Why did bank stocks crash during COVID-19?

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Abstract

We provide evidence consistent with a "credit-line drawdown channel" to explain the large and persistent crash of bank stock prices during the COVID-19 pandemic. Stock prices of banks with large *ex-ante* exposures to undrawn credit lines and large *ex-post* gross drawdowns declined more, especially of banks with weaker capital buffers. These banks reduced new lending, even after stabilization policies and even if drawdowns were accompanied by deposit inflows. Bank provision of credit lines appears akin to writing deep out-of-the-money put options on aggregate risk; we show how the resulting risks can be incorporated tractably into bank capital stress tests.

Keywords: Credit lines, liquidity risk, bank capital, loan supply, stress tests, pandemic, COVID-19.
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1. Introduction

Since the global financial crisis (GFC) of 2008--09, banks have greatly expanded their liquidity provision through credit lines to the United States (U.S.) non-financial sector. Panel A of Figure 1 shows that credit lines for the U.S. publicly listed firms increased from 0.7% of GDP in 2009 to 5.7% of GDP in 2019 leading to a substantial build-up of (aggregate) drawdown risk on bank balance-sheets. This risk materialized in March 2020 amid the outbreak of the COVID-19 pandemic and subsequent government-imposed lockdowns. Firms' cash flows dropped, in some cases by as much as 100%, while operating and financial leverage remained sticky, causing bond markets to freeze. As a consequence, U.S. firms with pre-arranged credit lines from banks drew down their undrawn facilities with a far greater intensity than in past recessions as shown in Panel B of Figure 1.[1] Recent data shows that firms benefited from having such access to pre-arranged credit lines during the pandemic when capital market funding froze (*e.g.*, Acharya and Steffen, 2020a; Chodorow-Reich *et al.*, 2021; Greenwald *et al.*, 2021).[2] On the flip side, however, banks faced unprecedented aggregate demand for credit-line drawdowns; an important but not well-appreciated consequence is that banks' share prices crashed and have persistently underperformed those of non-financial firms (Panel C of Figure 1).

In this paper, we investigate causes and consequences of the crash of bank stocks during the COVID-19 pandemic and highlight a central role played by bank credit-line drawdowns. Specifically, we ask what are the possible transmission channels through which the drawdowns affected bank stock returns and ultimately banks' intermediation functions for the real

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[1] A leading example is that of Ford Motor Company, which was one of the largest U.S. firms to draw down its credit lines in March 2020, withdrawing USD 15.4bn (Appendix I shows the SEC filings). It was still BBB- rated by S&P at this time. With USD 20bn in cash, credit lines make up a large part of its overall liquidity. Ford pays 15bps in commitment fees for any dollar-undrawn credit and 125bps once credit lines have been drawn down and thus USD 23.1mn as long as the credit line was undrawn, and USD 192.5mn annually once the credit line was fully utilized. Importantly, once Ford was downgraded to non-investment grade, commitment fees increased to 25bps and credit spreads to 175bps, an increase of 67% and 40%, respectively.

[2] Within three weeks, public firms drew down more than USD 300bn, with drawdowns particularly concentrated among riskier BBB-rated and non-investment-grade firms. Li et al. (2020) show – using call report data which includes drawdowns by private firms – that drawdowns amounted to more than USD 500bn.

economy? Which aspects of these channels during the COVID-19 episode are different compared to the GFC? And, how can bank regulation incorporate these channels to safeguard against the attendant risks in future? These appear to be first-order questions given the unique role played by banks in providing liquidity insurance to non-financial firms in the form of credit lines, and the substantial build-up of bank credit lines to these firms since the GFC.

[Figure 1 about here]

At the core of our analysis is a new and comprehensive measure of the balance-sheet *liquidity risk* of banks defined as *undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets).* We show that our measure of the liquidity risk of banks helps understand the decline of bank stock prices, especially during the first phase of the pandemic, *i.e.*, from January 1, 2020 until March 3, 2020, before decisive monetary and fiscal support measures were introduced.[3] During this phase of the pandemic, stock prices of banks with high balance-sheet liquidity risk underperformed relative to those of banks with low balance-sheet liquidity risk. A one-standard-deviation increase in liquidity risk decreased stock returns by about 8.5% during this period, or 12.5% of the unconditional mean return. A possible concern is that liquidity risk through the provision of credit lines is correlated with bank portfolio composition, as banks facing larger drawdowns may be engaged with riskier borrowers who are more vulnerable to financial and economic crises. We provide a variety of tests to isolate the effect of credit-line exposure on bank stock returns.

First, we include control variables to account for real estate exposure and derivatives activity and an indicator variable for dealer banks as well as off-balance-sheet credit card exposures and consumer loans.[4] We also include comprehensive portfolio risk measures such as the percentage of non-performing loans and a bank's distance-to-default, and proxies for

[3] See in particular Kovner and Martin (2020) on the range of special facilities set up by the Federal Reserve (Fed) to provide liquidity to a range of fixed-income markets.

[4] Dealer banks appear to have faced regulatory constraints in extending their balance-sheets for market-making, see Boyarchenko *et al.* (2020), Liang and Parkinson (2020), Kargar *et al.* (2021), and Vissing-Jorgensen (2021).

systematic risk and idiosyncratic volatility. Moreover, we add a measure for estimated bank capital shortfalls (based on data as of December 31, 2019) in "stress" (a market decline of 40%, similar to what was observed in March 2020, over a six-month period). We then focus on bank exposures to the most affected industries during the COVID-19 pandemic. Based on the prior literature, we employ 12 different ways to classify COVID-19-affected industries. As portfolio data for banks is not publicly available, we construct stock indices of firms in these industries and then use multifactor models in which the sensitivities (betas) of banks' stock returns to the returns of these indices measure their exposure to COVID-19-affected industries at the end of 2019. We use these betas as proxies for bank portfolio exposure to COVID in our regressions.

Our results on bank stock returns being affected by balance-sheet liquidity risk appear virtually unaffected by these measures of bank portfolio risk and provide a consistent interpretation that balance-sheet liquidity risk is a key driver of bank stock returns at the beginning of the pandemic – independent of the effect of bank portfolio exposures to COVID-affected industries.[5]

We then show that this cross-sectional explanatory power of balance-sheet liquidity risk for bank stock returns is *episodic* in nature. Using separate cross-sectional regressions during the months of January 2020, February 2020 and during the March 1, 2020 to March 23, 2020 period, we show that liquidity risk explains stock returns, particularly during the latter period, when firms' liquidity demand through credit-line drawdowns became highly correlated.[6] The effect disappeared in Q2 2020, *i.e.*, after the decisive monetary and fiscal interventions, but briefly re-surfaced amid the second wave of the pandemic and associated lockdowns in Q3

[5] To reduce dimensionality, we also construct the first principal component of these 12 betas. We also construct bank syndicated loan exposures to COVID-19-affected industries using Refinitiv Dealscan data. They correlate significantly with exposure betas and the first principal component. We use both also as exposures in our regressions. The results are unchanged.

[6] Time-series tests using an aggregate measure of realized cumulative credit line drawdowns show that (daily) bank stock returns are significantly lower when aggregate drawdowns in the economy increase and banks have more balance-sheet liquidity risk.

2020 (the effect is much smaller compared to March 2020).[7] Quantitatively, while banks lost, on average, USD 10bn in market equity until March 23, 2020 (corresponding to 61% of their Q4 2019 market capitalization), they recovered only about 37% of these market-value losses until Q4 2020.

To understand this partial recovery of bank stock prices, we construct a measure of credit-line repayments using a matched sample of banks and firms with data from Call Reports, Refinitiv Dealscan and Capital IQ. In Q2 and Q3 2020, high-quality firms started to repay credit lines once capital markets reopened (see, *e.g.*, Chodorow-Reich et al., 2021). Therefore, we relate the recovery of bank market value loss to the repayment of credit lines in Q2 and Q3 2020. Interestingly, we find that banks that experienced higher credit line repayments recovered *less* of their market value losses. Moreover, this effect is driven by repayments of risky (*i.e.*, non-IG-rated) firms. Note that risky firms contribute more to ongoing liquidity risk for banks once they repay the credit lines. Put differently, investors – while pricing bank stocks – appear to be more concerned with liquidity risk from credit line drawdowns of riskier firms in future if aggregate risk were to resurface, *e.g.*, if lockdown measures were reinstated during further waves of the pandemic, than with the on-balance-sheet credit risk of drawn-down lines.

We analyse two channels through which this sensitivity of bank stock prices to undrawn credit lines can arise: (1) funding liquidity to source new loans can become a binding constraint for banks if deposit funding does not keep pace with credit line drawdowns (the "funding channel"); and, (2) the drawdown of credit lines can lock up scarce bank capital against term loans and impair intermediation by preventing banks from making possibly more profitable loans (the "capital channel").[8]

[7] Interestingly, the Fed had already conducted large interventions in the repo market on March 12, 2020. The OIS-spread, a measure for liquidity conditions in financial markets, had already reverted following these interventions. These interventions were, however, insufficient to stop the further decline of bank stock prices suggesting that liquidity was not the binding constraint for banks at the beginning of the COVID-19 pandemic.

[8] The theoretical literature argues that a key function of bank capital is to absorb risk, *i.e.*, more capital facilitates bank lending. Bhattacharya and Thakor (1993), Repullo (2004), von Thadden (2004), and Coval and Thakor (2005), among others, argue that capital increases risk-bearing capacity. Allen and Santomero (1998) and Allen

To distinguish between these channels, we construct two proxies: (1) *Gross Drawdowns* as the change in credit line drawdowns (relative to total assets); and (2) *Net Drawdowns* as the change in drawdowns minus the change in deposit funding (also relative to total assets). Gross and net drawdowns are not highly correlated but net drawdowns are highly correlated with changes in deposits. Holding net drawdowns fixed, our measure of gross drawdowns can thus help isolate the effect of credit line drawdowns on banks attributable not to funding but to the capital channel. Our tests reveal that while bank stock returns are particularly sensitive to gross drawdowns, they do not load significantly on net drawdowns. Importantly, having more capital and a larger capital buffer at a bank attenuate the negative effect of gross drawdowns on its stock returns; conversely, banks with weaker capital buffers suffer worse stock returns upon drawdowns.

In summary, we infer that balance-sheet liquidity risk of banks affects their stock returns as the manifestation of such risk in the form of credit line drawdowns locks up bank capital away from more profitable intermediation activities. Next, we investigate this mechanism directly by testing whether banks with more balance-sheet liquidity risk reduced their lending during the COVID-19 pandemic by a greater degree relative to other banks. If banks' capital constraints matter, then we expect lending to be particularly sensitive to gross (but not to net) drawdowns.[9] To control for demand effects, *e.g.*, because of lower investments by riskier firms in a period characterized by high uncertainty or because riskier borrowers have already drawn

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and Gale (2004) show that banks with less capital might have to dispose of illiquid assets when facing an adverse shock.

[9] For the banks that provided credit lines to Ford Motors (as described in our introductory example in Footnote 1 above), these commitments were (in aggregate) a USD 15.4bn off-balance-sheet commercial and industrial (C&I) loan commitment as of December 31, 2019. The capital treatment of their commitment depends on whether banks follow the standardized (SA) or internal ratings-based (IRB) approach for credit risk. Under Basel III, the standardized approach differentiates between irrevocable and revocable commitments. Revocable commitments carry a credit conversion factor (CCF) of 10% and irrevocable commitments (with a maturity of more than 12 months) have a CCF of 50%. Assuming an 8% capital requirement, an undrawn credit line thus requires funding in the range of 0.8% to 4% for banks using the SA. For IRB banks – as applies to most of our sample banks – the CCF might be considerably lower (Behn *et al*., 2016). In other words, a bank might need to fund 90% or more of the required capital when a credit line is drawn down and becomes a balance-sheet loan, which adversely impacts other business activities, particularly in an aggregate downturn.

down existing lines of credit, we employ a Khwaja and Mian (2008) estimator, investigating the change in lending of banks to the *same* borrower before and after the outbreak of the pandemic. In additional to control variables that affected loan supply, we absorb time-varying and loan-type-specific loan demand using borrower × time × loan type fixed effect*s*.We use borrower × bank fixed effects to measure changes in credit supply within a borrowing relationship thereby controlling for time-invariant portfolio-composition effects.

We find that banks with high gross drawdowns (but not net drawdowns) actively reduce existing term-loan exposures relative to banks with low gross drawdowns. Moreover, banks with high gross drawdowns reduce new loan originations compared to banks with low gross drawdowns, for both credit lines and term loans. That is, holding the effect of deposit inflows constant, banks that incur a greater impact on equity capital through large credit-line drawdowns reduce lending more than other banks. Finally, we show that firms that borrow from banks with high gross drawdowns respond to the contraction of lending supply by reducing investments in working capital to a greater extent than firms that borrow from banks with low gross drawdowns; these firms also significantly reduce R&D spending and reduce dividend payouts. Overall, aggregate drawdowns at banks appear to have important spillovers for the real economy via the bank capital channel.

How does this pandemic fallout for banks from liquidity risk relate and contrast to that during the GFC, when banks struggled with funding liquidity to meet drawdowns (Acharya and Mora, 2015)? We use the same cross-sectional tests as before and run them quarterly over the Q2 2007 to Q2 2009 period and confirm that the episodic co-movement of stock returns and the balance-sheet liquidity risk of banks is not specific to aggregate drawdown risk during the pandemic, but was also a feature of the GFC. However, there is a significant difference in the compositional effects of liquidity risk between the pandemic and the GFC. Rollover risk for banks rose in Q3 and Q4 2007, *i.e*., in the first phase of the GFC, when the Asset Backed Commercial Paper (ABCP) market froze as documented in Acharya *et al*. (2013). The credit-line drawdown risk for banks increased only thereafter, particularly in Q4 2008 after the Lehman default, abating afterwards when the Federal Reserve and the U.S. government responded to the economic fallout of the Lehman Brothers default with a variety of liquidity, capital and guarantee programmes to support the financial sector. In contrast, rollover risk from wholesale funding risk remained of concern for banks even in Q2 2009, as evidenced in our tests. That is, while unused credit lines were also clearly important during the GFC, wholesale funding exposure and having access to funding liquidity (*i.e.*, cash or deposits) impacted bank stock returns more significantly. Our liquidity risk measure for banks spans both of these risks and works robustly in explaining bank stock returns during both episodes.

A final key question then is how can policy makers address aggregate drawdown risk in an *ex-ante* manner?[10] One possible way is for regulators to add the effect of credit line drawdowns to bank capital stress tests and require banks to fund these exposures with greater equity. Therefore, in our last step, we quantify the capital shortfall that arises due to banks' balance-sheet liquidity risk and show how it can be incorporated tractably into bank stress tests.

Acharya *et al*. (2012), Acharya *et al*. (2016) and Brownlees and Engle (2017) developed the concept of SRISK, a measure of the shortfall in the market equity capital of a bank if there were to be a stressed aggregate market correction (a 40% correction to the global stock market). This measure does not explicitly account for the impact of credit lines, since these are contingent or off-balance-sheet liabilities until drawn down.[11] Our proposed correction to SRISK has two components: (1) Contingent liabilities become loans on bank balance sheets once drawn down; so, we calculate the additional equity capital that would be required to

[10] A related question is whether and how banks already account for aggregate drawdown risk, *e.g.,* through loan contract terms that might limit the extent of correlated drawdowns during episodes of aggregate risk. We investigate two possible ways banks might do that: the pricing of credit lines and design of loan covenants. We find that banks do not appear to be considering the deep out-of-the-money put option associated with aggregate drawdown risk when setting *ex-ante* price terms of credit lines. Moreover, credit line drawdowns (also by firms in the hardest-hit industries) did not appear to be constrained by possible covenant violations during the pandemic.

[11] Adrian and Brunnermeier (2015) develop the concept *CoVaR*, which measures the risk to the financial system conditional on a bank being in distress. Their measure too, like *SRISK*, does not explicitly look at the role of contingent liabilities of banks or their episodic impact on bank returns.

maintain adequacy against higher realized liabilities in periods of stress. (2) We account for the negative episodic effect of liquidity risk on bank stock prices during periods of stress using our cross-sectional regression estimates and compute the associated equity shortfall. Summing both components, we show that the additional capital shortfall for the U.S. banking sector as a whole due to balance-sheet liquidity risk amounted to more than USD 340bn as of December 31, 2019 in such a stress scenario. The incremental capital shortfall of the top 10 banks is about 1.6 times larger than their capital shortfall estimate without accounting for contingent liabilities.

The paper proceeds as follows. Section 2 describes the related literature. In Section 3, we present the data and investigate the impact of balance-sheet liquidity risk on bank stock returns. In Section 4, we show the robustness and extensions of our results. We investigate in Section 5 the channels through which credit line drawdowns affect bank stock returns. Section 6 relates the results to outcomes during the GFC. Section 7 illustrates how to incorporate episodic liquidity risk of bank balance sheets in stress tests and assesses capital shortfalls. Section 8 concludes.

2. Related literature

Our paper relates to the literature highlighting the role of banks as liquidity providers. Kashyap *et al*. (2002) and Gatev and Strahan (2006) propose a risk-management motive to understand the unique role of banks as liquidity providers to both households and firms. Ivashina and Scharfstein (2010) provide evidence of an acceleration of credit-line drawdowns as well as an increase in deposits during the 2007-2009 crisis. During this crisis – in which the banking system itself was at the centre – Acharya and Mora (2015) show that banks faced a crisis as liquidity providers and could only perform this role because of significant support from the government. During the COVID-19 pandemic, however, which directly affected the corporate sector, Li *et al*. (2020) and Acharya and Steffen (2020b) show that aggregate deposit inflows were sufficient to fund the increase in liquidity demand from drawdowns. Chodorow-Reich *et al.* (2021) and Greenwald *et al.* (2021) document important lending spillovers and show that particularly small firms experienced a drop in the supply of bank credit when large firms drew down credit lines using F-14Q data. Kapan and Minoiu (2020) provide similar results using Dealscan data. None of these papers, however, explores the implications of banks as liquidity providers for their stock returns when drawdowns affect bank capital availability for other intermediation functions, and especially when the realized risk is aggregate in nature.[12] By examining both gross drawdowns and net (of deposit inflows) drawdowns, we demonstrate that credit-line drawdowns reduce banks' franchise value because of binding capital constraints.

There is a large corporate finance literature on the availability and pricing of credit lines as well as credit line usage.[13] In contrast to this literature, we take a bank-centric view and investigate the implications of drawdown risks for banks with large exposures to committed credit lines. Importantly, we show that – while idiosyncratic and systematic components of a firm's stock return volatility are incorporated by banks in the pricing of credit lines extended to a firm –banks do not appear to price the drawdown risk for the banking sector in the aggregate, *i.e.*, in large stress episodes such as the GFC or the pandemic. Acharya and Steffen (2020a) document a dash-for-cash and run on credit lines at the beginning of the COVID-19 pandemic.[14] Darmouni and Siani (2020) show that a large percentage of these credit lines were repaid through bond issuances in Q2 and Q3 2020. We show, however, that banks with large credit line repayments recovered *less* of their Q1 2020 market value losses highlighting that investors were still concerned with possible drawdown risk to banks from risky firms.

[12] Other focus on stock price reactions of mainly non-financial firms to the COVID-19 pandemic, emphasizing the importance of financial policies (Ramelli and Wagner, 2020), financial constraints and the cash needs of affected firms (Fahlenbrach et al., 2020), changing discount rates because of higher uncertainty (Gormsen and Koijen 2020, Landier and Thesmar 2020), social-distancing measures (Pagano et al., 2020) and corporate governance and ownership (Ding et al., 2021). Demirguc-Kunt et al. (2020) investigate the bank stock market response to the COVID-19 pandemic and policy responses globally. They highlight that the effectiveness of policy measures was dependent on bank capitalization and fiscal space in the respective country

[13] See, *e.g.*, Sufi (2009), Jiménez et al. (2009), Campello et al. (2010, 2011), Acharya et al. (2013, 2014, 2019), Ippolito et al. (2016), Berg et al. (2016, 2017), Nikolov et al. (2019) and Chodorow-Reich and Falato (2020).

[14] There is growing literature analyzing the implications of COVID for corporate finance and capital markets such as the disruption in corporate bond markets (*e.g.*, Haddad et al., 2021; O'Hara and Zhou, 2021), the role of FinTechs in providing credit (Erel and Liebersohn, 2020) or the impact of government support programs on the supply of loans (*e.g.*, Balyuk et al., 2021; Minoiu et al., 2021).

