When Liquidity Matters: Firm Balance Sheets during Large Crises*

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March 11, 2026

Abstract

We study how aggregate shocks shape the joint dynamics of credit spreads, debt, and liquid asset holdings for nonfinancial firms, focusing on the Great Financial Crisis (GFC) and COVID-19. Both episodes saw sharp credit spread increases and investment declines, but debt and liquidity fell during the GFC and rose during COVID-19. Cross-sectionally, leverage drove spreads and investment in the GFC, while liquidity dominated during COVID-19. We build a macro-finance model of firm capital structure with a liquidity motive for working capital. Calibrated to data, it attributes the GFC to real and financial shocks, while liquidity shocks also play a role during COVID-19.

JEL Classification: E6, G2

Keywords: Credit Spreads, Liquidity, Great Recession, COVID-19

*We thank David Andolfatto, Borağan Aruoba, Carlos Garriga, Priit Jeenas, Fernando Martin, Pablo Ottonello, Juan Sanchez, and Chris Waller for comments and suggestions. We also thank participants at seminars and conferences for helpful comments. We thank Samuel Jordan-Wood for his valuable assistance with the data. This work employed resources from the BigTex High Performance Computing Group at the Federal Reserve Bank of Dallas. The views expressed here are those of the authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or its Board of Governors. This paper was previously titled "Credit and Liquidity Policies during Large Crises." First version: September 28, 2020.

1 Introduction

Large crises tend to be associated with financial market disruptions that hamper firms' ability to borrow and invest (Reinhart and Rogoff, 2009). In this paper, we study how different large aggregate shocks influence the joint determination of credit spreads, debt, and liquid asset holdings for nonfinancial firms. The effectiveness of alternative policies in mitigating crises may depend not just on the nature of the underlying shocks but also on how they affect firms with heterogeneous financial characteristics. The analysis of aggregate and cross-sectional patterns is therefore relevant to identifying underlying shocks and designing effective credit and liquidity policies.

We study the behavior of firms' borrowing conditions and investment over two large recent crises, the Great Financial Crisis of 2008-09 (GFC) and the COVID-19 crisis of 2020. Both crises featured significant increases in firm borrowing costs and large drops in investment. Aggregate corporate debt and liquid asset holdings, however, moved in different directions during these two events. While debt and liquid assets both decreased during the GFC, they increased during COVID-19. First, we conduct an empirical analysis of how firm balance-sheet positions affected the response of borrowing conditions and investment at the firm level. Then, we develop a quantitative dynamic macro-finance model of firm balance sheets and capital structure to study the joint determination of leverage, liquidity, and investment. We show how confronting the model's aggregate and cross-sectional predictions with the data helps disentangle the nature of the prevalent shocks during the GFC and COVID-19.

Section 3 empirically studies how leverage and liquid asset holdings affect firms' borrowing conditions in the cross-section. We construct a panel of maturity-matched corporate credit spreads for US nonfinancial corporations that covers the GFC and the COVID-19 periods, in the spirit of Gilchrist and Zakrajsek (2012). We augment the panel with firm-level financials from Compustat. We find that firms entering the GFC with more leverage tended to experience more significant increases in credit spreads, while measures of liquidity did not seem to play any significant role. On the other hand, during the COVID-19 crisis, firms entering the crisis with higher liquid asset ratios experienced smaller increases in credit spreads, with leverage also playing a significant but more muted role. We find qualitatively similar effects of leverage and liquidity on firm-level investment rates across the two crises.

We also provide empirical evidence on the role of liquid assets in meeting working capital needs and their relationship to firms' short-term borrowing behavior. First, we show that firms with higher levels of liquid assets exhibit greater volatility in working capital needs. Second, we find that firms with lower liquid asset holdings rely more heavily on short-term borrowing in response to fluctuations in working capital needs, and that this behavior was amplified during the COVID-19 crisis.

Section 4 develops a quantitative macro-finance model where credit spreads, leverage, liquid asset holdings, and investment are endogenously determined. The goals of the model are to: (i) develop a framework that is consistent with the aggregate and cross-sectional facts that we present in the empirical sections of the paper, and (ii) perform counterfactual analyses that shed light in the nature of the aggregate shocks that were hitting the economy during each of the two crises we analyze. We take a standard, off-the-shelf, dynamic model of firm capital structure and investment and extend it to give a meaningful role to funding liquidity, in the spirit of Holmström and Tirole (1998). Firms invest in physical capital subject to adjustment costs, issue defaultable debt, and hold liquid assets for precautionary motives. While liquid assets are dominated in terms of rate of return, they are useful for satisfying a stochastic working-capital constraint. The only alternative way of satisfying this constraint is to undertake costly intraperiod borrowing. Firms are ex-ante heterogeneous with respect to their liquidity and leverage needs, as well as to their idiosyncratic risk, which generates cross-sectional variation in their responses to shocks.

Section 5 calibrates the economy in the steady state to match aggregate and cross-sectional moments. We capture the joint distribution of liquidity, leverage, and credit spreads of US nonfinancial corporations. The model matches aggregate intraperiod borrowing and its cost as well as aggregate profitability, and can match non-targeted aggregate moments such as debt-to-income, and the default rate.

Section 6 uses the model as a laboratory to study macro-financial crises at the aggregate and cross-sectional levels. We consider real TFPR shocks, financial shocks that affect firms' ability to issue debt, and liquidity shocks that tighten the working-capital constraint. By choosing shocks that replicate the movements of aggregate variables in the data, we show that the model also replicates the cross-sectional patterns found in the data for the COVID-19 crisis, even though these moments are untargeted. In addition, we show that the liquidity shock is essential to rationalize the joint movement of credit spreads, liquid assets, and borrowing that we observe during this crisis. We show that a crisis without the liquidity shock can generate the comovement of the aggregate variables and the cross-sectional patterns that we empirically estimate for the GFC, suggesting that this crisis mainly resembled a combination of real and financial shocks without a strong liquidity component.

To summarize, this paper makes two contributions. First, on the empirical side, we document the relevance of liquidity for financial and real firm-level outcomes during GFC and COVID-19. Second, on the positive side, we build a model that is consistent with both aggregate and cross-sectional empirical facts, with emphasis on the role of firms' liquid asset holdings.

Literature. This paper is related to a large body of literature that combines data and models to understand the effects of large shocks on the distribution of firms and how that distribution shapes the aggregate response of the economy. Kudlyak and Sánchez (2017) extend the seminal analysis of Gertler and Gilchrist (1994) to the GFC and study the behavior of small and large firms during this period. Ottonello and Winberry (2020) show how the response of investment to monetary policy shocks depends on the distribution of firm leverage and distance to default.

Jeenas (2019) also studies a similar question but focuses on firms' financial portfolios, finding that not just firm leverage but also holdings of liquid assets are important for the transmission of monetary policy shocks. While we do not specifically focus on monetary policy shocks, our analysis is related to theirs, as we argue that the distribution of leverage and liquidity is important for the transmission of aggregate shocks. Bolton et al. (2014) and Nikolov et al. (2019), among others, also provide microfoundations for firm holdings of liquid assets. Our mechanism is closely related to Xiao (2022), where firms hold liquid assets to finance investment opportunities in an intermediate period when external debt issuance is not possible. In our framework, a similar role is played by a working capital constraint, which firms can satisfy using either liquid assets or costly intraperiod borrowing. Relative to this paper, we make two contributions. First, we provide direct empirical evidence supporting the mechanism, documenting the importance of liquidity for meeting working capital needs and showing that firm liquidity positions mattered during the COVID-19 crisis but not as much during the GFC. Second, we quantitatively compare the role of liquidity across both crises, finding it to be much more relevant during COVID-19, whereas Xiao (2022) focuses only on the GFC.

Our work is related to Crouzet and Gourio (2020), who study the financial position of US public companies before and during the pandemic. Their analysis emphasizes the COVID-19 crisis as an earnings shock and the risks it posed to US corporations. We find that funding liquidity seems to have been a significant driver of changes in corporate borrowing costs during the pandemic, even more so than pre-pandemic solvency conditions. Ramelli and Wagner (2020) find that firms that entered the COVID-19 pandemic with more leverage and fewer cash holdings experienced more significant drops in market value; this is consistent with our empirical findings for corporate bond spreads and investment rates.

Our work is also related to a body of empirical work that studies the impact of Fed policies on secondary corporate bond markets during the pandemic. Kargar et al. (2021) study the evolution of liquidity conditions in corporate bond markets during the pandemic and its aftermath. Boyarchenko et al. (2022) and Gilchrist et al. (2024) study the effects of the Fed's programs in 2020 on corporate credit spreads, analyzing the same type of maturity-matched spreads that we study in this paper, based on Gilchrist and Zakrajsek (2012). Both studies find significant positive effects of these programs. We complement these authors' analysis by focusing on the determinants of credit spread increases before Fed interventions.

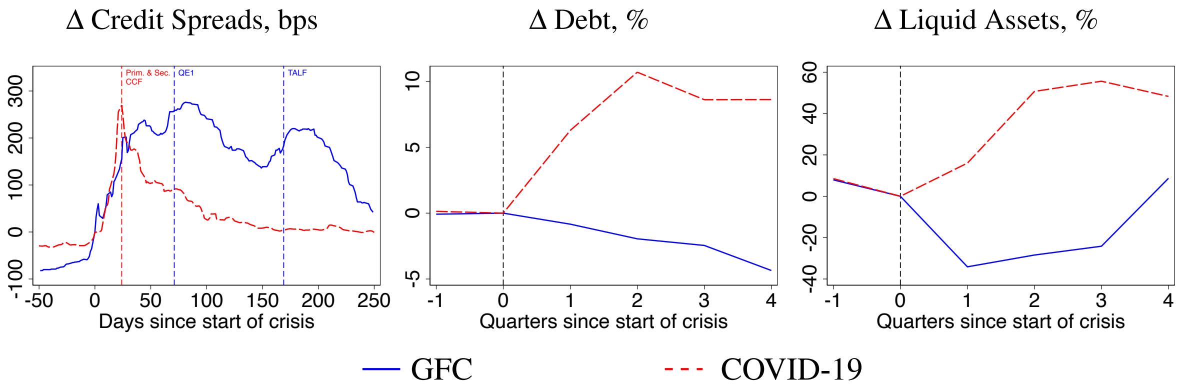
Finally, we relate to a growing literature that uses microdata to learn about the sources of aggregate fluctuations (Bayer et al., 2024; Mongey and Williams, 2017). As in these papers, we exploit variation in the cross-section to infer the nature of aggregate shocks. Bayer et al. (2024) uses household-level data to estimate macroeconomic shocks. Closer to our application, Mongey and Williams (2017) looks at firm-level data but focuses on real variables throughout business cycles, while we look at financial variables during large crises.

2 Aggregate Dynamics of Spreads, Debt, and Liquid Assets

We begin by studying the joint dynamics of aggregate credit spreads, debt, and liquid asset holdings of US nonfinancial corporations around the GFC and the COVID-19 crisis. We take the ICE Bank of America US Corporate Index Option-Adjusted Spread as a measure of aggregate credit spreads. For debt and liquid assets, we look at Flow of Funds data.[1] Figure 1

[1]Credit spread data are taken from FRED, series BAMLC0A0CM. Debt is the sum of debt securities (FL104122005) and loans (FL104123005). Liquid assets are equal to checkable deposits and currency (FL103020000). Debt and liquid assets are deflated using the GDP deflator (GDPDEF in FRED). Time series are plotted in Appendix A.1. Our findings are robust to using a broader definition of liquid asset holdings encompassing foreign deposits, time and savings deposits, and money market fund shares.

Figure 1: Aggregate Spreads, Debt and Liquid Assets



Notes: Blue solid lines are for GFC, and red dashed lines are for COVID-19. The first panel shows credit spreads; day 0 corresponds to the beginning of the increase in volatility (bankruptcy of Lehman Brothers for GFC on September 15, 2008, and February 28, 2020, for COVID-19). Vertical lines correspond to major Federal Reserve intervention announcements for corporate credit markets (11/25/2008, 03/03/2009, and 03/23/2020). The second and third panels show real total debt and liquid asset holdings. Vertical black dashed lines correspond to 2008Q3 and 2019Q4. Data sources: Financial Accounts of the United States and FRED.

shows the path of credit spreads, real debt, and liquid assets as deviations from their values at the onset of each of the crises.[2]

In terms of credit spreads, the onset of each crisis was relatively similar, with increases of around 300 basis points (bps). Overall, there are two critical differences between the behavior of credit spreads in these two events: (i) the GFC was slower moving, with credit spreads rising and remaining elevated for almost a year after the beginning of the crisis, and (ii) the Fed's announcements seem to have had a more negligible effect in containing spreads in 2008 than in 2020.[3]

The movements of debt and liquid assets, however, were significantly different between the two crises: while debt and liquid asset holdings fell at the onset of the GFC, both of these variables increased sharply at the beginning of the COVID-19 crisis. Real debt grew by over 10% during the COVID-19 period, while it dropped by about 5% four quarters into the GFC. Liquid assets experienced a jump of about 50% during the COVID-19 crisis, while liquid asset

[2] Credit spreads are in bps deviations, and debt and liquid assets are in percentage deviations. Credit spread data are available daily, so we use as a starting point the collapse of Lehman Brothers—September 15, 2008—and the start of the COVID-19 crisis—February 28, 2020. Debt and liquid assets data are quarterly, so we define the deviations relative to 2008Q3 for the GFC and 2019Q4 for COVID-19.

[3] The figure also displays the dates of major policy interventions that may have had a significant impact on credit spreads: the announcements of QE1 (November 25, 2008) and the Term Asset-Backed Securities Loan Facility (TALF, March 3, 2009) in the case of the GFC, and the announcement of the Primary and Secondary Corporate Credit Facilities (CCF) in the case of COVID-19 (March 23, 2020).

holdings fell during the first three quarters of the GFC by about 30%. While they recovered by the fourth quarter after the GFC, the opposite movements for these two variables during these two events are very noticeable.

The patterns observed during the GFC are consistent with a traditional interpretation of financial crisis that manifests itself via credit supply shocks. As credit become more expensive due to fragilities in the financial sector, firms reduce their borrowings and deplete their liquid asset buffers. The opposite co-movement of credit spreads, debt and liquid asset holdings suggest that an additional shock was in place during the COVID-19 crisis that may have boosted credit demand and the accumulation of liquid assets in spite of rising spreads. For example, Bosshardt and Kakhbod (2021); Chodorow-Reich et al. (2022); Crouzet and Gourio (2020); Greenwald et al. (2023) show that during the COVID-19 period, firms drew from their credit lines due to precautionary motives. Therefore, these co-movements are consistent with a shock that increases the liquidity needs of firms. In the next sections of the paper we formalize these hypotheses with micro data as well as a quantitative model.

It is worth emphasizing that the increase in debt during COVID-19 primarily came from private lenders as opposed to government policy. A prominent policy intervention (the PPP) led to an increase in loans. In Appendix A.1, we show that the increase in debt was driven both by loans as well as debt securities, the latter of which are independent of the PPP.

3 Firm-Level Empirical Evidence

The aggregate data shows that while credit spreads increased in both episodes, there were very different dynamics for the corporate sector's debt and liquid asset holdings, which fell during the GFC but rose sharply during the COVID-19 crisis. In this section, we investigate this change in comovement by exploring how leverage and liquidity interacted with corporate credit spreads at the firm level. We construct a panel of maturity-matched US corporate credit spreads and show that there seem to be systematic cross-sectional relationships between corporate credit spreads and firm leverage and liquidity that changed during these two events. In particular, we find that while pre-crisis leverage was the key determinant of changes in credit spreads in the cross-section firms during the GFC, liquidity also played an important role during the COVID-19 crisis (but not during the GFC).

3.1 Measurement

We construct a quarterly panel of US corporate bond spreads from 2002:Q2 to 2020:Q3. We closely follow Gilchrist and Zakrajsek (2012) in estimating credit spreads by first constructing synthetic securities, which mimic the cash flow of bonds but are discounted at the risk-free rate for the corresponding maturity. Our definition of credit spreads is the difference between the yield to maturity (YTM) of a corporate bond and the YTM of the corresponding synthetic bond. To estimate the credit spreads, we require secondary market prices, risk-free rates, and bond characteristics to reconstruct the cash flows for the observed bonds.

Corporate Bond Data. We obtain secondary market prices of corporate bonds from the TRACE database. TRACE provides transaction-level data on bond trades, with information on trade execution time, price, and quantity traded. We clean the TRACE data following Dick-Nielsen and Poulsen (2019), taking care of cancellations and reversals in reported transactions. We aggregate the transaction-level data to the weekly level, creating a weekly panel of bond prices.[4]

We obtain bond characteristics from the Mergent Fixed Income Securities Database (FISD), which covers a significant number of US corporate issues. We collect data on bond issuance and maturity dates, coupon, principal, and issuer. Then, we combine bond characteristics with weekly secondary market prices. For an issuer f, bond i, on week t in TRACE, we observe a trading price p_{ift}, and with FISD's data on bond characteristics we can construct cash flows $\{C_{ifs}\}_{s=t_{0i}}^{s=T_i}$, where t_{0i} and T_i are the issuance and maturity dates of bond i, respectively.

