Credit and Liquidity Policies during Large Crises*

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Abstract

We compare firms' financials during the Great Financial Crisis (GFC) and COVID-19. While the two crises featured similar increases in credit spreads, debt and liquid assets decreased during the GFC but increased during COVID-19. In the cross-section, leverage was the primary determinant of credit spreads and investment during the GFC, but liquidity was more important during COVID-19. We augment a quantitative model of firm capital structure with a motive to hold liquid assets. The GFC resembled a combination of real and financial shocks, while COVID-19 also featured liquidity shocks. We study the state-dependent effects of credit and liquidity policies.

JEL Classification: E6, G2

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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 and policy responses 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. Finally, we study the effects of credit and liquidity policies in the model. We show how different policy responses may be more or less appropriate to different types of shocks. We conclude that it is essential to correctly identify the type of underlying shocks triggering the crisis, as some policies may be less effective if deployed against the "wrong" shock. Cross-sectional data can help policymakers to disentangle shocks as they have heterogeneous effects on different types of firms.

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.

Section 4 develops a quantitative macro-finance model where credit spreads, leverage, liquid asset holdings, and investment are endogenously determined. 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, face costs of equity issuance, 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 default 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, and can match non-targeted aggregate moments such as income-to-assets, 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. Additionally, 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.

Finally, Section 7 studies credit and liquidity policies similar to those implemented in the US during these crises. Our baseline estimates for the shocks include the effects of credit policies, such as corporate credit facilities, that were activated in the US during each of these crises. Guided by empirical estimates on the causal effects of such policies, we study a counterfactual economy without these credit policies and find that the increase in both borrowing and liquid asset holdings during the COVID-19 crisis would have been more muted. We also find significant heterogeneity in the benefits and effects of these policies across firms, with low-liquidity firms benefiting relatively more. During COVID-19, the government also deployed lending programs such as the Paycheck Protection Program (PPP) and the Main Street Lending Program (MSLP). However, these interventions were targeted at small and medium enterprises. We study what would have happened if large corporations had borrowed from these lending programs. We find that these programs could have generated significant benefits as long as (i) the programs allowed firms to circumvent their liquidity constraints and (ii) the crisis had a significant liquidity component. This second point suggests that identifying the nature of the underlying shock is essential for the design of effective policies. Our empirical methodology helps in the identification of shocks in real-time.

To summarize, this paper makes three 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. Third, on the normative side, the model allows us to evaluate policy counterfactuals related to liquidity policies.

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 and the effectiveness of policies.[1]

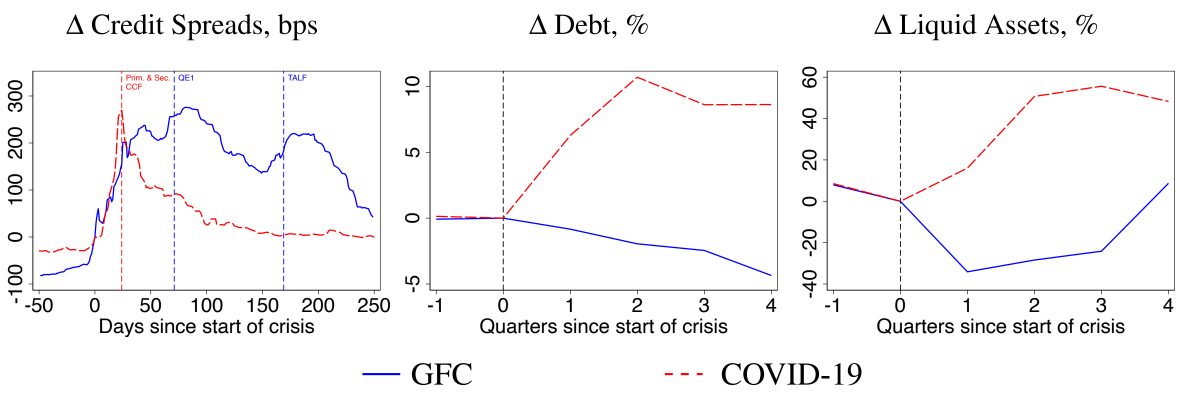
Our work is related to Crouzet and Gourio (2020), who study the financial position of US public companies before and during the pandemic. Their analysis emphasizes the COVID-19 crisis as an earnings shock and the risks it posed to US corporations. We find that funding liquidity seems to have been a significant 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. Elenev et al. (2022) study the effects of government programs directed at firms during the COVID-19 crisis in a dynamic model and find that these interventions play a prominent role in preventing corporate bankruptcies. These results are consistent with our findings that lending programs play an important role in preventing firm defaults, especially if they allow firms to circumvent liquidity constraints. Crouzet and Tourre (2021) use a model of firm capital structure to show that government interventions in corporate credit markets can cause debt overhang. While we do not explicitly model debt overhang, our model delivers similar results for real TFPR shocks, as government interventions can distort firms' optimal decisions to downsize and incentivize them to borrow more. We find, however, that these interventions can be particularly effective against other types of aggregate shocks, such as credit market and liquidity disruptions.

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. (2022) 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 and providing a structural framework to evaluate the policies.

Finally, we relate to a growing literature that uses microdata to learn about the sources of

[1] Bolton et al. (2022) and Nikolov et al. (2019), among others, also provide microfoundations for firm holdings of liquid assets.

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.

aggregate fluctuations (Bayer et al., 2020; 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. (2020) 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.[2] Figure 1 shows the path of credit spreads, real debt, and liquid assets as deviations from their values at the onset of each of the crises.[3]

[2]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.

[3]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.

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.[4]

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 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.

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.

[4] 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).

3.1 Measurement

We construct a weekly panel of US corporate bond spreads from mid-2002 to December 2020. 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.[5]

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 $y_{t,s}^{RF}$ be the yield on Trea-

[5]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).[6] Using the sequence of cash flows, we compute the price of the synthetic security as follows:

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

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

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

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

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

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 (unbalanced) sample of matched issues. We have about 3.5 million observations for 2,133 firms and 21,096 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. The final quarterly panel used in section 3.2 contains approximately 50,000 firm-quarter observations over the same time period.

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:

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

[6] 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/week	4.34	9.25	1.00	2.00	425.00
Market value of issue ($ mil)	548.55	582.73	1.80	400.00	15000.00
Maturity at issue (years)	9.80	6.71	1.00	9.25	30.00
Coupon (pct)	5.55	2.26	0.00	5.55	19.00
Credit Spread (basis points)	261.39	333.19	5.00	155.90	3499.93
Nominal yield (basis points)	575.68	446.87	17.55	494.09	10434.36
Number of observations	3,005,602				
Number of bonds	18,256				
Number of firms	2,019				
Callable (pct)	0.73				

Notes: Description of main sample. See text for details.

where N_{ft} is the number of outstanding bonds of firm f at time t and b_{ift} is the outstanding principal value of bond i. Finally, we define leverage as total liabilities (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.

