Credit and Liquidity Policies during Large Crises*

Mahdi Ebsim
New York University

Miguel Faria-e-Castro
FRB of St. Louis

Julian Kozlowski
FRB of St. Louis

January 24, 2022

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 main 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 productivity and financial shocks, while COVID-19 also featured liquidity shocks. We study the state-dependent effects of credit and liquidity policies.

JEL Classification: E6, G01 H00

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

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

1 Introduction

Large crises tend to be associated with financial market disruptions that hamper firms' ability to borrow and invest (Reinhart and Rogoff, 2009). In this paper, we study how different large aggregate shocks and policies 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 and recent crises, the Great Financial Crisis of 2008-09 (GFC) and the COVID-19 crisis of 2020.Both crises featured large 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. 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 is useful to disentangling the nature of the shocks that were prevalent during the GFC and COVID-19. Finally, we study the effects of credit and liquidity policies in the model, and show how different policies may be more or less appropriate responses to different types of shocks. We conclude that it is important to correctly identify the type of underlying shocks that are triggering the crisis, as some policies can be counter-effective if deployed against the "wrong" shock. Cross-sectional data can help policy makers to disentangle shocks as they have heterogeneous effects on different 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, similar to Gilchrist and Zakrajsek (2012). We augment the panel with firm-level financials from Compustat. Firms entering the GFC with more leverage tended to experience larger 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 also find that the effects of leverage and liquidity on investment rates for these two events are qualitatively similar to their effects on credit spreads.

Section 4 develops a quantitative macro-finance model where investment, credit spreads, leverage, and liquid asset holdings 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. 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. To study the cross-sectional properties, we model firms as being ex ante heterogeneous with respect to their liquidity and leverage needs, as well as to their idiosyncratic default risk.

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 as well as its cost and is able to replicate 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 productivity shocks, financial shocks that affect firms' ability to issue debt, and liquidity shocks that tighten the working-capital constraint. By comparing aggregate moments of the model to the data, we find that the GFC resembles mostly a combination of real and financial shocks, while the COVID-19 crisis also includes a significant liquidity shock component. The liquidity shock is essential to rationalize the joint movement of credit spreads, liquid assets, and borrowing that we observe during COVID-19. Importantly, the model is able to generate the cross-sectional elasticities that we observe in the panel regressions of credit spreads and investment rates on leverage and liquidity, even though these moments are untargeted.

Finally, Section 7 studies credit and liquidity policies that were activated in the US and other countries in the two crises. We find that credit policies, such as corporate credit facilities and credit guarantees, are particularly cost-effective, especially at offsetting aggregate financial shocks, reducing credit spreads, and stimulating investment. These policies, however, have little effect on bankruptcy rates, as they work by facilitating more borrowing. The effects of these programs are different across firms. Corporate credit facilities represent relatively larger subsidies to safer firms (e.g., with low leverage and high liquid assets), while credit guarantees tend to subsidize riskier firms (e.g., with high leverage and low liquid assets). The distribution of firm financial characteristics is therefore relevant to assessing the relative costs and benefits of these policies.

We find that other types of policies, such as direct loans and transfers, are effective at offsetting liquidity shocks, especially in terms of preventing firm defaults. Since they reduce firms' need to borrow in the face of liquidity and financial shocks, they help reduce firms' probabilities of default. However, we show that these policies are relatively ineffective in the absence of liquidity shocks. Our model experiments show that different types of policies may be more appropriate responses to different types of shocks, which makes identification of the type of shock important for policy design.

Literature This paper is related to a large body of literature that attempts to combine 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 focusing on firm's 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.

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 a funding liquidity shock and the risks that this poses to US corporations. We also find that funding liquidity seems to have been a major 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 less cash holdings experienced larger drops in market value; this is consistent with our empirical findings for corporate bond spreads and investment rates. Elenev et al. (2020) 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 large role in preventing corporate bankruptcies. These results are consistent with our findings that cash transfers and loans—our modeling of the Paycheck Protection Program (PPP) program—play an important role in preventing firm defaults. Crouzet and Tourre (2020) 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 one particular type of shocks (real shocks), as government interventions can distort firms' optimal decisions to downsize and incentivize them to borrow more instead. We find, however, that these interventions can be particularly effective against other types of aggregate shocks, such as credit market and liquidity disruptions.

Finally, 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. (2020) study the evolution of liquidity conditions in corporate bond markets during the pandemic and its aftermath. Boyarchenko et al. (2020) and Gilchrist et al. (2020) 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 large positive effects of these programs. We complement these authors' analysis by focusing on the determinants of credit spread increases before the Fed interventions and providing a structural framework to evaluate the policies.

2 Aggregate Dynamics of Spreads, Debt, and Liquid Assets

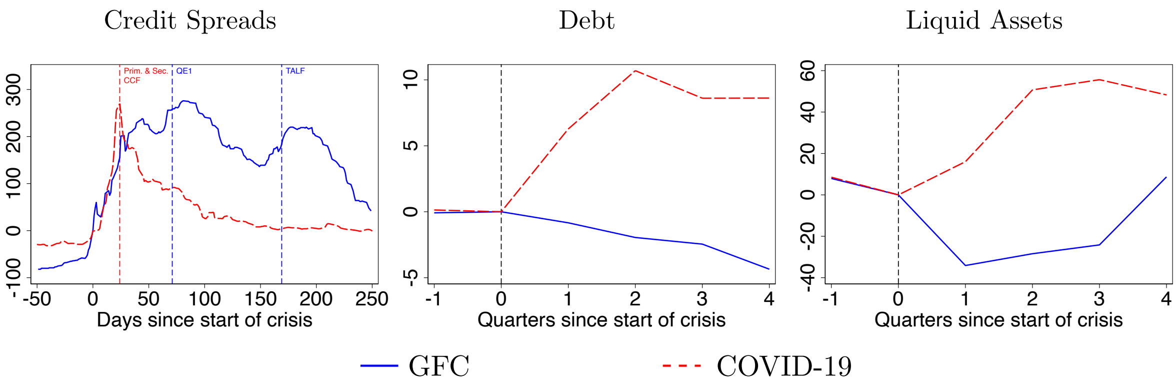
We begin by studying the joint dynamics of aggregate credit spreads, debt, and liquid asset holdings of US nonfinancial corporations around the GFC and the COVID-19 crisis. For credit spreads, we look at the ICE Bank of America US Corporate Index Option-Adjusted Spread. For debt and liquid assets, we look at flow of funds data.[1] 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.[2]

In terms of credit spreads, the onset of each crisis was relatively similar, with increases of

[1]Credit spread data is 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 that also encompasses foreign deposits, time and savings deposits, and money market fund shares.

[2]Credit spreads are in bps deviations, and debt and liquid assets are in percentage deviations. Credit spread data is available at a daily frequency, and 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 with respect to 2008Q3 for the GFC and 2019Q4 for COVID-19.

Figure 1: Aggregate Spreads, Debt and Liquid Assets



Notes: Blue solid lines are for GFC, red dashed lines 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 in 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). Second and third panels show real total debt and liquid asset holdings. Data sources: Financial Accounts of the United States and FRED. Vertical black dashed lines correspond to 2008Q3 and 2019Q4.

around 300 basis points (bps). Overall, there are two key 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 smaller effect in containing spreads in 2008 than in 2020.[3]

The movements of debt and liquid assets, however, were very different between the two crises: while debt and liquid asset holdings fell at the onset of the GFC, both of these variables increased sharply in 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 experiences 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 40%. While they recovered by the fourth quarter after the GFC, the opposite movements for these two variables during these two events is very noticeable.

It is worth emphasizing that the increase in debt during COVID-19 was primarily coming from private lenders as opposed to government policy. A large policy intervention (the PPP) led to an increase in Loans, but 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) in Appendix A.1.

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

3 Firm-Level Empirical Evidence

The aggregate data shows that while credit spreads increased in both episodes, there were very different dynamics for the debt and liquid asset holdings of the corporate sector, 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.

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 then the difference between the yield to maturity (YTM) of a corporate bond and the YTM of the corresponding synthetic bond. To estimate the credit spreads, we require secondary market prices, risk-free rates, and bond characteristics to reconstruct the cash flows for the observed bonds.

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

We obtain bond characteristics from 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.

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

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 Treasuries at date t and maturity s, which we obtain from Gurkaynak et al. (2007).[5] Using the sequence of cash flows, we compute 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.

For the analysis, we define credit spreads at the firm-level f as the average spread of out-

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

Table 1: Summary Statistics of Bond Panel

Variable	Mean	SD	Min	Median	Max
Number of bonds per firm/week	4.61	9.28	1.00	2.00	425.00
Market value of issue ($ mil)	525.16	553.24	1.80	400.00	15000.00
Maturity at issue (years)	10.34	7.23	1.00	9.67	30.00
Coupon (pct)	5.58	2.21	0.00	5.62	19.00
Credit Spread (basis points)	249.70	324.50	5.00	146.12	3499.93
Nominal yield (basis points)	565.73	441.44	17.55	484.39	10434.36
Number of observations	3,480,596				
Number of bonds	21,096				
Number of firms	2,133				
Callable (pct)	0.73				

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

standing bonds issued by a given firm, weighted by the size of those issuances:

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

where N_{ft} is the number of outstanding bonds of firm f at time t and b_{ift} is the outstanding 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 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 total assets of the firm. This measure captures the amount of resources that the firm has immediate access to.

Investment To measure investment at the firm level, we follow the approach in Clementi and Palazzo (2019). 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.

