Why did bank stocks crash during COVID-19?

Viral V. Acharya[†] Robert Engle[‡] Maximilian Jager[*] Sascha Steffen[**]

August 31, 2023

Abstract

A two-sided "credit-line channel" – relating to drawdowns and repayments – explains the severe drop and partial subsequent recovery in bank stock prices during the COVID-19 pandemic. Banks with greater exposure to undrawn credit lines saw larger stock price declines but performed better before the pandemic and after the policy interventions. Despite deposit inflows, high drawdowns led to reduced bank lending, suggestive of capital encumbrance upon drawdowns. Repayments of credit lines unencumbered capital which explains the stock price recovery starting Q2 2020. Bank provision of credit lines resembles writing deep out-of-the-money put options on aggregate risk, and we propose how to incorporate this feature into bank capital stress tests.

Keywords: Credit lines, liquidity risk, bank capital, loan supply, stress tests, pandemic, COVID-19.
JEL-Classification: G01, G21.

We thank Jennie Bai, Tobias Berg, Allen Berger, Christa Bouwman, Gabriel Chodorow-Reich, Olivier Darmouni, Darrell Duffie, Ruediger Fahlenbrach, Anna Kovner, Kevin Raghet, Rafael Repullo, Phil Strahan, Daniel Streitz, René Stulz, Anjan Thakor, Josef Zechner and participants at the 2020 Federal Reserve Stress Testing Conference and seminar participants at the Annual Columbia SIPA/BPI Bank Regulation Research Conference, Banco de Portugal, Bank of England, SFS Cavalcade 2022, CAF, EFA 2021, Federal Reserve Bank of Cleveland, NYU Stern Finance, RIDGE Workshop on Financial Stability, University of Southern Denmark, University of Durham, Villanova Webinars in Financial Intermediation, the Volatility and Risk Institute, World Bank, WU Vienna, for comments and suggestions and Sophie-Dorothee Rothermund and Christian Schmidt for excellent research assistance. Robert Engle would like to thank NSF 2018923, Norges Bank project "Financial Approach to Climate Risk" and Interamerican Development Bank Contract #C- RG-T3555-P001 for research support to the Volatility and Risk Institute of NYU Stern.

[†]NYU Stern School of Business, 44 West Fourth Street, Suite 9-65, New York, NY 10012-1126, Email: vacharya@stern.nyu.edu, Tel: +1 212 998 0354.
[‡]NYU Stern School of Business, 44 West Fourth Street, Suite 9-62, New York, NY 10012-1126, Email: rengle@stern.nyu.edu, Tel: +1 212 998 0710.
*Frankfurt School of Finance & Management, Adickesallee 32-34, 60323 Frankfurt, Germany, Email: m.jager@fs.de,Tel: +49 69 154008-304.
[**]Frankfurt School of Finance & Management, Adickesallee 32-34, 60323 Frankfurt, Germany, Email: s.steffen@fs.de,Tel: +49 69 154008-794.

1. Introduction

Since the global financial crisis (GFC) of 2008--09, banks have greatly expanded their liquidity provision through credit lines to the United States (U.S.) non-financial sector. Panel A of Figure 1 shows that bank credit lines for the U.S. publicly listed firms increased from 0.7% of GDP in 2009 to 5.7% of GDP in 2019 leading to a substantial build-up of drawdown risk on bank balance-sheets. This risk materialized in March 2020 amid the outbreak of the COVID-19 pandemic and subsequent government-imposed lockdowns. Firms' cash flows dropped, in some cases by as much as 100%, while operating and financial leverage remained sticky, causing bond markets to freeze. As a consequence, U.S. firms with pre-arranged credit lines from banks drew down their undrawn facilities with a far greater intensity than in past recessions (Panel B of Figure 1), specifically the prospective fallen angels or BBB-rated and junk-rated firms (Panel C of Figure 1).

[Figure 1 about here]

Recent data show that firms benefited from having such access to pre-arranged credit lines during the pandemic when capital market funding froze (*e.g.*, Acharya and Steffen, 2020a; Chodorow-Reich *et al*., 2022; Greenwald *et al*., 2023).[1] On the flip side, however, banks faced unprecedented aggregate risk in the form of a correlated demand for credit-line drawdowns; an important but not well-appreciated consequence is that banks' share prices crashed and persistently underperformed those of non-financial firms as well as non-bank financial firms (Panel D of Figure 1).

In this paper, we investigate causes and consequences of this crash of bank stocks during the COVID-19 pandemic and highlight a central role played by banks' credit-line business.

[1] Within three weeks, public firms drew down more than USD 300bn, with drawdowns particularly concentrated among riskier BBB-rated and non-investment-grade firms. For instance, Ford Motor Company drew down its credit lines in March 2020, withdrawing USD 15.4bn. With USD 20bn in cash, credit lines significantly impacted its liquidity. Originally, Ford paid 15bps for undrawn credits and 125bps for drawn credits. However, after a downgrade to non-investment grade, these fees increased substantially by 67% and 40% respectively. Li et al. (2020) show – using FDIC's Call Report data which includes drawdowns by private firms – that total drawdowns amounted to more than USD 500bn.

Specifically, we ask what are the possible transmission channels through which the drawdowns affected bank stock returns and ultimately banks' intermediation functions for the real economy? What was the role of credit line repayments for the recovery of bank stock prices in the second quarter of 2020 following the stark decline in 2020Q1? Which aspects of these channels during the COVID-19 episode are different compared to prior stress episodes such as the GFC? Lastly, we ask how bank regulation can incorporate the relevant channels of transmission from bank credit lines to financial fragility to safeguard against the attendant risks in future?

At the core of our analysis is a new and comprehensive measure of the balance-sheet *liquidity risk* of banks defined as *undrawn commitments plus wholesale finance minus cash or cash equivalents (all relative to assets).* Our null hypothesis is that investors price liquidity risk according to their expectations regarding the possible credit line drawdowns during crises. However, these expectations might naturally deviate from realized drawdowns in times of stress. At the beginning of the COVID-19 pandemic, capital markets froze increasing rollover risk for all, but particularly for riskier, firms. Firms responded by drawing down credit lines with significantly higher intensity and magnitude compared to the global financial crisis (GFC) 2007-2008. For example, the average drawdown rate in Q1 2020 was 37% and in Q4 2008 29%. The cross-section of stock-price declines of banks as a function of their ex-ante exposure to drawdown risk (during COVID) can therefore be intrepreted as reflecting the difference between expected and realized drawdown risks.

Consistent with this hypothesis, we find that our measure of the liquidity risk of banks helps understand the decline of bank stock prices, especially during the first phase of the pandemic from January 1, 2020 until March 3, 2020, i.e., before decisive monetary and fiscal support measures were introduced.[2] A one-standard-deviation increase in liquidity risk

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

decreased bank stock returns by about 8.4 percentage points during this period, or 12.5% of the unconditional mean return. A possible concern is that liquidity risk through the provision of credit lines is correlated with bank portfolio composition, as banks facing larger drawdowns may be engaged with riskier borrowers who are more vulnerable to financial and economic crises, and specifically to the onset of COVID-19 pandemic. We provide a variety of tests to isolate the effect of credit-line exposure on bank stock returns using different measures for bank exposure to COVID-19 affected industries. Our results on bank stock returns being affected by balance-sheet liquidity risk appear virtually unaffected by these measures of bank portfolio risk and provide a consistent interpretation that balance-sheet liquidity risk is a key driver of bank stock returns at the beginning of the pandemic – independent of the effect of bank portfolio exposures to COVID-affected industries.

We then show that this cross-sectional explanatory power of balance-sheet liquidity risk for bank stock returns is highly *episodic* in nature. Using separate cross-sectional regressions during the months of January 2020, February 2020 and during the March 1, 2020 to March 23, 2020 period, we show that liquidity risk explains stock returns, particularly during the latter period, when firms' liquidity demand through credit-line drawdowns sharply increased and became highly correlated. The effect disappeared in Q2 2020, *i.e.*, after the decisive monetary and fiscal interventions, but briefly re-surfaced amid the second wave of the pandemic and associated lockdowns in Q3 2020 (the effect is, however, much smaller compared to March 2020).[3]

We analyze two channels through which this sensitivity of bank stock prices to undrawn credit lines can arise: (1) funding liquidity to source new loans can become a binding constraint for banks if deposit funding does not keep pace with credit line drawdowns (the "funding

[3] The Fed intervened in the repo market on March 12, 2020, stabilizing the OIS-spread, a measure for liquidity conditions in financial markets. However, these actions did not halt the drop in bank stock prices, implying liquidity was not a binding constraint for banks at the pandemic's onset.

channel");[4] and, (2) the drawdown of credit lines can "lock up", *i.e.*, encumber, scarce bank capital against drawn facilities and impair intermediation by preventing banks from making possibly more profitable loans (the "capital channel").[5] To distinguish between these channels, we construct two proxies: (1) *Gross Drawdowns* as the change in credit line drawdowns (relative to total assets); and (2) *Net Drawdowns* as the change in drawdowns minus the change in deposit funding (also relative to total assets). Gross and net drawdowns are not highly correlated but net drawdowns are highly correlated with changes in deposits. Keeping net drawdowns constant, our gross drawdown metric distinguishes the credit line drawdowns' impact on banks due to capital channel, rather than the funding channel. Our analysis shows that bank stock returns during the COVID onset are sensitive to gross drawdowns but not significantly to net drawdowns. Banks with higher capital (buffers) experience less negative impact on stock returns during gross drawdowns. In essence, banks' balance-sheet liquidity risk influences stock returns, as credit line drawdowns encumber bank capital away from more lucrative intermediation opportunities.

Next, we investigate this mechanism directly by testing whether banks with more balance-sheet liquidity risk reduced their lending during the COVID-19 pandemic by a greater degree relative to other banks. If banks' capital constraints matter, then we expect lending to be particularly sensitive to gross (but not to net) drawdowns. To control for demand effects, *e.g.*, because of lower investments by riskier firms in a period characterized by high uncertainty or because riskier borrowers have already drawn down existing lines of credit, we employ a Khwaja and Mian (2008) estimator, investigating the change in lending of banks to the *same* borrower before and after the outbreak of the pandemic. We find that banks with high gross

[4] This was the case during the GFC as shown by Acharya and Mora (2015).

[5] 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 at a cost when facing an adverse shock, which may affect their ability to lend ex ante.

drawdowns (but not net drawdowns) actively reduce existing term-loan exposures relative to banks with low gross drawdowns. Moreover, banks with high gross drawdowns reduce new loan originations compared to banks with low gross drawdowns, for both credit lines and term loans. That is, holding the effect of deposit inflows constant, banks that incur a greater impact on equity capital through large credit line drawdowns reduce lending more than other banks. Overall, aggregate drawdowns at banks appear to have important spillovers for credit provision to the real economy via the bank capital channel.

Bank stock prices lagged notably behind non-financial firms in the post-intervention period. To elucidate this discrepancy, we introduce the two-sided "credit-line channel." Central to this are the dual options credit lines offer firms: the ability to draw and the choice to repay (or withhold repayment). Recognizing the significance of the repayment option is pivotal in understanding banks' stock performance during the post-intervention period. In Q2 and Q3 2020, as capital market issuances resumed, top-rated firms began exercising their repayment option (see, e.g., Chodorow-Reich et al., 2022). We construct a measure of credit-line repayments using a matched sample of banks and firms with data from FDIC Call Reports, Refinitiv Dealscan and Capital IQ. To distinguish between liquidity and capital effects of repayments, we formulate two variables. First, we measure the total liquidity returning to banks' balance sheets using the ratio of the repaid amount to the committed amount of a credit line. As a second measure, we employ the difference in the revenue (from fees and interest rate) between the drawn credit line and potential alternative investments of similar risk profiles.[6]

Our findings verify that both factors influenced the partial recovery of bank stock returns in 2020Q2. Repayments benefit stock returns due to the liquidity they provide. Yet, banks favor repayments from credit lines with lower (opportunity cost-adjusted) fees. Essentially, banks

[6] For an accurate comparison, we use as alternative a corporate bond index matching the credit line borrower's risk and regulatory capital cost (through risk-weights) as a proxy. Since capital costs of loans are rating-specific for banks, this measure captures the capital channel of credit line repayments. Suppose banks A and B charge borrowers the same interest, but bank A's borrower ties up more capital. We theorize that bank A gains more from credit line repayment, freeing up more capital, leading to a greater positive impact on its stock return than bank B.

and their investors seek compensation for their opportunity cost of encumbered capital and drawdown risk. The more capital is tied up by a drawdown, the more revenue a credit line must generate to satisfy investors. We therefore conclude that the capital channel is pivotal in understanding the two-sided nature of the impact of credit lines on stock returns, through drawdowns as well as repayments.

A natural question to ask is whether drawdown risk of banks materialized and was priced in other crisis periods, such as during the Dotcom bubble burst or the GFC, and whether investors in banks get compensated with higher stock returns outside of crisis periods for bearing this aggregate risk. To answer these questions, we regress quarterly bank stock returns on credit line commitments over the 1995Q1 to 2021Q1 period on a sample of high- and low-commitment banks matched on bank health (capitalization, NPL-to-loan ratios), size (assets) and business model (loan-to-assets), controlling for the five Fama-French factors. We find that high commitments – and therefore (ex-post) aggregate drawdown risk – adversely impacts bank stock returns during all three crisis periods, with the impact during Covid approximately 2.5 times more potent than during the Dotcom and GFC periods. We also find that investors are compensated for aggregate drawdown risk outside crises. Put differently, evidence does not support a total oversight or mispricing of this risk by bank stock investors. Instead, our findings align with the idea that investors *reassess* the implications of *unexpected* credit line drawdowns during states with significantly high aggregate risk.[7]

The finding that bank stock investors seem to bear the aggregate risk of credit line drawdowns prompts us to study credit line pricing by banks. While credit line spreads and fees can reflect idiosyncratic drawdown risk, as shown by Berg et al. (2016, 2017) and Acharya et al. (2013), they might not adequately reflect the aggregate nature of the risk. Our data reveals

[7] Compare, for example, English et al. (2018), who show how investors reassess banks' stock returns sensitivity to interest rate risk in the light of unexpected interest rate changes. Diep et al. (2021) document that investors try to price systematic prepayment risk in mortgage-backed securities (MBS). Similarly, we expect investors to adjust the pricing of banks' stocks in response to any signals/information about aggregate drawdown risk.

that idiosyncratic drawdown risk is considered in commitment fees and spreads. However, banks do not factor in aggregate drawdown risk when setting credit line prices, explaining their equity capital reliance during the pandemic. In essence, credit line pricing does not seem to fully signal aggregate drawdown risk. This is then consistent with investors having to adjust their expectations regarding drawdowns during periods of aggregate risk, and in turn, unexpected drawdowns in such times leading to an adverse bank response in bank stock prices.

How can policymakers proactively manage this aggregate drawdown risk? One approach is to include credit line drawdown effects in bank capital stress tests, mandating banks to support these exposures with more equity capital ex ante. We extend the concept of *SRISK*, a market-data based estimation of capital shortfall under aggregate stress, in Acharya *et al*. (2012), Acharya *et al*. (2016) and Brownlees and Engle (2017), to account explicitly for contingent credit line drawdowns. Specifically, we propose two adjustments: (1) Factor in the required equity capital when contingent liabilities become actual liabilities during stress periods; and, (2) Reflect this liquidity risk's adverse effect on bank market value during stress periods, as estimated in our prior regression analysis. These adjustments reveal an additional capital deficit of over USD 366bn for the U.S. banking sector as of end-2019 in a stress scenario of 40% correction to the S&P500 index and when subject to an 8% market-equity capital requirement under stress, with the top 10 banks' shortfall being 1.7 times greater.

2. Related literature

Our paper relates to the literature highlighting the role of banks in liquidity provision. Kashyap *et al*. (2002) and Gatev and Strahan (2006) propose a unique role for banks as liquidity providers to both households and firms, given efficiency in risk management (via cash holdings) and access to government backstops (which induces a flight to safety in deposits), respectively. Ivashina and Scharfstein (2010) document evidence of an acceleration of credit-line drawdowns as well as an increase in aggregate bank deposits during the 2007-2009 crisis. During this crisis – in which the banking system itself was at the centre and several individual banks faced significant deposit withdrawals – Acharya and Mora (2015) show that banks faced a crisis as liquidity providers and could manage credit line drawdowns only because of (and after) significant support from the government. During the COVID-19 pandemic, however, which directly affected the corporate sector, Li *et al*. (2020) and Acharya and Steffen (2020b) show that aggregate deposit inflows were sufficient to fund the increase in liquidity demand from drawdowns. Chodorow-Reich *et al.* (2022) and Greenwald *et al.* (2023) document important lending spillovers and show that particularly small firms experienced a drop in the supply of bank credit when large firms drew down credit lines using F-14Q data. Kapan and Minoiu (2021) provide similar results using Dealscan data.

None of these papers, however, explores the implications of banks as liquidity providers for their stock returns when drawdowns – and eventual repayments – affect bank capital availability for other intermediation functions.[8] By examining both gross drawdowns and net (of deposit inflows) drawdowns, we demonstrate that credit-line drawdowns reduce banks' franchise value because of binding capital constraints.