Credit Spreads. Let y_{ift} be the annualized YTM of a bond, which solves the following equation:

$$p_{ift} = \sum_{s=1}^{T_i - t} \frac{C_{ift+s}}{(1+y_{ift})^{s/52}}$$

As stated previously, to avoid duration mismatch between the YTM described and yields on Treasury securities, we follow Gilchrist and Zakrajsek (2012) in constructing a synthetic risk-free security that replicates the cash flows of a corporate bond. Let $y^{RF}_{t,s}$ be the yield on Trea-

[4]Weekly bond prices are the average trading price for a bond within a week, weighted by trade volume. We are using TRACE data recently released before further dissemination of trade information. As a consequence, for some large trades, only a lower bound on the quantity traded is reported.

suries at date t and maturity s, which we obtain from Gurkaynak et al. (2007).[5] Using the sequence of cash flows, we compute the price of the synthetic security as follows:

$$p^{RF}_{ift} = \sum_{s=1}^{T_i - t} \frac{C_{ift+s}}{(1+y^{RF}_{t,s})^{s/52}}$$

Then we compute the risk-free YTM for this synthetic price y^{RF}_{ift} by solving the following equation:

$$p^{RF}_{ift} = \sum_{s=1}^{T_i - t} \frac{C_{ift+s}}{(1+y^{RF}_{ift})^{s/52}}$$

Finally, the maturity-adjusted credit spread is the difference between the two computed yields:

$$s_{ift} = y_{ift} - y^{RF}_{ift} \tag{1}$$

We also follow Gilchrist and Zakrajsek (2012) in terms of sample selection. We keep only US nonfinancial corporate bonds, fixed- and zero-coupon bonds, bonds with credit spreads between 5 and 3500 bps, issuance amount greater than \$1 million, and maturity at issuance between 1 and 30 years.

Firm-Level Data. We merge our bond panel with quarterly firm financial data from Compustat. We use firm-ticker information from TRACE and Compustat to match issuers with their financial statements—we utilize the WRDS Bond-CRSP link. Table 1 describes the summary statistics for the final quarterly (unbalanced) sample of matched issues. We have about 63 thousand quarterly observations for 2 thousand firms and 18 thousand bonds. Appendix A.2 shows that the aggregate spreads that result from aggregating this micro data are very similar to those described in Figure 1.

For the analysis, we define credit spreads at the firm-level f as the average spread of outstanding bonds issued by a given firm, weighted by the size of those issuances:

$$s_{f,t} = \frac{\sum_{i=1}^{N_{ft}} b_{ift} s_{ift}}{\sum_{i=1}^{N_{ft}} b_{ift}}$$

where N_{ft} is the number of outstanding bonds of firm f at time t and b_{ift} is the outstanding

[5]Data can be downloaded from the Federal Reserve Board: https://www.federalreserve.gov/data/nominal-yield-curve.htm.

Table 1: Summary Statistics of Bond Panel

Variable	Mean	SD	Min	Median	Max
Number of bonds per firm/qtr	5.12	15.40	1.00	2.00	564.00
Market value of issue ($ mil)	906.58	2084.03	1.15	273.55	37719.53
Maturity at issue (years)	11.66	6.59	1.58	9.92	30.00
Coupon (pct)	7.13	2.65	0.00	7.32	19.00
Credit Spread (basis points)	392.32	460.40	5.01	251.00	3495.62
Nominal yield (basis points)	715.11	504.53	52.44	604.81	9321.60
Size ($ bil)	16.89	40.07	0.00	5.14	641.03
Investment Rate	0.02	0.08	-0.72	0.01	7.32
Liquidity	0.10	0.12	0.00	0.06	0.71
Leverage	0.37	0.19	0.02	0.34	1.19

Notes: The sample has 63,030 observations, 2,021 firms, and 18,255 bonds out of which 91% are callable. See text for details.

principal value of bond i. Finally, we define leverage as total debt (Compustat variables `dlcq` plus `dlttq`) divided by total assets (`atq` in Compustat), as a proxy for solvency, as is common in the literature. As a measure of funding liquidity, we focus on liquid assets (cash plus short-term investments, `cheq` in Compustat) divided by the firm's total assets. This measure captures the amount of resources that the firm has immediate access to.

In our sample, the average leverage ratio is 0.37, versus 0.34 in the full Compustat sample (non-financial firms). Average liquidity is 0.10, versus 0.20 in the full Compustat sample. Thus the firms in our matched sample have slightly higher leverage and lower liquidity, which is to be expected given that they have access to bond markets. The matched sample accounts for 85% of total sales and 91% of total assets in Compustat, and includes 2,021 firms out of a total of 11,468 firms.

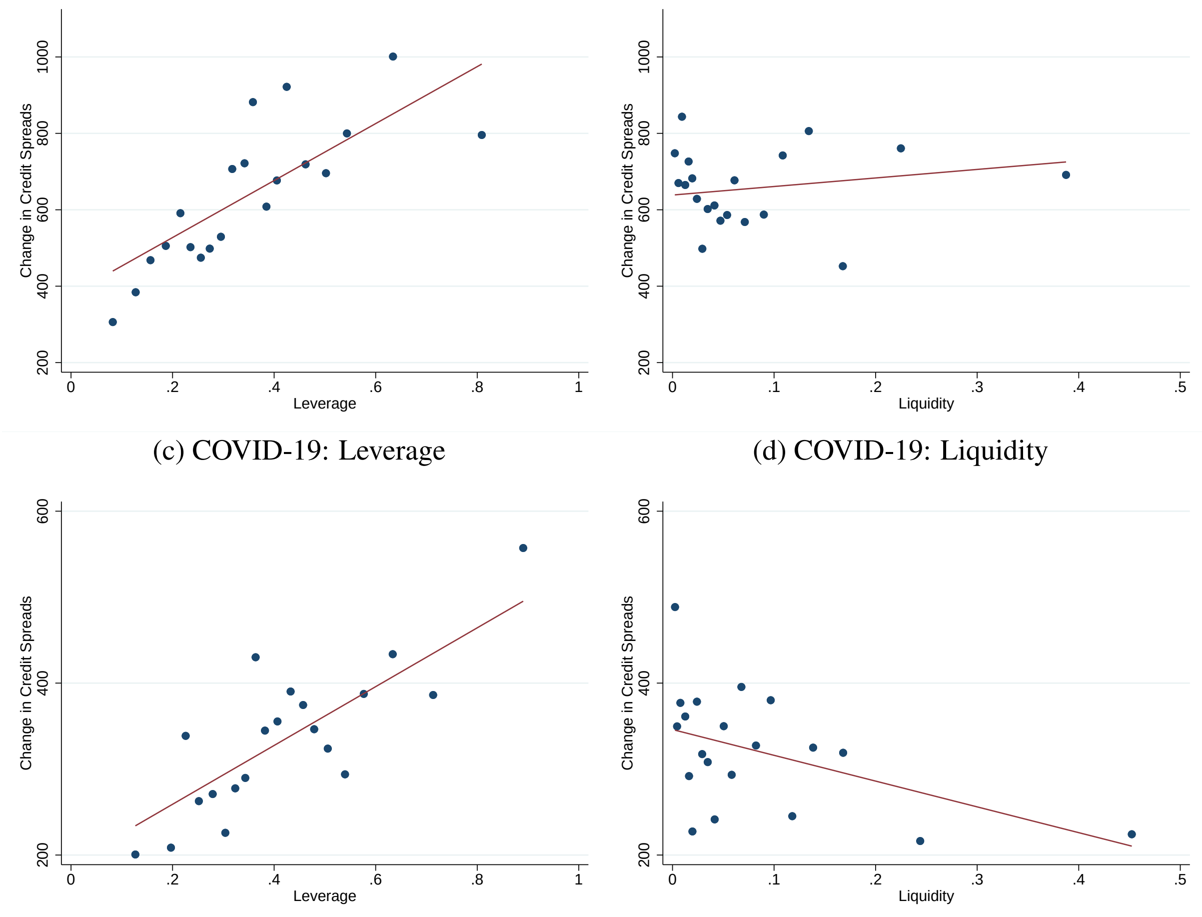
Investment. We follow the approach in Clementi and Palazzo (2019) to measure investment at the firm level. First, we construct a measure of capital: starting with an initial observation of the firm's capital stock, we cumulate net capital expenditures to construct a time series for capital. We then use depreciation to compute gross investment. Finally, we construct the investment rate as investment divided by lagged assets for that firm, following Begenau and Salomao (2018). Appendix A.3 provides more details on the construction of investment series.

3.2 Cross-Section of Leverage and Liquidity

We investigate whether there is a systematic relationship between credit spreads and firm-level characteristics during each crisis. We focus on two variables that are natural firm analogs to the aggregate measures of debt and liquid assets in Figure 1: (i) leverage and (ii) firm's holdings of liquid assets.

We begin with a non-parametric examination of the cross-section of changes in credit spreads during the GFC and COVID-19. For each crisis, we identify a pre-crisis and peak-crisis date. We then compute the average credit spread for the firm in a one-week window around these dates and take the difference to arrive at the change in credit spreads for the firm during the particular crisis.[6]

Figure 2: Binscatters: Credit Spreads, Leverage, and Liquidity



(a) GFC: Leverage (b) GFC: Liquidity

(c) COVID-19: Leverage (d) COVID-19: Liquidity

[6]We identify pre-crisis and peak-crisis following the aggregate time-series in Figure 1. For the GFC, the pre-crisis is the week before Lehman Brothers declared bankruptcy, and the peak of the crisis is the week of the QE1 announcement. For COVID-19, we identify the pre-crisis as the last week of 2019 and the peak as the first week of March 2020.

Our main interest is how relevant the pre-crisis value of liquidity and leverage is to the change in credit spreads. Figure 2 plots binscatters of the changes in credit spreads during the GFC and COVID-19 between pre-crisis and peak against the pre-crisis leverage and liquidity. First, Figures 2a and 2b show leverage and liquidity for the GFC, respectively. We see a positive relationship between leverage and change in credit spreads during the GFC. The change in credit spreads in the top bin is 500 basis points greater than the bottom bins for leverage. On the other hand, Figure 2b suggests little relevance of liquidity for the change in credit spreads of firms during the GFC.

Figures 2c and 2d show how leverage and liquidity matters during COVID-19. As in the GFC, there is a positive relationship between leverage and credit spreads. However, unlike the GFC, liquidity now appears relevant for credit spreads. Firms with greater levels of liquidity experienced smaller increases in their credit spreads during the pandemic. For example, the change in credit spreads in the top bin is 300 basis points lower than that in the bottom bins for liquidity.

Overall, this suggests a change in the comovement of credit spreads with leverage and liquidity between events. However, these binscatters do not control for other observable characteristics. In the next section we consider a formal empirical specification.

3.3 Cross-Sectional Elasticities: Credit Spreads

We now proceed with a formal econometric specification to study whether or not the comovement of credit spreads with leverage and liquidity changes between the GFC and COVID-19. We estimate the following panel regression:

$$y_{f,t} = \alpha_f + \gamma_t + \sum_{i \in \mathrm{E}} \beta_i \mathbb{I}_{t \in \mathrm{i}} \mathrm{liq}_{f,t-r} + \sum_{i \in \mathrm{E}} \phi_i \mathbb{I}_{t \in \mathrm{i}} \mathrm{lev}_{f,t-r} + \Gamma' X_{f,t} + \varepsilon_{f,t} \tag{2}$$

where $y_{f,t}$ is an outcome variable for firm f at quarter t, regressed on measures of liquidity and leverage at a lag of $r = 2$ quarters. E is a set of three different time periods, $\mathrm{E} = \{\mathrm{Normal}, \mathrm{GFC}, \mathrm{COVID\text{-}19}\}$. The indicator variable, $\mathbb{I}_{t \in i}$, identifies if quarter t falls into of the elements of E. We define the GFC as 2008:Q3 - 2009:Q2 and COVID-19 as 2020:Q1 - 2020:Q3, with the remaining quarters being "Normal."[7] The starting date for the GFC reflects the bankruptcy of Lehman Brothers in September 2008, while its end date corresponds

[7] Results are similar if we consider alternative definitions of the length of the GFC and COVID-19 crises.

to the announcement of TALF in March 2009, after which corporate credit spreads stabilize considerably.

Given the nature of the exercise, we use lagged regressors to avoid contemporaneity issues.[8] Leverage and liquidity may change over time, but we want to trace the differential effects for firms with different leverage and liquidity before quarter t. In addition, $X_{f,t}$ includes other firm-level controls such as firm size (log of total lagged assets), lagged average debt maturity, and lagged profitability measures, such as EBITDA to total assets.[9] We include a time fixed effect, α_t, and a firm fixed effect, γ_f. Finally, we cluster standard errors at the quarter level because aggregate shocks affect all firms but potentially affect each of them differently.[10]

Table 2 presents the estimation results of specification (2) for firm-level credit spreads, $y_{f,t} = s_{f,t}$. Column (1) shows the benchmark results: in normal times, firms with higher leverage have higher spreads, while firms with higher liquidity have lower spreads. There are two important differences between the GFC and COVID-19. First, while leverage is a significant predictor of higher spreads during both crises (as well as during normal times), the impact is quantitatively larger during the GFC. An increase in leverage of one standard deviation (0.19, see Table 1) is associated with an increase in spreads of 225 bps during the GFC (i.e., 0.19×1183) , 144 bps during COVID-19, and 91 bps during normal times. Second, funding liquidity seems to have significantly helped curb higher credit spreads during the COVID-19 crisis, but not during the GFC. The coefficient for the GFC is not statistically different from zero. An increase in liquidity of one standard deviation (0.12, see Table 1) implies a decrease in the credit spread of 45 bps during COVID-19, twice as much as during normal times (22 bps). The second and third columns show that the results are robust to including additional controls such as average maturity of outstanding issuances and a standard measure of firm profitability (EBITDA to assets). The last column shows that the results are robust to splitting the normal times period into pre- and post-GFC periods.

The two panels of Figure 3 summarize the benchmark cross-sectional results. Leverage is always statistically significant, but the corresponding coefficient is larger during the GFC

[8] Appendix A.5 shows regressions using contemporaneous explanatory variables instrumented by their lagged analogs. This strategy follows earlier empirical literature on investment and cash flows such as Fazzari et al. (1988) and Gilchrist and Himmelberg (1995).

[9] Our benchmark specification does not not interact the control variables with the period indicator variable, but our results are robust to doing it.

[10] We experimented with lags of 4 and 6 quarters and found similar results. We also estimated repeated cross-sectional regressions and found similar results.

Table 2: Panel Regressions of Credit Spreads

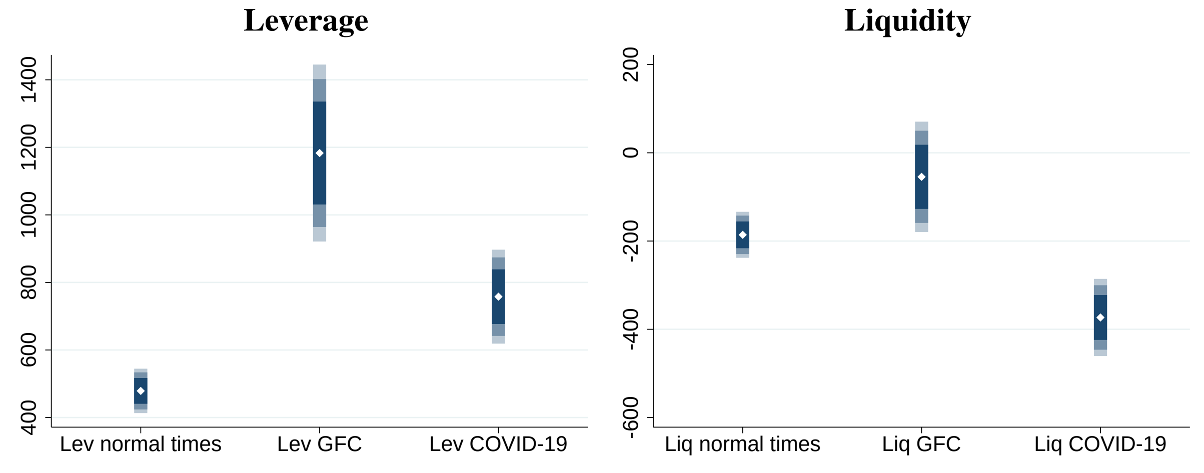
	(1)	(2)	(3)	(4)
Leverage				
Normal	478.865***	479.834***	435.077***	
	(32.944)	(32.860)	(30.977)	
Before GFC				340.053***
				(38.749)
After GFC				549.221***
				(34.140)
GFC	1183.048***	1184.561***	1138.516***	1170.753***
	(131.317)	(130.794)	(133.049)	(133.695)
COVID-19	757.770***	758.018***	691.462***	787.965***
	(69.695)	(69.580)	(59.634)	(69.306)
Liquidity				
Normal	-186.055***	-185.901***	-182.213***	
	(26.134)	(26.158)	(28.944)	
Before GFC				-165.512***
				(39.404)
After GFC				-195.613***
				(24.829)
GFC	-54.484	-55.652	-18.860	-57.279
	(62.690)	(62.983)	(67.920)	(61.155)
COVID-19	-373.366***	-373.808***	-347.538***	-384.192***
	(43.871)	(43.989)	(44.131)	(42.374)
Controls	Size	Size, Maturity	Size, Maturity, EBITDA	Size, Maturity
N	46532	46532	44430	46532
R^2	0.67	0.67	0.68	0.67

Notes: Regressions include both firm and quarter fixed effects. Standard errors are clustered by quarter. See appendix for data construction details. Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. *The dependent variable is credit spreads in basis points, while leverage and liquidity are in ratios.*

than during normal times or during COVID-19. Instead, liquidity was more important during COVID-19 and non-significant during the GFC. Table 3 presents the p-values for tests of equality of coefficients, where the null hypothesis is that the coefficients during the GFC and the COVID-19 crisis are equal to those in normal times. The table confirms that leverage has a different impact on spreads in each of the crises relative to normal times. While liquidity seems to have an unambiguously different impact during the COVID-19 recession, the same is not as clear for liquidity during the GFC (with a p-value of 5%).[11]

[11] For the sake of completeness, we conducted tests for equality of leverage and liquidity coefficients between GFC and COVID-19. We reject the hypothesis at the 95-percent confidence level.

