What explains the crash of bank stock prices during COVID-19?

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Abstract

We document and provide an explanation for the significant and persistent under-performance of bank stock returns relative to other financial and non-financial firms during the COVID-19 pandemic. First, as the pandemic unfolded, firms with pre-arranged lines of credit drew down their undrawn facilities – at a far greater intensity than during the past recessions – igniting liquidity risk for banks. We show that a measure of bank-level balance-sheet liquidity risk, viz., undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets), explains both the cross-section and the time-series of bank returns during the pandemic but not before. The effect only reverses after policy responses. Bank stock returns co-move more strongly with gross drawdowns rather than net drawdowns (which account for inflows in corporate deposits) suggesting bank capital as the binding constraint rather than bank liquidity. Consistently, we show that banks with large gross drawdowns reduce their supply of term loans; in contrast, banks with large net drawdowns reduce credit line originations. We relate this episodic nature of credit line drawdowns and balance-sheet liquidity risk to the evidence during the global financial crisis and demonstrate how it can be incorporated tractably into bank capital stress tests.

Keywords: Credit lines, liquidity risk, bank capital, loan supply, stress tests, pandemic
JEL-Classification: G01, G21.

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1. Introduction

This paper investigates the crash of bank stock returns during the COVID-19 pandemic and studies its causes, consequences and policy implications.

The pandemic and the governments' drastic lockdown steps have put the liquidity insurance function of banks for the U.S. economy to a real-life test, as firms' cash flows dropped as much as 100%, while operating and financial leverage remained sticky. As a consequence, U.S. firms with pre-arranged credit lines from banks drew down their undrawn facilities at a far greater intensity than in the past recessions. Panel A of Figure 1 shows an acceleration of credit line drawdowns of publicly listed U.S. firms since March 1, 2020.[1] Within three weeks, firms drew down more than USD 300 billion, with drawdowns particularly concentrated amongst riskier BBB-rated and non-investment grade rated firms.[2] Recent data shows that firms benefited from having access to credit lines during the pandemic when capital market funding froze (e.g., Acharya and Steffen, 2020a; Chodorow-Reich et al., 2020; Greenwald et al., 2020). Banks, however, faced an unprecedented aggregate demand for credit line drawdowns when the pandemic broke out at the beginning of March 2020. Since then, banks' share prices have persistently underperformed those of non-financial firms (Panel B of Figure 1).

[Figure 1 about here]

We construct a new measure of balance-sheet liquidity risk of banks defined as undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets).[3]

[1] For instance, Ford Motor Company was one of the largest U.S. firms to draw down USD 15.4bn of its credit lines in March 2020 (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. Based on its loan contracts, Ford pays 15bps commitment fees for any dollar undrawn credit and 125bps once credit lines have been drawn down. Ford thus paid 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] Li et al. (2020) show – using call report data – that drawdowns amounted to more than USD 500 billion likely because of private firms, even further increasing the pressure on bank balance-sheets.

[3] We develop and use a comprehensive measure of liquidity risk because the relative importance of its components (unused C&I commitments or wholesale funding) might change over time. For example, bank reliance on wholesale funding continued to decline since the global financial crisis while unused C&I loan have increased over 2017-2019.

We show that our measure of liquidity risk of banks explains the cross-section of bank stock price decline during the first phase of the pandemic, i.e. from 1/1/2020 until 3/23/2020, when decisive monetary and fiscal support measures were introduced. 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, controlling for key bank performance measures (capitalization, asset quality, profitability, liquidity and investments).[4]

We entertain alternative explanations for the underperformance of bank stock prices such as real estate exposure, warehousing activities of dealer-banks, or large derivative portfolios. Also other exposures came under stress during the pandemic (e.g., to the retail, hotel and leisure sector). Moreover, exposures to retail credit lines commitments or consumer loans might be important determinants when unemployment rates and furloughs rise. Exposure to oil prices is another important risk factor that might have contributed to the crash of bank stock prices.[5]

Using bank-loan-level exposure data to these sectors sourced from the Dealscan database, we show that bank stock returns do load significantly on some of these risk factors. These exposures, however, appear to be orthogonal to balance-sheet liquidity risk. Furthermore, including existing measures of a bank's capital shortfall conditional on a severe market correction (SRISK),[6] that do not take into account the role of undrawn credit lines, does not

[4] In contrast to bank capital, there is no consensus in the literature 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.

[5] The energy sector was severely hit when on March 9, 2020 oil prices dropped by more than 20% on a single day Both Saudi Arabia and Russia, two of the world's largest oil producers, decided to increase their oil output considerably when both countries could not enter into an agreement with OPEC on possible production cuts. After this oil price shock, oil price volatility increased by more than 6 times (to over 100% on an annualized basis) and energy stocks crashed. Banks are heavily exposed through loans provided to this sector.

[6] See NYU Stern Volatility & Risk Institute, https://vlab.stern.nyu.edu/welcome/srisk, Acharya et al. (2016) and Brownlees and Engle (2017).

affect the coefficient of liquidity risk. To summarize, the aggregate drawdown risk associated with bank credit lines does not appear to be captured in traditional measures of bank exposure or systemic risk.

We then show that this explanatory power of balance-sheet liquidity risk for bank stock returns is *episodically* in nature. Using separate cross-sectional regressions during the month of January 2020, February 2020 and during the 3/1-3/23/2020 period, we show that liquidity risk explains stock returns only during the last period of an aggregate economic downturn when firms' liquidity demand through credit line drawdowns becomes highly correlated, but not before.

We then employ time-series tests for bank stock returns to shed further light on this result. Interacting our bank-level liquidity risk measure with the aggregate measure of realized cumulative credit line drawdowns, we show that (daily) bank stock returns are significantly lower when aggregate drawdowns in the economy increase and banks have more balance-sheet liquidity risk. Further, stock returns for banks with greater liquidity risk are lower particularly when drawdowns of riskier firms accelerate.

Bank stock prices hardly recovered even after the monetary and fiscal measures (i.e., after 3/23/2020) until the end of Q2 2020. Average stock returns increased about 17% during this period (relative to a mean decline of 65% in the period before). Stock price effects reverse particularly for banks that suffered relatively more during the crash. We document a reversal of undrawn C&I credit lines on banks' balance sheets in Q2 and Q3 2020, however, not to pre-COVID levels. Consistently, we find that the episodic explanatory power of balance-sheet liquidity risk for bank stock returns also reverses post policy measures.

We confirm that the episodic co-movement of stock returns and balance-sheet liquidity of banks is not specific to aggregate drawdown risk during the pandemic but was also a feature of the global financial crisis (GFC), i.e., during the 2007 to 2009 period.[7] We use the same cross-sectional tests as before and run them quarterly over the Q1:2007 to Q1:2009 period. We show that liquidity risk for banks ignited in Q3 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). Liquidity risk remained priced in the cross-section of bank stock returns (even increased in economic magnitude) until the end of Q2 2008. 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 banking sector, following which we do not see any effect of liquidity risk on bank stock returns. In other words, the episodic nature of liquidity risk contributing to bank stock returns during the pandemic finds similar undertones during the GFC, the former caused by aggregate drawdown risk (credit lines) and the latter by aggregate rollover risk (wholesale finance).

Next, we examine the mechanisms as to why were bank stock prices particularly sensitive to undrawn C&I credit lines when the pandemic broke out. 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")?[8] To distinguish between these channels, we construct two

[7] Other papers explore the determinants of credit line drawdowns in previous crises. Ivashina and Scharfstein (2010) document an acceleration of credit line drawdowns during the 2007–2009 crisis; their evidence is consistent with ours. Berg et al. (2016) show that credit lines are more likely to be used if a borrower's economic performance deteriorates, particularly for nonIG and unrated firms. Berg et al. (2017) show that U.S. firms' drawdown behavior is particularly sensitive to the overall market return. We show that pandemic drawdowns have been more intense but similar in spirit.

[8] 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 C&I loan commitment as of Dec 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) 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 – what most of our sample banks are – 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 banks' other business activities particularly in an aggregate downturn.

proxies: (1) *Gross drawdowns* as the percentage change in credit line drawdowns; and (2) *Net drawdowns* as the percentage change in drawdowns minus the change in deposit funding. Holding gross drawdowns fixed, our measure of net drawdowns helps us understand the importance of changes in bank deposits for bank stock returns. We find that while bank stock returns during 1/1/2020 – 3/23/2020 are particularly sensitive to gross drawdowns, they do not load significantly on net drawdowns. Importantly, a higher level of bank capital buffer attenuates the negative effect of gross drawdowns on stock return. These results suggest that at the onset of the pandemic bank capital and not bank liquidity appears to be the binding constraint causing liquidity risk to adversely affect bank stock return. In this regard, the pandemic fallout for banks differs from that during the GFC when banks struggled on the liquidity-front to meet drawdowns (Acharya and Mora, 2015)

We then study the consequences of this phenomenon. We find that binding capital constraints also adversely impacts bank lending capacity as banks with large credit line drawdowns significantly reduce their supply of new loan originations.[9] We use a Khwaja and Mian (2008) estimator and aggregate our data at a borrower x bank x loan type x month level, collapse the sample into a pre- and post-COVID period (where the post is the period after 4/1/2020), and saturate the estimation with borrower x bank x loan type fixed effect. We show that both the number of loans as well as loan amounts are lower for borrowers with both higher gross and net drawdowns after the breakout of the COVID pandemic. Importantly, when we estimate separately the effect on term loans and credit lines (using borrower x bank fixed effects), term loan originations are substantially lower for banks with higher gross drawdowns, whereas new credit line commitments decrease mainly for banks with higher net drawdowns. This confirms that gross drawdowns reduce the capital available to banks and thus term lending,

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

whereas banks experiencing net drawdowns are reluctant to take on additional liquidity risk, but they can issue term loans as long as they have capital to provide for them.

Finally, 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) develop the concept of SRISK, a measure of the capital shortfall of a stressed aggregate market correction (e.g., 40% decline in the S&P 500 index), measured relative to an 8% requirement in terms of market value of equity to debt plus market value of equity. This measure, however, does not account for credit lines, which are off-balance-sheet or contingent liabilities. Given our results, such an impact can be decomposed into two components. First, contingent liabilities enter banks' balance sheets as realized liabilities during stress. Using drawdown data during the COVID-19 crisis, the GFC and the 2000-2003 recession, we extrapolate the expected drawdown in a stress scenario with a 40% market correction based on each of these three stressed periods. Using these expected drawdown rates, we calculate the additional equity capital that would be required to maintain adequacy against higher realized liabilities in stress. Second, we have to account for the negative episodic effect of liquidity risk on bank stock prices during stress. Using the loadings from our cross-sectional regressions of bank stock returns on balance-sheet liquidity risk during the COVID-19 crisis, we estimate the additional equity shortfall of banks based on their end of Q4 2019 market values of equity.

Adding both components, we show that the additional capital shortfall for the U.S. banking sector as a whole due to balance-sheet liquidity risk amounts to over $300 billion as of 31st Dec 2019 in a stress scenario of 40% correction to the global stock market with the top 10 banks contributing about USD 265 bn. The incremental capital shortfall of the top 10 banks is about 1.5 times larger than the capital shortfall estimate without accounting for contingent liabilities.

The paper proceeds as follows. We first describe the related literature. In Section 3, we present the data. In Section 4, we describe our measure of balance-sheet liquidity risk and investigate the effect of liquidity risk on bank stock returns. We investigate the liquidity measure's components in Section 5. Section 6 analyzes the funding vis-à-vis the capital channel and also studies the consequences for the real economy. Section 7 illustrates how to incorporate episodic liquidity risk of bank balance-sheets in stress tests and assess 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) propose a risk management motive to understand the unique role of banks as liquidity providers to both households and firms. As long as demand for deposits and loans is not too highly correlated, banks can pool both types of customers and hold less (costly) liquid assets. Gatev and Strahan (2006) build on this idea and argue that banks can insure firms even against systematic declines in liquidity because of deposit inflows during crises. Ivashina and Scharfstein (2010) provide evidence of an acceleration of credit line drawdowns during the 2007-2009 crisis as well as an increase in deposits. Acharya and Mora (2015) show that during the 2007-2009 crisis – in which the banking system itself was at the center of the crisis – banks faced a crisis as liquidity providers and could only perform this role because of large support from the government. Li et al. (2020) show that during the COVID-19 crisis, aggregate deposit inflows were sufficient to fund the increase in liquidity demand. Acharya and Steffen (2020b) use simulations based on drawdown scenarios from prior crises and arrive at similar conclusions. Kapan and Minoiu (2020) show that banks exposed to larger credit line drawdowns reduce lending. None of these papers, however, explores the implications of banks as liquidity providers for bank stock returns when drawdowns affect bank capital availability for other intermediation functions, and especially when the realized risk is aggregate in nature, which is the core of this paper.

There is a growing literature on the implications of COVID-19 for corporate finance, and the use of credit lines in particular. Chodorow-Reich et al. (2020) show that drawdowns of credit lines came exclusively from large firms during the first phase of the pandemic and document that banks did not honor commitments to smaller firms. Greenwald et al. (2020) also show that particularly large firms used their credit lines and banks with larger drawdowns reduced term lending to small firms more relative to other banks. By examining both gross drawdowns and net (of deposit inflows) drawdowns, we show that credit line drawdowns reduce the market value of banks because of binding capital constraints. While banks with higher gross drawdowns reduce term lending, banks with higher net drawdowns reduce credit line originations.

Other papers consider stock price reactions to the COVID-19 pandemic, emphasizing the importance of financial policies (Ramelli and Wagner forthcoming), financial constraints and the cash needs of affected firms (Fahlenbrach, Rageth, and Stulz 2020), changing discount rates because of higher uncertainty (Gormsen and Koijen 2020; Landier and Thesmar 2020), and social distancing measures (Pagano, Wagner, and Zechner 2020). These papers focus on stock prices of non-financial firms, not banks. Demirguc-Kunt et al. (2020) investigate 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 of the respective country. We focus instead on the implications of credit line drawdowns for bank stock returns.