There is a large corporate finance literature on the availability and pricing of credit lines as well as credit line usage.[9] In contrast to this literature, we take a bank-centric view and investigate the implications of drawdown risks for banks with large exposures to committed credit lines. Importantly, we show that – while idiosyncratic and systematic components of a *firm's* stock return volatility are incorporated by banks in the pricing of credit lines extended to a firm – banks do not appear to adequately or fully price the drawdown risk for the banking sector in the aggregate, *i.e.*, in large stress episodes such as the GFC or the pandemic. Acharya

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

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

and Steffen (2020a) document a dash-for-cash and run on credit lines at the beginning of the COVID-19 pandemic.[10] Darmouni and Siani (2020) show that a large percentage of these credit lines were repaid through bond issuances in Q2 and Q3 2020. We show, however, that not all banks (equally) benefited from the repayments and the capital that was freed-up. Some banks were earning high interest or fees on the drawn portion of the credit lines which they had to forego due to their repayment. To summarize, we propose a two-sided "credit-line" channel to make sense of the stock price performance of banks during the COVID-19 pandemic.

Finally, we also compare our liquidity risk measure – defined as unused credit line commitments plus wholesale funding minus liquidity, all relative to total assets – for banks with two frequently used measures in the literature, the Berger and Bouwman (2009) liquidity creation measure (which is based both on- and off-balance-sheet data) and the Bai et al. (2018) liquidity risk measure (which also employs markets data). All three measures significantly explain bank stock returns in individual regressions.[11] When we run a horse race including all measures, our liquidity risk measure remains significant (while the other two measures become insignificant) suggesting that it contains information about aggregate drawdown risk of credit lines that is not included or fully captured in the other liquidity measures.

3. Balance-sheet liquidity risk and bank stock returns

3.1. Data

We collect data for all publicly listed bank holding companies of commercial banks in the U.S. and construct our main dataset following Acharya and Mora (2015), dropping all banks with total assets below USD 100mn at the end of 2019 and keeping only those banks that we can

[10] There is growing literature analyzing the implications of COVID for corporate finance and capital markets such as the disruption in corporate bond markets (*e.g.*, Haddad et al., 2021; O'Hara and Zhou, 2021), the role of FinTechs in providing credit (Erel and Liebersohn, 2022) or the impact of government support programs on the supply of loans (*e.g.*, Balyuk et al., 2021; Boyarchenko et al., 2022; Minoiu et al., 2021; Vissing-Jorgensen, 2021).
[11] While there's no consensus in literature on measuring a bank's liquidity, various approaches exist. Deep and Schaefer (2004) focus on on-balance-sheet liquidity, using scaled assets minus liabilities. Berger and Bouwman (2009) offer a broad measure incorporating on- and off-balance-sheet components, emphasizing liquidity creation. We zero in on liquidity risk during economic downturns via credit lines and short-term funding. Bai et al. (2018) build a dynamic liquidity risk measure from both balance sheets, reflecting current market conditions. In contrast, our approach provides a simpler, ex-ante view of bank liquidity risk exposure.

match to the CRSP/Compustat database. All financial variables (on the holding-company level) are obtained from FDIC Call Reports (FR-Y9C) and augmented with data sourced from SNL Financial. We keep only those banks for which we have all data available for our main specifications during the COVID-19 pandemic, which limits our sample to 147 U.S. bank holding companies (accounting for about 99% of all outstanding credit lines).[12] All variables are explained below or in Appendix III.

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

3.2. Measuring balance-sheet liquidity risk of banks

To construct our measure of a bank's balance-sheet liquidity risk, we collect bank balance-sheet information as of Q4 2019 from FDIC Call Reports and construct three key variables following Acharya and Mora (2015): (1) *Unused C&I Commitments*: The sum of credit lines secured by 1–4 family homes, secured and unsecured commercial real estate credit lines, commitments

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

related to securities underwriting, commercial letter of credit, and other credit lines (which includes commitments to extend credit through overdraft facilities or commercial lines of credit); (2) *Wholesale Funding*: The sum of large time deposits, deposits booked in foreign offices, subordinated debt and debentures, gross federal funds purchased, repos, and other borrowed money; and, (3) *Liquidity*: The sum of cash, federal funds sold and reverse repos, and securities excluding MBS/ABS securities. All variables are defined in Appendix III. Using these components, we construct a comprehensive measure of bank balance-sheet liquidity risk (*Liquidity Risk*):

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

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

[Figure 2 about here]

Liquidity Risk of banks decreased since Q1 2010 to a level of about 20% relative to total assets by Q4 2016 (Panel A of Figure 2). In 2017, *Liquidity Risk* started to increase until Q4 2019, *i.e.*, before the start of the COVID-19 pandemic. At the beginning of the pandemic in Q1 2020, liquidity risk dropped about 40% and continued to decline somewhat between Q2 and Q4 of 2020.

Panel B of Figure 2 shows the different components of bank balance-sheet liquidity risk. The decrease since Q1 2010 is driven by the declining share of wholesale funding relative to total assets during the COVID-19 pandemic. However, since 2017, the marginal increase in the importance of unused C&I loans has been larger than the marginal decline in wholesale funding exposure; as a result, *Liquidity Risk* started to increase again. The large decline of *Liquidity Risk* during the first quarter in 2020 was driven by the decrease in unused C&I credit lines consistent with the increase in drawdowns documented in Figure 1. We saw an immediate reversal of

Unused C&I Credit Lines in Q2 and Q3 2020 albeit not to pre-COVID-19 levels, pointing to a partial repayment of credit lines by U.S. firms. We further investigate the role of repayments for bank stock returns in Section 6.

3.3. Methodology

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

$$r_i = \alpha + \gamma \; LiquidityRisk_i \; + \sum \beta \; X_i + \varepsilon_i \qquad (1)$$

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. γ is our coefficient of interest. As explained in the Introduction, our null hypothesis is that investors price liquidity risk according to their expectations regarding the possible credit line drawdowns during crises. However, these expectations might naturally deviate from realized drawdowns in times of stress. Larger stock price declines of banks with higher ex-ante exposure to drawdown risk during COVID (i.e., $\gamma < 0$) can therefore be intrepreted as reflecting the difference between expected and realized drawndown risk. X is a vector of control variables measured at the end of 2019 and captures key bank performance measures (capitalization, asset quality, profitability, liquidity and investments) that prior literature has shown to be important determinants of bank stock returns (*e.g.*, Fahlenbrach *et al.*, 2012; Beltratti and Stulz, 2012). All variables, including control variables, are described in detail in Appendix III and are shown in the regression specifications in the sections below. Standard errors in all cross-sectional regressions are heteroscedasticity robust.

3.4. Descriptive evidence

We first investigate graphically whether differences in *ex-ante* liquidity risk (measured as of Q4 2019) across banks can explain their stock price development since the outbreak of COVID-19. We classify banks into two categories based on high or low balance-sheet liquidity risk using a median split of our *Liquidity Risk* variable. We then create a stock index for each subsample of banks indexed at January 2, 2020 using the (market-value weighted) average stock returns of banks in each sample. We repeat this exercise for a median split of $Unused\ C\&I\ Commitments$. The differences in the stock indices using both measures are shown in Panel A of Figure 3. Bank stock prices collapsed as the COVID-19 pandemic started at the beginning of March 2020. Consistent with the idea that liquidity risk explains bank stock returns, we find that banks with higher liquidity risk perform worse than other banks. The development around March 2020 is almost identical for banks who had high unused credit line commitments indicating the importance of credit line commitments in our liquidity risk measure. In Panel B of Figure 3, we plot bank stock returns over the March 1 – March 23, 2020 period cross-sectionally against our measure of *Liquidity Risk*. The regression line through the scatter plot has a negative (and statistically significant) slope. That is, banks with higher *Liquidity Risk* had lower stock returns in the cross-section of our sample banks.

[Figure 3 about here]

Panel A of Table 1 shows the excess stock returns of the firms in our sample for three different periods: January 2020, February 2020, and the March 1, 2020 to March 23, 2020 period (i.e., until policy interventions). The average excess return is negative in all periods, ranging from -7.2% in January 2020 to -47.2% during the period March 1, 2020 to March 23, 2020 (and cumulatively as low as -66.9% from January 1, 2020 to March 23, 2020). Panel B of Table 1 shows descriptive statistics of bank characteristics as of Q4 2019.[13]

[Table 1 about here]

3.5. Multivariate results

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

[Table 2 about here]

[13] In addition to the control variables used in our regression, we also provide summary statistics of Liquidity Risk and its components. For example, the average Liquidity Risk is 19.5%, the average bank has unused C&I loan commitments of about 7.7% relative to total assets, and the average wholesale funding–asset ratio is 13.6%. The average bank has an equity beta of 1.2 measured against the S&P 500 (i.e., it broadly resembles the U.S. economy) and a capitalization (book equity–to-book asset ratio) of 12%.

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

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

Another confounding factor during the pandemic-onset stress of March 2020 could be a large exposure to the real estate sector (as measured using a *Real Estate Beta*), large security warehouses as banks act as dealer banks (*Current Primary Dealer Indicator*), or larger derivative portfolios (*Derivates/Assets*). Our regressions show, however, that stock returns do not load significantly on these factors (columns (3) to (4)) once these exposures are accounted for.

It could also be that those banks with high unused C&I credit lines are also those with high retail credit card commitments and consumer loan exposures. Given the potential stress induced by the pandemic in the retail sector due to, *e.g.*, lay-offs and furloughs, these borrowers might have higher liquidity needs. We collect each bank's exposure to off-balance-sheet credit card commitments and add this as a control variable to our regression model. This variable does not enter significantly in our regression (column 5); more importantly, the coefficient on *Liquidity Risk* remains unchanged. Using on-balance-sheet *Consumer Loans/Assets* does not change our results either. We also include in column (5) the *NPL/Loan*-ratio as a comprehensive measure of portfolio risk as well as control for a bank's distance-to-default as banks with more non-performing loans and lower distance-to-default tend to have lower stock returns during stress. We also include *Idiosyncratic Volatility* measured as the residual from a market model as banks with higher idiosyncratic volatility tend to have lower stock returns in stressed times. In column (6), we further add *SRISK/Assets* as a measure of a bank's systemic risk at the end of 2019.[14]

Importantly, the coefficient on *Liquidity Risk* remains consistent, even after accounting for other bank attributes. Moreover, *Liquidity Risk* is economically the most important determinant of bank stock returns at the beginning of the COVID-19 pandemic and accounts for 15% of the variation in bank stock returns, whereas *Equity Ratio* explains just 1%, indicating bank leverage does not drive the underperformance of bank stock returns.[15] Next, we analyse the impact of bank portfolio composition in further detail, especially exposure to industries hit hardest by the COVID-19 pandemic.

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

Examining the impact of portfolio composition on bank stock returns is complex due to limited public data on bank portfolios. Echoing Acharya and Steffen (2015), who inferred bank exposure to sovereign risk via stock return sensitivities to sovereign bond returns, we leverage market data to discern banks' exposure to industries hit hard during the COVID-19 pandemic.

---

[14] SRISK is a bank's capital shortfall over a six-month period in a stress scenario, which is a decline in the S&P 500 of 40%, similar to what we observed in March 2020. Banks with higher systemic risk have lower stock returns during aggregate shocks (such as the pandemic).

[15] We interact *Liquidity Risk* also with measures of bank size and do not find any evidence that, for example, bailout-expectations of larger banks are reflected in bank stock returns during the pandemic. Somewhat mechanical, we find that the effect is muted for banks with more available liquidity.

Using industry definitions from sources such as Fahlenbrach et al. (2021), which lists the 20 most impacted industries by March 23, 2020, we form 12 different stock-return indices of these affected industries. Through multifactor models, we gauge bank exposure by assessing stock return sensitivities (betas) to these respective indices for 2019, terming these as *"Affected Industries (β_{COVID})"*. These serve as controls in our regression analysis for bank portfolio composition. Details and methodologies are expanded upon in Appendix IV and Table 3.

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

[Table 3 about here]

Syndicated loan exposures. Another way to assess banks' exposure to COVID-19-affected industries is to use exposures via syndicated corporate loans sourced from Refinitiv Dealscan, which provides information about originating banks, firms and loan amounts, among others. We can thus construct a proxy for each bank's exposure to firms in the affected industries based on the 12 methods mentioned above.[16] This variable is called "*Loan Exposure/Assets*" and we scale all exposures by a bank's total assets.

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

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

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

The pandemic began in Asia in January 2020 and hit Western economies by mid-February 2020, culminating in stringent lockdowns by March. With corporate bond markets freezing, firms urgently sought liquidity, triggering a surge in credit line usage (Figure 1). We aim to understand how liquidity risk influenced bank stock returns in these phases of the onset and, in

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

particular, how undrawn C&I credit lines compared to wholesale funding in this influence. We also investigate the effect of policy interventions.

4.1. Balance-sheet liquidity periodically explains bank stock returns

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

[Table 4 about here]

While *Liquidity Risk* also somewhat explained stock returns at the time of the initial outbreak in Asia in January 2020, the economic magnitude of the impact is much smaller than that during the March 1 to 23, 2020 period. A one-standard-deviation increase in *Liquidity Risk* decreases stock returns by about 0.9pp in January 2020, compared to 6.5pp during the March period. The coefficient of interest is close to zero in February 2020 and increases to -0.462 (March 1, 2020 to March 23, 2020). At the same time, the R^2 increases by about 65% suggesting that *Liquidity Risk* has substantially more explanatory power after COVID-19 broke out in the Western economies. In the light of our main hypothesis, this suggests that actual drawdowns only deviated significantly from expected drawdowns in March 2020. From Panel B of Figure 1, we had already seen that massive drawdowns only happened in March, supporting this argument for why liquidity risk is priced (much) more in March 2020 than it was in February or January.[17]

4.2. Components of liquidity risk and bank stock returns

In the next step, we split *Liquidity Risk* into its components, viz., C&I credit lines and wholesale funding, to investigate their differential impact on bank stock returns during the first phase of the pandemic. The results are reported in Panel B of Table 4.

[17] We provide supporting evidence in the Online Appendix based on time-series regressions that relate daily aggregate drawdowns to bank-level stock returns.

We first include only *Unused C&I Loan Assets* (column 1), then only *Liquidity/Assets* (column 2), and then only *Wholesale Funding/Assets* (column 3), in the regression model. In columns (4) and (5) we add the components sequentially. Two results emerge: First, the size of the coefficients and the R-squared in the different regressions suggest that *Unused C&I Loans / Assets* is the most important component in explaining banks' stock returns at the beginning of the COVID pandemic. Specifically, a one-standard-deviation rise in unused C&I loans led to a roughly 5.5pp drop in stock returns. *Liquidity / Assets* is also statistically and economically significant: a one-standard-deviation increase led to a 5.2pp increase in stock returns.[18] However, *Wholesale Funding / Assets* is statistically insignificant. Second, the size of the coefficients of all three variables does not change much when we include them simultaneously (see column (5)) suggesting that these variables are not highly correlated.[19]

4.3. The importance of wholesale funding

During the 2008-2009 financial crisis, fears about the banking sector's health led to significant withdrawals by uninsured wholesale creditors of banks, causing funding liquidity risks for banks. However, during the COVID pandemic, the banking sector's health was not a primary concern. Our tests below offer further insights into the role of wholesale funding on bank stock returns during the pandemic.

We include two different measures for *Wholesale Funding* in our specifications, one from Acharya and Mora (2015), abbreviated as AM, and the other one from Dubois and Lambertini (2018), abbreviated as DL.[20] We report these results in Panel C of Table 4. In

[18] Our results suggest that credit lines are not similar to term loans regarding to their implications for bank stock returns. For example, the coefficient on *Unused C&I Loans/Assets* in Column (5) of Panel B in Table 4 is -1.084, which is about 2.5 times the size of the coefficient on *Loans/Assets*. That is, shareholders appear to price the exposure to aggregate drawdown risk over and above credit risk associated with term loans.

[19] We examine the correlations between key variables. For instance, the correlation between *Unused C&I Loans/Assets* and *Wholesale Funding/Assets* is -12% in our bank sample. A t-test comparing banks with above-median and below-median *Wholesale Funding/Assets* ratios reveals no significant difference in their average *Unused C&I Loans/Assets*. This suggests no clear relationship between access to wholesale funding and banks' decisions to underwrite credit lines.

[20] The key differences between both measures are: The DL measure does not include large time deposits nor subordinated debt. In contrast to AM, it adds commercial paper. A minor difference is that DL measure splits other borrowed money by maturity (< and >= 1 year) and differentiates between repos and fed fund purchased.

columns (2) and (3), we use the AM and DL wholesale funding proxies. In column (4), we include the individual components. The wholesale funding proxies are both insignificant during these crises. *Unused C&I Commitments / Assets* are economically more meaningful than wholesale funding components in the COVID period. Interestingly, *Large Time Deposits / Assets* negatively impacts bank stock returns, likely because they are uninsured and can thus quickly be withdrawn. Overall, wholesale funding does not appear to substantially affect bank stock returns during COVID.