Finally, we also compare our liquidity risk measure for banks with two frequently used measures in the literature, the Berger and Bouwman (2009) liquidity creation measure (which is based both on- and off-balance-sheet data) and the Bai et al. (2018) liquidity risk measure (which also employs markets data). All three measures significantly explain bank stock returns in individual regressions.[15] When we run a horse race including all measures, our liquidity risk measure remains significant (while the other two measures become insignificant) suggesting that it contains information about aggregate drawdown risk of credit lines that is not included or fully captured in the other liquidity measures.

3. Balance-sheet liquidity risk and bank stock returns

3.1. Data

We collect data for all publicly listed bank holding companies of commercial banks in the U.S. and construct our main dataset following Acharya and Mora (2015), dropping all banks with total assets below USD 100mn at the end of 2019 and keeping only those banks that we can match to the CRSP/Compustat database. All financial variables (on the holding-company level) are obtained from the call reports (FR-Y9C) and augmented with data sourced from SNL Financial. We keep only those banks for which we have all data available for our main specifications during the COVID-19 pandemic, which limits our sample to 147 U.S. bank holding companies (accounting for about 99% of all outstanding credit lines).[16] All variables are explained below or in Appendix III.

[15] In contrast to bank capital, there is no consensus in the literature on how to measure liquidity, and those measures that have been used follow different concepts. For example, Deep and Schaefer (2004) use the difference between scaled liquid assets and liabilities, focusing on on-balance-sheet components of liquidity. Berger and Bouwman (2009) construct a comprehensive liquidity measure using on- and off-balance-sheet components. Both measures follow the concept of liquidity creation. Our measure focuses on liquidity risk, particularly during aggregate economic downturns, through credit lines and short-term wholesale funding. Bai et al. (2018) use on- and off-balance-sheet items to construct a measure of liquidity risk incorporating current market liquidity conditions. While their measure is more complex and reacts (contemporaneously) once market liquidity conditions deteriorate, our measure is a relatively simple (ex-ante) measure of bank exposure to liquidity risk.

[16] Berger and Bouwman (2009), among others, document that off-balance-sheet credit commitments are important for large banks, but not medium-sized and small banks. The smaller number of banks in our dataset is a consequence of changes in reporting requirements over time (*i.e.* an increase in the size threshold above which banks have to provide specific information).

We match our sample with a variety of different datasets. Data on daily drawdowns during the start of the COVID-19 pandemic as well as information about loan amendments is obtained from the EDGAR database and firms' 10-K/10-Q filings. We obtain daily stock returns for our sample banks from CRSP. Capital IQ provides quarterly data on credit-line drawdowns and repayments by firm as well as credit ratings. We manually match our banks to the Refinitiv Dealscan database to obtain outstanding credit lines on a bank–firm level as well as term loan exposures for the banks in our data set. Information about industries affected by COVID-19 is obtained from other studies as further described in this paper below. For some tests and statistics, we use secondary market data about different industry sectors (*e.g.*, the oil or retail sector) from Refinitiv. We obtain information about a bank's systemic risk from the Volatility and Risk Institute at NYU Stern.[17] Other market information is downloaded from Bloomberg (*e.g.*, oil volatility (CVOX), VIX, and S&P 500 market return).

3.2. Measuring balance-sheet liquidity risk of banks

To construct our measure of balance-sheet liquidity risk, we collect bank balance-sheet information as of Q4 2019 from call reports and construct three key variables associated with bank liquidity risk following Acharya and Mora (2015): (1) *Unused Commitments*: The sum of credit lines secured by 1–4 family homes, secured and unsecured commercial real estate credit lines, commitments related to securities underwriting, commercial letter of credit, and other credit lines (which includes commitments to extend credit through overdraft facilities or commercial lines of credit); (2) *Wholesale Funding*: The sum of large time deposits, deposits booked in foreign offices, subordinated debt and debentures, gross federal funds purchased, repos, and other borrowed money; and, (3) *Liquidity*: The sum of cash, federal funds sold and reverse repos, and securities excluding MBS/ABS securities. All variables are defined in Appendix II.

[17] See NYU Stern Volatility & Risk Institute, https://vlab.stern.nyu.edu/welcome/srisk, Acharya *et al.* (2016) and Brownlees and Engle (2017) for definition and estimation of LRMES and SRISK.

We construct a comprehensive measure of bank balance-sheet liquidity risk (*Liquidity Risk*):

$$Liquidity\ Risk = \frac{Unused\ Commitments + Wholesale\ Funding - Liquidity}{Total\ Assets}$$

Figure 2 shows the time-series of the cross-sectional mean of *Liquidity Risk* (using our sample banks and weighted by total assets) quarterly since January 2010 as well as its components, *i.e.*, *Unused C&I Credit Lines* and *Wholesale Funding*, both relative to total assets.

[Figure 2 about here]

Liquidity Risk has decreased since Q1 2010 to a level of about 20% relative to total assets (Panel A of Figure 2). In 2017, *Liquidity Risk* started to increase until Q4 2019, *i.e*., before the start of the COVID-19 pandemic. At the beginning of the pandemic in Q1 2020, liquidity risk dropped about 40% and continued to decline somewhat between Q2 and Q4 of 2020.

Panel B of Figure 2 shows the different components of bank balance-sheet liquidity risk. The decrease since Q1 2010 is driven by the declining share of wholesale funding relative to total assets during the COVID-19 pandemic. However, since 2017, the marginal increase in the importance of unused C&I loans has been larger than the marginal decline in wholesale funding exposure; as a result, *Liquidity Risk* has started to increase again. The large decline of *Liquidity Risk* during the first quarter in 2020 was driven by the decrease in unused C&I credit lines consistent with the increase in drawdowns documented in Figure 1. We saw an immediate reversal of *Unused C&I Credit Lines* in Q2 and Q3 2020 albeit not to pre-COVID-19 levels, pointing to a partial repayment of credit lines by the U.S. firms. In Online Appendix A, we show that non-investment grade rated firms in particular did not repay their credit lines, likely because they only gradually regained access to capital markets, as documented by Acharya and Steffen (2020a). We investigate the importance of unused C&I credit lines for the stock price crash of U.S. banks, banks' recovery of market equity losses during the Q2 to Q4 2020 period and their lending activities further in this paper. Note that banks experience only limited capital relief when high-quality firms repay their credit lines, with possible implications for their lending and investment activities.

3.3. Methodology

To show that balance-sheet liquidity risk affects the cross-section of bank stock returns, we run the following ordinary-least-squares (OLS) regressions:

$$r_i = \alpha + \gamma LiquidityRisk_i \ + \sum \beta \, X_i + \varepsilon_i \quad (1)$$

We compute daily excess returns (r_i), which we define as the log of one plus the total return on a stock minus the risk-free rate defined as the one-month daily Treasury-bill rate. *X* is a vector of control variables measured at the end of 2019 and captures key bank performance measures (capitalization, asset quality, profitability, liquidity and investments) that prior literature has shown to be important determinants of bank stock returns (*e.g.*, Fahlenbrach *et al.*, 2012; Beltratti and Stulz, 2012). More specifically, these variables include, among others: a bank's *Equity Beta*, constructed using monthly data over the 2015 to 2019 period and the S&P 500 as market index; the natural logarithm of total assets (*Log(Assets)*); the non-performing loans to loans ratio (*NPL/Loans*); the equity–asset ratio (*Equity Ratio*); *Non-Interest Income*[18]; return on assets (*ROA*); and, the deposit–loan ratio (*Deposits*). All variables are described in detail in Appendix III and are shown in the regression specifications in the sections below. Standard errors in all cross-sectional regressions are heteroscedasticity robust.

3.4. Descriptive evidence

We first investigate graphically whether differences in *ex-ante* liquidity risk (measured as of Q4 2019) across banks can explain their stock price development since the outbreak of COVID-19. We classify banks into two categories based on high or low balance-sheet liquidity risk using a median split of our *Liquidity Risk* variable. We then create a stock index for each subsample of banks indexed at January 2, 2020 using the (market-value weighted) average

[18] Demsetz and Strahan (1997) use non-interest income to net interest income ratio as a measure of how bank holding companies rely on off-balance-sheet activities more broadly (*e.g.*, through derivatives contracts).

stock returns of banks in each sample. The difference in the stock index between the two subsamples is shown in Panel A of Figure 3. Bank stock prices collapsed as the COVID-19 pandemic started at the beginning of March 2020. Consistent with the idea that liquidity risk explains bank stock returns, we find that banks with higher liquidity risk perform worse than other banks. In Panel B of Figure 3, we plot bank stock returns cross-sectionally against our measure of *Liquidity Risk*. The regression line through the scatter plot has a negative (and statistically significant) slope. That is, banks with higher *Liquidity Risk* had lower stock returns in the cross-section of our sample banks.

[Figure 3 about here]

Panel A of Table 1 shows the stock returns of the firms in our sample for different periods: January 2020, February 2020 and the March 1, 2020 to March 23, 2020 period and we calculate excess returns over these time periods. The average excess return is negative in all periods, ranging from -7.2% in January 2020 to -47.2% during the period March 1, 2020 to March 23, 2020 (and as low as -66.9% from January 1, 2020 to March 23, 2020).

Panel B of Table 1 shows descriptive statistics of bank characteristics as of Q4 2019. In addition to the control variables used in our regression, we also provide summary statistics of *Liquidity Risk* and its components. For example, the average *Liquidity Risk* is 0.195, the average bank has unused C&I loan commitments of about 7.7% relative to total assets, and the average wholesale funding–asset ratio is 13.6%. The average bank has a beta of 1.2 measured against the S&P 500 (*i.e.*, it broadly resembles the U.S. economy) and a capitalization (equity–asset ratio) of 12%. We have omitted a discussion of the other variables but include their summary statistics to facilitate the interpretation of our estimates in the coming sections.

[Table 1 about here]

3.5. Multivariate results

The estimation results for regression (1) are reported in Table 2.

[Table 2 about here]

As a dependent variable we use bank stock returns measured as excess returns in January 1, 2020 to March 23, 2020, *i.e.*, the first phase of the current COVID-19 pandemic and before the decisive fiscal and monetary interventions. In column (1), we only include *Liquidity Risk* and *Equity Beta* and show that banks with a higher *ex-ante* balance-sheet liquidity risk and (as expected) higher beta have lower stock returns during this period. When we add the different control variables, the coefficient of *Liquidity Risk* becomes, if anything, economically stronger and the explanatory power of the regressions almost doubles from column (1) to column (6). Economically, a one-standard-deviation increase in *Liquidity Risk* reduces stock returns during this period between 4.9% and 8.4% (which is 12.5% of the unconditional mean return).

A possible concern is that liquidity risk through the provision of credit lines is correlated with bank portfolio composition. As credit-line drawdowns in a time of stress tend to come from riskier borrowers or those most in need of liquidity, banks facing larger drawdowns may be engaged with riskier borrowers or industries and firms more vulnerable to financial and economic crises. Flexibly controlling for industry and risk composition of bank portfolios is therefore essential for isolating the effect of credit-line exposure on bank stock returns.

One confounding factor could be a large exposure to the real estate sector (as measured using a *Real Estate Beta*), large security warehouses as banks act as dealer banks (*Current Primary Dealer Indicator*), or larger derivative portfolios (*Derivates/Assets*). Our regressions show, however, that stock returns do not load significantly on these factors (columns (3) to (4)) once these exposures are accounted for.

It could also be that those banks with high unused C&I credit lines are also those with high retail credit card commitments and consumer loan exposures. Given the potential stress in the retail sector due to, *e.g.*, lay-offs and furloughs, these borrowers might have higher liquidity needs. We collect each bank's exposure to off-balance-sheet credit card commitments and add this as a control variable to our regression model. This variable does not enter significantly in our regression (column 5); more importantly, the coefficient on *Liquidity Risk* remains unchanged. Using on-balance-sheet *Consumer Loans/Assets* does not change our results either.

We include the *NPL/Loan*-ratio as a comprehensive measure of portfolio risk as well as control for a bank's distance-to-default. Banks with more non-performing loans and lower distance-to-default have lower stock returns. We also include the *Equity Beta* as a market measure of bank exposure to the overall economy as well as *Idiosyncratic Volatility* measured as the residual from a market model. Banks with higher idiosyncratic volatility have lower stock returns. In column (6), we further add *SRISK/Assets* as a measure of a bank's systemic risk at the end of 2019. *SRISK* is a bank's capital shortfall over a six-month period in a stress scenario, which is a decline in the S&P 500 of 40%, similar to what we observed in March 2020.[19] Banks with higher systemic risk have lower stock returns, a one-standard-deviation in *SRISK/Assets* decreases stock returns by about 4.5%, which is economically meaningful.

Importantly, the coefficient on *Liquidity Risk* does not change after these extensive controls for other bank characteristics. Overall, our results suggest that liquidity risk from undrawn credit lines appears to be almost orthogonal to bank portfolio risk. In the next subsection, we analyse the impact of bank portfolio composition in further detail focusing on bank exposure to the most-affected industries during the COVID-19 pandemic.

3.6. Bank portfolio composition: Exposure to COVID-19-affected industries

Investigating the effects of portfolio composition on stock returns at the bank level is challenging as bank portfolio information is scarcely publicly available. Thus, following Acharya and Steffen (2015), who use sensitivities of banks' stock returns to sovereign bond returns to measure their exposure to sovereign risk, we use market data as a window into banks' exposure to affected industries during the COVID-19 pandemic. More precisely, the recent literature provides definitions as to which industries (usually at the level of three- or six-digit

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[19] Cai *et al.* (2018) show that *SRISK* correlates with bank portfolio composition and common asset exposure of banks.

NAIC code) have been particularly affected during the pandemic. For example, Fahlenbrach *et al.* (2020) report the 20 industries with the worst stock market performance until March 23, 2020 at the three-digit NAIC level. We use all public firms in these 20 industries to create an index of affected firms. We then use multifactor models in which the sensitivities (betas) of banks' stock returns to the returns of this index measure their exposure to these affected industries at the end of 2019. We call these sensitivities *"Affected Industries (β_{COVID})"*. These betas enter our regression equation (1) as an additional control for bank portfolio composition. Overall, we use 12 definitions of affected industries based on prior literature, which are defined in Appendix IV. The corresponding methods and multifactor models are described in Table 3.

The results are reported in columns (1) to (12) of Table 3 including all control variables. The negative coefficient on all 12 betas shows that banks with larger exposures to industries particularly affected by the pandemic had lower stock returns over the January 1, 2020 to March 23, 2020 period. Importantly, the coefficient of *Liquidity Risk* hardly changes once exposure betas are controlled for. The correlation between the exposure betas ranges from 0.2 to 0.8 (*i.e.*, they are far from perfectly correlated). The correlation between *Liquidity Risk* and our exposure betas is, on average, 0.2, reducing concerns regarding possible spurious correlations. To reduce the dimensionality of the data associated with 12 different exposure betas, we also use their first principal component. In column (13), we use the first principal component (PC1) instead of the exposure beta in our regression and find results consistent with the interpretation that balance-sheet liquidity risk is a key driver of bank stock returns at the beginning of the pandemic, independent of the effect of bank portfolio exposures to COVID-19-affected industries.

[Table 3 about here]

Syndicated loan exposures. Another way to assess banks' exposure to COVID-19-affected industries is to use exposures via syndicated corporate loans sourced from Refinitiv Dealscan, which provides information about originating banks, firms and loan amounts, among others.

We can thus construct a proxy for each bank's exposure to firms in the affected industries based on the 12 methods mentioned above.[20] This variable is called "*Loan Exposure/Assets*" and we scale all exposures by a bank's total assets.

We use these exposures in three steps: First, we construct an average exposure to affected industries (*Loan Exposure/Assets*) based on the 12 different methods and correlate *Loan Exposure/Assets* with *PC1* (the first principal component of our exposure betas). The correlation is 26% and is significant at the 1% level, suggesting that our exposure betas at least in part reflect syndicated loan exposures but also that banks are exposed to COVID-19-affected industries not only through their syndicated loan portfolio. Second, we include *Loan Exposure/Assets* instead of the exposure betas in our regression. The results are reported in column (14). Banks with larger syndicated loan exposures to affected industries experience lower stock returns, but the coefficient on *Liquidity Risk* remains almost unaffected. Third, we run the regressions using the individual loan exposures (always scaled by total assets) constructed using the different methods and obtain similar results. They are omitted for brevity but available upon request.

Overall, these results suggest that liquidity risk from undrawn credit lines appears to be almost orthogonal to bank portfolio risk in terms of its effect on bank stock returns during the pandemic's onset.

4. Balance-sheet liquidity risk and bank stock returns: Robustness and extensions

The pandemic started in Asia in January and in Western economies by mid-February 2020 to the beginning of March 2020 when severe lockdown measures were put in place. Access to liquidity suddenly became a major concern for most firms as bond markets froze leading to a

[20] We allocate loan amounts among syndicate banks following the prior literature (*e.g.*, Ivashina, 2009). The loan share of each bank is available for only 25% of loans. We can thus use a limited set of exposure based on these shares, or allocate the full loan amount to each lender or 1/*N* of the loan amount, where *N* is the number of banks in the syndicate. As we are not interested in the exact exposure of each bank but rather the relative exposure across lenders, all methods provide similar results.

run of firms on credit lines at the beginning of March 2020 (Figure 1).[21] Did the effect of bank balance-sheet liquidity risk on bank stock returns also become economically more meaningful when aggregate drawdown risk increased? Which components of *Liquidity Risk* matter and how important are undrawn C&I credit lines relative to wholesale funding during the COVID-19 pandemic? Did the fiscal and monetary response help attenuate aggregate drawdown risk? Which banks eventually do recover market-value losses incurred in the first phase of the pandemic? These are the questions we set out to address in this section.

4.1. Balance-sheet liquidity periodically explains bank stock returns

Panel A of Table 4 shows the estimation results from equation (1) separately for three periods: the coefficient estimates for January 2020 are shown in columns (1) and (2), February 2020 estimates are in columns (3) to (4) and those for March 1, 2020 to March 23, 2020 are in columns (5) to (6).

[Table 4 about here]

During the March 1, 2020 to March 23, 2020 period, liquidity risk emerges as an important risk factor, *i.e.*, banks with higher balance-sheet liquidity risk had significantly lower stock returns during this period. While *Liquidity Risk* also somewhat explained stock returns at the time of the initial outbreak in Asia in January 2020, the economic magnitude is much smaller. A one-standard-deviation increase in *Liquidity Risk* decreases stock returns by about 0.9% in January 2020, compared to 6.5% during the March period. The effect is close to zero in February 2020 and increases from -0.04 (February 2020) to -0.462 (March 1, 2020 to March 23, 2020). At the same time, the R^2 increases by about 65% suggesting that *Liquidity Risk* has substantially more explanatory power after COVID-19 broke out in the Western economies.

[21] Refinitiv surveyed banks as to the key risks (investment grade) corporate clients were concerned about in March 2020. The key risks mentioned include cash flow impact, availability and access to liquidity, and access to future capital, highlighting the aggregate demand for credit-line drawdowns at the beginning of the pandemic.

4.2. Components of liquidity risk and bank stock returns

Figure 2 shows that *Liquidity Risk* decreased since the global financial crisis but has increased again since 2016. This increase is driven by a surge in unused C&I credit lines, while wholesale funding (a major driver of liquidity risk during the GFC) continued to decrease relative to total assets. In the next step, we split *Liquidity Risk* into its components to investigate their differential impact on bank stock returns during the first phase of the pandemic. The results are reported in Panel B of Table 4.

[Table 4 about here]

We first include only *Unused C&I Loan Assets* (column 1), then add *Liquidity/Assets* (column 2) and then add *Wholesale Funding/Assets* (column 3) to the regression model. The results suggest that at the onset of the pandemic, the impact of *ex-ante* balance-sheet liquidity risk of banks on their stock returns is driven by banks' exposure to unused C&I loans as well as the level of liquidity that banks have access to. Bank stock returns load significantly on both factors while the coefficient on wholesale funding is economically small and statistically insignificant. In terms of economic magnitude, a one-standard-deviation increase in unused C&I loans decreases stock returns by about 5.5%. In other words, banks' exposure to unused C&I loans is key to understanding bank stock returns during the early stages of the pandemic.

4.3. Time-series evidence

Our cross-sectional results linking bank stock returns to bank-level exposure to credit-line drawdowns also has a time-series counterpart. Using time-series regressions, we find that aggregate drawdowns can explain bank stock returns with high *ex-ante* exposure to *Liquidity Risk* during the March 1, 2020 to March 23, 2020 period. We run the following time-series regression[22]:

$$r_{i,t} = \beta_0 + \gamma \ \left[Liquidity\ Risk_i \times Log(DD)_{i,t}\right] + \beta_m r_{m,t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \mu_i + \varepsilon_{i,t} \quad (2)$$

[22] We also run a pooled cross-sectional regression using OLS and standard errors clustered at the bank level. The results remain unchanged.