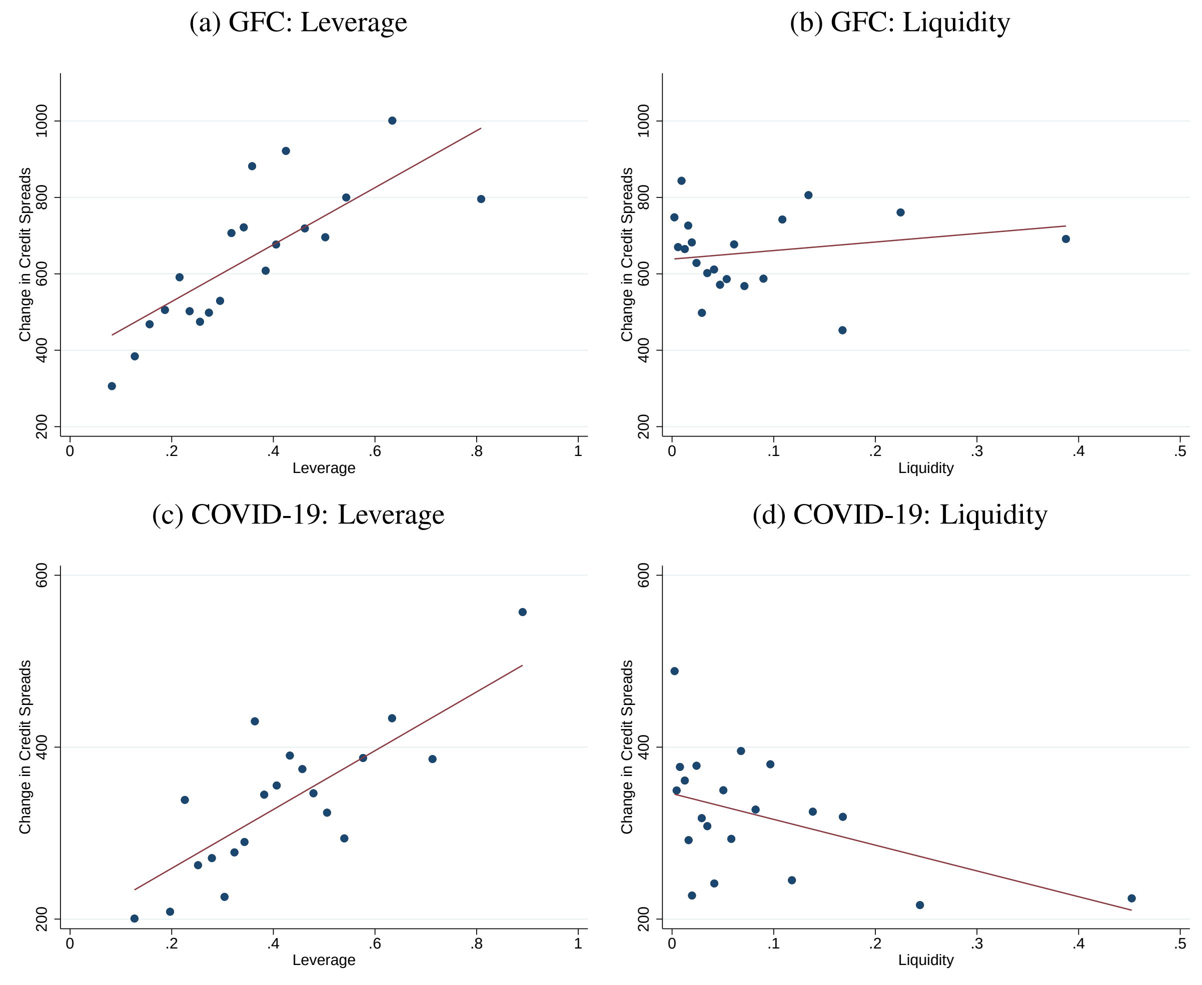
Investment. We follow the approach in Clementi and Palazzo (2019) to measure investment at the firm level. First, we construct a measure of capital: starting with an initial observation of the firm's capital stock, we cumulate net capital expenditures to construct a time series for capital. We then use depreciation to compute net 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.[7]

Figure 2: Credit Spreads, Leverage, and Liquidity



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.

[7]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.

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:Q2 - 2009:Q2 and COVID-19 as 2020:Q1 - 2020:Q2, with the remaining quarters being "Normal."[8] The starting date for the GFC reflects the failure of Bear Sterns in March 2008, while its end date corresponds to the announcement of TALF in March 2009, after which corporate credit spreads stabilize considerably.

Given the nature of the exercise, we use lagged variables to avoid contemporaneity issues.[9] 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.[10] We include a time fixed effect,

[8] Results are similar if we exclude post 2020:Q2 observations.

[9] 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).

[10] Our benchmark specification does not not interact the control variables with the period indicator variable, but

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.[11]

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 effect is quantitatively larger during the GFC. An increase in leverage of one standard deviation is associated with an increase in spreads of 228 bps during the GFC, 146 bps during COVID-19, and 92 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 implies a decrease in the credit spread of 44 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 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 different effects on spreads in each of the crises relative to normal times. While liquidity seems to have an unambiguously different effect during the COVID-19 recession, the same is not as clear for liquidity during the GFC (with a p-value of 5%).[12]

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our results are robust to doing it.

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

[12] 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.

Table 2: Panel Regressions of Credit Spreads

	(1)	(2)	(3)	(4)
Leverage				
Normal	478.842***	479.817***	435.049***	
	(32.942)	(32.859)	(30.977)	
Before GFC				340.031***
				(38.749)
After GFC				549.198***
				(34.137)
GFC	1183.187***	1184.709***	1138.658***	1170.893***
	(131.358)	(130.837)	(133.092)	(133.736)
COVID-19	757.864***	758.117***	691.565***	788.070***
	(69.725)	(69.610)	(59.664)	(69.337)
Liquidity				
Normal	-185.914***	-185.759***	-182.068***	
	(26.131)	(26.154)	(28.934)	
Before GFC				-165.340***
				(39.406)
After GFC				-195.488***
				(24.823)
GFC	-54.488	-55.665	-18.865	-57.279
	(62.667)	(62.961)	(67.885)	(61.131)
COVID-19	-373.238***	-373.683***	-347.407***	-384.071***
	(43.854)	(43.974)	(44.106)	(42.353)
Controls	Size	Size, Maturity	Size, Maturity, EBITDA	Size, Maturity
N	46534	46534	44432	46534
R^2	0.67	0.67	0.68	0.67

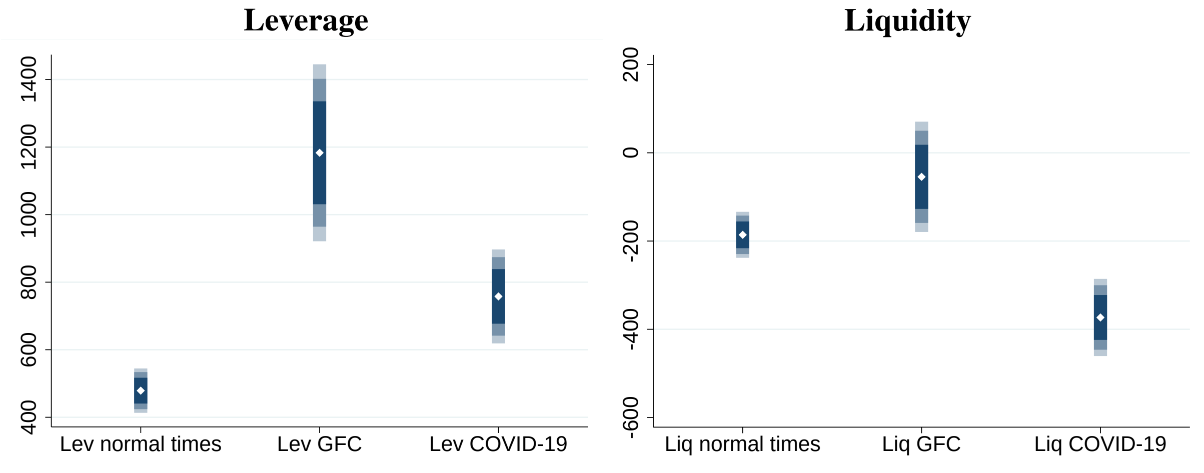
Notes: Regressions include both firm and quarter fixed effects. Standard errors are clustered by quarter. See appendix for data construction details. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 we control by firm size (its value in 2019Q4) and include two-digit NAICS sector fixed effects, α_s. Figure 4 plots the value of the estimated coefficients over time. The two vertical lines correspond to the last week of February (the beginning of the COVID-19 crisis) and the

Figure 3: Credit Spreads Coefficients



Notes: Effects 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

	Credit Spreads	Investment Rate
Leverage		
GFC	0.00	0.25
COVID-19	0.00	0.92
Liquidity		
GFC	0.05	0.39
COVID-19	0.00	0.00

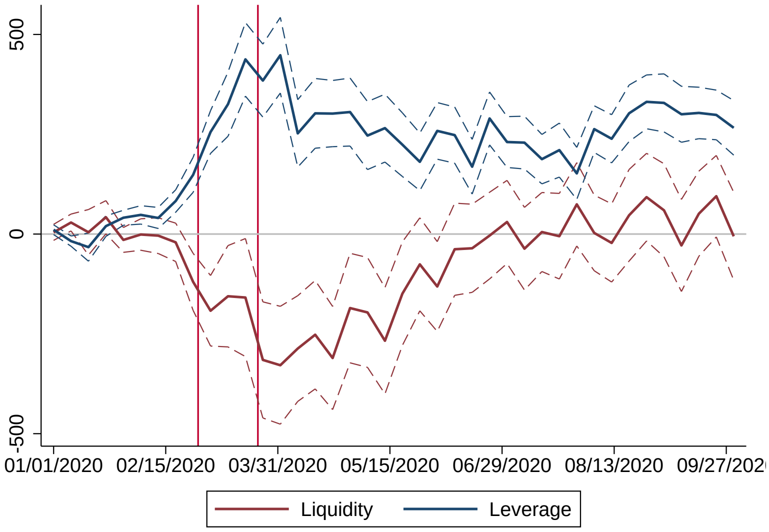
Notes: The null hypothesis is that the coefficients during the GFC and the COVID-19 crisis are equal to those during normal times.

week of March 23, when the Federal Reserve made a series of policy announcements. The figure shows that the effects of leverage and liquidity on 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 as-

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.*

sociated 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 effect 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 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 1.0 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 effect 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 seems to play a statistically different role during the COVID-19 period in terms of affecting investment rates.