Our paper also contributes methodologically to the literature on bank stress tests. After the 2007-2009 crisis, a variety of measures have been developed to quantify the systemic risk of the banking sector. In addition to the SRISK measure of Acharya et al. (2012), Acharya et al. (2016) and Brownlees and Engle (2017), which we discussed in the introduction, Adrian and

Brunnermeier (2015) develop the concept "CoVaR" that measures the risk to the financial system conditional on a bank being in distress. These papers do not look at the role of contingent liabilities of banks or their episodic impact on bank returns; we show how these important aspects can be embedded into bank stress tests.

3. Data

We collect data for all publicly listed bank holding companies of commercial banks in the U.S.. To construct or main dataset, we follow Acharya and Mora (2015) and drop all banks with total assets below USD 100 million at the end of 2019 and also only keep 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 127 U.S. bank holding companies.[10] All variables are explained below or in Appendix II.

We obtain daily stock returns for our sample banks from CRSP. We manually match these banks to the Thomson Reuter Dealscan database to obtain loan-level exposure data of banks. For some tests and statistics, we use secondary market data about different industry sectors (e.g., oil or retail sector) from Refinitiv. We obtain information about a bank's systemic risk from the Volatility and Risk Institute at NYU Stern. Other market information is downloaded from Bloomberg (e.g. oil volatility (CVOX), VIX, S&P 500 market return).

4. Can balance-sheet liquidity risk explain bank stock returns?

4.1. Balance-sheet liquidity risk of banks

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

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, deposited booked in foreign offices, subordinated debt and debentures, gross federal funds purchased, repos and other borrowed money; (3) *Liquidity*: The sum of cash, federal funds sold & reverse repos, and securities excluding MBS/ABS securities. All variables are defined in Appendix II.

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

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

We show the time-series of the mean of *Liquidity Risk* (using our sample banks and weighted by total assets) quarterly since January 2010 as well as its components in Figure 2, 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 pandemic. At the beginning of the pandemic in Q1 2020, liquidity risk dropped about 40% and continued to decline somewhat also in Q2 and Q3 of 2020.

Panel B of Figure2 shows the components. The decrease is driven by the declining share of wholesale funding relative to total assets that even accelerated during the COVID-19 pandemic. Since 2017, the marginal increase in the importance of unused C&I loans was larger than the marginal decline in wholesale funding exposure and *Liquidity Risk* started to increase again. The large decline of *Liquidity Risk* during the first quarter in 2020 is driven by the decrease in unused C&I credit lines consistent with the increase in drawdowns documented in Figure 1 above. We observe an immediate reversal of *Unused C&I Credit Lines* in Q2 and Q3 2020, however not to pre-COVID levels, pointing to a partial repayment of credit lines by U.S. firms. In Online Appendix B, we show that particularly non-investment grade rated firms do not repay their credit lines, likely as they only gradually regained access to capital markets as documented in Acharya and Steffen (2020). Banks experience only limited capital relief when high-quality firms repay their credit lines with possible implications for their lending and investment activities. We investigate the importance of unused C&I credit lines for the stock price crash of U.S. banks as well as their lending activities further below in this paper.

4.2. Methodology

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

$$r_i = \alpha + \gamma LiquidityRisk_i + \sum \beta \, X_i + \varepsilon_i \tag{1}$$

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 (e.g., bank balance-sheet characteristics) that have been shown to affect bank stock returns. All control variables capture 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 loan ratio (*NPL/Loans*), the equity-asset-ratio (*Equity Ratio*), *Non-Interest Income*[11], return-on-assets (*ROA*) and the deposit-loan-ratio (*Deposits*). All variables are described in detail in Appendix II and are shown in the regression specifications in the sections below. Standard errors in all cross-sectional regressions are heteroscedasticity robust.

4.3. Descriptive evidence

We first investigate graphically whether differences in ex-ante liquidity risk across banks can explain their stock price development since the outbreak of COVID-19. We classify banks into two categories with 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 Jan 2, 2020 using the (market-value weighted) average stock returns of banks in each sample. The difference between both 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 return, we find that banks with higher liquidity risk perform worse than other banks. In Panel B of Figure 3, we plot bank stock returns on 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 3/1 to 3/23/2020 period and we calculate excess returns over these time periods. The average excess return is negative in all periods, ranging from -7.9% in January 2020 to -47.1% during the period 3/1 – 3/23/2020 (and even -67.5% from 1/1 – 3/23/2020).

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

We show descriptive statistics of bank characteristics as of Q4 2019 in Panel B of Table 1. In addition to the control variables used in our regression, we also provide summary statistics of *Liquidity Risk* and its components. All these risk measures appear to be economically relevant. For example, the average *Liquidity Risk* is 0.209, the average bank has unused C&I loan commitments of about 8.1% relative to total assets, and the average wholesale funding-asset-ratio is 13.2%. The average bank has a beta of 1.2 measured against the S&P 500 (i.e. resembles broadly the U.S. economy) and a capitalization (equity-asset-ratio) of 12%. We omit a discussion of the other variables but include their summary statistics to facilitate the interpretation of our estimates in the next sections.

[Table 1 about here]

4.4. Multivariate results

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

[Table 2 about here]

As dependent variable we use bank stock returns measured as excess returns over the collapse period 1/1/2020 to 3/23/2020, 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 bank with a higher ex-ante balance-sheet liquidity risk and (as expected) high 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 increase as well (by more than 50% from column (1) to column (5)). Economically, a one standard deviation increase in *Liquidity Risk* reduces stock returns during this period by about 5%. The other control variables behave as expected (focusing on those that turn out to have significant explanatory power): banks with more non-performing loans (*NPL/Loans*), lower return-on-assets (*ROA*), lower *Distance-to-*

Default, and banks with higher deposit ratios (Deposits/Assets) have lower stock returns during this period.[12]

A possible explanation for bank stock returns during this period could be a large exposure to the real estate sector (as measured using a *Real Estate Beta*), large 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 (5)), once the other control variables are accounted for.

Robustness tests. Panel B of Table 2 reports the results of our robustness tests. For example, it could be that those banks with high unused C&I credit lines are also those with high retail credit card commitments. Given the potential stress in the retail sector due to e.g. lay-offs and furloughs, our *Liquidity Risk* measure might pick up these effects. We collect each bank's exposure (we could not clearly identify this for 1 bank in our sample) to off-balance-sheet credit card commitments and add this to our regression model (we use the model from column (5) of Panel A of Table 2). This variable does not enter significantly in our regression (column (1)), more importantly, the coefficient on *Liquidity Risk* remains unchanged. Using on-balance sheet *Consumer Loans / Assets* (column (2) does not change our results either.

Exposure to oil price risk is another important (macro) risk factor that might have also contributed to the crash of bank stock prices. After the oil price shock on March 9, 2020, the market performance of the oil & gas sector considerably deteriorated.[13] Moreover, other sectors were particularly impacted by the pandemic, e.g., the retail, leisure, and hotel & gaming

[12] Gatev and Strahan (2006) show that banks with large credit line commitments are also high deposit banks.

[13] We provide some descriptive evidence consistent with this in Online Appendix A. Figure A.1 shows the performance of the oil & gas sector vis-à-vis other sectors directly affected by the pandemic (i.e., retail, leisure and hotel & gaming) using returns from loans traded in the secondary market in these sectors. While the returns in the loan market declined substantially in all sectors, loan return of oil & gas and mining firms significantly underperformed the other sectors even after the announcement of the interventions by the Fed on March 23, 2020. Figure A.2 shows the time-series of oil-price volatility using the CVOX oil price volatility index. While oil price volatility increases episodically during economic downturns (e.g., during the global financial crisis (GFC), i.e., the 2007 to 2009 period), the European sovereign debt crisis (2011-2012), and the oil & gas crisis in 2015-2016), volatility has increased by more than 6 times (to over 100% on an annualized basis) around March 9th, 2020 and energy stocks crashed.

industry. Banks with large exposures to these sectors (through credit line but also term loan exposures) might experience larger stock price declines. We construct a bank's exposure to the oil & gas and other sectors using its loan exposures as of 12/31/2019. We obtain this data from the Thomson Reuters LPC and allocate loan amounts among syndicate banks following the prior literature (e.g., Ivashina, 2009). We construct a new variable *Oil Exposure / Assets*, which is a bank's sum of all active loan exposures to oil & gas firms scaled by total assets. Similarly, we construct a similar measure of exposures to firms in the retail, leisure, and hotel & gaming industry, add all these exposures and scale them by total assets (*Other Sectoral Exposures / Assets*).

We include both exposures variables in our regression (columns (3) and (4)). Moreover, as all oil & gas and sectoral exposures are based on loans reported in Dealscan and thus available only for a subset of banks, we include a dummy for those banks we could not find exposure data for (unreported). The results show that banks with larger exposures to oil and the other sectors experience lower stock returns during the first phase of the pandemic. Stock returns still load significantly on *Liquidity Risk*, the economic magnitude is somewhat lower which was expected given the smaller subset of banks for which exposure data is available.

5. Understanding balance-sheet liquidity risk of banks

Our previous results show that liquidity risk of banks matters to explain bank stock return during the first phase of COVID-19. The pandemic started in western economies at the beginning of March 2020, before then, firms had no problems accessing liquidity. But at the beginning of March 2020, it became a major concern for most firms (e.g., compare the increase in aggregate drawdowns in Figure 1 above).[14] Does liquidity risk also ignite as an explanatory risk factor when aggregate drawdown risk increased? Which components of *Liquidity Risk*

[14] 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 & access to liquidity and access to future capital, highlighting the aggregate demand for credit line drawdowns at the beginning of the pandemic.

matter and how important are undrawn C&I credit lines relative to e.g. wholesale funding during the COVID-19 pandemic? Did the fiscal and monetary response help attenuate aggregate drawdown risk? And, is this pattern unique for the COVID-19 pandemic or do we observe these repeatedly during episodes of aggregate drawdown risk? These are the questions we set out to address in this section.

5.1. Does balance-sheet liquidity risk ignite in bank stock return?

Panel A of Table 3 shows the estimation results from equation (1) separately for the three time periods.

[Table 3 about here]

The coefficient estimates for January 2020 are shown in columns (1) to (2), for February 2020 in columns (3) to (4) and for the 3/1-3/23/2020 period in column (5) to (6), with and without the control variables described above. During the first two months in 2020, bank stock returns do not load significantly on liquidity risk. However, during the March 1st to 23rd period, it emerges as an important risk factor, i.e., banks with higher balance-sheet liquidity risk had significantly lower stock returns during this period. Also the economic magnitude of the equity beta increases substantially during this stress period.

Time-series evidence. Using time-series regressions, we then show aggregate drawdowns can explain bank stock returns with high ex-ante exposure to *Liquidity Risk* during the 3/1/-3/23/2020 period. We run the following time-series regression.

$$r_{i,t} = \alpha + \gamma LiquidityRisk_i \; x \; Drawdowns_t + \beta \; r_{S\&P,t} + \mu_i + \varepsilon_{i,t} \qquad (2)$$

We interact *Liquidity Risk* with the natural logarithm of the realized daily aggregate credit line drawdowns (*Log(Cumulative Total Drawdowns)*) and add the daily realized return of the S&P 500 stock index ($r_{S\&P,t}$) as well as a bank fixed effect (μ_i). We use Newey-West standard errors. The results are reported in Panel B of Table 3.

In column (1), use the total aggregate credit line drawdowns. We then aggregate credit line drawdowns across BBB-rated firms (column (2), non-investment-grade rated firms (column (3)) and unrated firms (column (4)).[15] Bank (daily) stock returns are significantly lower when aggregate drawdowns in the economy increase and banks have more balance-sheet liquidity risk. Stock returns for banks with greater liquidity risk are lower particularly when drawdowns of riskier firms accelerate. Overall, both our cross-sectional as well as time-series tests suggest that bank balance-sheet liquidity risk can episodically explain bank stock returns, emerging in an aggregate downturn with an increase aggregate liquidity demand for credit lines.

5.2. Components of liquidity risk and bank stock returns

Figure 2 shows that *Liquidity Risk* has 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 a 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 Table 4. We include all control variables described in model (5) in Panel A of Table 2.

[Table 4 about here]

We first include only *Unused C&I Loans / 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 ex-ante balance-sheet liquidity risk of banks is driven by banks' exposure to unused C&I loans. Bank stock returns load significantly on this factor while the coefficients on both wholesale funding and liquidity are economically small and statistically insignificant. In other words, banks' exposure to unused C&I loans are key to understand bank stock returns during the early stages of the pandemic.

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

In columns (4) and (5), we add oil exposure and other sectoral exposure to the hotel, leisure and retail industry (all scaled by total assets) to the regression model. All oil & gas and sectoral exposures are based on loans reported in DealScan and thus available only for a subset of banks. In column (6), we add *SRISK/Assets* as an additional control. These regressions include a dummy for banks for which we do not find exposure data or no SRISK (unreported). As before, banks with more exposure to the oil and other affected sectors as well as higher systemic risk have lower stock returns but the coefficient on *Unused C&I Loans / Assets* does not change.

5.3. Reversal of the effect of liquidity risk on bank stock prices

Our previous tests show that 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 (2020) show that capital market funding became immediately available after the Federal Reserve interventions on 3/23/2020 stopping the credit line drawdowns for all but the riskier firms as bond market access still eluded them. Aggregate demand for credit line drawdowns attenuated after the interventions. Importantly, Figure 2 above suggests that high-quality firms have repaid credit lines, leading to a reversal of unused C&I credit lines on bank balance sheets. We thus investigate whether we observe a similar reversal in bank stock prices following the Fed interventions in March 2020.

Panel A of Table 5 shows descriptive statistics of bank stock returns in April, May and June 2020 and during the 3/24 – 6/30/2020 period. On average, stock prices of our sample banks have increased about 18% over the entire period, which is small given the mean drop of 67% during the 1/1 – 3/23/2020 period. In other words, bank market capitalization has, on average, hardly improved during this time period.