We interact *Liquidity Risk* with the natural logarithm of the realized daily aggregate credit-line drawdowns (*Log(DD)*). $r_{i,t}$ is the daily bank excess return, $r_{m,t}$ is the daily market excess return, *HML* (high minus low) and *SML* (small minus large) are the Fama-French factors; μ_i are bank fixed effects. We use Newey–West standard errors. The results are reported in Panel C of Table 4.

Column 1 shows the impact of total aggregate credit-line drawdowns. Bank (daily) stock returns are significantly lower when aggregate drawdowns in the economy increase and banks have more balance-sheet liquidity risk. We then disaggregate credit-line drawdowns across BBB-rated firms (column (2)), non-investment-grade rated firms (column (3)) and unrated firms (column (4)).[23] Stock returns for banks with greater liquidity risk are lower, particularly when drawdowns of riskier firms accelerate. Overall, both our cross-sectional and time-series tests suggest that bank balance-sheet liquidity risk can episodically affect bank stock returns, emerging in an aggregate downturn due to an increased aggregate demand for drawing down bank credit lines.

4.4. Balance-sheet liquidity risk in the post-intervention period: Q2–Q4 2020

Our previous tests show that balance-sheet liquidity risk explains bank stock returns during the first few weeks of the COVID-19 pandemic, *i.e.*, before the monetary and fiscal response in the U.S. toward the end of March 2020. In a related paper, Acharya and Steffen (2020a) show that the availability of capital market funding was immediately restored after the Federal Reserve interventions on March 23, 2020, resulting in a halt to the credit-line drawdowns for all but the riskier firms as bond market access still eluded them. Importantly, Figure 2 above suggests that (likely high-quality) firms in fact repaid credit lines, leading to a reversal of unused C&I credit lines on bank balance sheets. We thus investigate whether we observe a corresponding reversal in bank stock prices following the Fed interventions in March 2020.

[23] Due to the high correlations between cumulative credit-line drawdowns across different rating classes, common variance inflator tests reject using them together in a single regression.

Panel A of Table 5 shows descriptive statistics of bank stock returns for each of the four quarters in 2020. After an average decrease of about 51% in Q1 2020, bank stock return increased about 10% in Q2 2020. Amid the second wave of the pandemic in Q3 2020, bank stock returns again decreased about 8% on average, while in Q4 2020 – a period including the U.S. presidential election as well as the arrival of the first vaccinations – bank stock returns increased by about 35%. Over the entire year, however, bank stock returns decreased about 4%. In other words, bank market capitalization has, on average, decreased during 2020.

[Table 5 about here]

Panel B of Table 5 shows the results from panel regressions of bank stock return on *Liquidity Risk* (columns (1) and (2)) and its components (columns (3) and (4)) with and without quarter fixed effects over the Q2 to Q4 2020 period. Standard errors are clustered in these regressions at the bank level. While the coefficient on *Liquidity Risk* is close to zero, the coefficient on *Unused C&I Loans* is small and only significant at the 10% level in a model with quarter fixed effects. We split the sample into the three different quarters and find that, while the coefficient on Liquidity Risk is close to zero in Q2 and Q4 2020, *Liquidity Risk* appears to become a concern again in Q3, when stock prices of banks declined amid a possible second wave of COVID-19 and lockdown measures.

Taken together, our results so far show that liquidity risk episodically explains bank stock returns when aggregate economic shock is severe. Banks with high liquidity risk experience a stock price decline during the first phase of the COVID-19 pandemic, *i.e.*, during a period of high aggregate liquidity demand for bank credit lines of firms, but not before, and recover only after the considerable monetary and fiscal interventions amid a second COVID-19 wave and associated lockdown measures.

4.5. Credit risk versus liquidity risk

While credit-line drawdown risk has been a major concern for bank investors in March 2020, particularly high-quality firms have started to repay credit lines once capital markets reopened in Q2 and Q3 2020 (*e.g.*, Chodorow-Reich *et al.*, 2021). In other words, while balance-sheet liquidity risk increases through credit-line repayments, drawn credit lines – particularly riskier ones – manifest as term loans on bank balance sheets. An interesting question is, thus, whether, in the post-intervention period, investors are more concerned with liquidity risk of repaid credit lines or credit risk of those that remain on bank balance sheets.

We first investigate to what extent banks recover market-value losses incurred during the January 1, 2020 to March 23, 2020 period (*Market-value loss (USD mn)*) in Q2 to Q4 2020. Panel C of Table 5 shows the market-value losses and their respective recovery. Banks lost, on average, USD 10bn in market capitalization until March 23, 2020, with losses ranging from USD 101mn to USD 228bn (JP Morgan), which corresponds to about 61% of the December 31, 2019 market capitalization. We also report the percentage of market-value losses that banks recovered in Q2, Q2–Q3 and the Q2–Q4 2020 period; this variable is called "*Recovery of market-value loss"*. For example, banks only recovered about 37% of their market capitalization losses until Q4 2020 (*Recovery of market-value loss Q2-Q4 (%)*).

It is a testable hypothesis that this partial recovery depends on the (also partial) credit line repayments of firms that started once capital markets reopened. Credit-line repayments, however, are hard to measure empirically. Call report data provides the amount of outstanding credit lines, but does not differentiate between repayments and new originations. Capital IQ, however, provides credit-line information at the firm level, for publicly listed firms, as well as the firm's credit rating. Refinitiv Dealscan provides information about which banks lend to these firms as well as information about new credit-line originations. And so, the intersection of call reports, Refinitiv Dealscan and Capital IQ allows us to estimate firm credit-line originations and repayments that we can aggregate at the bank level. We construct a new variable *Repayment*, which is the credit-line repayment at the bank level in a quarter (as percentage of Q1 credit-line drawdowns). This information is available to us in Q2 and Q3 2020.

We regress *Recovery of Market-Value Loss* on *Repayment* (as well as our control variables) for the Q2 (columns (1) and (2)) and Q2 to Q3 periods (columns (3) and (4)). A negative coefficient on *Recovery* would suggest that investors are more concerned with balance-sheet liquidity risk of banks and aggregate drawdown risk. A positive coefficient (*i.e.*, more recovery of market-value losses when firms repay their credit lines) would suggest that credit risk of loans that remain on balance sheets is a major concern.

We find that banks with a larger *Repayment* recover less of their market-value loss (column (2)). We then disaggregate *Repayment* by rating class and find that the recovery of market-value losses is driven by repayments of non-investment grade rated companies in particular (only the coefficient of *Repayment Q2* × *NonIG Rated* is negative and significant). This effect is even more pronounced using recovery of market-value losses in Q2 and Q3 2020 as the dependent variable. In other words, investors appear to be more concerned with credit-line drawdowns of riskier firms if aggregate risks were to emerge in the future, *e.g.*, when lockdown measures are reinstated during a second wave of the pandemic.

5. Understanding the mechanisms: Funding versus bank capital

In this section, we investigate the mechanisms driving the effect of balance-sheet liquidity risk on bank stock returns during the COVID-19 pandemic. Does funding liquidity to source new loans become a binding constraint for banks when deposit funding dries up (the "funding channel")? Or, does the drawdown of credit lines lock up bank capital against term loans and impair bank loan origination, preventing banks from making possibly more profitable loans (the "capital channel")?

5.1. Net versus gross credit-line drawdowns and bank stock returns

To distinguish between the funding and the capital channels, we construct two measures based on actual drawdowns experienced by our sample banks during the first quarter in 2020. *Gross Drawdowns* is defined as the change of a banks' off-balance-sheet unused C&I loan commitments between Q4 2019 and Q1 2020 relative to total assets using call report data.

Ivashina and Scharfstein (2010) and Li *et al*. (2020) show that lagged unused C&I credit commitments are a good predictor for changes in banks' C&I loans. We construct a second proxy, *Net Drawdowns*, which is defined as the absolute change in banks' unused C&I commitments minus the change in deposits (in percentage of total assets) over the same period. Holding gross drawdowns fixed, our measure of net drawdowns helps us understand the importance of changes in bank deposits on bank stock returns. In other words, *Gross Drawdowns* proxies for the importance of capital, while *Net Drawdowns* is a proxy for the importance of bank deposit funding; the measures help us identify the relative importance of the funding versus the capital channels.[24]

We plot the time-series of both measures since Q1 2010 in Figure 4. Panel A of Figure 6 shows the evolution of *Gross Drawdowns*. While *Gross Drawdowns* have been relatively stable since 2015, we observe a sudden increase in credit-line drawdowns by about 13.5% from Q4 2019 to Q1 2020. As observed for banks' off-balance-sheet levels of unused C&I loans, *Gross Drawdowns* had already reverted back to pre-COVID-19 levels by the end of Q2 2020.

[Figure 4 about here]

Panel B of Figure 4 displays the development of *Net Drawdowns* since Q1 2010. *Net Drawdowns* have been relatively stable since 2015 and in fact decreased by about 5% in Q1 2020. In other words, the change in deposits during the first quarter of 2020 has been larger than the change in unused C&I commitments, suggesting that funding of new loans should not have been a binding constraint for banks. Similar to gross drawdowns, net drawdowns also returned to pre-COVID-19 levels over the next two quarters (in Q3 2020).

We investigate the effect of gross and net drawdowns on bank stock returns formally using the model specification and control variables from column (5) of Table 2. Table 6 reports the results.

[24] The correlation between *Gross Drawdowns* and *Net Drawdowns* of our sample banks is below 10% and statistically insignificant at the beginning of the COVID-19 pandemic, addressing potential concerns that we are measuring the same economic effect with both variables.

[Table 6 about here]

We introduce both proxies sequentially in columns (1) and (2) and then together in column (3). The coefficient of *Net Drawdowns* is small and insignificant, while the coefficient of *Gross Drawdowns* is statistically significant and economically meaningful (column 2). A one-standard-deviation increase in *Gross Drawdowns* reduces bank stock returns by about 4.8% (= -5.128 × 0.0094), which is economically large and corresponds to about 10% of the unconditional stock price decline. When we include both proxies in column 3 we find that, holding *Gross Drawdowns* fixed, *Net Drawdowns* still has no significant effect on bank stock returns. That is, since the variation in *Net Drawdowns* is driven by changes in bank deposits (holding *Gross Drawdowns* fixed), funding of drawdowns through bank deposits does not appear to be a binding constraint for banks. Finally, adding *SRISK/Assets* as additional control (column 4) does not change the coefficient of *Gross Drawdowns*, suggesting that SRISK does not seem to capture systemic implications associated with aggregate credit-line drawdowns.

We interact *Gross Drawdowns* with *High Capital*, an indicator equal to 1 if bank equity capital is above the median of the distribution (column (5)). In column (6), we observe the interaction between *Gross Drawdowns* and *Capital Buffer*, which is the difference between a bank's equity–asset ratio and the cross-sectional average of the equity–asset ratio of all sample banks in Q4 2019. A larger difference implies that a bank has a higher capital buffer. The coefficient of both interaction terms is positive and significant emphasizing that the negative effect of drawdowns on stock returns is attenuated for banks with better capitalization. Consistently, the coefficient of the interaction term of *High Capital* (*Capital Buffer)* and *Net Drawdowns* is not significant (columns (7) and (8)). Columns (9) and (10) confirm these results including interaction terms of *High Capital* (*Capital Buffer)* with both *Gross Drawdowns* and *Net Drawdowns*. In Panel B, we replace *Net Drawdowns* with *Deposits*, defined as the deposit inflow in Q1 2020 relative to total assets. We run the same regressions (including *SRISK/Assets*, interaction terms with *High Capital* and *Capital Buffer* and include also the interaction terms of *Gross Drawdowns* and the capital measures) and find qualitatively and quantitatively similar results.

Overall, we infer that balance-sheet liquidity risk of banks affect their stock returns as the manifestation of such risk in the form of credit line drawdowns locks up bank capital away from more profitable investment opportunities. In the next section, we investigate this mechanism directly focussing on the impact of credit line drawdowns on corporate bank lending.

5.2. Implications for bank lending during the COVID-19 pandemic

What does balance-sheet liquidity risk mean for bank lending during the COVID-19 pandemic? The increase in loans in relation to bond spreads documented in Online Appendix B suggests that bank health was materially affected by the pandemic, and not just temporarily, impacting the access of firms to bank loans as well as the cost of bank credit. Loan-level data shows that bank issuance of new corporate loans has indeed substantially declined since the start of the COVID-19 pandemic. We consider next the testable hypothesis that banks with more balance-sheet liquidity risk reduced their lending by a greater extent than other banks. If banks' capital constraints matter, then we expect lending to be particularly sensitive to gross (but not to net) drawdowns.

We use data from Refinitiv Dealscan to investigate these issues. We use data on both outstanding exposures and new loan originations from January 2019 to October 2020 and divide our sample into a pre and post period, where the post period is defined as the period starting April 1, 2020 (Q2 2020), *i.e.*, during the COVID-19 pandemic. In unreported tests, we collapse our sample at the bank × month level and show that banks with higher *Liquidity Risk* and higher *Gross Drawdowns* decrease lending in the post period relative to the pre-period and relative to banks with lower exposures using bank and month fixed effects. *Net Drawdowns* have no effect on lending. Banks reduce lending to riskier borrowers in particular, consistent with the higher capital requirements associated with these loans. However, while these tests are promising they do not allow us to control for loan demand. A plausible alternative explanation could be a reduction in loan demand due to lower investments by riskier firms in a period characterized by high uncertainty or because riskier borrowers have already drawn down existing lines of credit. Another alternative explanation for a reduction in lending could be a loss of intermediation rents due to the low-interest-rate environment.

Methodology. We use a Khwaja and Mian (2008) estimator to formally disentangle demand and supply in a regression framework, investigating the change in lending of banks to the same borrower before and after the outbreak of the COVID-19 pandemic. We construct two variables, $Exposure_{i,b,m,t}$, which is the natural logarithm of the outstanding loan amount issued to firm i by bank b as loan-type m as of quarter *t, and* $Origination_{i,b,m,t}$, which is the natural logarithm of the newly issued loan amount to firm i by bank b as loan-type m in quarter t. We estimate two primary model specifications. We first use $Exposure_{i,b,m,t}$ as the LHS (Y) variable and absorb time-varying (and loan-type specific) loan demand using borrower (η_i) × time (η_t) × loan type (η_m) fixed effects. Moreover, we saturate the specification with borrower (η_i) × bank (η_b) fixed effects to measure changes in credit supply within a borrowing relationship thereby controlling for (time-invariant) portfolio composition effects. Lastly, we add bank lending controls following prior literature ($X_{b,t-1}$: NPL ratio, log of total assets, ROA, tier 1 capital ratio, loan-to-assets ratio) giving us the specification:

$$Y_{i,b,m,t} = \beta_1 \times DD_b \times Post + \left(\eta_i \times \eta_t \times \eta_m\right) + \left(\eta_i \times \eta_b\right) + X_{b,t-1} + \varepsilon_{i,b,m,t}$$

In a second model, we use $Origination_{i,b,m,t}$ as Y-variable and restrict our sample to one pre- (Q4 2019) and one post period (Q2 2020).[25] We then directly compare the issuance behaviour between these two points in time, while again controlling for time-varying loan demand and measuring the lending impact within a credit relationship through fixed effects. In all our specifications, we cluster standard errors at the bank level.

[25] This approach is similar to the one used in Kapan and Minoiu (2021).

A negative β_1 implies that a bank with more exposure to drawdown risk (DD_b) – measured as either *Gross Drawdowns* or *Net Drawdowns* – decreases lending more than banks with less exposure during the COVID-19 pandemic after controlling for loan demand and other bank- and loan-specific effects. *Gross Drawdowns* and *Net Drawdowns* are measured over the Q1 2020 period. To detect potential non-linearities in the reaction of banks' lending behaviour to the level of drawdown risk, we further create two dummy variables that take the value 1 if the *Gross (Net) Drawdowns* of a bank are above the median of *Gross (Net) Drawdowns* of all banks in the sample.

Results. The results are reported in Table 7. Columns (1)–(4) show the results with $Exposure_{i,b,m,t}$, and columns (5)–(8) with $Origination_{i,b,m,t}$ as dependent variables.

[Table 7 about here]

Columns (1) and (2) show that banks with large gross drawdowns (also accounting for possible non-linearities in column (2)) do not adjust their loan exposure to firms differently from banks with low gross drawdowns after COVID-19 broke out. We then differentiate by loan type and find that banks with high gross drawdowns increase credit-line exposures relative to low gross drawdown banks during COVID-19, consistent with the interpretation that these banks can sustain off-balance-sheet rather than on-balance-sheet exposures as the former require less upfront equity. However, banks with high gross drawdowns actively reduce term loan exposures relative to low gross drawdown banks as the triple interaction term in column (3) suggests, for example by actively selling term loans or by not rolling them over. In column (4) we add lagged control variables, which further accounts for compositional differences of the treatment and the control group. The size and significance of the effects described above remain unaffected.

Columns (5) to (8) show the results for new loan originations. Similar to before, banks appear to be concerned about their loan portfolio once drawdowns become large (relative to the sample median). Banks with high gross and net drawdowns both reduce new loan originations compared to low drawdown banks and they reduce both credit lines and term loans as the coefficients on the triple interaction terms are insignificant (column (7)). Once we include our control variables, the effect of net drawdowns becomes insignificant. That is, holding the effect of deposit inflows constant, banks with larger impact on equity capital through large credit-line drawdowns reduce lending more than other banks during COVID-19, highlighting the relative importance of the capital channel in relation to the funding channel.[26]

5.3. Real effects for firms borrowing from high gross drawdown banks

How do firms who borrow from banks with high gross drawdowns respond to the contraction of lending supply? We focus on a subsample of publicly listed borrowers in Refinitiv Dealscan that can be matched to Compustat and loan exposures as of Q4 2019. For every firm, we calculate the weighted average of gross drawdowns across its syndicate lenders, where the weights are the size of the loan exposure of each lender to this firm. We then construct an indicator that takes the value one if this average drawdown share is above the median of its distribution across firms. These firms borrow from high gross drawdown banks in our terminology.

Within the short period of time in the post-COVID-19 phase that is available to us for econometric analysis, significant shifts in slow-moving variables such as assets or investments are unlikely and we do not find significant differences investigating these variables. However, firms can quickly make changes to their working capital requirement and respective funding needs. In unreported tests (we use simple mean differences) whose results are available upon request, we find that borrowers that borrow from banks with high gross drawdowns increase current assets less relative to those firms borrowing from low drawdown banks, but current

[26] Several papers provide evidence consistent with a reduction of banks' intermediation activity during COVID-19. Chodorow-Reich *et al.* (2021) and Greenwald *et al.* (2021) show that banks cut credit lines and term lending to small firms because of credit-line drawdowns of large firms, likely due to capital constraints. Moreover, we show in Online Appendix B that loan spreads of small firms in secondary loan markets have significantly increased when compared with the spreads of large firms since the beginning of the pandemic, consistent with a loss of intermediation activity for small firms dependent on bank financing.

liabilities are unaffected. That is, these firms reduce the necessary investments in working capital, likely because access to bank loans becomes more difficult, as demonstrated above. Moreover, these firms reduce their R&D expenditures (relative to total assets) four times as much compared to unaffected firms. Given the importance of R&D for innovation and competition, even a short-term reduction in R&D expenditure might adversely impact these firms over the long run. Firms might also make immediate changes in their payouts to shareholders. We obtain this data from Capital IQ for our sample firms. While we do not find a significant differential effect on stock repurchases, we find that affected firms borrowing from banks with high gross drawdowns significantly reduce dividend payouts (the reduction is twice as large compared to non-affected firms).

Overall, during our sample period, we find significant effects on firms' investment and payout policies when borrowing from banks that have experienced high gross drawdowns.

6. Discussion

In this section we discuss our results and their extensions along three dimensions: (1) we compare balance-sheet liquidity risk during COVID-19 and the global financial crisis (GFC) period; (2) we compare our balance-sheet liquidity measure with alternative liquidity measures used in the literature; and, (3) we ask to what extent loan contracts account for aggregate drawdown risk.

6.1. Balance-sheet liquidity risk: COVID-19 versus the global financial crisis of 2007–2009

Are the effects we have documented so far specific to the COVID-19 pandemic or did liquidity risk also episodically explain stock returns during other times of aggregate risk? To understand whether this effect occurs more generally during aggregate economic downturns, we first plot the stock prices of banks with high versus low *Liquidity Risk* over the GFC period in Figure 5.

[Figure 5 about here]

We plot the difference in the stock price of banks with high versus low *Liquidity Risk* indexed at January 1, 2007. The difference in the stock price performance between the two groups of banks is even more pronounced than during the COVID-19 crisis. Stock of banks with high *Liquidity Risk* fell by about 40% more than banks with low liquidity risk between Q2 2007 and Q3 2008. The stock price performance was then similar until the end of Q2 2009 and stock price improved afterwards.