Table 4: Panel Regressions of Investment Rate

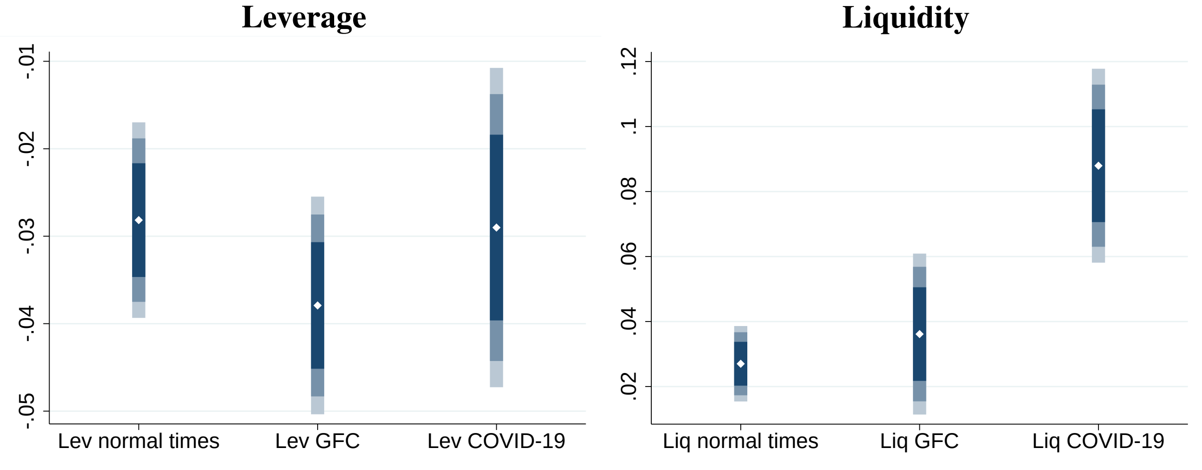
	(1)	(2)	(3)	(4)
Leverage				
Normal	-0.028***	-0.028***	-0.021***	
	(0.006)	(0.006)	(0.007)	
Before GFC				-0.035***
				(0.005)
After GFC				-0.025***
				(0.007)
GFC	-0.038***	-0.038***	-0.028***	-0.039***
	(0.006)	(0.006)	(0.006)	(0.006)
COVID-19	-0.029***	-0.029***	-0.021**	-0.028***
	(0.009)	(0.009)	(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	43126	43126	42596	43126
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. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

3.5 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 holds 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

Figure 5: Investment Coefficients



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

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. This result is line with Acharya et al. (2014).

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

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 equity issuance costs. 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 assets and interest rates: interperiod defaultable debt, liquid assets, and intraperiod debt. Firms are ex-ante heterogeneous in their idiosyncratic risk level and in their liquidity and leverage needs. We then use this framework to study how different shocks and policy interventions 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.[13] 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:

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

where $\psi > 0$.

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

[13] 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.

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 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.[14]

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. 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.[15] 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. 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 sudden expenses. 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. 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 $q(k', a', b')$

[14] 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.

[15] As in Holmström and Tirole (1998) the intraperiod debt can be interpreted as a credit line. We also allow the firm to hold liquid assets, while this is not an option in Holmström and Tirole (1998).

for a given principal repayment b'.

Let $\mathscr{P}(k',a',b')$ be the expected repayment probability of a firm that chooses capital k', liquid assets a', and debt b'. The price schedule is then given by

$$q(k',a',b') = (1+\chi)\frac{\mathscr{P}(k',a',b')}{1+r} \tag{8}$$

where the parameter χ summarizes financial frictions in debt markets and the relative benefits of debt financing, such as a tax shield (Miller, 1977).

Costly Equity Issuance. The firm is subject to costly equity issuance. Let div denote firm dividends:

$$div = \pi(z,k) + (1-\delta)k - k' - \mathscr{A}^K(k',k) - b + q(k',a',b')b' + a - q_a a' - \mathscr{A}^L(\ell) \tag{9}$$

Dividends are equal to static profits $\pi(z,k)$ net of capital investment, borrowing in defaultable debt, changes in liquid assets, and intraperiod liquidity costs. Firms with negative dividends are subject to convex equity issuance costs

$$\mathscr{A}^D(div) = \frac{\rho}{2}\max\{-div, 0\}^2 \tag{10}$$

where $\rho > 0$.

Default. At the beginning of each period, after the liquidity shock ω has been realized, the firm receives i.i.d. extreme-value preference shocks that induce some firms to default in equilibrium (Dvorkin et al., 2021). At the beginning of the period, the firm decides to repay its debt obligations or default:

$$V(k,a,b,\omega,\varepsilon^P,\varepsilon^D) = \max\left\{V^P(k,a,b,\omega)+\varepsilon^P, V^D(k,a,b,\omega)+\varepsilon^D\right\} \tag{11}$$

where V^P is the value of repayment given states (k,a,b,ω) and V^D is the value of default, which we assume to be equal to zero for simplicity, $V^D = 0$. The preference shocks follow an extreme-value distribution, and so $\varepsilon = \varepsilon^P - \varepsilon^D$ has a mean-zero logistic distribution with scale parameter κ. The repayment probability can be written as

$$\mathscr{P}(k,a,b,\omega) = \frac{\exp[V^P(k,a,b,\omega)/\kappa]}{\exp[V^P(k,a,b,\omega)/\kappa] + \exp[V^D(k,a,b,\omega)/\kappa]}$$

Given that the liquidity shocks ω are also i.i.d., we can write the repayment probability as

$$\mathscr{P}(k,a,b) = p_\omega \mathscr{P}(k,a,b,\bar{\omega}) + (1-p_\omega)\mathscr{P}(k,a,b,0) \tag{12}$$

The assumptions on these shocks also allow us to derive a closed-form expression for the expected value function. First, the expectation with respect to the extreme-value shocks is

$$\mathscr{V}(k,a,b,\omega) \equiv \mathbb{E}_\varepsilon[V(k,a,b,\omega,\varepsilon^P,\varepsilon^D)] \quad = \kappa \log\{\exp[V^P(k,a,b,\omega)/\kappa] + \exp[V^D(k,a,b,\omega)/\kappa]\}$$

Then, the expectation with respect to the liquidity shocks is simply

$$\mathscr{V}(k,a,b) \equiv \mathbb{E}_\omega[\mathscr{V}(k,a,b,\omega)] = p_\omega \mathscr{V}(k,a,b,\bar{\omega}) + (1-p_\omega)\mathscr{V}(k,a,b,0)$$

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

$$\begin{aligned} V^P(k,a,b,\omega) = \max_{k',a',b',\ell} \quad & div - \mathscr{A}^D(div) + \beta \mathscr{V}(k',a',b') \\ \text{s.t.} \quad & div = \pi(z,k) + (1-\delta)k - k' - b + q(k',b',a')b' + a - q_a a' - \mathscr{A}^K(k',k) - \mathscr{A}^L(\ell) \\ & \omega k \leq a + \ell \\ & a',b',k',\ell \geq 0 \end{aligned} \tag{13}$$

where $\beta \in (0,1)$, and $\mathscr{V}, q, \mathscr{A}^K, \mathscr{A}^L, \mathscr{A}^D$ are defined in the text above.

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 is

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

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 positive and $1+\rho(-div) \geq 1$ if they are negative. The right-hand side represents the benefits of acquiring liquidity. The first term shows that acquiring more liquid assets raises the 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 $a' < \bar{\omega}k'$ (if a' exceeds $\bar{\omega}k'$, 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 is no default and no equity issuance costs. Then, the Euler equation for liquid assets simplifies to

$$
q_a - \beta = \beta p_\omega \mathbb{I}[\bar{\omega}k' > a'] \frac{\partial \mathscr{A}^L(\ell')}{\partial \ell'} \tag{14}
$$

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

$$
q_a - \beta = \beta r p_\omega [1 + s_\ell \ell'] \exp[s_\ell(\ell')] \tag{15}
$$

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'.