[Table 5 about here]

We report results from regressions of bank stock return on *Liquidity Risk* and its components and all control variables used before in Panel B of Table 5. Columns (1) and (2) show the results for April and May 2020. While the coefficient of *Liquidity Risk* is positive, it does not significantly enter into the regression. The effects somewhat increase in June 2020 and become statistically significant (column (3)) but are driven largely by banks with high ex-ante unused C&I lines of credit (column (4)). The results become less noisy when measuring stock returns over the 3/24/2020 to 6/30/2020 period and also become economically larger (columns (5) and (6)). That is, stock prices of those banks that have experienced a large decline in stock price during the first weeks of the pandemic recover somewhat in the period after the Fed interventions. The control variables (not reported) show a similar reversal.

Taken together, our results so far show that liquidity risk episodically explains bank stock returns. 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. This relationship even reverses when capital market funding became available after policy stabilization measures were put in place.

5.4. Balance-sheet liquidity risk of banks during the global financial crisis (2007-2009)

Are these effects specific to the current COVID-19 pandemic or did liquidity risk episodically explain stock returns also 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 vs. low *Liquidity Risk* over the 2007 to 2009 period in Figure 4.

[Figure 4 about here]

We plot the difference in the stock price of banks with high vs. low *Liquidity Risk* indexed at Jan 1, 2007. The difference in the stock price performance between both group of banks is even more pronounced compared to the COVID crisis. Stock of banks with high Liquidity Risk fell by about 40% more compared to banks with low liquidity risk between the Q2 2007 and Q3 2008 period. The stock price performance was then similar until the end of 2009.

We construct our variables at the end of Q4 2006 for our regressions in 2007 and at the end of Q4 2007 for the regressions in 2008 and 2009 and estimate equation (1) quarterly over the Q1:2007 to Q1:2009 period. The estimation results are reported in Table 6.

[Table 6 about here]

In Panel A of Table 6, we confirm that liquidity risk episodically explained bank stock returns also during the GFC, i.e., during the 2007 to 2009 period. Liquidity risk for banks ignited in Q3 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, liquidity risk remained priced in the cross-section of bank stock returns (and even increased in economic magnitude) until the end of Q2 2008. 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 programs, following which we do not see any effect of liquidity risk on bank stock returns.

In Panel B of Table 6, we split *Liquidity Risk* into its components. While unused C&I credit lines are clearly important, the results also show that wholesale funding exposure as well as having access to liquidity (i.e. cash) impacts bank stock returns highlighting that a holistic measure of balance-sheet liquidity risk is useful. Otherwise we would force an average effect across banks for individual components.

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

6. Understanding the mechanisms: Funding versus bank capital

In this section, we investigate the mechanisms as to 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")?

6.1. Net versus gross credit line drawdowns and bank stock returns

To distinguish between the funding and capital channel, we construct two measures based on actual drawdowns experienced by our sample banks during the first quarter in 2020. *Gross Drawdowns* are defined as the percentage change of banks' off-balance sheet unused C&I loan commitments between Q4 2019 and Q1 2020 using call report data. Ivashina and Strahan (2012) 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 (all relative to 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; both measures help us identify the potence of the funding vs. capital channel.

We plot the time-series of both measures in Figure 5 since Q1 2010. Panel A of Figure 5 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 revert back to pre-COVID levels already by the end of Q2 2020.

[Figure 5 about here]

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

We investigate the effect of gross and net drawdowns on bank stock returns more formally using the model specification and control variables from column (5) of Panel A of Table 2. Instead of *Liquidity Risk*, we use our two new proxies to understand the importance of the funding vis-à-vis the capital channel. Table 7 reports the results.

[Table 7 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 4.2%, which is large and in magnitude similar to our *Liquidity Risk* proxy used in Table 2 earlier in this paper. We include both proxies in column (3) and find that, holding gross drawdowns fixed, net drawdowns have still no significant effect on bank stock returns. That is, as 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.

In column (4), we interact *Gross Drawdowns* with *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 the interaction term is positive and significant emphasizing that the negative effect of drawdowns on stock returns is attenuated if banks fund their credit line exposure with more capital. Adding *SRISK/Assets* as additional control (column (5)) does not change the coefficient of Gross Drawdowns, suggesting that SRISK does not capture systemic implications associated with aggregate credit lines drawdowns.

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

What does balance-sheet liquidity risk imply for bank lending during the COVID-19 pandemic? Bank issuance of new corporate loans has substantially declined since the start of the COVID-19 pandemic. It is a testable hypothesis that banks with more balance-sheet liquidity risk reduce lending more relative to other banks. Moreover, if banks' capital constraints matter, we expect (term loan) lending to be particularly sensitive to gross (but not to net) drawdowns.

We use data from Dealscan to investigate these important issues. We use data on new loan originations over the January 2019 to October 2020 period and divide our sample into a pre and post period, where post 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 x month level and show that banks with higher *Liquidity Risk* and higher *Gross Drawdowns* decrease lending in the post 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 particularly to riskier borrowers consistent with 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 of firms in a period characterized with high uncertainty. 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 pandemic. We construct a new variable $Loan_{i,b,m,t}$, which is the loan amount (or number of loans) issued to firm i by bank b as loan-type m in month t. As our data contains syndicated loans, we use all banks and their lending to firm i in a syndicate in the pre- and post COVID-19 period. Absorbing loan demand shocks using borrower (η_i), x bank (η_b), x loan-type fixed effect (η_m), we can isolate the effect of balance-sheet liquidity risk on bank loan supply:

$$Loan_{i,b,m} = \beta_1 \times Post + \beta_2 \times DD_b \times Post + \left(\eta_i \times \eta_b \times \eta_m\right) + \varepsilon_{i,b,m}$$

Following Bertrand et al. (2004), we collapse our data on a *firm x bank x loan-type* level into a pre- and post-COVID-19 period to account for possible autocorrelation in the standard errors. $Loan_{i,b,m}$ is the natural log of the loan amount (or natural log of 1 plus the number of loans) issued to firm i by bank b as loan-type m. A negative β_2 implies that bank with more exposure to drawdown risk (DD_b) – measured as either *Gross* or *Net Drawdowns* – decrease lending more compared to banks with less exposure during the COVID-19 pandemic after controlling for loan demand and other bank and loan-specific effects via borrower x bank x tranche type fixed effects $\left(\eta_i \times \eta_b \times \eta_m\right)$. *Gross* and *Net Drawdowns* are measured over the Q1 2020 period and the post period starts, as explained above, in Q2 2020. We cluster standard errors on the borrower x bank x tranche level in all regressions.

Results. We provide results with the nat. log of loan amounts as dependent variable in Panel A of Table 8.

[Table 8 about here]

Banks that have experienced larger gross drawdowns during Q1 2020 reduce lending more during the COVID-19 pandemic and the effect is highly statistically significant and economically large (column (1)). A one standard deviation increase in *Gross Drawdowns* decreases loan amounts by 5%. While the effect of *Net Drawdowns* is also significant (column (2)), its economic meaning is smaller compared to *Gross Drawdowns*. When including both proxies in the regression, we find that the coefficient of *Gross Drawdowns* becomes smaller and statistically insignificant (column (3)). β_1 is negative and significant suggesting that bank lending has, on average, decreased after the outbreak of COVID-19 across all banks. A possible explanation is the loss of intermediation rents for banks at large.

This regression, however, might mask that both proxies are important but that capital or liquidity might play different roles depending on whether or not the loan needs to be fully funded at origination. We thus split the sample into term loans (column (4)) and credit lines (column (5)) and run the same regressions. As expected, banks with larger *Gross Drawdowns* reduce term lending more post-COVID-19 and banks with larger *Net Drawdowns* reduce credit commitments. That is, banks who experience net drawdowns appear to be reluctant to take on additional liquidity risk. Banks, however, can make term loans as long as they have capital to provide for them. Gross drawdowns reduce the available capital and thus term lending. The economic magnitudes of both proxies are similar compared to columns (1) and (2). The statistical significance, however, is somewhat lower, as standard errors have increase, likely due to the smaller samples.

We find very similar results when using the nat. log of 1 plus the number of loans as dependent variable. The economic magnitude of *Gross Drawdowns* and thus the relative importance of the capital vis-à-vis the funding channel is even more pronounced.

7. Contingent capital shortfall in a crisis

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. 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 measures of stress tests do not account for the impact of banks' contingent liabilities in times of stress. This is what 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 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 6 months (h=6m). *K* is the regulatory capital ratio of 8%.

As described above, such an impact can be decomposed into two components. First, off-balance-sheet (i.e., contingent) liabilities enter banks' balance sheets as loans and need to be funded with capital. Second, we also have to account for the effects 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:

$$\begin{aligned} SRISK - C_{i,t} = SRISK_{i,t} &+ \\ Incremental\ SRISK_{i,t}^{CL} &+ \\ Incremental\ SRISK_{i,t}^{LRMES-C} & \end{aligned}$$

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

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

$$= K \times E[Drawdown - rate \mid Crisis] \times Undrawn\ Credit\ Lines_{i,t}$$

$E[Drawdown - rate \mid Crisis]$ 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:

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

where $\Delta LRMES - C_{i,t} = \hat{\gamma} \times Liquidity\ Risk_{i,t}$ and $\hat{\gamma}$ is the estimated episodic effect 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 during the COVID-19 crisis, the GFC and the 2000-2003 recession, and estimate the expected drawdown in a stress scenario with a 40% market correction for each of these three stressed periods or crises. We show plots of this exercise in Figure 6.

[Figure 6]

In Panel A of Figure 6, we plot cumulative daily drawdowns during the 03/01-03/23/2020 period (as a percentage of total credit lines outstanding – which we obtain from Capital IQ as of Q4 2019) on the cumulative S&P 500 market return. The larger the cumulate negative market return, the higher the cumulative drawdowns (the slope coefficient of a regression line assuming a linear relationship between both variables is -0.377). Predicting the drawdown in stress scenario with a 40% market correction, we show that the expected (quarterly) drawdown rate is 42.11%.

In Panel B of Figure 6, we plot the cumulative quarterly drawdown rates during the Q1 2007 to Q4 2009 period on quarterly S&P 500 returns. Interestingly, we find a very similar sensitivity of credit line drawdowns to changes in the market return in the GFC as in the COVID-19 crisis (-0.32). The projected drawdown rate in a market downturn of 40%, however, is somewhat lower (30.23%). 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 firm balance sheets resulting in an elevated demand for liquidity from pre-arranged credit lines as compared to the GFC.

We plot cumulative quarterly credit line drawdowns on quarterly S&P 500 market returns during the GFC and during the 2000 to 2003 recession together in Panel C of Figure 6. Again, the sensitivity of credit line drawdowns to changes in the market return is very similar compared to the GFC and the COVID-19 crisis (-0.325). But also during the 2000-2003 crisis, drawdown behavior of firms seems elevated compared to the GFC resulting in a predicted drawdown in a stress scenario (again assuming a 40% market correction) of 54.44%. The quarterly drawdown rates in each of the three stress scenarios or crises are summarized together with the sensitivities of the drawdown rates in a market correction in Panel A of Table 9.

[Table 9 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 lines commitments of banks and apply the drawdown rates calculated in the three different stress scenarios assuming a prudential capital ratio of 8%:

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

In Panel B of Table 9, we show the ten top 10 banks with the largest undrawn commitments as of Q4 2019 and report $Incremental\ SRISK_i^{CL}$ individually for each of these 10 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 36bn to USD 65bn depending on the estimates of the drawdown rate.

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

We also have to account for the effect of liquidity risk on bank stock return 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 $Incremental\ SRISK_i^{LRMES-C}$:

$$\begin{aligned} Incremental\ SRISK_i^{LRMES-C} &= (1-k) \times MV_i \times LRMES - C_i \\ &= (1-k) \times MV_i \times \hat{\gamma} \times Liquidity\ Risk_i \end{aligned} \tag{5}$$

$LRMES - C_i$ is 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 $LRMES - C_{min}$ and $LRMES - C_{max}$, which is between 6.9% and 24.9%. The corresponding $Incremental\ SRISK_i^{LRMES-C}$ amounts to USD 158bn to USD 250bn.

In a final step, we calculate the conditional SRISK (*SRISK-C*) adding the two incremental SRISK components:

$$SRISK - C = Incremental\ SRISK_i^{CL} + Incremental\ SRISK_i^{LRMES-C} \quad (6)$$

Adding both components we show that the additional capital shortfall for the U.S. banking sector due to balance-sheet liquidity risk amounts to over $300 billion as of 31st Dec 2019 in a stress scenario of 40% correction to the global stock market, with the top 10 banks contributing USD 265bn. The incremental capital shortfall of the top 10 bank 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-sheet, and, importantly, because of an (even larger) incremental capital requirement due to an episodic impact of bank balance-sheet liquidity risk on bank stock returns.

8. Conclusion

This paper shows balance-sheet liquidity risk of banks is an explanation for the significant and persistent under-performance of bank stock returns relative to other financial and non-financial firms during the ongoing pandemic. It explains both the cross-section and the time-series of bank returns during the pandemic but not before. This episodic impact of balance-sheet liquidity risk on bank stock returns is not unique to the COVID-19 crisis, but was observed also during the global financial crisis, i.e. during the 2007 to 2009 crisis. That is, balance-sheet liquidity risk of banks affects bank stock prices during an aggregate economic downturn when firms' liquidity demand through credit line drawdowns becomes highly correlated, but not before.

While bank stock returns during the pandemic also co-move heavily with bank-level loan exposure to the oil sector (another sector with significant under-performance and elevated (oil-price) volatility relative to others during the pandemic), liquidity risk of banks' balance sheet remains a key factor in explaining bank stock prices both in the cross-section as well as the time-series.

Bank stock return co-move more strongly with gross drawdowns rather than net drawdowns (which account for inflows in corporate deposit) suggesting that bank capital is a binding constraint. Consistently, we show that banks with large gross drawdowns reduce their supply of term loans (not credit lines). Banks with less deposit inflows, however, reduce credit line originations. We demonstrate how the episodic nature of credit line drawdowns and balance-sheet liquidity risk can be incorporated tractably into bank stress tests. Our results suggest an additional capital shortfall for the U.S. banking sector of over $300 billion as of 31st Dec 2019 in a stress scenario of 40% correction to the global stock market.