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

We estimate the following panel regression:

$$y_{f,t} = \alpha_t + \gamma_f + \beta_{E(t)}\text{liq}_{f,t-r} + \phi_{E(t)}\text{lev}_{f,t-r} + \Gamma' X_{f,t-r} + \varepsilon_{f,t} \tag{2}$$

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. Given the nature of the exercise, we use lagged variables to avoid contemporaneity issues. 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, $X_{f,t}$ are other firm-level controls such as firm size (log of total lagged assets), lagged average debt maturity, and/or lagged measure of profitability, such as EBITDA to total assets. We include a time fixed-effect, α_t, and a firm fixed-effect, γ_f. Finally, we cluster standard errors at the quarter level because aggregate shocks affect all firms, but potentially affect them in different ways.[6]

The main question of interest is whether β and/or ϕ are different across periods. $E(t)$ is an indicator variable that identifies whether quarter t falls in the period corresponding to the GFC (2008:Q2 - 2009:Q2), COVID-19 (2020:Q1 - 2020:Q2), or normal times.

3.2 Cross-Sectional Elasticities: Credit Spreads

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 224 bps during the GFC, 144 bps during COVID-19, and 91 bps during normal times. Second, funding liquidity seems to have significantly helped curb higher credit spreads during the COVID-19 crisis, but not during the GFC. In fact, 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 43 bps during COVID-19, more than twice as much as during normal times (21 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

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

robust to splitting the normal times period into pre- and post-GFC periods.

Table 2: Panel Regressions of Credit Spreads

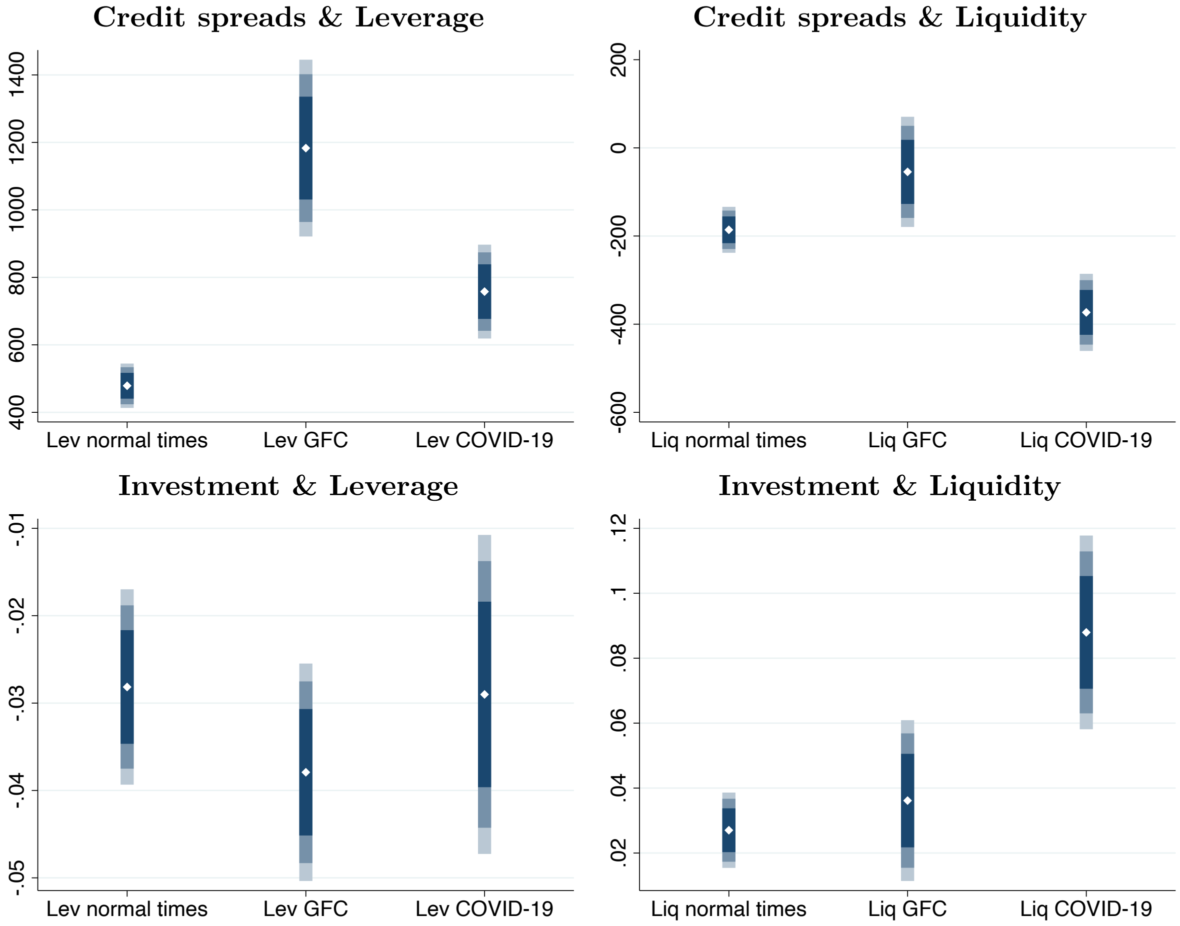
	(1)	(2)	(3)	(4)
Leverage				
Normal	478.846***	479.821***	435.054***	
	(32.943)	(32.860)	(30.977)	
Before GFC				340.033***
				(38.749)
After GFC				549.202***
				(34.137)
GFC	1183.190***	1184.712***	1138.661***	1170.895***
	(131.359)	(130.838)	(133.093)	(133.737)
COVID-19	757.866***	758.120***	691.568***	788.072***
	(69.725)	(69.610)	(59.665)	(69.338)
Liquidity				
Normal	-185.915***	-185.760***	-182.070***	
	(26.131)	(26.154)	(28.934)	
Before GFC				-165.341***
				(39.406)
After GFC				-195.489***
				(24.823)
GFC	-54.489	-55.665	-18.866	-57.280
	(62.668)	(62.961)	(67.885)	(61.132)
COVID-19	-373.240***	-373.685***	-347.409***	-384.073***
	(43.854)	(43.974)	(44.106)	(42.353)
Controls	Size	Size, Maturity	Size, Maturity, EBITDA	Size, Maturity
N	46540	46540	44438	46540
R^2	0.67	0.67	0.68	0.67

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

The top panel of Figure 2 summarizes the main cross-sectional results. Leverage is always statistically significant, but the corresponding coefficient is larger during the GFC than during normal times and 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%).[7]

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

Figure 2: Credit spreads & Investment



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

An Event Study of COVID-19 We also study the evolution of credit spreads during 2020 at the 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 as of 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 (as its value in 2019Q4) and include two-digit NAICS sector fixed effects, α_s.

Figure 3 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 week of March 23, when the Federal Reserve made a series of policy announcements. The figure

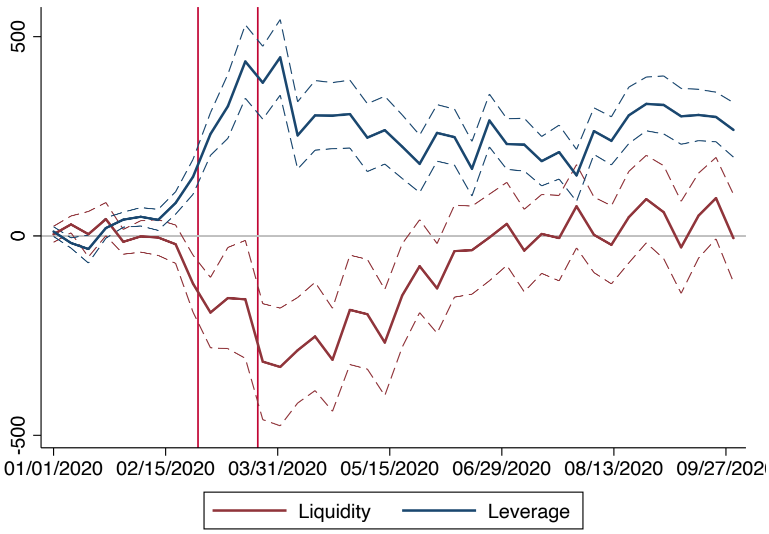
Table 3: p-values for Test of Equality of Coefficients

	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 crises are equal to those during normal times.

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, after which they begin decreasing. These results suggest that the effects that we find on the quarterly panel regressions are not primarily driven by policy, as both leverage and liquidity were important during the early weeks of March when COVID-19 was present but no policies had yet been announced.

Figure 3: 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.

3.3 Cross-Sectional Elasticities: Investment

Table 4 shows the results of specification (2) for investment rates as the outcome variable, $y_{f,t} = i_{f,t}$. During normal times, lower leverage and higher liquid asset holdings are both associated with higher investment rates. The effect of leverage on investment rates does not seem to have substantially changed during either the GFC or the COVID-19 periods. Liquidity, however, seems to have played a different role in each of these periods: the coefficient on liquidity is similar in terms of magnitude but less precise during the GFC. During the COVID-19 crisis, liquidity appears to have become more important, with the point estimate for the coefficient tripling. The other columns show that the results are robust to additional controls and to dividing the normal times into before and after the GFC period. Appendix A.4 shows that the results are robust to alternative definitions of investment.

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	43130	43130	42600	43130
R^2	0.099	0.099	0.11	0.099

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

The second panel of Figure 2 summarizes the main cross-sectional results. For investment, leverage has a constant effect in the different periods, while liquidity is more important during COVID-19. 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 periods 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.

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 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. 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 the level of idiosyncratic risk they face as well as in their liquidity and leverage needs. We then use this framework to study how different shocks and policy interventions affect both 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 $i = 1, \ldots, N$. 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 total factor productivity (TFP) z. 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

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

where $\psi > 0$.