Figure 3: Credit Spreads Coefficients



Notes: Regression of leverage and liquidity on credit spreads and investment. The different bar colors represent 75%, 90%, and 95% confidence intervals.

Table 3: p-values for Test of Equality of Coefficients

	$s_{f,t}$	$inv_{f,t}$
Leverage GFC	0.00	0.25
Leverage COVID	0.00	0.93
Liquidity GFC	0.05	0.39
Liquidity COVID	0.00	0.00

Notes: The null hypothesis is that the coefficients during the GFC and the COVID-19 crisis are equal to those during normal times.

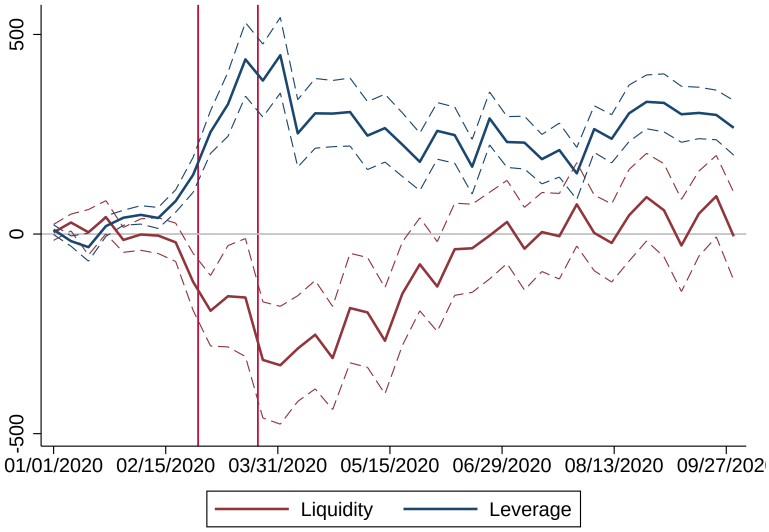
An Event Study of COVID-19. We also study the evolution of credit spreads during 2020 at a weekly frequency. We define leverage and liquidity as their values at the end of 2019Q4. Similarly, we define the changes in credit spreads relative to their values on January 1, 2020. We focus on a repeated cross-section version of our main specification, and so for each week t we estimate the following cross-sectional regression:

$$\Delta s_{f,t} = \alpha_s + \beta_t \text{liq}_f + \phi_t \text{lev}_f + \Gamma' X_f + \varepsilon_{f,t} \tag{3}$$

where $\Delta s_{f,t} = s_{f,t} - s_{f,t_0}$ for t_0 being January 1, 2020. We control for firm size in 2019Q4 and include two-digit NAICS sector fixed effects, α_s. Note that we include a sector instead of a firm fixed-effect because leverage and liquidity are pre-determined at the firm level.

Figure 4 plots the value of the estimated coefficients over time. The two vertical lines cor-

Figure 4: Event Study: Credit Spreads During COVID-19



Notes: Coefficient estimates from (3) *and one-standard-deviation confidence intervals. The vertical lines correspond to the weeks of February 28 and March 23, respectively.*

respond to the last week of February (the beginning of the COVID-19 crisis) and the week of March 23, when the Federal Reserve made a series of policy announcements. The figure shows that the relationships between leverage and liquidity and credit spreads become positive and negative, respectively, at the time of the shock and before the policy announcements. In fact, these coefficients increase in absolute value until a few weeks after the policy announcement date when they begin decreasing. These results suggest that the effects we find on the quarterly panel regressions are not primarily driven by policy, as both leverage and liquidity were important for credit spreads during the early weeks of March when COVID-19 was already present but no policies had yet been announced.

3.4 Cross-Sectional Elasticities: Investment

Table 4 shows the results of specification (2) for investment rates as the outcome variable, $y_{f,t} = inv_{f,t}$. During normal times, lower leverage and higher liquid asset holdings are associated with higher investment rates. An increase in leverage of one standard deviation is associated with a decrease in investment rates of about 0.5 percentage points (pp) in normal times as well as during COVID-19. During the GFC the impact is even larger, of about 0.7 pp. Liquidity, however, seems to have played a different role in each of these periods: the coefficient on liquidity during the GFC is similar in magnitude to that of normal times. During the

Table 4: Panel Regressions of Investment Rate

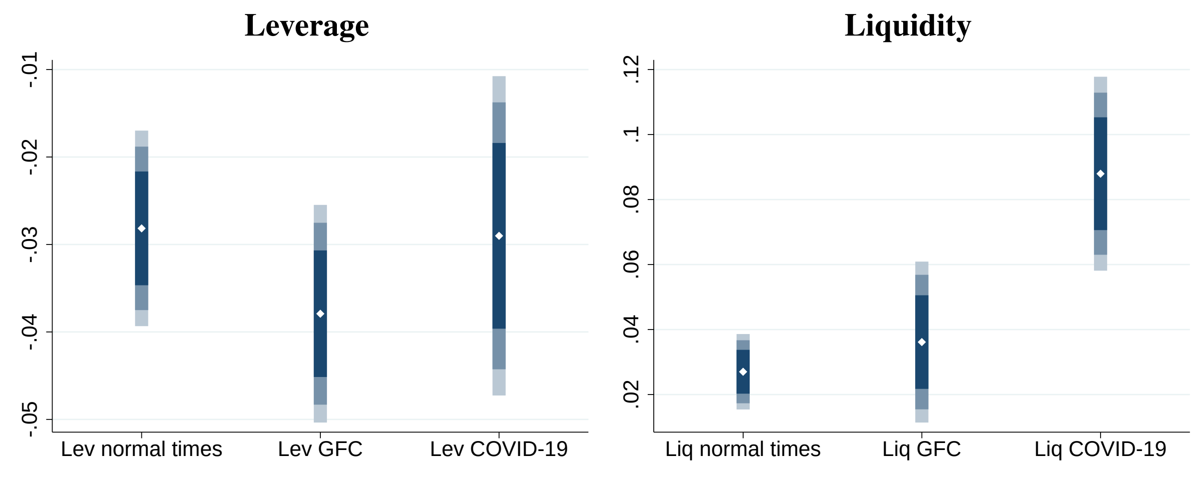
	(1)	(2)	(3)	(4)
Leverage				
Normal	-0.028***	-0.028***	-0.021***	
	(0.006)	(0.006)	(0.007)	
Before GFC				-0.035***
				(0.005)
After GFC				-0.025***
				(0.007)
GFC	-0.038***	-0.038***	-0.028***	-0.039***
	(0.006)	(0.006)	(0.006)	(0.006)
COVID-19	-0.029***	-0.029***	-0.021**	-0.028***
	(0.009)	(0.009)	(0.010)	(0.009)
Liquidity				
Normal	0.027***	0.027***	0.026***	
	(0.006)	(0.006)	(0.006)	
Before GFC				0.014**
				(0.006)
After GFC				0.034***
				(0.006)
GFC	0.036***	0.036***	0.038***	0.034***
	(0.012)	(0.012)	(0.013)	(0.012)
COVID-19	0.088***	0.088***	0.082***	0.092***
	(0.015)	(0.015)	(0.015)	(0.015)
Controls	Size	Size, Maturity	Size, Maturity, EBITDA	Size, Maturity
N	43125	43125	42595	43125
R^2	0.099	0.099	0.11	0.099

Notes: Regressions include both firm and quarter fixed effects. Standard errors are clustered by quarter. See appendix for data construction details. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

COVID-19 crisis, liquidity becomes more important. An increase in liquidity of one standard deviation is associated with an increase in investment rates of about 0.3, 0.4, and 1.1 pp in normal periods, GFC, and COVID-19, respectively. The other columns show that the results are robust to adding additional controls and to splitting normal times into pre- and post-GFC periods. Appendix A.4 shows that the results are robust to alternative definitions of investment.

The two panels of Figure 5 summarize the benchmark cross-sectional results. For investment, leverage has a similar impact across different periods, while liquidity is more important during COVID-19. The second column of Table 3 presents the p-values for tests for the equality of coefficients, where the null hypothesis is that the coefficients during the GFC and the COVID-19 crisis are equal to those during normal times. The table shows that only liquidity

Figure 5: Investment Coefficients



Notes: Regression of leverage and liquidity on credit spreads and investment. The different bar colors represent 75%, 90%, and 95% confidence intervals.

seems to play a statistically different role during the COVID-19 period in terms of affecting investment rates.

3.5 Liquidity and Shocks to Working Capital

Our empirical analysis suggests that, during the pandemic, firms with relatively less liquid assets experienced larger increases in credit spreads. In this section, we examine a potential channel connecting liquidity and credit spreads: shocks to working capital.

In their day-to-day operations, firms actively manage cash flows to meet payment obligations while collecting receivables from customers. On the revenue side, inflows primarily arise from payments for goods sold or services rendered, either (i) in cash or (ii) through trade credit, recorded as accounts receivable. On the expenditure side, firms regularly disburse funds to cover wages, utilities, taxes, and payments for intermediate inputs.

We proxy fluctuations in working capital needs by the change in accounts receivable relative to total assets. An increase in accounts receivable indicates that firms are receiving less cash for goods and services sold, creating a shortfall that may need to be covered through short-term credit or existing cash reserves. This measure is highly dispersed in our data, offering an important source of heterogeneity. Furthermore, a substantial share of the variation in working capital fluctuations cannot be explained by past values alone.[12]

While a natural alternative to our baseline proxy (gross accounts receivable) is a net mea-

[12]See Figure A3 in Appendix A.8.

sure of working-capital needs (e.g., receivables net of payables), we focus on gross receivables because our goal is to capture *exogenous* fluctuations in working-capital liquidity needs rather than overall working-capital position. Conceptually, accounts payable are not plausibly exogenous: firms can adjust payment timing and terms, so short-run movements in payables partly reflect active liquidity management, raising endogeneity concerns when payables are netted out. By contrast, changes in accounts receivable more mechanically translate into cash-collection shortfalls for goods already sold and, at quarterly frequency, are less directly and immediately manipulable. With firm and time fixed effects, our identification relies on within-firm deviations over time, so time-invariant differences in trade-credit policy and common aggregate shocks are absorbed.[13]

When a firm experiences an increase in working capital needs and has limited cash on hand, it may need to borrow more. Issuing short-term debt can raise default risk, thereby increasing credit spreads. First, we show that firms with higher levels of liquid assets exhibit greater volatility in working capital needs, consistent with the use of liquid assets to absorb adverse working capital shocks. Second, we show that short-term borrowing rises with trade receivables, with larger increases for firms with lower liquid assets, and these effects are amplified during the pandemic.

Volatility of working capital shocks. We begin by showing that firms with higher levels of liquid assets exhibit greater volatility in working capital needs. To measure this, we evaluate the dispersion of changes in accounts receivable relative to total assets at the firm level.

For each firm, we compute a one-year (four-quarter) rolling standard deviation of the working-capital shock measure. Table 5 reports the mean of this firm-level volatility measure in the full sample and separately for low- and high-liquidity firms. To make the comparison transparent, the table also reports 95% confidence intervals for the estimated means. These intervals illustrate that the difference in means between low- and high-liquidity firms is statistically significant.

Economically, we find that high liquidity firms have a working capital volatility measure that is 28% larger than that of low liquidity firms. We see this as being consistent with the

[13] As it will become clear in the model section, this interpretation also aligns better with our model structure: we view gross receivables as a proxy for the exogenous working-capital shock, whereas payables are closer in spirit to the endogenous short-term liquidity-management margin.

interpretation that firms with more liquid assets are better positioned to absorb fluctuations in working-capital needs.

Table 5: Volatility of working capital shocks & Liquid Assets

	Mean	95% CI
All	0.0291	[0.0290, 0.0293]
Low Liquidity	0.0256	[0.0254, 0.0259]
High Liquidity	0.0327	[0.0324, 0.0329]

Notes: For each firm we compute a one-year (four-quarter) rolling standard deviation of the working-capital shock measure. The table reports the mean of this volatility measure across firms, along with 95% confidence intervals for the mean.

Working capital shocks and short-term debt. To examine the effects of fluctuations in working capital needs on short-term borrowing, we estimate the following specification:

$$\text{short-term leverage}_{f,t} = \alpha_f + \gamma_t + \sum_{i \in \mathrm{E}} \beta_i \, \mathbb{I}_{t \in i} \, \Delta\text{working capital shock}_{f,t}$$
$$+ \sum_{i \in \mathrm{E}} \delta_i \, \mathbb{I}_{t \in i} \, \Delta\text{working capital shock}_{f,t} \, \mathbb{I}\left[\text{liq}_{f,t} > \text{median}_t(\text{liq}_{f,t})\right] + \Gamma' X_{f,t} + \varepsilon_{f,t},$$

where $\mathrm{E} = \{\text{Normal}, \text{GFC}, \text{COVID-19}\}$ denotes the set of three distinct time periods. The indicator $\mathbb{I}_{t \in i}$ identifies whether quarter t falls within period i. These time periods are identical to those used in Section 3.3.

The dependent variable, short-term leverage, is defined as debt maturing in less than one year divided by total assets. The main regressor is the year-to-year change in working capital needs, measured as described above. We also include an interaction term with an indicator for whether the firm's liquidity position is above the cross-sectional median in quarter t. The control vector $X_{f,t}$ contains sales and liquidity. Unobserved heterogeneity is addressed by including both firm and time fixed effects.

Table 6 reports the estimation results. Column (1) includes sales as a control, while Column (2) also controls for liquidity. In both specifications, firms experiencing an increase in receivables tend to exhibit higher short-term leverage. Moreover, the estimated coefficient is significantly larger during the COVID-19 period than in normal times or during the GFC. These effects are more pronounced for firms with lower liquidity. The interaction effect is strongest during COVID-19, but is not statistically significant during the GFC.

Table 6: Short-term Leverage and Change in Receivables

	(1)	(2)
Δ Receivables – Normal	0.149***	0.127***
	(0.014)	(0.014)
Δ Receivables – GFC	0.180***	0.163***
	(0.048)	(0.048)
Δ Receivables – Covid	0.252***	0.237***
	(0.079)	(0.078)
Δ Receivables × High Liq – Normal	-0.085***	-0.144***
	(0.018)	(0.018)
Δ Receivables × High Liq – GFC	-0.055	-0.102
	(0.063)	(0.062)
Δ Receivables × High Liq – Covid	-0.133	-0.250**
	(0.100)	(0.099)
Controls	log(Sales)	log(Sales), Liquidity
N	205148	205143
R^2	0.52	0.53

Notes: Regressions include both firm and quarter fixed effects. Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

In summary, our results suggest that there is a positive relationship between changes in working capital needs and short-term borrowings. This relationship is stronger for firms with low levels of liquidity. These forces seemed to be amplified during the pandemic crisis.

3.6 Robustness and Discussion

The main results are robust to several potential concerns. The first concern relates to the presence of outliers in the distribution of liquid asset holdings. Appendix A.6 shows that the results hold even when we drop outliers. The second concern is that firms with high liquidity might have more intangible capital and therefore may have been better able to operate remotely. This might explain why firms with high liquidity performed better during COVID-19. In Appendix A.6 we rule out this hypothesis by showing that our results hold when we control for intangible capital. Third, a significant fraction of the bonds in our sample are callable, which can contaminate the estimates of the credit spreads. In Appendix A.6 we follow the same methodology as in Gilchrist and Zakrajsek (2012) to control for the callability option using the Treasury term structure and we conclude that our results are robust to controling for callability. Finally, Appendix A.6 also studies the role of undrawn credit lines as potential liquidity. We show that cash and undrawn credit lines are not perfect substitutes, with the intuition being that firm debt increases as firms with undrawn credit lines tap them at the onset of a crisis. This may contribute to diluting existing bond holders and worsens the increase in spreads.

Overall, our findings suggest that the roles of firm leverage and liquidity in determining outcomes such as the cost of borrowing and investment rates may have been different during the two crises that we study. While the effect of leverage on investment rates does not seem to have changed substantially, leverage seems to have played a more important role in determining credit spreads during the GFC than during the COVID-19 recession. Liquidity, on the other hand, seems to have been considerably more important during the COVID-19 recession than during either normal times or the GFC, both in terms of credit spreads and investment rates. In the next section, we develop a quantitative model that helps us reconcile these results and think about the roles of credit and liquidity policies during large crises.

4 A Macro-Financial Model with Liquidity Shocks

In this section, we present a model that we will use as a quantitative laboratory to rationalize the empirical patterns that we document in sections 2 and 3: (i) the differing co-movement between aggregate credit spreads, debt and liquid assets in the GFC and COVID-19 crisis; (ii) the differing cross-sectional responses of credit spreads to the ex-ante positions of leverage and liquidity between the two events; and (iii) the relationship between working capital needs, debt, and liquidity.

We study the dynamic problem of firm investment with a specific focus on firms' balance sheet items. Our model has both standard elements of macro-finance models and a novel type of liquidity friction, which is key to studying liquid asset holdings. On the standard side, firms issue defaultable debt and face a non-negative dividend constraint. We augment this model by allowing firms to hold liquid assets to cover stochastic liquidity shocks as in Holmström and Tirole (1998). We allow them to access costly intraperiod debt to overcome the liquidity shock. Hence, the model has three different financial securities and interest rates: interperiod defaultable debt, liquid assets, and intraperiod debt.

