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

September 10, 2021

Abstract

We study the evolution of firm financials during two large crises: the Great Financial Crisis (GFC) and the COVID-19 pandemic. While the two crises featured similar increases in corporate spreads, corporate debt and liquid asset holdings moved in opposite directions. The micro-data reveal that firm leverage was a more important predictor of firm-level credit spreads and investment during the GFC, but that firm funding liquidity was more important during the pandemic. We augment a dynamic model of firm capital structure with an explicit motive to hold liquid assets, and calibrate it to match the joint distribution of firm leverage, liquidity and credit spreads. The model shows that the GFC resembled a combination of TFP and credit market shocks, while the pandemic also featured aggregate liquidity shocks. We study the effectiveness of credit and liquidity policies in response to these shocks. Credit policies, such as corporate credit facilities or credit guarantees, are effective in terms of reducing the fall in investment, while liquidity policies, such as direct loans or transfers to firms, are particularly effective at preventing bankruptcies.

JEL Classification: E6, G01 H00

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

*We thank David Andolfatto, Carlos Garriga, Fernando Martin, and Juan Sanchez for comments and suggestions. We also thank seminar and conference participants at the St. Louis Fed, Society of Economic Dynamics, European Economic Association, North American Meetings of the Econometric Society, and the Annual Meetings of the Portuguese Economic Journal. 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). An important question for policymakers is what type of policies are effective in countering the effects of these shocks. Alternative policies may be more effective in mitigating different crises, not just because of the nature of the underlying shock but also because firms with heterogeneous financial characteristics may be differentially affected. The analysis of aggregate and cross-sectional patterns is therefore of interest in terms of identifying the types of shocks and hence designing effective credit and liquidity policies.

We study the responses of firms' borrowing conditions and investment over two large 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. We conduct an empirical analysis about how firms' financials affected the response of firm-level borrowing conditions and investment. Then, we develop a quantitative dynamic 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 disentangle the nature of the shocks. 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 among the *wrong* shock. In turn, cross-sectional data can help policy makers to disentangle among shocks as they have heterogeneous effects for different firms. Moreover, credit spreads data is available in real time and looking at its cross-sectional characteristics can help identify the source of the underlying aggregate shock.

First, we perform an empirical study about the evolution of firm financial and borrowing conditions throughout the two crises. At the aggregate level, total borrowing and holdings of liquid assets by US nonfinancial corporates moved in opposite directions in these two events. While both borrowing and liquid asset holdings fell during the GFC, these two measures increases significantly during the COVID-19 period. We then study firm borrowing conditions, using maturity-matched corporate credit spreads as in Gilchrist and Zakrajsek (2012). We construct a panel of corporate credit spreads for US nonfinancial corporations that covers the GFC and the COVID-19 period. We find that the initial increase in aggregate corporate credit spreads were similar in the two events, in spite of the different dynamics that we document for aggregate firm financials. We then augment the panel with firm-level financials from Compustat. We find that 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 qualitatively similar (but more muted) effects of leverage and liquidity on investment rates for these two events.

Next, we develop a quantitative model that allows us to jointly study credit spreads, leverage, and liquidity to evaluate the empirical evidence and study the role of credit and liquidity policies during large crises. 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 to satisfy a stochastic working capital constraint. The only alternative way of satisfying this constraint is to borrow from a costly intra-period liquidity market. 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.

The calibrated model matches the joint distribution of liquidity, leverage, and credit spreads of US nonfinancial corporations. The model replicates non-targeted moments such as the cost of the intra-period liquidity, income-to-assets, and the default rate, among others. We then use the model as a laboratory to study how firms with different levels of liquidity and leverage respond to a series of large unexpected shocks. We consider real TFP shocks, financial shocks that affect their ability to issue debt, and liquidity shocks that tighten their liquid asset constraint. By comparing aggregate moments and cross-sectional elasticities 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 included 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 in the data, as well as to generate the cross-sectional elasticities that we observe in our panel regressions.

Finally, we study how different credit and liquidity policies affect the aggregate economy and firms at different points of the joint leverage-liquidity distribution, and how their effectiveness depends on the nature of the aggregate shock. We consider a variety of policies that were activated in the US in either of the two crises, such as corporate credit facilities, direct subsidized loans to firms, and direct grants/transfers to firms. These interventions resemble some of the most visible firm-support policies deployed both by the Federal Reserve and the Treasury during the GFC and COVID-19: the Primary and Secondary Market Credit Facilities, the Automotive Industry Financing Program of TARP, the Paycheck Protection Program of the CARES Act, among others. We also consider other policies that were not directly implemented in the US but were deployed in other countries, such as credit guarantees to the corporate sector. Our analysis yields a series of insights.