4.4. Liquidity risk and bank stock returns after policy interventions

During the early stages of the COVID-19 pandemic, balance-sheet liquidity risk significantly influenced bank stock returns. However, after the Federal Reserve's interventions on March 23, 2020, capital market funding was swiftly restored, pausing credit-line drawdowns for most firms except the riskiest (Acharya and Steffen, 2020a). We thus explore the impact of liquidity risk on bank stock returns post-Fed actions in this section.

Panel D of Table 4 outlines bank stock returns in 2020: a 51% drop in Q1, a 10% rise in Q2, an 8% fall in Q3, and a 35% increase in Q4 (during significant events like the U.S. elections and vaccine introductions). Overall, bank stocks ended the year 4% lower.

Panel E of Table 4 shows the results from panel regressions of bank stock return on *Liquidity Ris*k (columns (1) and (2)) and its components (columns (3) and (4)) with and without quarter fixed effects over the post-intervention period, i.e., Q2 to Q4 2020 period. Standard errors are clustered in these regressions at the bank level. While the coefficient on *Liquidity Risk* is close to zero, the coefficient on *Unused C&I Loans* is small and only significant at the 10% level in a model with quarter fixed effects. We split the sample into the three different quarters, and find that, while the coefficient on *Liquidity Risk* is close to zero in Q2 and Q4 2020 (columns (5) and (7)), liquidity risk appears to become a concern again in Q3 (column (6)) when stock prices of banks declined amid a possible second wave of COVID-19 and lockdown measures. Taken together, banks with high liquidity risk experienced a stock price decline during the first phase of the COVID-19 pandemic as well as the second wave but recovered after the considerable monetary and fiscal interventions as well as vaccine arrivals.

5. Understanding the mechanisms: Funding versus bank capital

In this section, we investigate the mechanisms driving the effect of balance-sheet liquidity risk on bank stock returns during the COVID-19 pandemic. Does funding liquidity to source new loans become a binding constraint for banks whose deposit funding dries up (the "funding channel")? Or, does the drawdown of credit lines lock up bank capital and impair bank loan origination, preventing banks from making possibly more profitable loans (the "capital channel")? And, what are the credit implications for firms borrowing from banks with large ex-ante credit line exposures?

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

To distinguish between the funding and the capital channels in how credit line drawdowns affect intermediation by banks and their stock returns, we construct two measures based on actual drawdowns experienced by our sample banks during the first quarter in 2020. *Gross Drawdowns* is defined as the change of a banks' off-balance-sheet unused C&I loan commitments between Q4 2019 and Q1 2020 relative to total assets using FDIC's Call Report data. We construct a second proxy, *Net Drawdowns,* which is defined as the change in banks' unused C&I commitments minus the change in deposits, in percentage of total assets, over the same period. Holding gross drawdowns fixed, our measure of net drawdowns helps us understand the importance of changes in bank deposits on bank stock returns. In other words, *Gross Drawdowns* proxies for the importance of drawdowns *per se* which encumber capital, while *Net Drawdowns* is a proxy for the importance of bank deposit funding which affects its ability to meet drawdowns; therefore, the measures help us identify the relative importance of the capital versus the funding channels.[21]

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

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

[Figure 4 about here]

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

[Table 5 about here]

We investigate the effect of gross and net drawdowns on bank stock returns formally using the model specification and control variables from column (5) of Table 2. Table 5 reports the results. 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 4.8pp (= -5.128 × 0.0094), which is economically large and corresponds to approximately 10% of the unconditional stock price decline. When we include both proxies in column (3) we find that, holding *Gross Drawdowns* fixed, *Net Drawdowns* still has no significant effect on bank stock returns. That is, since the variation in *Net Drawdowns* is driven by changes in bank deposits (holding *Gross Drawdowns* fixed), funding of drawdowns through bank deposits does not appear to be a binding constraint for banks during the pandemic drawdowns. Finally, adding *SRISK/Assets* as additional control (column (4)) does not change the coefficient of *Gross*

Drawdowns, suggesting that *SRISK* likely does not seem to capture systemic implications associated with aggregate credit-line drawdowns (a point we will revisit later).

We interact *Gross Drawdowns* with *High Capital*, an indicator equal to 1 if bank equity capital is above the median of the distribution (column (5)). In column (6), we observe the interaction between *Gross Drawdowns* and *Capital Buffer*, which is the difference between a bank's equity–asset ratio and the cross-sectional average of the equity–asset ratio of all sample banks in Q4 2019. A larger difference implies that a bank has a higher capital buffer. The coefficient of both interaction terms is positive and statistically significant emphasizing that the negative effect of drawdowns on stock returns is attenuated for banks with better capitalization. Consistently, the coefficient of the interaction term of *High Capital* (*Capital Buffer)* and *Net Drawdowns* is not significant (columns (7) and (8)). Columns (9) and (10) confirm these results including interaction terms of *High Capital* (*Capital Buffer)* with both *Gross Drawdowns* and *Net Drawdowns*.[22]

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

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

We now explore a testable hypothesis that banks with more balance-sheet liquidity risk reduced their credit supply during 2020 by a greater extent than other banks. In particular, if banks' capital constraints matter, then we expect lending to be particularly sensitive to gross (but not to net) drawdowns.

We use data from Refinitiv Dealscan to investigate these issues. We use data on both outstanding exposures and new loan originations from January 2019 to October 2020 and divide

[22] Robustness tests with other liquidity proxies and time windows are documented in Online Appendix E.

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

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

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

In a second model, we use $Origination_{i,b,m,t}$ as the Y-variable and restrict our sample to one pre- (Q4 2019) and one post period (Q2 2020).[23] We then directly compare the issuance behaviour between these two points in time, while again controlling for time-varying loan demand and measuring the lending impact within a credit relationship through fixed effects. In all our specifications, we cluster standard errors at the bank level.

A negative β_1 implies that a bank with more exposure to drawdown risk (DD_b) – measured as either *Gross Drawdowns* or *Net Drawdowns* – decreases lending more than banks with less exposure during the COVID-19 pandemic after controlling for loan demand and other bank- and loan-specific effects. *Gross Drawdowns* and *Net Drawdowns* are measured over the Q1 2020 period. To detect potential non-linearities in the reaction of banks' lending behaviour to the level of drawdown risk, we further create two dummy variables that take the value 1 if the *Gross (Net) Drawdowns* of a bank are above the median of *Gross (Net) Drawdowns* of all banks in the sample (*High Gross (Net)*). Finally, we consider both term loan and credit line exposures and originations. While a reduction in term loans is consistent with banks experiencing a shock to their capital, a reduction in credit line originations might be consistent with the interpretation that banks have learned from COVID-related drawdowns.[24]

Results. The results are reported in Table 6. Columns (1)–(4) show the results with $Exposure_{i,b,m,t}$, and columns (5)–(8) with $Origination_{i,b,m,t}$ as dependent variables.

[Table 6 about here]

Columns (1) and (2) show that banks with large gross drawdowns (also accounting for possible non-linearities in column (2)) do not adjust their loan exposure to firms differently from banks with low gross drawdowns after COVID-19 broke out. We then differentiate by loan type and

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

[24] Our analysis diverges from Greenwald et al. (2023) who emphasize macroeconomic aggregates and distributional impacts of credit line drawdowns on firms lacking such access. Instead, we delve into the broader lending behavior of banks and the effects of credit line drawdowns on the supply of both credit lines and term loans. Supporting this, both Chodorow-Reich et al. (2022) and Greenwald et al. (2023) demonstrate that credit-line drawdowns by large firms led banks to reduce lending to smaller firms, possibly due to capital constraints. Furthermore, our Online Appendix B indicates increased loan spreads for small firms in secondary markets since the pandemic's onset, underscoring reduced intermediation for those reliant on bank financing.

find that banks with high gross drawdowns increase credit-line exposures relative to low gross drawdown banks during COVID-19, consistent with the interpretation that these banks can sustain off-balance-sheet rather than on-balance-sheet exposures as the former require less upfront equity capital. Also consistent with the bank capital channel, we find that banks with high gross drawdowns actively reduce term-loan exposures relative to low gross drawdown banks as the triple interaction term in column (3) suggests (for example, by actively selling term loans or by not rolling them over). In column (4) we add lagged control variables, to further account for compositional differences of the treatment and the control group. The size and significance of the effects described above remain unaffected.

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

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

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

Within the short period of time in the post-COVID-19 phase that is part of our sample period, significant shifts in slow-moving variables such as assets or investments are unlikely, and we do not find significant differences investigating these variables. However, firms can quickly make changes to their working capital requirement and respective funding needs. In unreported tests, whose results are available upon request, we find (using simple mean differences) that firms which borrow from banks with high gross drawdowns increase current assets less relative to those firms borrowing from low drawdown banks, but current liabilities are unaffected. That is, these firms reduce the necessary investments in working capital, likely because access to bank loans becomes more difficult, as demonstrated above. Moreover, these firms reduce their R&D expenditures (relative to total assets) four times as much compared to unaffected firms. Given the importance of R&D for innovation and competition, even a short-term reduction in R&D expenditure might adversely impact these firms over the long run. Firms might also make immediate changes in their payouts to shareholders. We obtain data on payouts from Capital IQ for our sample firms. While we do not find a significant differential effect on stock repurchases, we find that affected firms borrowing from banks with high gross drawdowns significantly reduce dividend payouts (the reduction is twice as large compared to non-affected firms).

6 The value of credit line repayments

Our previous results suggest that bank stock prices did not recover fulls by end of 2020 from the Q1 2020 correction and substantially underperformed those of non-financial firms even in the post-intervention period. In this section, we propose a two-sided "credit-line channel" to make sense of the stock price performance of banks during this period. Importantly, credit lines provide firms with *two options*, an *option to draw* from the credit line, but also an *option to repay* (or not repay) the part of the credit line they have already drawn down. Understanding the value of the repayment option for banks appears crucial in this context.

6.1. Methodology

The value of the repayment option for the bank is the difference between the revenue it generates if the credit line remains drawn (fees, interest rate) and the revenue of alternative investments it could undertake with the repaid amount. For a fair assessment of the revenue of alternative investments, this investment should carry the same risk and regulatory capital cost (e.g., a corporate bond with the same rating as the credit line borrower). Our hypothesis is therefore that banks should benefit less from repayment if the fee structure of their drawn credit lines being repaid, compared to the refinancing costs of the underlying borrowers, is comparatively high, and vice versa if fees are relatively low.

We construct a new variable *FeesEarned* as a proxy for the option value of firm repayment for the bank. This variable is defined as

$$FeesEarned_j = \sum_i \left[\left(\mathrm{AI}SD_{ij} - (\mathrm{R}_f + \mathrm{RP}_i)\right) * \text{ DrawdownVolume}_{ij} * 8\%\right]$$

and scaled by total commitments, where j is a bank and i is a borrowing firm of bank j. It sums up the return or all-in-drawn spread ($AISD_{ij}$) on the capital deployed ($DrawdownVolume_{ij} *$ 8%) for each credit line borrower, adjusted for the opportunity costs – the risk-free rate ($\mathrm{R_f}$) plus a risk premium (RP_i) which is rating-specific – that the banks could earn from investing the freed-up capital into another interest-bearing asset. We measure the term $R_f + RP_i$ as the secondary market bond yield for corporate bonds in the same rating category as borrower *i*. Importantly, this measure depends on the drawn amount of the credit line (not the undrawn amount), i.e., the bank earns the all-in-spread-drawn (*AISD)* paid by the borrower and not the commitment fee (*AISU*). We use the rating as a proxy for freed-up capital as we lack detailed information on the actual risk weights applied by banks on their credit lines to individual borrowers.

This variable allows us to compare for two banks with the same volume of drawdowns and the same level of *AISD* charged to borrowers, how much equity capital is being freed-up. Suppose there are two banks A and B, both experience 100 million USD in drawdowns

(*DrawdownVolume*) and earn from their borrowers 5% *AISD* (as per the ex-ante contract). The only difference in the *FeesEarned* variable then comes from a difference in RP_i, which translates to different capitalization levels as capital requirements are risk-sensitive. For example, assume that the borrowers of bank A have a higher credit rating than the borrowers of bank B. If the risk-free rate (R_f) is zero and the risk premium (RP_i) for higher credit ratings is 2%, and for lower credit ratings is 4% then *FeesEarned* is 3% for bank A and 1% for bank B. Hence, bank A (B) gains an additional 3 (1) percentage points per unit of capital on the drawn credit line compared to investing the freed-up capital in a comparable investment. Our hypothesis is that the value of the borrowers' repayment option for bank A is lower than for the bank B, because bank A loses the same amount of revenue (*5% AISD*) but effectively gets less risk-adjusted capital freed up. In line with the analysis of the 2020Q1 period, this is our measure for the *capital channel*, while the ratio of repayments to committed amounts (*Repayments*) serve as the measure for the *funding channel*. Thus, *FeesEarned* incorporates the opportunity cost for banks when borrowers draw down credit lines, and interacting it with the repayments ratio captures the differential value of repayment given these opportunity costs.

6.2. Empirical results

We first look at summary statistics related to credit line repayments by rating category in Panel A of Table 7. We find that borrowers with higher credit ratings repay more compared to borrowers with lower credit ratings, both in the second and the third quarter of 2020, relative to their previous drawdowns. In terms of repayment relative to the overall committed volume, better-rated borrowers repay more in the second quarter (i.e., earlier) and worse-rated borrowers more in the third quarter (i.e., they repay later). Overall, we see that there are significant differences in the repayment behavior of firms by rating category. Since rating categories matter for the deployed bank capital, it is a testable hypothesis that this heterogeneity at the firm-level aggregates up to the bank level and affects banks' stock returns.

[Table 7 about here]

To test this hypothesis, we estimate the following regression specification in OLS:

$$r_{it} = \beta_1 * FeesEarned_i + \beta_2 * Repayments_i +$$

$$\beta_3 * Repayments_i \ x \ FeesEarned_i + Drawdowns \ 2020Q1_i + Controls_{it} + u_{it}$$

We control for *Drawdowns2020Q1*, i.e., the drawdowns in Q1 2020 scaled by total assets. We also include a set of controls variables such as equity beta, capitalization levels, systemic risk, and business model proxies (unreported). Panel B of Table 7 summarizes the results of the above baseline specification and further tests regarding repayments. Column (1) measures the impact of *FeesEarned* as well as *Repayments* on stock returns. Our results show that banks that can earn higher fees on their credit lines, adjusted for the borrower's rating category, perform better during the second quarter of 2020. Conditional on the level of Q1 drawdowns and the fees earned on those drawdowns, credit line repayments appear to be positive for banks. In other words, repayments matter both for the capital and the funding channel. A one standard-deviation increase in *FeesEarned* translates to an 8.9 pp increase in the stock return, while an additional standard deviation of *Repayments* increases the stock return by 5 pp. The average stock return in the second quarter of 2020 is 23.5%. That is, these economic magnitudes are sizeable.

In column (2), we add an interaction term between *FeesEarned* and *Repayments*. As explained earlier, the higher the fees a bank earns, the lower its benefit from repayment. The results confirm this hypothesis with a negative sign for the interaction term. Next, if repayments are the reversal of drawdowns, then the higher the market value loss during COVID (the higher the sensitivity to the aggregate drawdown risk), the more a bank should benefit from repayment, e.g., because the higher market value loss reflects a tighter capital constraint as we document. To test this hypothesis, we further interact Repayments with the market value loss during the first quarter of 2020. We add this to the regression in column (3). The interaction term is positive and highly significant, while all other coefficients remain largely unchanged. That is, repayments increase a bank's stock return more if it had lost more of its market value at the beginning of the COVID-19 pandemic.

Similarly, if the capital channel is the main driver of the market value loss in Q1, then we conjecture that the recovery depends also on the capital levels. We test this hypothesis in column (4) by interacting *Repayments* with the *Capital Buffer*. Stock returns in Q2 significantly depend on the interaction of capital levels and repayments. The lower the capital level in Q1, the more a bank profits from repayments. In column (5), we interact *Repayments* with Q1 drawdowns. The interaction term turns out to be insignificant in both specifications. In column (6), we run a horse race between all interaction terms described above. The market value loss and capital buffer interactions remain significant and prove to be the most important determinants in understanding the importance of repayments for banks' stock return.

In summary, we document the importance of a two-sided "credit-line channel" for bank stock returns. While correlated credit line drawdowns negatively affect banks' performance, the cash flows generated by the fees and the drawdown interest rate can soften the blow. Repayments are good for bank stock returns on average because they free up encumbered capital, but banks prefer to have low (opportunity cost-adjusted) fee credit lines repaid. In the end, the banks (and their investors) want to be compensated in fees for the opportunity cost and the exposure to drawdown risk.

7. Discussion

In this section we discuss our results and their extensions along three dimensions: (1) how credit line commitments affect bank stock returns during and outside crisis periods; (2) whether credit line spread provide a signal to investors regarding aggregate drawdown risk; and, (3) whether banks change their credit line lending behaviour following the drawdowns in Q1 2020.