We want to build a model that can replicate the empirical results in (2). That specification allows us to study how pre-determined variation in leverage and liquidity positions of firms influences variation in the change of credit spreads during different crises periods. For that reason, we allow firms to be ex-ante heterogeneous in their liquidity and leverage needs. Note that our goal is not to explain why firms arrived at those different levels of liquidity and leverage, but rather how do those different levels affect the response of firm-level variables to aggregate shocks. We then use this framework to study how different shocks affect the aggregate economy and firms that differ in their leverage and/or liquidity positions.

Environment. Time is discrete and infinite. The economy is populated by ex-ante heterogeneous firms. There is a finite set of firm types indexed by $i = 1,\dots,N$. There is a continuum of firms of each type with mass $\lambda_i \in [0,1]$ such that $\sum_{i=1}^{N} \lambda_i = 1$. Below, we omit the firm type subscript unless relevant and describe the problem of an individual firm.

Production and Investment. The firm has access to a decreasing returns-to-scale production technology over capital k and labor n, with productivity z.[14] Firms hire labor at market wage w. The labor choice solves the following static problem:

$$\pi(z,k) = \max_{n} \quad z^{1-\upsilon} k^{\alpha} n^{\upsilon} - wn \tag{4}$$

where $\alpha + \nu < 1$. Static profits from production for a given level of capital k and productivity z are $\pi(z,k)$.

The capital stock of the firm depreciates with rate $\delta \in (0,1)$. Capital accumulation is subject to convex adjustment costs:

$$\mathscr{A}^K(\hat{k}', k) = \frac{\psi}{2}\left(\frac{\hat{k}' - k}{k}\right)^2 k \tag{5}$$

where $\psi > 0$. A firm that enters the period with capital $\hat{k}$ has effective capital $k = \phi \hat{k}$, where ϕ is a capital quality shock. The modeling of the capital quality shocks follows Ottonello and Winberry (2020). These shocks are i.i.d. across firms and time, and follow a truncated log-normal distribution with support $[-4\sigma, 0]$, where σ is the standard deviation of the underlying normal distribution. This process implies that with some probability, no capital quality shock is realized, but with complementary probability, capital quality is drawn from the region of a normal distribution within those bounds. The capital quality shock also affects the value of the firm's undepreciated capital.

[14] Since we do not explicitly model the demand for firm products, this can be thought of as TFPR and captures not just factors that directly affect firm productivity but also fluctuations in demand for and prices of firm products.

Liquid Assets. The firm holds liquid financial assets a. Liquid assets can be purchased at a price of q_a and yield 1 in the following period. A sufficiently high price q_a means that liquid assets are dominated assets, and there is, in principle, no motive to hold them. We introduce a precautionary motive for holding liquid assets: the firm faces a stochastic working-capital constraint to cover operational costs before revenue is received. The need for working capital is motivated by the empirical evidence in section 3.5, and arises from the difference in the timing of when costs are incurred and when revenue is received as in Holmström and Tirole (1998). This need for working capital can stem, for example, from delayed payments of trade credit provided to clients. Such payment disruptions can be substantial during large financial and economic crises.[15]

We formalize the working-capital constraint as follows: with probability p_ω the firm needs to hold an amount of liquid assets equal to $\overline{\omega}k$, while with probability $1-p_\omega$ the firm does not face any working-capital needs.[16] Formally, the constraint parameter is a binomial random variable that is equal to $\omega=\bar{\omega}$ with probability p_ω and $\omega=0$ with complementary probability. To cover these needs, the firm can either use existing liquid assets a or borrow ℓ in costly intraperiod debt. The working-capital constraint is

$$\omega k \leq a+\ell \tag{6}$$

where intraperiod debt ℓ needs to be repaid at the end of the period and is subject to an exogenous and increasing interest rate schedule.[17] The total net cost of borrowing an amount ℓ is given by

$$\mathscr{A}^L(\ell) = r\exp(s_\ell \ell)\ell \tag{7}$$

where r is the risk-free rate, and s_ℓ is a parameter that governs the slope of the cost with respect to the amount borrowed. This convex cost captures the idea that it is increasingly costly to raise liquid funds when firms are in a hurry and do not have funds readily available to cover

[15]This constraint is similar to Bacchetta et al. (2019). See Boissay et al. (2020) for a description of trade credit disruptions during the COVID-19 crisis and Baqaee and Farhi (2022) for a general analysis of supply chain disruptions.

[16]Appendix A.8 motivates this functional form for the working capital constraint, showing that there is a tight relationship between accounts receivable and firm size.

[17]Our measure for working capital requirements, receivables to total-assets, also scales with physical capital. See Figure A4 in Section A.8.

sudden expenses. As in Holmström and Tirole (1998), the intraperiod debt can be interpreted as a costly credit line, or any other source of short-term funding that can be accessed at a higher cost than standard funding sources.[18] We view this increasing cost as a reduced-form proxy for deeper frictions in short-term funding markets, such as those modeled by Poole (1968) in the context of intraday bank reserve management. Even if liquid assets are dominated, the combination of the stochastic liquidity needs ω, and the increasing costs of intraperiod debt induce firms to hold liquid assets on their balance sheet.

Debt and Default. The firm can also borrow in one-period defaultable debt, priced by risk-neutral financial intermediaries with a discount rate of r. The debt contract specifies a price schedule $q(\hat{k}', b', a')$ for a given principal repayment b'.

Let $\mathbb{I}(\phi'\hat{k}', b', a', \omega')$ be the indicator of repayment of a firm that chooses capital $\hat{k}'$, liquid assets a', and debt b', and experience shock realizations ϕ' and ω'. The price schedule is then given by

$$q(\hat{k}', b', a') = (1+\chi)\frac{\mathbb{E}_{\phi',\omega'}\left[\mathbb{I}(\phi'\hat{k}', b', a', \omega') + (1 - \mathbb{I}(\phi'\hat{k}', b', a', \omega'))\mu \min\{1, (\phi'\hat{k}' + a')/b'\}\right]}{1+r} \tag{8}$$

where μ is the recovery rate in case of default, and χ is a firm-specific parameter that affects firm incentives to borrow. In states of the world where the firm repays, $\mathbb{I}(\phi'\hat{k}', b', a', \omega') = 1$ and the lender recovers one unit of resources. Otherwise, the firm defaults, and the lender recovers a fraction μ of available assets $\phi'\hat{k}' + a'$, which are distributed pro-rata among bondholders, which is bounded by 1. $\mu < 1$ represents resource costs of default.

The parameter χ plays two roles. First, it is a way of breaking Modigliani-Miller and creating a motive for firms to borrow. In this sense, it could be interpreted as a difference in discount factors between borrowers and lenders or as a tax shield (Miller, 1977). Second, we use it as a source of ex-ante heterogeneity, summarizing financial frictions and other technological or institutional features that may affect firms' preference to borrow. In practice, firms choose different levels of leverage for reasons that we do not model, and χ captures such reasons. Finally, we assume that the firm cannot issue equity, and thus faces a non-negative dividend constraint $div \geq 0$ (Khan and Thomas, 2013; Ottonello and Winberry, 2020).

[18] We also allow the firm to hold liquid assets, while this is not an option in Holmström and Tirole (1998). See also Boileau and Moyen (2016) for a model where firms use credit lines to circumvent liquidity constraints.

Firm Problem. Conditional on not defaulting, the full problem of the firm is

$$
\begin{aligned}
V^P(k,b,a,\omega) = \max_{\hat{k}',b',a',\ell} \quad & div + \beta \mathbb{E}_{\phi',\omega'}\left[\max\{V^P(\phi'\hat{k}',b',a',\omega'),0\}\right] \qquad (9)\\
\text{s.t.} \quad & div = \pi(z,k) - c + (1-\delta)k - \hat{k}' - b + q(\hat{k}',a',b')b' + a - q_a a' - \mathscr{A}^K(\hat{k}',k) - \mathscr{A}^L(\ell)\\
& \omega k \leq a + \ell\\
& div \geq 0\\
& a', b', \hat{k}', \ell \geq 0
\end{aligned}
$$

where $\beta \in (0,1)$, $c \geq 0$ is a fixed cost of operation, and $q, \mathscr{A}^K, \mathscr{A}^L$ are defined in the text above.

Ours is a model of strategic default, as the firm can always raise funds to overcome both of its constraints: intraperiod debt in the case of the liquidity constraint, and interperiod debt in the case of the dividend constraint. Use of these funding sources is costly, which can make the continuation default negative and thus induce strategic default.

4.1 Liquid Asset Choice

While the firm's problem cannot be solved in closed form, we can gain some insight into the factors that drive the firm's choice of liquid assets. First, it is easy to see that $\ell = \max\{0, \omega k - a\}$, since holding positive ℓ is costly and offers no benefit other than satisfying the liquidity constraint. Then, the Euler equation for liquid assets, assuming an interior solution, is

$$
\begin{aligned}
(1+\rho)\, q_a = {} & (1+\rho)\, \frac{\partial q(\hat{k}',b',a')}{\partial a'} b'\\
& + \beta(1-p_\omega)\mathbb{E}_{\phi'}\left\{\mathbb{I}(\phi'\hat{k}',b',a',0)\left[1+\rho'(\omega'=0)\right]\right\}\\
& + \beta p_\omega \mathbb{E}_{\phi'}\left\{\mathbb{I}(\phi'\hat{k}',b',a',\bar{\omega})\left[1+\rho'(\omega'=\bar{\omega})\right]\left[1 + \mathbf{1}[\bar{\omega}\phi'\hat{k}' > a']\frac{\partial \mathscr{A}^L(\ell')}{\partial \ell'}\right]\right\}
\end{aligned}
$$

On the left-hand side, we have the cost of acquiring an extra unit of liquid assets today, which is equal to the price q_a times the marginal value of the internal funds of the firm. This marginal value is equal to 1 if dividends are strictly positive and $1+\rho \geq 1$ if the firm is at the zero-dividend constraint, where ρ is the Lagrange multiplier for this constraint. The right-hand side represents the benefits of acquiring liquidity. The first term shows that acquiring more liquid assets raises the firm value tomorrow, directly affecting the probability of default and hence the price of debt. The second and third terms represent the expected future benefits of liquidity: if the firm's liquidity shock is not realized (second term), then the marginal benefit of liquidity is equal to the marginal value of the internal funds, as liquid asset holdings offer no special benefit. However, if the liquidity shock is realized, liquid asset holdings reduce the need to borrow costly intraperiod debt. Therefore, the benefit is not just equal to the marginal value of internal funds but is compounded by the marginal cost of accessing intraperiod debt, $\frac{\partial \mathscr{A}^L(\ell')}{\partial \ell'}$, as long as $a' < \bar{\omega}\phi'\hat{k}'$. If a' exceeds $\bar{\omega}\phi'\hat{k}'$, then there is no added benefit, as the firm's liquidity constraint is not binding in this case.

With additional assumptions, we can simplify this expression. Assume that there no capital quality shocks (i.e., $\phi = 1$), no default, and the non-negative dividend constraint does not bind. Then, the Euler equation for liquid assets simplifies to

$$q_a - \beta = \beta p_\omega \mathbf{1}[\bar{\omega}k' > a'] \frac{\partial \mathscr{A}^L(\ell')}{\partial \ell'} \tag{10}$$

If $q_a > \beta$ (as we will assume in the calibration), then the first-order condition implies that $a' < \bar{\omega}k'$. Thus, we can assume without loss of generality that $\ell' = \bar{\omega}k' - a'$ if the liquidity shock is realized for the firm. This allows us to rewrite the Euler equation as

$$q_a - \beta = \beta r p_\omega [1 + s_\ell \ell'] \exp[s_\ell(\ell')] \tag{11}$$

This equation highlights the fundamental trade-off faced by the firm: the left-hand side is the opportunity cost of holding liquid assets, while the right-hand side is the expected marginal benefit of holding liquid assets. As the cost of intraperiod debt is increasing in the amount borrowed, this marginal benefit is strictly decreasing in a' for a given k'.

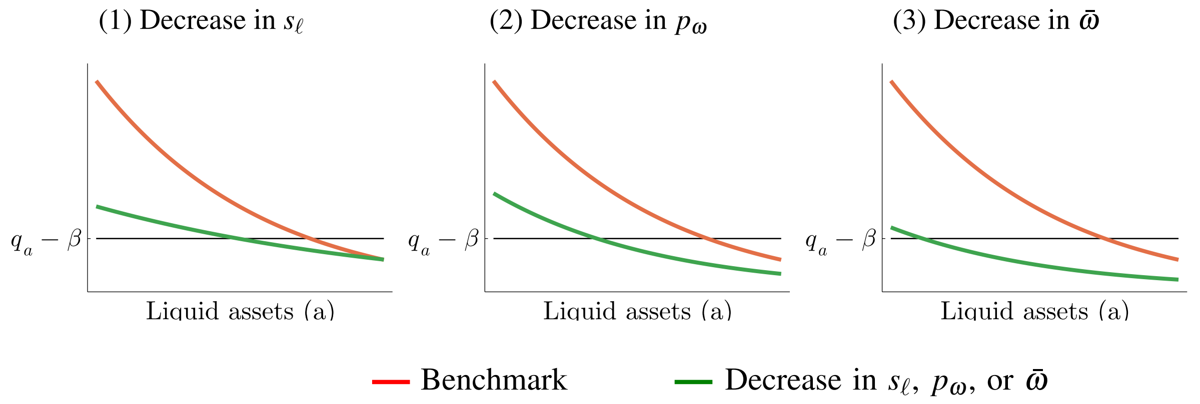
Lemma 1. *The demand of liquid assets a' is increasing in s_ℓ, p_ω , and $\bar{\omega}$.*

Figure 6 illustrates the results in Lemma 1 by showing the left- and right-hand sides of equation (11) for different parameters.[19] In each of the panels, the black line corresponds to $q_a - \beta$, while the orange line corresponds to the right-hand side of the expression for a given choice of k'. The different panels show comparative statics with respect to s_ℓ, p_ω, and $\bar{\omega}$. It is useful to define the spread of intraperiod debt with respect to the risk-free rate as

$$\text{spread}_\ell = r\exp(s_\ell \ell) - r = r[\exp(s_\ell \ell) - 1] \tag{12}$$

[19]Proof of the Lemma is in Appendix B.1.

Figure 6: Liquid Assets Choice: Comparative Statics



The first panel shows the effects of a decrease in the parameter s_ℓ, which governs the slope of the intraperiod debt cost function. Note that s_ℓ is always multiplied by ℓ' in (11), and so a decrease in s_ℓ causes ℓ' to increase proportionally so that the first-order condition holds. That means that s_ℓ affects the quantity of intraperiod debt conditional on the realization of the firm liquidity shock. However, $s_\ell \ell$ is constant and so the spread in (12) does not change with s_ℓ. Since ℓ' increases with a decline in s_ℓ, a' must fall for a fixed choice of capital k'. The demand for liquid assets shifts to the left: intuitively, by making the price of intraperiod debt less steep, the firm chooses to hold fewer liquid assets and borrow more in the intraperiod market.

Regarding p_ω, on the second panel, a decrease in the probability of receiving the liquidity shock requires the product $s_\ell \ell'$ to increase so that the Euler equation holds. This necessarily entails an increase in the spread of intraperiod debt and an increase in ℓ', which is achieved with a decrease in a' for a fixed choice of capital. Again, this result is very intuitive: firms choose to hold fewer liquid assets if the liquidity shock becomes less likely. This choice means they need to borrow more intraperiod debt when the shock is realized, thus raising the spread.

Finally, the third panel shows the effects of a decrease in $\bar{\omega}$, the size of the liquidity shock. For the Euler equation to hold, a' must decrease to keep ℓ' constant. Again, this is intuitive: if liquidity needs are lower conditional on the realization of the shock, the firm chooses to hold fewer liquid assets.

5 Calibration and Solution

The calibration is annual and targets moments associated with publicly traded nonfinancial US firms. The model calibration combines externally and internally calibrated parameters. First, we take some standard parameters from the literature. Some internally calibrated parameters are common across firms, while others vary across firm types. We choose the parameters to target both aggregate and cross-sectional moments.

We solve the model globally using value function iteration. The problem features portfolio choice over three continuous variables-capital, debt, and liquid assets-along with a binary default decision and two inequality constraints (working capital and dividends). To facilitate the numerical solution, we employ two auxiliary techniques. First, we introduce a small amount of noise into the default decision by adding extreme-value shocks (Dvorkin et al., 2021), setting the scale parameter governing their variance to a very small value (0.05). Second, we approximate the non-negativity constraint on dividends using a quadratic loss function with a large scale parameter.[20]

To calibrate the economy we assume that firms do not expect/anticipate aggregate shocks but form expectations over the realization of idiosyncratic shocks (ω, ϕ). We define the steady state for firm i as the fixed point of the endogenous state variables (capital, debt, and liquid assets) for that firm under no realization of the liquidity and capital quality shocks, $\omega = 0$ and $\phi = 1$ (and, therefore, no default). All quantitative experiments begin with all firms in this state. As we show in Appendix B.2 the cross-sectional distribution of firm financials were similar at the onset of each crisis, which justifies the choice of using the same starting point.