Comparative Statics. Figure 6 shows the left- and right-hand sides of equation (15) for different parameters. 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

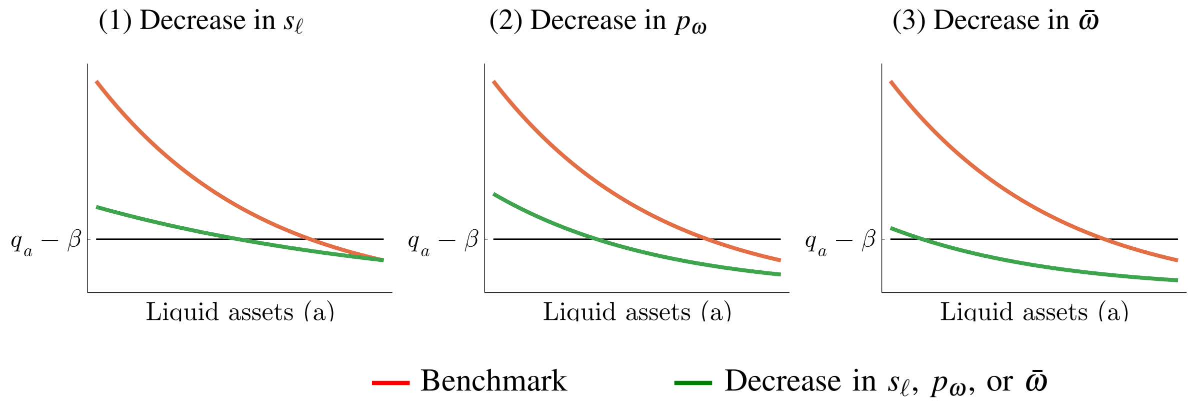
$$\text{spread}_\ell = r\exp(s_\ell \ell) - r = r[\exp(s_\ell \ell) - 1] \tag{16}$$

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 (15), 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 (16) 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.

Figure 6: Liquid Assets Choice: Comparative Statics



5 Calibration

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.

To calibrate the economy we assume that firms do not expect/anticipate aggregate shocks but form expectations over the realization of idiosyncratic shocks $(\omega, \varepsilon^P, \varepsilon^D)$. We define the steady state for firm i as the fixed point of the endogenous state variables (capital, debt, and liquid assets) of that firm under no realization of the liquidity shock, $\omega = 0$, and no default. All quantitative experiments start with all firms in this state. As we show in Appendix B.1 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 5 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 set the interest rate on liquid assets to zero; thus $q_a = 1$. We also normalize the wage and TFPR to 1. Finally, the curvature parameter of the equity issuance cost function ρ is set to 3, which means that firms do not issue equity at

Table 5: 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
ρ	3.0000	Zero equity issuance in steady state
Prices		
β	0.9500	Discount factor
r	0.0526	Interest rate
q_a	1.0000	Price of liquid assets

the steady state. Khan and Thomas (2013) and Ottonello and Winberry (2020), for example, impose a hard non-negativity constraint on dividends, not allowing firms to issue equity. Instead, we allow firms to potentially issue equity but make it costly to do so as in Cooley and Quadrini (2001). We present robustness with respect to this parameter in Appendix B.3.

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 κ_i, to match leverage, the share of liquid assets, and credit spreads for each type of firm. Appendix B.2 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. Third, we compute the average between the two dates to define the target moment in the data.[16] 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.

[16] Tables with the moments in these periods are reported in Appendix B.1.

Table 6: 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	0.0165	0.0052	0.0157	0.0054
Liquidity needs	$\bar{\omega}$	0.2053	0.1763	0.0959	0.0694
Idiosyncratic risk	κ	0.3589	0.2953	0.3809	0.3180
Mass	λ	0.2117	0.2877	0.3094	0.1913
Leverage	*Data*	0.4820	0.2580	0.4820	0.2580
	Model	0.4864	0.2574	0.4860	0.2579
Liquidity	*Data*	0.1080	0.1080	0.0160	0.0160
	Model	0.1080	0.1081	0.0160	0.0160
Spreads	*Data*	198.51	91.26	215.61	108.36
	Model	198.68	91.23	216.61	108.29

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 6 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 borrowing friction 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 κ, 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 two common 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 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, $r \times [\exp(s_\ell \ell) - 1]$.[17] If one thinks of this intraperiod debt as a proxy for bank credit lines, a natural target for the spread is the spread between the bank prime loan rate

[17]The discussion in Section 4.1 applies to a simpler version of the model, without default and equity issuance shocks. In Appendix B.2, we show that each of these moments helps identify the respective parameter even in the full model with default and equity issuance costs.

Table 7: 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%	3.1%
s_ℓ	19.1	$\frac{\ell}{\ell + b'}$	15.0%	15.0%

and the risk-free rate, which averaged 3.1% in the 2004-2021 period (FRED series DPRIME net of FEDFUNDS). Ideally, we would like to measure credit line usage within our TRACE-Compustat matched panel. In the absence of this data we rely on aggregate data and obtain a target for credit lines 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.[18] 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 or (drawn) credit lines. We rely on the estimates of Greenwald et al. (2021), 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 target and model moments and values for each internally calibrated parameter are presented in Table 7.

Untargeted Moments. Table 8 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 three moments: a measure of operating income-to-assets, debt-to-income, and the default rate. For income-to-assets, we take the firms' median ratio of operating income to lagged assets in our matched firm-bond panel. Similarly, we take the median ratio of firm debt to operating income. 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 2.5%, which is lower than but close to the default rate of 3% of speculative-grade firms (Moody's Investors Service, 2015).

6 Macro-Financial Crises

We now use the model as a laboratory to quantitatively study different crises and policy experiments. This helps us rationalize the differences in the behavior of credit spreads, debt,

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

Table 8: Untargeted Moments: Model vs. Data

Aggregate Moment	Data		Model
	2007Q2	2019Q4	
Income-to-assets, percent	13.40	11.10	14.38
Debt-to-income	2.21	3.24	2.61
Default rate	3.00	3.00	2.51

and liquid assets during the GFC and COVID-19 crisis.

6.1 Modeling Crises

We want to understand how firms behaved during the GFC and COVID-19 crises. 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. Let Φ^i denote the set of parameters whose values may change with shocks, such as the level of TFPR z_i, the level of financial frictions in debt markets χ_i, and/or the size of liquidity shocks $\bar{\omega}_i$:

$$\Phi^i = \{z_i, \chi_i, \bar{\omega}_i\} \tag{17}$$

Let Φ^i_0 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^i_1. 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^i_0 and remain there from then on, while with the remaining probability $1-\zeta$ it remains at Φ^i_1. Hence, the expected duration of the shock is $1/\zeta$.

Let $\mathscr{V}(k,b,a|\Phi)$ be the expected value function of the firm at state (k,b,a) 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

$$V^P(k,b,a,\omega|\Phi_1) = \max_{k',a',b',\ell} \quad div - \mathscr{A}^D(div) + \zeta\beta\mathscr{V}(k',b',a'|\Phi_0) + (1-\zeta)\beta\mathscr{V}(k',b',a'|\Phi_1) \tag{18}$$

where $\mathscr{V}(k',b',a'|\Phi_0)$ is the expected value of returning to the original set Φ_0 (the steady state), and $\mathscr{V}(k',b',a'|\Phi_1)$ is the expected value of remaining in the new set Φ_1 (the crisis state).

Aggregate Responses. All firm types are hit with the same shocks in Φ_1, i.e. $\Phi_1^i = \Phi_1, \forall i$. 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., 2022; Fernald, 2014). 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 fall in the financial friction/tax-advantage 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.[19] While χ_i is firm-specific, we assume that the shock corresponds to a situation where χ_i falls to χ^c for all firms. That is, we assume that while different firms experience different levels of distortion of their borrowing decision in the steady state, these distortions are equalized during a crisis.

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 drew from their credit lines due to a precautionary motive to mitigate future liquidity risk (e.g., Bosshardt and Kakhbod,

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

2021; Chodorow-Reich et al., 2022; Crouzet and Gourio, 2020; Greenwald et al., 2021). Again, while different firms have different levels of liquidity needs $\bar{\omega}_i$, during this aggregate shock, firms experience an increase to a level that is the same across all firms, $\bar{\omega}^c$. 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).

Government Policy We explicitly model the primary government intervention relevant for large firms during the GFC and COVID-19. During the GFC, the Federal Reserve established liquidity facilities such as the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF), which provided funding to financial institutions to purchase asset-backed commercial paper from money market funds. These credit market interventions were more explicit during the COVID-19 crisis, as the Fed set up the Primary and Secondary Market Corporate Credit Facilities, which involved the outright purchases of corporate bonds by eligible US companies during 2020. We label this type of intervention as Corporate Credit Facilities (CCF), standing for direct and indirect purchases of corporate debt by the Federal Reserve.

For simplicity, we assume a one-to-one mapping between quantities purchased and the price of corporate debt securities. We model these programs as a direct subsidy for lenders to purchase corporate debt. The price function for debt in (8) becomes

$$q^{CCF}(k',a',b') = (1+\chi+\chi^{CCF})\frac{\mathscr{P}(k',a',b')}{1+r}. \tag{19}$$

Note that given a target for the observed increase in credit spreads (which contains the effects of policy), we can only identify $\chi+\chi^{CCF}$. Later, in Section 7, to undertake the counterfactual analysis of no policy, we disentangle the policy component χ^{CCF} from the pure financial shock χ by using empirical estimates of the impact of these policies on credit spreads.