7.1 Credit line commitments and bank stock returns in and out of crises

Is the aggregate drawdown risk of banks priced in bank stock returns more generally or is it priced only in crises periods? And, do investors get compensated in normal market times for lower returns under aggregate stress? **To answer these questions, we regress quarterly bank stock returns (r_{it}) "through-the-cycle" on credit line commitments over three different samples in the 1995Q1 to 2021Q1 period:** 2019Q4 to 2021Q1 (Covid), 2004Q1 to 2011Q4 (GFC) and 2000Q1 to 2002Q4 (Dotcom). We document the results for the COVID pandemc in columns (1) to (3), for the GFC in columns (4) to (6), and for the Dotcom crisis in columns (7) to (9) in Table 8, where we estimate the following specification:

$$r_{it} = \gamma * FF5_t + \delta * Crisis_t + \beta_1 * Commitment\ (High)_i +$$
$$\beta_2 * Crisis_t\ x\ Commitment(High)_i + u_t$$

where *FF5* are the five Fama-French factors (Market, Small Minus Big, High Minus Low, Robust Minus Weak, Conservative Minus Aggressive), *Crisis* is a dummy variable equal to 1 if the economy is in a recession according to the NBER business cycle dating committee, and *Commitment (High)* is a dummy variable indicating if bank volume of committed but undrawn credit lines is above the median. We construct a matched sample of banks with **high and low cedit-line commitments – defined one quarter before the respective crisis – based on other bank characteristics (capitalization,** NPL-to-loan ratio, **asset size and the loan-to-asset ratio). This ensures that we are comparing stock returns of banks with similar health, size and business model.**

We find that high commitments – and therefore (ex-post) aggregate drawdown risk – negatively affects stock returns during all crises periods in our sample: Covid, GFC, and Dotcom. That is, the coefficient β_2 on the interaction term of crises periods and above-median commitments is negative and significant. Importantly, we find that β_1 is positive and statistically significant in the Covid and the GFC period, that is, investors do get compensated for aggregate drawdown risk outside of crises periods. Our results thus indicate no evidence for a complete neglect or mispricing of (aggregate) drawdown risk but are consistent with the intrepretation that investors re-evaluate the implications of

(higher than expected) credit line drawdowns during an aggregate liquidity crunch like the one we observed during the pandemic.

[Table 9 about here]

Across crises periods, the coefficient estimates for β_2 in the Dotcom and GFC episodes are of very similar magnitudes. The coefficient during the Covid crisis, however, is about 2.5 times larger than the coefficient in the previous two crisis episodes. Similarly, the R-squared values increase substantially in chronological order from crisis to crisis. This shows that the impact of aggregate drawdown risk on bank stock returns during periods of stress has increased with the buildup of credit line volumes, particularly after the GFC.

7.2. Do credit line fees provide investors a signal regarding aggregate drawdown risk?

We follow earlier work on the pricing of credit lines such as Acharya et al. (2013) and Berg et al. (2016) and build a panel data set of U.S. non-financial firms that have obtained credit lines in the primary loan market over the 2010 to 2019 period. That is, using all originated loans from the Refinitiv Dealscan database, we keep only credit lines issued over the sample period, keep the lead arranger (following the procedures outlined in many previous papers), and collapse the All-In-Spread-Drawn (*AISD*) and the All-In-Spread-Undrawn (*AISU*) at their respective means at the firm-year-lead-arranger level to construct a panel dataset.

We then use the merged CRSP/Compustat database to add firm characteristics that affect a firm's cost of credit, in particular a firm's equity volatility as a measure of idiosyncratic risk and a firm's market beta for systematic risk. Other control variables include size, profitability, tangibility, Tobin's Q and leverage. We source bank characteristics from FDIC's Call Report data including NPL/Loans, capital, non-interest income, bank size and bank profitability. Importantly, we also use data from Call Reports, CRSP and the NYU Volatility Lab to obtain banks' aggregate risk exposure including *Bank Equity Beta* (as a measure of systematic risk), *LRMES* (as a measure of a bank's market equity's aggregate downside risk), *SRISK/Assets* (as a measure of equity shortfall in times of an aggregate or market-wide shock), and *Liquidity Risk* (as a measure of aggregate drawdown risk). *LIBOR* is included as all contracts are floating rate and prior literature has shown that spreads and fees are sensitive to the current level of LIBOR. We estimate the following regression:

$$Cost_{i,j,t} = \mu_0 + \mu_1 AggRisk_{j,t} + \mu_3 LIBOR_t + \mu_4 X_{j,t} + \mu_5 X_{i,t} + \gamma_t + \lambda_k + \varepsilon_{i,j,t}$$

where $AggRisk_{j,t}$ are bank-specific aggregate risk proxies, $X_{j,t}$ ($X_{i,t}$) are bank (firm) characteristics, γ_t are year and λ_k industry fixed effects. *Cost* is either the *AISD* or *AISU*.

The results are reported in Table 10. We first show that idiosyncratic drawdown risk (measured using a firm's realized equity volatility over the past 12 months) and systematic drawdown risk (measured using a firm's stock beta) are priced in both commitment fee (*AISU*) and spread (*AISD*). This is consistent with, for example, Acharya et al. (2013) and Berg et al. (2016). However, while a higher *Bank Beta* and *LRMES* both somewhat increase the price of credit lines, *Liquidity Risk* or *Unused C&I / Assets*, on average, do not. Also, *SRISK / Assets*, which measures bank capital shortfall in times of aggregate market downturn, does not appear to be priced in credit line fees. In other words, banks do not appear to be considering the deep out-of-the-money put option associated with aggregate drawdown risk when setting ex-ante price terms of credit lines. This may partly explain their need to cut back term loans when aggregate drawdown risk materializes as their equity capital then gets unexpectedly encumbered, as witnessed during the pandemic.[25]

In summary, credit line pricing does not contain perfect or adequate signals regarding exposure to aggregate drawdown risk that is episodic or in the tails of the distribution. Investors thus may be unable to adjust their expectations fully regarding credit line drawdowns in periods of aggregate stress. Overall, these results are consistent with our earlier interpretation that

[25] Banks in our study, regardless of their liquidity risk, committed to credit lines, suggesting that matching biases are more likely influenced by borrower traits than just bank liquidity risk. Our data analysis confirms that borrowers from banks with varying liquidity risks show no significant differences in credit risk or drawdown intensity, implying that selection bias is unlikely to impact our findings on credit line pricing.

investors have to reprice in response to unexpectedly high drawdowns during periods of heightened aggregate stress.

7.3 Did banks change their credit line issuance behavior post COVID?

If credit lines turned out to be value-destroying for banks due to unexpectedly large aggregate drawdowns during COVID, did banks change their issuance behaviour thereafter? We first investigate descriptively changes in the volume and pricing of credit lines before and after the COVID-19 pandemic. Panel A of Figure 5 shows the aggregate quarterly issuance volume of credit lines by U.S. banks in billion U.S. dollar during the Q1 2018 to Q4 2021 period sourced from Refinitiv Dealscan. The horizontal lines show the mean issuance volume in the pre- and post-COVID period during this sample period. We observe a temporary decline in credit line issuances after the start of the COVID-19 pandemic. This is in line with our results documented in Section 5.2. Issuances, however, recovered sharply after the Q2 2020 period and even exceeded pre-COVID-19 levels already in Q2 2021. On average, credit lines issuance volumes have not been statistically (or economically) significantly different between the pre-pandemic and pandemic periods.

What about the pricing of credit lines? Key pricing terms that banks might adjust to reflect risks associated with the issuances of credit lines are the all-in-spread-drawn (*AISD*), the all-in-spread-undrawn (*AISU*), which is the commitment fee banks charge to provide the liquidity commitment, and the upfront fee (UFR). Prior literature has shown that the UFR is highly cyclical and adjusts fast when economic conditions deteriorate. However, the *UFR* is not frequently recorded in our data. Below, we use only those credit lines issuances for which the *UFR* is available, when we plot the *UFR* graph.

In Panel B of Figure 5, we chart the average AISD for credit lines issued between Q1 2018 and Q4 2021 on a quarterly basis. Before the COVID-19 pandemic, the average AISD hovered around 240bps, with minimal fluctuations. In Q1 2020, the AISD declined as only high-quality borrowers secured new credit lines. Subsequently, we noted a brief surge in the

AISD for new issuances, which then retreated to pre-pandemic levels by Q1 2021. This aligns with our findings in Section 5.2, suggesting that, temporarily, a reduction in credit supply due to capital encumbrance led to both diminished volumes and elevated prices. As banks received more repayments in the latter quarters of 2020, they gradually resumed regular lending practices. Overall, comparing pre- and post-COVID-19 periods, the AISD averages show no significant discrepancies. In Panel C of Figure 5, we show the quarterly average *AISU* (left panel) and the quarterly average *UFR* (right panel). Also these pricing measures remain, on average, unchanged in the post-COVID-19 period.

Overall, both volume and pricing of credit line originations remain unchanged, on average, in the post-COVID-19 period highlighting that it remained – at least privately – optimal for banks to issue credit lines to firms. Descriptively, there does not appear to be evidence in the data that banks regard the issuance of credit lines as a value-destroying activity or that their assessment as to the riskiness has changed after the start of the COVID-19 pandemic.

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

We showed that balance-sheet liquidity risk of banks – mainly driven by undrawn credit lines – has severe implications on their ability to extend new loans because drawn credit lines encumber capital. How can policymakers address this aggregate drawdown risk in an *ex-ante* manner? We suggest incorporating these commitments to better assess capital requirements during aggregate stress periods by illustrating how to adjust *SRISK*.

8.1. 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,

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

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

where $Debt_{i,t}$ is the nominal on-balance-sheet debt of bank *i*'s liabilities, assumed to be constant between time *t* and *Crisis* over *t* to *t+h*. $Equity_{i,t}$ is bank's *i* market value of equity at time *t*. *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 such as the S&P 500 or MSCI Global falls by 40% over the next six months (h=6m). K is an assumed required quasi-market-value-to-quasi-market-assets capital ratio of 8%, where quasi-market-assets is the sum of book debt and market value of equity.[26]

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

i) $$Incremental\ SRISK_{i,t}^{CL} = 8\% \times E[Drawdown\ rate \mid Crisis] \times Unused\ Commitments_{i,t}$$

This is the additional capital needed due to drawdown rates in crises periods. We estimate the drawdown function with a simple OLS regression between aggregate drawdowns for non-financial borrowers and the return of the S&P 500 index and define a crisis period as a 40% fall in the market index.

[26] SRISK is based on market equity. That is, if banks fund credit line commitments with some equity, the market value of equity and LRMES should already reflect it. In other words, we do not need to make further adjustments when calculating the incremental SRISK needed to adjust for credit line commitments.

ii) $\quad Incremental\ SRISK_{i,t}^{LRMES^{C}} = (100\% - 8\%) \times \hat{\gamma} \times Liquidity\ Risk_{i,t} \times Equity_{i,t}$

This is the additional equity market value loss due to high drawdowns in stress periods. $\hat{\gamma}$ is the estimated episodic effect of liquidity risk on bank stock returns on balance-sheet liquidity risk from our tests.

8.2. Estimating the drawdown function under aggregate stress

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

[Figure 6]

In Panel A of Figure 6, we plot the cumulative quarterly drawdown rates during the COVID-19 pandemic (*i.e.*, Q4 2019 and Q1 2020) and the GFC (*i.e.*, Q1 2007 to Q4 2009) as a function of the respective quarterly S&P 500 returns. We also show the linear regression fits for both periods. In Panel B of Figure 6, we use the lowest cumulative daily S&P 500 return within each quarter (instead of the quarterly return). This presentation has two advantages. First, it shows that for quarters with relatively low negative S&P 500 returns (*i.e.*, "normal times"), drawdowns are somewhat clustered.[27] Second, drawdown decisions are arguably based on how bad a quarter has been within rather than on the situation at the end of each quarter. We therefore calculate drawdown rates based on Panel B of Figure 6.

We find that the sensitivity of credit-line drawdowns to changes in market returns was higher during the COVID-19 pandemic (the slope coefficient, β, is -0.57) compared with the GFC (the slope coefficient, β, is -0.27). The projected drawdown rate in a market downturn of 40% is thus also substantially higher in the COVID-19 pandemic (39.97% versus 25.79%). A possible explanation of the differential impact on absolute drawdowns could be that corporate

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

balance sheets were less impacted during the GFC, which originated in the banking and household sector. The COVID-19 pandemic, however, had an immediate effect on firms' balance sheets, resulting in elevated demand for liquidity from pre-arranged credit lines compared with the GFC. The quarterly drawdown rates in both stress scenarios or crises are summarized together with the sensitivities of the drawdown rates in a market correction in Panel A of Table 11.

[Table 11 about here]

8.3. Incremental SRISK due to credit-line drawdowns

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

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

In Panel B of Table 11, we show the top 10 banks with the largest undrawn commitments as of Q4 2019 and report $Incremental\ SRISK_i^{CL}$ individually for each of these banks. We also report the total $Incremental\ SRISK^{CL}$ for the top 10 and for all banks in our sample. Overall, we find that $Incremental\ SRISK^{CL}$, *i.e.*, the additional capital, amounts to about USD 37.9bn to USD 58.7bn depending on the estimates of the drawdown rate.

8.4. Incremental SRISK due to MES^{C} and contingent SRISK (SRISK^{C})

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

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

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

where $LRMES_i^C$ is the contingent marginal expected shortfall due to the impact of liquidity risk on bank stock returns. We report the $Incremental\ SRISK_i^{LRMES^C}$ in Panel C of Table 11. We use a minimum and maximum loading (γ) estimated from different regressions based on equation (1) and calculate a range of $LRMES_{min}^C$ and $LRMES_{max}^C$, which is between 9.5% and 16.4%. The corresponding $Incremental\ SRISK_i^{LRMES^C}$ amounts to USD 177bn to USD 307bn.

In a final step, we calculate the conditional *SRISK* ($SRISK^C$) adding the two incremental SRISK components. Adding both components we show that the additional capital shortfall for the U.S. banking sector due to balance-sheet liquidity risk amounts to more than \$366 billion as of December 31, 2019 in a stress scenario of a 40% correction to the stock market, with the top 10 banks contributing USD 293bn. The incremental capital shortfall of the top 10 banks is about 1.7 times the SRISK estimate without accounting for contingent liabilities and the effect of liquidity risk.

Overall, our estimates show that the incremental capital shortfall in an aggregate economic downturn due to banks' contingent liabilities is sizeable, because it requires an additional amount of capital to fund the new loans on their balance sheets and, importantly, there is an (even larger) incremental capital shortfall due to the episodic impact of bank balance-sheet liquidity risk on bank stock returns. Our results, however, show clearly that most of the impact on banks' balance sheets arises due to the market's re-evaluation of liquidity risk in banks' equity. As described throughout the paper, markets react when actual drawdown rates deviate from expected ones by re-pricing bank equity. This channel is economically highly relevant (as the numbers above document) and should thus be considered in stress tests and similar exercises.

9. Conclusion

Our research underscores the importance of banks' liquidity risk in explaining the decline of bank stock prices during the pandemic's initial phase. We identified balance-sheet liquidity risk as a vital determinant of bank stock returns, regardless of banks' exposure to COVID-affected sectors. We delved into two main channels affecting bank stock prices: the "funding channel" and the "capital channel". By constructing proxies for gross and net drawdowns, we discerned that bank stock returns were more influenced by gross drawdowns, especially for banks with higher capital and superior capital buffers.

Our analysis of bank stock price recovery in 2020Q2 spotlighted the significant role of credit-line repayments. We established two primary factors: liquidity returned to banks and the revenue discrepancy between the drawn credit line and potential alternative investments. Our data validates the importance of both elements, indicating banks and their investors prioritize compensation for capital opportunity cost and drawdown risk. The capital channel proves crucial not only in understanding the ramifications of credit line drawdowns but also in the effects of repayments.

These findings have potential implications for how economic shocks may affect banks in future. Darmouni and Siani (2020) show that U.S. non-financial firms issued bonds following the monetary policy and fiscal interventions starting March 2020 and used the proceeds to repay credit lines. While a large proportion of credit lines have been repaid in Q2 and Q3 2020, corporate preference for cash of firms has remained high (Online Appendix A) and total debt on firms' balance sheet has substantially increased. The non-financial sector's leverage and exposure to capital markets thus increased further during and after the COVID-19 pandemic. In other words, ex-ante aggregate drawdown risk of banks is again high in case of another aggregate shock such as a rise in interest rates or a recession (or both, i.e., a stagflation) were to stress capital markets. In that scenario, the value of the put option in the form of bank credit lines for corporates and capital markets would be even more pronounced if bond market liquidity conditions were to severely deteriorate. In summary, additional corporate leverage accumulated since the pandemic has likely increased the likelihood of future impact on bank stock returns via the credit-line drawdown channel. This makes it crucial for stress tests to factor in aggregate drawdown risk and its impact on bank equity, as we illustrated. Clearly, much scope for research and policy reform around bank credit lines remains.

References

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

Acharya, V., H. Almeida, and M. Campello, 2013, Aggregate Risk and the Choice Between Cash and Lines of Credit. *The Journal of Finance* 68 (5), 2059–116.

Acharya, V., R. Engle, and M. Richardson, 2012, Capital Shortfall: a New Approach to Ranking and Regulating Systemic Risks. *American Economic Review* 102, 59–64.

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

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

Acharya, V. and S. Steffen, 2015, The "Greatest" Carry Trade Ever? Understanding Eurozone Bank Risk. *Journal of Financial Economics* 115 (2), 215-36.