Liquid Assets The firm holds liquid financial assets a. Liquid assets can be purchased at price q_a and yield 1 in the following period. A sufficiently high price q_a means that liquid assets are dominated assets and there is, in principle, no motive to hold them. We introduce a precautionary motive for holding liquid assets: the firm faces a stochastic working-capital constraint, to cover operational costs before revenue is received. The need for working capital arises from the difference in the timing of when costs are incurred and when revenue is received. 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 times of large financial and economic crises.[8]

We formalize the working-capital constraint as follows. With probability p_ω the firms 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 use either existing liquid assets a, or borrow ℓ in costly intraperiod debt. The working-capital constraint is

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

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

[8]See Boissay et al. (2020) for a description of trade credit disruptions during the COVID-19 crisis and Baqaee and Farhi (2020) for a general analysis of supply chain disruptions.

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

where 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 a dominated asset, the combination of the stochastic liquidity need ω and the increasing costs of intraperiod debt induces 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 discount factor r. The debt contract specifies a price schedule $q(k', a', b')$ for a given principal repayment b'.

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

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

where the parameter χ summarizes financial frictions in debt markets as well as 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:

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

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

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

where $\rho > 0$.

Default At the beginning of each period, 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

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

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

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

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

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

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

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

Firm's Problem Conditional on not defaulting, the problem of the firm is

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

where $\beta \in (0,1)$, and $\mathcal{V}, q, \mathcal{A}^K, \mathcal{A}^L, \mathcal{A}^D$ 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 insights 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 benefits other than satisfying the liquidity constraint. Then, the Euler equation for liquid assets is

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

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 $1+\rho\max\{-div,0\} \geq 1$ 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, which directly affects the probability of default and hence the price of debt. The second and third terms represent the 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, $\frac{\partial \mathcal{A}^L(\ell')}{\partial \ell'}$, 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).

With extra 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

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

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 key 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 4 shows the left- and right-hand side of equation (15) for different parameters. The black lines correspond to $q_a - \beta$, while the orange lines correspond to the right-hand side 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

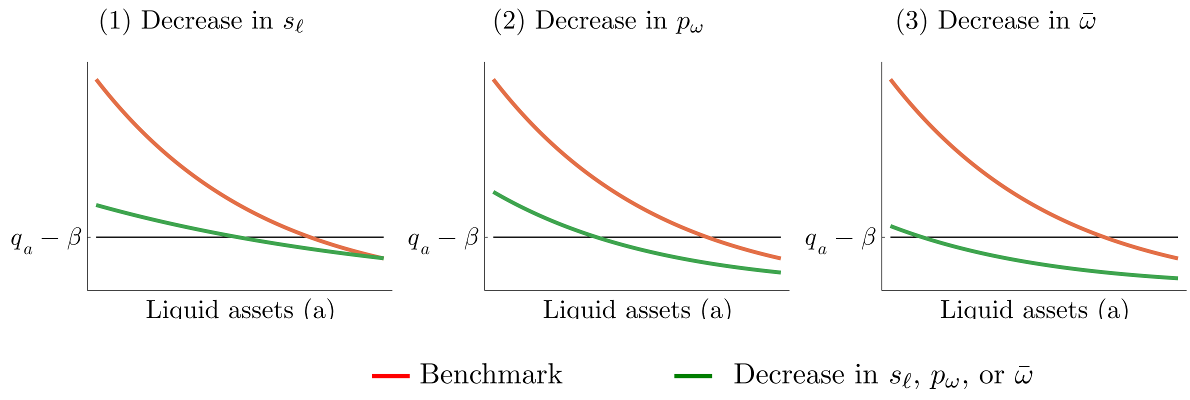
$$\text{spread}_\ell = r\exp(s_\ell \ell) - r = r[\exp(s_\ell \ell) - 1] \tag{16}$$

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 entails necessarily 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: if the liquidity shock becomes less likely, firms choose to hold fewer liquid assets. This choice means that they need to borrow more intraperiod debt when the shock is realized, thus raising the spreads.

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, so as 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 4: 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 common parameters from the literature. Some internally calibrated parameters are common across firms, while others vary across firm types. We choose the parameters to target both aggregate and cross-sectional moments.

We calibrate the economy at the stochastic steady state. Firms do not expect/anticipate aggregate shocks but form expectations over the realization of idiosyncratic shocks $(\omega, \varepsilon^P, \varepsilon^D)$. The stochastic steady state for firm i corresponds to the fixed point of the endogenous state variables (capital, debt, and liquid assets) of firm i under no realization of the liquidity shock, $\omega = 0$, and no default. All quantitative experiments start with all firms in this state.

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 curvature parameter of the equity issuance cost function ρ is set to 3, which means that firms do not issue equity at the steady state.[9] 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 $q_a = 1$. Finally, we normalize the wage and TFP to 1.

[9] Khan and Thomas (2013) and Ottonello and Winberry (2020), for example, impose a non-negativity hard constraint on dividends, not allowing firms to issue equity. To simplify the numerical solution, we allow firms to potentially issue equity, but make it very costly to do so. We present robustness with respect to this parameter in Appendix B.3.

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	TFP, 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

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, in order to match leverage, share of liquid assets, and credit spreads for each type of firm. Appendix B.2 shows that these moments can be identified by each of the parameters mentioned above. We define the four groups of firms depending on whether firms have high or low leverage and liquidity. To define the target values for high/low leverage and liquidity, we rely on our matched panel of firms and credit spreads, as described in section 3. We split the panel into four groups, depending on whether their leverage and liquid asset holdings are below or above the median value in 2007Q2 and 2019Q4, and target median values of leverage/liquidity for each group across the two dates.[10] 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 is equal to 153 bps, the average of the median spread in the two targeted periods. This ensures that the steady state of the model reproduces the cross-sectional relationship between the credit spreads, leverage, and liquidity that we estimate during normal times. We use the number of firms in each subgroup as a percentage of the total number of firms to construct the weights λ_i.

Table 6 summarizes the targeted data moments, as well as the endogenously calibrated parameters for each firm type, and the corresponding model moments. Model moments match very closely the moments we target in the data. Each of the moments is informative about one of the parameters: the borrowing friction parameter χ is larger for firms with high leverage,

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

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 levels of leverage and liquidity for each firm. Appendix B.2 illustrates how each of these moments helps identify each parameter.

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	0.0163	0.0053	0.0155	0.0054
Liquidity needs	$\bar{\omega}$	0.2011	0.1736	0.0917	0.0669
Idiosyncratic risk	κ	0.3595	0.2959	0.3812	0.3186
Mass	λ	0.212	0.309	0.288	0.191
Leverage	*Data*	0.482	0.258	0.482	0.258
	Model	0.482	0.258	0.482	0.258
Liquidity	*Data*	0.108	0.108	0.016	0.016
	Model	0.108	0.108	0.016	0.016
Spreads	*Data*	198.86	91.39	215.46	107.98
	Model	198.56	91.25	215.68	108.36

We also internally calibrate two common parameters that are 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, $r \times [\exp(s_\ell \ell) - 1]$.[11] 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 and the risk-free rate, which averaged 3.1% in the 2004-2021 period (FRED series DPRIME net of FEDFUNDS). To obtain a target for credit lines as a fraction of total debt, we proceed as follows: first, from the flow of funds, we can compute loans as a percentage of total debt for nonfinancial corporate businesses.[12] 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. (2020), 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

[11]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.

[12]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.

at an estimated target of 15% for the $\frac{\ell}{\ell+b'}$ ratio. The target and model moments, along with the values for each internally calibrated parameters, are presented in Table 7.

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	20	$\frac{\ell}{\ell+b'}$	15%	14.4%

Untargeted Moments Table 8 presents a 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 median ratio of operating income to lagged assets for the firms in our matched firm-bond panel. Similarly, we take the median of the 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 2.50%, which is a bit lower than but close to the default rate of 3% of speculative-grade firms (Moody's Investors Service, 2015).

Table 8: Untargeted Moments: Model vs. Data

Aggregate Moment	Data		Model
	2007Q2	2019Q4	
Income to Assets, percent	13.40	11.10	14.36
Debt to Income	2.21	3.24	2.60
Default rate	3.00	3.00	2.50

6 Macro-Financial Crises

We now use the model as a quantitative laboratory to study different crises and policy experiments, which helps us to rationalize the differences in the behavior of credit spreads, debt, and liquid assets in the past two crises. Furthermore, this analysis allows us to study the costs and benefits of different policy interventions akin to those deployed in these two recent crises.

6.1 Modeling Crises

We want to understand how firms behaved during the GFC and the COVID-19 crisis. Neither of these events were traditional business cycle fluctuations, but rather large and unexpected aggregate shocks. Hence, we explore the responses of firms to unexpected and transitory shocks.

Let Φ denote the set of parameters whose values may change with shocks, such as the level of TFP z, the level of financial frictions in debt markets χ_i, and/or the size of liquidity shocks $\bar{\omega}_i$:

$$\Phi = \{z, \chi_i, \bar{\omega}_i\} \tag{17}$$

Let Φ_1 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_2. For example, productivity z or the extent of financial frictions χ could change. After the shock is realized, firms learn that each period, with probability ζ, the economy will return to Φ_1 and remain there from then on, while with the remaining probability $1-\zeta$ it remains at Φ_2. Hence, the expected duration of the shock is $1/\zeta$.