During the COVID-19 crisis, the government also implemented other lending programs such as the Paycheck Protection Program (PPP) or the Main Street Lending Program (MSLP). The PPP had strict eligibility criteria that were not satisfied by the large public firms in our sample. While the MSLP had looser participation criteria, take-up was very limited among large public firms (Brauning and Paligorova, 2021). For these reasons, we do not include these policies in the benchmark analysis. Instead, we analyze counterfactual scenarios related to these lending programs (LP) in Section 7.

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.

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.[20] 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.

The first panel of Table 9 shows the aggregate results for the COVID-19 crisis experiment. The first three rows correspond to the explicitly targeted moments. By construction, the crisis results in a 270 bps rise in credit spreads, a 3.35% fall in GDP, and a 29.5% rise in aggregate holdings of liquid assets. The following rows correspond to untargeted variables. The crisis leads to a significant increase in debt owed, which is defined as the sum of interperiod debt issued b' and intraperiod debt $[1+\mathscr{A}^L(\ell)]\ell$. 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

[20]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.3 shows that our main qualitative results are robust to changing shock persistence.

Table 9: The COVID-19 Crisis

	Data	Model
Aggregate		
Spreads, bps	270.00	270.00
GDP, percent	-3.35	-3.35
Liquid assets, percent	29.49	29.53
Debt owed, percent	5.68	31.40
Cross-sectional elasticities		
Spreads wrt leverage	757.87	522.57
	(69.73)	(0.84)
Spreads wrt liquidity	-373.24	-220.59
	(43.85)	(2.09)
Investment rate wrt leverage	-2.90	-1.70
	(0.90)	(0.02)
Investment rate wrt liquidity	8.80	6.22
	(1.50)	(0.06)

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 end of the period, which decreases profits and may make them negative. To avoid this, firms adjust other margins to avoid costly equity issuances. 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.

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.

6.3 Cross-Sectional Responses in the COVID-19 Crisis

The second panel of Table 9 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: 523 in the model vs. 758 in the data for leverage, and -221 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 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 -1.7 in the model vs. -2.9 in the data, while the elasticity with respect to liquid assets is 6.2 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.

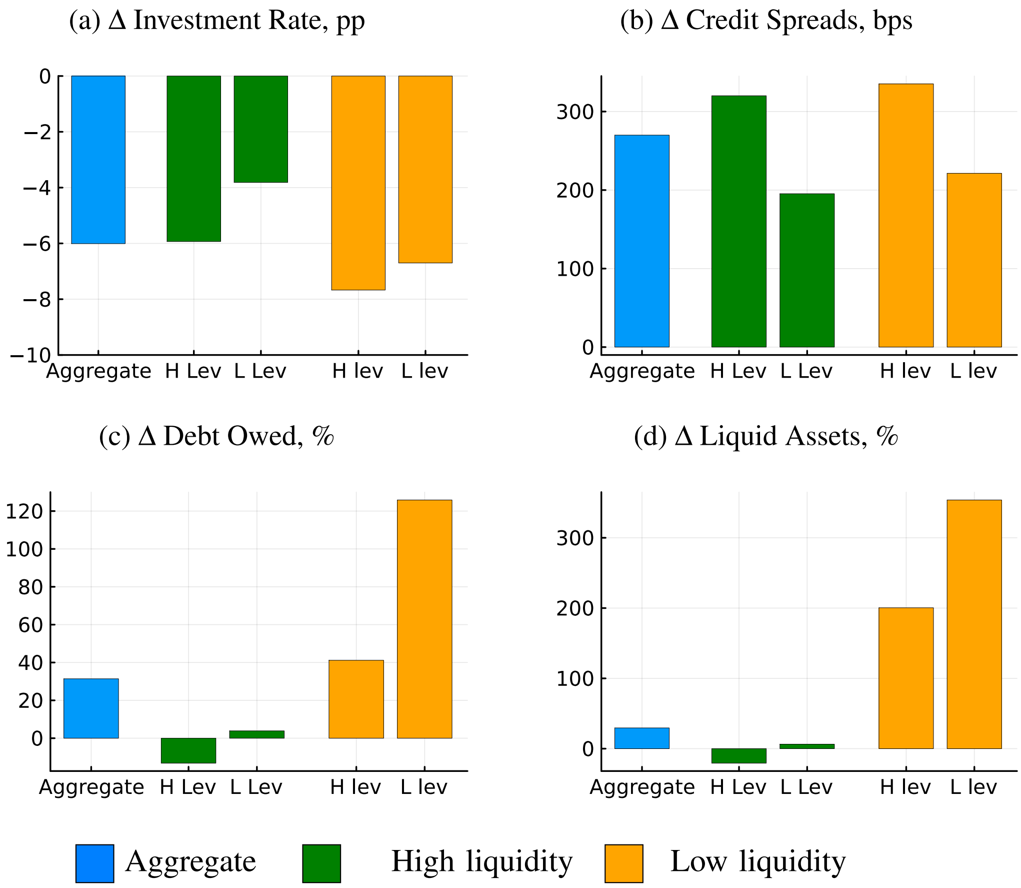
Figure 7 plots the distribution of changes for investment rates, credit spreads, debt owed, and liquid assets for the four types of firms. First, conditional on leverage, firms with low liquidity display worse outcomes (i.e., larger drop in investment and a larger increase in credit spreads). Second, conditional on liquidity, firms with high leverage have worse outcomes. Most of the heterogeneity in terms of the debt and liquid asset responses arises from differences in initial liquidity: firms with low liquidity increase their debt and liquid asset holdings much more than those with high liquidity.

Evidence on Cross-Sectional Liquidity Responses. The model predicts that firms with low liquidity should increase their holdings of liquid assets more than firms with high liquidity do upon a liquidity shock (fourth panel of Figure 7). 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

Figure 7: Cross-Sectional Responses: Benchmark Experiment



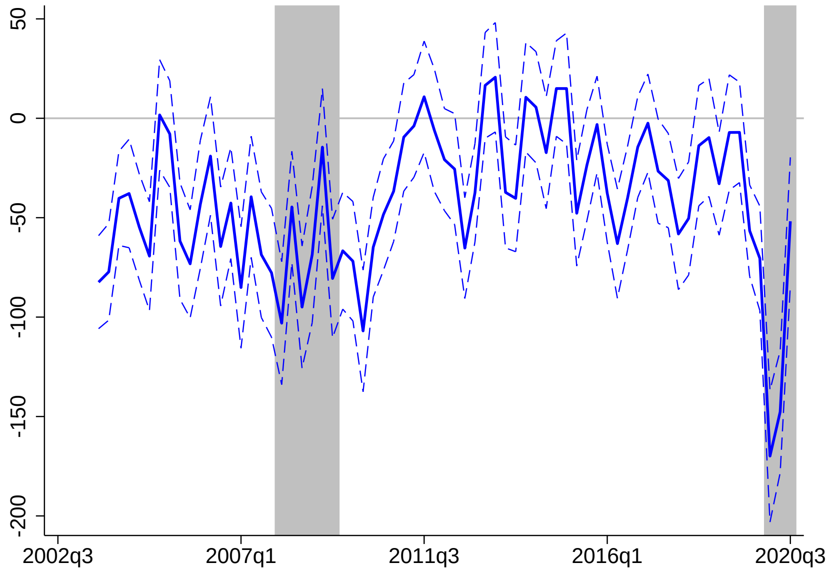
with lower liquidity tend to accumulate more liquidity over this period than those with more liquidity, consistent with the cross-sectional predictions of the model.

6.4 Shock Interaction and Amplification

The model generates a significant amount of endogenous amplification from the interactions between the three shocks. The first three columns of Table 10 present the results of feeding each shock one by one to the model, with the same shock sizes as in the COVID-19 crisis. The fourth column presents the results for the COVID-19 crisis (where all the shocks are fed simultaneously), and the fifth column presents a measure of the interaction between the shocks: it is equal to the response of a given variable in the benchmark case (where all three shocks are fed to the model) minus the sum of the responses when each shock is separately fed to the model.

This decomposition shows that the financial shock drives most of the movements in credit spreads. On the other hand, liquidity is essential to generate movements in liquid assets, debt, and the default probability. The interaction between the shocks can be significant for liquid

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



assets and debt. In the case of liquid assets, the interaction is negative, implying that the total response is less than the sum of its parts: in the absence of the financial shock, it is cheaper for firms to borrow and so the liquidity shock triggers a significant increase in debt used to finance liquid assets. The financial shock, however, makes it costly to borrow, which contributes to muting the response of liquid assets. Similarly, for debt, the financial shock in isolation triggers a large decrease in borrowing. The liquidity shock, however, raises the benefits of borrowing (to finance liquid assets), which generates a positive interaction term.