5.1 Externally Calibrated Parameters

Table 7 summarizes the parameters that are externally calibrated. The production function parameters (α, ν) and depreciation δ are drawn from Gilchrist et al. (2014). The capital adjustment cost parameter ψ is drawn from Cooper and Haltiwanger (2006) for the case of quadratic adjustment costs. The discount rate, which is the same for lenders and firms, implies an annual discount of 5%; that is, $\beta = 0.95$ and $r = 1/\beta - 1$. We want to capture the idea that holding liquidity is potentially costly for firms in real terms: if we assume their liquidity holdings were only cash, the real return should be equal to minus expected inflation. However, these liquid assets may also encompass holdings of short-term interest-bearing liquid assets that pay potentially positive but small real rates. As a compromise, we set the real interest rate on liquid assets to zero; thus $q_a = 1$. We also normalize the wage and TFPR to 1. Finally, we assume that the recovery rate is $\mu = 0.4$, in line with the findings of Kermani and Ma (2023) on recovery

[20] Specifically, we assume the firm's period utility is given by $div - \rho \max\{0, -div\}^2$, with $\rho = 10$. This ensures that firms do not issue equity in the steady state and issue only negligible amounts when facing very large unexpected shocks.

Table 7: Externally Calibrated Parameters

Parameter	Value	Description
Production		
α	0.2550	Capital share, Gilchrist et al. (2014)
ν	0.5950	Labor share, Gilchrist et al. (2014)
δ	0.0963	Depreciation rate, Gilchrist et al. (2014)
ψ	0.4550	Capital adjustment, Cooper and Haltiwanger (2006)
w	1.0000	Wage, normalization
z	1.0000	TFPR, normalization
μ	0.4000	Recovery rate, Kermani and Ma (2023)
Prices		
β	0.9500	Discount factor
r	0.0526	Interest rate
q_a	1.0000	Price of liquid assets

values for firm-specific capital.

5.2 Internally Calibrated Parameters and Firm Types

We consider four different types of firms, $N = 4$. We choose three parameters, χ_i, $\bar{\omega}_i$, and σ_i, to match credit spreads, the share of liquid assets, and leverage for each type of firm.[21] Appendix B.3 demonstrates that each of the aforementioned parameters can identify these moments. We define the four groups of firms depending on whether firms have high or low leverage and liquidity. We rely on our matched panel of firms and credit spreads to define the target values for high/low leverage and liquidity, as described in Section 3. First, for each date in 2007Q2 and 2019Q4, we split the data into four groups, depending on whether their leverage and liquid asset holdings are below or above the median value. Second, within each group we compute the median leverage and liquid asset holdings. In order to isolate the cross-sectional effects of differences in leverage and liquidity in the model, it is useful that firms have the same leverage ex-ante and vary only in terms of liquidity, and vice-versa. Moreover, the median levels of leverage and liquid asset holdings in the data are very similar across time and across groups (for example, the four high-liquidity groups have liquidity measures ranging between 9.3% and 12.1%, while the low-liquidity groups range between 1.3% and 1.8%). For that reason, we choose four targets for high and low leverage, and high and low liquidity, which correspond to averages across time and respective firm groups in the data (continuing with the liquidity example, we pick 10.8% for the high liquidity group and 1.6% for the low liquidity

[21] Throughout the paper, we refer to the difference between the yield on intertemporal debt and the risk-free rate as the credit spread. That is, spread $= 1/q - (1+r)$. We define leverage as $b/(k+a)$ and liquidity as $a/(k+a)$.

Table 8: Internally Calibrated Parameters and Cross-Sectional Targets

		High lev High liq	Low lev High liq	High lev Low liq	Low lev Low liq
Debt preference	χ	0.0120	0.0010	0.0129	0.0006
Liquidity needs	$\bar{\omega}$	0.2200	0.1805	0.1016	0.0680
Var. capital quality	σ	0.2564	0.2360	0.2749	0.2487
Mass	λ	0.2117	0.2877	0.3094	0.1913
Leverage	*Data*	0.4820	0.2580	0.4820	0.2580
	Model	0.4818	0.2594	0.4844	0.2628
Liquidity	*Data*	0.1080	0.1080	0.0160	0.0160
	Model	0.1137	0.1074	0.0163	0.0155
Spreads	*Data*	198.51	91.26	215.61	108.36
	Model	198.13	90.89	215.61	108.93

group).[22]

We construct the credit spread targets with the results from the baseline regression specification (2) in normal times: for each firm type, we target the levels of credit spreads that are consistent with the leverage and liquidity targets and with the coefficients from our baseline regression results. We select a constant such that the average credit spread equals 153 bps, the average median spread in the two targeted periods. This ensures that the steady state of the model reproduces the cross-sectional relationship between the credit spreads, leverage, and liquidity that we estimate during normal times. We use the number of firms in each subgroup as a percentage of the total number of firms to construct the weights λ_i.

Table 8 summarizes the targeted data moments, the endogenously calibrated parameters for each firm type, and the corresponding model moments. Model moments match the moments we target in the data very closely. Each of the moments is informative about one of the parameters: the debt preference parameter χ is larger for firms with high leverage, and the liquidity cost parameter $\bar{\omega}$ is larger for firms with more liquid assets. Credit spreads are increasing in σ, with this parameter being set so that the model replicates the normal-times implied spread from our baseline regressions, given the targeted leverage and liquidity levels for each firm.

We also internally calibrate three common parameters. First, two parameters related to the liquidity shock: the slope of the cost of intraperiod debt s_ℓ and the probability of each firm receiving the liquidity shock p_ω. As discussed in Section 4.1, a simpler version of the model illustrates that s_ℓ helps determine the equilibrium share of intraperiod debt that each

[22]Tables with the moments in these periods are reported in Appendix B.2.

Table 9: Internally Calibrated Parameters Common Across Firms

Parameter	Value	Target Moment	Data	Model
p_ω	0.555	$r \times [\exp(s_\ell \ell) - 1]$	3.1%	3.9%
s_ℓ	65.0	$\ell/(\ell + b')$	15.0%	15.7%
c	0.015	$[\pi(z,k) - c]/k$	0.31	0.29

firm borrows upon receiving the liquidity shock, $\frac{\ell}{\ell+b'}$ for $\omega = \bar{\omega}$. We also showed that the probability parameter p_ω helps identify the average spread that firms pay per unit of intraperiod debt conditional on receiving the liquidity shock, $r \times [\exp(s_\ell \ell) - 1]$.[23]

As discussed in the model section, we interpret ℓ as any type of short-term funding that the firm can access, such as credit lines or accounts payable, among others. To measure the cost of this type of credit, we rely on a measure of the base rate used by the top 25 banks to price short-term business loans, the so-called bank prime loan rate that is published daily in the Federal Reserve's H.15 release. This spread between the bank prime loan rate and the risk-free rate averaged 3.1% in the 2004-2021 period (FRED series DPRIME net of FEDFUNDS).

Unfortunately, we do not have good micro data on the usage of short-term credit within our TRACE-Compustat matched panel. We therefore rely on aggregate data to obtain a target for short-term credit as a fraction of total debt as follows. From the flow of funds, we compute loans as a percentage of total debt for nonfinancial corporate businesses.[24] This ratio is close to 30% on average for the post-2000 period. The flow of funds does not specify whether these loans are term loans, (drawn) credit lines, or other types of loans. We rely on the estimates of Greenwald et al. (2023), who use bank regulatory data from the Federal Reserve to show that credit lines correspond to 50% of total originated credit on the balance sheets of major bank holding companies. Combining these two numbers, we arrive at an estimated target of 15% for the $\frac{\ell}{\ell+b'}$ ratio.

The third internally calibrated parameter is the fixed cost of operation, which we choose to match the average ratio of EBITDA to capital.[25] In the model, we define EBITDA as sales minus labor and fixed costs. The target and model moments and values for each internally calibrated parameter are presented in Table 9.

[23] Appendix B.3, shows that each of these moments helps identify the respective parameter even in the full model.

[24] Loans are item FL104123005 in Table B.103, while total debt is the sum of loans and debt securities, which are item FL104122005 in that same table.

[25] We measure EBITDA as `oibdpq` in Compustat.

Table 10: Untargeted Moments: Model vs. Data

Aggregate Moment	Data		Model
	2007Q2	2019Q4	
Debt-to-income	2.21	3.24	2.44
Default rate	3.00	3.00	3.54

Untargeted Moments. Table 10 presents the first test of model and calibration validity by comparing untargeted moments from the data (at the two calibration target dates) to corresponding moments in the model. We focus on two moments: a measure of debt-to-income, and the default rate. For debt-to-income, we take the firms' median ratio of firm debt to operating income in our matched firm-bond panel. The table shows that the model does a relatively good job of matching all of these moments, especially in 2007Q2. Finally, the model generates a default rate of 3.54%, which is slightly higher but close to the default rate of 3% for speculative-grade firms (Moody's Investors Service, 2015).

6 Macro-Financial Crises

We now use the model as a laboratory to quantitatively study different types of crisis experiments. This helps us rationalize the differences in the behavior of credit spreads, debt, and liquid assets during the GFC and COVID-19 crisis.

6.1 Modeling Crises

We want to understand how firms behaved during these episodes. Neither of these events was a traditional business cycle fluctuation but rather a large and unexpected aggregate shock. Hence, we explore the responses of firms to unexpected and transitory shocks to the productivity, z_i^c, the financial frictions in debt markets, χ_i^c, and/or the size of liquidity shocks $\bar{\omega}_i^c$:

$$
\begin{aligned}
z_i^c &= \varepsilon^z \\
\chi_i^c &= \varepsilon^\chi \\
\bar{\omega}_i^c &= \max\{\bar{\omega}_i, \varepsilon^\omega\}
\end{aligned}
$$

Let $\Phi^i = \{z_i, \chi_i, \bar{\omega}_i\}$ denote the set of parameters whose values may change with shocks. Let Φ_0^i be the initial set of firm-specific parameters at the calibrated steady state. At period t, a shock occurs, and these parameters may change, with the set becoming Φ_1^i. For example, TFPR z or the extent of financial frictions χ could change. After the shock is realized, firms learn that in each period with probability ζ, the economy will return to Φ_0^i and remain there from then on, while with the remaining probability $1-\zeta$ it remains at Φ_1^i. Hence, the expected duration of the shock is $1/\zeta$.

Let $V^P(k,b,a,\omega|\Phi)$ be the value function of the firm conditional on repayment at state (k,b,a,ω) and a given set of parameters Φ. The problem of the repaying firm at period t when parameters change from Φ_0 to Φ_1 is

$$V^P(k,b,a,\omega|\Phi_1) = \max_{\hat{k}',a',b',\ell} \quad div + \zeta\beta\mathbb{E}_{\phi',\omega'}\left[\max\{0, V^P(\phi'\hat{k}',b',a',\omega'|\Phi_0)\}\right] \qquad (13)$$
$$+(1-\zeta)\beta\mathbb{E}_{\phi',\omega'}\left[\max\{0, V^P(\phi'\hat{k}',b',a',\omega'|\Phi_1)\}\right]$$

The aggregate response of outcome x is simply the weighted response of each firm

$$x = \sum_{i=1}^{N} \lambda_i x_i$$

Types of Shocks. We consider three type of shocks: (i) a real or fundamental shock, (ii) a financial shock, and (iii) a liquidity shock.

The real shock corresponds to a fall in TFPR z, to a new level z^c, and can either be interpreted as a drop in production efficiency or a fall in demand for the goods produced by the firm. This is motivated by the empirical findings of a decline in productivity both for the GFC and the COVID-19 periods (Bloom et al., 2025; Fernald, 2012). However, the drop in productivity was not the only shock in both periods and is not enough to replicate the behavior of macro-financial variables.

Second, the financial shock corresponds to a change in the financial friction/debt preference parameter χ and stands for disruptions in financial markets that lead to an increase in the cost of borrowing above and beyond what is warranted by the firm's state and policies. This is similar to a shock to the lender's discount factor, which is common in the sovereign default literature, for example, Bocola and Dovis (2019). This is meant to capture changes in macroeconomic and financial conditions that affect firms' ability to finance themselves externally, such as problems in the banking sector or in the broader financial system that limit the supply of credit. This factor is likely to be particularly important during the GFC, for example, which originated in the real estate sector and then propagated to the rest of the economy through the banking system.[26]

Third, the liquidity shock corresponds to an increase in $\bar{\omega}$, which raises the demand for liquid assets, especially for firms with low liquid assets. Consistent with the interpretation of this shock, there is evidence that during the COVID-19 period, firms relied heavily on short-term sources of funding, such as drawing from their credit lines, due to a precautionary motive to mitigate future liquidity risk (e.g., Bosshardt and Kakhbod, 2021; Chodorow-Reich et al., 2022; Crouzet and Gourio, 2020; Greenwald et al., 2023). Recall that in normal times the liquidity shock ω is an idiosyncratic shock which happens with probability p_ω. In our simulation of a crisis, we further assume that, while firms continue to form expectations using p_ω, all firms are simultaneously hit by a realization of this shock. Hence this corresponds to an aggregate liquidity shock in the spirit of Holmström and Tirole (1998).

Homogeneous vs. Heterogeneous Shocks. There are different ways of modeling the shocks. For example, one can assume that while Φ_0^i is heterogeneous across firms, all firms switch to the same Φ_1 during the crisis. This corresponds to the changes in the components of Φ being heterogeneous across firms. Alternatively, one could assume that the change in the components of Φ is the same across firms, i.e. shocks are homogeneous across firms. A priori it is not obvious which case is more plausible. We experiment with these different possibilities and solve both cases. We find that the first case, where shocks are heterogeneous across firms (i.e. all firms switch to the same Φ_1 during the crisis) fits the data better, and so we focus on this approach throughout the main text. Appendix B.5 considers the case in which firms receive homogeneous shocks and discusses its implications.

Government Policy. The periods we analyze were characterized by large government interventions in financial markets and extensive firm-support policies. Because we calibrate aggregate shocks to match observed outcomes, our calibrated shocks inevitably incorporate the effects of these policies. This does not pose a problem for our purposes, as our objective is not to conduct policy counterfactuals but rather to analyze the impact of these shocks on firm

[26] Jermann and Quadrini (2012), for example, demonstrate that financial shocks are needed to rationalize the comovement of macro-financial variables during the GFC.

behavior from a positive perspective.[27]

Partial vs. General Equilibrium. Our model is cast in partial equilibrium, treating wages and the real interest rate as exogenous. This choice reflects both computational tractability and the focus of our analysis. First, wage movements matter primarily through their impact on firm profits, which in our framework are captured by TFPR shocks. Second, our main interest lies in the effects of shocks on firm credit spreads, rather than on the levels of interest rates paid by firms. Since the risk-free rate would influence the latter more directly, holding it fixed is appropriate for our purposes.

6.2 The COVID-19 Crisis

Our benchmark experiment consists of replicating the COVID-19 crisis by hitting the economy with real, financial, and liquidity shocks at the same time. We choose the sizes of the shocks to match the responses of macro-financial aggregates in the data.

For credit spreads, we target a rise in spreads of 270 bps, consistent with Figure 1 between February 2nd and March 23rd, 2020. For aggregate quantities, we target one-year cyclical variations in real GDP and liquid assets during each crisis. We consider a linear trend for the log of real GDP and aggregate liquid asset holdings (the same data that we describe in Figure 1). We target the one-year difference between the cyclical components in 2020Q4 and 2019Q4. These targets imply a drop in real GDP of 3.35% and a rise in liquid asset holdings of 29.5%. Finally, using the same detrending, the cyclical variation in debt owed is 5.7%, which we treat as a non-targeted moment. This results in the following values for the aggregate shocks: $z^c = 0.967, \chi^c = -0.013, \bar{\omega}^c = 0.267$.

The probability of returning to the steady-state set of parameters is set to $\zeta = 0.75$; hence, the crisis has an expected duration of 1.33 years to match an optimistic forecast for the expected time until a vaccine is available.[28] For our analysis, and unless otherwise noted, we focus on deviations of a specific variable from the steady state in the first period after the shocks.

[27] In an earlier version of this paper (Ebsim et al., 2020), we conducted explicit policy analysis, which required disentangling the components of the aggregate shocks attributable to policy interventions from those due to structural disturbances.

[28] On April 30, 2020, the *New York Times* reports that officials like Dr. Anthony S. Fauci, the top infectious disease expert on the Trump administration's coronavirus task force, estimate a vaccine could arrive in at least 12 to 18 months. See Thompson (2020). Appendix B.4 shows that our main qualitative results are robust to changing shock persistence.

Table 11: The COVID-19 and GFC Crises

	COVID			GFC		
	(1)	(2)	(3)	(4)	(5)	(6)
	Data	Model	Model, no liq.	Data	Model	Model, no liq.
1. Targeted moments						
Spreads, bps	270.00	269.95	228.70	258.00	257.96	247.78
GDP, percent	-3.35	-3.35	-3.35	-5.01	-5.01	-5.01
Liquid assets, percent	29.49	29.01	-23.57	-1.34	-1.31	-27.01
2. Debt measures						
Debt in the data, percent	5.68			-6.81		
Debt owed, percent		16.41	-36.46		-21.85	-38.95
Debt owed, percent, w/ interest		32.04	-34.77		-17.31	-37.27
b', percent of b		-34.45	-54.82		-51.31	-57.32
ℓ, percent of b		50.87	18.36		29.46	18.36
3. Cross-sectional elasticities						
Spreads wrt leverage	757.87	730.67	678.67	1183.19	769.93	751.18
	(69.73)	(2.27)	(1.23)	(131.36)	(1.79)	(1.31)
Spreads wrt liquidity	-373.24	-666.86	-20.48	-54.49	-239.17	-31.22
	(43.85)	(5.36)	(2.90)	(62.67)	(4.23)	(3.09)
Investment rate wrt leverage	-2.90	-1.31	-1.78	-3.80	-2.32	-2.44
	(0.90)	(0.02)	(0.01)	(0.60)	(0.02)	(0.01)
Investment rate wrt liquidity	8.80	5.13	-0.87	3.60	2.84	-0.98
	(1.50)	(0.04)	(0.02)	(1.20)	(0.04)	(0.02)
4. Shocks						
z^c		0.967	0.967		0.949	0.949
χ^c		-0.013	-0.013		-0.013	-0.013
$\bar{\omega}^c$		0.267			0.173	

Notes: Aggregate and cross-sectional responses on impact, bps stands for basis points. The cross-sectional responses are based on regressions of the change in spreads or the investment rate on impact on the initial (steady state) levels of leverage and liquidity. Standard errors in parenthesis. The data correspond to the baseline empirical estimates in Section 3.