We find that credit policies, such as corporate credit facilities and credit guarantees are particularly cost-effective, especially at offsetting aggregate financial shocks and stimulating investment. These policies, however, have little effect on default probabilities. Moreover, these programs benefit different types of firms. Corporate credit facilities represent relatively larger subsidies to safer firms, while credit guarantees tend to subsidize riskier firms. The distribution of firm financial characteristics is therefore important to assess the relative costs and benefits of these policies.

Liquidity policies, such as direct loans and transfers are effective at offsetting liquidity shocks, but tend to be less cost-effective than other programs. Subsidized loans are cheaper than transfers, but may be counterproductive if deployed against aggregate TFP shocks. Liquidity policies are the most effective type of policies if the policymaker's objective is to prevent firm defaults (as opposed to maximizing the per-dollar impact on output or investment, for example). 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 in their design.

Literature This paper is related to a large body of literature that attempts to combine data and models to understand the effects of crises and large shocks in 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. They argue that the fact that larger, less financially constrained firms experienced larger decreases in sales and debt suggests that the traditional "financial shock" view of the GFC may be misguided. Our paper also contributes to the understanding of the nature of aggregate shocks by using firm and corporate bond micro data. Ottonello and Winberry (2020) combine a structural model with data to show how the response of investment to monetary policy shocks crucially depends on the distribution of firm leverage and firm distance to default. 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. Jeenas (2019) also uses model and data to study a similar question, but focusing on firm's financial portfolios, finding that not just leverage but also firms' holdings of liquid assets are important for the transmission of monetary policy shocks. We emphasize the role of the joint distribution of these two characteristics for the transmission of other types of shocks.

Boyarchenko et al. (2020) and Gilchrist et al. (2020) directly study the effects of the Fed's programs on corporate credit spreads, analyzing the same type of maturity-matched spreads that we study in this paper and that are based on previous work by Gilchrist and Zakrajsek (2012). Both studies focus on Federal Reserve programs directly involved with corporate bond purchases and find large positive effects of these programs. Boyarchenko et al. (2020) focus on both the primary and secondary market facilities (PMCCF and SMCCF) and attribute about one third of the total effect to the announcement, with the remainder being associated with the purchases themselves. Gilchrist et al. (2020) focus on the secondary market program (SMCCF) and find a 70 bp reduction in credit spreads for eligible bonds on announcement. They find a particularly significant effect on "fallen angels," companies that were downgraded during this period. They also find additional effects from the purchases themselves. Kargar et al. (2020) study the evolution of liquidity conditions in corporate bond markets during the pandemic and its aftermath. We complement these authors' analysis by focusing on the determinants of credit spread increases before the Fed interventions.

Also related to our work is a series of blog posts by 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. In this paper, we 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.

Finally, our work is related to structural studies of fiscal and monetary policies aimed at firms during the COVID-19 crisis. 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 (our modeling of the PPP program) plays 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.

2 Empirical Analysis of Debt, Liquidity, and Spreads

We begin by studying the aggregate dynamics of debt, liquid asset holdings, and credit spreads of US non-financial corporations around the GFC and the COVID-19 recession. Both corporate debt and liquid assets fell during the GFC, but rose sharply during the COVID-19 crisis. To analyze the role of this opposite comovement during the two crises we explore 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 (i) aggregate credit spreads experience similar increases in the two events, (ii) there seem to be systematic cross-sectional relationships between corporate credit spreads and firm leverage and liquidity that changed during each of the two events.