Acharya, V. and S. Steffen, 2020a, The Risk of Being a Fallen Angel and the Corporate Dash for Cash in the Midst of COVID. *Review of Corporate Finance Studies* 9 (3), 430-71.

Acharya, V. and S. Steffen, 2020b, 'Stress Tests' for Banks as Liquidity Insurers in a Time of COVID. CEPR VoxEU.org.

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

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

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

Bai, J., A. Krishnamurthy, and C.-H. Weymuller, 2018, Measuring Liquidity Mismatch in the Banking Sector. *Journal of Finance* 73, 51-93.

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

Beltratti, A. and R. Stulz, 2012, The Credit Crisis around the Globe: Why did some Banks Perform Better? *Journal of Financial Economics* 105 (1), 1-17.

Berg, T., A. Saunders and S. Steffen, 2016, The Total Cost of Borrowing in the Loan Market – Don't Ignore the Fees. *Journal of Finance* 71 (3), 1357-92.

Berg, T., A. Saunders, S. Steffen and D. Streitz, 2017, Mind the Gap: The Difference between U.S. and European Loan Rates. *Review of Financial Studies* 30 (3), 948-87.

Berger, A., and C. Bouwman, 2009, Bank Liquidity Creation. *Review of Financial Studies*, 22 (9), 3779-837.

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

Boyarchenko, N., A. Kovner and O. Shachar. 2022. It's What You Say and What You Buy: A Holistic Evaluation of the Corporate Credit Facilities. *Journal of Financial Economics* 144(3), 695-731.

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

Campello, M., J. Graham and C. Harvey, 2010, The Real Effects of Financial Constraints: Evidence from a Financial Crisis, *Journal of Financial Economics* 97, 470-487.

Campello, M., J. Graham and C. Harvey, 2011, Liquidity Management and Firm Investment in a Financial Crisis, *Review of Financial Studies* 24, 1944-1979.

Cai, J., F. Eidam, A. Saunders, and S. Steffen, 2018, Syndication, Interconnectedness, and Systemic Risk. *Journal of Financial Stability* 34, 105-20.

Chodorow-Reich, Gabriel, and Antonio Falato, 2022. The Loan Covenant Channel: How Bank Health Transmits to the Real Economy, *Journal of Finance* 77 (1), 85-128.

Chodorow-Reich, G., O. Darmouni, S. Luck, and M. Plosser, 2022, Bank Liquidity Provision across the Firm Size Distribution. *Journal of Financial Economics* 144 (3), 908-32.

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

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

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

Demsetz, R., and P. Strahan, 1997, Diversification, Size, and Risk at Bank Holding Companies. *Journal of Money, Credit and Banking* 29 (3), 300-13.

Demirguc-Kunt, A., A. Pedraza, and C. Ruiz-Ortega, 2021, Banking Sector Performance during the COVID-19 Crisis. *Journal of Banking & Finance* 133, 106305.

Diep, P., Eisfeldt, A.L. and Richardson, S., 2021, The cross section of MBS returns, *The Journal of Finance* 76(5), 2093-2151.

Dubois, C., and L. Lambertini, 2018, A Macroeconomic Model of Liquidity, Wholesale Funding and Banking Regulation. Working Paper École Polytechnique Féd Érale de Lausanne.

English, W.B., Van den Heuvel, S.J., and Zakrajšek, E., 2018, Interest rate risk and bank equity valuations, *Journal of Monetary Economics* 98, 80-97.

Erel, I., and J. Liebersohn, 2022, Can FinTech Reduce Disparities in Access to Finance? Evidence from the Paycheck Protection Program, *Journal of Financial Economics* 146 (1), 90-118.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz, 2012, This Time is the Same: Using Bank Performance in 1998 to Explain Bank Performance During the Recent Financial Crisis. *Journal of Finance* 67, 2139-85.

Fahlenbrach, R., K. Rageth, and R. M. Stulz, 2021, How Valuable is Financial Flexibility when Revenue Stops? Evidence from the Covid-19 crisis. *Review of Financial Studies* 34 (11), 5474-521.

Gatev, E., and P. Strahan, 2006, Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. *Journal of Finance 61 (2)*, 867-92.

Gormsen, N. J., and R. S. J. Koijen, 2020, Coronavirus: Impact on Stock Prices and Growth Expectations. *Review of Asset Pricing Studies* 10 (4), 574-97.

Greenwald, D. L., J. Krainer, and P. Paul, 2023, The Credit Line Channel, Working Paper, New York University Stern School of Business.

Haddad, V., A. Moreira, and T. Muir, 2021, When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response, *Review of Financial Studies* 34 (11), 5309–5351.

Ippolito, F., J.-L. Peydró, A. Polo, and E. Sette, 2016, Double Bank Runs and Liquidity Risk Management. *Journal of Financial Economics* 122 (1), 135–54.

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

Ivashina, V., and D. Scharfstein, 2010, Bank Lending During the Financial Crisis of 2008. *Journal of Financial Economics* 97(3), 319–38.

Jiménez, G., J. A Lopez, and J. Saurina, 2009, Empirical Analysis of Corporate Credit Lines. *Review of Financial Studies* 22 (12), 5069–98.

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

Kashyap, A., R. Rajan and J. Stein, 2002, Banks as Liquidity Providers: An Explanation for the Coexistence of Lending and Deposit-taking. *Journal of Finance* 57 (1), 33-73.

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

Khwaja, A. and A. Mian, 2008, Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *American Economic Review* 98 (4), 1413–42.

Landier, A., and D. Thesmar, 2020, Earnings Expectations in the COVID Crisis. *Review of Asset Pricing Studies* 10 (4), 598-617.

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

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

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

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

Pagano, M., C. Wagner, and J. Zechner, 2022, Disaster resilience and asset prices. *Journal of Financial Economics*, forthcoming.

Ramelli, S., and A. F. Wagner, 2020, Feverish Stock Price Reactions to COVID-19. *Review of Corporate Finance Studies* 9 (3), 622-55.

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

Sufi, A., 2009, Bank Lines of Credit in Corporate Finance: An Empirical Analysis. *Review of Financial Studies* 22 (3), 1057–88.

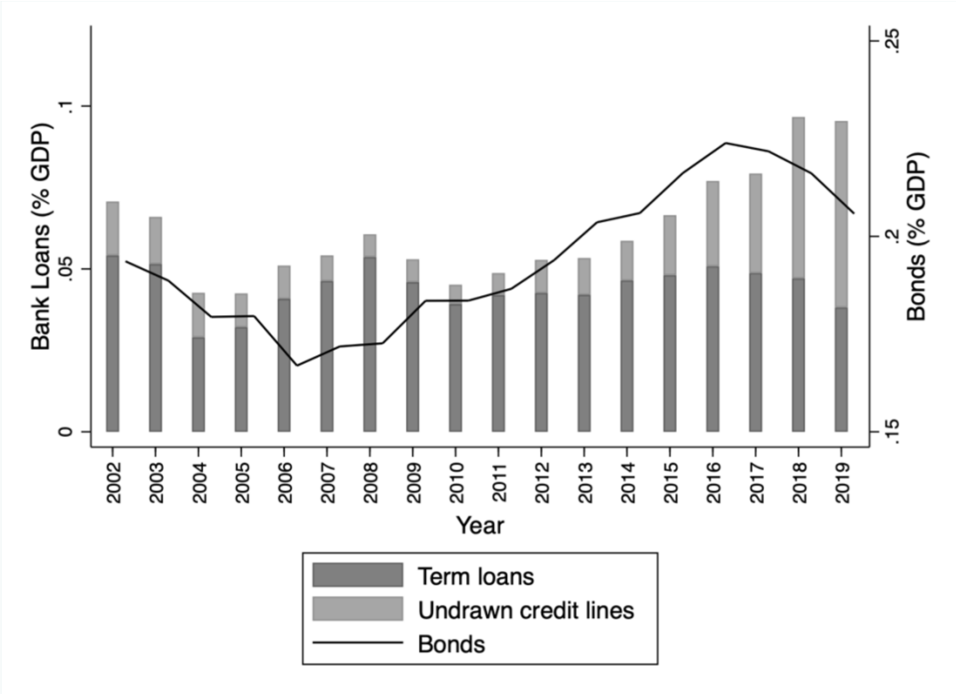
Vissing-Jorgensen, 2021, The Treasury Market in Spring 2020 and the Response of the Federal Reserve, *Journal of Monetary Economics* 124, 19–47.

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

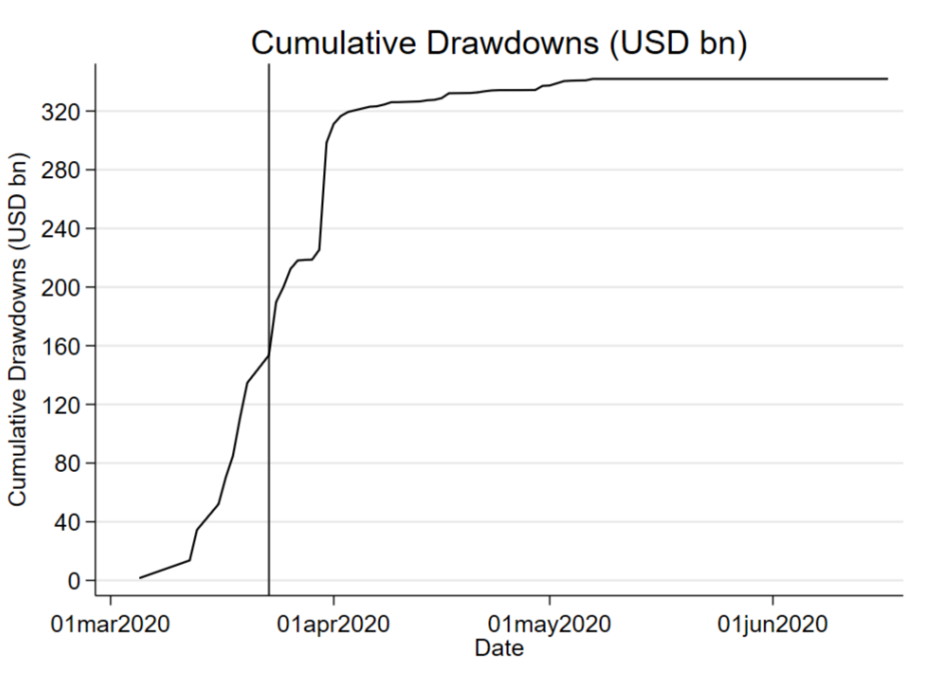
Figure 1. Credit lines, cumulative drawdowns and bank stock prices

Panel A shows the annual financing of U.S. publicly listed firms by term loans, undrawn credit lines and bonds (as a percentage of GDP) over the 2002-2019 period. Panel B shows cumulative drawdowns of US publicly listed firms at the beginning of the COVID-19 pandemic during the period Mar-June 2020. Panel C shows cumulative drawdowns by rating class. Panel D shows the stock prices of U.S. publicly listed banks, non-bank financial and non-financial firms over the Jan 1st to Dec 31st, 2020 period. The sample of 147 banks is documented in Appendix II.

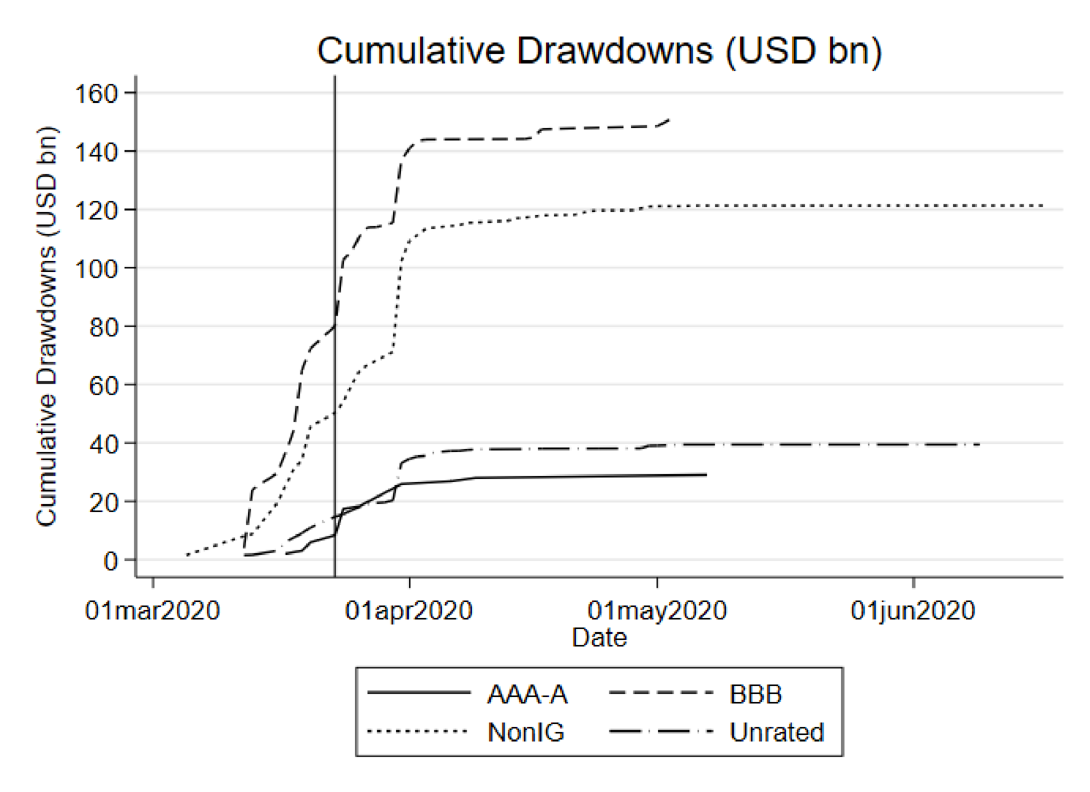
Panel A. Bond vs loan financing of U.S. publicly listed firms



Panel B. Cumulative drawdowns (in USD bn)



Panel C. Cumulative drawdowns by rating class (in USD bn)



Panel D. Stock prices

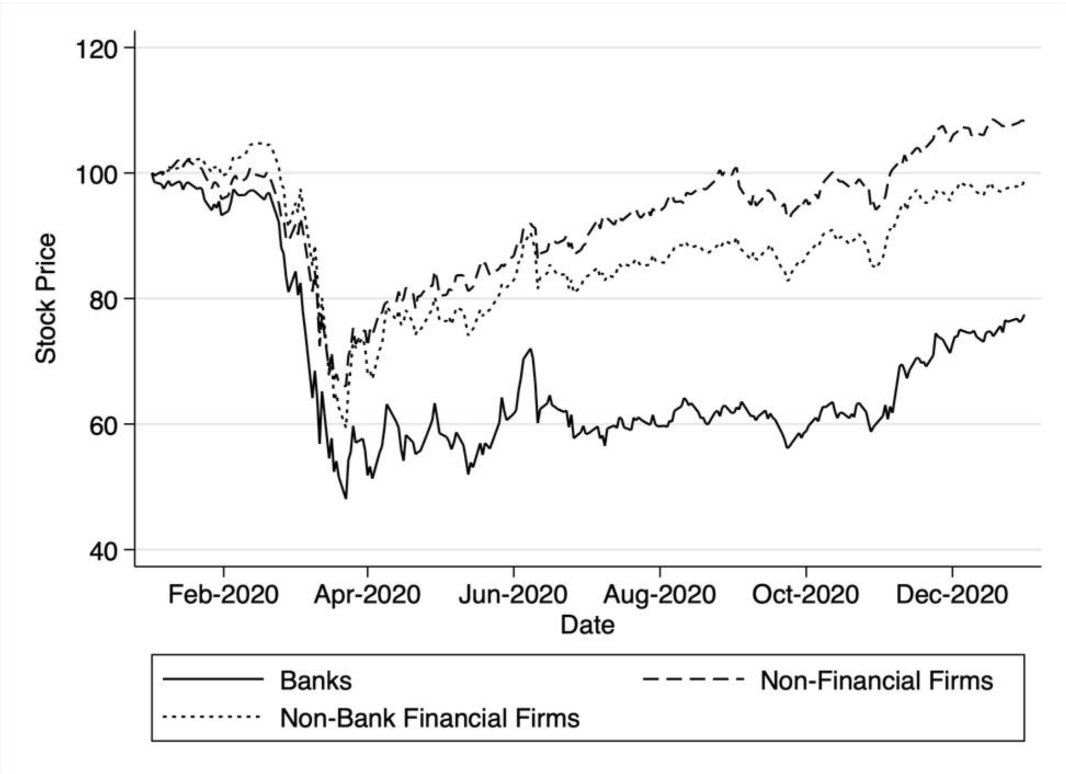
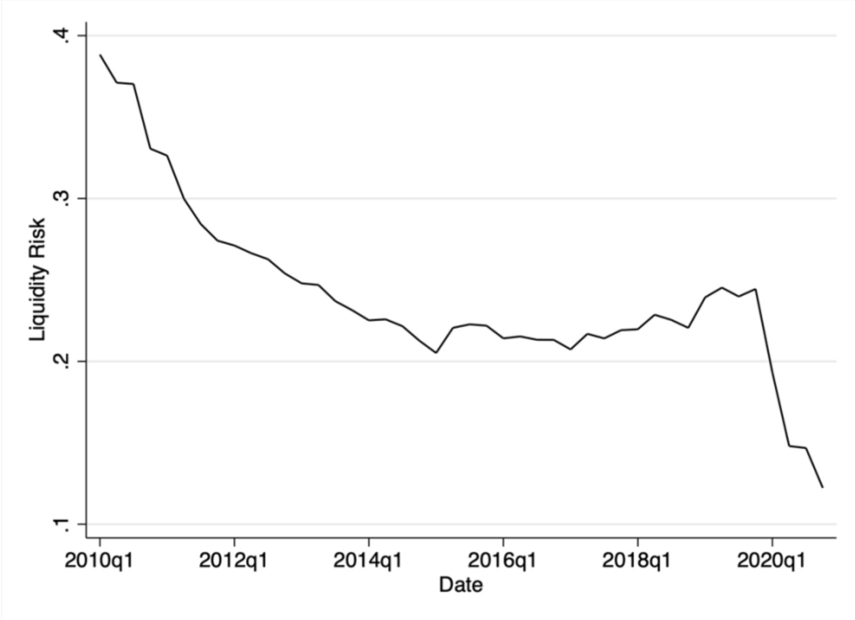


Figure 2. Bank balance-sheet liquidity risk

Panel A of Figure 2 shows the time-series of balance-sheet *Liquidity Risk* over the Q1 2010 to Q4 2020 period. We measure *Liquidity Risk* as undrawn commitments to commercial and industrial (C&I) firms plus wholesale funding minus cash or cash equivalents (all relative to assets). Panel B shows the time-series of its components. All variables are defined in Appendix III.