The first two columns of Table 11 show the data and model results for the COVID-19 crisis experiment. The first panel reports results for targeted aggregate moments. By construction, the crisis results in a 270 bps rise in credit spreads, a 3.35% fall in GDP, and a 29% rise in aggregate holdings of liquid assets.

The second panel reports results for debt variables, which are not targeted. In the model, the change in total debt reflects a sharp decline in interperiod debt (-34.45%) together with an increase in intraperiod debt (50.87%). Mapping this prediction to the data is not straightforward because intraperiod borrowing is only partially captured in a balance-sheet snapshot: depending on timing and rollover, only a fraction of intraperiod debt will be outstanding at the reporting date. This measurement issue is analogous to the problem of estimating returns using beginning- and end-of-period asset values (Dietz, 1968), where intermediate flows are only imperfectly observed. In the baseline table we assume that the entirety of intraperiod debt is counted towards debt owed, which generates a larger increase than in the data (16.4% versus 5.7%). By counting only 80% of intraperiod debt in total debt owed, the model could match the increase in debt in the data exactly.

Additionally, we report two measures of debt owed: without the interest on intraperiod debt, $b' + \ell$, as well as inclusive of interest on intraperiod debt, $b' + \ell + \mathscr{A}^L(\ell)$. Again, we do this since firm financial data corresponds to a snapshot of balance sheets at a given date, and whether debt costs are included in firm liabilities or not depends on the exact maturity of short-term as well as other details of the contract.[29]

The experiment reproduces the comovements we observed during the COVID-19 crisis: a significant increase in credit spreads accompanied by an increase in liquid asset holdings and corporate borrowing. The liquidity shock and constraint drive this increase in borrowing: as firms face an unexpectedly higher liquidity requirement $\bar{\omega}^c$, they are forced to increase their intraperiod borrowing. These borrowings have to be repaid by the end of the period, which decreases profits and may make them negative, pushing firms against the dividend constraint. In summary, the benchmark experiment that includes the three shocks appears to do a good job in replicating the comovement of macro-financial variables during the COVID-19 crisis documented in Figure 1.

This experiment highlights that the liquidity shock is essential to match the simultaneous rise in debt and credit spreads, accompanied by a fall in real activity. Macroeconomic models of financial frictions typically predict a joint increase in credit spreads and amounts borrowed in response to a positive credit demand shock, which tends to generate an expansion in real activity (Gilchrist et al., 2014). On the contrary, the liquidity shock in our model simultaneously generates an expansion in the demand for debt and a slowdown in real activity, as observed during the recent COVID-19 crisis. We further explore the role of the liquidity shock in Section 6.5.

[29]We have also experimented with choosing the financial shock χ^c to target the movement in debt instead of credit spreads. In this alternative exercise, matching the modest rise in total debt requires a smaller liquidity shock, which lowers firms' working-capital needs and thus dampens intraperiod borrowing. This limits debt growth but consequently understates the increase in liquid asset holdings. This result highlights that in our framework total debt is largely governed by liquidity needs rather than the financial shock.

6.3 Cross-Sectional Responses in the COVID-19 Crisis

The third panel of Table 11 presents the cross-sectional elasticities implied by the model that are comparable to those estimated from the data in Section 3. These elasticities summarize how heterogeneity in terms of leverage and liquid assets affects movements in credit spreads and investment rates across firms during the crisis. The elasticities of credit spreads with respect to leverage and liquidity are in line with the ones estimated in the data for the COVID-19 crisis: 731 in the model vs. 758 in the data for leverage, and -667 in the model vs. -373 in the data for liquid assets. While the coefficients are not exactly the same, they have the correct signs and orders of magnitude, and, importantly, these moments are not targeted. Thus, firms that are more leveraged and have less liquidity experience relatively larger increases in credit spreads in both the model and the data. For the investment rate, we observe very similar patterns. Again, none of these moments are targeted. The elasticity of the investment rate with respect to leverage is -1.3 in the model vs. -2.9 in the data, while the elasticity with respect to liquid assets is 5.1 in the model vs. 8.8 in the data. Hence, firms that were more leveraged and held fewer liquid assets experienced relatively larger drops in their investment rates in the model, consistent with the evidence for the COVID-19 crisis.

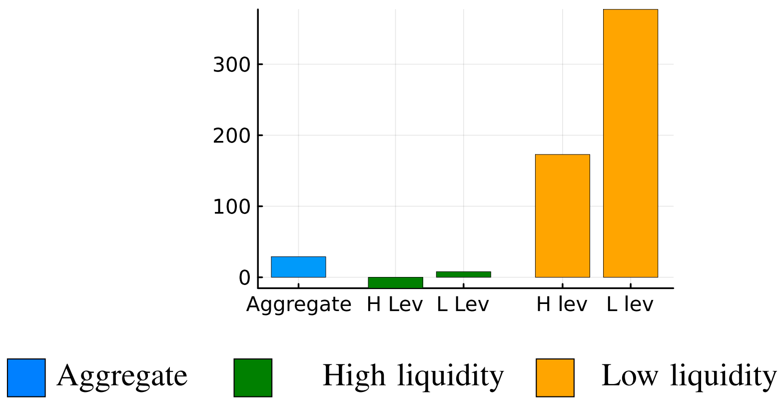
Evidence on Cross-Sectional Liquidity Responses. Figure 7 plots the cross-sectional responses of firm liquid asset holdings to the shocks. The model predicts that low liquidity firms increase their holdings of liquid assets by much more than high liquidity firms (who, in some cases, actually decrease them).

We directly test this prediction in the data, by running repeated cross-sectional regressions of the type

$$\frac{a_{f,t} - a_{f,t-2}}{a_{f,t-2}} = \alpha_t + \beta_t \text{liq}_{f,t-2} + \phi_t \text{lev}_{f,t-2} + \Gamma_t' X_{f,t-2} + \varepsilon_{f,t}$$

where the dependent variable is the real growth rate of liquid assets for firm f over a 2-quarter horizon. We focus on the behavior of the coefficient β_t, plotted in Figure 8, along with standard error bands. The figure shows that the coefficient is, on average, negative, suggesting a mean reversion in firms' liquidity positions. However, the coefficient falls considerably at the onset of the COVID-19 crisis, suggesting a strengthening of this mean-reversion behavior: firms with lower liquidity tend to accumulate more liquidity over this period than those with more liquidity, consistent with the cross-sectional predictions of the model.

Figure 7: Cross-Sectional Responses of Liquid Assets



Notes: The figures show the aggregate and cross-sectional response by comparing the variables at the period of the shock relative to its value at the steady state.

6.4 Shock Decomposition

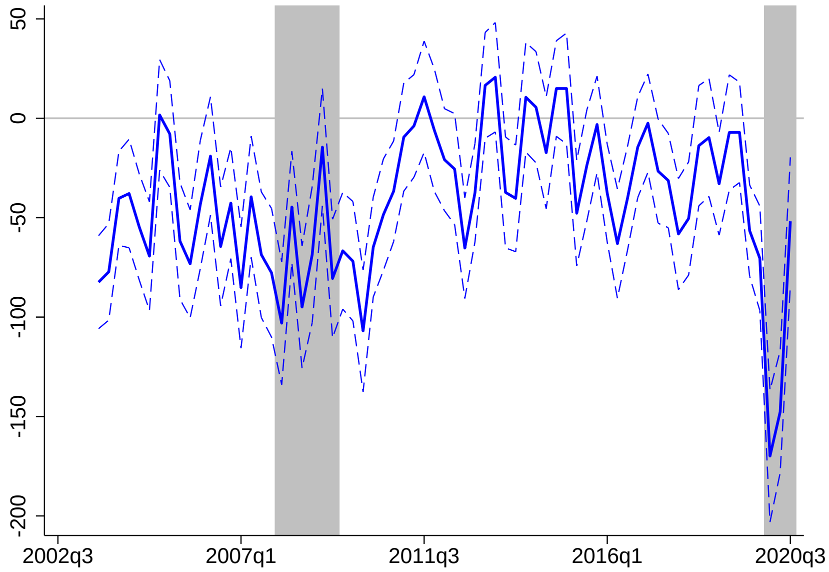
To quantify the relative importance of each shock for movements in endogenous variables in our baseline COVID-19 experiment, we use a Shapley–Owen–Shorrocks decomposition. This additive decomposition assigns a contribution to each of the three shocks (real, financial, and liquidity), and the contributions sum to one. Let $x(z^c, \chi^c, \bar{\omega}^c)$ denote an outcome of interest (e.g., credit spreads) as a function of the aggregate shocks. For example, the contribution of the real shock z^c to variable x is computed as:

$$\begin{aligned}
\text{effect of } z^c \text{ on } x = & \frac{1}{3}\left(x(z^c,0,0) - x(0,0,0)\right) \\
& + \frac{1}{6}\left(x(z^c,\chi^c,0) - x(0,\chi^c,0)\right) \\
& + \frac{1}{6}\left(x(z^c,0,\bar{\omega}^c) - x(0,0,\bar{\omega}^c)\right) \\
& + \frac{1}{3}\left(x(z^c,\chi^c,\bar{\omega}^c) - x(0,\chi^c,\bar{\omega}^c)\right)
\end{aligned}$$

Table 12 reports the contribution of each shock to the movements in the variables of interest using the decomposition above. Qualitatively, the liquidity shock generates the joint increase in spreads, liquid assets, and borrowing. It raises the internal value of liquid assets, leading firms to accumulate them. Firms finance this accumulation by borrowing more. Higher borrowing, together with the shock itself, increases default risk and thereby raises credit spreads.

By itself, the financial shock raises the cost of borrowing and induces firms to borrow less

Figure 8: Time Series for the Coefficient of Lagged Liquidity on the Growth Rate of Liquidity



and reduce their liquid asset holdings. As a result, it cannot match the qualitative patterns observed during the COVID-19 crisis, since it generates comovement opposite to that in the data between credit spreads and borrowing and liquid assets. The financial shock alone produces effects that are qualitatively closer to those observed during the GFC.

While the liquidity shock alone generates the correct qualitative comovement, it is insufficient to match the data quantitatively. Matching the magnitudes requires the combination of all shocks.

Real effects. The contemporaneous effects of the shocks on GDP are largely mechanical, since GDP depends on productivity (an exogenous shock) and the predetermined capital stock. More informative implications arise for GDP in the period after the shock, reported in Table 12. The real shock accounts for 14%, the financial shock for 52%, and the liquidity shock for 35%. The real shock affects GDP through mechanical persistence and by pushing firms against the dividend constraint on impact, forcing cuts in investment. The financial shock raises the cost of debt, prompting firms to increase the expected marginal product of capital by reducing investment. The liquidity shock induces precautionary behavior, leading firms to scale down in order to reduce expected working capital needs.

Table 12: Shock Decomposition

	(1) Real	(2) Financial	(3) Liquidity	(4) Total
Spreads	14	61	24	100
GDP	100	0	0	100
Liquid assets	-10	-81	191	100
Debt owed	-3	-175	278	100
Debt owed, w/ interest	0	-88	188	100
Investment	14	51	35	100
Default prob.	24	9	67	100
GDP next year	14	52	35	100
b'	19	101	-20	100
ℓ	12	12	76	100

Notes: Results from a Shapley–Owen–Shorrocks decomposition of the COVID-19 crisis. Row totals may not sum to 100 due to rounding. See text for details.

6.5 The Role of Liquidity

Column (3) of Table 11 presents a counterfactual exercise in which we feed the model the real and financial shocks estimated for COVID-19, but exclude the estimated liquidity shock. This exercise confirms key findings from the shock decomposition: the financial shock alone generates an increase in spreads accompanied by reductions in both borrowing and liquid asset holdings. However, without the liquidity shock, the model fails to reproduce the cross-sectional patterns in spreads and investment with respect to firms' liquidity positions, as shown in the panel below.

Liquid assets now fall due to two forces that complement each other. First, mechanically, firms do not perceive the risk of having to fund a larger share of their capital stock with liquid assets. Second, the financial shock makes it more difficult for firms to borrow in interperiod debt and maintain positive profits for predetermined capital and debt levels. For this reason, firms disinvest and reduce their stock of capital, which in turn reduces the amount of liquid assets they need to hold for precautionary motives. Because firms do not need to hoard liquid assets and borrowing has been made more expensive by the financial shock, total borrowing falls. This exercise shows that the model without the liquidity shock can generate the right comovement between credit spreads, liquid assets, and firm borrowing that was observed during the GFC: a rise in spreads that was accompanied by a fall in liquid asset holdings and debt.

6.6 The Great Financial Crisis

We next simulate the GFC in our model, recalibrating the aggregate shocks to match the crisis-specific targets: an increase in spreads of 258 bps (the rise between September 15 and November 25 of 2008, as in Figure 1), a 5% drop in GDP, and a 1.3% decline in liquid asset holdings. We assume that the persistence of the shock is equal to $\zeta = 0.5$, higher than the COVID-19 crisis. While it is hard to measure the ex-ante expected duration of a crisis, the GFC turned out to be significantly more persistent than COVID-19. The results, reported in columns (4) and (5) of Table 11, show that the model qualitatively replicates the non-targeted drop in debt owed. Consequently, the simulated GFC produces the opposite comovement of spreads, liquid assets, and debt compared to the COVID-19 experiment: spreads rise while both liquid assets and debt fall.

The fourth panel of Table 11 reports the estimated aggregate shocks. TFP and financial shocks are quantitatively similar across crises, but the liquidity shock is much smaller in the GFC. In our framework, this implies that high-liquidity firms are largely unaffected by the liquidity shock in the GFC scenario. As a result, they have no incentive to increase liquid asset holdings, making the experiment resemble column (3)—the COVID-19 crisis without a liquidity shock. The financial shock therefore dominates, raising spreads while both liquid assets and debt decline.

Column (6) repeats the GFC experiment without the liquidity shock. The qualitative patterns remain, but spreads increase slightly less, while liquid assets and debt contract more sharply. The main difference between columns (5) and (6) arises in the cross-sectional responses of spreads and investment to liquidity. With the liquidity shock (column 5), the model predicts a significant cross-sectional sensitivity of spreads to liquidity, contrary to the data. Without the liquidity shock (column 6), the cross-sectional effect is more muted and aligns more closely with the evidence.

Taken together, these results suggest that, through the lens of the model, the GFC was a combination of financial and real shocks without a strong liquidity component.

7 Conclusion

While the GFC and the COVID-19 pandemic caused similar increases in aggregate corporate credit spreads, the two events featured opposite movements in corporate debt and holdings of liquid assets. Using a panel of maturity-matched corporate credit spreads for US nonfinancial firms, we find that firm leverage was a more important predictor of credit spreads and investment rates during the GFC. However, liquidity was more important during the COVID-19 crisis.

To rationalize these facts, we developed a quantitative model of the firm's capital structure, where we explicitly modeled a motive for holding liquid assets. Combining the insights of a calibrated version of the model with the empirical evidence at the aggregate and micro levels, we concluded that the COVID-19 crisis had a strong liquidity shock component, unlike the GFC. Moreover, we showed that these liquidity shocks are essential not just to generate the right comovement of aggregate variables, that is, a simultaneous increase in credit spreads, debt, and liquid asset holdings, but also to generate the correct relationship between spreads, leverage, and liquidity in the cross-section. Our model suggests that the GFC did not have a strong liquidity shock component but was rather a combination of credit market and real shocks.

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Online Appendix

This material is for a separate, on-line appendix and not intended to be printed with the paper.

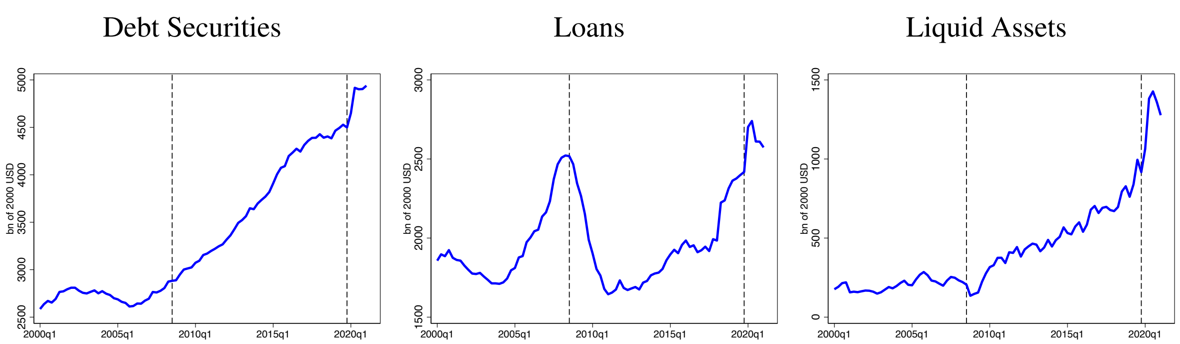
A Data Appendix

A.1 Flow of Funds Data

Section 2 shows the changes in aggregate debt and liquid assets during the GFC and COVID-19. In this Appendix we show the time series. Furthermore, we show that the main results hold for both debt securities and loans.