Let $\mathcal{V}(k, b, a|\Phi)$ be the expected value function of the firm at state (k, b, a) and a given set Φ. The problem of the repaying firm at period t when parameters change from Φ_1 to Φ_2 is

$$V^P(k, b, a, \omega|\Phi_2) = \max_{k', a', b', \ell} \quad div - \mathcal{A}^D(div) + \zeta\beta\mathcal{V}(k', b', a'|\Phi_1) + (1-\zeta)\beta\mathcal{V}(k', b', a'|\Phi_2) \tag{18}$$

where $\mathcal{V}(k', b', a'|\Phi_1)$ is the expected value of returning to the original set Φ_1 (the steady state), and $\mathcal{V}(k', b', a'|\Phi_2)$ is the expected value of remaining in the new set Φ_2 (the crisis state).

Aggregate Responses All firm types are hit with the same shocks in Φ_2. The aggregate response of outcome x is simply the weighted response of each individual 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 productivity z, to a new level z^c, and can either be interpreted as a drop in the efficiency of production or as a fall in demand for the good produced by the firm.

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.[13] 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

[13]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).

decision in the steady state, these distortions are "equalized" during a crisis.

Finally, the liquidity shock corresponds to an increase in $\bar{\omega}$, which raises the demand for liquid assets, especially for firms with low liquid assets. Again, while different firms have different levels of liquidity needs $\bar{\omega}_i$, during this aggregate shock firms experience an increase that is the same across all firms, $\bar{\omega}^c$. We assume that the realization of the individual liquidity shock is $\omega = \bar{\omega}^c$ for the duration of the aggregate shock, after which it returns to the steady state, $\omega = 0$.

6.2 Benchmark Crisis: Real, Financial, and Liquidity Shocks

Our benchmark experiment consists of hitting the economy with the real, financial, and liquidity shocks at the same time. We choose the sizes of the shocks to generate a large financial and economic crisis. First, we target a fall in GDP of 5%, which corresponds to a 5% drop in productivity. Second, we target a rise in spreads of 300 bps, similar to the rise of spreads on impact in each of the crises that we study. This rise implies a level of distortions χ^c equal to -0.015. Third, we target a rise in liquid asset holdings of 50%, similar to what was observed at the beginning of the COVID-19 crisis. For this rise, we need $\bar{\omega}^c = 0.303$. 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.[14] For the purposes of our analysis, and unless otherwise noted, we focus on deviations of a certain variable from the steady state on the first period after the shocks.

Table 9: Responses With and Without Liquidity Shock

	(1) Benchmark	(2) No Liquidity
Spreads, bps	300.01	272.87
GDP, percent	-5.00	-5.00
Liquid assets, percent	50.00	-36.60
Debt owed, percent	52.11	-61.98
Investment rate, pp	-7.10	-4.38
Default prob., pp	0.32	0.06

Notes: Aggregate responses on impact for the benchmark case with all three shocks (first column) and for the case with no liquidity shock (second column). pp stands for percentage points and bps for bps.

The first column of Table 9 shows the aggregate results of the benchmark crisis experiment.

[14] 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 more persistent shocks.

The first three rows correspond to the explicitly targeted moments. The benchmark crisis, by construction, results in a 300 bps rise in credit spreads, a 5% fall in GDP, and a 50% rise in aggregate holdings of liquid assets. The following rows correspond to untargeted variables. Our benchmark crisis experiment leads to a significant increase in debt owed, which is defined as the sum of interperiod debt issued b' and intraperiod debt $[1 + \mathcal{A}^L(\ell)]\ell$. The experiment reproduces the comovements that we observed during the COVID-19 crisis: a significant increase in credit spreads that was accompanied by an increase in liquid asset holdings and corporate borrowing. This increase in borrowing is driven by the liquidity shock and constraint: as firms face an unexpectedly higher liquidity requirement $\bar{\omega}^c$, they are forced to increase their intraperiod borrowing. These borrowing have to be repaid by the end of the period, which decreases profits and may make them negative. In order to avoid this, firms adjust in other margins to avoid costly equity issuances. In particular, they disinvest, which leads to a large 7.1 percentage points drop in the investment rate. Due to the increase in borrowing and the potential persistence of the shock, the average probability of default rises significantly. 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.

6.3 The Role of Liquidity

The two columns of Table 9 compare the aggregate results of the benchmark experiment with those of an experiment where we feed financial and real shocks of the same size to the model, but exclude the liquidity shock.[15] The drop in GDP is the same since the real shock is the same: GDP in the period of the shock is determined solely by TFP; capital, which is predetermined; and labor, which results from a purely static decision that depends only on TFP and capital. The rise in spreads is about 30 bps smaller than in the case with the liquidity shock, which shows that the bulk of the rise in spreads happens due to the financial shock. Differently from the benchmark experiment, liquid assets now fall instead of rise. This is 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 this period, and hence to maintain positive profits for predetermined levels of capital and debt. For this reason, firms disinvest and reduce their stock of capital, which in turn reduces the amount of liquid assets that they need to hold for precautionary motives. Because firms do not need to hoard liquid assets, and because borrowing has been made more expensive by the financial shock, total borrowing falls.

[15] We obtain similar results when we recalibrate the shocks to match the targets of GDP and the spreads.

This comovement of credit spreads, liquid assets, and firm borrowing is therefore consistent with what we observed during the GFC: a rise in spreads that was accompanied by a fall in liquid asset holdings and debt. The investment rate falls by less, as the liquidity shock induces an extra incentive to disinvest by amplifying the precautionary motive to hold liquid assets. The probability of default increases by less than in the benchmark case, as firms significantly cut their borrowing and therefore endogenously offset the increase in risk.

This experiment highlights that the liquidity shock is essential to match the simultaneous rise in debt and credit spreads, which is accompanied by a fall in investment and 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). 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.

6.4 Cross-Sectional Responses

We now investigate how firms respond to shocks in the cross section.

Benchmark Experiment Table 10 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. Notice that 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: 524.86 in the model vs. 757.87 in the data for leverage, and -343.07 in the model vs. -373.24 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 statistics are completely untargeted. Thus, firms that are more leveraged and have less liquidity experience relatively larger increases in credit spreads both in the model and the data. For the investment rate, we observe very similar patterns, even if the model magnitudes are slightly larger. Again, none of these moments are targeted. The elasticity of the investment rate with respect to leverage is -0.018 in the model vs. -0.029 in the data, while the elasticity with respect to liquid assets is 0.077 in the model vs. 0.088 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.

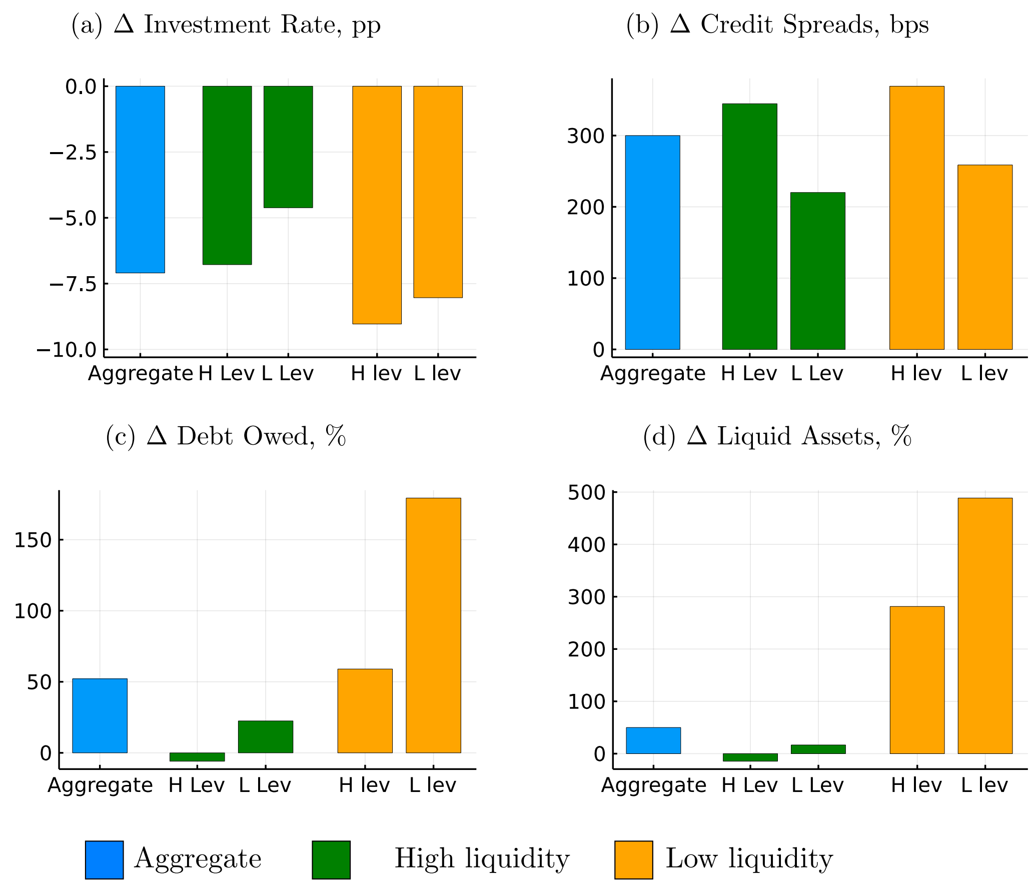
Table 10: Quantitative Results: Cross-Sectional Responses

	Model		Data	
	Benchmark	No Liquidity	COVID-19	GFC
Elasticity of spreads wrt leverage	524.86	523.53	757.87	1183.19
Elasticity of spreads wrt liquidity	-343.07	29.53	-373.24	-54.49
Elasticity of inv. rate wrt leverage	-0.018	-0.024	-0.029	-0.038
Elasticity of inv. rate wrt liquidity	0.077	-0.009	0.088	0.036

Notes: The first two columns report the regression coefficients for cross-sectional regressions of the change in spreads or the investment rate on impact on initial (steady state) leverage and liquidity. The third and fourth columns correspond to the baseline empirical estimates in section 3.

