and a_t represent bank and month fixed effects, respectively. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA5: Fiscal transfers during Covid-19

	1	2	3	4
Dependent variable:	Log(Total retail insured deposits)		Log(Corporate insured deposits)	
QE * Shares	0.158	0.157	-0.086	-0.093
	(1.460)	(1.185)	(-0.799)	(-0.895)
Bank control		Y		Y
QT control		Y		Y
Month FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Observations	2,339	2,335	2,212	2,208
R-squared	0.974	0.978	0.958	0.967

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $log(Y_{i,t}) = \lambda \cdot (QE_t \cdot Shares_i) + \beta \cdot Controls_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $Y_{i,t}$) is the dependent variable, denoting either total retail insured deposits (Columns 1–2) or corporate insured deposits (Columns 3–4) for bank i in month t. QE_t is a dummy equal to one from March 2020 to March 2022. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. $Bank\ Size_{i,t}$ is the logarithm of total assets. The *Bank control* indicates whether we control for time-varying bank size (logarithm of total assets), and the *QT control* indicates whether the interaction term $QT_t \cdot Shares_i$ is included. The terms a_i and a_t represent bank and month fixed effects, respectively. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA6: Other deposit categories & Liquidity Coverage Ratios

	1	2	3	4
Dependent variable:	Log(Total deposits)	Log(Total uninsured deposits)	Log(Total uninsured deposits exc. NBFI)	Log(Total insured deposits)
QE*Shares	-0.042	-0.237***	-0.384***	1.599***
	(-1.175)	(-6.093)	(-8.268)	(14.072)
QE*LCR	0.001***	0.002***	0.002***	-0.012***
	(2.856)	(6.648)	(6.123)	(-6.466)
Bank control	Y	Y	Y	Y
QT control	Y	Y	Y	Y
QT·LCR control	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Observations	2,145	2,145	2,145	2,000
R-squared	0.988	0.982	0.980	0.959

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,t}) = \lambda \cdot (QE_t \cdot Shares_i) + \mu \cdot (QE_t \cdot LCR_i) + \beta \cdot Controls_{i,t} + a_i + a_t + \varepsilon_{i,t}$, where $Y_{i,t}$ is the dependent variable labeled in each column for bank i in month t. QE_t is a dummy equal to one from March 2020 to March 2022. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. LCR_i is the liquidity coverage ratio of bank i in 2019Q4. The *Bank control* indicates whether we control for time-varying bank size (logarithm of total assets), and the *QT control* indicates whether the interaction term $QT_t \cdot Shares_i$ and $QT_t \cdot LCR_i$ is included. The terms a_i and a_t represent bank and month fixed effects, respectively. Observations are monthly, except for total assets, which are reported quarterly. Standard errors are clustered at the month level. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA7: Net Charge-Offs categories and NBFI Exposure: Pre-QE period

	1	2	3	4
Dependent variable:	C&I Loans	Land Loans	Consumer Loans	Family Residential
Shares	-5.31^{***}	-0.13	-2.73^{**}	-0.02
	(1.21)	(1.02)	(0.12)	(0.35)
Time FE	Yes	Yes	Yes	Yes
Observations	350	350	350	350
R-squared	0.131	0.042	0.019	0.038

Note: This table reports coefficients from cross-sectional regressions of net charge-offs on bank's *shares*. All dependent variables are net charge-offs (NCOs) normalized by total assets. The sample includes data from the pre-QE period. Time fixed effects are included in all specifications. Robust standard errors are in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA8: Credit lines, Term loans, and Total Loan Commitments

	1	2	3	4	5	6
Dependent variable:	Log(Credit lines)		Log(Term loans)		Log(Total loan commitments)	
QE*Shares	-0.120***	-0.133***	-0.007	0.038	-0.134***	-0.164***
	(-2.888)	(-3.354)	(-0.073)	(0.416)	(-3.192)	(-3.895)
QT*Shares	-0.260***	-0.270***	-0.090	-0.087	-0.305***	-0.359***
	(-3.891)	(-4.633)	(-0.570)	(-0.579)	(-4.221)	(-5.186)
Bank*Firm FE	Y	Y	Y	Y	Y	Y
ILST FE	Y		Y		Y	
Firm*Time FE		Y		Y		Y
Observations	655,814	328,905	243,258	95,469	952,707	404,116
R-squared	0.966	0.942	0.953	0.919	0.962	0.935

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot Shares_i) + \lambda_2(QT_t \cdot Shares_i) + \beta X_{i,t} + a_i + a_{f,t} + \varepsilon_{i,f,t}$. The dependent variable for each bank i, firm f, and time period t is the logarithm of credit lines (columns 1 to 2), the logarithm of term loans (columns 3 to 4), and the logarithm of total commitment, which is the sum of the two (columns 5-6). QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Observations are at the bank-firm-time level and are reported quarterly. Standard errors are clustered at the bank-quarter and firm levels. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA9: Utilized & Undrawn Credit Lines, and Total On-balance sheet Loan Commitments