Panel A. Liquidity risk



Panel B. Components of liquidity risk

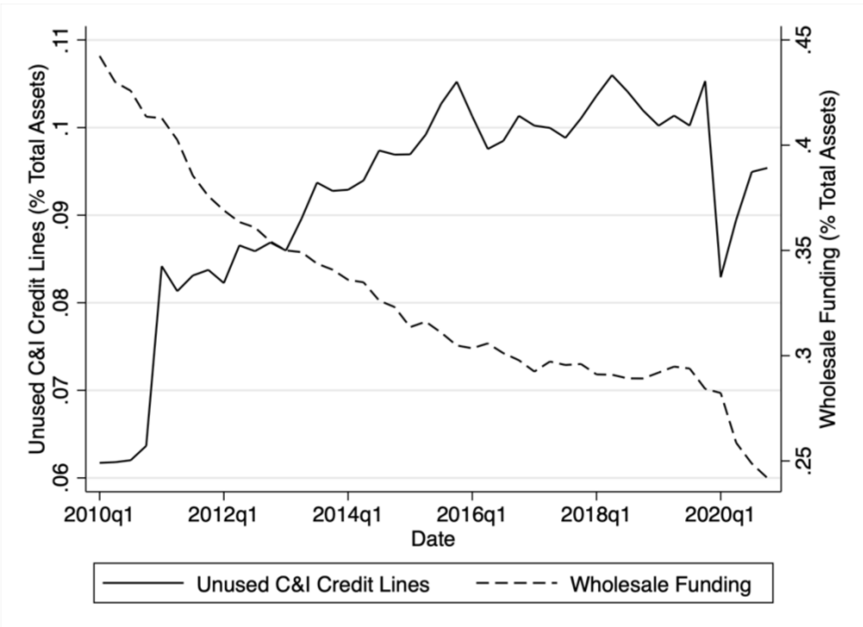
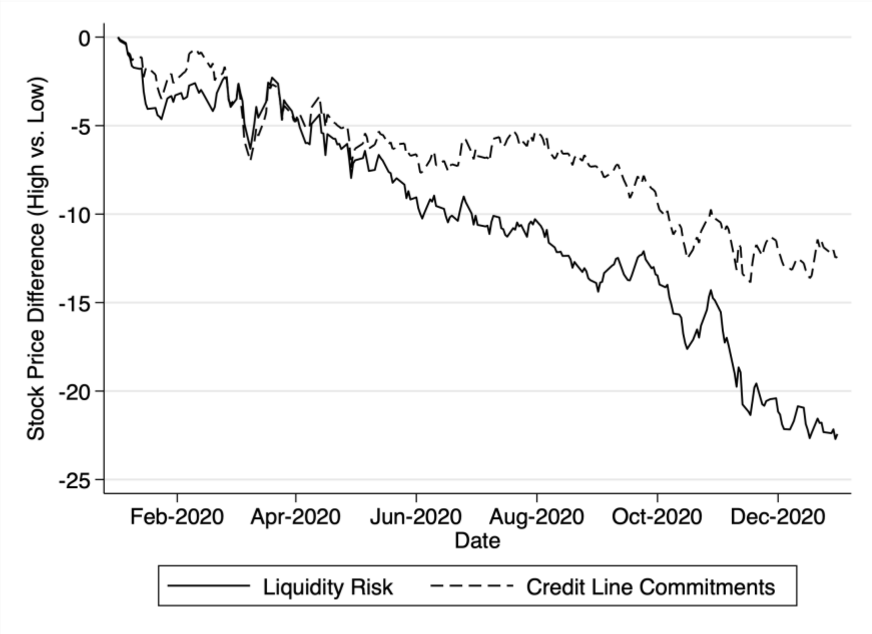


Figure 3. Stock prices and liquidity risk of U.S. banks

This figure shows stock prices of U.S. banks in relationship to their liquidity risk. Panel A uses (1) a median split to distinguish between banks with *Low* vs. *High Liquidity Risk* and (2) a median split to distinguish between banks with *Low* vs. *High Credit Line Commitments* and shows the time-series of stock price difference of each respective group of banks indexed at Jan 1, 2020. We measure *Liquidity Risk* as undrawn C&I commitments plus wholesale finance minus cash or cash equivalents (all relative to assets). Panel B plots the cross-section of bank stock returns during the March 1 – March 23, 2020 period as a function of banks' *Liquidity Risk*. All variables are defined in Appendix III.

Panel A. Bank stock prices for high vs low liquidity risk/credit line commitment banks



Panel B. Bank stock return and liquidity risk

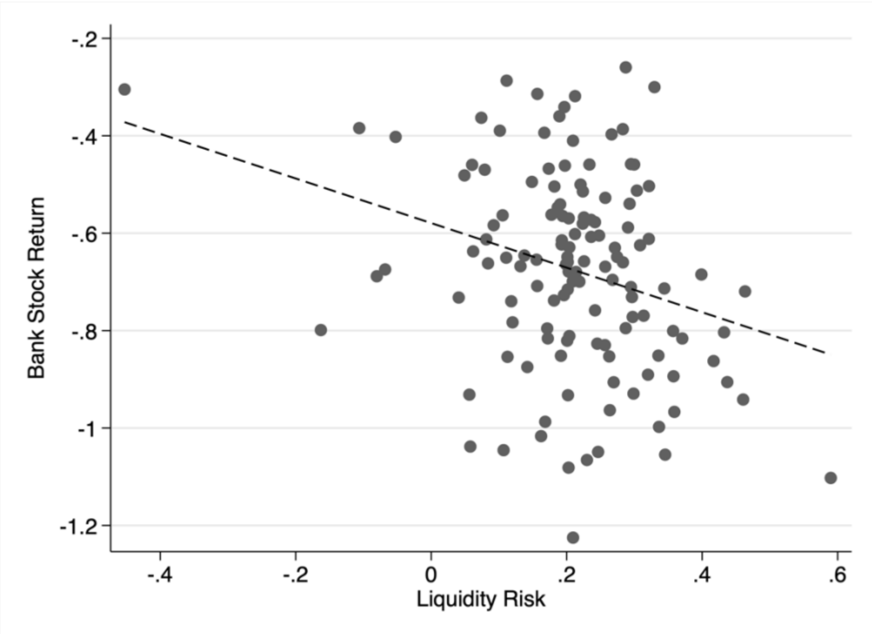
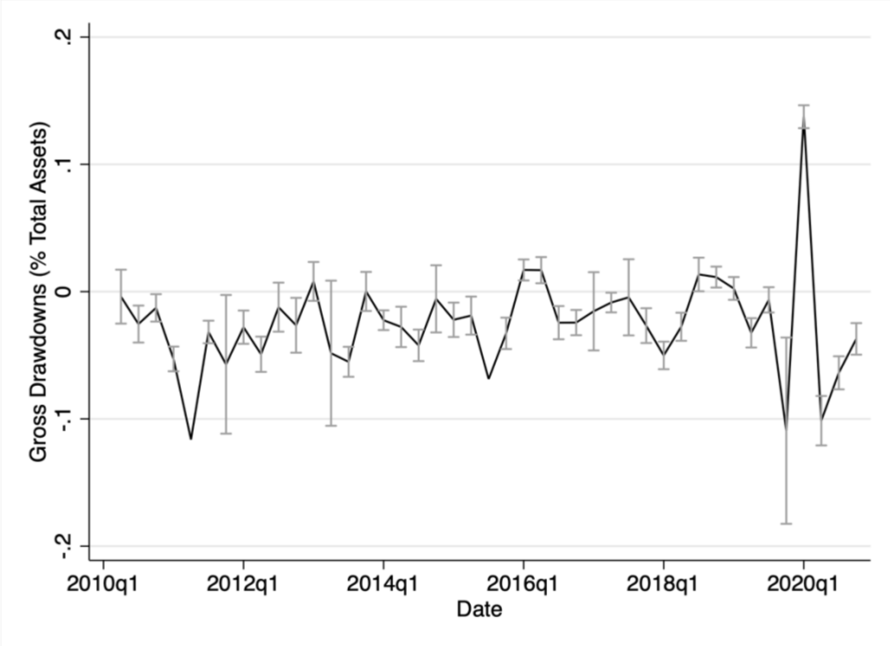


Figure 4. Net vs. gross drawdowns

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

Panel A. Gross Drawdowns



Panel B. Net Drawdowns

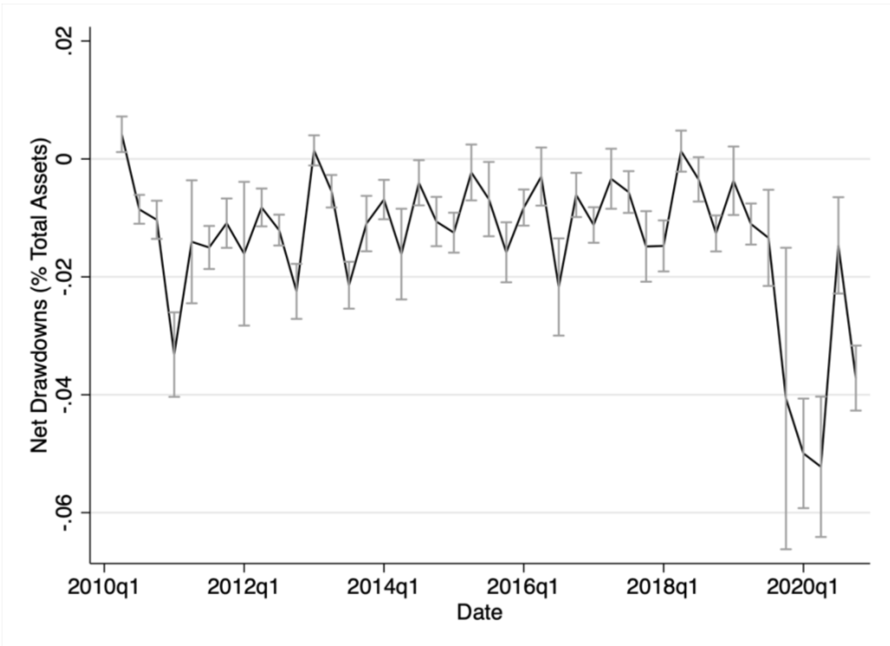
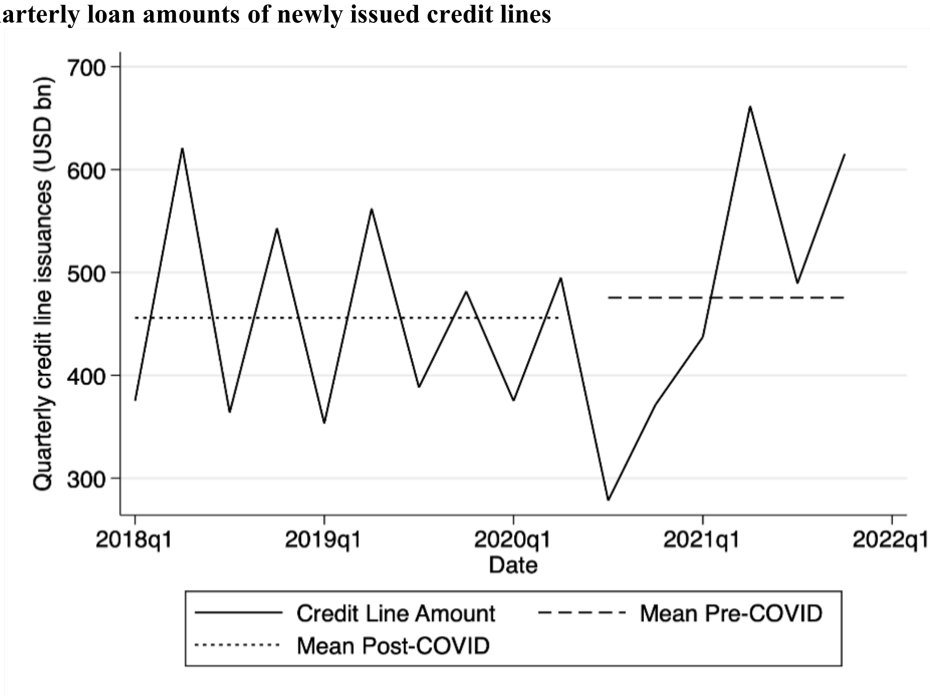


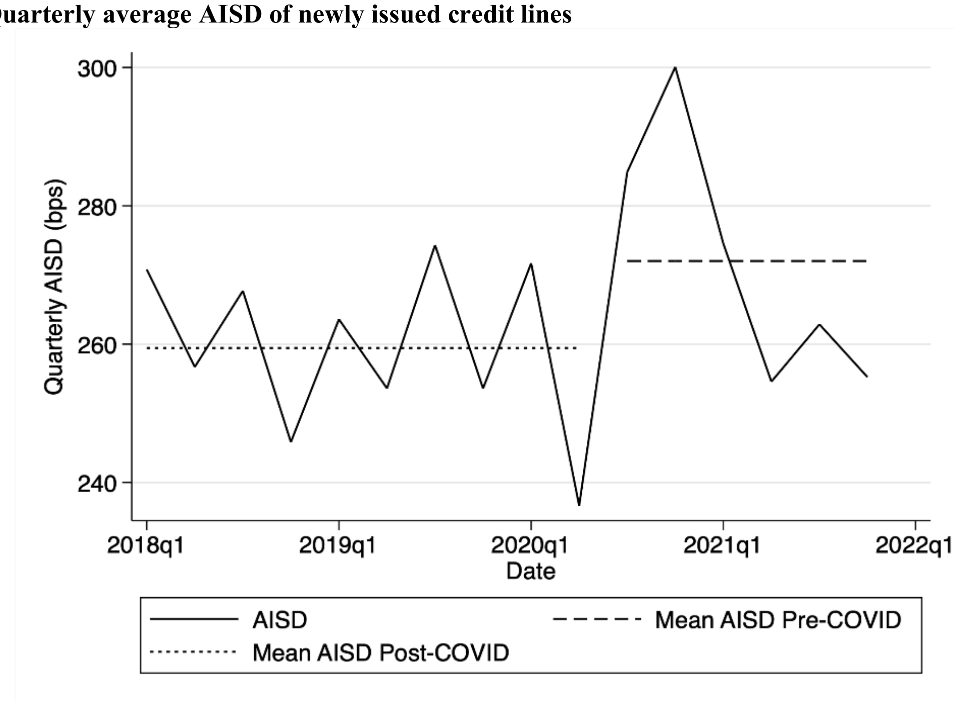
Figure 5. Credit line issuances (volume and spread/fees)

This figure shows quarterly issuance volume in USD billion (Panel A), all-in-spread-drawn or AISD (Panel B), all-in-spread-undrawn or AISU (Panel C), and upfront fees or UFR (Panel D), with spreads and fees in basis points (bps), of credit line issuances by U.S. firms over the 2018 to 2021 period. All variables are defined in Appendix III.