We then test the effect of liquidity risk on stock returns during the GFC period using the same methodology described above. The results are reported in Table 8. In a first step, we run a regression of bank stock returns on *Liquidity Risk* (column (1)) and its components (column (2)) over the Q2 2007 to Q2 2009 period, including one quarter lagged control variables as well as quarterly fixed effects. Standard errors are clustered at the bank level.

[Table 8 about here]

Similar to the COVID-19 episode, banks with higher *ex-ante* balance-sheet liquidity risk had lower stock returns during the GFC period, which is in part driven by banks' exposure to undrawn credit lines. In contrast to the pandemic, however, banks' rollover risk through wholesale funding exposure also had an economically large effect during the GFC period consistent with Acharya and Mora (2015).

We then investigate these effects separately for each quarter (columns (3)–(11)). We confirm that balance-sheet liquidity risk also episodically explained bank stock returns during the GFC period. In particular, rollover risk for banks rose in Q3 and Q4 2007, *i.e.*, in the first phase of the GFC, when the Asset Backed Commercial Paper (ABCP) market froze as documented in Acharya *et al*. (2013). Thereafter, credit-line drawdown risk for banks increased, particularly in Q4 2008 after the Lehman default and abated afterwards, when the Federal Reserve and U.S. government responded to the economic fallout of the Lehman Brothers default with a variety of measures to support the liquidity of the banking sector, including large guarantee programmes. Wholesale funding risk still remained of concern for banks even in Q2

2009. That is, while unused C&I credit lines are also clearly important during the GFC, the results also show that wholesale funding exposure and having access to liquidity (cash) impacts bank stock returns, highlighting that a holistic measure of balance-sheet liquidity risk is useful for its robust measurement across different stress episodes (otherwise, we would force an average effect across banks for individual components).

Overall, episodes in which the balance-sheet liquidity risk of banks explains their stock returns seem to occur more broadly during aggregate economic downturns, when an aggregate liquidity demand for bank credit lines emerges.

6.2. Comparing balance-sheet liquidity risk to alternative liquidity proxies

We proposed and developed a new measure of balance-sheet liquidity risk as there is no consensus in the literature on how to measure liquidity risk. In this section, we compare our measure with two frequently used measures in the literature, the Berger and Bouwman (2009) liquidity creation measure (*BB*) and the Bai *et al.* (2018) liquidity risk measure (*LMI*). *BB* is a book measure based on a "stock" notion of liquidity including banks' on- and off-balance-sheet positions. In contrast, the *LMI* is a contemporaneous measure as it incorporates current market liquidity conditions. Bai *et al.* (2018) use the spread between the Treasury-bill rate and the Overnight Indexed Swap rate (hereafter the OIS-Tbill spread) as the funding liquidity factor. We construct the *LMI* following the approach outlined in Bai *et al.* (2018), using the worst funding liquidity conditions in March 2020. We provide a more detailed discussion of the creation of the liquidity measures in Online Appendix C.

[Table 9]

Panel B of Table 9 reports the regression results. We estimate regression (1) using the alternative liquidity proxies. We find that the *BB* measure is negatively and significantly related to stock returns during the March 1, 2020 to March 23, 2020 period (column (3)). The variable *LMI* also has a large and significant impact on stock returns and is also highly correlated with *Liquidity Risk* (column (4)). This is consistent with the interpretation that a worsening of liquidity conditions in financial markets increases aggregate drawdown risk for banks, thereby increasing the value of the put option sold to corporates, which negatively impacts bank stock returns. In column (5), we run a horse race of *Liquidity Risk* and both alternative liquidity measures in separate regressions. Both *LMI* and *BB* become small and insignificant, while *Liquidity Risk* remains negative and significant, suggesting that our liquidity measure contains information not captured in these alternative liquidity proxies.[27]

6.3. Do loan contracts account for aggregate drawdown risk?

An important question is whether and how banks already account for aggregate drawdown risk, *e.g.*, through loan contract terms that might limit the extent of correlated drawdowns during episodes of aggregate risk. We investigate two possible ways banks might do that: (1) the pricing of credit lines, and (2) loan covenants.

Pricing of credit lines. Do banks price aggregate drawdown risk through fees and/or credit spreads when issuing new credit lines? In Online Appendix D, we investigate this question using all credit lines issued to U.S. non-financial firms over the 2010 to 2019 period, sourced from Refinitiv Dealscan. We first show that idiosyncratic drawdown risk (measured using a firm's realized equity volatility over the past 12 months) and systematic drawdown risk (measured using a firm's stock beta) are priced in both commitment fee (*AISU*) and spread (*AISD*). This is consistent with, for example, Acharya *et al.* (2013) and Berg *et al.* (2016).

We construct different measures at the bank level. *Bank Equity Beta* proxies for the systematic risk of banks using the S&P 500 as market portfolio. *LRMES* is the Long Run Marginal Expected Shortfall, approximated in Acharya *et al.* (2012) as $1 - e^{(-18\times \mathrm{MES})}$, where MES is the one-day loss expected in bank *i*'s return if market returns are less than -2%. *SRISK/Assets* (as defined in Section 3 above in this paper) measures bank capital shortfall in times of aggregate market downturn. While a higher *Bank Equity Beta* and *LRMES* both

[27] The correlations between *Liquidity Risk* and *BB* (*LMI*) are 0.33 (-0.32). A variance inflator test suggests that multicollinearity is not a concern.

somewhat increase the price of credit lines, *Liquidity Risk* or *Unused C&I/Assets*, on average, do not. Also, *SRISK/Assets* does not appear to be priced. In other words, banks do not appear to be considering the deep out-of-the-money put option associated with aggregate drawdown risk when setting *ex-ante* price terms of credit lines. This may partly explain their need to fund aggregate drawdown risk with equity capital, as witnessed during the pandemic.

Covenants. Did covenants constrain drawdowns of credit lines at the beginning of the pandemic in March 2020, or later during the year when firms' financial situation had deteriorated? We follow the extant literature (*e.g.*, Roberts and Sufi, 2009) and use textual analysis to identify all loan amendments of publicly listed U.S. non-financial firms in SEC filings sourced from EDGAR from March to Q3 2020. We found that not a single loan amendment was initiated through a covenant violation. On the contrary, banks and firms regularly negotiated a covenant relief period (usually up to Q1 2021 or later) early in the pandemic to account for its fallout. In summary, credit-line drawdowns (also by firms in the hardest-hit industries) did not appear to be constrained by possible covenant violations during the pandemic.

7. Addressing aggregate drawdown risk *ex-ante* using stress tests

We showed that balance-sheet liquidity risk of banks – mainly driven by undrawn credit lines – has severe implications on their ability to extend new loans because it requires capital once these credit lines are drawn. How can policymakers address aggregate drawdown risk in an *ex-ante* manner? One possible way is for regulators to add the effect of drawdowns to stress tests and require banks to fund these exposures with equity. In the last part of the paper, we quantify the capital shortfall that arises due to balance-sheet liquidity risk and show how balance-sheet liquidity risk can be incorporated tractably into bank stress tests. Existing stress tests do not account for the impact of banks' contingent liabilities in times of stress. This is what we set out to do in this section.

7.1. Methodology

Capital shortfall in a systemic crisis (SRISK). SRISK is defined as the capital that a firm is expected to need if we have another financial crisis. Symbolically it can be defined as:

$$SRISK_{i,t} = E_t(Capital\ Shortfall_i | Crisis)$$

That is,

$$SRISK_{i,t} = E\ \ [k\ (Debt + Equity) - Equity\ \ |Crisis]$$

$$= K\ Debt_{i,t} - (1 - K)(1 - LRMES_{i,t})Equity_{i,t}$$

where $Debt_{i,t}$ is the nominal on-balance-sheet debt of bank *i*'s liabilities, assumed to be constant between time *t* and *Crisis* over *t* to t+h. LRMES is the Long Run Marginal Expected Shortfall, approximated in Acharya *et al*. (2012) as $1 - e^{(-18 \times MES)}$, where MES is the one-day loss expected in bank *i*'s return if market returns are less than -2% and *Crisis* is taken to be a scenario where the broad index falls by 40% over the next six months (h=6m). *K* is an assumed required quasi-market-value-to-book-debt capital ratio of 8%.

To account for off-balance-sheet liabilities fully, the necessary adjustments to *SRISK* can be broken down into two components. First, off-balance-sheet (contingent) liabilities such as bank credit lines enter banks' balance sheets as loans once they are drawn and need to be funded with capital. Second, we also have to account for the effects of drawdown risk on stock returns as demonstrated in our calculations above.

"Contingent" capital shortfall in a systemic crisis (SRISK^{C}). We calculate the capital shortfall of banks in a systemic crisis with contingent liabilities as follows:

$$SRISK^{C}_{i,t} = \ Incremental\ SRISK^{CL}_{i,t} + Incremental\ SRISK^{LRMES^{C}}_{i,t}$$

(i) $Incremental\ SRISK^{CL}_{i,t}$ recognizes that drawdowns of credit lines in crisis states represent contingent liabilities of banks ($Debt_{i,t+h}|Crisis\ \ \neq Debt_{i,t}$):

$$Incremental\ SRISK^{CL}_{i,t} = K\ \left[E\left[Debt_{i,t+h}|Crisis\right] - Debt_{i,t}\right]$$

$$= K\ \times\ E[Drawdown\ rate\ |\ Crisis]\ \times Unused\ Commitments_{i,t}$$

$E[Drawdown\ rate \mid Crisis]$ is estimated using past drawdown rates extrapolated for a market index fall of 40%.

(ii) $Incremental\ SRISK_{i,t}^{LRMES^C}$ recognizes that LRMES estimated using "small" (or local) -2% market corrections in normal times does not account for the episodic effect of balance-sheet liquidity risk on bank stock returns during episodes of large aggregate shocks:

$$Incremental\ SRISK_{i,t}^{LRMES^C} = (1-K)\times\ \Delta LRMES_{i,t}^{C} \times Equity_{i,t}$$

where $\Delta LRMES_{i,t}^{C} = \hat{\gamma} \times\ Liquidity\ Risk_{i,t}$ and $\hat{\gamma}$ is the estimated episodic effect of liquidity risk on bank stock returns from our tests on balance-sheet liquidity risk.

7.2. Estimating the drawdown function

To calculate the expected percentage drawdown in a crisis, we use drawdown data from during the COVID-19 pandemic as well as the GFC crisis and estimate the expected drawdown in a stress scenario with a 40% market correction for both stressed periods. We show plots of this exercise in Figure 6.

[Figure 6]

In Panel A of Figure 6, we plot the cumulative quarterly drawdown rates during the COVID-19 pandemic (*i.e.*, Q4 2019 and Q1 2020) and the GFC (*i.e.*, Q1 2007 to Q4 2009) as a function of the respective quarterly S&P 500 returns. We also show the linear regression fits for both periods. In Panel B of Figure 6, we use the lowest cumulative daily S&P 500 return within each quarter (instead of the quarterly return). This presentation has two advantages. First, it shows that for quarters with relatively low negative S&P 500 returns (*i.e.*, "normal times"), drawdowns are somewhat clustered.[28] Second, drawdown decisions are arguably based on how bad a quarter has actually been rather than on the situation at the end of each quarter. We therefore calculate drawdown rates based on Panel B of Figure 6.

[28] The intercept in the COVID-19 pandemic and the GFC are 17% and 15%, respectively.

We find that the sensitivity of credit-line drawdowns to changes in market returns was higher during the COVID-19 pandemic (the slope coefficient, β, is -0.57) compared with the GFC (the slope coefficient, β, is -0.27). The projected drawdown rate in a market downturn of 40% (-40% × β) is thus also substantially higher in the COVID-19 pandemic (22.91% versus 10.82%). A possible explanation of the differential impact on absolute drawdowns could be that corporate balance sheets were less impacted during the GFC, which originated in the banking and household sector. The COVID-19 pandemic, however, had an immediate effect on firms' balance sheets, resulting in elevated demand for liquidity from pre-arranged credit lines compared with the GFC. The quarterly drawdown rates in both stress scenarios or crises are summarized together with the sensitivities of the drawdown rates in a market correction in Panel A of Table 10.

[Table 10 about here]

7.3. Incremental SRISK due to credit-line drawdowns

Using these expected drawdown rates, we calculate the equity capital that would be required to fund these new loans based on banks' unused commitments at the end of Q4 2019 ($Incremental\ SRISK_i^{CL}$). We use the Q4 2019 unused credit-line commitments of banks and apply the drawdown rates calculated in the three different stress scenarios assuming a prudential capital ratio of 8%:

$$Incremental\ SRISK_i^{CL} = Drawdown\ rate \times 8\% \times Unused\ Commitments \quad (4)$$

In Panel B of Table 10, we show the top 10 banks with the largest undrawn commitments as of Q4 2019 and report $Incremental\ SRISK_i^{CL}$ individually for each of these banks. We also report the total $Incremental\ SRISK^{CL}$ for the top 10 and for all banks in our sample. Overall, we find that $Incremental\ SRISK^{CL}$, *i.e.*, the additional capital, amounts to about USD 16bn to USD 34bn depending on the estimates of the drawdown rate.

7.4. Incremental SRISK due to MES^C and contingent SRISK (SRISK^C)

We also account for the effect of liquidity risk on bank stock returns as demonstrated in our calculations above. Using the loadings from our regressions of bank stock returns on balance-sheet liquidity risk during the COVID-19 crisis (*i.e.*, the γ in equation (2)), we estimate the additional (marginal) equity shortfall of banks based on their end of Q4 2019 market values of equity (MV), called the $Incremental\ SRISK_i^{LRMES^C}$:

$$Incremental\ SRISK_i^{LRMES^C} = (1-k) \times MV_i \times LRMES_i^C$$

$$= (1-k) \times MV_i \times \hat{\gamma} \times Liquidity\ Risk_i \quad (5)$$

$LRMES_i^C$ is the contingent marginal expected shortfall due to the impact of liquidity risk on bank stock returns. We report the $Incremental\ SRISK_i^{LRMES^C}$ in Panel C of Table 9.

We use a minimum and maximum loading (γ) estimated from different regressions based on equation (1) and calculate a range of $LRMES_{min}^C$ and $LRMES_{max}^C$, which is between 9.5% and 16.4%. The corresponding $Incremental\ SRISK_i^{LRMES^C}$ amounts to USD 177bn to USD 308bn.

In a final step, we calculate the conditional *SRISK* ($SRISK^C$) adding the two incremental SRISK components. Adding both components we show that the additional capital shortfall for the U.S. banking sector due to balance-sheet liquidity risk amounts to more than $340 billion as of December 31, 2019 in a stress scenario of a 40% correction to the global stock market, with the top 10 banks contributing USD 273bn. The incremental capital shortfall of the top 10 banks is about 1.6 times the SRISK estimate without accounting for contingent liabilities and the effect of liquidity risk.

Overall, our estimates show that the incremental capital shortfall in an aggregate economic downturn due to banks' contingent liabilities is sizeable, because it requires an additional amount of capital to fund the new loans on their balance sheets and, importantly, this leads to an (even larger) incremental capital requirement due to an episodic impact of bank balance-sheet liquidity risk on bank stock returns.

8. Conclusion

We documented that the balance-sheet liquidity risk of banks helps understand the significant and persistent underperformance of bank stocks relative to other financial and non-financial firms during the COVID-19 pandemic, explaining both the cross-section and the time-series of bank returns during the pandemic but not before, and even after controlling for banks' on-balance-sheet portfolio exposure to the pandemic. Importantly, stock returns of banks and their intermediation activity during the pandemic react adversely to *gross* drawdowns – which lead to bank capital charge against term loans – rather than *net* drawdowns (which account for inflows in bank deposits), suggesting that bank capital rather than funding liquidity was perceived by markets as a binding constraint for banks. Consistently, we find that banks with large gross drawdowns reduce their immediate supply of term loans; banks with less deposit inflows also reduce credit-line originations. While the overall episodic impact of balance-sheet liquidity risk on bank stock returns is not unique to the pandemic and was also seen during the global financial crisis of 2007 to 2009, the latter was driven primarily by rollover risk and wholesale funding liquidity. We demonstrate how the episodic nature of credit-line drawdowns and balance-sheet liquidity risk can be incorporated tractably into bank stress tests.

These findings have potential implications for how economic shocks may affect banks in future. Darmouni and Siani (2020) show that U.S. non-financial firms issued bonds following the monetary policy and fiscal interventions starting March 2020 and used the proceeds to repay credit lines. While a large proportion of credit lines have been repaid in Q2 and Q3 2020, corporate preference for cash of firms has remained high (Online Appendix A) and total debt on firms' balance sheet has substantially increased. The non-financial sector's leverage and exposure to capital markets has thus increased further during the COVID-19 pandemic. In other words, ex-ante aggregate drawdown risk of banks is again high in case of another wave of the pandemic or due to another aggregate shock. In turn, the value of the put option in the form of bank credit lines for corporates and capital markets would be even more pronounced if bond market liquidity conditions were to severely deteriorate. In summary, additional corporate leverage accumulated during the initial phase of the pandemic has likely increased the likelihood of future impact on bank stock returns via the credit-line drawdown channel.

References

Acharya, V., H. Almeida, F. Ippolito, and A. Pérez Orive, 2014, Credit Lines As Monitored Liquidity Insurance: Theory and Evidence. *Journal of Financial Economics* 112 (3), 287–319.

Acharya, V., H. Almeida, F. Ippolito, and A. Pérez Orive, 2020, Bank lines of credit as contingent liquidity: Covenant violations and their implications. *Journal of Financial Intermediation* 44, 100871.

Acharya, V., H. Almeida, and M. Campello, 2013, Aggregate risk and the choice between cash and lines of credit. *The Journal of Finance* 68 (5), 2059–2116.

Acharya, V., R. Engle, and M. Richardson, 2012, Capital shortfall: a new approach to ranking and regulating systemic risks. *American Economic Review* 102, 59–64.

Acharya, V. and N. Mora, 2015, A Crisis of Banks as Liquidity Providers, *Journal of Finance*, 2015, 70(1), 1-44.

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson, 2016, Measuring systemic risk, *Review of Financial Studies*, 30, 2-47.

Acharya, V., P. Schnabl, G. Suarez, 2013, Securitization Without Risk Transfer, *Journal of Financial Economics*, 107, 515-536

Acharya, V. and S. Steffen, 2015, The "Greatest" Carry Trade Ever? Understanding Eurozone Bank Risk, *Journal of Financial Economics* 115 (2), 215-236.

Acharya, V. and S. Steffen, 2020a, The risk of being a fallen angel and the corporate dash for cash in the midst of COVID. *Review of Corporate Finance Studies* 9 (3), 430-471.

Acharya, V. and S. Steffen, 2020b, 'Stress tests' for banks as liquidity insurers in a time of COVID. CEPR VoxEU.org.

Adrian, T. and M. Brunnermeier, 2016, *American Economic Review* 106 (7), 1705-1741.

Agarwal, V. and N.Y. Naik, 2004. Risks and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies* 17 (1), 63-98.

Allen, F., and D. Gale. 2004. Financial Intermediaries and Markets. *Econometrica* 72:1023–61.

Allen, F., and A. M. Santomero. 1998. The Theory of Financial Intermediation. *Journal of Banking and Finance* 21:1461–85.

Bai, J., A. Krishnamurthy, C.-H. Weymuller, 2018, Measuring liquidity mismatch in the banking sector. *Journal of Finance* 73, 51-93.

Balyuk, T., M. Puri, and N. Prabhala, 2021, Indirect Costs of Government Aid and Intermediary Supply Effects: Lessons From the Paycheck Protection Program, Working Paper.

Behn, M., R. Haselmann, and V. Vig, 2016, The limits of model-based regulation, Working Paper.

Beltratti, A. and R. Stulz, 2012, The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics* 105 (1), 1-17.

Berg, T., A. Saunders and S. Steffen, 2016, The Total Cost of Borrowing in the Loan Market – Don't Ignore the Fees, *Journal of Finance*, 71(3), 1357-1392.

Berg, T., A. Saunders, S. Steffen and D. Streitz, 2017, Mind the Gap: The Difference between U.S. and European Loan Rates, *Review of Financial Studies*, 30(3), 948-987.

Berger, A., and C. Bouwman, 2009, Bank liquidity creation, *Review of Financial Studies*, 22(9), 3779-3837.

Bhattacharya, S., and A. V. Thakor. 1993. Contemporary Banking Theory. *Journal of Financial Intermediation* 3:2–50

Boyarchenko, N., A. Kovner and O. Shachar. 2020. It's What You Say and What You Buy: A Holistic Evaluation of the Corporate Credit Facilities. Federal Reserve Bank of New York Staff Reports.