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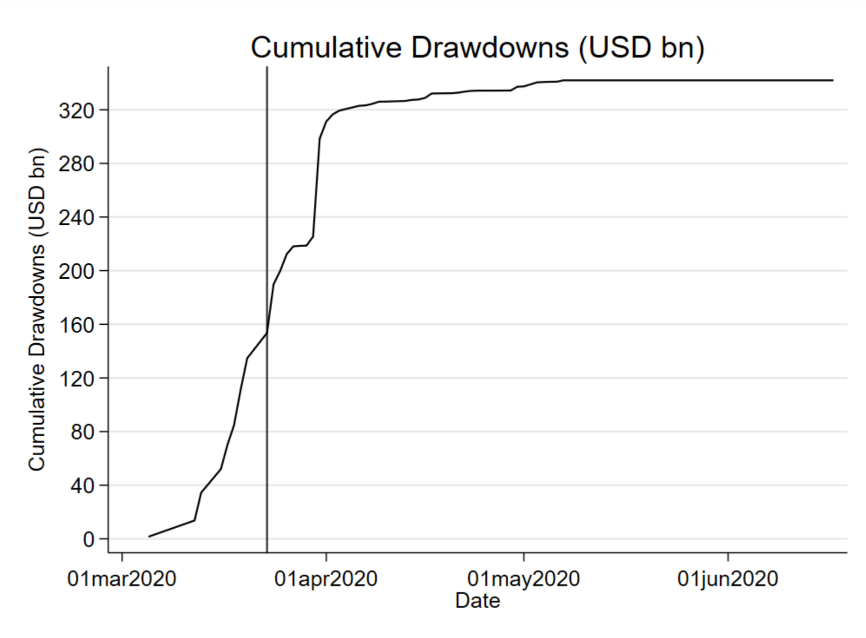
Figure 1. Cumulative drawdowns and bank stock prices
Panel A shows the cumulative credit line drawdowns of U.S. firms over the March 1, 2020 to July 1, 2020 period in billion USD. Panel B shows the stock prices of U.S. firms by sector, specifically firms from the energy, banking and other sectors, since Jan 1st, 2020. All variables are defined in Appendix II.

Panel A. Cumulative drawdowns (in USD bn)



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

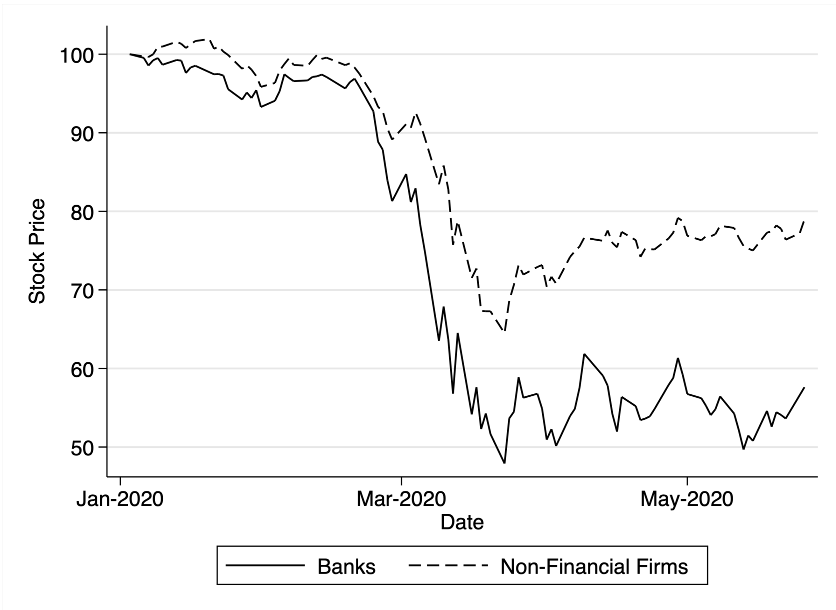
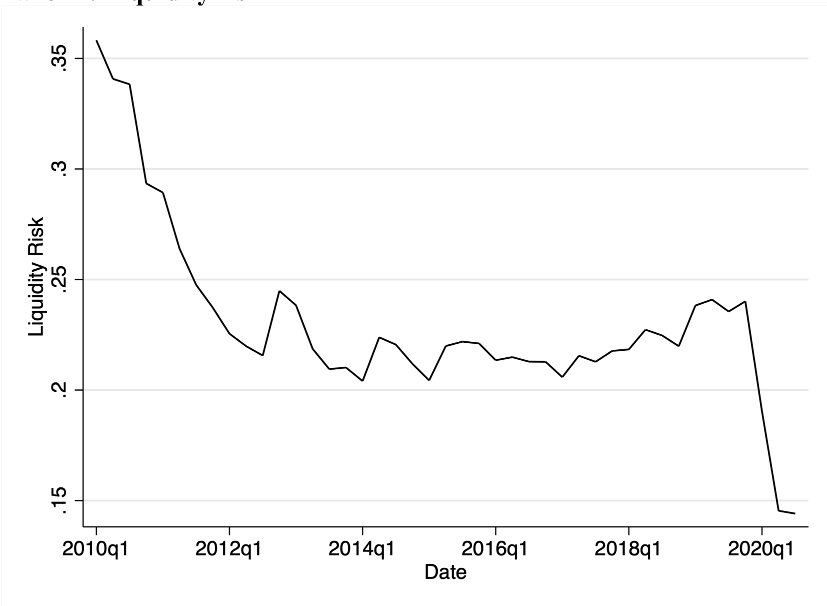


Figure 2. Bank balance-sheet liquidity risk

This figure shows the time-series of balance-sheet *Liquidity Risk* over the Q1 2010 to Q3 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 II.

Panel A. Liquidity risk



Panel B. Components of liquidity risk

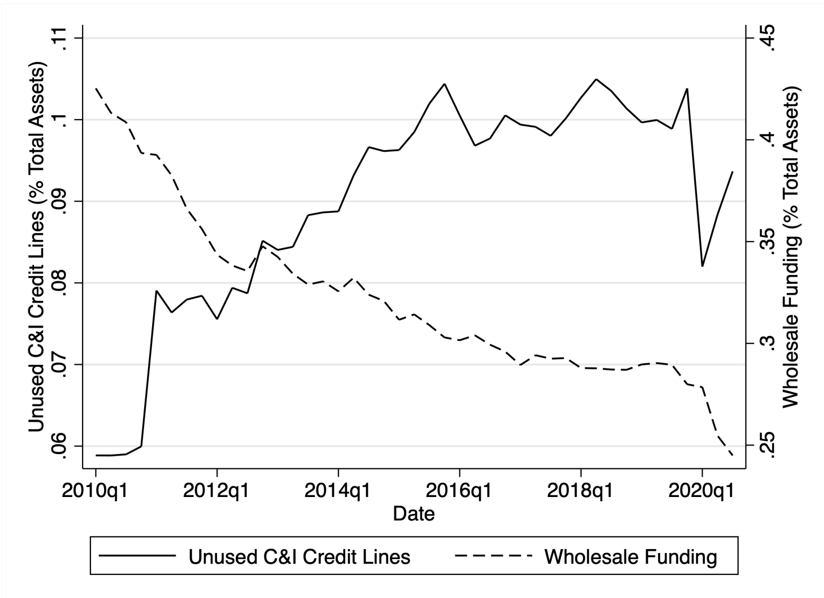
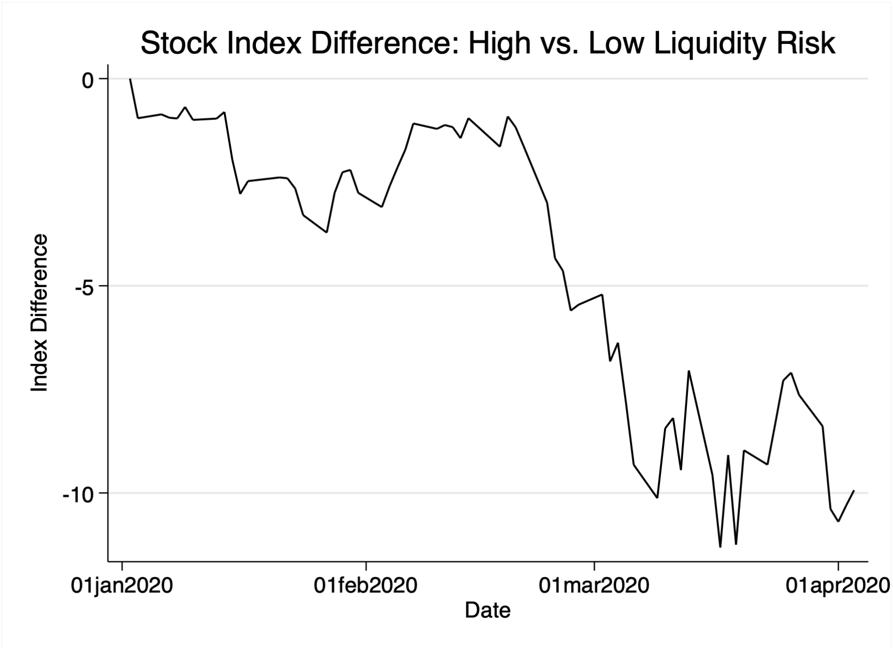


Figure 3. Stock prices and liquidity risk of U.S. banks

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 II.

Panel A. Bank stock returns



Panel B. Bank stock return and liquidity risk

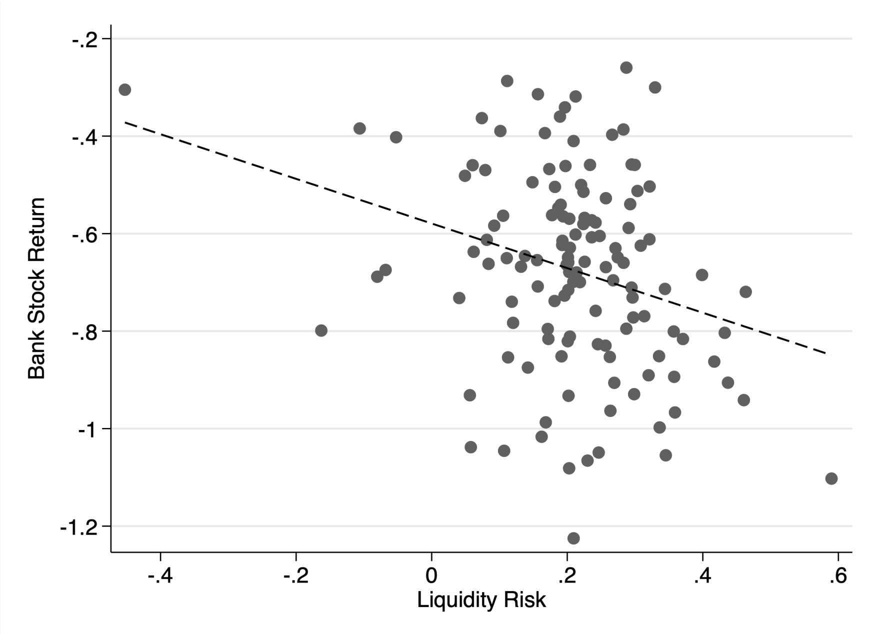


Figure 4. Stock prices and liquidity risk of U.S. banks (2007-2009)

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.

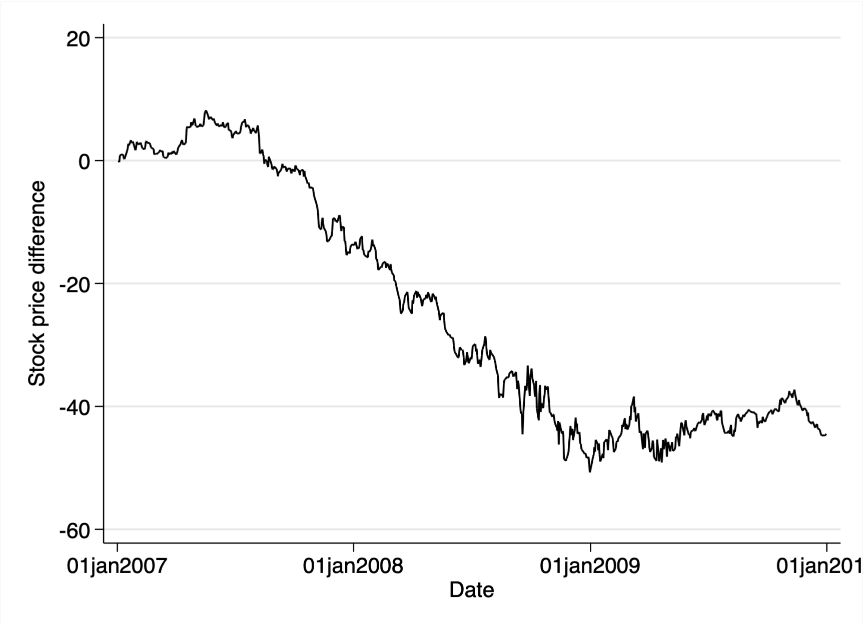
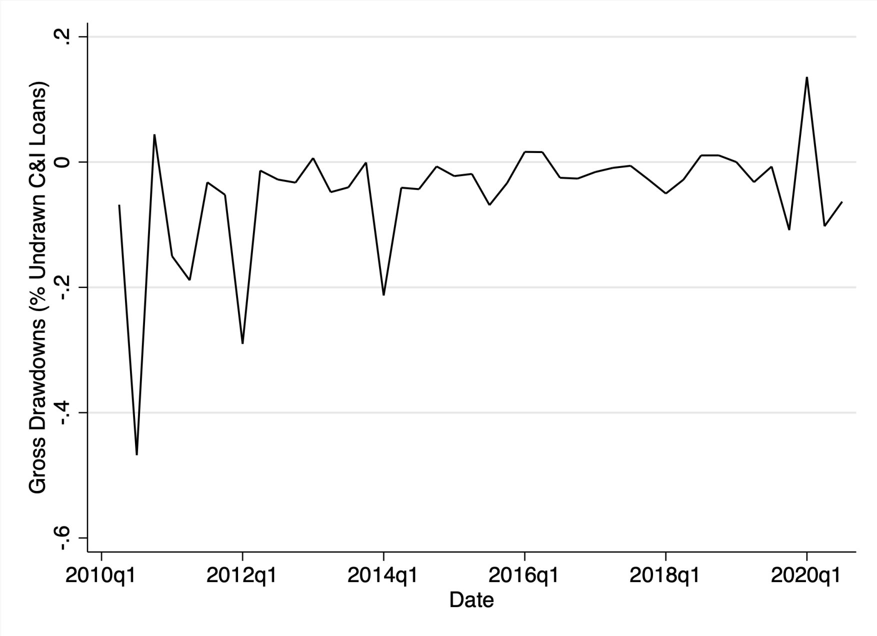


Figure 5. Net vs. gross drawdowns

This figure shows the time-series of *Gross Drawdowns* (Panel A) and *Net Drawdowns* (Panel B) over the Q1 2010 to Q3 2020 period. *Gross Drawdowns* is the percentage change in a bank's off balance sheet unused C&I loan commitments (measured during Q1 2020). *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. All variables are defined in Appendix II.