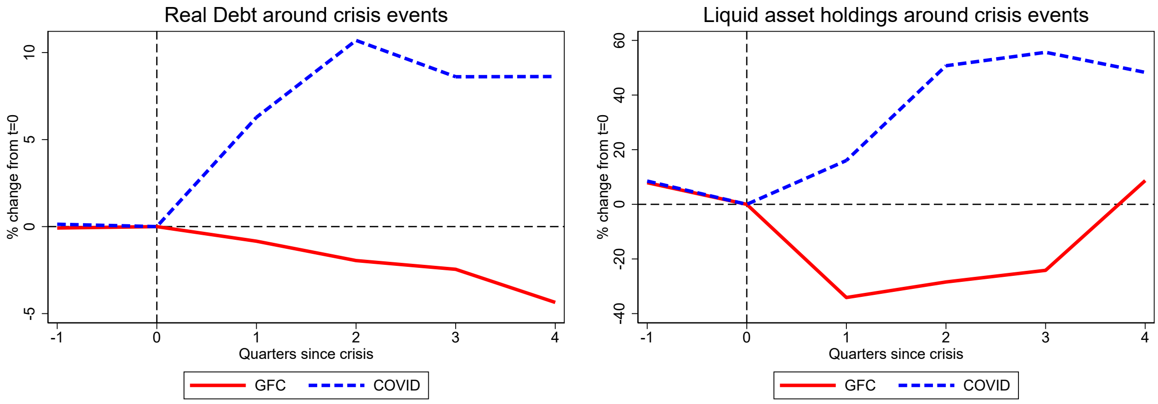
2.1 Corporate Debt and Liquid Assets

We start by analyzing the evolution of aggregate debt and liquid asset holdings for US non-financial corporations. We take aggregate data for total corporate borrowings and corporate holdings of liquid assets from the Flow of Funds.[1] Figure 1 plots the path of real debt and liquid assets as a percentage deviation from its value at the onset of each of the crises (2008Q3 for the GFC and 2019Q4 for COVID-19). The figure shows that the movements of these variables 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 grows by over 10% during the COVID-19 period, while it drops by about 5% four quarters into the GFC. Liquid assets experience a jump of about 50% during the COVID-19 crisis; while liquid-asset holdings fall during the first three quarters of the GFC, by about 40%. While they recover by the fourth quarter after the GFC, the opposite movements for these two

[1] Data taken from the Financial Accounts of the United States (FRB) and FRED (St. Louis Fed). Debt is constructed as the sum of FL104122005 (Debt Securities) and FL104123005 (Loans); liquid assets are equal to FL103020000 (Checkable deposits and currency). Both series are deflated using the GDP deflator (GDPDEF on FRED). The time series are plotted in appendix A.1.

variables during these two events is very noticeable.[2]

Figure 1: Aggregate Debt and Liquid Assets



Notes: Real total debt for US nonfinancial corporates (left panel) and real liquid asset holdings for US nonfinancial corporates (right panel). Data sources: Financial Accounts of the United States (FRB) and FRED (St. Louis Fed). Vertical dashed lines correspond to 2008Q3 and 2019Q4.

2.2 Credit Spreads

This opposite comovement of firms' financial assets and liabilities during the two crises warrants further analysis. We proceed to explore how firm leverage and liquidity interacted with corporate credit spreads. We start by describing the construction of the dataset and then perform the main empirical analysis.

Data. We construct a weekly panel of US corporate bond spreads from mid-2002 through the duration of the COVID-19 pandemic, 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 of the corporate bond and the yield-to-maturity 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.

We obtain secondary market price 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.[3] We clean TRACE data following Dick-Nielsen and Poulsen (2019), taking

[2]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.

[3]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.

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

Credit Spreads Let y_{ift} be the annualized yield to maturity (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:

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

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 broadly 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 basis points, issuance amount greater than $1 million, and maturity at issuance between 1 and 30 years. In addition, we keep only non-financial firms.

[4] Weekly bond prices are average trading price for a bond within a week, weighted by trade volume.

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

Finally, we merge our bond panel with quarterly firm financial data from Compustat. We observe Compustat firms from 2002:Q2 to 2020:Q4. We use firm-ticker information from TRACE and Compustat to match issuers with their financial statements.[6] Table 1 describes the summary statistics for the final (unbalanced) sample of matched issues. We have more than 3 million observations, of 2,131 firms and 21,091 bonds.

Table 1: Summary Statistics of Bond Panel

Variable	Mean	SD	Min	Median	Max
Number of bonds per firm/week	4.59	9.28	1.00	2.00	425.00
Market value of issue ($ mil)	524.34	553.59	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)	249.51	324.83	5.00	145.69	3499.93
Nominal yield (basis points)	565.18	442.40	17.55	483.16	10434.36
Number of observations	3,451,219				
Number of bonds	21,091				
Number of firms	2,131				
Callable (pct)	0.73				

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

2.3 Aggregate Spreads during the Great Financial Crisis and COVID-19

We begin our analysis of credit spreads by looking at aggregate measures, in the spirit of Gilchrist and Zakrajsek (2012), and comparing their evolution during the GFC and the COVID-19 crises. Figure 2 plots the evolution of the median credit spread in our sample around the GFC and the COVID-19 crisis, respectively.[7] The figure plots the evolution of the median credit spread in each event relative to the level of spreads on the first week of the crisis. This is defined as the week of September 15, 2008 for the case of the GFC and the week of February 28, 2020 for the case of COVID-19. 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).