Brownlees, C., and R. Engle, 2017, SRISK: A Conditional Capital Shortfall Measure of Systemic Risk, *Review of Financial Studies*, 30 (1), 48–79.

Cai, J., F. Eidam, A. Saunders, and S. Steffen, 2018, Syndication, interconnectedness, and systemic risk, *Journal of Financial Stability*, 34, 105-120.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. Plosser, 2021, Bank liquidity provision across the firm size distribution, *Journal of Financial Economics*, forthcoming.

Coval, J. D., and A. V. Thakor. 2005. Financial Intermediation as a Beliefs-Bridge between Optimists and Pessimists. *Journal of Financial Economics* 75:535–69.

Darmouni, O., and K. Y. Siani, 2020. Crowding Out Bank Loans: Liquidity-Driven Bond Issuance. Working Paper, Columbia University.

Deep, A., and G. Schaefer. 2004. Are Banks Liquidity Transformers? Working Paper, Harvard University.

Demsetz, R., and P. Strahan, 1997, Diversification, size, and risk at bank holding companies, *Journal of Money, Credit and Banking* 29(3), 300-313.

Demirguc-Kunt, A., A. Pedraza, and C. Ruiz-Ortega, 2020, Banking sector performance during the COVID-19 crisis, Working Paper, World Bank.

Egan, M., S. Lewellen, A. Sunderam, 2020, The cross section of bank value. Working Paper.

Erel, I., and J. Liebersohn, 2020, Does FinTech Substitute for Banks? Evidence from the Paycheck Protection Program, Working Paper.

Haddad, V., A. Moreira, and T. Muir, 2021, When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response, *Review of Financial Studies*, forthcoming.

Fahlenbrach, R., R. Prilmeier, and R.s M. Stulz, 2012, This Time is the Same: Using Bank Performance in 1998 to Explain Bank Performance During the Recent Financial Crisis, *Journal of Finance* 67, 2139-2185.

Fahlenbrach, R., K. Rageth, and R. M. Stulz, 2020, How valuable is financial flexibility when revenue stops? Evidence from the Covid-19 crisis. *Review of Financial Studies*, forthcoming.

Gatev, E., and P. Strahan, 2006, Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. Journal of Finance 61(2), 867-892.

Gilchrist, S., and E. Zakrajšek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692-1720.

Gormsen, N. J., and R. S. J. Koijen. 2020. Coronavirus: Impact on stock prices and growth expectations. *Review of Asset Pricing Studies* 10 (4), 574-597.

Greenwald, D. L., J. Krainer, and P. Paul, 2021, The credit line channel, Working Paper.

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.

Ivashina, V., 2009, Asymmetric Information Effects on Loan Spreads, *Journal of Financial Economics* 92, 300–319.

Ivashina, V., and D. Scharfstein, 2010, Bank Lending During the Financial Crisis of 2008, *Journal of Financial Economics*, 97(3), 319–338.

Jiménez, G., J. A Lopez, and J. Saurina, 2009, Empirical analysis of corporate credit lines. *The Review of Financial Studies* 22 (12), 5069–5098.

Kapan, T., and C. Minoiu, 2021, Liquidity Insurance vs. Credit Provision: Evidence from the COVID-19 Crisis, Working Paper.

Kargar, M., B. Lester, D., S. Liu, P.O. Weill, and D. Zúñiga, 2021, Corporate Bond Liquidity During the COVID-19 Crisis, *Review of Financial Studies*, forthcoming.

Kashyap, A., R. Rajan and J. Stein, 2002, Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-taking, *Journal of Finance* 57(1) 33.73.

Kovner, A. and A. Martin, 2020, Expanding the Toolkit: Facilities Established to Respond to the COVID-19 Pandemic, Federal Reserve Bank of New York Liberty Street Economics.

Khwaja, A. and A. Mian, 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *American Economic Review* 98(4):1413–42.

Landier, A., and D. Thesmar, 2020, Earnings Expectations in the COVID Crisis, MIT Working Paper.

Liang, N. and P. Parkinson, 2020, Enhancing liquidity of the US Treasury market under stress, Working Paper #72, Hutchins Center on Fiscal & Monetary Policy at Brookings.

Li, L., P. Strahan, and S. Zhang, 2020, Banks as Lenders of First Resort: Evidence from the COVID-19 Crisis, *Review of Corporate Finance Studies* 9(3), 472-500.

Minoiu, C., R. Zarutskie, and A. Zlate, 2021, Motivating Banks to Lend? Credit Spillover Effects of the Main Street Lending Program, Working Paper.

Nikolov, B., L. Schmid, and R. Steri, 2019, Dynamic Corporate Liquidity. *Journal of Financial Economics* 132 (1), 76–102.

O'Hara, M., and X. A. Zhou, 2021, Anatomy of a Liquidity Crisis: Corporate Bonds in the Covid-19 Crisis, *Journal of Financial Economics*, 142, 46-68.

Pagano, M., C. Wagner, and J. Zechner, 2020, Disaster resilience and asset prices. Working Paper, University of Naples.

Ramelli, S., and A. F. Wagner, 2020, Feverish stock price reactions to COVID-19. *Review of Corporate Finance Studies* 9 (3), 622-655.

Repullo, R. 2004. Capital Requirements, Market Power, and Risk-Taking in Banking. *Journal of Financial Intermediation* 13:156–82.

Roberts, M. and A. Sufi, 2009, Control Rights and Capital Structure: An Empirical Investigation, *Journal of Finance* 64, 1657-1695.

Saunders, A., A. Spina, S. Steffen, and D. Streitz, 2021, Corporate loan spreads and economic activity, Working Paper.

Sufi, A., 2009, Bank Lines of Credit in Corporate Finance: An Empirical Analysis. The *Review of Financial Studies* 22 (3),1057–1088.

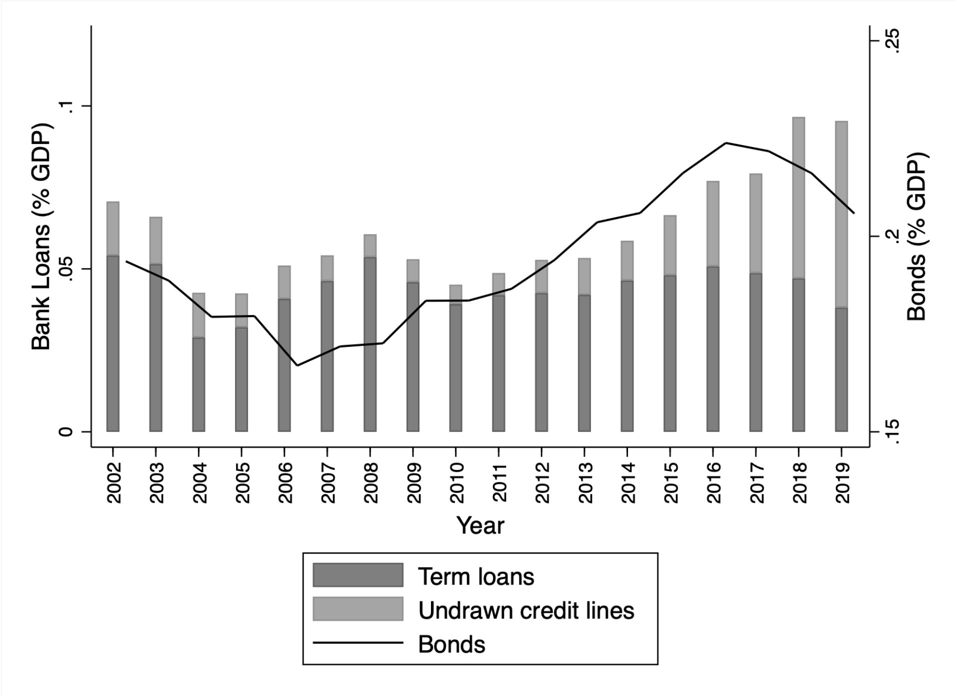
Vissing-Jorgensen, 2021, The Treasury Market in Spring 2020 and the Response of the Federal Reserve, Working Paper.

Von Thadden, E.-L. 2004. Bank Capital Adequacy Regulation under the New Basel Accord. *Journal of Financial Intermediation* 13:90–95.

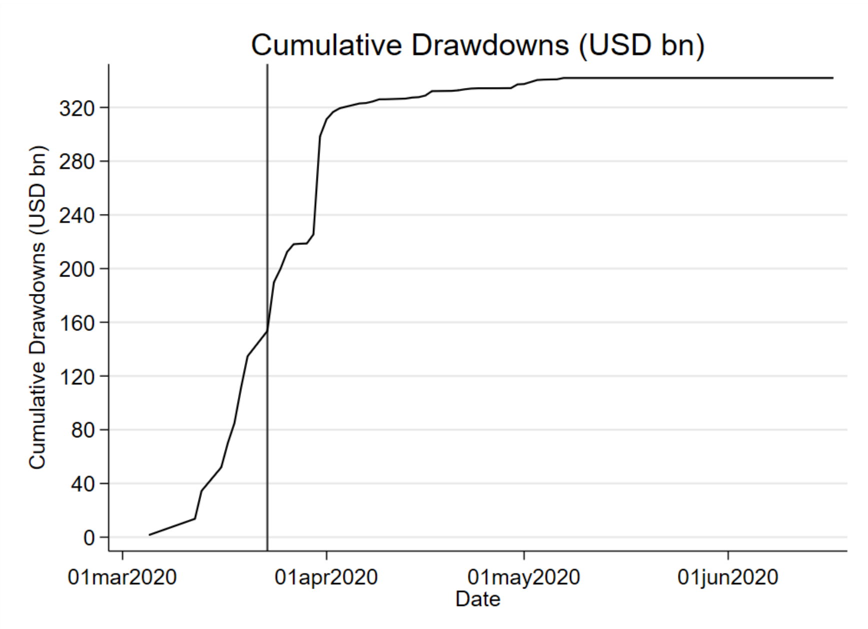
Figure 1. Credit lines, cumulative drawdowns and bank stock prices

Panel A shows the cumulative credit line drawdowns of U.S. firms over the March 1, 2020 to July 1, 2020 period in billion USD. Panel B shows the stock prices of U.S. firms, banks vs. non-banks, over the Jan 1st to Dec 31st, 2020 period. Banks are the 147 banks shown in Appendix II.

Panel A. Bond vs loan financing of U.S. publicly listed firms



Panel B. Cumulative drawdowns (in USD bn)



Panel C. Stock prices of banks vs. non-financial firms

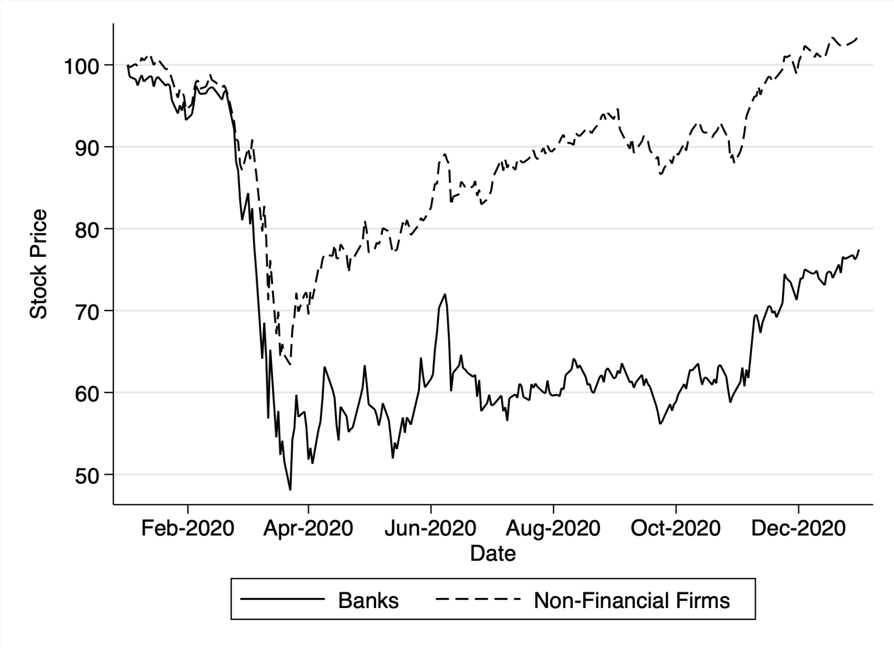
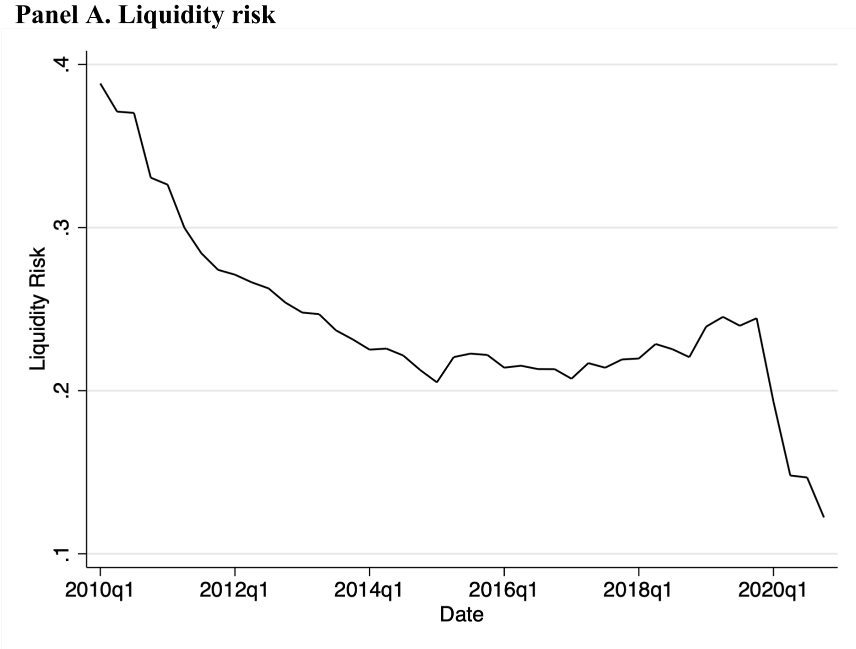


Figure 2. Bank balance-sheet liquidity risk

This figure shows the time-series of balance-sheet *Liquidity Risk* over the Q1 2010 to Q4 2020 period. We measure *Liquidity Risk* as undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets). All variables are defined in Appendix III.

Panel A. Liquidity risk



Panel B. Components of liquidity risk

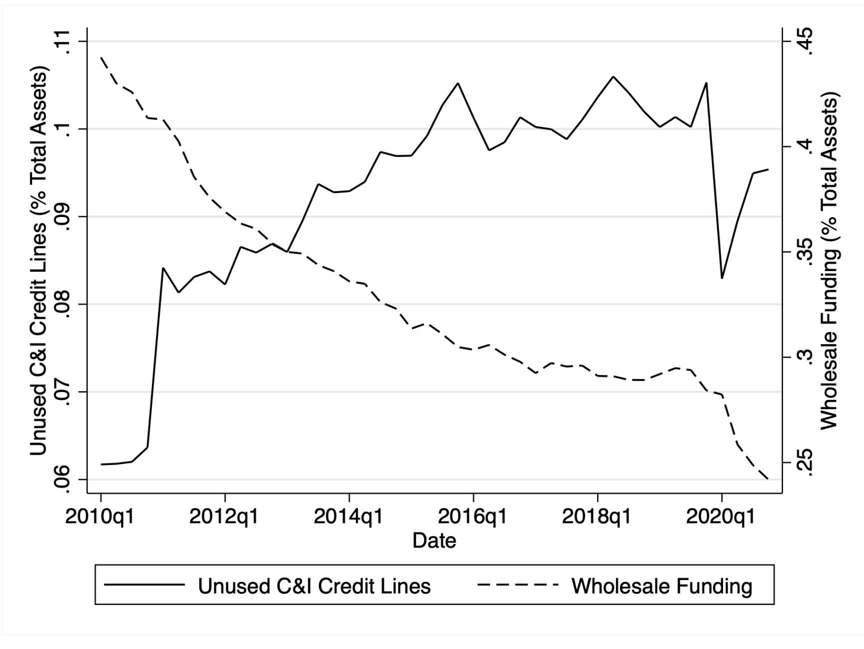
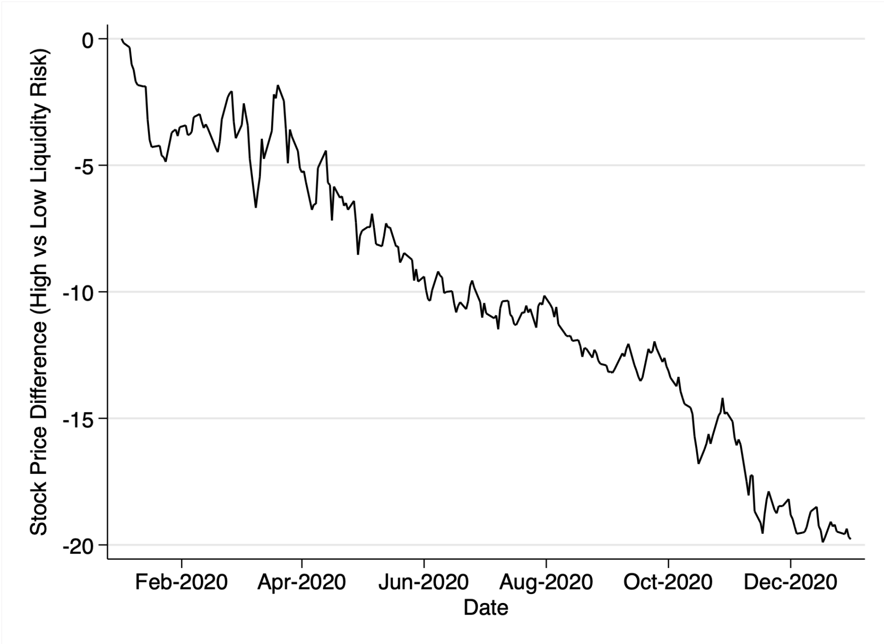


Figure 3. Stock prices and liquidity risk of U.S. banks

This figure shows stock prices of U.S. banks with *Low* or *High Liquidity Risk*. We measure *Liquidity Risk* as undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets) and use a median split to distinguish between banks with *Low* vs. *High Liquidity Risk*. Panel A shows the stock prices of both group of banks indexed at Jan 1, 2020, Panel B shows the difference between the stock prices (in percentage point). Panel B plots bank stock returns during the March 1 – March 23, 2020 period on *Liquidity Risk*. All variables are defined in Appendix III.