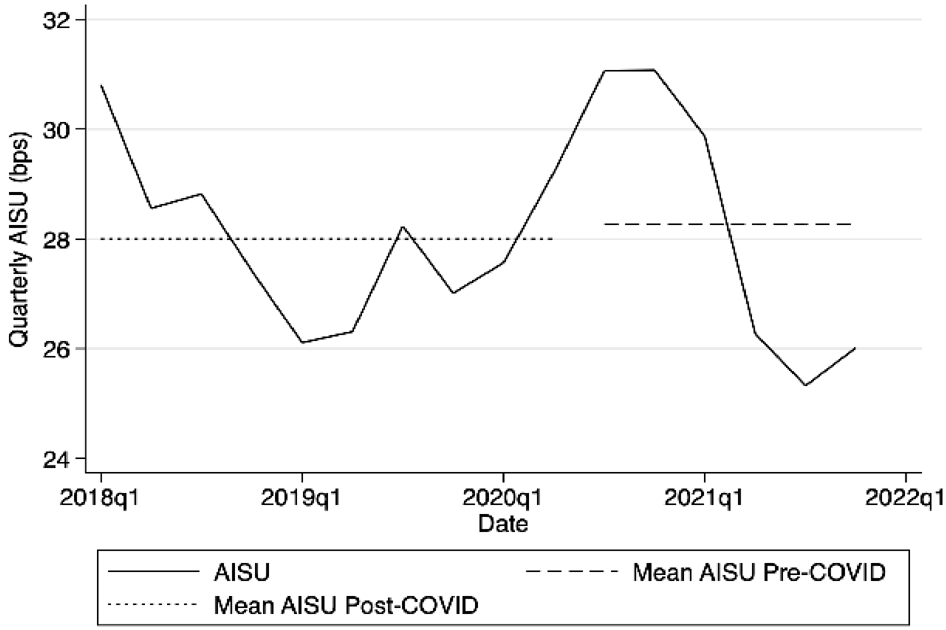
Panel A. Quarterly loan amounts of newly issued credit lines



Panel B. Quarterly average AISD of newly issued credit lines



Panel C. Quarterly average AISU of newly issued credit lines



Panel D. Quarterly average upfront fees of newly issued credit lines

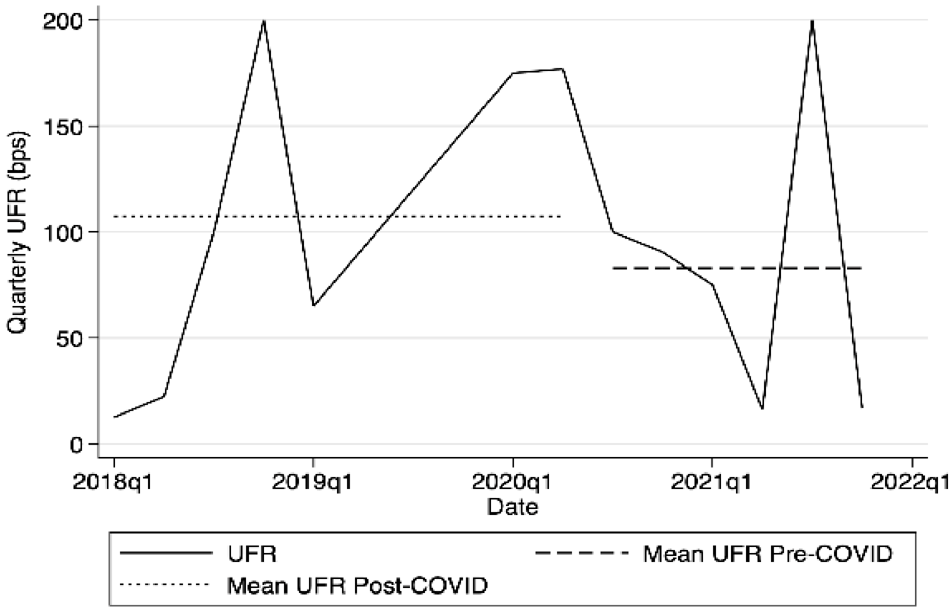
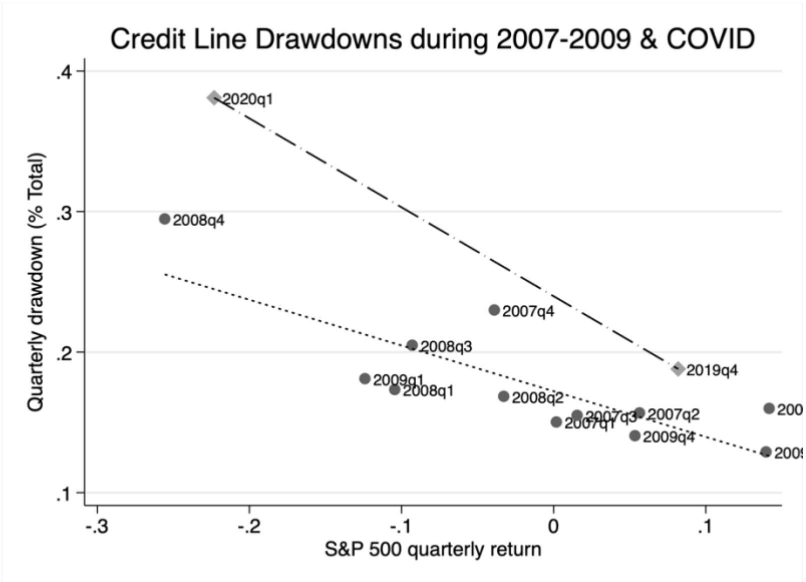


Figure 6. Credit line drawdowns and stock market returns

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

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



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

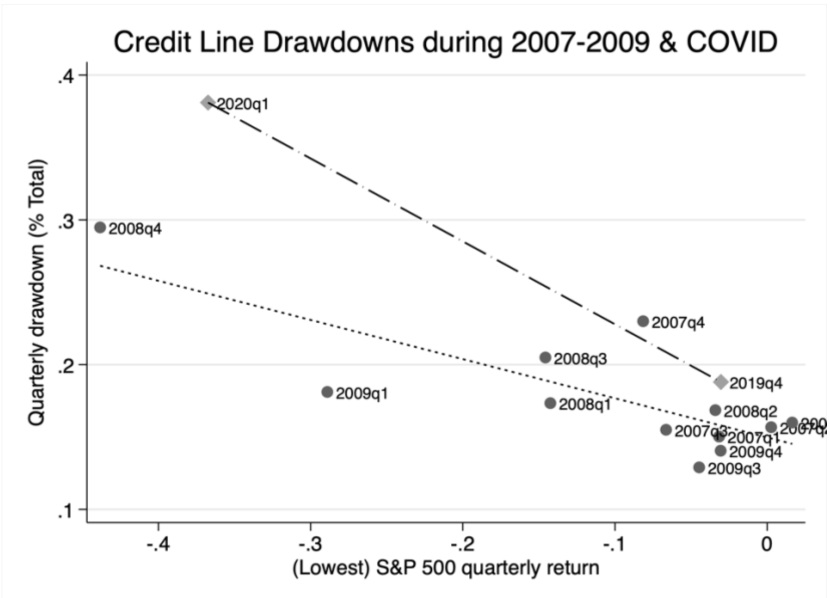


Table 1. Descriptive statistics

This table shows descriptive statistics of the variables included in the cross-sectional regressions. The list of sample banks is shown in Appendix II. All variables are defined in Appendix III.

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

Table 2. Liquidity risk and bank stock returns

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

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

Table 3. Controlling for bank portfolio composition via exposure to COVID-19-affected industries

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

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

	(7)	(8)	(9)	(10)	(11)	(12)
Liquidity Risk	-0.515***	-0.518***	-0.541***	-0.524***	-0.534***	-0.521***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Affected Industries (β_{COVID})	-0.541**	-0.709***	-0.221*	-0.910**	-1.528***	-2.090***
	(0.013)	(0.004)	(0.090)	(0.018)	(0.001)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Affected Measure	Koren and Peto (2020) – Teamwork share	YoY sales decline	Chodorow-Reich *et al.* (2022) – Abnormal employment decline	ONET – Physical proximity	ONET – Face-to-face discussion	ONET – External customers
R-squared	0.496	0.519	0.476	0.501	0.517	0.504
Number obs.	147	147	147	147	147	147

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

<u>Note:</u>

Detailed data describing bank portfolio composition are hardly available to empirical researchers. Our approach to estimate banks' exposure to COVID-19-affected industries is similar to the procedure employed, e.g., by Agarwal and Naik (2004) to characterize the exposures of hedge funds or the approach in Acharya and Steffen (2015) in estimating European banks' exposure to sovereign debt. We use multifactor models in which the sensitivities of banks' stock returns to "COVID-19-affected industry" returns are measures of banks' exposure to these industries. We call these sensitivities "*Affected Industries* (β_{COVID})". The lack of micro level portfolio holdings of banks gives these tests more power and increases the efficiency of the estimates. More precisely, we run the following regression daily over the Jan 1, 2019 to Dec 31, 2019 period <u>for each bank *i*:</u>

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

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

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

Panel A reports the results of OLS regressions of U.S. bank' realized stock returns during January 2020 (columns (1)-(2)), February 2020 (columns (3) to (4)) and 1-23 March 2020 (columns (5) to (6)). Regressions with control variables are based on column (5) in Table 2. P-values based on robust standard errors are in parentheses. Panel B reports the results of OLS regressions of U.S. banks' excess 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 Table 2. We first show each component separately in columns (1)-(3) and then add them sequentially in columns (4) and (5). P-values based on robust standard errors are in parentheses. Panel C reports the results of OLS regressions of U.S. banks' excess stock returns over the 1/3/2020 – 3/23/2020 period on the different components of *Liquidity Risk* and different proxies for wholesale funding with control variables as in column (5) in Table 2. Columns (1) to (5) sequentially add additional components and proxies. P-values based on robust standard errors are in parentheses. Panel D reports descriptive statistics of bank excess stock returns for Q1 – Q4 2020. Panel E reports the results of OLS regressions of U.S. banks' excess stock returns over the Q2 to Q4 2020 period on bank *Liquidity Risk*, *Equity Beta* and control variables as shown in column (5) of Table 2. Control variables are lagged by one quarter. Columns (1) and (2) report the results using Liquidity Risk and columns (3) and (4) the components of Liquidity Risk. Columns (2) and (4) include quarter fixed effects. Standard errors are clustered at the bank level. Columns (5) to (7) repeat the results separately for each quarter. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

Panel A. Liquidity risk and bank stock returns by month

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

Panel B. Components of liquidity risk

	(1)	(2)	(3)	(4)	(5)
			3/1-3/23/2020		
Unused C&I Loans / Assets	-1.110***			-1.006***	-1.084***
	(0.001)			(0.001)	(0.001)
Liquidity / Assets		0.563***		0.477***	0.488***
		(0.004)		(0.009)	(0.006)
Wholesale Funding / Assets			-0.114		-0.279
			(0.562)		(0.107)
Equity Beta	-0.578***	-0.513**	-0.498**	0.599***	0.597***
	(0.004)	(0.012)	(0.015)	(0.004)	(0.003)
SRISK /Assets	-6.559**	-6.733***	-7.128***	-6.208**	-5.922**
	(0.015)	(0.005)	(0.005)	(0.014)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.456	0.439	0.408	0.479	0.486
Number obs.	147	147	147	147	147

Panel C. Wholesale funding and bank stock returns during COVID

	(1)	(2)	(3)	(4)
Liquidity Risk	-0.445***			
	(0.000)			
Unused Commitments / Assets		-1.084***	-1.020***	-1.149***
		(0.001)	(0.001)	(0.000)
Liquidity / Assets		0.488***	0.487***	0.326*
		(0.006)	(0.008)	(0.083)
Wholesale Funding / Assets		-0.279		
(Acharya and Mora, 2015)		(0.107)		
Wholesale Funding / Assets			-0.0788	
(Dubios and Lambertini, 2018)			(0.689)	
Large Time Deposits / Assets				-1.164**
				(0.034)
Foreign Deposits / Assets				-0.0464
				(0.846)
Subordinated Debt / Assets				-1.581
				(0.445)
Fed Funds Purchased / Assets				1.681
				(0.117)
Other Borrowed Money / Assets				0.0778
				(0.892)
R-squared	0.471	0.486	0.480	0.523
Number obs.	147	147	147	147

Panel D. Descriptive statistics of bank stock returns over the quarters of 2020

Variable	Obs.	Mean	Std. dev.	Min	Max
2020Q1	147	-0.511	0.181	-0.996	-0.075
2020Q2	146	0.096	0.149	-0.398	0.537
2020Q3	145	-0.079	0.104	-0.282	0.249
2020Q4	144	0.346	0.115	0.014	0.706
Total	582	-0.039	0.343	-0.996	0.706

Panel E. Liquidity risk and bank stock returns after the policy interventions of March 2020

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

Table 5. Understanding the mechanisms: Funding versus capital during Q1 2020 (prior to policy interventions)

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

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

Table 6. Implications for bank lending during the COVID-19 pandemic

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exposures				New originations			
Gross Drawdowns (Gross) x Post	0.169				-1.364			
	(0.611)				(0.323)			
Net Drawdowns (Net) x Post	0.0299				-0.317			
	(0.579)				(0.228)			
High Gross x Post		0.00115	0.0140*	0.0131*		-0.0426**	-0.0467***	-0.0417*
		(0.849)	(0.070)	(0.075)		(0.011)	(0.007)	(0.086)
High Net x Post		0.00554	-0.000600	-0.00303		-0.0320	-0.0334	-0.0108
		(0.366)	(0.940)	(0.684)		(0.135)	(0.153)	(0.741)
High Gross x Post x Term Loan Indicator			-0.0363***	-0.0366***			0.0158	0.0240
			(0.009)	(0.009)			(0.345)	(0.216)
High Net x Post x Term Loan Indicator			0.0173	0.0174			0.00626	0.0134
			(0.220)	(0.229)			(0.641)	(0.470)
Controls	No	No	No	Yes	No	No	No	Yes
Borrower x Time x Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank x Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.976	0.976	0.976	0.977	0.993	0.993	0.993	0.993
Number obs.	340641	340641	340641	296779	6745	6745	6745	6745

Table 7. Understanding the mechanisms: Credit line repayments during 2020Q2-Q3 (post policy interventions)

Panel A of Table 8 shows descriptive statistics for the repayment behavior of borrowers by rating category. Sub-panels A.i and A.ii display the behavior in 2020Q2 in relation to total committed credit or remaining drawdown balance, and sub-panels A.iii and A.iv show the analogue for 2020Q3. Panel B reports the results of OLS regressions of US banks' stock returns between March 23, 2020, and June 30, 2020, on bank-level variables capturing the opportunity-cost adjusted *Fees Earned* on outstanding credit lines as well as credit-line *Repayments* during the 2020Q2 period. Columns (3), (4), and (5) interact *Repayments* with indicators of previous distress: market value loss between December 31, 2019, and March 23, 2020 *(MV Loss Covid)*, the regulatory capital level (*Capital Buffer*), and the bank-level credit line drawdowns in the first quarter of 2020 (*Drawdowns 2020Q1*). Credit-line repayments are constructed by combining FDIC Call Report, Dealscan and Capital IQ data and are thus only available for a subset of banks. P-values based on robust standard errors are in parentheses. All variables are defined in Appendix III.

Panel A. Repayment statistics in 2020Q2 and 2020Q3

Panel A.i. 2020Q2 repayments scaled by commitment

Rating	Mean	Median	SD	Min	Max
AAA-A	0.24	0.159	0.266	0.000	0.990
BBB	0.26	0.199	0.245	0.000	1.000
non-IG	0.26	0.149	0.276	0.000	1.000
NR	0.2	0.107	0.243	0.000	1.000

Panel A.ii. 2020Q2 repayments scaled by remaining drawdown balance

Rating	Mean	Median	SD	Min	Max
AAA-A	0.69	0.988	0.373	0.000	1.000
BBB	0.64	0.736	0.365	0.000	1.000
non-IG	0.5	0.409	0.393	0.000	1.000
NR	0.39	0.256	0.369	0.000	1.000

Panel A.iii. 2020Q3 repayments scaled by commitment

Rating	Mean	Median	SD	Min	Max
AAA-A	0.08	0.000	0.166	0.000	0.802
BBB	0.12	0.024	0.184	0.000	1.000
non-IG	0.15	0.059	0.208	0.000	1.000
NR	0.14	0.068	0.197	0.000	1.000

Panel A.iv. 2020Q3 repayments scaled by remaining drawdown balance

Rating	Mean	Median	SD	Min	Max
AAA-A	0.57	0.670	0.395	0.000	1.000
BBB	0.52	0.497	0.382	0.000	1.000
non-IG	0.43	0.303	0.380	0.000	1.000
NR	0.4	0.286	0.378	0.000	1.000

Panel B. Which banks recover market-value losses?