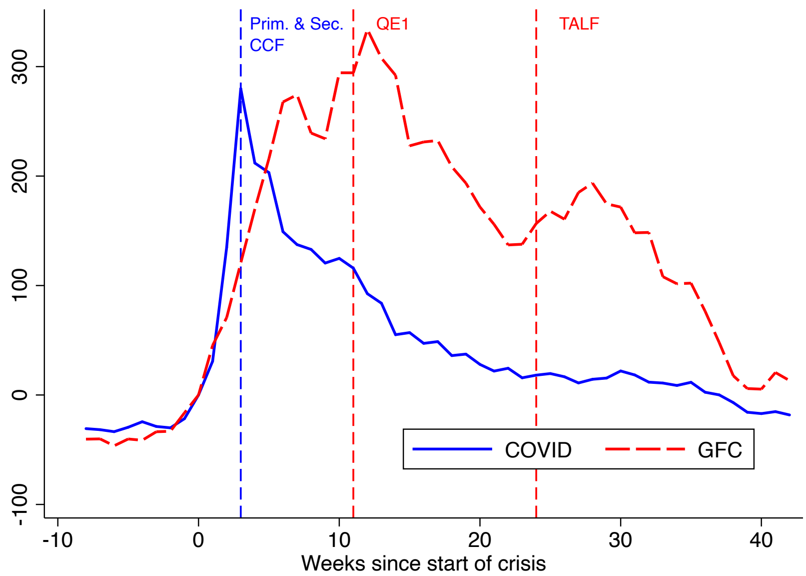
The figure highlights that the onset of each crisis was relatively similar in both cases and featured spread increases of around 300 bps. Overall, there are two key differences between the behavior of median spreads in these two events: (i) the Great Recession was a much more

[6]We utilize the WRDS Bond-CRSP link.

[7]We focus on the median instead of the mean because the distribution of credit spreads features countercyclical skewness, which generates larger movements on the mean than the median. The time series for each crisis can be found in Appendix A.2.

slow-moving affair, with a sustained increase in spreads for a year before the onset of the crisis, and (ii) the Fed's announcements seem to have had a smaller effect in containing spreads in 2008. All in all, the figure shows that while the subsequent dynamics were different, the initial movements in credit spreads were quantitatively similar in the two crises, in stark opposition of what we found for corporate debt and liquid assets.

Figure 2: Median Credit Spreads during the Great Recession and the COVID-19 Pandemic



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). Vertical lines correspond to major Federal Reserve intervention announcements in corporate credit markets (11/25/2008, 03/03/2009, and 03/23/2020).

2.4 Cross-sectional elasticities: Leverage and Liquid Assets

We now proceed to investigate whether there is a systematic relationship between the increase in credit spreads during each of the events and firm-level characteristics. We focus on two characteristics: (i) a measure of solvency, such as leverage, and (ii) a measure of funding liquidity, such as a firm's holdings of liquid assets or its liquid net worth. Both of these variables are natural firm analogues to the aggregate measures of debt and liquid assets that we plotted in Figure 1.

More specifically, 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, which is regressed on measures of liquidity and leverage at a lag of r quarters and $E(t)$ indicates whether at quarter t the observation is during the Great Recession (2008:Q2 - 2009:Q2), COVID-19 (2020:Q1 - 2020:Q2), or normal times. In addition, $X_{f,t}$ are other firm-level controls such as firm size, α_t is a time fixed-effect, and γ_f is a firm fixed-effect.

We take leverage, defined as total liabilities divided by total assets, as a proxy for solvency as it is common in the literature. As a measure of funding liquidity, we focus on liquid assets (cash plus short-term investments) divided by total assets of the firm.[8] This measure captures the amount of resources that the firm has immediate access to. Firm size is defined as the log of total assets. We consider balance sheet characteristics at a lag of four quarters to consider pre-event solvency and liquidity risk faced by firms.