Panel A. Gross Drawdowns



Panel B. Net Drawdowns

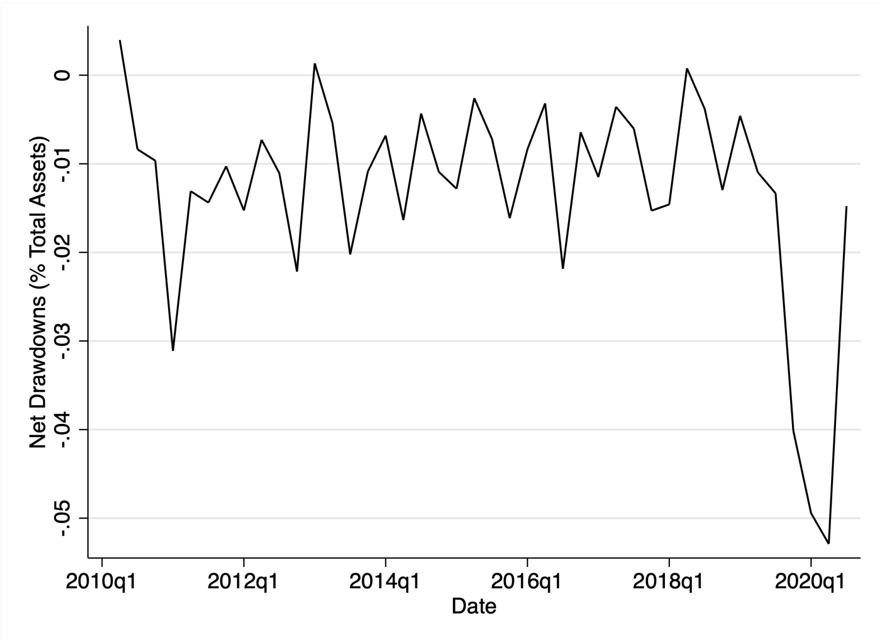
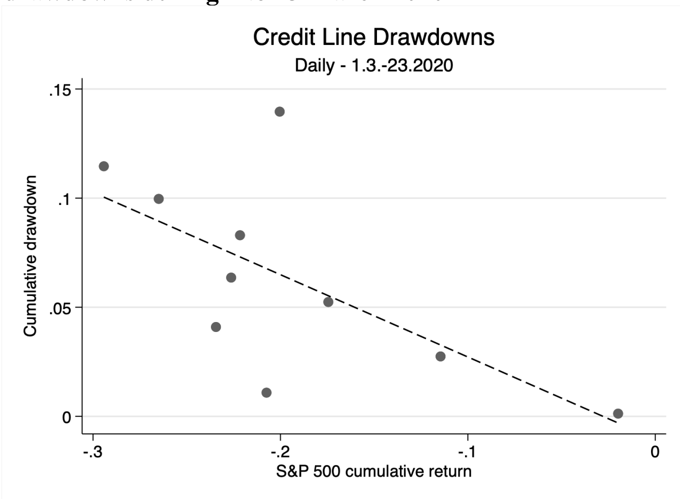


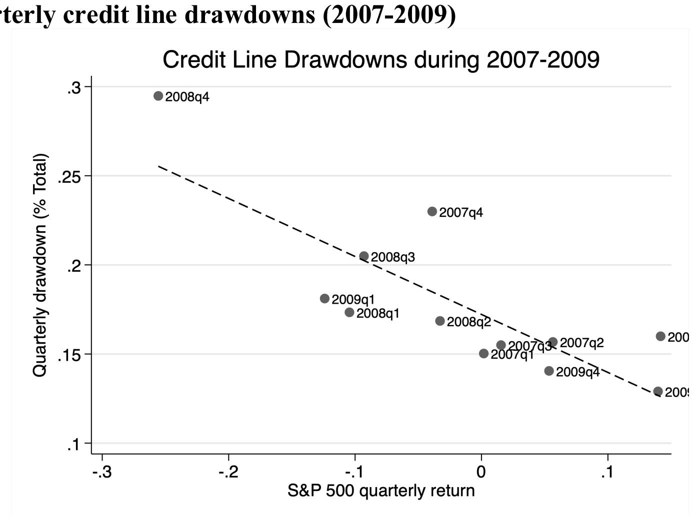
Figure 6. Credit line drawdowns and market returns

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). Panel A uses daily loan-level drawdown data for the March 1-23, 2020 period. Panel B uses quarterly drawdowns during the 2007-2009 global financial crisis. And Panel C shows the results using the quarterly drawdowns during the 2007-2009 global financial crisis and the 2000-2003 crisis. All variables are defined in Appendix II.

Panel A. Daily drawdowns during 1 to 23 March 2020



Panel B. Quarterly credit line drawdowns (2007-2009)



Panel C. Quarterly credit line drawdowns (2007-2009 and 2000-2003)

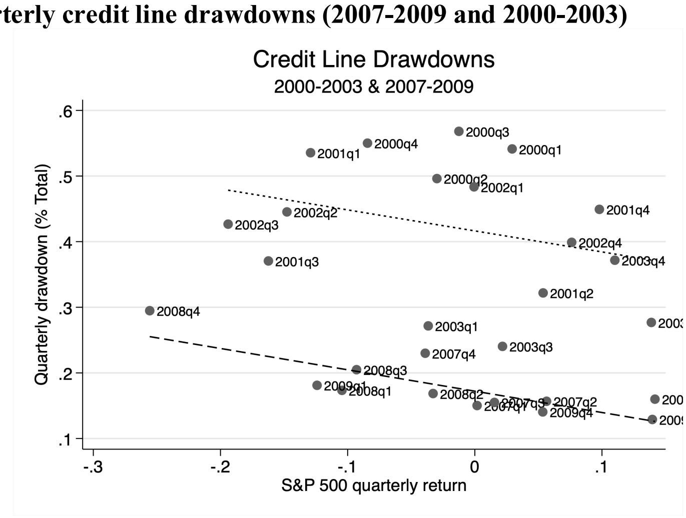


Table 1. Descriptive statistics

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

Panel A. Bank stock returns

Variable	Obs.	Mean	Std. dev.	Min	Max
Return January 2020	127	-0.079	0.039	-0.181	0.024
Return February 2020	127	-0.125	0.037	-0.194	0.011
Return 3/1-3/23 2020	127	-0.471	0.184	-1.084	-0.131
Return 1/1-3/23 2020	127	-0.675	0.204	-1.225	-0.260

Panel B. Bank characteristics

Variable	Obs.	Mean	Std. dev.	Min	Max
Liquidity Risk	127	0.209	0.128	-0.453	0.590
Unused LC / Assets	127	0.081	0.051	0.000	0.263
Liquidity / Assets	127	0.117	0.079	0.029	0.513
Wholesale Funding / Assets	127	0.132	0.075	0.013	0.544
Beta	127	1.173	0.310	0.390	2.313
NPL / Loans	127	0.007	0.007	0.000	0.044
Non-Interest Income	127	0.227	0.118	0.005	0.732
Log(Assets)	127	16.785	1.267	14.638	21.712
ROA	127	0.012	0.003	0.003	0.020
Deposits / Loans	127	1.124	0.338	0.756	4.272
Income Diversity	127	0.445	0.213	0.010	0.993
Distance-to-Default	127	3.648	0.522	1.859	5.060
Loans / Assets	127	0.702	0.113	0.196	0.899
Deposits / Assets	127	0.766	0.062	0.549	0.874
Idiosyncratic Volatility	127	0.202	0.044	0.121	0.417
Real Estate Beta	127	0.555	0.193	-0.266	1.136
Primary Dealer	127	0.031	0.175	0.000	1.000
Derivatives / Assets	127	0.648	2.515	0.000	19.565

Table 2. Liquidity risk and bank stock returns

This table reports the results of OLS regressions of U.S. bank' beta adjusted stock returns over the 1/1/2020 – 3/23/2020 period with different set of control variables. Panel A shows baseline results sequentially adding control variables (as described in Table 1 and defined in Appendix A). Panel B shows robustness tests adding off-balance-sheet credit card exposures (column (1)), consumer loans (column (2)), exposure to the oil & gas industry (column (3)) and other sectoral exposures (to hotel, leisure and retail industry) (column (4)) as additional control variables. Column (5) includes *SRISK/Assets* as additional control. All oil & gas and sectoral exposures are based on loans reported in DealScan and thus available only for a subset of banks. SRISK is only available for banks in the vlab database. These regressions include 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 II.

Panel A. Baseline results

	(1)	(2)	(3)	(4)	(5)
Liquidity Risk	-0.363***	-0.341*	-0.532***	-0.526**	-0.538**
	(0.003)	(0.072)	(0.004)	(0.010)	(0.016)
Equity Beta	-0.266***	-0.271***	-0.165**	-0.122	-0.123
	(0.000)	(0.000)	(0.025)	(0.112)	(0.113)
NPL / Loans		-6.641***	-5.726**	-4.728**	-4.671**
		(0.001)	(0.013)	(0.034)	(0.050)
Equity Ratio		0.206	-0.00843	-1.017	-0.996
		(0.790)	(0.990)	(0.240)	(0.294)
Non-Interest Income		0.0231	0.0543	-0.218	-0.212
		(0.894)	(0.806)	(0.368)	(0.405)
Log(Assets)		0.00892		-0.0299*	-0.0295
		(0.588)		(0.097)	(0.169)
ROA		8.735		13.56**	13.41**
		(0.110)		(0.041)	(0.048)
Deposits / Loans		0.0262		0.0289	0.0279
		(0.594)		(0.631)	(0.654)
Income Diversity			0.0106	0.191	0.189
			(0.942)	(0.198)	(0.217)
Distance-to-Default			0.0582	0.0695**	0.0722*
			(0.102)	(0.045)	(0.052)
Loans / Assets			-0.00441	0.115	0.128
			(0.984)	(0.735)	(0.713)
Deposits / Assets			-0.263	-0.841**	-0.815*
			(0.457)	(0.038)	(0.094)
Idiosyncratic Volatility			-0.741	-0.733	-0.733
			(0.139)	(0.156)	(0.169)
Real Estate Beta			0.00727	-0.00554	-0.00561
			(0.958)	(0.968)	(0.968)
Current Primary Dealer Indicator					-0.0652
					(0.677)
Derivatives / Assets					0.00551
					(0.626)
R-squared	0.243	0.334	0.361	0.392	0.392
Number obs.	127	127	127	127	127

Panel B. Robustness tests

	(1)	(2)	(3)	(4)	(5)
Liquidity Risk	-0.522**	-0.542**	-0.409*	-0.369*	-0.552**
	(0.010)	(0.016)	(0.051)	(0.082)	(0.014)
Credit Card Commitments /Assets	0.616				
	(0.120)				
Consumer Loans / Assets		0.0668			
		(0.878)			
Oil Exposures / Assets			-2.325***	-2.001***	
			(0.007)	(0.010)	
Other Sectoral Exposures / Assets				-6.326**	
				(0.050)	
SRISK / Assets					-8.209***
					(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.423	0.392	0.399	0.415	0.444
Number obs.	126	127	127	127	127

Table 3. Liquidity risk and bank stock returns by month

This table reports the results of OLS regressions of U.S. bank' realized stock returns during January 2020 (columns (1)-(2), February 2020 (columns (4) to (4)) and 1-23 March 2020 (columns (5) to (6)). Regressions with control variables are based on column (5) in Panel A of Table 2. Panel B 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 line by U.S. firms until this day over the 1 – 23 March 2020 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 always include the contemporaneous return of the S&P 500 and bank fixed effects. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix II.

Panel A. Cross-sectional test

	(1)	(2)	(3)	(4)	(5)	(6)
	January 2020		February 2020		3/1-3/23/2020	
Liquidity Risk	-0.0254	-0.0521	-0.0001	-0.0138	-0.338***	-0.472**
	(0.231)	(0.208)	(0.997)	(0.739)	(0.002)	(0.020)
Equity Beta	-0.0112	-0.0200	-0.0404***	-0.0002	-0.214***	-0.103
	(0.362)	(0.212)	(0.000)	(0.985)	(0.002)	(0.190)
Controls		Yes		Yes		Yes
R-squared	0.0167	0.157	0.113	0.282	0.211	0.359
Number obs.	127	127	127	127	127	127

Panel B. Time-series test

Dependent Variable: Banks' Daily Stock Returns (3/1 – 3/23/2020)	(1)	(2)	(3)	(4)
Liquidity Risk x Log(Cumulative Total Drawdowns)	-0.007**			
	(0.031)			
Liquidity Risk x Log(Cumulative BBB Drawdowns)		-0.017***		
		(0.002)		
Liquidity Risk x Log(Cumulative NonIG Drawdowns)			-0.0091**	
			(0.024)	
Liquidity Risk x Log(Cumulative Not Rated Drawdowns)				-0.014***
				(0.01)
S&P 500	1.194***	1.203***	1.193***	1.193***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.632	0.630	0.632	0.630
Number obs.	2595	2465	2595	2465

Table 4. Components of liquidity risk

This table reports the results of OLS regressions of U.S. bank' beta adjusted stock returns over the 1/3/2020 – 3/23/2020 period on the different components of Liquidity Risk with control variables as in column (5) in Panel A of Table 2. We add the different components sequentially in columns (1)-(3) and add exposure to the oil & gas industry (column (4)) and other sectoral exposures (to hotel, leisure and retail industry) as additional control variables (column (5)). We add *SRISK/Assets* as additional control (column (6)). All oil & gas and sectoral exposures are based on loans reported in DealScan and thus available only for a subset of banks. SRISK is only available for banks in the vlab database. These regressions include 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 II.