Panel A. Bank stock prices for high vs low liquidity risk banks



Panel B. Bank stock return and liquidity risk

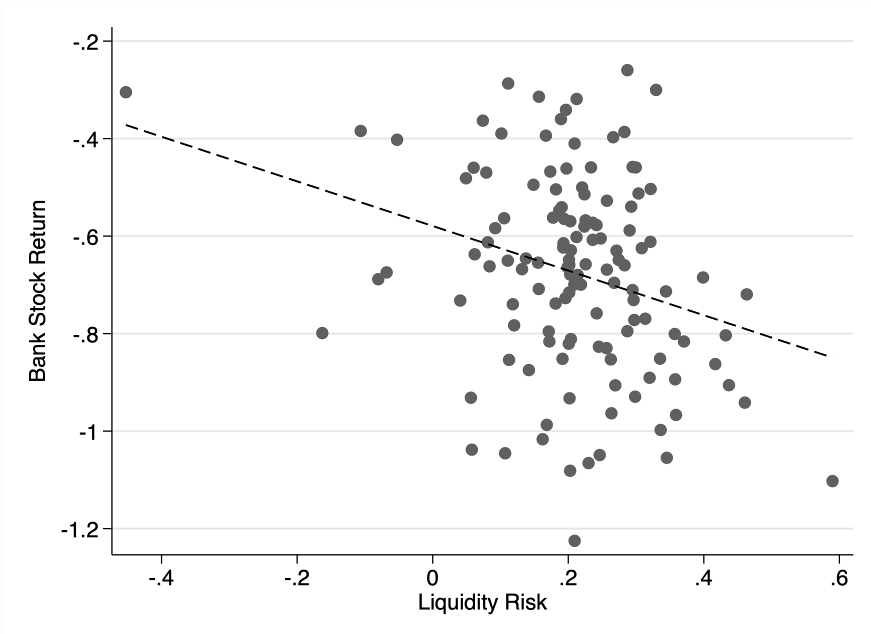
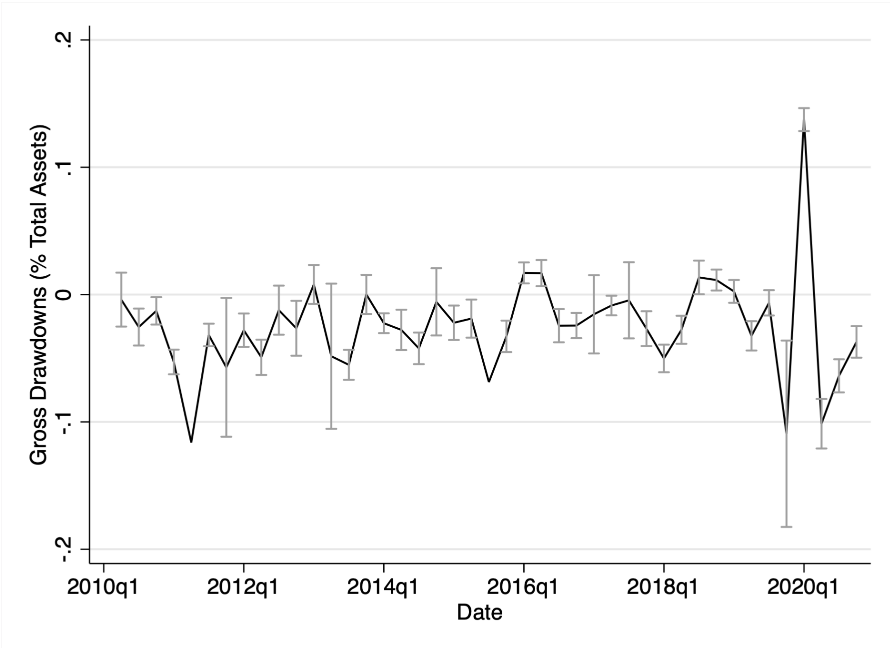


Figure 4. Net vs. gross drawdowns

This figure shows the time-series of *Gross Drawdowns* (Panel A) and *Net Drawdowns* (Panel B) over the Q1 2010 to Q4 2020 period. *Gross Drawdowns* is the percentage change in a bank's off-balance-sheet unused C&I loan commitments. *Net Drawdowns* are defined as the change in a bank's off-balance-sheet unused C&I loan commitments minus the change in deposits relative to total assets. All variables are defined in Appendix III.

Panel A. Gross Drawdowns



Panel B. Net Drawdowns

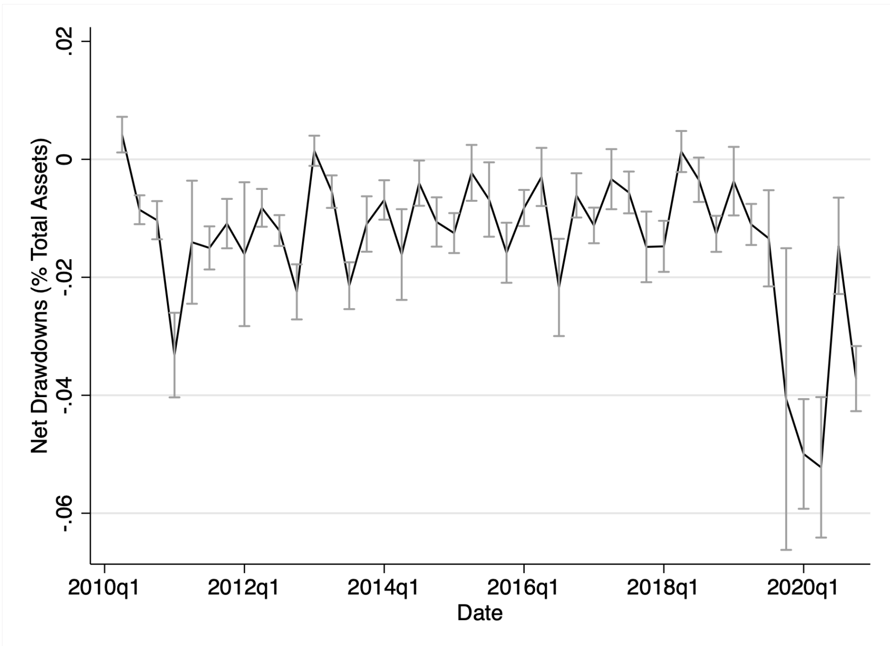


Figure 5. Stock prices and liquidity risk of U.S. banks (2007-2009)

This figure shows stock prices of U.S. banks with *Low* or *High Liquidity Risk* for the Jan 2007 to Jan 2010 period. We measure *Liquidity Risk*.as undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets) and use a median split to distinguish between banks with *Low* vs. *High Liquidity Risk*. Panel A shows the stock prices of both group of banks indexed at Jan 1, 2007, Panel B shows the difference between the stock prices (in percentage point). All variables are defined in Appendix II.

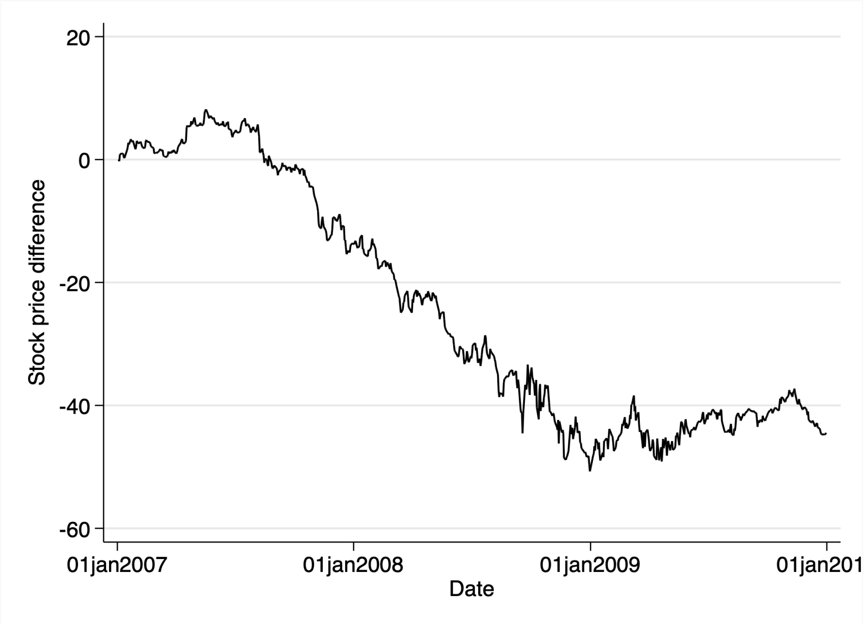
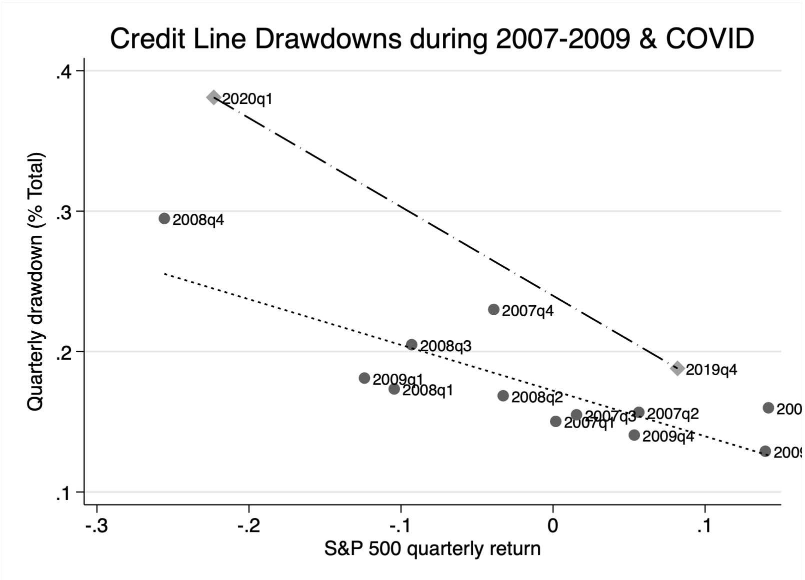


Figure 6. Credit-line drawdowns and market returns

This figure plots the cumulative drawdown of credit lines of non-financial firms on the cumulative market return (using the S&P 500 as the market). In Panel A, we plot the cumulative quarterly drawdown rates during the COVID-19 pandemic (i.e. Q4 2019 and Q1 2020) and the GFC (i.e. the Q1 2007 to Q4 2009 period) on the respective quarterly S&P 500 returns. We also show the linear regressions for both periods. In Panel B of Figure 6, we use the lowest cumulative daily S&P 500 return within each quarter (instead of the quarterly return). All variables are defined in Appendix II.

Panel A. Quarterly drawdowns vs quarterly S&P 500 returns



Panel B. Quarterly drawdowns vs lowest cumulative S&P 500 return in each quarter

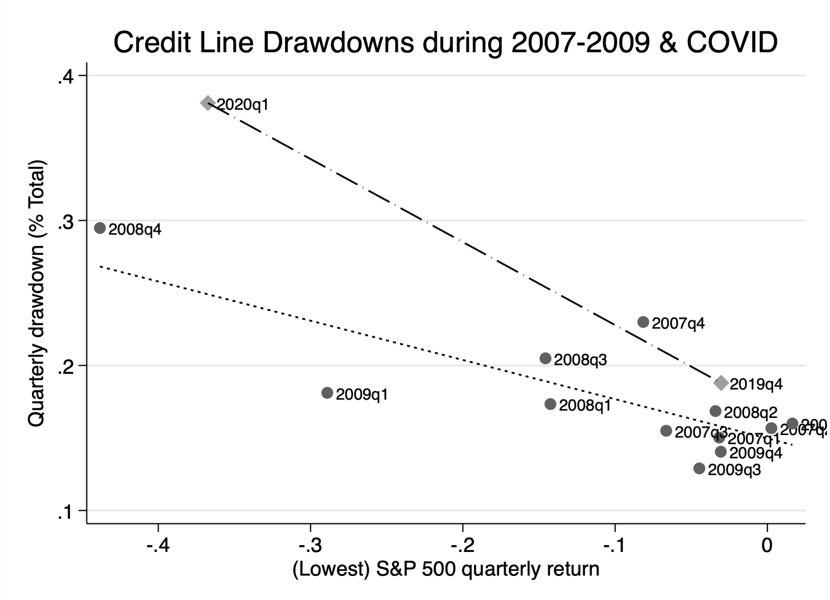


Table 1. Descriptive statistics

Table 1 shows descriptive statistics of the variables included in the cross-sectional regressions. Sample banks are shown in Appendix II. All variables are defined in Appendix III.

Variable	**Obs.**	**Mean**	**Std. dev.**	**Min**	**Max**
Panel A. Bank stock returns					
Return January 2020	147	-0.072	0.046	-0.181	0.064
Return February 2020	147	-0.125	0.040	-0.246	0.071
Return 3/1-3/23 2020	147	-0.472	0.186	-1.084	-0.131
Return 1/1-3/23 2020	147	-0.669	0.206	-1.225	-0.227
Panel B. Bank characteristics					
Liquidity Risk	147	0.195	0.147	-0.453	0.590
Unused LC / Assets	147	0.077	0.051	0.000	0.263
Liquidity / Assets	147	0.136	0.109	0.029	0.607
Wholesale Funding / Assets	147	0.144	0.100	0.013	0.624
Beta	147	1.170	0.328	0.156	2.313
NPL / Loans	147	0.008	0.008	0.000	0.044
Non-Interest Income	147	0.268	0.185	0.021	0.966
Log(Assets)	147	16.982	1.437	14.397	21.712
ROA	147	0.013	0.006	0.003	0.061
Deposits / Loans	147	1.306	1.130	0.504	11.002
Income Diversity	147	0.446	0.212	0.043	0.993
Z-Score	147	3.619	0.536	1.859	5.060
Loans / Assets	147	0.670	0.166	0.027	0.899
Deposits / Assets	147	0.745	0.105	0.191	0.879
Idiosyncratic Volatility	147	0.200	0.041	0.121	0.417
Real Estate Beta	147	0.544	0.197	-0.266	1.136
Primary Dealer	147	0.041	0.199	0.000	1.000
Derivatives / Assets	147	1.161	4.753	0.000	37.242
Credit Card Commitments /Assets	147	0.075	0.389	0.000	3.998
Consumer Loans / Assets	147	0.056	0.117	0.000	0.828
SRISK /Assets	147	0.003	0.007	0.000	0.039

Table 2. Liquidity risk and bank stock returns

This table reports the results of OLS regressions of U.S. banks' excess stock returns over the 1/1/2020 – 3/23/2020 period on bank *Liquidity Risk* and a bank's *Equity Beta* and control variables. *Equity Beta* is constructed relative to the S&P 500 using daily stock returns over the 2019 period and multiplied with the realized excess return of the S&P 500 over the 1/1/2020 – 3/23/2020 period. We add *SRISK/Assets* as additional control (column (6)). *SRISK* is available for banks in the vlab database. The regression includes a dummy for banks for whom we do not find exposure data (unreported). P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity Risk	-0.329***	-0.409***	-0.565***	-0.550***	-0.568***	-0.551***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Equity Beta	0.734***	0.706***	0.566***	0.557***	0.577***	0.476***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.004)
NPL / Loans		-7.038***	-3.682**	-3.603**	-3.408*	-3.665**
		(0.000)	(0.033)	(0.039)	(0.054)	(0.035)
Equity Ratio		0.522	-0.119	-0.103	-0.519	-0.897
		(0.425)	(0.858)	(0.878)	(0.443)	(0.179)
Non-Interest Income		0.297***	0.169	0.189	0.132	0.0973
		(0.003)	(0.139)	(0.106)	(0.273)	(0.412)
Log(Assets)		-0.000996	-0.0330**	-0.0363**	-0.0210	0.00422
		(0.938)	(0.046)	(0.036)	(0.267)	(0.844)
ROA		-3.726	1.193	1.167	5.406	6.158
		(0.310)	(0.757)	(0.766)	(0.237)	(0.163)
Deposits / Loans		-0.0217	-0.057***	-0.054***	-0.015***	-0.054***
		(0.115)	(0.001)	(0.002)	(0.002)	(0.003)
Income Diversity			-0.0226	-0.0343	-0.0257	-0.0263
			(0.799)	(0.705)	(0.775)	(0.747)
Distance-to-Default			0.0606*	0.0581*	0.0583*	0.0517*
			(0.061)	(0.075)	(0.067)	(0.075)
Loans / Assets			-0.483**	-0.461**	-0.408*	-0.352*
			(0.020)	(0.032)	(0.062)	(0.099)
Deposits / Assets			-0.0587	-0.0207	-0.0873	-0.235
			(0.786)	(0.938)	(0.735)	(0.346)
Idiosyncratic Volatility			-1.174***	-1.206***	-1.018**	-1.051**
			(0.003)	(0.002)	(0.017)	(0.014)
Real Estate Beta			0.180*	0.184*	0.113	0.0951
			(0.099)	(0.093)	(0.380)	(0.441)
Current Primary Dealer Indicator				0.0845	0.00641	-0.0951
				(0.430)	(0.958)	(0.381)
Derivatives / Assets				-0.00151	-0.000340	0.00526
				(0.808)	(0.958)	(0.415)
Credit Card Commitments /Assets					-0.0371	-0.0926
					(0.510)	(0.135)
Consumer Loans / Assets					-0.218	-0.147
					(0.395)	(0.591)
SRISK /Assets						-6.409***
						(0.009)
R-squared	0.256	0.354	0.448	0.449	0.462	0.502
Number obs.	147	147	147	147	147	147

Table 3. Bank portfolio composition: Exposure to COVID-19-affected industries

Panel A reports the results of OLS regressions of U.S. banks' excess stock returns over the 3/1/2020 – 3/23/2020 period on bank *Liquidity Risk* and a bank's *Equity Beta*, control variables and different proxies for bank portfolio risk. *Equity Beta* is constructed relative to the S&P 500 using daily stock returns over the 2019 period and multiplied with the realized excess return of the S&P 500 over the 1/1/2020 – 3/23/2020 period. Columns (1) – (12) add different measures that proxy for bank exposures to COVID-19-affected industries. These measures are defined in Appendix IV. Exposures "*Affected Industries (β_{COVID})*" are calculated in regressions of bank excess stock returns on stock returns of COVID-19-affected industries and various (macro) variables: *Market return*, *SMB, HML, risk-free interest rate, VIX, term spread, BBB-AAA* spread, the *CPI* (see below in this table). Column (13) uses the first principal component based on all 12 exposure betas. Column (14) uses the average Dealscan syndicated loan exposure to affected industries based on different definitions relative to total assets (*Loan Exposure / Assets*). P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity Risk	-0.568***	-0.543***	-0.546***	-0.527***	-0.481***	-0.530***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Affected Industries (β_{COVID})	-1.410***	-0.531*	-0.455	-0.526***	-0.635***	-0.493**
	(0.005)	(0.097)	(0.116)	(0.005)	(0.000)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Affected Measure	Fahlenbrach *et al.* (2021) – stock performance	Moody's (2020) COVID industries	Koren and Peto (2020) – Customer share	Dingel and Neiman (2020) – Telework	Fahlenbrach *et al.* (2021) – 6 NAIC level COVID industries	Koren and Peto (2020) – Presence share
R-squared	0.505	0.475	0.475	0.502	0.537	0.498
Number obs.	147	147	147	147	147	147

	(7)	(8)	(9)	(10)	(11)	(12)
Liquidity Risk	-0.515***	-0.518***	-0.541***	-0.524***	-0.534***	-0.521***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Affected Industries (β_{COVID})	-0.541**	-0.709***	-0.221*	-0.910**	-1.528***	-2.090***
	(0.013)	(0.004)	(0.090)	(0.018)	(0.001)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Affected Measure	Koren and Peto (2020) – Teamwork share	YoY sales decline	Chodorow-Reich *et al.* (2021) – Abnormal employment decline	ONET – Physical proximity	ONET – Face-to-face discussion	ONET – External customers
R-squared	0.496	0.519	0.476	0.501	0.517	0.504
Number obs.	147	147	147	147	147	147

	(13)	(14)
Liquidity Risk	-0.515***	-0.496***
	(0.000)	(0.000)
Affected Industries (β_{COVID})	-0.040**	
	(0.012)	
Loan Exposure / Assets		-0.074**
		(0.024)
Controls	Yes	Yes
Affected Measure	First Principal Component of exposure betas to affected industries	Average Syndicated Loan Exposure to affected industries
R-squared	0.524	0.478
Number obs.	147	147

Note:
Detailed data describing bank portfolio composition are hardly available to empirical researchers. Our approach to estimate banks' exposure to COVID-19-affected industries is similar to the procedure employed e.g. by Agarwal and Naik (2004) to characterize the exposures of hedge funds or the approach in Acharya and Steffen (2015) in estimating European banks' exposure to sovereign debt. We use multifactor models in which the sensitivities of banks' stock returns to "COVID-19-affected industry" returns are measures of banks' exposure to these industries. We call these sensitivities "*Affected Industries* (β_{COVID})". The lack of micro level portfolio holdings of banks gives these tests more power and increases the efficiency of the estimates.

More precisely, we run the following regression daily over the Jan 1, 2019 to Dec 31, 2019 period for each bank i:

$$r_t = \beta_0 + \beta_{COVID} r_{COVID,t} + \beta_m r_{m,t} + \beta_{HML} HML_t + \beta_{SMB} SMB_t + \gamma \sum \boldsymbol{X}_t + \varepsilon_t$$

r_t is the daily bank excess return. $r_{COVID,t}$ is the daily excess return of the COVID-19-affected industry. $r_{m,t}$ is the daily market excess return. HML and SML are the Fama-French factors.
$\boldsymbol{X}_t$ is a vector of control variables: *risk-free interest rate, VIX, term spread, BBB-AAA spread,* and the *CPI.* Because of the co-movement of $r_{m,t}$ and $r_{COVID,t}$, we orthogonalize $r_{m,t}$ to $r_{COVID,t}$.

Table 4. Liquidity risk and bank stock returns – Robustness tests

Panel A reports the results of OLS regressions of U.S. bank' realized stock returns during January 2020 (columns (1)-(2)), February 2020 (columns (3) to (4)) and 1-23 March 2020 (columns (5) to (7)). Regressions with control variables are based on column (5) in Table 2. Panel B reports the results of OLS regressions of U.S. banks' excess stock returns over the 1/3/2020 – 3/23/2020 over the 1/3/2020 – 3/23/2020 period on the different components of *Liquidity Risk* with control variables as in column (5) in Table 2. We add the different components sequentially in columns (1)-(3) and add *SRISK/Assets* as additional control (column (4)). P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III. Panel C reports the results of the regression of U.S. banks' daily stock returns on *Liquidity Risk* interacted with natural logarithm of cumulative drawdowns from credit lines by U.S. firms until this day over the 1 – 23 March 20201 period. We include all firms (column (1)), the BBB-rated firms only (column (2)), then focus on non-investment grade rated firms (column (3)) and then on unrated firms (column (4)). We also include the daily market access return (r_m), *HML* and *SMB* as well as bank fixed effects; standard errors are Newey–West.