Importantly, the liquidity shock is enough to qualitatively generate the positive comovement between spreads, liquid assets, and debt. However, the liquidity shock is insufficient to match the increase in credit spreads quantitatively. This is achieved by the financial shock, which, in isolation, generates the opposite type of comovement between these variables, similar to what we observed during the GFC. We explore this further in the following subsection.

6.5 The GFC and the Role of Liquidity

We now simulate the GFC in our model. For this exercise, we hit the economy with only the real and the financial shocks. We target a drop in GDP of 5.01% and an increase in spreads of 258 bps, which corresponds to the increase in aggregate spreads between September 15 and November 25 of 2008, as in Figure 1. The results are presented in Table 11. The model replicates qualitatively the non-targeted drop of liquid asset holdings. We also experimented

Table 10: Shock Decomposition

	(1) Real	(2) Financial	(3) Liquidity	(4) Benchmark (all)	(5) Interaction
Spreads, bps	3.11	247.95	17.38	270.00	1.55
GDP, percent	-3.35	0.00	0.00	-3.35	0.00
Liquid assets, percent	-0.85	-34.31	85.39	29.53	-20.70
Debt owed, percent	-0.49	-62.38	75.94	31.40	18.33
Default prob., pp	0.03	0.02	0.17	0.22	0.01

Notes: The first three columns present results for feeding each shock one by one to the model (shock sizes same as in the benchmark case). The fourth column presents the results for the benchmark case, where all three shocks are fed simultaneously to the model. The final column is equal to the value in the benchmark column minus the sum of the values in the first three columns: $(5) = (4) - (3) - (2) - (1)$.

with adding a liquidity shock to target the exact change in liquid assets, but this generated very similar results and a significantly smaller value for the liquidity shock, which we take as further evidence that the liquidity shock did not play a very significant role during the GFC. In summary, the model without the liquidity shock can qualitatively match the non-targeted drops in liquid assets and debt owed during the GFC.

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.

We also compute the cross-sectional elasticities, presented in the second part of Table 11. We find that leverage still plays a role in determining spreads and investment rates: more leveraged firms experience larger increases in spreads and larger decreases in investment. Liquidity loses most of its previous importance, having much more muted effects on both investment rates and credit spreads. These results seem to be consistent with the regression results for the GFC. During the GFC, leverage still plays a significant role in the determination of credit spreads and investment rates, but the role played by liquidity is economically less significant. Taken

Table 11: The Global Financial Crisis

	Data	Model
Aggregate		
Spreads, bps	258.00	258.00
GDP, percent	-5.01	-5.01
Liquid assets, percent	-1.34	-36.23
Debt owed, percent	-6.81	-60.87
Cross-sectional elasticities		
Spreads wrt leverage	1183.19	520.43
	(131.36)	(0.77)
Spreads wrt liquidity	-54.49	32.27
	(62.67)	(1.91)
Investment rate wrt leverage	-3.80	-2.34
	(0.60)	(0.01)
Investment rate wrt liquidity	3.60	-0.99
	(1.20)	(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.

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 Policy Interventions

We now analyze the effects of policy interventions during crises. We first study these interventions in the context of the COVID-19 crisis and then study how the effects of policy interact with the liquidity shock. We consider two types of policies: the already described CCF, and lending programs (LP).

7.1 Corporate Credit Facilities

We evaluate the effects of CCF by comparing the benchmark results to those of a counterfactual without CCF. To this end, we need to disentangle the effects of the "pure" financial shock χ from the effects of the policy χ^{CCF}. To discipline this decomposition, we rely on the empirical estimates by Gilchrist et al. (2022), who find that CCF programs caused a reduction of approximately 70 bps on aggregate credit spreads during COVID-19.

Table 12 presents the results from our benchmark exercise (with policy) in the first column and the results for the counterfactual COVID-19 crisis without CCF in the second column.

Table 12: The Role of CCF during COVID-19

	With Policy	Without Policy
Aggregate		
Spreads, bps	270.00	340.00
GDP, percent	-3.35	-3.35
Liquid assets, percent	29.53	16.17
Debt owed, percent	31.40	23.89
Cross-sectional elasticities		
Spreads wrt leverage	522.57	531.16
	(0.84)	(0.84)
Spreads wrt liquidity	-220.59	-225.81
	(2.09)	(2.09)
Investment rate wrt leverage	-1.70	-1.89
	(0.02)	(0.02)
Investment rate wrt liquidity	6.22	6.38
	(0.06)	(0.06)

Notes: Aggregate and cross-sectional responses on impact. Bps 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.

Without policy, we observe a smaller increase in liquid assets and debt. The reason is that with higher spreads, firms choose to borrow less and consequently accumulate fewer liquid assets. We also observe larger elasticities (in absolute value) for both spreads and investment with respect to liquidity, which suggests that the effects of CCF are heterogeneous across firms.

Table 13 shows the cross-sectional effects of CCF. The first three columns compute the difference between outcomes with and without policy. First, we see roughly the same 70 bps increase in spreads in the absence of the CCF for each type of firm. However, the effects on liquid assets, debt, and the value of the policy are different across firms. Firms with low liquidity see a larger drop in liquid assets without policy, and firms with low leverage see a larger drop in debt without policy. This suggests that the CCF is effective at allowing low-liquidity firms to borrow more and accumulate more liquid assets to face the liquidity constraint.

To evaluate the policy, we use a measure analogous to the consumption equivalent as in Lucas (1987), but for firms. We compute how many resources would have to be lump-sum transferred to the firm in the absence of policy so that each firm obtains the same present discounted value as with policy. Column 4 reports this value as a percentage of EBITDA at the steady state. We find that the aggregate value of the policy is about 0.8% of EBITDA. However, firms with lower liquidity or higher leverage benefit more from the CCF, which is consistent

Table 13: The Cross-sectional Effects of CCF

	Δ Spreads, bps	Δ Liquid assets, percent	Δ Debt owed, percent	Value of Policy, % of EBITDA
Aggregate	70.00	-13.36	-7.51	0.81
High lev, high liq	70.71	-9.10	-6.21	0.89
Low lev, high liq	68.73	-8.32	-10.16	0.35
High lev, low liq	71.18	-57.03	-6.19	1.20
Low lev, low liq	69.22	-34.65	-8.92	0.78

Notes: The table shows the effects of CCF by computing the difference between outcomes both with and without policy in the aggregate and for each type of firm.

with the fact that the former are able to reduce their holdings of liquid assets by less, and the latter are able to reduce their borrowings by less thanks to the policy.

7.2 Lending Programs

We now consider the possibility of loans made by the government directly to corporations. An important component of the fiscal and monetary policy responses during COVID-19 consisted of programs such as the PPP, the MSLP, or the expansion of Small Business Administration lending programs. These corporate and business lending programs comprised almost 44% of the $2 trillion CARES Act signed into law in March 2020. Most of these programs consisted of low-interest loans offered by the government to eligible businesses, usually under certain conditions that incentivized firms to keep employees on their payroll. Importantly, the types of firms that we focus on in our analysis were either not eligible for many of these programs (such as the PPP or the SBA) or used them in a very limited capacity.[21] We evaluate what would have happened if these lending programs were widely accessible and used by large public firms.

We treat these subsidized loans as direct one-period loans of fixed-size L.[22] This loan involves a direct transfer of resources to the firm in the current period and is thus added to the total cash flow of the firm in (9). Thus, the firm also gains a liability of $(1+r^l)L$ that has to be repaid in the following period and is added to any other borrowing. This means that total debt owed at the end of the period is equal to $b' + (1+r^l)L$ and is taken into account by lenders when pricing loans originated in the current period; that is, the price of debt becomes

[21] Brauning and Paligorova (2021) report that 99% of all MSLP loans, corresponding to 94% of program volume, were taken out by firms that reported less than $50 million EBITDA. As of the 4th quarter of 2019, only 6.6% of firms in our sample had an EBITDA of less than $50 million, corresponding to 0.8% of assets.

[22] The maximum loan size for MSLP was $ 300 million, and the interest rate was set at LIBOR + 3% (Brauning and Paligorova, 2021). In the model, we map LIBOR to the risk-free rate r.

Table 14: Lending Programs

Policy	Spreads, bps	Liquid assets, percent	Debt owed, percent	Value of Policy, % of EBITDA
Aggregate				
CCF	270.00	29.53	31.40	0.81
CCF+LP	266.87	19.69	21.37	6.75
High leverage, high liquidity				
CCF	320.12	-20.63	-13.18	0.89
CCF+LP	318.41	-25.18	-18.47	3.52
Low leverage, high liquidity				
CCF	195.34	6.37	3.90	0.35
CCF+LP	194.22	1.04	-6.52	3.64
High leverage, low liquidity				
CCF	335.21	200.46	41.18	1.20
CCF+LP	330.30	149.16	31.94	8.35
Low leverage, low liquidity				
CCF	221.36	353.79	125.86	0.78
CCF+LP	216.53	318.98	106.34	12.40

$q[k', a', b' + (1 + r^l)L]$.