	(1)	(2)	(3)	(4)	(5)	(6)
Fees Earned	0.118***	0.216***	0.186***	0.0772	0.205***	0.109*
	(0.010)	(0.003)	(0.000)	(0.299)	(0.009)	(0.082)
Repayments	0.673**	0.442	-1.886***	-0.195	0.609	-1.409**
	(0.046)	(0.294)	(0.004)	(0.493)	(0.265)	(0.019)
MV Loss Covid	0.499***	0.561***	0.294***	0.565***	0.569***	0.388***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Drawdowns 2020Q1	3.004***	3.190***	3.017***	4.264***	5.836*	5.038**
	(0.006)	(0.006)	(0.004)	(0.000)	(0.089)	(0.021)
Fees Earned x Repayments		-0.382*	-0.562***	0.135	-0.369	-0.193
		(0.061)	(0.001)	(0.567)	(0.102)	(0.385)
Repayments x MV Loss Covid			2.817***			1.889**
			(0.000)			(0.016)
Repayments x Capital Buffer				-31.25***		-18.34*
				(0.003)		(0.061)
Repayments x Drawdowns 2020Q1					-20.57	-10.37
					(0.415)	(0.555)
Constant	-0.232**	-0.161	0.144	-0.120	-0.183	0.0564
	(0.016)	(0.137)	(0.106)	(0.215)	(0.133)	(0.569)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.901	0.914	0.951	0.949	0.917	0.961
Number obs.	32	32	32	32	32	32

Table 8. Credit line commitments, liquidity risk and bank stock returns during crises (including pre-COVID crisis)

This table reports the results of OLS regressions of quarterly U.S. banks' excess stock returns for three samples on a dummy variable indicating banks with above median credit line commitments (assigned one quarter before the respective crisis), a dummy variable indicating a crisis quarter and control variables. Separate time-series samples are 2019Q4 to 2021Q1 (Covid), 2004Q1 to 2011Q4 (GFC) and 2000Q1 to 2002Q4 (Dotcom). Crisis quarters are 2001Q1 to 2001Q4 (Dotcom), 2007Q3 to 2009Q2 (GFC) and 2020Q1 (Covid). Columns sequentially add control variables and bank fixed effects for each sample. The sample of banks is matched on total assets, capitalization, NPL-to-loans and loans-to-assets ratio. All variables are defined in Appendix III. P-values based on robust standard errors are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Commitment Above Median	0.0166	0.0144**		0.0143**	0.0145***		0.00204	0.00229	
	(0.144)	(0.045)		(0.010)	(0.005)		(0.773)	(0.742)	
Crisis	-0.466***	-0.253***	-0.253***	-0.0791***	-0.00839	-0.00343	0.0683***	0.0520***	0.0536***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.336)	(0.725)	(0.000)	(0.000)	(0.000)
Commitment Above Median x Crisis	-0.0811**	-0.0789***	-0.0784***	-0.0302***	-0.0299***	-0.0308***	-0.0317***	-0.0318***	-0.0325***
	(0.017)	(0.000)	(0.001)	(0.006)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)
MKTRF		-0.277*	-0.276		0.387***	0.386***		0.201***	0.205***
		(0.055)	(0.107)		(0.000)	(0.000)		(0.000)	(0.000)
SMB FF3		2.217***	2.219***		0.448***	0.448***		0.529***	0.530***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
HML		0.349***	0.351***		1.099***	1.112***		0.540***	0.547***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Constant	0.117***	0.0814***	0.0919***	-0.00325	-0.0270***	-0.0178***	0.0272***	0.00223	0.00299
	(0.000)	(0.000)	(0.000)	(0.489)	(0.000)	(0.000)	(0.000)	(0.717)	(0.261)
Sample	Covid	Covid	Covid	GFC	GFC	GFC	Dotcom	Dotcom	Dotcom
Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.485	0.806	0.806	0.047	0.221	0.221	0.024	0.103	0.103
Number obs.	1364	1364	1364	8109	8109	8109	3914	3914	3914

Table 9. Pricing of drawdown options in credit line fees

This table reports the results of OLS regressions of the All-In-Spread-Drawn (AISD) in Panel A and the All-In-Spread-Undrawn (AISU) in Panel B on **banks' aggregate risk exposures** including *Bank Equity Beta* (as a measure of systematic risk), *LRMES* (as a measure of downside risk; 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 a bank's return if market returns are less than -2%), *SRISK/Assets* (as a measure of equity shortfall in times of a severe crisis) and *Liquidity Risk* (as a measure of aggregate drawdown risk and defined as Unused Commitments plus Wholesale Funding minus Liquidity (% Assets)). We include them individually in regressions (2) to (5) and (7) to (10). All regressions include **bank characteristics**: *NPL/Loans* (Non-performing loans (% Loans)), *Capital* (Equity/Assets), *Non-Interest Income* (Non-interest-income (%Operating revenues)), *Bank Size* (Log of Total Assets), *Bank Profitability* (Return on assets: Net Income / Assets). All regressions further include **borrower characteristics**: *Equity Volatility* (12-months equity volatility), *Firm Equity Beta* (12-month daily beta with the S&P 500 return), *Firm Size* (Log of Total Assets; deflated using the U.S. PPI), *Firm Profitability* (EBITDA / Assets), *Tangibility* (Net PP&E / Assets), *Tobin's Q* (Market Assets / Assets), *Leverage* ((LT Debt + ST Debt) / Market Assets). All regressions include the LIBOR as well as year and industry (2-digit) fixed effects. Standard errors are clustered at the firm level. All variables are defined in Appendix III.

Panel A. AISD

	(1)	(2)	(3) AISD	(4)	(5)
Bank Equity Beta		0.0582			
		(0.147)			
LRMES			1.293**		
			(0.039)		
SRISK / Assets				1.772	
				(0.293)	
Liquidity Risk					-0.330
					(0.185)
LIBOR	-0.288***	-0.278***	-0.243***	-0.272***	-0.311***
	(0.000)	(0.001)	(0.006)	(0.002)	(0.000)
Bank Characteristics					
NPL / Loans	1.864	2.298	2.120	2.474	1.832
	(0.342)	(0.261)	(0.281)	(0.242)	(0.339)
Capital	-5.395**	-4.925**	-4.967**	-4.981**	-5.412***
	(0.013)	(0.018)	(0.013)	(0.020)	(0.009)
Non-Interest Income	-0.0560	-0.0490	-0.171	-0.0628	-0.163
	(0.796)	(0.820)	(0.458)	(0.773)	(0.476)
Bank Size	-0.107***	-0.111***	-0.110***	-0.119***	-0.126***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Bank Profitability	-10.20**	-8.032	0.132	-2.877	-10.47**
	(0.042)	(0.113)	(0.984)	(0.741)	(0.036)
Firm Characteristics					
Equity Volatility	0.360**	0.366**	0.367**	0.364**	0.360**
	(0.019)	(0.015)	(0.015)	(0.016)	(0.020)
Firm Equity Beta	0.175***	0.176***	0.173***	0.174***	0.176***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Size	-0.170***	-0.169***	-0.167***	-0.169***	-0.170***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Profitability	-0.200	-0.201	-0.193	-0.203	-0.211
	(0.327)	(0.328)	(0.345)	(0.318)	(0.290)
Tangibility	-0.475***	-0.478***	-0.475***	-0.474***	-0.476***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	-0.0279**	-0.0281**	-0.0274**	-0.0275**	-0.0265**
	(0.040)	(0.038)	(0.042)	(0.042)	(0.049)
Leverage	1.756***	1.753***	1.764***	1.755***	1.757***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.463	0.463	0.464	0.463	0.463
Number obs.	2657	2657	2657	2657	2657

Panel B. AISU

	(1)	(2)	(3) AISU	(4)	(5)
Bank Equity Beta		0.0161**			
		(0.021)			
LRMES			0.187*		
			(0.085)		
SRISK / Assets				0.255	
				(0.382)	
Liquidity Risk					-0.0253
					(0.581)
LIBOR	-0.0516***	-0.0488***	-0.0451***	-0.0492***	-0.0534***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)
Bank Characteristics					
NPL / Loans	0.565*	0.684**	0.602*	0.652*	0.562*
	(0.072)	(0.032)	(0.054)	(0.053)	(0.072)
Capital	-0.576	-0.446	-0.514	-0.516	-0.577
	(0.153)	(0.246)	(0.173)	(0.198)	(0.146)
Non-Interest Income	0.0103	0.0122	-0.00638	0.00930	0.00208
	(0.795)	(0.752)	(0.880)	(0.815)	(0.962)
Bank Size	-0.0117**	-0.0127**	-0.0122**	-0.0135**	-0.0132**
	(0.034)	(0.019)	(0.022)	(0.025)	(0.040)
Bank Profitability	-1.486*	-0.887	0.0100	-0.430	-1.507*
	(0.077)	(0.300)	(0.993)	(0.765)	(0.074)
Firm Characteristics					
Equity Volatility	0.0700***	0.0716***	0.0709***	0.0706***	0.0700***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Equity Beta	0.0482***	0.0485***	0.0480***	0.0480***	0.0482***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Size	-0.0326***	-0.0324***	-0.0323***	-0.0325***	-0.0327***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Profitability	0.0113	0.0110	0.0123	0.0108	0.0105
	(0.716)	(0.725)	(0.693)	(0.726)	(0.735)
Tangibility	-0.0904***	-0.0913***	-0.0905***	-0.0903***	-0.0905***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tobin's Q	-0.0103***	-0.0104***	-0.0103***	-0.0103***	-0.0102***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.320***	0.319***	0.321***	0.320***	0.320***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.472	0.473	0.473	0.472	0.472
Number obs.	2657	2657	2657	2657	2657

Table 10. Credit-line drawdowns and Conditional SRISK

This table reports the predicted drawdown rates (*Drawdown Rate*) from credit lines in a stress scenario of 40% correction to the global stock market (Panel A) and the *Slope* of the drawdown function (compare Figure 6). In Panel B, we report the *Unused Commitments* (C&I loans), and the incremental required capital to fund the predicted drawdowns (*Incremental* $SRISK^{CL}$) using both (stressed) historical drawdown rates: *Incremental* $SRISK^{CL}$ = *Drawdown Rate* x 8% x *Unused Commitments* (C&I loans). *Debt* is total liabilities (from NYU Stern School of Business VLAB site, vlab.stern.nyu.edu/srisk). Panel C reports the calculation of *Incremental* $SRISK^{LRMES\text{-}C}$ due to the sensitivity of bank stock returns to *Liquidity Risk* using the minimum (γ_{min}) and maximum (γ_{max}) sensitivity from different model specifications shown in prior tables. *Incremental* $LRMES\text{-}C_{min}$ *(%)* is calculated as *Liquidity Risk x* γ_{min}. *Incremental* $SRISK^{LRMES\text{-}Cmin}$ is calculated as (1 – 8%) *x Liquidity Risk x* γ_{min} *x MV* where MV is market value of bank equity. Other variants are calculated accordingly. In Panel D, we show the Conditional SRISK (*SRISK-C*) which is the sum of *Incremental* $SRISK^{CL}$ and *Incremental* $SRISK^{LRMES\text{-}C}$. All variables are defined in Appendix III.

Panel A. Estimating the drawdown rates in a stress scenario

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

Panel B. Incremental $SRISK^{CL}$

Name	Unused C&I Commitments (USD mn)	Incremental $SRISK^{CL}$ with Drawdown rate: 25.79%	Incremental $SRISK^{CL}$ with Drawdown rate: 39.97%	Debt (USD mn)
JPMORGAN CHASE & CO.	273,278	5,638	8,738	2,496,125
BANK OF AMERICA CORPORATION	310,824	6,413	9,939	2,158,067
CITIGROUP INC.	200,912	4,145	6,424	1,817,838
WELLS FARGO & COMPANY	198,316	4,092	6,341	1,748,234
GOLDMAN SACHS GROUP, INC., THE	111,247	2,295	3,557	913,472
MORGAN STANLEY	78,411	1,618	2,507	818,732
U.S. BANCORP	96,020	1,981	3,070	433,158
TRUIST FINANCIAL CORPORATION	86,995	1,795	2,782	204,178
PNC FINANCIAL SERVICES GROUP, INC., THE	84,238	1,738	2,694	358,342
CAPITAL ONE FINANCIAL CORPORATION	18,618	384	595	320,520
Top 10 BHC	1,458,858	30,099	46,648	11,268,666
Vlab BHC	1,777,617	36,676	56,841	14,524,200
All BHC	1,837,220	37,906	58,747	

Panel C. Incremental SRISK^{LRMESC}

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

Panel D. SRISK^{C} (USD mn)

Name	SRISK (Q4 2019) w/o neg SRISK	w/ neg SRISK	SRISK-C_{min}	SRISK-C_{max}
JPMORGAN CHASE & CO.	0	-27,848	34,050	58,014
BANK OF AMERICA CORPORATION	14,898	14,898	32,465	55,122
WELLS FARGO & COMPANY	24,425	24,425	21,704	36,887
CITIGROUP INC.	60,887	60,887	24,835	42,308
AMERICAN EXPRESS COMPANY	0	-35,344	5,688	9,864
U.S. BANCORP	0	-19,352	15,711	26,883
MORGAN STANLEY	28,302	28,302	5,398	9,064
GOLDMAN SACHS GROUP, INC., THE	38,774	38,774	9,766	16,515
TRUIST FINANCIAL CORPORATION	0	-23,608	11,738	20,026
PNC FINANCIAL SERVICES GROUP, INC., THE	0	-9,895	10,666	18,179
Total (Top 10 Banks)	167,287	51,238	172,020	292,863
Total (Vlab Banks)	195,033	40,994	205,113	348,975
Total (All Sample Banks)			215,318	366,446

Appendix I. Example – Drawdowns during COVID-19

Ford | NEWS

www.twitter.com/ford www.facebook.com/ford www.instagram.com/ford www.medium.com/@ford

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

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

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

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

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

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

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

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

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

Appendix II. Sample Banks

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

Appendix III. Variable definitions

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

	1-e^((-18×MES)), where MES is the one-day loss expected in bank i's return if market returns are less than -2%	
$LRMES^C$	Contingent marginal expected shortfall due to the impact of liquidity risk on bank stock returns.	Call Reports, CRSP
MV Loss Covid	Market equity loss during the 1/1/2020 – 3/23/2020 period (USD mn) as % of market equity as of 1/1/2020	CRSP
Net Drawdowns	Absolute change in banks' unused C&I commitments minus the change in deposits (% Assets) over the same period	Call Reports
Non-Interest Income	Non-interest-income (%Operating revenues)	Call Reports
NPL / Loans	Non-performing loans (%Loans)	Call Reports
Post	Post is defined as the period starting April 1, 2020	
Ratings: Not Rated, AAA-A, BBB, NonIG Rated	Indicator variables equal to 1 if firms are in either rating category	CapitalIQ
Real Estate Beta	Slope of the regression of weekly excess stock returns on the Fama and French real estate industry excess return in a regression that controls for the MSCI World excess return	CRSP
Repayments	Total repayment of credit lines by customers in Q2 as % of 2019Q4 commitments	CapitalIQ, Dealscan
Return 1/1-3/23/2020	Cumulative stock return from January 1 to March 23, 2020; log excess returns are calculated as the log(1 + r - r_f), where r is the simple daily return (based on the daily closing price, adjusted for total return factor and daily adjustment factor), and r_f is the 1-month daily Treasury-bill rate	CRSP
ROA	Return on assets: Net Income / Assets	Call Reports
S&P 500 Return	(Daily) excess return of the S&P 500 index; log excess returns are calculated as the log(1 + r - r_f), where r is the simple daily return (based on the daily closing price, adjusted for total return factor and daily adjustment factor), and r_f is the 1-month daily Treasury-bill rate	CRSP
SMB	Fama-French-Factor: Small-minus-Big (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_bench_factor.html)	Ken French Website
SRISK	Bank capital shortfall in a systemic crisis as in Acharya *et al.* (2012); See NYU Stern Volatility & Risk Institute, https://vlab.stern.nyu.edu/welcome/srisk, Acharya et al. (2016) and Brownlees and Engle (2017) for definition and estimation of LRMES and SRISK.	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

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

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

Variable name	**Explanation**
Stock Performance	20 industries with worst stock performance as in Fahlenbrach *et al.* (2021)
COVID industries	Firms that are part of the Fama-French 49 industries identified by Moody's (2020) as particularly exposed to COVID-19.
Customer share	Customer share as defined by Koren and Peto (2020) at the three-digit NAICS level. Measures the percentage of workers in customer-facing occupations. Exposed firms belong to industries in the top quartile of the customer share distribution.
Telework	Share of jobs that can be performed at home from Dingel and Neiman (2020), defined at the three-digit NAICS industry level. Exposed firms are part of industries in the bottom quartile of the distribution.
Manual classification	Manual classification of industries at the six-digit NAICS level. These are the firms we manually classified as highly affected in Fahlenbrach *et al.* (2021).
Presence Share	Presence share as defined by Koren and Peto (2020) at the three-digit NAICS level. Measures the percentage of workers in occupations requiring physical contact. Exposed firms belong to industries in the top quartile of the presence share distribution.
Teamwork Share	Teamwork share as defined by Koren and Peto (2020) at the three-digit NAICS level. Measures the percentage of workers in teamwork-intensive occupations. Exposed firms belong to industries in the top quartile of the teamwork share distribution.
YoY Sale Decline	Q2 2020 year-on-year change in sales, defined at the firm level. Exposed firms are the ones in the bottom quartile of the change in sales.
Abnormal employment decline	Abnormal employment decline in the industry between 2019:Q2 and 2020:Q2 at the three-digit NAICS level as in Chodorow-Reich *et al.* (2022). Exposed firms belong to industries in the top quartile of the distribution.
Physical proximity	To what extent does this job require the worker to perform job tasks in close physical proximity to others (at the three-digit NAICS)? Based on ONET survey. Exposed firms belong to industries in the top quartile of the distribution.
Face-to-face discussion	How often do you have to have face-to-face discussions with individuals or teams in this job (at the three-digit NAICS)? Based on ONET survey. Exposed firms belong to industries in the top quartile of the distribution.
External customers	How important is it to work with external customers (at the three-digit NAICS)? Based on ONET survey. Exposed firms belong to industries in the top quartile of the distribution.