	(1)	(2)	(3)	(4)	(5)	(6)
Unused C&I Loans / Assets	-1.278***	-1.308***	-1.383***	-1.148**	-1.012**	-1.278***
	(0.002)	(0.002)	(0.001)	(0.013)	(0.043)	(0.002)
Liquidity / Assets		0.284	0.293	0.204	0.153	0.347
		(0.376)	(0.357)	(0.541)	(0.642)	(0.273)
Wholesale Funding / Assets			-0.349	-0.401	-0.349	-0.290
			(0.430)	(0.376)	(0.440)	(0.462)
Equity Beta	-0.140**	-0.135*	-0.124*	-0.107	-0.122*	-0.0841
	(0.043)	(0.052)	(0.089)	(0.132)	(0.096)	(0.205)
Oil Exposure				-2.187***	-2.000**	
				(0.009)	(0.012)	
Other Sectoral Exposures					-4.763	
					(0.194)	
SRISK /Assets						-7.173**
						(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.386	0.390	0.393	0.417	0.425	0.450
Number obs.	127	127	127	127	127	127

Table 5. Reversal of liquidity risk

Panel A reports descriptive statistics of bank stock returns for the months April, May and June 2020 (i.e. after the Federal Reserve Intervention on 3/23/2020). Panel B reports the results of OLS regressions of U.S. bank' realized stock returns on *Liquidity Risk* and its components during each of these months (columns (1) – (4)) and then for the period 3/24/2020 – 6/30/2020 (columns (5) and (6)). Control variables as in column (5) in Panel A of Table 2 are included. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix II.

Panel A. Descriptive statistics of bank stock returns

	Obs.	Mean	Std Dev	Min	Max
Return April 2020	127	.1140058	.0878647	-.0997281	.385558
Return May 2020	127	-.039326	.080453	-.4542235	.2228914
Return June 2020	127	.0119836	.0528534	-.1546759	.1514292
Return 3/24-6/30/2020	127	.1793604	.1639635	-.3437108	.6509989

Panel B. Pricing of liquidity risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Apr 20	May 2020	June 2020		3/24/-6/30/2020	
Liquidity Risk	0.0876	0.0626	0.103*		0.349	
	(0.466)	(0.433)	(0.089)		(0.108)	
Unused C&I Loans / Assets				0.282**		1.048***
				(0.028)		(0.002)
Liquidity / Assets				-0.0920		0.0260
				(0.461)		(0.949)
Wholesale Funding / Assets				-0.0185		1.206***
				(0.908)		(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.284	0.275	0.154	0.174	0.304	0.358
Number obs.	127	127	127	127	127	127

Table 6. Liquidity risk and bank stock return during the Global Financial Crisis

This table reports the results of OLS regressions of U.S. bank' realized stock returns separately for each quarter during the Q1:2007 to Q4:2009 period. We show the estimates of the coefficients of the *Equity Beta* of a bank with the S&P 500 (measured monthly over the 2002-2006 period for tests in 2007 and measured monthly over the 2003-2007 period for tests in 2008/9), but include also all other control variables shown in Panel A of Table 2 (column (5)). P-values based on robust standard errors are in parentheses. All variables are defined in Appendix II.

Panel A. Liquidity risk and bank stock returns

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
	Q1 2007	Q2 2007	Q3 2007	Q4 2007	Q1 2008	Q2 2008	Q3 2008	Q4 2008	Q1 2009
Liquidity Risk	0.0118	-0.00262	-0.0727**	-0.153***	-0.160**	-0.262***	0.0469	-0.102	-0.00628
	(0.745)	(0.962)	(0.046)	(0.002)	(0.017)	(0.000)	(0.644)	(0.386)	(0.956)
Equity Beta	-0.00720	-0.0117	0.0114	-0.0389	0.0377	-0.0707	0.0299	-0.0586	-0.149
	(0.612)	(0.588)	(0.439)	(0.167)	(0.073)	(0.008)	(0.336)	(0.080)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.030	0.030	0.084	0.173	0.097	0.326	0.338	0.201	0.301
Number obs.	225	225	225	225	237	237	237	237	237

Panel B. Components of liquidity risk

	(1)	(2)	(3)	(4)
	Q3 2007	Q4 2007	Q1 2008	Q2 2008
Unused C&I Loans / Assets	-0.222**	-0.0263	-0.360***	-0.188
	(0.013)	(0.864)	(0.000)	(0.375)
Wholesale Funding / Assets	-0.0360	-0.151**	-0.0436	-0.162*
	(0.519)	(0.037)	(0.602)	(0.077)
Liquidity / Assets	0.0678	0.277***	0.171	0.523***
	(0.363)	(0.002)	(0.125)	(0.000)
Equity Beta	0.0247	-0.0622	0.0355	-0.0779
	(0.108)	(0.030)	(0.087)	(0.003)
Controls	Yes	Yes	Yes	Yes
R-squared	0.104	0.221	0.123	0.339
Number obs.	225	225	237	237

Table 7. Understanding the mechanisms: Funding versus capital

This table reports the results of OLS regressions of U.S. bank' realized 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) includes an interaction term of *Gross Drawdowns* with *Capital Buffer* (the secular term is included but not shown). Column (5) 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). Control variables as in column (5) in Panel A of Table 2 are included. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix II.

	(1)	(2)	(3)	(4)	(5)
Net drawdowns	0.0926		0.219	0.128	0.0866
	(0.885)		(0.736)	(0.844)	(0.889)
Gross drawdowns		-4.457**	-4.593**	-3.929**	-4.172**
		(0.034)	(0.023)	(0.044)	(0.046)
Gross drawdowns x Capital Buffer				1.588*	
				(0.084)	
SRISK / Assets					-6.706*
					(0.071)
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.353	0.378	0.379	0.393	0.424
Number obs.	127	127	127	127	127

Table 8. Implications for bank lending during the COVID-19 pandemic

This table provides results of difference-in-differences regressions of the change in amount/number of loan issuance pre- and post-COVID-19 on credit line drawdowns. The analysis is based on data on firm-bank-loan type level between Jan 2019 October 2020 that is collapsed to a pre- and post-COVID-19 period (post is denoted as the period starting 4/1/2020). Panel A (B) shows the results using gross (net) drawdowns. The dependent variables are the natural log of 1 + the loan amount or the natural log of 1 + the number of loans issued. Columns (1)-(2) controls for the demand side with borrower fixed effects; column (3) additionally controls for the supply side with borrower x bank fixed effects; and column (4) additionally controls for tranche type effects with borrower x bank x tranche-type fixed effects. Detailed variable definitions can be found Appendix A. Standard errors are clustered at level of the fixed effect in each column. ***, **, * denote significance at the 1%, 5% and 10% level, respectively. All variables are defined in Appendix II.

Panel A. Loan amount

	(1)	(2)	(3)	(4) Term Loans	(5) Credit Lines
Post x Gross Drawdowns	-15.69***		-8.651	-16.35*	-3.129
	(0.001)		(0.117)	(0.070)	(0.657)
Post x Net Drawdowns		-5.676***	-4.267**	-5.232	-4.099*
		(0.001)	(0.028)	(0.141)	(0.078)
Post	-2.270***	-2.758***	-2.544***	-2.290***	-2.710***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower x Bank x Loan Type FE	Yes	Yes	Yes		
Borrower x Bank FE				Yes	Yes
R-squared	0.200	0.200	0.200	0.186	0.208
Number obs.	17944	17944	17944	5770	12174

Panel B. Number of loans

	(1)	(2)	(3)	(4) Term Loans	(5) Credit Lines
Post x Gross Drawdowns	-2.609***		-1.710**	-2.315*	-1.086
	(0.000)		(0.040)	(0.067)	(0.323)
Post x Net Drawdowns		-0.824***	-0.545**	-0.741	-0.548*
		(0.001)	(0.048)	(0.137)	(0.098)
Post	-0.342***	-0.419***	-0.377***	-0.315***	-0.416***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower x Bank x Loan Type FE	Yes	Yes	Yes		
Borrower x Bank FE				Yes	Yes
R-squared	0.223	0.223	0.223	0.189	0.240
Number obs.	17944	17944	17944	5770	12174

Table 9. 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 8). 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-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-C}*. All variables are defined in Appendix II.

Panel A. Estimating the drawdown rates in a stress scenario

			Drawdown Rate S&P Return -40%	Slope Drawdown Function
Predicted Drawdowns	Quarterly	Q1 2020	42.11%	-0.377
	Quarterly	2007-2009	30.23%	-0.32
	Quarterly	2000-2003	54.44%	-0.325

Panel B. Incremental SRISK^{CL}

Name	Unused C&I Commitments (USD mn)	Incremental SRISK^{CL} Drawdown rates 30.23%	42.11%	54.44%	Debt
JPMORGAN CHASE & CO.	273,278	6,609	9,206	11,902	2,496,125
BANK OF AMERICA CORPORATION	310,824	7,517	10,471	13,537	2,158,067
WELLS FARGO & COMPANY	198,316	4,796	6,681	8,637	1,748,234
CITIGROUP INC.	200,912	4,859	6,768	8,750	1,817,838
U.S. BANCORP	96,020	2,322	3,235	4,182	433,158
PNC FINANCIAL SERVICES GROUP, INC., THE	84,238	2,037	2,838	3,669	358,342
M&T BANK CORPORATION	9,260	224	312	403	109,692
FIFTH THIRD BANCORP	39,328	951	1,325	1,713	148,517
KEYCORP	33,070	800	1,114	1,440	129,380
CITIZENS FINANCIAL GROUP, INC.	33,682	815	1,135	1,467	142,497
Total (Top 10 Banks)	1,278,928	30,930	43,085	55,700	9,541,849
Total (Vlab Banks)	1,434,367	34,689	48,321	62,470	10,759,335
Total (All Sample Banks)	1,492,916	36,105	50,293	65,020	

Panel C. Incremental SRISK$^{LRMES\text{-}C}$

Name	MV	LRMES	Liquidity Risk	γ_{min}	γ_{max}	LRMES-C_{min}	LRMES-C_{max}	Incremental SRISK $^{LRMES\text{-}C}$ LRMES-C_{min}	Incremental SRISK $^{LRMES\text{-}C}$ LRMES-C_{max}
JPMORGAN CHASE & CO.	437,226	43.4%	20.3%	-0.34	-0.54	6.9%	10.9%	30,276	47,766
BANK OF AMERICA CORPORATION	316,808	45.9%	25.7%	-0.34	-0.54	8.8%	13.8%	27,761	43,799
WELLS FARGO & COMPANY	227,540	44.9%	24.2%	-0.34	-0.54	8.2%	13.0%	18,768	29,610
CITIGROUP INC.	174,415	47.3%	37.1%	-0.34	-0.54	12.6%	19.9%	22,047	34,784
U.S. BANCORP	92,603	36.6%	46.3%	-0.34	-0.54	15.8%	24.9%	14,631	23,084
PNC FINANCIAL SERVICES GROUP, INC., THE	69,945	40.1%	39.9%	-0.34	-0.54	13.6%	21.5%	9,514	15,011
M&T BANK CORPORATION	22,400	38.7%	22.6%	-0.34	-0.54	7.7%	12.1%	1,724	2,720
FIFTH THIRD BANCORP	21,815	51.1%	29.9%	-0.34	-0.54	10.2%	16.1%	2,222	3,506
KEYCORP	19,936	45.2%	41.7%	-0.34	-0.54	14.2%	22.4%	2,834	4,472
CITIZENS FINANCIAL GROUP, INC.	17,654	48.3%	46.1%	-0.34	-0.54	15.7%	24.8%	2,772	4,374
Total (Top 10 Banks)	1,400,341							132,550	209,126
Total (Vlab Banks)	1,601,754							149,543	235,935
Total (All Sample Banks)	1,756,619							158,024	249,316

Panel D. SRISK-C

Name	SRISK (Q4 2019)		SRISK-C_{min}	SRISK-C_{max}
	w/o neg SRISK	w/ neg SRISK		
JPMORGAN CHASE & CO.	0	-27,848	36,885	59,668
BANK OF AMERICA CORPORATION	14,898	14,898	35,278	57,336
WELLS FARGO & COMPANY	24,425	24,425	23,564	38,247
CITIGROUP INC.	60,887	60,887	26,906	43,534
U.S. BANCORP	0	-19,352	16,953	27,265
PNC FINANCIAL SERVICES GROUP, INC., THE	0	-9,895	11,551	18,679
M&T BANK CORPORATION	0	-3,862	1,948	3,123
FIFTH THIRD BANCORP	2,067	2,067	3,173	5,219
KEYCORP	299	299	3,634	5,912
CITIZENS FINANCIAL GROUP, INC.	3,005	3,005	3,587	5,841
Total (Top 10 Banks)	105,581	44,623	163,480	264,826
Total (Vlab Banks)	111,135	36,680	184,231	298,405
Total (All Sample Banks)			194,129	314,336

Appendix I. Example – Drawdowns during COVID-19

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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. 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 rat 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
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 $SRISK^{LRMES\text{-}C}$	(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
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
Oil Exposure / Assets	Sum of a bank's active loan exposures to oil & gas firms (%Assets)	Dealscan
Other Sectoral Exposures / Assets	Sum of a bank's active loan exposures to the retail, leisure, and hotel & gaming industry (%Assets)	Dealscan
Post	Post is defined as the period starting April 1, 2020	
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
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
Return January 2020	Cumulative stock return from January 1 to January 31, 2020	CRSP
Return February 2020	Cumulative stock return from February 1 to February 29, 2020	CRSP
Return 3/1-3/23/2020	Cumulative stock return from March 1 to March 23, 2020	CRSP
Return April 2020	Cumulative stock return from 01.04.-30.04.2020	CRSP
Return May 2020	Cumulative stock return from 01.05.-31.05.2020	CRSP
Return June 2020	Cumulative stock return from 01.06.-30.06.2020	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
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 $SRISK^{LRMES\text{-}C}$	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

What explains the crash of bank stock prices during COVID-19?