Figure 5 plots the distributions of changes for investment rates, credit spreads, debt owed, and liquid assets, for the four type of firms. First, conditional on leverage, firms with low liquidity have worse outcomes. Second, conditional on liquidity, firms with high leverage also have worse outcomes. For debt and liquid assets, note the large heterogeneous response with respect to liquid holdings. Firms with high liquidity changed their debt and liquid assets very little. However, firms with low liquidity increased their debt and liquid assets much more.

Figure 5: Cross-Sectional Responses: Benchmark Experiment

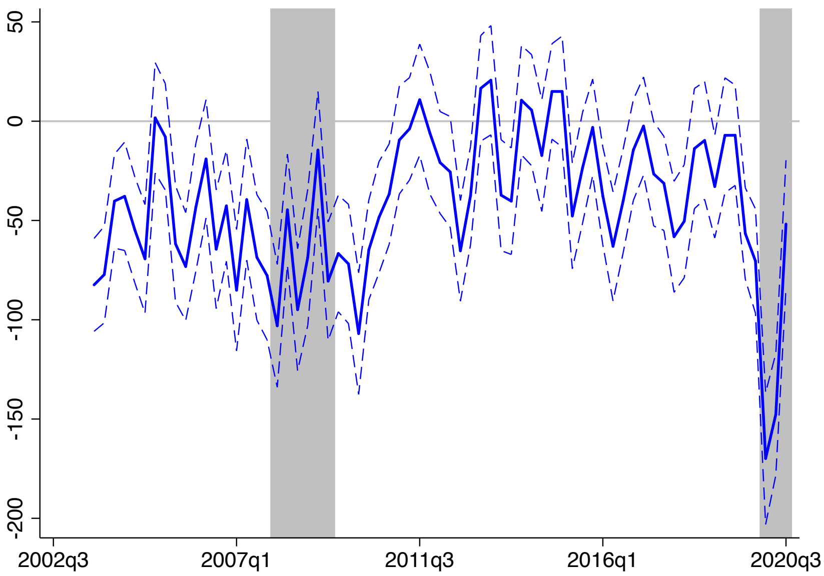


Evidence on Cross-Sectional Liquidity Responses The model predicts that firms with low liquidity should increase their holdings of liquid assets by more than firms with high liquidity do upon a liquidity shock (see the last panel of Figure 5). We can test this prediction in the data. More specifically, we run 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 6, along with standard error bands. The figure shows that the coefficient is, on average, negative, suggesting that there is mean reversion in firms' liquidity positions. However, the coefficient falls considerably at the onset of the COVID-19 crisis, suggesting a strengthening of this mean-reversion behavior: firms with lower liquidity tend to accumulate more liquidity over this period than those with more liquidity, consistent with the cross-sectional predictions of the model.

Figure 6: Time Series for the Coefficient of Lagged Liquidity on the Growth Rate of Liquidity



No Liquidity Shock We also compute the cross-sectional elasticities for the case of no liquidity shock, presented in the second column of Table 10. We find that leverage still plays a similar role in determining spreads and investment rates: more leveraged firms experience larger increases in spreads and larger decreases in investment. Liquidity, however, loses most of its previous importance: it has basically no effect on investment rates, and a much more muted (and positive) effect on credit spreads. These results seem to be consistent with the regression results for the GFC, which are reported in the fourth column: 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 both economically and statistically less significant. Taken together, these results suggest that, through the lens of the model, the GFC was a combination of financial and real shocks, without a strong liquidity component.

6.5 Shock Interaction and Amplification

In this section, we show that the model generates a significant amount of endogenous amplification arising from the interactions between the three shocks. The first three columns of Table 11 present the results of feeding each shock one-by-one to the model, with the same shock sizes as in the benchmark case. The fourth column presents the results for the benchmark case, 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.[16]

This decomposition shows that the majority of the movements in credit spreads and the investment rate are driven by the financial shock. Liquidity, on the other hand, is essential to generate movements in liquid assets, debt, and the default probability. The interaction between the shocks can be significant for liquid assets, debt, and the investment rate. 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 cheap for firms to borrow. Therefore, the liquidity shock triggers a large increase in debt that is 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. Finally, the interaction term for the investment rate is quite significant (almost 20% of the total response): the interaction between the liquidity shock (which induces firms to reduce their size due to the expectation of a tight liquidity constraint in the future) and the financial shock (which also induces firms to reduce their size due to the rise in borrowing costs) generates amplification, making the investment rate fall by more than the sum of the falls when these shocks are fed in isolation.

[16] Appendix B.4 considers an alternative decompositions where we turn off the shocks one at a time.

Table 11: Shock Decomposition

	(1) Liquidity	(2) Financial	(3) Real	(4) Benchmark (all)	(5) Interaction
Spreads, bps	24.80	265.61	4.60	300.01	5.00
GDP, percent	0.00	0.00	-5.00	-5.00	0.00
Liquid assets, percent	103.71	-34.80	-1.21	50.00	-17.71
Debt owed, percent	94.81	-64.46	-0.78	52.11	22.54
Investment rate, pp	-1.61	-3.83	-0.42	-7.10	-1.24
Default prob., pp	0.24	0.02	0.04	0.32	0.02

Notes: The first three columns present results for when we feed 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: $(5) = (4) - (3) - (2) - (1)$.

7 Credit and Liquidity Policies

We now analyze the effects of different credit and liquidity policies. We first study them in the context of the benchmark shock experiment and then consider the case without the liquidity shock. We consider four types of policies that resemble major interventions deployed during the GFC and the COVID-19 period. First, we consider credit interventions, such as corporate credit facilities and credit guarantees. Then we consider liquidity policies such as cash transfers/grants to firms and subsidized direct loans. We begin by describing the modeling of each of these programs in more detail.

7.1 Credit Policies

Corporate Credit Facilities(CCF) CCF stands for direct or indirect purchases of corporate debt by the Federal Reserve in primary and secondary markets, respectively. 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 (PMCCF and SMCCF), which involved the outright purchases of corporate bonds by eligible US companies during 2020.

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

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

The cost of this intervention for the policymaker can be computed as the total subsidy that is given to debt issuance by all types of firms:

$$\mathcal{C}_t^{CCF} = \chi_t^{CCF} \sum_{i=1}^{N} \lambda_i \frac{\mathcal{P}(k_{i,t+1}, a_{i,t+1}, b_{i,t+1})}{1 + r} \times b_{i,t+1} \tag{20}$$

Credit Guarantees While neither the US Treasury nor the Federal Reserve explicitly issued credit guarantees to nonfinancial companies during either crisis, this type of policy was widely implemented in other countries, most notably in Europe: as of June 2020, 11% of total private nonfinancial debt was subject to public guarantee programs in Spain, and 5% in France, for example.[17] By issuing credit guarantees, the government commits to repaying the lender a fraction ϕ^{CG} in case the firm defaults. The price function for debt in (8) then becomes

$$q^{CG}(k', a', b') = (1 + \chi) \frac{\mathcal{P}(k', a', b')}{1 + r} + \phi^{CG} \frac{[1 - \mathcal{P}(k', a', b')]}{1 + r} \tag{21}$$

The total cost with this policy is then the value of all guarantees triggered by firms in each group; that is,

$$\mathcal{C}_t^{CG} = \phi_t^{CG} \sum_{i=1}^{N} \lambda_i \frac{[1 - \mathcal{P}(k_{i,t+1}, a_{i,t+1}, b_{i,t+1})]}{1 + r} \times b_{i,t+1} \tag{22}$$

7.2 Liquidity Policies

Subsidized Direct Loans We also consider the possibility of loans made by the government directly to corporations. During the GFC, the US Department of the Treasury directly lent $80.7 billion to major automakers General Motors and Chrysler as part of the Troubled Assets Relief Program (TARP). During the COVID-19 crisis, a very important component of the fiscal and monetary policy responses consisted of programs such as the PPP, the Economic Stabilization Fund, and the expansion of Small Business Administration lending programs. Taken together, these corporate and business lending programs comprised almost 44% of the $2 trillion CARES Act that was signed into law on March 2020. The majority 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.

[17] In the US, TARP did contain some credit guarantee programs for financial institutions, which are not the focus of this paper.

We treat these subsidized loans as direct one-period loans of fixed-size L and assume that these loans can be used to satisfy/relax the liquidity constraint. That is, given a loan of size L, the liquidity constraint in (6) now becomes

$$\omega k \leq a + \ell + L \tag{23}$$

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). Since this is a subsidized loan, we assume that the interest rate is simply the risk-free real rate r. Thus, the firm also gains a liability of $(1+r)L$ 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 $b' + (1+r)L$ and is taken into account by lenders when pricing loans originated in the current period, that is, the price of debt becomes $q[k', a', b' + (1+r)L]$.

The total cost of a one-time loan is computed as the cost of loan originations net of expected repayments, which takes into account the possibility that some borrowers may default on the loan. We assume that the government discounts the future at the same risk-free interest rate, which allows us to write the cost of this policy as

$$\mathcal{C}_t^L = \sum_{i=1}^{N} \lambda_i \left[L_t - \frac{(1+r)L_t \mathcal{P}_{it}}{1+r} \right] = L_t \sum_{i=1}^{N} \lambda_i \left[1 - \mathcal{P}_{it}\right] \tag{24}$$

Cash Transfers Under several circumstances, some of the business loan programs included in the CARES Act allowed the loans to be forgiven by the government and/or turned into grants. For this reason, we explicitly consider a modification of the previous policy that involves direct cash transfers to firms. This policy works exactly as subsidized direct loans, but creates no new liability for the firm: transfers can be used to satisfy the liquidity constraint, and also involve a direct transfer of resources that are added to the cash flow in (9). The effect of a transfer of size T_t on the liquidity constraint is then

$$\omega k \leq a + \ell + T \tag{25}$$

And the total cost of this policy is simply

$$\mathcal{C}_t^T = T_t \sum_{i=1}^{N} \lambda_i = T_t \tag{26}$$

7.3 Credit and Liquidity Policies in Macro-Financial Crises

We consider "blanket" untargeted policies, where the intervention is offered equally to all firms. Table 12 compares the no policy benchmark case to experiments where we hit the economy with the same benchmark set of shocks plus one policy at a time. We choose the sizes of the policies so they reduce the drop in the aggregate investment rate by 1 pp (so that it falls by 6.1 pp as opposed to 7.1 given the baseline shocks). Column (1) refers to the no policy benchmark case described in the previous section.