For our main analysis, we assume that these loans can be used to satisfy the liquidity constraint, but we later evaluate an LP that does not provide liquidity. That is, given a loan of size L, the liquidity constraint in (6) now becomes

$$\omega k \leq a + \ell + L. \tag{20}$$

Table 14 compares an economy with only CCF (our benchmark) with an economy with both CCF and LP. We find that the LP is particularly valuable for firms with low liquidity, while the CCF helped firms with high leverage (conditional on liquidity). Moreover, with government loans, we observe a lower increase in liquid assets and debt. This is because these loans offset the liquidity shock and allow firms to increase their holdings of liquid assets by much less, which in turn allows them to decrease their borrowing. This endogenous decrease in borrowing contributes to a reduction in credit spreads. Since the loans involve the direct transfer of real resources that help firms avoid negative dividends, there is a large direct effect on firm value, which is reflected in the large value of this policy.

7.3 Lending Programs and the Liquidity shock

We now evaluate the interaction between lending programs and the liquidity shock. Table 15 considers three different scenarios: (i) Only LP, (ii) LP in a crisis without the liquidity shock, and (iii) LP in a crisis with the liquidity shock but in which the loan cannot be used to satisfy the liquidity constraint.

First, we find that LP in a scenario without the liquidity shock has much lower benefits: the value of the policy decreases from 6.1% to 0.28%. Second, we find that if the firm cannot use the loan to satisfy the liquidity constraint, the value of the policy falls further to 0.13% in the aggregate. These results imply that the relatively high value of LP that we find crucially relies on its ability to circumvent the liquidity constraint. This allows firms to not engage in costly intraperiod borrowing, reducing their likelihood of having to issue costly equity. Moreover, we find that the LP without liquidity benefit has very little value, generating negative value for firms with low leverage and high liquidity.

An important question is why the large public firms in our sample did not take advantage of MSLP even though many were eligible. Our analysis suggests that the benefits of this program crucially depend on its ability to satisfy liquidity constraints and that the value of the LP can be very low or even negative if this is not the case.

8 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,

Table 15: Lending Programs and Liquidity

Policy	Spreads, bps	Liquid assets, percent	Debt owed, percent	Value of Policy, % of EBITDA
Aggregate				
LP	336.78	7.20	14.14	6.05
No liquidity shock	320.73	-41.57	-64.93	0.28
No liquidity benefit	339.91	16.34	24.13	0.13
High leverage, high liquidity				
LP	389.04	-33.98	-24.49	2.72
No liquidity shock	382.26	-48.52	-59.34	0.44
No liquidity benefit	390.68	-29.34	-19.08	0.22
Low leverage, high liquidity				
LP	262.91	-6.51	-16.10	3.38
No liquidity shock	257.82	-25.19	-82.63	0.13
No liquidity benefit	264.08	-1.93	-6.05	-0.01
High leverage, low liquidity				
LP	401.33	92.11	25.78	7.28
No liquidity shock	374.60	-100.00	-51.70	0.41
No liquidity benefit	406.20	143.25	35.09	0.25
Low leverage, low liquidity				
LP	285.66	290.99	97.98	11.75
No liquidity shock	260.10	-92.35	-79.99	0.13
No liquidity benefit	290.56	320.03	117.40	0.04

Notes: LP refers to the benchmark exercise, no liquidity shock refers to LP in a scenario without liquidity shock, and no liquidity benefit refers to LP in a crisis with liquidity shock but in which the loan cannot be used to satisfy the liquidity needs.

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.

We find that corporate credit facilities benefited firms and contributed to the rise in liquid asset accumulation and corporate borrowing during the COVID-19 crisis. Lending programs accessible to large public firms could have generated significant benefits as long as they helped firms circumvent liquidity constraints in the presence of an aggregate liquidity shock. In the absence of such constraint relaxation or liquidity shocks, the value of these policies reduces significantly. The fact that several public firms were eligible to access the Main Street Lending Program but chose not to may reflect the possibility that the program design limited the capacity of such lending to circumvent liquidity constraints.

Different policies can have different effects depending on the nature of the underlying shock, which implies that shock identification is crucial for effective policy design. One significant advantage is that credit spreads are available in real-time, at a daily frequency. Therefore, we propose that the study of their cross-sectional properties can be added to policymakers' toolkits to help determine which firms are more severely affected during crises and, together with a structural model, disentangle the sources of aggregate distortions.

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Online Appendix

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

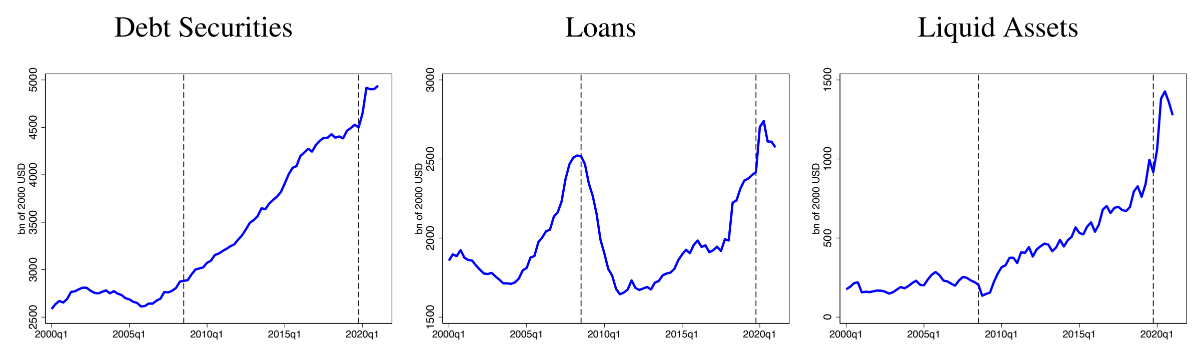
A Data Appendix

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

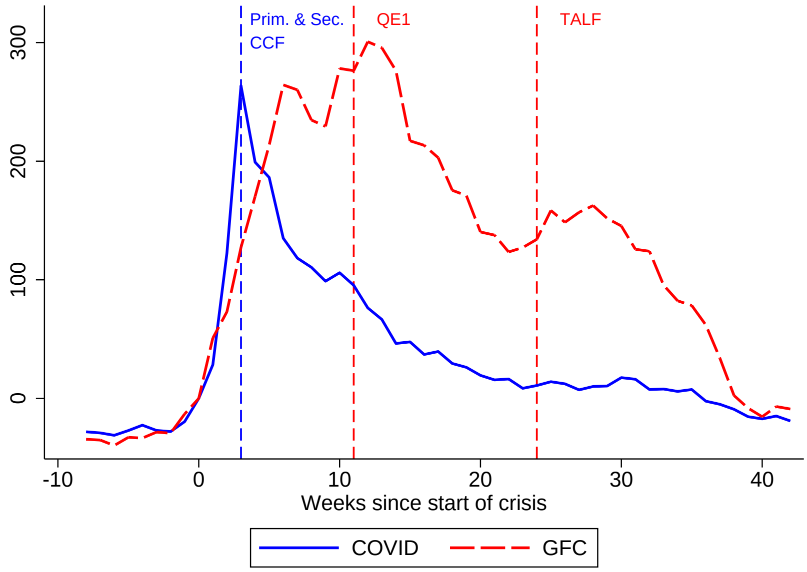
Figure A2 shows the median credit spreads for the micro data. Note that the figure is very similar to the aggregate data in the first panel of Figure 1.

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 net 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 gross 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 net investment rate, the second column shows the results for the gross 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:

$$y_{f,t} = \alpha_f + \gamma_t + \sum_{i \in \mathrm{E}} \beta_i \mathbb{I}_{t\in \mathrm{i}} \mathrm{liq}_{f,t} + \sum_{i \in \mathrm{E}} \phi_i \mathbb{I}_{t\in \mathrm{i}} \mathrm{lev}_{f,t} + \Gamma' X_{f,t} + \varepsilon_{f,t} \tag{21}$$

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	43126	44403	44640
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 (21) 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 (21) 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	479.817***	581.564***	587.267***
	(32.859)	(14.754)	(14.730)
GFC	1184.709***	1364.644***	1404.010***
	(130.837)	(31.051)	(30.707)
COVID-19	758.117***	803.018***	826.180***
	(69.610)	(37.731)	(36.619)
Liquidity			
Normal	-185.759***	-215.508***	-195.198***
	(26.154)	(29.533)	(29.634)
GFC	-55.665	4.446	115.861**
	(62.961)	(54.855)	(55.122)
COVID-19	-373.683***	-500.490***	-481.407***
	(43.974)	(75.833)	(76.546)
IV	No	$r = 1$	$r = 1,2$
N	46534	45614	42980

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)	(0.004)	(0.004)
GFC	-0.038***	-0.038***	-0.041***
	(0.006)	(0.009)	(0.009)
COVID-19	-0.029***	-0.038***	-0.036***
	(0.009)	(0.010)	(0.011)
Liquidity			
Normal	0.027***	0.066***	0.065***
	(0.006)	(0.008)	(0.009)
GFC	0.036***	0.064***	0.067***
	(0.012)	(0.015)	(0.016)
COVID-19	0.088***	0.133***	0.131***
	(0.015)	(0.021)	(0.022)
IV	No	$r = 1$	$r = 1, 2$
N	43126	44148	41662

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. The use of credit lines as a source of liquidity has been studied by Acharya et al. (2014), who noted that credit lines are not perfect substitutes for cash, especially for firms with high liquidity risk. We complement our panel with Capital-IQ data. We measure undrawn

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. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

credit lines using undrawn revolving credit from 10-Q statements.[23] We normalize undrawn revolving credit by total assets and winsorize observations at the 1% level.