Figure A1 shows the time series of debt and liquid assets for nonfinancial corporates from the Financial Accounts of the United States. All variables are deflated with the GDP deflator (GDPDEF in FRED). The first panel shows debt securities (FL104122005), the second panel shows loans (FL104123005), and the third panel shows liquid assets (FL103020000).

Figure A1: Debt and Liquid Assets



Notes: All variables are in real terms for US nonfinancial corporates. Data sources: Financial Accounts of the United States and FRED. Vertical dashed lines correspond to 2008Q3 and 2019Q4.

A.2 Median Credit Spreads

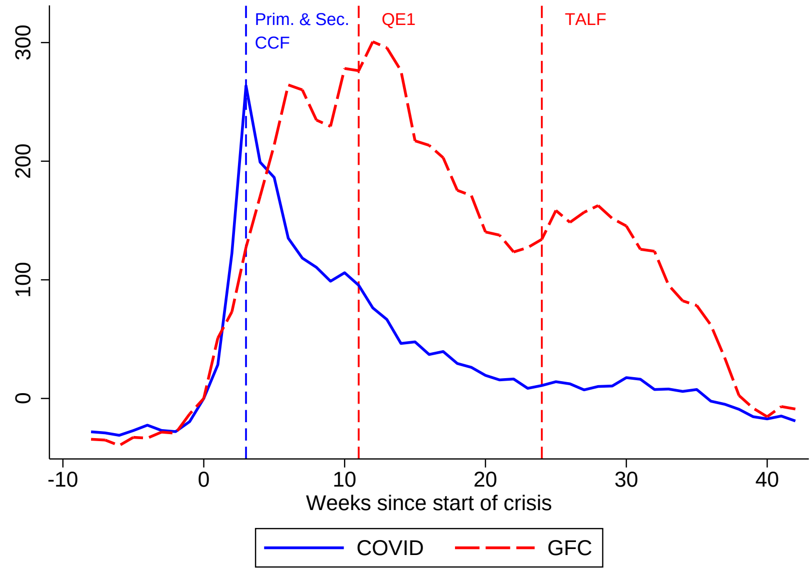
Figure A2 shows the median credit spreads for the micro data. Note that the figure is very similar to the aggregate data in the first panel of Figure 1.

A.3 Details on the Construction of Investment Data

To measure investment we first construct $k_{f,t}$ from Compustat using gross plant, property, and equipment (`ppegtq`) and changes in net plant, property, and equipment (`ppentq`). Taking the earliest observation of gross `ppeqtq`, we form investment spells by adding the changes in `ppentq`. The depreciation rate is estimated as $\delta_{f,t} = \texttt{dpq}/k_{f,t-1}$. Following Begenau and Salomao (2018), we define the investment rate as gross investment divided by (lagged) total assets:

$$inv_{f,t} = \frac{k_{f,t} - (1-\delta_{f,t})k_{f,t-1}}{\text{total assets}_{f,t-1}}$$

Figure A2: Median Credit Spreads During the GFC and COVID-19



Notes: Median credit spreads during the GFC and the COVID-19 crisis, normalized by the starting date of each crisis. Week 0 corresponds to the beginning of the increase in volatility (bankruptcy of Lehman Brothers for GFC in September 2008, and the end of February 2020 for COVID-19). Vertical lines correspond to major Federal Reserve intervention announcements for corporate credit markets (11/25/2008, 03/03/2009, and 03/23/2020).

We define the net investment rate ($\widetilde{inv}_{f,t}$) as $k_{f,t} - k_{f,t-1}$ divided by total assets of firm f in quarter $t-1$. We also consider estimating investment in the data using capital expenditures. We define $inv^c_{f,t}$ as capital expenditures divided by total assets in the previous quarter.

A.4 Alternative Investment Rate Definitions

Table A1 presents results of the panel regressions, equation (2), with alternative investment definitions. The first column shows the benchmark results for the gross investment rate, the second column shows the results for the net investment rate, and the third column shows the results for $inv^c_{f,t}$ (i.e., capital expenditures divided by total assets in the previous quarter). Overall, the results are quite similar for the three definitions of investment.

A.5 Instrumental Variables Regression

Consider the following specification:

$$y_{f,t} = \alpha_f + \gamma_t + \sum_{i \in \mathrm{E}} \beta_i \mathbb{I}_{t \in \mathrm{i}} \mathrm{liq}_{f,t} + \sum_{i \in \mathrm{E}} \phi_i \mathbb{I}_{t \in \mathrm{i}} \mathrm{lev}_{f,t} + \Gamma' X_{f,t} + \varepsilon_{f,t} \tag{14}$$

Table A1: Alternative Investment Measures

	(1)	(2)	(3)
Leverage			
Normal	-0.028***	-0.028***	-0.016***
	(0.006)	(0.006)	(0.001)
GFC	-0.038***	-0.038***	-0.019***
	(0.006)	(0.006)	(0.002)
COVID-19	-0.029***	-0.028***	-0.015***
	(0.009)	(0.009)	(0.001)
Liquidity			
Normal	0.027***	0.033***	0.005***
	(0.006)	(0.006)	(0.001)
GFC	0.036***	0.042***	0.006***
	(0.012)	(0.011)	(0.002)
COVID-19	0.088***	0.093***	0.019***
	(0.015)	(0.015)	(0.003)
N	43125	44402	44639
R2	0.099	0.086	0.52

Notes: Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

This is the contemporaneous analog to equation (2). Define the instrumental variable as $Z_{f,t-r} = (\text{liq}_{f,t-r}, \text{lev}_{f,t-r}, X_{f,t-r})$. We will use lagged variables of leverage, liquidity, and other controls as instruments for current financials. This is because at time t, with firm fixed effects included, past firm financials are orthogonal to the error $\varepsilon_{f,t}$.

Table A2 shows the results for the specification (14) with $y_{f,t} = s_{f,t}$, credit spreads. The first column contains regression results without any instrument. The second column contains regression results using $Z_{f,t-1}$ as an instrument for the contemporaneous financials. The final column includes $Z_{f,t-1}$ and $Z_{f,t-2}$ as instruments. The main quantitative conclusions remain. What changes is that in the final column the response of credit spreads to liquidity in the GFC runs in the positive direction. It is statistically significant but the magnitude is relatively small. Overall, conclusions from Table 2 are robust.

Table A3 shows the results for the specification (14) with $y_{f,t} = inv_{f,t}$, investment rate. Instruments are the same across the three columns as described earlier for credit spreads. Leverage coefficients do not change very much as you include more lagged financials as instruments. Leverage coefficients are very similar to the results from column (1) in Table 4. For liquidity, the second column shows the magnitude of the elasticities nearly doubles as you include $Z_{f,t-1}$

Table A2: Instrumental Variables Regressions: Credit Spreads

	(1)	(2)	(3)
Leverage			
Normal	479.834***	581.474***	587.290***
	(32.860)	(37.578)	(39.407)
GFC	1184.561***	1364.331***	1403.857***
	(130.794)	(175.787)	(180.442)
COVID-19	758.018***	802.908***	826.204***
	(69.580)	(73.439)	(82.124)
Liquidity			
Normal	-185.901***	-215.729***	-195.319***
	(26.158)	(32.673)	(32.599)
GFC	-55.652	4.439	115.911
	(62.983)	(77.367)	(110.558)
COVID-19	-373.808***	-500.625***	-481.469***
	(43.989)	(92.212)	(89.908)
IV	No	$r = 1$	$r = 1,2$
N	46532	45612	42979

Notes: Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

as an instrument. The effect in normal times remains similar to the GFC, with COVID-19 having a noticeably larger positive effect on investment. We can conclude as earlier that the comovement of investment with liquidity changed during COVID-19, but the movement with leverage in all events remained very similar.

A.6 Robustness

This appendix shows that our empirical results are robust to several potential concerns.

Liquidity Outliers. To ensure that our results are not driven by outliers in the liquidity measure, we drop observations with extreme values of liquidity and estimate the benchmark specification. Table A4 and A5 show the results for panels with different lower and upper bounds for liquidity, dropping all observations outside those bounds. In the benchmark regressions we keep only observations between the 1-st and 99-th percentiles. Columns (2) through (5) estimate with 2-nd and 99-th percentile cuts through 5-th and 95-th percentile cuts. Qualitatively our main results hold for both the investment and credit spread regressions.

Table A3: Instrumental Variables Regressions: Investment

	(1)	(2)	(3)
Leverage			
Normal	-0.028***	-0.035***	-0.035***
	(0.006)	(0.006)	(0.007)
GFC	-0.038***	-0.038***	-0.041***
	(0.006)	(0.010)	(0.008)
COVID-19	-0.029***	-0.038***	-0.036***
	(0.009)	(0.007)	(0.008)
Liquidity			
Normal	0.027***	0.066***	0.065***
	(0.006)	(0.009)	(0.010)
GFC	0.036***	0.064***	0.067***
	(0.012)	(0.015)	(0.017)
COVID-19	0.088***	0.133***	0.131***
	(0.015)	(0.016)	(0.016)
IV	No	$r = 1$	$r = 1,2$
N	43125	44146	41661

Notes: Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Intangibles. We include a measure of intangibles to the main specification. We use the measure of intangibles provided by Compustat which includes research and development and acquisitions by firms. We normalize this amount by total assets. Table A6 contains the results. Overall, our results are qualitatively robust to including intangibles.

Callable Bonds. As noted in Gilchrist and Zakrajsek (2012), the option value of calling a bond depends on interest rate variation. Our date has a substantial amount of callable bonds. We show that our results are robust to controlling for this callability option. We follow Gilchrist and Zakrajsek (2012) and interact an indicator for callability with the level, slope and curvature of the yield curve from Gurkaynak et al. (2007). We also interact the callable indicator with interest rate volatility, measured as the monthly standard deviation in the 10-year Treasury. Table A7 contains the results. The results are quantitatively very close our benchmark results.

Credit Lines. To study the role of a credit lines as a source of liquidity, we complement our panel with Capital-IQ data that contains information on drawn and undrawn credit lines.

Table A4: Alternative Liquidity Cuts: Credit Spreads

	(1)	(2)	(3)	(4)	(5)
Leverage					
Normal	479.834***	485.311***	485.051***	490.810***	499.582***
	(32.860)	(32.811)	(32.913)	(33.460)	(34.391)
GFC	1184.561***	1202.983***	1184.506***	1173.611***	1185.770***
	(130.794)	(132.345)	(128.848)	(135.455)	(132.408)
COVID-19	758.018***	750.914***	752.111***	773.984***	771.294***
	(69.580)	(70.583)	(65.848)	(65.967)	(75.423)
Liquidity					
Normal	-185.901***	-180.494***	-179.608***	-177.110***	-157.253***
	(26.158)	(22.917)	(23.131)	(24.366)	(29.134)
GFC	-55.652	42.229	17.543	14.995	53.358
	(62.983)	(51.763)	(64.892)	(66.652)	(74.024)
COVID-19	-373.808***	-368.876***	-323.515***	-298.458***	-274.392***
	(43.989)	(58.023)	(43.616)	(36.583)	(45.240)
Cuts	(1, 99)	(2, 98)	(3, 97)	(4, 96)	(5, 95)
N	46532	45685	44837	43994	43128
R^2	0.67	0.67	0.67	0.67	0.68

Notes: Controls for firm size and average bond maturity included. Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We measure undrawn credit lines using undrawn revolving credit from 10-Q statements.[30] We normalize undrawn revolving credit by total assets and winsorize observations at the 1% level.

Table A8 defines variables as in the main text. We regress credit spreads on leverage, liquidity, and undrawn credit lines. All independent variables are included with a two-quarter lag. The undrawn credit-line variable is normalized by total assets, consistent with the treatment of leverage and liquidity.

The main empirical message is that undrawn credit lines behave differently from cash (our measure of liquidity). In particular, firms with more undrawn credit lines experience *higher* credit spreads, an effect that goes in the opposite direction of cash (see the third panel of Table A8). We interpret this pattern through the balance-sheet mechanics of credit-line usage: while access to undrawn credit lines provides a source of funding, drawing on the line increases both assets and liabilities. As a result, once the firm taps the credit line, leverage rises, and spreads increase. In this sense, the effect of undrawn credit lines is closer to leverage than to liquidity.

This result is in line with the mechanism in the quantitative model. Firms entering the crisis

[30] We impute missing observations by interpolating between quarters where the previous and next quarter are not missing. Results hold with unimputed panel as well.

Table A5: Alternative Liquidity Cuts: Investment

	(1)	(2)	(3)	(4)	(5)
Leverage					
Normal	-0.028***	-0.028***	-0.027***	-0.027***	-0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
GFC	-0.038***	-0.038***	-0.038***	-0.039***	-0.040***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
COVID-19	-0.029***	-0.025***	-0.020**	-0.022**	-0.020*
	(0.009)	(0.008)	(0.009)	(0.010)	(0.010)
Liquidity					
Normal	0.027***	0.031***	0.034***	0.037***	0.030***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)
GFC	0.036***	0.045**	0.046**	0.051**	0.060**
	(0.012)	(0.019)	(0.021)	(0.025)	(0.024)
COVID-19	0.088***	0.085***	0.079***	0.077***	0.073***
	(0.015)	(0.015)	(0.012)	(0.015)	(0.016)
Cuts	(1, 99)	(2, 98)	(3, 97)	(4, 96)	(5, 95)
N	43125	42338	41539	40767	39968
R^2	0.099	0.11	0.12	0.12	0.13

Notes: Controls for firm size and average bond maturity included. Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

with smaller liquid asset holdings need to tap on the intraperiod debt market and those firms had a large increase in credit spreads.

To establish that firms do indeed draw on their undrawn credit lines at the onset of a crisis, we regress the post-crisis change in drawn credit lines (normalized by total assets) on pre-crisis undrawn credit (again, normalized by total assets). The results are in Table A9. For COVID-19, the pre-crisis period is 2019Q4 and the crisis period is 2020Q2. For the GFC, the pre-crisis period is 2008Q2 and the crisis period is 2009Q1. For each of the crisis events, we find that firms entering the crisis with more undrawn credit end up using credit lines more intensively, which validates the mechanism that we postulated in the previous paragraph.

Finally, we define liquidity capacity as the sum of undrawn credit lines plus cash in the balance sheet, and analyze the sources of changes in liquidity capacity during the two crises events. Specifically, we compute changes in liquidity capacity attributable to cash as:

$$\Delta\text{liq. capacity due to cash} = \frac{\Delta\text{cash}}{\Delta\text{cash} + \Delta\text{undrawn credit lines}}$$

Table A6: Controlling for Intangibles: Credit Spreads and Investment

	Credit spreads		Investment	
	(1)	(2)	(3)	(4)
Leverage				
Normal	479.834***	486.442***	-0.028***	-0.029***
	(32.860)	(33.466)	(0.006)	(0.005)
GFC	1184.561***	1190.984***	-0.038***	-0.039***
	(130.794)	(130.765)	(0.006)	(0.006)
COVID-19	758.018***	760.892***	-0.029***	-0.029***
	(69.580)	(70.364)	(0.009)	(0.009)
Liquidity				
Normal	-185.901***	-220.428***	0.027***	0.034***
	(26.158)	(25.032)	(0.006)	(0.006)
GFC	-55.652	-91.549	0.036***	0.043***
	(62.983)	(66.040)	(0.012)	(0.013)
COVID-19	-373.808***	-406.999***	0.088***	0.093***
	(43.989)	(44.608)	(0.015)	(0.015)
Intangibles	No	Yes	No	Yes
N	46532	46168	43125	43000
R^2	0.67	0.67	0.099	0.099

Notes: Columns (1) and (2) use credit-spreads and (3) and (4) use investment as a dependent variable. Controls for firm size and average bond maturity included. "Yes" columns include intangibles as controls. Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

We find that firms rely more heavily on cash than undrawn credit lines to increase their liquidity capacity. For the median firm, the change in liquidity capacity due to cash was 74% during the GFC and 90% during COVID.

A.7 Permanent Differences in Liquidity and Leverage

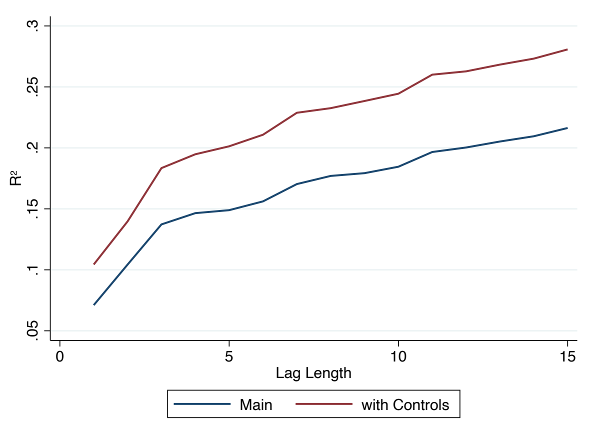
The model includes ex-ante heterogeneity that generates differences in the liquidity and leverage of firms. In this appendix, we argue that this a reasonable assumption. First, we note that both leverage and liquidity are extremely persistent characteristics within each firm. Second, we consider variants of our main empirical specification in (2) that show that our results are robust to controlling for permanent firm characteristics. Table A10 shows the results. The first column reproduces the benchmark result. Column (2) removes the firm-FE and replaces it with a sector fixed effect. Results are quantitatively very similar. This ensures that the firm fixed effect in our main specification is not simply capturing firm-level permanent characteristics that determine their leverage and liquidity.