Table 12: Policy Interventions

Variation wrt SS	(1) No Policy	(2) CCF	(3) Credit Guarantees	(4) Transfer	(5) Loan
Spreads, bps	300.01	246.47	235.79	272.28	285.07
GDP, percent	-5.00	-5.00	-5.00	-5.00	-5.00
Liquid assets, percent	50.00	60.72	60.67	18.25	7.90
Debt owed, percent	52.11	58.08	58.37	13.27	15.45
Investment rate, pp	-7.10	-6.10	-6.10	-6.10	-6.10
Default prob., pp	0.32	0.31	0.31	0.06	0.18
Cost of policy over GDP, pp	0.00	0.20	0.23	6.46	0.20
Elasticity of spreads wrt leverage	524.86	518.22	307.27	475.83	516.77
Elasticity of spreads wrt liquidity	-343.07	-337.43	-226.14	-190.98	-166.10
Elasticity of inv. rate wrt leverage	-0.02	-0.02	-0.01	-0.01	-0.02
Elasticity of inv. rate wrt liquidity	0.08	0.07	0.07	0.06	0.07

Notes: Model results from each of the policy experiments: the "No Policy" column corresponds to the benchmark experiment, with all three shocks, and each of the consecutive columns corresponds to the results with the policies activated one at a time. Size of policy interventions chosen to target an increase of 1pp in the investment rate relative to the no policy benchmark.

Credit Policies Column (2) shows the effects of CCF. As described earlier, these essentially correspond to a subsidy of the interest rate at which firms can borrow. This subsidy offsets the effects of the financial shock and allows firms to borrow more to counter the effects of the liquidity shock: more borrowing results in larger increases in debt owed and liquid asset holdings and curtails the drop in the investment rate, as the disinvestment incentive arising from the liquidity shock is now weaker. Even though firms borrow more, there is a small reduction in the probability of default vis-à-vis the benchmark case, as firms perceive the policy support to be persistent. Finally, none of the model-based elasticities are significantly altered by the presence of this policy. These effects are consistent with the empirical evidence documented by Boyarchenko et al. (2020) and Gilchrist et al. (2020) that Fed policy announcements regarding credit market interventions can have a significant positive effect on firms' financing conditions.

Column (3) shows the effects of credit guarantees. Similar to the CCF, credit guarantees operate essentially as lending subsidies, which results in relatively similar effects to this other policy (larger in the case of credit spreads).

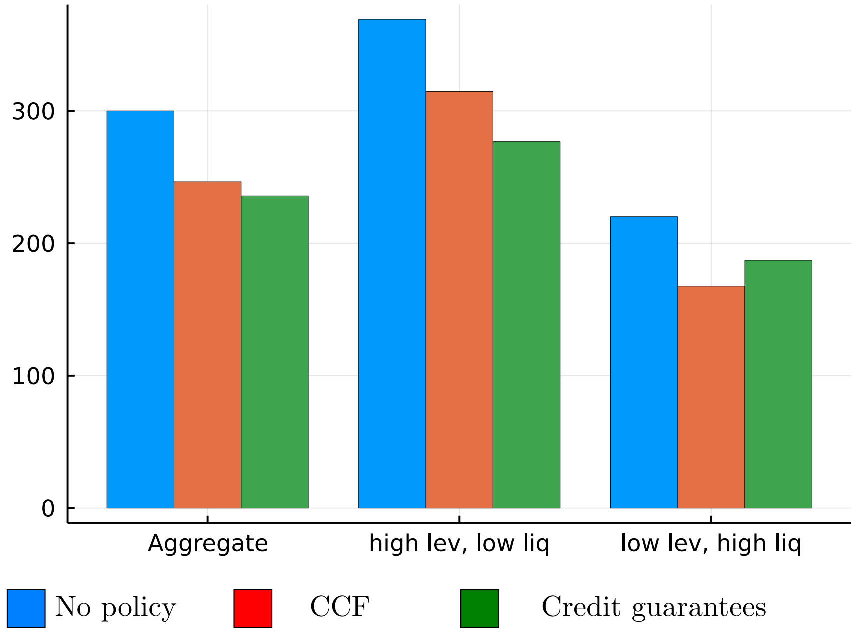
One important difference between CCF and guarantees is that CCF are relatively larger subsidies to safer firms, while guarantees are relatively larger subsidies to riskier firms. To see this, recall the effects on debt prices of these two policies in (19) and (21). The "direct" effect (i.e., keeping policies constant) of CCF on debt prices is equal to $\chi^{CCF}\frac{\mathcal{P}(k',a',b')}{1+r}$, while the direct effect of guarantees is given by $\phi^{CG}\frac{[1-\mathcal{P}(k',a',b')]}{1+r}$. Thus, firms with higher expected probability of repayment $\mathcal{P}(k',a',b')$ benefit relatively more from CCF and less from guarantees. This is important for understanding why guarantees seem to have a larger impact on the elasticities of spreads and investment rates with respect to leverage and liquidity than CCF do, especially when the aggregate effects are not that different. These elasticities tend to be driven by the fact that firms with higher leverage and less liquidity respond relatively more to shocks, as they effectively become more constrained. These are also the firms whose probabilities of default rise more during a crisis. By helping these firms relatively more, guarantees contribute to muting the response of spreads and investment to differences in leverage and liquidity.

Figure 7 illustrates this result by plotting the differential responses of credit spreads to different policies and for two types of firms: (i) high-leverage, low-liquidity firms, which are presumably more impacted both by financial and liquidity shocks, and (ii) low-leverage, high-liquidity, which are less impacted. The figure shows that credit guarantees generate a relatively larger drop in credit spreads for the high-leverage, low-liquidity firm in relation to the CCF (the red bar is taller than the green bar), while the opposite is true for the low-leverage, high-liquidity firm (the red bar is shorter than the green bar). Hence, riskier firms benefit more from credit guarantees, while safer firms benefit more from CCF.

To summarize, while the two types of credit policies we consider benefit types of firms differently, they both operate in a similar way: by directly reducing borrowing costs, they allow firms to borrow more relative to the benchmark case and thus accumulate more liquid assets in order to face the liquidity shock. Since firms increase their borrowing due to lower credit spreads, the effects on the probability of default end up being relatively small.

Liquidity Policies Column (4) of Table 12 corresponds to the transfer that, as described, helps firms satisfy the liquidity constraint. This transfer offsets the liquidity shock and allows firms to increase their holdings of liquid assets by much less as well as decrease their borrowing. This endogenous decrease in debt contributes to the reduction in credit spreads. As firms no longer need to devote their resources to liquid assets to satisfy the constraint, the disinvestment

Figure 7: Cross-Sectional Effects of Credit Policies



Notes: Response of credit spreads under no policy, CCF, and credit guarantees. Aggregate response as well as responses for two types of firms: high leverage/low liquidity, and low leverage/high liquidity.

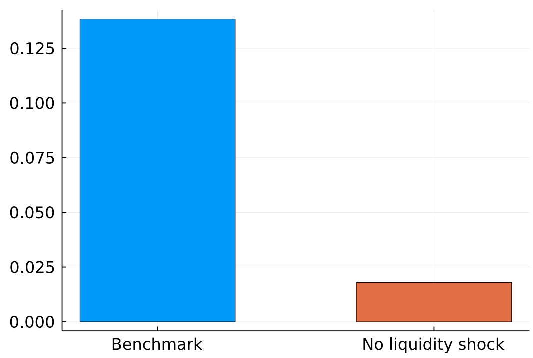
incentive is weakened, which is the main channel through which the fall in investment is curbed. Since the transfer involves the direct transfer of real resources that helps firms avoid negative dividends, there is a large direct effect on firm value, which is reflected in a large decrease in the probability of default. Note that while this transfer has large effects on the probability of default, it is also significantly more expensive than other policies, costing over 6% of steady-state GDP (compared to 0.20% of GDP for CCF, for example). Finally, the transfer policy weakens the elasticity of spreads and investment with respect to liquidity, which suggests that the policy is relatively effective at offsetting the liquidity shock.

Column (5) shows the effects of the subsidized loan program. The results are similar to those of the transfer, but with a few differences. First, debt owed falls by less than in the case of the transfer. This happens by construction, as debt owed now includes the new liability that is owed to the government. For this reason, with debt not falling by as much (relative to the benchmark), the loan program has a very small effect on credit spreads, much smaller than any other policy. Unlike the credit policies (CCF and credit guarantees), this policy does not target directly the cost of borrowing in the bond market, but it increases total borrowing relative to the case of the transfer. Still, since firms use the cheaper government loan to substitute away from interperiod debt, debt owed falls and generates a significant drop in the probability of default relative to the benchmark (but smaller than in the case of the transfer). The fact that the loan has to be repaid in the following period does generate some disinvestment incentives; this, coupled with the fact that the loan helps relax the liquidity constraint, contributes to the drop in liquid asset holdings. While the loan policy is not as effective at reducing probabilities of default as the transfer, it is much cheaper than the transfer, with a cost that is similar to that of CCF. Also note that subsidized loans along with transfers reduce the magnitude of the elasticity of the spreads and investment rates with respect to liquidity, which suggests that both policies together are particularly effective at offsetting liquidity shocks and reducing the importance of firm liquidity overall during crises.