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Online Appendix

(Not for publication)

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Table of Content

Appendix A. Industry exposure and performance

After the oil price shock on March 9, 2020, the market performance of the oil & gas sector considerably deteriorated. Panel A of Figure A.1. shows the performance of this sector vis-à-vis other sectors directly affected by the pandemic (i.e., retail, leisure and hotel & gaming) using returns from loans traded in the secondary market in these sectors. While the returns in the loan market declined substantially in all sectors, loan return of oil & gas and mining firms significantly underperformed the other sectors even after the announcement of the interventions by the Fed on March 23, 2020.

Panel B of Figure A.1. show the time-series of oil-price volatility using the CVOX oil price volatility index. While oil price volatility increases episodically during economic downturns (e.g., during the global financial crisis (GFC), i.e., the 2007 to 2009 period), the European sovereign debt crisis (2011-2012), and the oil & gas crisis in 2015-2016), volatility has increased by more than 6 times (to over 100% on an annualized basis) around March 9th, 2020 and energy stocks crashed.

Banks are heavily exposed through loans provided to this sector. Both bank exposures and the riskiness of energy firm balance sheets have risen steadily in the recent years. We measure a bank's exposure to the oil sector using all active loans at the end of Q4:2019 and scaled by Tier 1 capital.

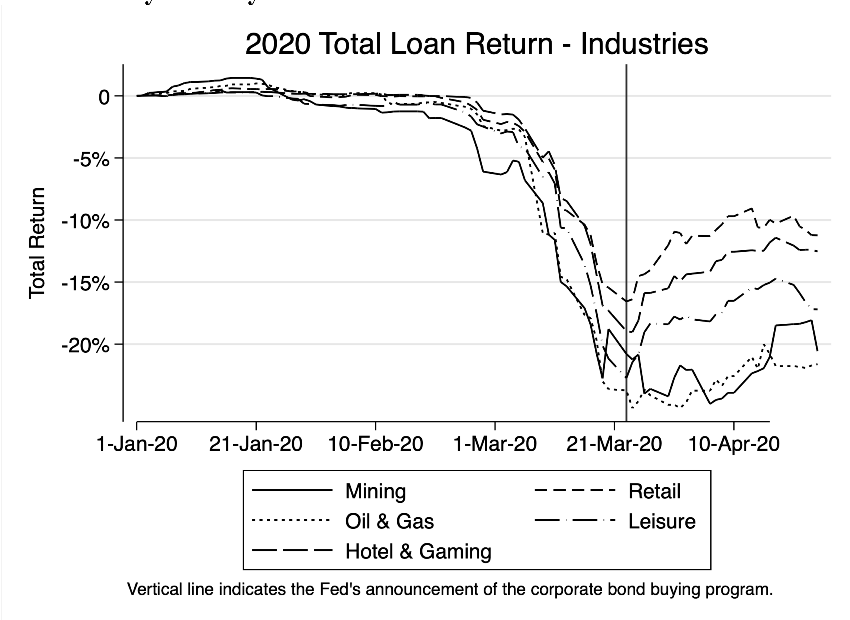
In addition to the tests in the main paper, we perform an event study using a 2-day window around 9 March 2020 and plot banks' 2-day beta adjusted return ($= r_i - \beta_i r_{S\&P}$)[16] on banks' exposure to the oil & gas sector scaled by Tier 1 capital (Figure A.2.). We find a significant negative correlation suggesting that oil price risk is priced in bank stock returns.

[16] The beta is measured pre-crisis, i.e., at the end of Q4 2019.

Figure A1. Industry performance during COVID-19

This figure shows the performance of some sectors during COVID-19 using different measures. In Panel A, we plot the total loan return since Jan 1, 2020 of traded in the secondary market in the following sectors: mining, oil & gas retail, leisure, hotel & gaming. In Panel B, we plot oil price volatility (CVOX) since July 1, 2007.

Panel A. Total loan return by industry



Panel B. Oil price volatility

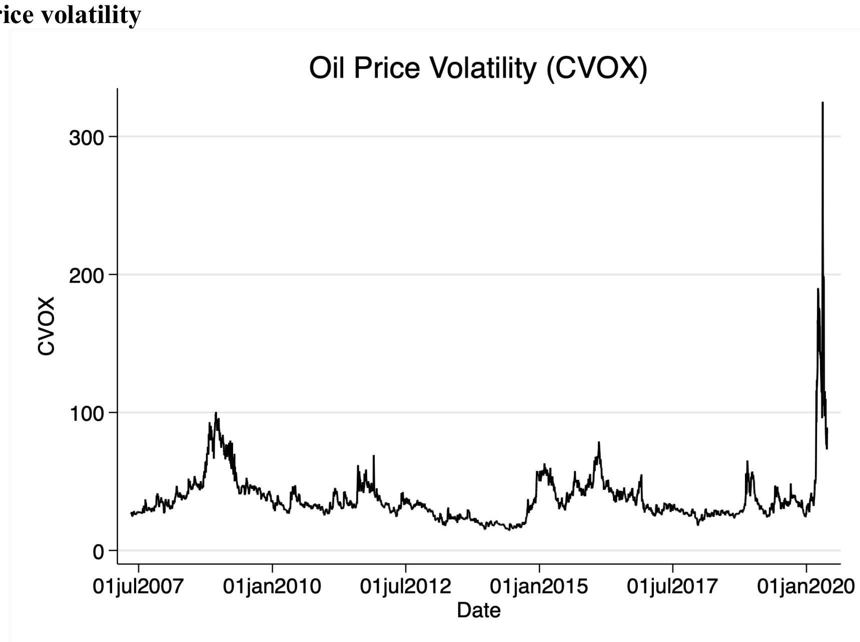
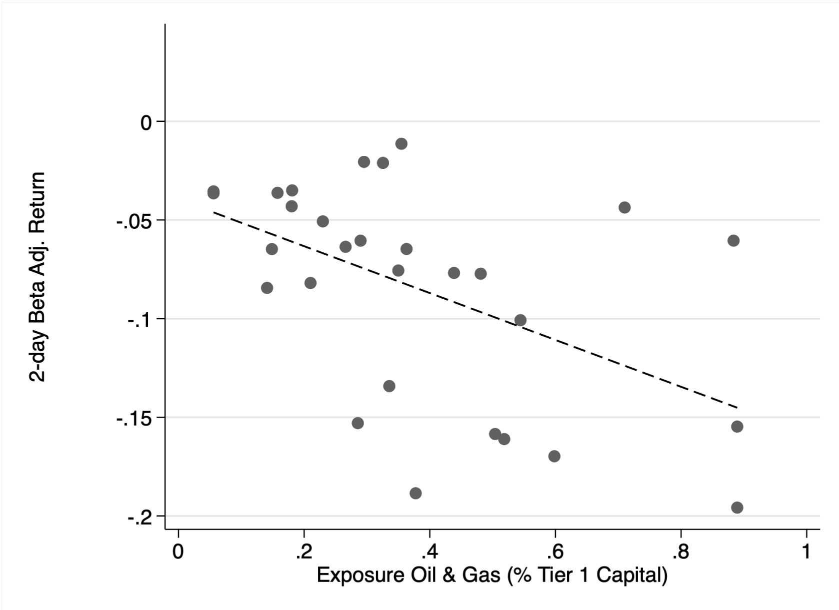


Figure A2. Event study around the oil price shock (9 March 2020)

This figure plots the 2-day beta adjusted bank stock return around the oil price shock on March 9, 2002 on banks' loan exposure to the oil & gas industry scaled by Tier 1 capital.



Appendix B. Reversal of Credit Line Drawdowns

To investigate the effect of credit risk on corporate cash holdings during the COVID-19 pandemic, we construct a sample of all publicly listed U.S. firms, for which financial variables are available at the end of 2019 in Capital IQ. We drop financial firms and utilities and firms with total assets below US$100 million at the end of 2019. Our final sample comprises 1,971 U.S. nonfinancial firms. We construct the sample following Acharya and Steffen (2020).

We use quarterly debt capital structure data from CapitalIQ and investigate changes in different debt capital structure components during Q4 2019 and Q4 2020 (Table A.1) and quarterly from Q4 2019 to Q3 2020 (Table A.2). Specifically, we inspect the following: drawn credit lines (*Drawn CL/Assets*), credit line usage (*Drawn CL/(Drawn CL + Undrawn CL)*), bond debt (*Bonds /Assets*), term loans (*Term loans/Assets*), total debt (*Total Debt / Assets*), and preference for cash (*Cash / (Cash + Undrawn CL)*).

B.1 Descriptive statistics of firm's capital structure (Q4 2019 vs. Q3 2020)

	Q4 2019	Q3 2020	Delta	t-stat
A. Full sample				
Drawn CL / (Drawn CL + Undrawn CL)	0.188	0.193	0.005	-1.469
Drawn CL / Assets	0.036	0.033	-0.003	2.874***
Bonds / Assets	0.156	0.166	0.01	-4.589***
Term Loans / Assets	0.078	0.070	-0.008	4.761***
Total Debt / Assets	0.344	0.355	0.011	-5.153***
Cash / (Cash + Undrawn CL)	0.497	0.580	0.083	-16.892***
B. AAA-A rated firms				
Drawn CL / (Drawn CL + Undrawn CL)	0.031	0.027	-0.004	0.394
Drawn CL / Assets	0.003	0.002	-0.001	1.445
Bonds / Assets	0.299	0.308	0.009	-0.894
Term Loans / Assets	0.007	0.007	0	0.386
Total Debt / Assets	0.349	0.363	0.014	-2.647***
Cash / (Cash + Undrawn CL)	0.498	0.548	0.05	-2.723***
C. BBB rated firms				
Drawn CL / (Drawn CL + Undrawn CL)	0.072	0.079	0.007	-0.412
Drawn CL / Assets	0.011	0.010	-0.001	0.531
Bonds / Assets	0.274	0.290	0.016	-3.395***
Term Loans / Assets	0.017	0.018	0.001	-0.357
Total Debt / Assets	0.356	0.372	0.016	-4.641***
Cash / (Cash + Undrawn CL)	0.333	0.437	0.104	-8.574***
D. NonIG rated firms				
Drawn CL / (Drawn CL + Undrawn CL)	0.162	0.215	0.053	-3.706***
Drawn CL / Assets	0.033	0.036	0.003	-1.57
Bonds / Assets	0.235	0.246	0.011	-2.042**
Term Loans / Assets	0.142	0.132	-0.01	3.264***
Total Debt / Assets	0.482	0.499	0.017	-3.861***
Cash / (Cash + Undrawn CL)	0.363	0.482	0.119	-10.894***
E. Unrated firms				
Drawn CL / (Drawn CL + Undrawn CL)	0.259	0.237	-0.022	1.303
Drawn CL / Assets	0.046	0.040	-0.006	4.227***
Bonds / Assets	0.080	0.089	0.009	-3.139***
Term Loans / Assets	0.070	0.061	-0.009	3.775***
Total Debt / Assets	0.280	0.286	0.006	-2.241**
Cash / (Cash + Undrawn CL)	0.592	0.658	0.066	-10.344***

Table B.2. Descriptive statistics of firm's capital structure (Q4 2019 to Q3 2020)

Panel A. Full sample

Variable	Mean	Std dev	Min	Max
Drawn CL / (Drawn CL + Undrawn CL) - Q4 2019	0.188	0.269	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q1 2020	0.381	0.353	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q2 2020	0.277	0.332	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q3 2020	0.193	0.288	0.000	1.000
Drawn CL / Assets - Q4 2019	0.036	0.073	0.000	0.355
Drawn CL / Assets - Q1 2020	0.058	0.086	0.000	0.400
Drawn CL / Assets - Q2 2020	0.046	0.081	0.000	0.396
Drawn CL / Assets - Q3 2020	0.033	0.069	0.000	0.340
Bonds / Assets - Q4 2019	0.156	0.192	0.000	0.909
Bonds / Assets - Q1 2020	0.158	0.194	0.000	0.923
Bonds / Assets - Q2 2020	0.167	0.198	0.000	0.873
Bonds / Assets - Q3 2020	0.166	0.198	0.000	0.855
Term Loans / Assets - Q4 2019	0.078	0.134	0.000	0.645
Term Loans / Assets - Q1 2020	0.078	0.132	0.000	0.617
Term Loans / Assets - Q2 2020	0.078	0.131	0.000	0.598
Term Loans / Assets - Q3 2020	0.070	0.124	0.000	0.565
Total Debt / Assets - Q4 2019	0.344	0.229	0.002	1.134
Total Debt / Assets - Q1 2020	0.370	0.240	0.002	1.180
Total Debt / Assets - Q2 2020	0.368	0.243	0.002	1.242
Total Debt / Assets - Q3 2020	0.355	0.241	0.002	1.228
Cash / (Cash + Undrawn CL) - Q4 2019	0.497	0.344	0.002	1.000
Cash / (Cash + Undrawn CL) - Q1 2020	0.608	0.333	0.005	1.000
Cash / (Cash + Undrawn CL) - Q2 2020	0.593	0.329	0.004	1.000
Cash / (Cash + Undrawn CL) - Q3 2020	0.580	0.331	0.006	1.000