	1	2	3	4	5	6
Dependent variable:	Log(Utilized credit lines)		Log(Undrawn credit lines)		Log(On-balance sheet commit.)	
QE*Shares	-0.006	-0.115	-0.191***	-0.142***	-0.090	-0.120
	(-0.057)	(-1.178)	(-3.472)	(-3.337)	(-1.033)	(-1.452)
QT*Shares	-0.055	-0.119	-0.360***	-0.295***	-0.122	-0.167
	(-0.322)	(-0.819)	(-4.384)	(-4.807)	(-0.883)	(-1.218)
Bank*Firm FE	Y	Y	Y	Y	Y	Y
ILST FE	Y		Y		Y	
Firm*Time FE		Y		Y		Y
Observations	425,895	192,968	569,704	310,230	736,103	296,247
R-squared	0.859	0.870	0.897	0.941	0.869	0.867

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot \mathit{Shares}_i) + \lambda_2(QT_t \cdot \mathit{Shares}_i) + \beta X_{i,t} + a_i + a_{f,t} + \varepsilon_{i,f,t}$. The dependent variable for each bank i, firm f, and time period t is the logarithm of utilized credit lines (columns 1 to 2), the logarithm of undrawn credit lines (columns 3 to 4), and the logarithm of on-balance sheet loan commitments, which is the sum of the two (columns 5-6). QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. Shares_i indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Observations are at the bank-firm-time level and are reported quarterly. Standard errors are clustered at the bank-quarter and firm levels. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA10: Credit lines: Interest rates & new issuance

	1	2	3	4	5	6	7	8
Dependent variable:	Log(Interest rate on credit lines)				Log(Newly issued credit lines)			
QE*Shares	0.003	0.001	0.003	0.002	-0.197	-0.294**	-0.143	-0.234
	(0.787)	(0.354)	(0.645)	(0.474)	(-1.362)	(-2.417)	(-0.796)	(-1.561)
QT*Shares	0.021***	0.021***	0.025***	0.026***	-0.119	-0.117	-0.114	-0.103
	(3.067)	(3.091)	(3.275)	(3.645)	(-0.811)	(-0.990)	(-0.706)	(-0.804)
Bank size			0.002	0.004			-0.163	-0.228
			(0.618)	(1.240)			(-0.636)	(-1.126)
Bank reserves			0.000	0.000			0.029	0.022
			(0.519)	(0.098)			(1.059)	(1.050)
Bank treasuries & agencies			0.001*	0.002**			0.005	0.013
			(1.888)	(2.254)			(0.096)	(0.304)
Bank insured deposits			0.000	-0.000			0.077	0.093
			(0.172)	(-0.122)			(0.807)	(1.159)
Bank uninsured deposits			0.009***	0.009***			-0.049	-0.028
			(4.340)	(4.206)			(-0.410)	(-0.309)
Bank*Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
ILST FE	Y		Y		Y		Y	
Firm*Time FE		Y		Y		Y		Y
Observations	617,829	308,407	595,106	297,643	9,991	9,058	9,825	8,899
R-squared	0.775	0.798	0.777	0.799	0.839	0.780	0.843	0.783

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot Shares_i) + \lambda_2(QT_t \cdot Shares_i) + \beta X_{i,t} + a_i + a_{f,t} + \varepsilon_{i,f,t}$. The dependent variable for each bank i, firm f, and time period t is the logarithm of rates on credit lines (columns 1 and 4) and the new credit lines (columns 5 to 8). QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. *Bank size*$_{i,t}$ is the logarithm of total assets, and *Bank reserves* is the logarithm of reserves. The variables *Bank insured deposits* and *Bank uninsured deposits* represent the logarithm of insured and uninsured deposits, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Observations are at the bank-firm-time level and are reported quarterly. Standard errors are clustered at the bank-quarter and firm levels. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA11: Undrawn credit lines for liquidity constrained firms

	1	2
Dependent variable:	Log(Undrawn credit lines)	
QE*Shares	-0.150***	-0.181***
	(-3.148)	(-3.619)
QE*Shares*Liquidity	0.060	0.026
	(0.688)	(0.283)
QE*Shares*Covid	-0.507	-0.419
	(-1.057)	(-0.814)
QE*Shares*Covid*Liquidity	-1.616***	-1.663***
	(-2.766)	(-2.731)
QT*Shares	-0.320***	-0.349***
	(-4.651)	(-5.065)
QT*Shares*Liquidity	0.092	0.059
	(0.766)	(0.485)
QT*Shares*Covid	-0.029	0.040
	(-0.064)	(0.084)
QT*Shares*Covid*Liquidity	1.202	1.413
	(0.633)	(0.658)
Bank Size		0.070**
		(2.083)
Bank reserves		-0.005
		(-0.976)
Bank treasuries & agencies		-0.021**
		(-2.278)
Bank insured deposits		-0.029
		(-1.542)
Bank uninsured deposits		0.023
		(0.933)
Bank*Firm FE	Y	Y
Firm*Time FE	Y	Y
Observations	293,416	284,562
R-squared	0.941	0.941