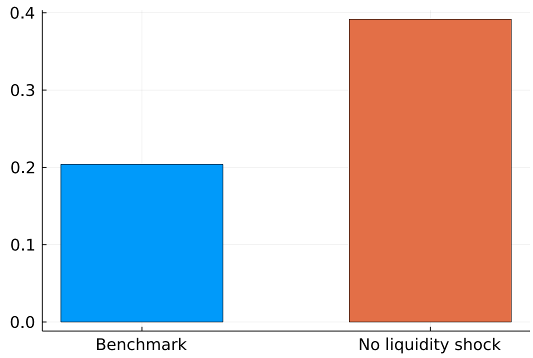
Figure 8 illustrates the state-dependent effects of the loan policy: the blue bar corresponds to the effects on default rates and the cost of the policy for the benchmark case, while the red bar corresponds to the no liquidity shock case where we recalibrate the size of the policy so that it achieves the same 1 pp gain in the investment rate relative to the no policy case. Clearly, the loan policy is much more effective at curbing the average default rates in the presence of a liquidity shock, reducing it by over 0.125 pps vs. less than 0.025 pps in the absence of the liquidity shock. The second panel shows that the loan policy is cheaper in the presence of the liquidity shock, as a smaller loan program is required in order to achieve the same gains in terms of the investment rate. Thus, liquidity policies such as subsidized loan programs are cost-effective in the presence of aggregate liquidity shocks, but not in their absence.

Figure 8: Effects of Loan Policy, With and Without Liquidity Shock

(a) Δ Default Rate, pp



(b) Policy Cost, % of SS GDP



In summary, liquidity policies allow firms to bypass credit markets when facing liquidity shocks. Unlike credit policies, they do not have a very direct effect on borrowing costs, but allow firms to satisfy their liquidity constraint without having to borrow and accumulate large amounts of liquid assets. As a consequence, firm debt and liquid assets increase by less than in the no policy case, and this smaller increase in borrowing leads to a large effect on default probabilities.

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, but liquidity was more important during the COVID-19 crisis.

In order 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 both at the aggregate and at the micro levels, we concluded that the COVID-19 crisis had a strong liquidity shock component, unlike the GFC. We showed that these liquidity shocks are essential not just to generate the right comovement of aggregate variables, that is, a simultaneous increase in credit spreads, debt, and liquid asset holdings, but also to generate the right 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 more traditional credit market freeze.

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 important advantage is that credit spreads are available in real time, at daily frequency. We propose that the study of their cross-sectional properties can be added to policymakers' toolkit to help determine which types of firms are more severely affected during crises and, together with a structural model, disentangle the sources of aggregate distortions.

References

Baqaee, D. and Farhi, E. (2020). Supply and demand in disaggregated keynesian economies with an application to the covid-19 crisis. Working Paper 27152, National Bureau of Economic Research.

Begenau, J. and Salomao, J. (2018). Firm Financing over the Business Cycle. *The Review of Financial Studies*, 32(4):1235–1274.

Bocola, L. and Dovis, A. (2019). Self-fulfilling debt crises: A quantitative analysis. *American Economic Review*, 109(12):4343–77.

Boissay, F., Patel, N., and Shin, H. S. (2020). Trade credit, trade finance, and the Covid-19 Crisis. BIS Bulletins 24, Bank for International Settlements.

Boyarchenko, N., Kovner, A., and Shachar, O. (2020). It's what you say and what you buy: A holistic evaluation of the corporate credit facilities. *FRB of New York Staff Report*, (935).

Clementi, G. L. and Palazzo, B. (2019). Investment and the cross-section of equity returns. *The Journal of Finance*, 74(1):281–321.

Cooper, R. W. and Haltiwanger, J. C. (2006). On the Nature of Capital Adjustment Costs. *Review of Economic Studies*, 73(3):611–633.

Crouzet, N. and Gourio, F. (2020). Financial positions of u.s. public corporations: Part 3, projecting liquidity and solvency risks. Chicago fed insights, FRB Chicago.

Crouzet, N. and Tourre, F. (2020). Can the cure kill the patient? corporate credit interventions and debt overhang. Working paper.

Dick-Nielsen, J. and Poulsen, T. K. (2019). How to clean academic trace data. *Available at SSRN 3456082*.

Dvorkin, M., Sánchez, J. M., Sapriza, H., and Yurdagul, E. (2021). Sovereign debt restructurings. *American Economic Journal: Macroeconomics*, 13(2):26–77.

Elenev, V., Landvoigt, T., and Van Nieuwerburgh, S. (2020). Can the covid bailouts save the economy? Working Paper 27207, National Bureau of Economic Research.

Gertler, M. and Gilchrist, S. (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics*, 109(2):309–340.

Gilchrist, S., Sim, J. W., and Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research.

Gilchrist, S., Wei, B., Yue, V. Z., and Zakrajšek, E. (2020). The fed takes on corporate credit risk: An analysis of the efficacy of the smccf. Working Paper 27809, National Bureau of Economic Research.

Gilchrist, S. and Zakrajsek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720.

Greenwald, D. L., Krainer, J., and Paul, P. (2020). The Credit Line Channel. Working Paper Series 2020-26, Federal Reserve Bank of San Francisco.

Gurkaynak, R. S., Sack, B., and Wright, J. H. (2007). The u.s. treasury yield curve: 1961 to the present. *Journal of Monetary Economics*, 54(8):2291–2304.

Jeenas, P. (2019). Firm balance sheet liquidity, monetary policy shocks, and investment dynamics.

Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P.-O., and Zúñiga, D. (2020). Corporate bond liquidity during the covid-19 crisis. Working Paper 27355, National Bureau of Economic Research.

Khan, A. and Thomas, J. K. (2013). Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity. *Journal of Political Economy*, 121(6):1055–1107.

Kudlyak, M. and Sánchez, J. M. (2017). Revisiting the behavior of small and large firms during the 2008 financial crisis. *Journal of Economic Dynamics and Control*, 77(C):48–69.

Miller, M. H. (1977). Debt and taxes. *the Journal of Finance*, 32(2):261–275.

Moody's Investors Service (2015). Annual Default Study: Corporate Default and Recovery Rates, 1920-2014. Working paper.

Ottonello, P. and Winberry, T. (2020). Financial Heterogeneity and the Investment Channel of Monetary Policy. *Econometrica*, 88(6):2473–2502.

Ramelli, S. and Wagner, A. F. (2020). Feverish Stock Price Reactions to COVID-19*. *The Review of Corporate Finance Studies*, 9(3):622–655.

Reinhart, C. M. and Rogoff, K. S. (2009). *This time is different: Eight centuries of financial folly.* princeton university press.

Thompson, S. A. (2020). How long will a vaccine really take? New york times.

Appendix

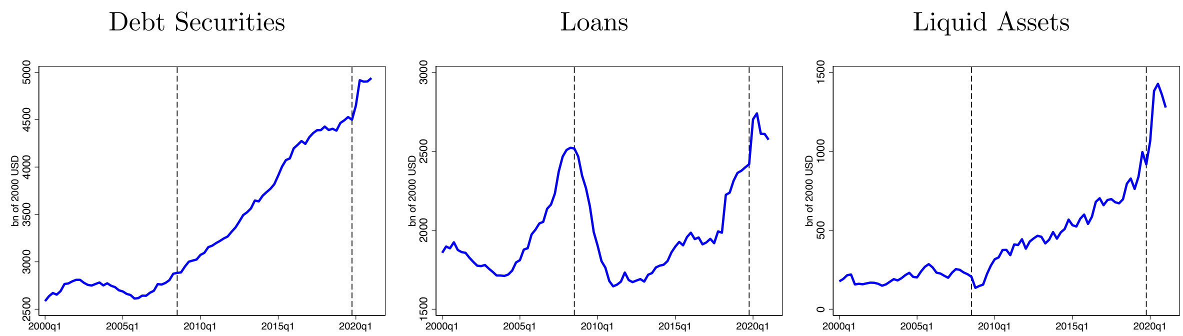
A Data Appendix

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 both for 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.

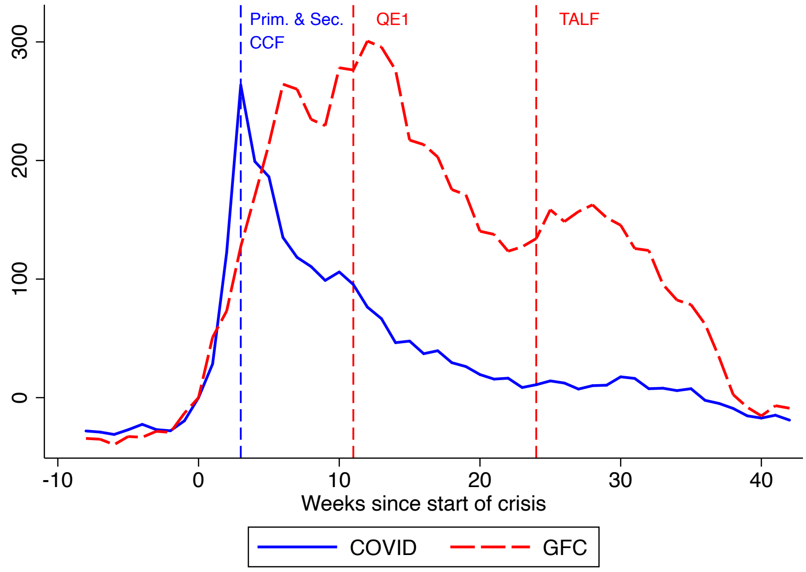
A.2 Median Credit Spreads

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`.