Panel B. AAA-A rated firms

Variable	Mean	Std dev	Min	Max
Drawn CL / (Drawn CL + Undrawn CL) - Q4 2019	0.031	0.113	0.000	0.911
Drawn CL / (Drawn CL + Undrawn CL) - Q1 2020	0.156	0.290	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q2 2020	0.069	0.195	0.000	0.958
Drawn CL / (Drawn CL + Undrawn CL) - Q3 2020	0.027	0.085	0.000	0.445
Drawn CL / Assets - Q4 2019	0.003	0.014	0.000	0.125
Drawn CL / Assets - Q1 2020	0.013	0.028	0.000	0.142
Drawn CL / Assets - Q2 2020	0.007	0.023	0.000	0.147
Drawn CL / Assets - Q3 2020	0.002	0.008	0.000	0.053
Bonds / Assets - Q4 2019	0.299	0.154	0.000	0.754
Bonds / Assets - Q1 2020	0.308	0.151	0.000	0.781
Bonds / Assets - Q2 2020	0.319	0.138	0.011	0.779
Bonds / Assets - Q3 2020	0.308	0.133	0.000	0.770
Term Loans / Assets - Q4 2019	0.007	0.017	0.000	0.108
Term Loans / Assets - Q1 2020	0.008	0.019	0.000	0.145
Term Loans / Assets - Q2 2020	0.007	0.013	0.000	0.058
Term Loans / Assets - Q3 2020	0.007	0.013	0.000	0.060
Total Debt / Assets - Q4 2019	0.349	0.145	0.046	0.753
Total Debt / Assets - Q1 2020	0.369	0.147	0.045	0.757
Total Debt / Assets - Q2 2020	0.376	0.135	0.062	0.757
Total Debt / Assets - Q3 2020	0.363	0.130	0.057	0.754
Cash / (Cash + Undrawn CL) - Q4 2019	0.498	0.322	0.002	1.000
Cash / (Cash + Undrawn CL) - Q1 2020	0.585	0.308	0.005	1.000
Cash / (Cash + Undrawn CL) - Q2 2020	0.564	0.296	0.004	1.000
Cash / (Cash + Undrawn CL) - Q3 2020	0.548	0.304	0.006	1.000

Panel C. BBB rated firms

Variable	Mean	Std dev	Min	Max
Drawn CL / (Drawn CL + Undrawn CL) - Q4 2019	0.072	0.165	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q1 2020	0.235	0.285	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q2 2020	0.129	0.241	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q3 2020	0.079	0.182	0.000	1.000
Drawn CL / Assets - Q4 2019	0.011	0.039	0.000	0.344
Drawn CL / Assets - Q1 2020	0.030	0.053	0.000	0.400
Drawn CL / Assets - Q2 2020	0.019	0.046	0.000	0.396
Drawn CL / Assets - Q3 2020	0.010	0.026	0.000	0.240
Bonds / Assets - Q4 2019	0.274	0.136	0.000	0.909
Bonds / Assets - Q1 2020	0.279	0.138	0.000	0.923
Bonds / Assets - Q2 2020	0.292	0.141	0.000	0.873
Bonds / Assets - Q3 2020	0.290	0.146	0.000	0.855
Term Loans / Assets - Q4 2019	0.017	0.035	0.000	0.203
Term Loans / Assets - Q1 2020	0.022	0.042	0.000	0.286
Term Loans / Assets - Q2 2020	0.021	0.038	0.000	0.221
Term Loans / Assets - Q3 2020	0.018	0.036	0.000	0.232
Total Debt / Assets - Q4 2019	0.356	0.145	0.048	1.001
Total Debt / Assets - Q1 2020	0.381	0.148	0.075	1.034
Total Debt / Assets - Q2 2020	0.382	0.148	0.064	1.040
Total Debt / Assets - Q3 2020	0.372	0.145	0.054	1.017
Cash / (Cash + Undrawn CL) - Q4 2019	0.333	0.254	0.002	1.000
Cash / (Cash + Undrawn CL) - Q1 2020	0.439	0.269	0.015	1.000
Cash / (Cash + Undrawn CL) - Q2 2020	0.446	0.267	0.004	1.000
Cash / (Cash + Undrawn CL) - Q3 2020	0.437	0.268	0.006	1.000

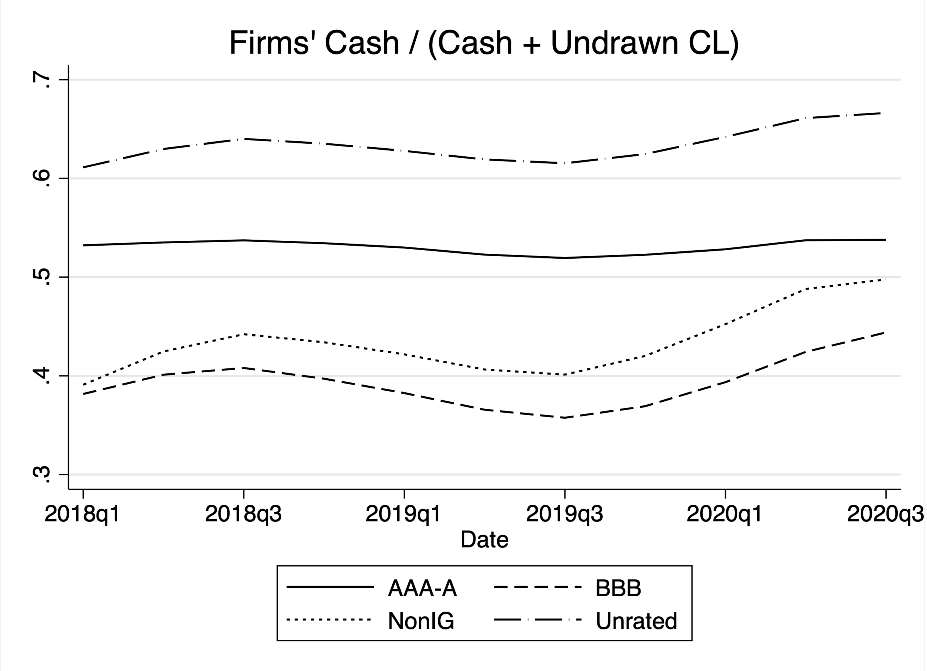
Panel D. NonIG rated firms

Variable	Mean	Std dev	Min	Max
Drawn CL / (Drawn CL + Undrawn CL) - Q4 2019	0.162	0.241	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q1 2020	0.443	0.353	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q2 2020	0.310	0.335	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q3 2020	0.215	0.301	0.000	1.000
Drawn CL / Assets - Q4 2019	0.033	0.066	0.000	0.355
Drawn CL / Assets - Q1 2020	0.067	0.078	0.000	0.400
Drawn CL / Assets - Q2 2020	0.048	0.071	0.000	0.396
Drawn CL / Assets - Q3 2020	0.036	0.068	0.000	0.340
Bonds / Assets - Q4 2019	0.235	0.187	0.000	0.909
Bonds / Assets - Q1 2020	0.236	0.190	0.000	0.923
Bonds / Assets - Q2 2020	0.252	0.199	0.000	0.873
Bonds / Assets - Q3 2020	0.246	0.199	0.000	0.855
Term Loans / Assets - Q4 2019	0.142	0.157	0.000	0.645
Term Loans / Assets - Q1 2020	0.141	0.157	0.000	0.617
Term Loans / Assets - Q2 2020	0.141	0.156	0.000	0.598
Term Loans / Assets - Q3 2020	0.132	0.150	0.000	0.565
Total Debt / Assets - Q4 2019	0.482	0.198	0.051	1.134
Total Debt / Assets - Q1 2020	0.518	0.205	0.059	1.180
Total Debt / Assets - Q2 2020	0.518	0.215	0.058	1.242
Total Debt / Assets - Q3 2020	0.499	0.217	0.053	1.228
Cash / (Cash + Undrawn CL) - Q4 2019	0.363	0.263	0.002	1.000
Cash / (Cash + Undrawn CL) - Q1 2020	0.540	0.320	0.005	1.000
Cash / (Cash + Undrawn CL) - Q2 2020	0.500	0.311	0.004	1.000
Cash / (Cash + Undrawn CL) - Q3 2020	0.482	0.302	0.006	1.000

Panel E. Unrated firms

Variable	Mean	Std dev	Min	Max
Drawn CL / (Drawn CL + Undrawn CL) - Q4 2019	0.259	0.300	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q1 2020	0.415	0.356	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q2 2020	0.329	0.345	0.000	1.000
Drawn CL / (Drawn CL + Undrawn CL) - Q3 2020	0.237	0.307	0.000	1.000
Drawn CL / Assets - Q4 2019	0.046	0.083	0.000	0.355
Drawn CL / Assets - Q1 2020	0.065	0.096	0.000	0.400
Drawn CL / Assets - Q2 2020	0.055	0.091	0.000	0.396
Drawn CL / Assets - Q3 2020	0.040	0.078	0.000	0.340
Bonds / Assets - Q4 2019	0.080	0.171	0.000	0.909
Bonds / Assets - Q1 2020	0.082	0.172	0.000	0.923
Bonds / Assets - Q2 2020	0.087	0.175	0.000	0.873
Bonds / Assets - Q3 2020	0.089	0.176	0.000	0.855
Term Loans / Assets - Q4 2019	0.070	0.132	0.000	0.645
Term Loans / Assets - Q1 2020	0.069	0.129	0.000	0.617
Term Loans / Assets - Q2 2020	0.070	0.127	0.000	0.598
Term Loans / Assets - Q3 2020	0.061	0.119	0.000	0.565
Total Debt / Assets - Q4 2019	0.280	0.236	0.002	1.134
Total Debt / Assets - Q1 2020	0.303	0.248	0.002	1.180
Total Debt / Assets - Q2 2020	0.299	0.250	0.002	1.242
Total Debt / Assets - Q3 2020	0.286	0.248	0.002	1.228
Cash / (Cash + Undrawn CL) - Q4 2019	0.592	0.362	0.002	1.000
Cash / (Cash + Undrawn CL) - Q1 2020	0.677	0.334	0.005	1.000
Cash / (Cash + Undrawn CL) - Q2 2020	0.670	0.331	0.004	1.000
Cash / (Cash + Undrawn CL) - Q3 2020	0.658	0.337	0.006	1.000

Figure B.1. Preference for cash
This figure shows the median Cash / (Cash + Undrawn CL) ratio (panel B) of U.S. nonfinancial firms over the Q1 2018 to Q3 2020 period.



Preference for cash has increased / remained high during the 3 quarters in 2020, particularly of lower rated and unrated firms.

Appendix B – SRISK-C using only unused C&I loans

In Online Appendix B, we calculate SRISK-C but use only unused C&I loans (and the estimated coffients) . Everything else is as in Table 9 of the main paper.

Table B.1 Incremental SRISK$^{LRMES\text{-}C}$

Panel A reports the calculation of *Incremental SRISK$^{MES\text{-}C}$* due to the sensitivity of bank stock returns to *Unused C&I Credit Lines* 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$_{min}$ ($)* is calculated as *Liquidity Risk x γ_{min} x MV*. Other variables are calculated accordingly. In Panel B, we show the Conditional SRISK (*SRISK-C*) which is the sum of *Incremental SRISK^{CL}* and *Incremental SRISK$^{MES\text{-}C}$*. All variables are defined in Appendix I.

Panel A.

								Incremental SRISK $^{LRMES\text{-}C}$	
	MV	LRMES	Liquidity Risk	γ_{min}	γ_{max}	LRMES-C$_{min}$	LRMES-C$_{max}$	LRMES-C$_{min}$	LRMES-C$_{max}$
JPMORGAN CHASE & CO.	437,226	43.4%	20.3%	-1.012	-1.383	10.3%	14.1%	44,995	61,490
BANK OF AMERICA CORPORATION	316,808	45.9%	25.7%	-1.012	-1.383	12.9%	17.7%	40,941	55,950
WELLS FARGO & COMPANY	227,540	44.9%	24.2%	-1.012	-1.383	10.4%	14.2%	23,691	32,377
CITIGROUP INC.	174,415	47.3%	37.1%	-1.012	-1.383	10.4%	14.2%	18,175	24,838
U.S. BANCORP	92,603	36.6%	46.3%	-1.012	-1.383	19.6%	26.8%	18,163	24,822
PNC FINANCIAL SERVICES GROUP, INC., THE	69,945	40.1%	39.9%	-1.012	-1.383	20.8%	28.4%	14,530	19,857
M&T BANK CORPORATION	22,400	38.7%	22.6%	-1.012	-1.383	7.8%	10.7%	1,751	2,393
FIFTH THIRD BANCORP	21,815	51.1%	29.9%	-1.012	-1.383	23.5%	32.1%	5,126	7,006
KEYCORP	19,936	45.2%	41.7%	-1.012	-1.383	23.0%	31.4%	4,583	6,264
CITIZENS FINANCIAL GROUP, INC.	17,654	48.3%	46.1%	-1.012	-1.383	20.5%	28.0%	3,623	4,951
Total (Top 10 Banks)	1,400,341							175,579	239,946
Total (Vlab Banks)	1,601,754							197,984	270,565
Total (All Sample Banks)	1,756,619							207,978	284,223

Panel B. SRISK-C

Name	SRISK (Q4 2019)		SRISK-C_{min}	SRISK-C_{max}
	w/o neg SRISK	w/ neg SRISK		
JPMORGAN CHASE & CO.	0	-27,848	51,604	73,392
BANK OF AMERICA CORPORATION	14,898	14,898	48,458	69,487
WELLS FARGO & COMPANY	24,425	24,425	28,487	41,014
CITIGROUP INC.	60,887	60,887	23,034	33,588
U.S. BANCORP	0	-19,352	20,485	29,003
PNC FINANCIAL SERVICES GROUP, INC., THE	0	-9,895	16,567	23,525
M&T BANK CORPORATION	0	-3,862	1,975	2,796
FIFTH THIRD BANCORP	2,067	2,067	6,077	8,718
KEYCORP	299	299	5,383	7,704
CITIZENS FINANCIAL GROUP, INC.	3,005	3,005	4,438	6,418
Total (Top 10 Banks)	105,581	44,623	206,508	295,646
Total (Vlab Banks)	111,135	36,680	232,673	333,034
Total (All Sample Banks)			244,083	349,243