Panel A. Liquidity risk and bank stock returns by month

	(1)	(2)	(3)	(4)	(5)	(6)
	January 2020		February 2020		1/3-23/3/2020	
Liquidity Risk	-0.0594**	-0.0625**	-0.0470	-0.0439	-0.462***	-0.445***
	(0.022)	(0.023)	(0.306)	(0.357)	(0.000)	(0.000)
Equity Beta	0.0452	0.0699*	0.0350	0.0197	0.497***	0.386**
	(0.253)	(0.066)	(0.185)	(0.465)	(0.003)	(0.011)
SRISK /Assets		1.317**		-1.122*		-6.604***
		(0.048)		(0.075)		(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.341	0.387	0.258	0.285	0.413	0.471
Number obs.	147	147	147	147	147	147

Panel B. Components of liquidity risk

	(1)	(2)	(3)
		3/1-3/23/2020	
Unused C&I Loans / Assets	-1.110***	-1.006***	-1.084***
	(0.001)	(0.001)	(0.001)
Liquidity / Assets		0.477***	0.488***
		(0.009)	(0.006)
Wholesale Funding / Assets			-0.279
			(0.107)
Equity Beta	0.595***	0.599***	0.597***
	(0.004)	(0.004)	(0.003)
SRISK /Assets	-6.559**	-6.208**	-5.922**
	(0.015)	(0.014)	(0.018)
Controls	Yes	Yes	Yes
R-squared	0.456	0.479	0.486
Number obs.	147	147	147

Panel C. Time-series (Daily drawdown sample)

	(1)	(2)	(3)	(4)
	3/1-3/23/2020			
Liquidity Risk x Log(DD)	-0.00862***			
	(0.001)			
Liquidity Risk x Log(DD^{BBB})		-0.00221**		
		(0.011)		
Liquidity Risk x Log(DD^{NonIG})			-0.0109***	
			(0.001)	
Liquidity Risk x Log($DD^{Not\ rated}$)				-0.00238**
				(0.019)
r_m	1.064***	1.068***	1.068***	1.064***
	(0.000)	(0.000)	(0.000)	(0.000)
SMB	0.871***	0.895***	0.897***	0.871***
	(0.000)	(0.000)	(0.000)	(0.000)
HML	1.014***	0.995***	0.989***	1.010***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank Fixed Effect	Yes	Yes	Yes	Yes
Number obs.	2,626	2,626	2,626	2,626

Table 5. Liquidity risk in the post-Fed intervention period

Panel A reports descriptive statistics of bank excess stock returns for Q1 – Q4 2020. Panel B reports the results of OLS regressions of U.S. banks' excess stock returns over the Q2 to Q4 2020 period on bank *Liquidity Risk, Equity Beta* and control variables as shown in column (5) of Table 2. Control variables are lagged by one quarter. Columns (1) and (2) report the results using Liquidity Risk and columns (3) and (4) the components of Liquidity Risk. Columns (2) and (4) include quarter fixed effects. Standard errors are clustered at the bank level. Columns (5) to (7) repeat the results separately for each quarter. In these regressions, p-values are based on robust standard errors. All variables are defined in Appendix III. Panel C reports descriptive statistics of market-value losses (*Loss*) incurred during the 1/1/2020 – 3/23/2020 period, relative to the 1/1/2020 market value of equity (*Loss (% MV)*), recovery of losses during Q2 (*Recovery of market-value loss Q2*) and during the Q2 to Q3 (Recovery of market-value loss *Q2-Q3*) period, and between Q2 and Q4 (*Recovery of market-value loss Q2-Q4*). Panel D reports the results of OLS regressions of *Recovery of market-value loss* on bank credit-line repayments during the Q2 period (columns (1) and (2)) and the Q2 to Q3 period (columns (3) and (4)) and control variables as in columns (5) in Table 2. Columns (2) and (4) uses credit lines repayments by rating categories. Credit-line repayments are constructed based on a sample combining call report, Dealscan and Capital IQ data is thus available only for a subset of banks. The regressions include a dummy for banks for whom we do not find repayment data (unreported). P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

Panel A. Descriptive statistics of bank stock returns

Variable	Obs.	Mean	Std. dev.	Min	Max
2020q1	147	-0.511	0.181	-0.996	-0.075
2020q2	146	0.096	0.149	-0.398	0.537
2020q3	145	-0.079	0.104	-0.282	0.249
2020q4	144	0.346	0.115	0.014	0.706
Total	582	-0.039	0.343	-0.996	0.706

Panel B. Liquidity risk and bank stock returns after the Fed interventions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Q2–Q4 2020			Q2 2020	Q3 2020	Q4 2020
Liquidity Risk	0.0104	-0.0406			-0.00979	-0.132*	-0.0368
	(0.856)	(0.446)			(0.931)	(0.073)	(0.714)
Unused C&I Loans / Assets			-0.105	-0.194*			
			(0.481)	(0.094)			
Liquidity / Assets			-0.0726	0.00860			
			(0.352)	(0.901)			
Wholesale Funding / Assets			-0.0845	-0.101			
			(0.268)	(0.148)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE		Yes		Yes			
Cluster	Bank	Bank	Bank	Bank			
R-squared	0.122	0.751	0.123	0.751	0.434	0.380	0.441
Number obs.	435	435	435	435	146	145	144

Panel C. Market-value losses

Market-value losses are calculated over the 1/1/2020 to 3/23/2023 period.

	N	Mean	Std Dev	Min	Max
Market-value loss (USD mn)	147	-10,102	30,547	-227,663	-101
Market-value loss (%)	147	-61.16%	20.61%	-121.37%	-19.51%
Recovery of market-value loss Q2 (%)	147	14.88%	14.48%	-47.13%	69.45%
Recovery of market-value loss Q2-Q3 (%)	147	5.79%	21.02%	-70.50%	70.26%
Recovery of market-value loss Q2-Q4 (%)	147	37.31%	17.59%	-5.63%	103.79%

Panel D. Which banks do recover market-value losses?

	(1)	(2)	(3)	(4)
	Recovery of market value loss Q2		Recovery of market value loss Q2-Q3	
Repayment Q2	-0.089***			
	(0.002)			
Repayment Q2 x Not Rated		0.001		
		(0.329)		
Repayment Q2 x AAA-A Rated		0.0121		
		(0.712)		
Repayment Q2 x BBB Rated		-0.0361		
		(0.271)		
Repayment Q2 x NonIG Rated		-0.030**		
		(0.021)		
Repayment Q2-Q3			-0.0171	
			(0.709)	
Repayment Q2-Q3 x Not Rated				-0.002
				(0.800)
Repayment Q2-Q3 x AAA-A Rated				0.0471
				(0.269)
Repayment Q2-Q3 x BBB Rated				0.0646
				(0.272)
Repayment Q2-Q3 x NonIG Rated				-0.099**
				(0.010)
Controls	Yes	Yes	Yes	Yes
R-squared	0.340	0.338	0.446	0.467
Number obs.	146	146	146	146

Table 6. Understanding the mechanisms: Funding versus capital

Panel A reports the results of OLS regressions of U.S. bank' excess stock returns during the 1/1/2020 to 3/23/2020 period on *Net Drawdowns* (column (1)) and *Gross Drawdowns* (column (2)) and control variables. *Net Drawdowns* are defined as the change in a bank's off-balance-sheet unused C&I loan commitments minus the change in deposits (all measured during Q1 2020) relative to total assets. *Gross Drawdowns* is the percentage change in a bank's off-balance-sheet unused C&I loan commitments (measured during Q1 2020). Column (4) adds *SRISK/Assets* as additional control. SRISK is only available for banks in the vlab database. These regressions include a dummy for banks for whom we do not find SRISK (unreported). Column (5) includes an interaction term of *Gross Drawdowns* with *High Capital*, and indicator variable that is one if a bank's equity capital ratio is above the median of the distribution. Column (6) includes an interaction term of *Gross Drawdowns* with *Capital Buffer,* which is the difference between a bank's equity capital ratio and the average capital ratio of all sample banks. The secular term Capital Buffer is thus absorbed. Column (7) (column ((8)) include interaction terms of *Net Drawdowns* and *High Capital* (*Capital Buffer*). In columns (9) and (10), we compare both interaction terms of *Gross* and *Net Drawdowns*. Panel B reports the results using *Deposits*, defined as deposit inflows in Q1 2020 relative to total assets, instead of *Net Drawdowns*. Control variables as in column (5) in Table 2 are included. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

Panel A. Gross vs net drawdowns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Net Drawdowns	0.0686		0.356	0.393	0.382	0.357	0.366	0.305	0.366	0.295
	(0.881)		(0.421)	(0.333)	(0.363)	(0.398)	(0.538)	(0.469)	(0.527)	(0.461)
Gross Drawdowns		-5.142***	-5.618***	-5.357***	-9.156***	-5.213***	-5.615***	-5.551***	-9.153***	-5.117***
		(0.009)	(0.003)	(0.007)	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)	(0.006)
SRISK / Assets				-6.236**						
				(0.039)						
Gross Drawdowns x High Capital					5.927**				5.913**	
					(0.034)				(0.033)	
Gross Drawdowns x Capital Buffer						1.840**				1.909**
						(0.046)				(0.035)
Net Drawdowns x High Capital							0.186		0.0356	
							(0.845)		(0.969)	
Net Drawdowns x Capital Buffer								-0.115		-0.139
								(0.454)		(0.324)
High Capital					0.0298		0.0671		0.0304	
					(0.559)		(0.132)		(0.554)	
Capital Buffer						-1.375*		-0.697		-1.676*
						(0.094)		(0.377)		(0.065)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.377	0.411	0.415	0.457	0.439	0.435	0.425	0.418	0.439	0.439
Number obs.	147	147	147	147	147	147	147	147	147	147

Panel B. Robustness using deposit inflows

	(1)	(2)	(3)	(4)	(5)	(6)
Deposits	-0.356	-0.393	-0.534	-0.284	-0.366	-0.295
	(0.421)	(0.333)	(0.347)	(0.497)	(0.527)	(0.461)
Gross drawdowns	-5.262***	-4.964***	-5.128***	-5.204***	-8.788***	-4.822**
	(0.006)	(0.010)	(0.006)	(0.006)	(0.001)	(0.011)
SRISK / Assets		-6.236**				
		(0.039)				
Deposits x High Capital			0.177		-0.0356	
			(0.848)		(0.969)	
Deposits x Capital Buffer				0.161		0.139
				(0.285)		(0.324)
Gross drawdowns x High Capital					5.948**	
					(0.043)	
Gross drawdowns x Capital Buffer						1.770*
						(0.051)
High Capital			0.0610		0.0304	
			(0.190)		(0.554)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.415	0.457	0.424	0.421	0.439	0.439
Number obs.	147	147	147	147	147	147

Table 7. Implications for bank lending during the COVID-19 pandemic

This table provides results of difference-in-differences regressions of the change in the loan exposures / originations in the pre- versus post-COVID-19 period on *Gross* and *Net Drawdowns*. The analysis is based on exposures / originations in the Jan 2019 October 2020 period (*Post* is denoted as the period starting 4/1/2020). Columns (1) to (4) show the results using Exposures (defined as quarterly (non-matured) exposures in Dealscan as dependent variable). *High Gross (Net) Drawdowns* are indicator variables equal to 1 if drawdowns are in the upper quartile of the distribution. Term Loan Indicator is an indicator variable equal to 1 if the loan is a term loan. All regressions include borrower x time and borrower x bank fixed effects. Columns (5) – (8) show the results using new loan originations as dependent variables. The sample is collapsed into a pre- and post-COVID-19 period and all regressions include borrower and borrower x bank fixed effects. Standard errors are clustered at the bank level. Control variables include banks' NPL ratio, log of total assets, ROA, Tier 1 capital ratio and loan-asset-ratio. Detailed variable definitions can be found Appendix III. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Exposures				New Originations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gross Drawdowns x Post	-0.0202				-1.208			
	(0.842)				(0.430)			
Net Drawdowns x Post	0.00336				-0.330			
	(0.925)				(0.104)			
High Gross Drawdowns x Post		0.00270	0.0147**	0.0163**		-0.0455***	-0.0481***	-0.0534**
		(0.284)	(0.048)	(0.010)		(0.005)	(0.008)	(0.030)
High Net Drawdowns x Post		-0.00276	0.000265	0.000863		-0.0532**	-0.0590**	-0.0251
		(0.308)	(0.963)	(0.858)		(0.036)	(0.036)	(0.473)
High Gross Drawdowns x Post x Term Loan Indicator			-0.0454*	-0.0470*			0.0188	0.0413
			(0.060)	(0.054)			(0.556)	(0.382)
High Net Drawdowns x Post x Term Loan Indicator			-0.0111	-0.0123			0.0361	0.0513
			(0.532)	(0.500)			(0.101)	(0.236)
Controls				Yes				Yes
Borrower x Time FE x Loan Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank x Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.992	0.992	0.992	0.992	0.997	0.997	0.997	0.997
Number obs.	315,038	315,038	315,038	277,976	3,482	3,482	3,482	3,482

Table 8. Liquidity risk and bank stock return during the global financial crisis

This table reports the results of OLS regressions of U.S. bank' excess stock returns on *Liquidity Risk* and its components during the Q2:2007 to Q2:2009 period. Columns (1) and (2) show panel regressions over the entire period and include control variables from column (5) of Table 2 and quarter fixed effects. Standard errors are clustered at the BHC level. Columns (3) to (11) show the results for each quarter. Control variables are lagged by one quarter. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Q2 2007–Q2 2009		Q2 2007	Q3 2007	Q4 2007	Q1 2008	Q2 2008	Q3 2008	Q4 2008	Q1 2009	Q2 2009
Liquidity Risk	-0.0961***										
	(0.000)										
Unused C&I Loans / Assets		-0.133***	0.0639	-0.0379	-0.0534	-0.295***	-0.383*	-0.0419	-0.549**	0.239	0.214
		(0.005)	(0.271)	(0.649)	(0.549)	(0.001)	(0.071)	(0.811)	(0.037)	(0.346)	(0.402)
Liquidity / Assets		-0.00562	-0.0839	0.0114	0.238**	0.105	0.302*	-0.101	0.0312	0.0381	-0.490*
		(0.915)	(0.365)	(0.901)	(0.023)	(0.374)	(0.099)	(0.687)	(0.898)	(0.880)	(0.069)
Wholesale Funding / Assets		-0.144***	-0.0447	-0.131**	-0.154*	-0.0281	-0.229	-0.158	-0.285	-0.0421	-0.332*
		(0.008)	(0.369)	(0.022)	(0.097)	(0.805)	(0.180)	(0.388)	(0.202)	(0.858)	(0.097)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes									
Cluster (Bank)	Yes	Yes									
R-squared	0.340	0.341	0.200	0.137	0.335	0.164	0.298	0.291	0.346	0.318	0.103
Number obs.	3,072	3,072	364	359	355	346	342	340	327	323	316

Table 9. Alternative liquidity risk measures

This tables shows descriptive statistics of different liquidity measures (Panel A) and the results of OLS regressions of U.S. bank' beta adjusted stock returns over the 3/1/2020 – 3/23/2020 period (Panel B) using these liquidity measures and control variables. These are the liquidity measures: *Liquidity Risk* (*Unused Commitments* plus *Wholesale Funding* minus *Liquidity* (% Assets)); *Unused C&I Loans / Assets* are Unused C&I credit lines over total assets; *BB* is the Berger and Bouwman (2009) "catfat" measure; *LMI* is the Bai *et al.* (2018) liquidity measure using the worst liquidity condition in March 2020.

Panel A. Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
Liquidity Risk	147	0.195	0.147	-0.453	0.590
Unused C&I Loans / Assets	147	0.077	0.051	0.000	0.263
BB	147	0.505	0.261	-0.638	1.924
LMI	147	0.287	0.200	-1.029	0.837

Panel B. Liquidity risk measures and stock returns

	(1)	(2)	(3)	(4)	(5)
Liquidity Risk	-0.462***				-0.293**
	(0.000)				(0.023)
Unused C&I Loans / Assets		-1.251***			
		(0.000)			
BB			-0.438***		-0.169
			(0.000)		(0.204)
LMI				0.343***	0.151
				(0.000)	(0.171)
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.413	0.408	0.404	0.397	0.429
Number obs.	147	147	147	147	147

Table 10. Credit-line drawdowns and Incremental SRISK^{CL}

This table reports the predicted drawdown rates (*Drawdown Rate*) from credit lines in a stress scenario of 40% correction to the global stock market (Panel A) and the *Slope* of the drawdown function (compare Figure 6). In Panel B, we report the *Unused Commitments* (C&I loans), and the marginal required capital to fund the predicted drawdowns (Marginal SRISK) using all three (stressed) historical drawdown rates. *Incremental SRISK*^{CL} = *Drawdown Rate* x 8% x *Unused Commitments* (C&I loans). *Debt* is total liabilities (from vlab). Panel C reports the calculation of *Incremental SRISK*$^{MES\text{-}C}$ due to the sensitivity of bank stock returns to *Liquidity Risk* using the minimum (γ_{min}) and maximum (γ_{max}) sensitivity from different model specifications shown in prior tables. *MES-*C_{min} *(%)* is calculated as *Liquidity Risk x* γ_{min}. *MES-*C_{min} *($)* is calculated as *Liquidity Risk x* γ_{min} *x MV*. Other variables are calculated accordingly. In Panel D, we show the Conditional SRISK (*SRISK-C*) which is the sum of *Incremental SRISK*^{CL} and *Incremental SRISK*$^{MES\text{-}C}$. All variables are defined in Appendix II.

Panel A. Estimating the drawdown rates in a stress scenario

			Slope	Drawdown Rate (S&P Return -40%)
Predicted	Quarterly	Q1 2020	-0.57	22.91%
Drawdowns	Quarterly	2007-2009	-0.27	10.82%

Panel B. Incremental SRISK^{CL}

Name	Unused C&I Commitments (USD mn)	Drawdown rate: 10.82%	Drawdown rate: 22.91%	Debt (USD mn)
JPMORGAN CHASE & CO.	273,278	2,365	5,009	2,496,125
BANK OF AMERICA CORPORATION	310,824	2,690	5,697	2,158,067
CITIGROUP INC.	200,912	1,739	3,682	1,817,838
WELLS FARGO & COMPANY	198,316	1,717	3,635	1,748,234
GOLDMAN SACHS GROUP, INC., THE	111,247	963	2,039	913,472
MORGAN STANLEY	78,411	679	1,437	818,732
U.S. BANCORP	96,020	831	1,760	433,158
TRUIST FINANCIAL CORPORATION	86,995	753	1,594	204,178
PNC FINANCIAL SERVICES GROUP, INC., THE	84,238	729	1,544	358,342
CAPITAL ONE FINANCIAL CORPORATION	18,618	161	341	320,520
Top 10 BHC	1,458,858	12,628	26,738	11,268,666
Vlab BHC	1,777,617	15,387	32,580	14,524,200
All BHC	1,837,220	15,903	33,673	

Panel C. Incremental SRISK^{LRMESC}

	MV	LRMES	Liquidity Risk	g_{min}	g_{max}	LRMES-C_{min}	LRMES-C_{max}	Incremental SRISK $^{LRMES-C}$ LRMES-C_{min}	LRMES-C_{max}
JPMORGAN CHASE & CO.	437,226	43.4%	20.3%	-0.32	-0.56	6.5%	11.3%	28,411	49,276
BANK OF AMERICA CORPORATION	316,808	45.9%	25.7%	-0.32	-0.56	8.2%	14.3%	26,052	45,183
CITIGROUP INC.	174,415	47.3%	37.1%	-0.32	-0.56	11.9%	20.6%	20,690	35,883
WELLS FARGO & COMPANY	227,540	44.9%	24.2%	-0.32	-0.56	7.7%	13.4%	17,612	30,546
GOLDMAN SACHS GROUP, INC., THE	81,415	54.2%	28.7%	-0.32	-0.56	9.2%	15.9%	7,471	12,958
MORGAN STANLEY	82,743	51.1%	14.3%	-0.32	-0.56	4.6%	7.9%	3,781	6,557
U.S. BANCORP	92,603	36.6%	46.3%	-0.32	-0.56	14.8%	25.7%	13,730	23,813
TRUIST FINANCIAL CORPORATION	75,544	42.5%	41.1%	-0.32	-0.56	13.2%	22.8%	9,943	17,245
PNC FINANCIAL SERVICES GROUP, INC., THE	69,945	40.1%	39.9%	-0.32	-0.56	12.8%	22.1%	8,928	15,485
CAPITAL ONE FINANCIAL CORPORATION	47,927	49.2%	18.6%	-0.32	-0.56	5.9%	10.3%	2,849	4,942
Top 10 BHC	1,606,166					9.5%	16.4%	139,467	241,888
Vlab BHC	2,226,522							168,438	292,134
All BHC	2,408,434							177,412	307,699

Panel D. SRISK^{C}

Name	SRISK (Q4 2019) w/o neg SRISK	w/ neg SRISK	SRISK-C_{min}	SRISK-C_{max}
JPMORGAN CHASE & CO.	0	-27,848	30,777	54,284
BANK OF AMERICA CORPORATION	14,898	14,898	28,742	50,880
WELLS FARGO & COMPANY	24,425	24,425	19,329	34,181
CITIGROUP INC.	60,887	60,887	22,429	39,566
U.S. BANCORP	0	-35,344	5,685	9,860
PNC FINANCIAL SERVICES GROUP, INC., THE	0	-19,352	14,561	25,573
M&T BANK CORPORATION	28,302	28,302	4,459	7,994
FIFTH THIRD BANCORP	38,774	38,774	8,434	14,997
KEYCORP	0	-23,608	10,696	18,839
CITIZENS FINANCIAL GROUP, INC.	0	-9,895	9,658	17,029
Total (Top 10 Banks)	167,287	51,238	154,769	273,203
Total (Vlab Banks)	195,033	40,994	183,825	324,714
Total (All Sample Banks)			193,315	341,372

Appendix I. Example – Drawdowns during COVID-19

| NEWS

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Ford Takes Action to Address Effects of Coronavirus Pandemic; Company Offers New-Car Customers Six-Month Payment Relief

- $15.4 billion of additional cash on balance sheet, drawing from two credit lines
- Dividend suspension to preserve cash and provide additional flexibility in the current environment
- Withdrawal of company guidance for 2020 financial performance
- Three month payment deferral for eligible U.S. new-car customers, plus three more paid by Ford, for up to six months of payment peace of mind

DEARBORN, Mich., March 19, 2020 – Ford Motor Company is taking a series of initiatives to further bolster the company's cash position amid the coronavirus health crisis, maintain strategic flexibility on behalf of its team and customers, and set up Ford to separate itself from competitors when the global economy emerges from the current period of acute uncertainty.