Table A8 corroborates the results in Acharya et al. (2014). During normal times undrawn credit lines do not seem to affect credit spreads. During both GFC and COVID-19, however, firms entering the crises with more undrawn credit lines experienced a larger increase in credit spreads. The intuition for this result is as these firms enter a crisis, they tap on their credit lines which implies larger debt which hurts previous outstanding bond holders in the corporate debt market. As a result, credit spreads in secondary markets increase. This result highlights that cash and credit lines are not perfect substitutes.

This result is in line with the mechanism in the quantitative model. Firms entering the crisis with smaller liquid asset holdings need to tap on the intraperiod debt market and those firms had a large increase in credit spreads.

[23] 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. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

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.

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	521.894***	520.057***	459.805***
	(42.889)	(43.076)	(36.327)
GFC	740.806***	736.293***	642.311***
	(77.235)	(77.036)	(71.358)
COVID-19	863.957***	862.694***	786.868***
	(101.883)	(101.686)	(90.176)
Undrawn credit lines			
Normal	99.820	99.406	83.424
	(72.881)	(72.908)	(64.444)
GFC	876.718**	878.428**	903.606***
	(394.342)	(395.610)	(333.626)
COVID-19	781.988***	778.534***	667.791***
	(99.498)	(99.575)	(134.345)
Controls	Size	Size, Maturity	Size, Maturity, EBITDA
N	23093	23093	22386
R^2	0.69	0.69	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 B9: 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 B10: 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.

B Model Appendix

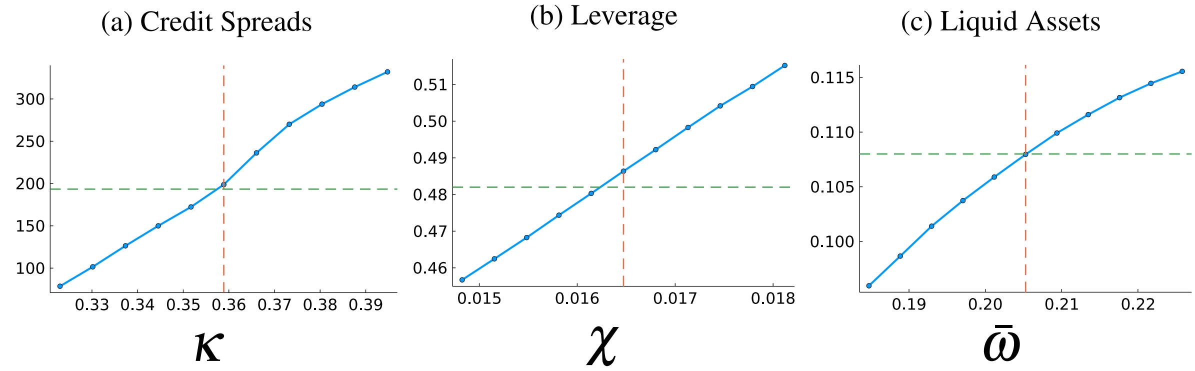
B.1 Calibration: Leverage and Liquidity Before Each Crisis

Tables B9 and B10 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).

B.2 Identification

Figure B3 shows how credit spreads help us identify the parameter κ, leverage helps us identify χ, 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 B3: Individual Parameter Identification



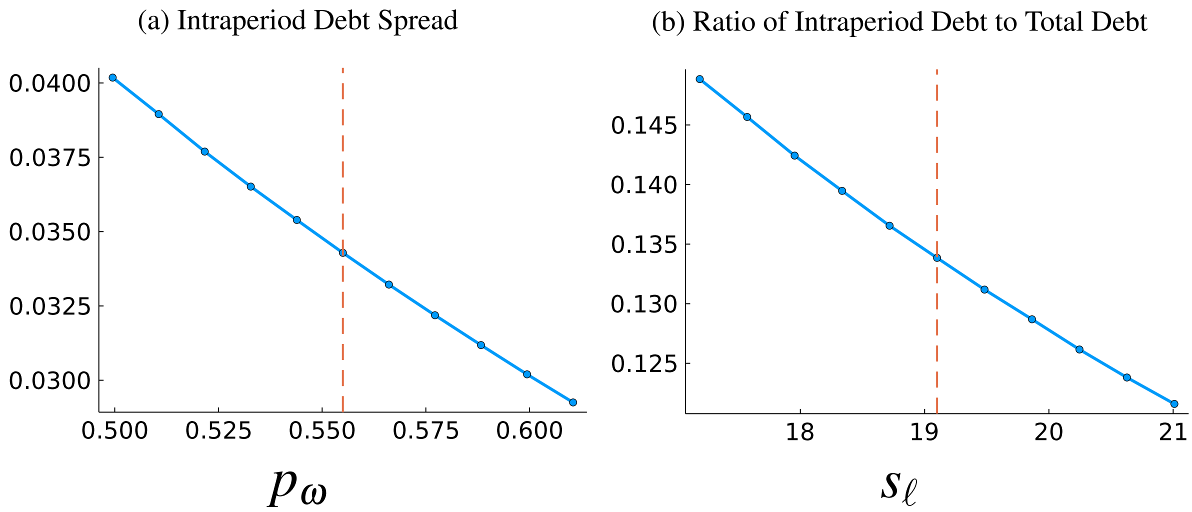
Notes: The figures show how credit spreads, leverage, and liquid assets change when we move κ, χ, and $\bar{\omega}$, respectively. For illustration we consider the firm with high leverage and high liquidity. Each vertical line corresponds to the value of the calibrated parameter, and the horizontal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

Figure B4 repeats the exercise, but for the common parameters p_ω and s_ℓ, which target 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.

B.3 Calibration: Robustness

Table B11 presents robustness with respect to the equity issuance cost parameter ρ showing that the results are very similar for both larger and smaller values of the equity issuance cost ρ. Our main qualitative results remain unchanged. Table B12 repeats the exercise for an increase in the persistence of the shocks, $\zeta = 0.5$ and $\zeta = 0.25$, meaning that the expected duration of each crisis is now two and four years, respectively. Again, in spite of some quantitative differences, the qualitative results are robust to more persistent shocks. We perform both of these robustness exercises in the context of the COVID-19 crisis.

Figure B4: Common Parameter Identification



Notes: The figures show how the intraperiod debt spread and the share of intraperiod debt out of total debt change when we move p_ω and s_ℓ, respectively. For illustration we consider a firm with high leverage and high liquidity.

Table B11: Robustness With Respect to Equity Issuance Costs

	Benchmark, $\rho = 3$	Lower $\rho = 0.5$	Higher $\rho = 6$
Spreads, bps	270.00	269.64	270.05
GDP, percent	-3.35	-3.35	-3.35
Liquid assets, percent	29.53	34.83	28.82
Debt owed, percent	31.40	11.28	33.93
Elasticity of spreads wrt leverage	522.57	520.80	522.82
Elasticity of spreads wrt liquidity	-220.59	-219.02	-220.81
Elasticity of inv. rate wrt leverage	-1.70	-1.18	-1.77
Elasticity of inv. rate wrt liquidity	6.22	5.87	6.25

Table B12: Robustness With Respect to Crisis Persistence

	Benchmark, $\zeta = 0.75$	$\zeta = 0.50$	$\zeta = 0.25$
Spreads, bps	270.00	274.18	283.37
GDP, percent	-3.35	-3.35	-3.35
Liquid assets, percent	29.53	75.86	100.24
Debt owed, percent	31.40	34.34	31.96
Elasticity of spreads wrt leverage	522.57	531.98	552.21
Elasticity of spreads wrt liquidity	-220.59	-246.28	-293.42
Elasticity of inv. rate wrt leverage	-1.70	-2.62	-3.55
Elasticity of inv. rate wrt liquidity	6.22	8.23	10.86