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



Notes: Median credit spreads during the Great Recession and the COVID-19 Pandemic, 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).

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:

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

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.

Table A1: Alternative Investment Measures

	(1)	(2)	(3)
Leverage			
Normal times	-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	-0.029***	-0.028***	-0.015***
	(0.009)	(0.009)	(0.001)
Liquidity			
Normal times	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	0.088***	0.093***	0.019***
	(0.015)	(0.015)	(0.003)
N	43130	44407	44644
R^2	0.099	0.086	0.52

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

B Model Appendix

B.1 Calibration: Leverage and Liquidity Before Each Crisis

Tables B2 and B3 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 only conducted for a firm with high leverage and high liquidity.

Table B2: 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 B3: 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.

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.

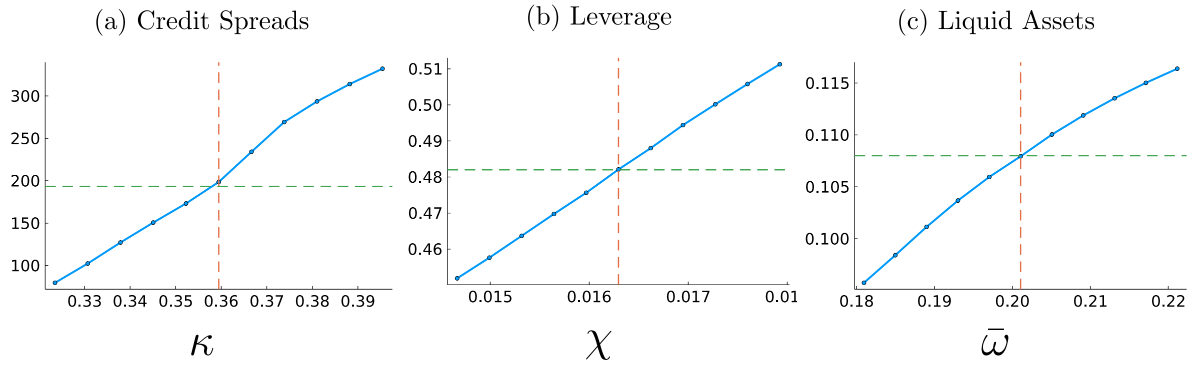
B.3 Calibration: Robustness

Table B4 presents robustness with respect to the equity issuance cost parameter ρ showing that the results are very similar for larger values of ρ, and that the effects of the crises are somewhat dampened by lower values of ρ. Still, our main qualitative results remain unchanged. Table B5 repeats the exercise for an increase in the persistence of the shocks, $\zeta = 0.5$, meaning that the expected duration of each shock is now two years. Again, in spite of some quantitative differences (smaller increase in debt but larger drop in investment), the qualitative results are robust to more persistent shocks.

B.4 Crisis Decomposition

The main text focuses on the comparison between the benchmark experiment and the case without a liquidity shock. For completeness, this appendix describes the effects of shutting off

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.

Table B4: Robustness With Respect to Equity Issuance Costs

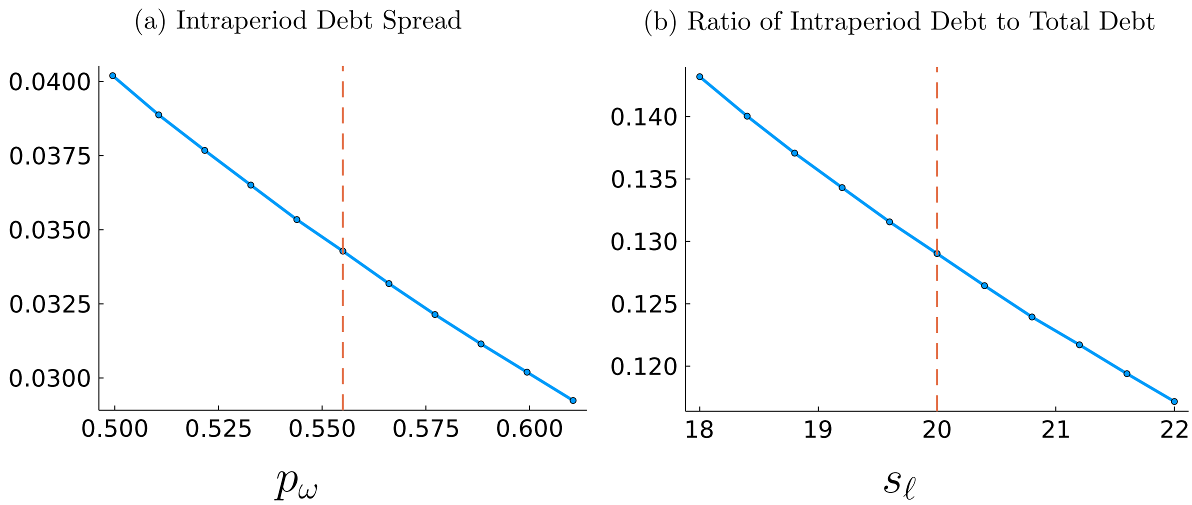
	Benchmark, $\rho = 3$	Higher $\rho = 6$	Lower $\rho = 0.5$
Spreads, bps	300.01	300.01	299.97
GDP, percent	-5.00	-5.00	-5.00
Liquid assets, percent	50.00	49.99	49.98
Debt owed, percent	52.11	56.79	22.54
Investment rate, pp	-7.10	-7.26	-6.25
Default prob., pp	0.32	0.32	0.29
Elasticity of spreads wrt leverage	524.86	524.68	524.49
Elasticity of spreads wrt liquidity	-343.07	-352.76	-310.84
Elasticity of inv. rate wrt leverage	-0.02	-0.02	-0.01
Elasticity of inv. rate wrt liquidity	0.08	0.08	0.07

Notes: The second column recalibrates the model and the sizes of the shocks for $\rho = 6$, and the third column recalibrates the model and the size of the shocks for $\rho = 0.5$.

each of the other shocks, one by one, shown in Columns (2)-(4) of Table B6. We omit description of the cases in columns (1)-(2), as they are analyzed in the main text.

No Financial Shock Column (3) repeats the benchmark exercise, but without the financial shock. In this case, there are rises in the spreads that are much more muted than in the benchmark case. Spreads still rise, as the liquidity shock induces firms to borrow to cover increased perceived liquidity needs. The increase in liquid assets is much larger in this case: since spreads do not rise by nearly as much, it is now much cheaper to borrow in interperiod debt, and hence accumulate all the liquidity that is required to cover the constraint without resorting to expensive, intraperiod borrowing. This is reflected in the large increase in total borrowing. Investment falls, but less than in the previous cases: the fall in investment is driven both by the fact that a larger stock of capital is now more expensive as it requires holding

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 B5: Robustness With Respect to Crisis Persistence

	Benchmark, $\zeta = 0.75$	Lower $\zeta = 0.50$
Spreads, bps	300.00	300.00
GDP, percent	-5.00	-5.00
Liquid assets, percent	50.00	49.94
Debt owed, percent	52.10	15.60
Investment rate, pp	-7.09	-7.99
Default prob., pp	0.32	0.24
Elasticity of spreads wrt leverage	525.39	544.73
Elasticity of spreads wrt liquidity	-341.65	-199.11
Elasticity of inv. rate wrt leverage	-0.02	-0.03
Elasticity of inv. rate wrt liquidity	0.08	0.07

Notes: The second column recalibrates the model and the sizes of the shocks for $\zeta = 0.5$.

more liquid assets, and also by the fact that the firm tries to adjust along multiple margins in order to prevent equity issuances, one of those margins being disinvestment. The cross-sectional elasticities now attribute a very small role to leverage and a very large one to liquid assets, which is not consistent with either of the two events that we analyze in the data.

No Real Shock Column (4) shows that the real shock has relatively muted effects in our model: the effects on all variables are essentially the same as in the benchmark case, but more moderate. As explained above, there is a direct mapping between the real shock and the drop in GDP. Beyond this, most of the effects of the real shock arise from its persistence: if firms expect the real shock to be persistent, they will try to disinvest and downsize to a new and smaller

Table B6: Quantitative Results

Variation wrt SS	(1) Benchmark	(2) No Liquidity	(3) No Financial	(4) No Real
Aggregate				
Spreads, bps	300.01	272.87	29.92	294.63
GDP, percent	-5.00	-5.00	-5.00	0.00
Liquid assets, percent	50.00	-36.60	101.10	52.46
Debt owed, percent	52.11	-61.98	93.61	50.27
Investment rate, pp	-7.10	-4.38	-2.03	-6.60
Default prob., pp	0.32	0.06	0.29	0.27
Cross Section				
Elasticity of spreads wrt leverage	524.86	523.53	8.97	513.71
Elasticity of spreads wrt liquidity	-343.07	29.53	-350.97	-333.33
Elasticity of inv. rate wrt leverage	-0.02	-0.02	0.00	-0.02
Elasticity of inv. rate wrt liquidity	0.08	-0.01	0.06	0.08

Notes: Model results from each of the shock experiments: the "benchmark" experiment includes all three shocks. Each successive column omits each one of the shocks. See text for details.

optimal scale. As investment and capital drop, so do liquid assets as the liquidity constraint is relaxed. Finally, firms also reduce their borrowing and leverage so as to keep their interperiod borrowing costs roughly constant.