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{i,f,t}) = \lambda_1(QE_t \cdot Shares_i) + \mu_1(QE_t \cdot Shares_i \cdot Liquidity_f) + \zeta_1(QE_t \cdot Shares_i \cdot Covid_f) + \psi_1(QE_t \cdot Shares_i \cdot Covid_f \cdot Liquidity_f) + \lambda_2(QT_t \cdot Shares_i) + \mu_2(QT_t \cdot Shares_i \cdot Liquidity_f) + \zeta_2(QT_t \cdot Shares_i \cdot Covid_f) + \psi_2(QT_t \cdot Shares_i \cdot Covid_f \cdot Liquidity_f) + \beta X_{i,t} + a_i + a_{f,t} + \varepsilon_{i,f,t}$. The dependent variable for each bank i, firm f, and time period t is the logarithm of undrawn credit lines. QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onward. $Shares_i$ indicates the share of uninsured NBFI deposits in total deposits for bank i as of February 2020. $Covid_f$ is a dummy indicating that firm f operates in an industry heavily impacted by the COVID-19 pandemic. We following NAICS industries are defined to be heavily impacted by the pandemic: 721110–Hotels (except Casino Hotels) and Motels; 722511–Full-service restaurants; 722513–Limited-Service Restaurants; 722514–Cafeterias, Grill Buffets, and Buffets; and 722515–Snack and Nonalcoholic Beverage Bars. $Liquidity_f$ is a dummy that takes the value of one if the ratio of sales to accounts receivable for firm f at 2019Q4 is higher than the median for all firms at 2019Q4. $Bank\ size_{i,t}$ is the logarithm of total assets, and *Bank reserves* is the logarithm of reserves. The variables *Bank insured deposits* and *Bank uninsured deposits* represent the logarithm of insured and uninsured deposits, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Observations are at the bank-firm-time level and are reported quarterly. Standard errors are clustered at the bank-quarter and firm levels. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table OA12: Aggregate effects at firm level: Alternative exposure measures

	1	2	3	4	5
Dependent variable: Dependent variable:	Log(Utilized credit lines)	Log(Undrawn credit lines)	Log(Term loans)	Log(Total commitments)	Log(Investment)
QE *Weighted Shares Exposure	0.217	-0.346*	0.124	-0.051	-2.629***
	(1.266)	(-1.902)	(0.866)	(-0.763)	(-2.931)
QT *Weighted Shares Exposure	0.165	-0.596**	0.133	-0.220*	-1.792
	(0.579)	(-2.656)	(0.570)	(-2.022)	(-1.554)
Observations	223,976	256,001	122,718	497,200	43,199
R-squared	0.820	0.798	0.929	0.951	0.817
QE *Relationships Dummy	-0.014	-0.071***	0.001	-0.014*	-0.354***
	(-0.515)	(-2.926)	(0.072)	(-1.800)	(-4.130)
QT *Relationships Dummy	-0.105**	-0.095***	0.036	-0.029**	-0.454***
	(-2.729)	(-3.507)	(1.428)	(-2.301)	(-3.573)
Observations	223,976	256,001	122,718	497,200	43,199
R-squared	0.820	0.798	0.929	0.951	0.817
ILST FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y

Note: The table reports coefficients and t-statistics (in parentheses) for the following regression equation: $\log(Y_{f,t}) = \lambda_1(QE_t \cdot Exposure_f) + \lambda_2(QT_t \cdot Exposure_f) + a_{ILST} + a_f + \varepsilon_{f,t}$, where the dependent variable for each firm f in time period t is the sum of credit the firm received. The dependent variables are: the logarithm of utilized credit lines (column 1), the logarithm of undrawn credit lines (column 2), the logarithm of term loans (column 3), the logarithm of total commitments (column 4) and the logarithm of investments (column 5). $Exposure_f$ is a measure of how exposed a firm is to the QE-induced fragility via the loan relationships that firm has with exposed banks. We report results for two measures of exposure, $Exposure_f = \{Weighted\ Shares\ Exposure_f, Relationships\ Dummy_f\}$, all computed using information at 2019Q4. $Weighted\ Shares\ Exposure_f$ is the weighted average share S_i among those banks with which a firm f has loan relationships at 2019Q4, where the weights are given by the loan commitments firm f has with bank i other the total firm-f commitments with all banks. $RelationshipsDummy_F$ is a dummy equal to one for firms with $AverageRelationships_f > 0.5$, i.e, with more than 50% of their lending relationships are with more exposed banks. QE_t is a dummy equal to one from March 2020 to March 2022, and QT_t is a dummy equal to one from June 2022 onwards. The regression includes industry-location-size-time (a_{ILST}) and firm (a_f) fixed effects. Standard errors are clustered at the firm level. Variable definitions and data sources are provided in Appendix C. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.