Column (3) replaces liq and lev in equation (2) with firm-level averages. Under the assumption that the mean leverage and liquidity of the firm reflects the permanent component, results again are quantitatively identical.[31] Lastly, column (4) replaces liq and lev with 4-quarter rolling means. Again, results are robust to this specification. Overall, these exercises shows that it is reasonable to assume ex-ante differences across firms that generate heterogeneity in leverage and liquidity.

A.8 Working Capital

Predictability. The working capital needs measure displays substantial variation and is generally difficult to forecast. To assess its predictability, we estimate an autoregressive model of order L, AR(L), for the measure across a range of lag lengths. We consider two specifications: a baseline AR(L) without controls and a version that includes firm fixed effects. Figure A3 plots the R^2 values from these regressions, which remain below 30% even with 15 lags, indicating that most of the variation in working capital needs cannot be explained by past values alone.

Figure A3: R^2 by Lag Length



Working and Physical Capital. Figure A4 presents a binscatter of log physical capital against log accounts receivable. The figure shows a clear positive correlation between working capital needs—measured by receivables—and physical capital, supporting the functional form of the working capital constraint used in the model.

[31] Results are also robust to allowing for means to be different in each subperiod: Pre-GFC, GFC, Post-GFC, and COVID.

Figure A4: Binscatter: Capital on Receivables

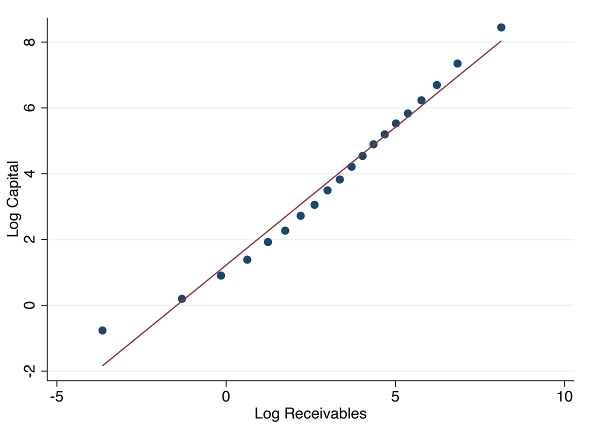


Table A7: Checking Callable Bonds: Credit Spreads

	(1)	(2)	(3)	(4)
Leverage				
Normal	481.776***	481.801***	436.810***	
	(33.045)	(32.943)	(30.981)	
Before GFC				359.259***
				(38.575)
After GFC				543.510***
				(34.575)
GFC	1183.484***	1183.526***	1137.238***	1173.587***
	(131.914)	(131.459)	(133.356)	(134.191)
COVID-19	755.688***	755.696***	689.204***	782.920***
	(69.491)	(69.456)	(59.640)	(69.316)
Liquidity				
Normal	-186.748***	-186.744***	-183.555***	
	(25.948)	(25.987)	(28.796)	
Before GFC				-163.121***
				(39.780)
After GFC				-197.468***
				(24.662)
GFC	-77.112	-77.141	-41.374	-74.754
	(60.397)	(60.643)	(66.048)	(58.913)
COVID-19	-367.920***	-367.942***	-342.454***	-379.628***
	(41.163)	(41.006)	(42.066)	(39.960)
Factors				
Level x Call	-15.558***	-15.544***	-15.173***	-12.943***
	(2.713)	(2.692)	(2.622)	(2.697)
Slope x Call	-11.096***	-11.092***	-11.209***	-8.187***
	(1.631)	(1.604)	(1.564)	(1.583)
Curve x Call	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Vol x Call	-72.185**	-72.144**	-73.419***	-63.541**
	(29.375)	(29.992)	(26.967)	(29.438)
Controls	Size	Size, Maturity	Size, Maturity, EBITDA	Size, Maturity
N	46532	46532	44430	46532
R^2	0.67	0.67	0.68	0.67

Notes: Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A8: Controlling for Credit Lines: Credit Spreads

	(1)	(2)	(3)
Leverage			
Normal	462.953***	459.805***	463.901***
	(37.335)	(36.327)	(37.135)
GFC	775.111***	642.311***	704.872***
	(93.981)	(71.358)	(89.742)
COVID-19	769.957***	786.868***	758.376***
	(90.085)	(90.176)	(88.763)
Liquidity			
Normal	-98.132***		-97.388***
	(29.596)		(29.162)
GFC	239.759*		254.844**
	(129.200)		(117.979)
COVID-19	-306.519***		-300.758***
	(55.369)		(48.100)
Undrawn credit lines			
Normal		83.424	78.233
		(64.444)	(53.768)
GFC		903.606***	886.946***
		(333.626)	(333.435)
COVID-19		667.791***	597.425***
		(134.345)	(118.584)
N	22067	22386	22067
R^2	0.70	0.70	0.70

Notes: Controls for firm size and average bond maturity included. Firm, quarter FEs. Standard errors are clustered by quarter. Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A9: Change in Drawdown of Credit

	(1) GFC	(2) COVID
Undrawn	0.076*	0.053**
	(0.043)	(0.025)
N	111	437
R^2	0.027	0.010

Notes: Variables are normalized by pre-crisis total assets. Standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A10: Permanent Liquidity and Leverage: Credit Spreads

	(1)	(2)	(3)	(4)
Leverage				
Normal	478.865***	503.842***	506.248***	400.702***
	(32.944)	(21.846)	(21.786)	(30.992)
GFC	1183.048***	1066.157***	1135.862***	1125.599***
	(131.317)	(104.966)	(131.817)	(102.017)
COVID-19	757.770***	633.951***	688.625***	685.929***
	(69.695)	(54.847)	(67.334)	(61.854)
Liquidity				
Normal	-186.055***	-70.288***	-41.429	-194.959***
	(26.134)	(17.963)	(25.488)	(27.635)
GFC	-54.484	9.814	14.107	113.326**
	(62.690)	(119.083)	(136.636)	(47.968)
COVID-19	-373.366***	-415.059***	-491.621***	-412.601***
	(43.871)	(53.838)	(82.954)	(49.164)
N	46532	46634	51997	38288
R2	0.67	0.35	0.34	0.68
Model	Benchmark	Sector FE	Permanent	Rolling Mean

Notes: Firm, quarter FEs for columns (1),(3),and (4). Standard errors are clustered by quarter. Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

B Model Appendix

B.1 Proof of Lemma 1

All results follows from a simple application of the implicit function theorem. First we differentiate 11 with respect to ℓ' and s_ℓ

$$0 = \left(s_\ell \beta r p_\omega exp\left\{s_\ell \ell'\right\}\left(2+s_\ell \ell'\right)\right) d\ell' + \left(\ell' \beta r p_\omega exp\left\{s_\ell \ell'\right\}\left(2+s_\ell \ell'\right)\right) ds_\ell$$

From $\ell' = \bar{\omega} - a'$ we get that

$$d\ell' = -da'$$

As a result,

$$\frac{da'}{ds_\ell} = \frac{\ell' \beta r p_\omega exp\{s_\ell \ell'\}(2+s_\ell \ell')}{s_\ell \beta r p_\omega exp\{s_\ell \ell'\}(2+s_\ell \ell')}$$
$$\frac{da'}{ds_\ell} = \frac{\ell'}{s_\ell} > 0$$

Second, we differentiate 11 with respect to ℓ' and p_ω

$$0 = \left(s_\ell \beta r p_\omega exp\left\{s_\ell \ell'\right\}\left(2+s_\ell \ell'\right)\right) d\ell' + \left(\beta r\left(1+s_\ell \ell'\right) exp\left\{s_\ell \ell'\right\}\right) dp_\omega$$

So

$$\frac{da'}{dp_\omega} = \frac{\beta r(1+s_\ell \ell') exp\{s_\ell \ell'\}}{s_\ell \beta r p_\omega exp\{s_\ell \ell'\}(2+s_\ell \ell')}$$
$$\frac{da'}{dp_\omega} = \frac{1+s_\ell \ell'}{s_\ell p_\omega (2+s_\ell \ell')} > 0$$

Third, note that

$$d\ell' = d\bar{\omega}k' - da'$$

and

$$0 = \left(s_\ell \beta r p_\omega exp\left\{s_\ell \ell'\right\}\left(2+s_\ell \ell'\right)\right)\left(d\bar{\omega}k' - da'\right)$$

Table B11: Calibration Moments 2007Q2

	Sample	H-Lev,H-Liq	H-Lev,L-Liq	L-Lev,H-Liq	L-Lev,L-Liq
Leverage (%)	31.6	46.2	42.8	20.2	23.1
Liquidity (%)	3.9	10.1	1.3	12.1	1.8
Credit Spreads (bp)	160	230	195	134	118
# of Firms	737	156	212	228	141

Notes: Calibration targets from the merged Compustat-FISD/TRACE dataset as of 2007Q2. The first column "Sample" reports median values for the full sample, while the following columns report median values for each subgroup.

Table B12: Calibration Moments 2019Q4

	Sample	H-Lev,H-Liq	H-Lev,L-Liq	L-Lev,H-Liq	L-Lev,L-Liq
Leverage (%)	39.2	53.1	50.8	28.2	31.7
Liquidity (%)	4.2	9.3	1.5	11.8	1.6
Credit Spreads (bp)	146	207	163	115	116
# of Firms	665	134	198	201	132

Notes: Calibration targets from the merged Compustat-FISD/TRACE dataset as of 2019Q4. The first column "Sample" reports median values for the full sample, while the following columns report median values for each subgroup.

As a consequence,

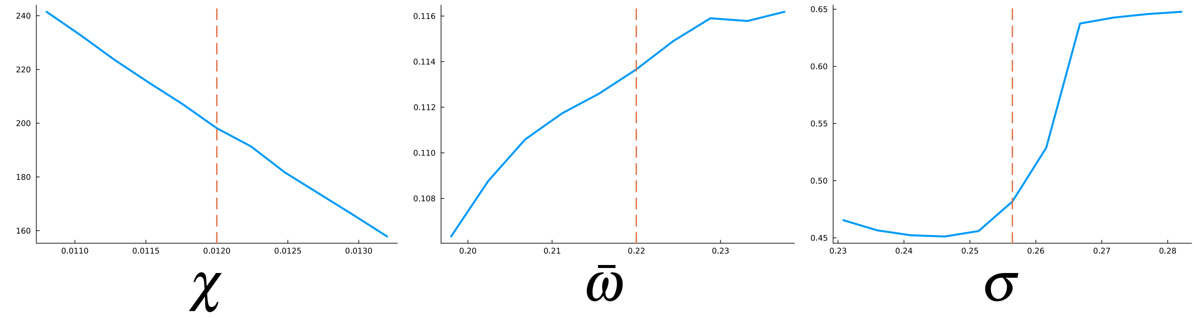
$$d\bar{\omega}k' = da'$$
$$\frac{da'}{d\bar{\omega}} = k' > 0$$

B.2 Calibration: Leverage and Liquidity Before Each Crisis

Tables B11 and B12 present median levels of leverage, liquidity, and credit spreads for each group of firms in 2007Q2 and 2019Q4, respectively. Leverage and liquidity groupings are defined with respect to whether firms have leverage and liquidity above or below the median level for the full sample. Medians are used as opposed to averages, so as to minimize the effects of outliers. For example, a high-leverage, high-liquidity firm in 2007Q2 is a firm whose leverage is higher than 31.6% and liquidity larger than 3.9%. Our calibration targets consist of averages for median leverage and liquidity across dates and firm groups. Our target for high leverage, for example, is the average of the leverage levels for high-leverage firms across 2007Q2 and 2019Q4 (that is, the average of 46.2, 42.8, 53.1, and 50.8).

Figure B5: Individual Parameter Identification

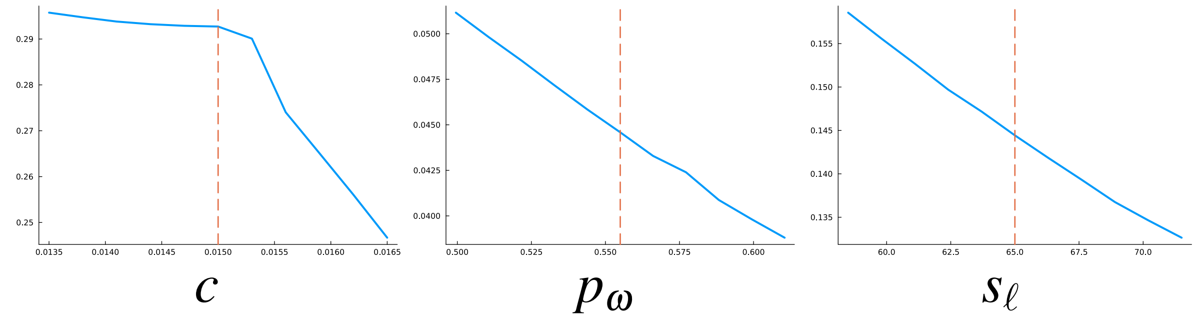
(a) Credit spreads (b) Liquid assets (c) Leverage



Notes: The figures show how credit spreads, leverage, and liquid assets change when we move χ, $\bar{\omega}$, and σ, respectively. For illustration we consider the firm with high leverage and high liquidity. Each vertical line corresponds to the value of the calibrated parameter.

Figure B6: Common Parameter Identification

(a) EBITDA to capital (b) Intraperiod Debt Spread (c) Intraperiod Debt to Total Debt



Notes: The figures show how the EBITDA to capital ratio, the intraperiod debt spread and the share of intraperiod debt out of total debt change when we move c, p_{ω} and s_{ℓ}, respectively. For illustration we consider a firm with high leverage and high liquidity.

B.3 Identification

Figure B5 shows how credit spreads help us identify the parameter χ, leverage helps us identify σ, and liquid assets help us identify $\bar{\omega}$. For illustration, the exercise is conducted only for a firm with high leverage and high liquidity.

Figure B6 repeats the exercise, but for the common parameters c, p_{ω}, and s_{ℓ}, which target the EBITDA to capital ratio, the intraperiod debt spread and the ratio of intraperiod-to-total debt, respectively. Note that the exact values of each moment do not exactly line up with the values for the data moments, as we target aggregates and this exercise corresponds to one type of firm only. Still, the figures illustrate that each of the moments can be used to identify each of these parameters.

Table B13: Robustness With Respect to Crisis Persistence

	Benchmark $\zeta = 0.75$	$\zeta = 0.50$	$\zeta = 0.25$
Spreads, bps	269.94	282.03	308.25
GDP, percent	-3.35	-3.35	-3.35
Liquid assets, percent	29.01	65.59	84.72
Debt owed, percent	32.04	34.84	32.43
Elasticity of spreads wrt leverage	730.62	778.74	877.90
Elasticity of spreads wrt liquidity	-666.76	-742.67	-888.29
Elasticity of inv. rate wrt leverage	-1.32	-1.99	-3.45
Elasticity of inv. rate wrt liquidity	5.12	7.00	9.32

B.4 Robustness: crisis persistence

Table B13 presents robustness with respect to the crisis persistence parameter ζ. Specifically, we raise the expected duration of the crisis by lowering the probability of returning to the baseline set of parameters: $\zeta = 0.5$ and $\zeta = 0.25$, meaning that the expected duration of the COVID-19 crisis is now two and four years, respectively. Again, in spite of some quantitative differences, the qualitative results are robust to more persistent shocks.

B.5 Homogeneous Shocks

In this appendix, we consider the case in which all firms are hit by the same aggregate shocks. That is, instead of the realization of the aggregate state becoming the same for all firms, we assume that:

$$
\begin{aligned}
z_i^a &= z_i + \varepsilon^z \\
\chi_i^a &= \chi_i + \varepsilon^\chi \\
\bar{\omega}_i^a &= \bar{\omega}_i + \varepsilon^\omega
\end{aligned}
$$

We calibrate the sizes of the shocks to match the aggregate movements in credit spreads, GDP, and liquid assets as in our baseline exercise. Table B14 replicates the first two columns of Table 11 in the main text. Overall, the aggregate results are very similar both quantitatively and qualitatively. However, the cross-sectional elasticities for spreads are one order of magnitude smaller than those of the data, and the cross-sectional elasticities for investment have the wrong signs. Thus our benchmark formulation is better aligned with the empirical evidence on cross-sectional responses.

Table B14: The COVID-19 Crisis, Homogeneous Shocks

	(1) Data	(2) Model
1. Targeted moments		
Spreads, bps	270.00	270.03
GDP, percent	-3.35	-3.35
Liquid assets, percent	29.49	29.66
2. Debt measures		
Debt in the data, percent	5.68	
Debt owed, percent		15.35
Debt owed, percent, w/ interest		28.81
b', percent of b		-37.03
ℓ, percent of b		52.38
3. Cross-sectional elasticities		
Spreads wrt leverage	757.87	242.31
	(69.73)	(0.03)
Spreads wrt liquidity	-373.24	-9.94
	(43.85)	(0.07)
Investment rate wrt leverage	-2.90	0.34
	(0.90)	(0.01)
Investment rate wrt liquidity	8.80	-0.71
	(1.50)	(0.03)

Notes: Aggregate and cross-sectional responses on impact, bps stands for basis points. The cross-sectional responses are based on regressions of the change in spreads or the investment rate on impact on the initial (steady state) levels of leverage and liquidity. Standard errors in parenthesis. The data correspond to the baseline empirical estimates in Section 3.