"Like we did in the Great Recession, Ford is managing through the coronavirus crisis in a way that safeguards our business, our workforce, our customers and our dealers during this vital period," said Ford CEO Jim Hackett. "As America's largest producer of vehicles and largest employer of autoworkers, we plan to emerge from this crisis as a stronger company that can be an engine for the recovery of the economy moving forward."

The company today notified lenders that it will borrow the total unused amounts against two lines of credit: $13.4 billion under its corporate credit facility and $2 billion under its supplemental credit facility. The incremental cash from these borrowings will be used to offset the temporary working capital impacts of the coronavirus-related production shut downs and to preserve Ford's financial flexibility.

"While we obviously didn't foresee the coronavirus pandemic, we have maintained a strong balance sheet and ample liquidity so that we could weather economic uncertainty and continue to invest in our future," Hackett said. "Our Ford people are extremely resilient and motivated, and I'm confident in the actions we are taking to navigate the current uncertainty while continuing to build toward the future."

Ford has regularly described targets of having $20 billion in cash and $30 billion in liquidity heading into an economic downturn. At the end of 2019, those levels were $22 billion and $35 billion, respectively.

At the same time, Ford announced it has suspended the company's dividend, prioritizing near-term financial flexibility and continued investments in an ambitious series of new-product launches in 2020 and long-term growth initiatives.

Also, Ford said it is withdrawing the guidance it gave on Feb. 4 for 2020 financial performance, which did not factor in effects of the coronavirus, given uncertainties in the business environment. The company will provide an update on the year when it announces first-quarter results, which is currently scheduled for April 28.

Appendix II. Sample Banks

Name	Total Assets	Name	Total Assets	Name	Total Assets
JPMORGAN CHASE & CO.	2,687,379	UMPQUA HOLDINGS CORPORATION	28,847	PROVIDENT FINANCIAL SERVICES, INC.	9,809
BANK OF AMERICA CORPORATION	2,434,079	PINNACLE FINANCIAL PARTNERS, INC.	27,805	NBT BANCORP INC.	9,716
CITIGROUP INC.	1,951,158	WESTERN ALLIANCE BANCORPORATION	26,822	FIRST BUSEY CORPORATION	9,696
WELLS FARGO & COMPANY	1,927,555	INVESTORS BANCORP, INC.	26,773	OFG BANCORP	9,298
GOLDMAN SACHS GROUP, INC., THE	992,996	PACWEST BANCORP	26,771	CAPITOL FEDERAL FINANCIAL, INC.	9,255
MORGAN STANLEY	895,429	UMB FINANCIAL CORPORATION	26,561	EAGLE BANCORP, INC.	8,989
U.S. BANCORP	495,426	COMMERCE BANCSHARES, INC.	26,084	SERVISFIRST BANCSHARES, INC.	8,948
TRUIST FINANCIAL CORPORATION	473,078	STIFEL FINANCIAL CORP.	24,610	BOSTON PRIVATE FINANCIAL HOLDINGS, INC.	8,832
PNC FINANCIAL SERVICES GROUP, INC., THE	410,373	FLAGSTAR BANCORP, INC.	23,265	S&T BANCORP, INC.	8,765
CAPITAL ONE FINANCIAL CORPORATION	390,365	FULTON FINANCIAL CORPORATION	21,862	SANDY SPRING BANCORP, INC.	8,629
BANK OF NEW YORK MELLON CORPORATION, THE	381,508	SIMMONS FIRST NATIONAL CORPORATION	21,265	BANCFIRST CORPORATION	8,566
CHARLES SCHWAB CORPORATION, THE	294,005	OLD NATIONAL BANCORP	20,412	PARK NATIONAL CORPORATION	8,563
STATE STREET CORPORATION	245,610	FIRST HAWAIIAN, INC.	20,167	FIRST COMMONWEALTH FINANCIAL CORPORATION	8,309
AMERICAN EXPRESS COMPANY	198,314	UNITED BANKSHARES, INC.	19,662	FIRST FINANCIAL BANKSHARES, INC.	8,262
ALLY FINANCIAL INC.	180,644	AMERIS BANCORP	18,243	OCEANFIRST FINANCIAL CORP.	8,260
FIFTH THIRD BANCORP	169,369	BANK OF HAWAII CORPORATION	18,095	COLUMBIA BANK MHC	8,187
CITIZENS FINANCIAL GROUP, INC.	166,090	CATHAY GENERAL BANCORP	18,094	BROOKLINE BANCORP, INC.	7,875
KEYCORP	145,570	FIRST MIDWEST BANCORP, INC.	17,850	BANC OF CALIFORNIA, INC.	7,828
NORTHERN TRUST CORPORATION	136,828	ATLANTIC UNION BANKSHARES CORPORATION	17,563	TRISTATE CAPITAL HOLDINGS, INC	7,766
REGIONS FINANCIAL CORPORATION	126,633	CENTERSTATE BANK CORPORATION	17,142	ENTERPRISE FINANCIAL SERVICES CORP	7,334
M&T BANK CORPORATION	119,873	WASHINGTON FEDERAL, INC.	16,423	SEACOAST BANKING CORPORATION OF FLORIDA	7,109
DISCOVER FINANCIAL SERVICES	113,996	SOUTH STATE CORPORATION	15,921	FLUSHING FINANCIAL CORPORATION	7,018
HUNTINGTON BANCSHARES INCORPORATED	109,002	WESBANCO, INC.	15,719	HOMESTREET, INC.	6,812
SYNCHRONY FINANCIAL	104,826	HOPE BANCORP, INC.	15,668	SOUTHSIDE BANCSHARES, INC.	6,749
COMERICA INCORPORATED	73,519	HILLTOP HOLDINGS, INC	15,172	TOMPKINS FINANCIAL CORPORATION	6,726
SVB FINANCIAL GROUP	71,384	HOME BANCSHARES, INC.	15,032	LAKELAND BANCORP, INC.	6,712
E*TRADE FINANCIAL CORPORATION	61,416	INDEPENDENT BANK GROUP, INC.	14,958	1ST SOURCE CORPORATION	6,623
PEOPLE'S UNITED FINANCIAL, INC.	58,580	FIRST INTERSTATE BANCSYSTEM, INC.	14,644	KEARNY FINANCIAL CORPORATION	6,610
NEW YORK COMMUNITY BANCORP, INC.	53,641	FIRST FINANCIAL BANCORP	14,512	DIME COMMUNITY BANCSHARES, INC.	6,354
POPULAR, INC.	52,115	COLUMBIA BANKING SYSTEM, INC.	14,080	MERIDIAN BANCORP, INC.	6,344
CIT GROUP INC.	50,833	GLACIER BANCORP, INC.	13,684	FIRST FOUNDATION INC.	6,314
SYNOVUS FINANCIAL CORP.	48,203	TRUSTMARK CORPORATION	13,498	CONNECTONE BANCORP, INC.	6,174
TCF FINANCIAL CORPORATION	46,672	RENASANT CORPORATION	13,401	FIRST BANCORP	6,144
EAST WEST BANCORP, INC.	44,196	BERKSHIRE HILLS BANCORP, INC	13,217	MIDLAND STATES BANCORP, INC.	6,087
FIRST HORIZON NATIONAL CORPORATION	43,314	HEARTLAND FINANCIAL USA, INC.	13,210	CENTRAL PACIFIC FINANCIAL CORP.	6,013
BOK FINANCIAL CORPORATION	42,324	UNITED COMMUNITY BANKS, INC.	12,919	NATIONAL BANK HOLDINGS CORPORATION	5,896
RAYMOND JAMES FINANCIAL, INC.	40,154	GREAT WESTERN BANCORP, INC.	12,852	WESTAMERICA BANCORPORATION	5,646
FIRST CITIZENS BANCSHARES, INC.	39,824	FIRST BANCORP	12,611	REPUBLIC BANCORP, INC.	5,620
VALLEY NATIONAL BANCORP	37,453	BANNER CORPORATION	12,604	HANMI FINANCIAL CORPORATION	5,538
WINTRUST FINANCIAL CORPORATION	36,608	FIRST MERCHANTS CORPORATION	12,457	UNIVEST FINANCIAL CORPORATION	5,381
F.N.B. CORPORATION	34,620	AXOS FINANCIAL, INC.	12,269	TRIUMPH BANCORP, INC.	5,060
CULLEN/FROST BANKERS, INC.	34,097	WSFS FINANCIAL CORPORATION	12,256	CITY HOLDING COMPANY	5,019
BANKUNITED, INC.	32,871	INTERNATIONAL BANCSHARES CORPORATION	12,113	QCR HOLDINGS, INC.	4,909
TEXAS CAPITAL BANCSHARES, INC.	32,548	PACIFIC PREMIER BANCORP, INC.	11,776	GERMAN AMERICAN BANCORP, INC.	4,399
ASSOCIATED BANC-CORP	32,386	CUSTOMERS BANCORP, INC	11,521	FIRST FINANCIAL CORPORATION	4,020
PROSPERITY BANCSHARES, INC.	32,195	FIRST AMERICAN FINANCIAL CORPORATION	11,519	BUSINESS FIRST BANCSHARES, INC.	2,276
IBERIABANK CORPORATION	31,713	COMMUNITY BANK SYSTEM, INC.	11,410	CHEMUNG FINANCIAL CORPORATION	1,788
STERLING BANCORP	30,639	INDEPENDENT BANK CORP.	11,403		
HANCOCK WHITNEY CORPORATION	30,620	CVB FINANCIAL CORP.	11,282		
WEBSTER FINANCIAL CORPORATION	30,424	NORTHWEST BANCSHARES INC	10,638		

Appendix III. Variable definitions

Variable name	Definition	Source
Assets	Total Assets	Call Reports
Capital Buffer	Difference between a bank's equity–asset ratio and the cross-sectional average of the equity–asset-ratio of all sample banks in Q4 2019	Call Reports
Consumer Loans / Assets	Consumer loans (%Assets)	Call Reports
Credit Card Commitments / Assets	Unused credit card commitments (%Assets)	Call Reports
Credit Lines	Indicator if loan type within list:	Dealscan
Cumulative Total Drawdowns	Natural logarithm of the realized daily cumulative credit-line drawdowns across all firms	8-K
Cumulative BBB Drawdowns	Natural logarithm of the realized daily cumulative credit-line drawdowns across all BBB-rated firms	8-K
Cumulative NonIG Drawdowns	Natural logarithm of the realized daily cumulative credit-line drawdowns across all NonIG rated firms	8-K
Cumulative Not Rated Drawdowns	Natural logarithm of the realized daily cumulative credit-line drawdowns across all unrated firms	8-K
Current Primary Dealer Indicator	Indicator = 1 if bank is current primary dealer bank (https://www.newyorkfed.org/markets/primarydealers#primary-dealers)	NY Fed
Debt	Market value of bank liabilities (12/31/2019)	Vlab
Deposits / Assets	Deposits (%Assets)	Call Reports
Deposits / Loans	Deposits (%Loans)	Call Reports
Derivatives / Assets	Interest rate, exchange rate and credit derivatives (% Assets)	Call Reports
Distance-to-Default	Mean(ROA+CAR)/volatility(ROA) where CAR is the capital-to-asset ratio and ROA is return on assets	Call Reports
Drawdown Rate	Sensitivity of changes in credit-line drawdowns to changes in the market returns (projected in a market downturn of 40%)	Capital IQ, 8-K, CRSP
Equity Beta	Constructed using monthly data over the 2015 to 2019 period and the S&P 500 as market index	CRSP
Equity Ratio	Equity (%Assets)	Call Reports
Gross Drawdowns	Percentage change of banks' off-balance-sheet unused C&I commitments between Q4 2019 and Q1 2020	Call Reports
HML	Fama-French-Factor: High-minus-Low (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_bench_factor.html)	Ken French Website
Idiosyncratic Volatility	Annualized standard deviation of the residuals from the market model	CRSP
Income Diversity	1 minus the absolute value of the ratio of the difference between net interest income and other operating income to total operating income	Call Reports
Incremental $SRISK^{CL}$	Equity capital that would be required to fund new loans based on banks' unused commitments (CL = credit lines) at the end of Q4 2019	Call Reports
Incremental $SRISK^{LRMESC}$	(Marginal) equity shortfall of banks based on their end of Q4 2019 market values of equity due to effect of liquidity risk on stock returns	Call Reports
Liquidity	The sum of cash, federal funds sold & reverse repos, and securities excluding MBS/ABS securities.	Call Reports
Liquidity Risk	Unused Commitments plus Wholesale Funding minus Liquidity (% Assets)	Call Reports
Loan	Either natural log of loan amount or natural log of 1+number of loans	Dealscan
Loans / Assets	Total loans (%Assets)	Call Reports
Log(Assets)	Natural log of Assets	Call Reports
LRMES	LRMES is the Long Run Marginal Expected Shortfall, approximated in Acharya *et al.* (2012) as 1-e^((-18×MES)), where MES is the one-day loss expected in bank i's return if market returns are less than -2%	Call Reports
$LRMES^{C}$	Contingent marginal expected shortfall due to the impact of liquidity risk on bank stock returns.	Call Reports, CRSP

Loss	Market equity loss during the 1/1/2020 – 3/23/2020 period (USD mn); excess return x market equity as of 1/1/2020	CRSP
Loss (%MV)	Market equity loss during the 1/1/2020 – 3/23/2020 period (USD mn) as % of market equity as of 1/1/2020	CRSP
Loss Recovery Q2	Percentage of Loss recovered in Q2 2020	CRSP
Loss Recovery Q2-Q3	Percentage of Loss recovered in Q2 and Q3 2020	CRSP
MV	Market value of equity (12/31/2019)	Vlab
Net Drawdowns	Absolute change in banks' unused C&I commitments minus the change in deposits (% Assets) over the same period	Call Reports
Non-Interest Income	Non-interest-income (%Operating revenues)	Call Reports
NPL / Loans	Non-performing loans (%Loans)	Call Reports
Post	Post is defined as the period starting April 1, 2020	
Ratings: Not Rated, AAA-A, BBB, NonIG Rated	Indicator variables equal to 1 if firms are in either rating category	CapitalIQ
Real Estate Beta	Slope of the regression of weekly excess stock returns on the Fama and French real estate industry excess return in a regression that controls for the MSCI World excess return	CRSP
Repayment Q2	Total repayment of credit lines by customers in Q2 as % of Q1 drawdowns	CapitalIQ, Dealscan
Repayment Q2-Q3	Total repayment of credit lines by customers inQ2 and Q3 as % of Q1 drawdowns	CapitalIQ, Dealscan
Return 1/1-3/23/2020	Cumulative stock return from January 1 to March 23, 2020; log excess returns are calculated as the log(1 + r - r_f), where r is the simple daily return (based on the daily closing price, adjusted for total return factor and daily adjustment factor), and r_f is the 1-month daily Treasury-bill rate	CRSP
ROA	Return on assets: Net Income / Assets	Call Reports
S&P 500 Return	(Daily) excess return of the S&P 500 index; log excess returns are calculated as the log(1 + r - r_f), where r is the simple daily return (based on the daily closing price, adjusted for total return factor and daily adjustment factor), and r_f is the 1-month daily Treasury-bill rate	CRSP
SMB	Fama-French-Factor: Small-minus-Big (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_bench_factor.html)	Ken French Website
SRISK	Bank capital shortfall in a systemic crisis as in Acharya *et al.* (2012)	Vlab
SRISK/Assets	SRISK scaled by total assets	Vlab and Call Reports
$SRISK^{C}$	Incremental $SRISK^{CL}$ + Incremental $SRISK^{LRMES-C}$	Call Reports
Term Loan	Indicator if loan type within list:	Dealscan
Unused C&I Commitments	Unused C&I credit lines	Call Reports
Unused Commitments	The sum of credit lines secured by 1-4 family homes, secured and unsecured commercial real estate credit lines, commitments related to securities underwriting, commercial letter of credit, and other credit lines (which includes commitments to extend credit through overdraft facilities or commercial lines of credit)	Call Reports
Wholesale Funding	The sum of large time deposits, deposited booked in foreign offices, subordinated debt and debentures, gross federal funds purchased, repos and other borrowed money.	Call Reports

Appendix IV. Different measures for "COVID-19-affected industries"

This table shows the "COVID-19-affected industries" definition used to construct portfolio risk proxies.

Variable name	Explanation
Stock Performance	20 industries with worst stock performance as in Fahlenbrach *et al.* (2021)
COVID industries	Firms that are part of the Fama-French 49 industries identified by Moody's (2020) as particularly exposed to COVID-19.
Customer share	Customer share as defined by Koren and Peto (2020) at the three-digit NAICS level. Measures the percentage of workers in customer-facing occupations. Exposed firms belong to industries in the top quartile of the customer share distribution.
Telework	Share of jobs that can be performed at home from Dingel and Neiman (2020), defined at the three-digit NAICS industry level. Exposed firms are part of industries in the bottom quartile of the distribution.
Manual classification	Manual classification of industries at the six-digit NAICS level. These are the firms we manually classified as highly affected in Fahlenbrach *et al.* (2021).
Presence Share	Presence share as defined by Koren and Peto (2020) at the three-digit NAICS level. Measures the percentage of workers in occupations requiring physical contact. Exposed firms belong to industries in the top quartile of the presence share distribution.
Teamwork Share	Teamwork share as defined by Koren and Peto (2020) at the three-digit NAICS level. Measures the percentage of workers in teamwork-intensive occupations. Exposed firms belong to industries in the top quartile of the teamwork share distribution.
YoY Sale Decline	Q2 2020 year-on-year change in sales, defined at the firm level. Exposed firms are the ones in the bottom quartile of the change in sales.
Abnormal employment decline	Abnormal employment decline in the industry between 2019:Q2 and 2020:Q2 at the three-digit NAICS level as in Chodorow-Reich *et al.* (2021). Exposed firms belong to industries in the top quartile of the distribution.
Physical proximity	To what extent does this job require the worker to perform job tasks in close physical proximity to others (at the three-digit NAICS)? Based on ONET survey. Exposed firms belong to industries in the top quartile of the distribution.
Face-to-face discussion	How often do you have to have face-to-face discussions with individuals or teams in this job (at the three-digit NAICS)? Based on ONET survey. Exposed firms belong to industries in the top quartile of the distribution.
External customers	How important is it to work with external customers (at the three-digit NAICS)? Based on ONET survey. Exposed firms belong to industries in the top quartile of the distribution.