The outcomes of interest are credit spreads $s_{f,t}$ and the investment rate $inv_{f,t}$. Credit spreads at the firm level are computed as the average spread of outstanding bonds issued by a given firm, weighted by the size of those issuances. To compute investment, we use an approach similar to the one described in Ottonello and Winberry (2018). 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).[9]

Table 2 presents the estimation results for specification (2). Column (1) presents the results for credit spreads: in normal times firms with higher leverage have higher spreads while firms with higher liquidity have lower spreads. We also observe two important differences between the Great Recession and COVID-19. First, while leverage was a significant predictor of higher spreads during both crisis and normal times, it is quantitatively more significant during the Great Recession. An increase in leverage of one standard deviation is associated with an increase in spreads of 232 bps during the Great Recession, 129 bps during COVID-19, and 73 bps during normal times. Second, funding liquidity seems to have significantly helped curb higher credit spreads during the COVID crisis, but not during the Great Recession. In fact, the coefficient for the Great Recession is not statistically different from zero. An increase in liquidity of one standard deviation implies an decrease in credit spread of 53 bps during COVID-19, more than twice as much as during normal times (22 bps).

Column (2) presents results for the effects on investment rates. During normal times, lower

[8] Compustat definitions: total assets (`atq`), total liabilities (`dlcq` + `dlttq`) , liquid assets (`chq`).

[9] More details on the construction of this variable can be found in Appendix A.

Table 2: Panel Regressions of Spreads and Investment

	(1) Credit Spreads	(2) Investment Rate
Leverage		
Normal	303.609***	-0.015***
	(27.669)	(0.002)
GFC	972.985***	-0.013***
	(127.077)	(0.003)
COVID	539.741***	-0.018***
	(58.122)	(0.002)
Liquidity		
Normal	-160.309***	0.008***
	(28.415)	(0.002)
GFC	109.933	0.008*
	(67.620)	(0.004)
COVID	-387.543***	0.022***
	(49.373)	(0.005)
N	39211	37352
R2	0.69	0.36

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

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, however, liquidity appears to have become more important, with the point estimate for the coefficient almost tripling.

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 crises are equal to those in normal times. The table confirms that both liquidity and leverage have different effects on spreads in each of the crises, relative to normal times. However, only liquidity seems to play a statistically different role during the COVID-19 regression in terms of affecting investment rates.

These results suggest that the role of firm leverage and liquidity in determining outcomes such as costs 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 much more important role in determining credit spreads during the GFC than during the COVID-19 recession. Liquidity, on the other hand,

Table 3: P-values for test of equality of coefficients

	Credit Spreads	Investment Rate
Leverage		
GFC	0.00	0.31
COVID	0.00	0.14
Liquidity		
GFC	0.00	0.87
COVID	0.00	0.00

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

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 present a quantitative model that help us reconcile these results and think about the role of credit and liquidity policies during large crises.

3 A Macro-Financial Model with Liquidity Shocks

We study the dynamic problem of investing firms with specific focus on their balance sheet items. Our model has both standard elements of macro-finance models, as well as a novel liquidity friction which is key to studying liquid asset holdings. On the standard side, the firm issues defaultable debt and has equity issuance costs. We then augment this model by allowing firms to hold liquid assets to cover stochastic liquidity-needs shocks, and allow them to access a costly intra-period liquidity provision to overcome the liquidity shock. Hence, the model has three different assets and interest rates: defaultable debt, liquid assets, and the intra-period liquidity. Firms are ex-ante heterogeneous in their idiosyncratic risks, 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 as well as firms that differ in their leverage and/or liquidity positions.

Environment. Time is discrete and infinite. The economy is populated by ex-ante heterogeneous firms. There is a finite set of firm types indexed by $i = 1, \dots, N$. There is a continuum of firms of each type with mass $\lambda_i \in [0, 1]$ such that $\sum_{i=1}^{N} \lambda_i = 1$. Below, we omit the firm type subscript (unless where 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 z. Firms hire labor at market wage w. The labor choice solves the following static problem:

$$\pi(z,k) = \max_{n} \quad z^{1-\upsilon}k^{\alpha}n^{\upsilon} - wn \tag{3}$$

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 firms depreciates with rate $\delta \in (0,1)$. Capital accumulation is subject to convex adjustment costs

$$\mathcal{A}^K(k',k) = \frac{\psi}{2}\left(\frac{k'-k}{k}\right)^2 k \tag{4}$$

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 operation costs before revenue is received. The need for working capital thus arises from the difference in the timing of when costs are incurred and when revenue is received. These can stem, for example, from delayed payments of trade credit provided to clients. These payment disruptions can be substantial during times of large financial and economic crises.[10]

We formalize the working-capital constraint as follows. With probability p_ω the firms needs to hold liquid assets equivalent 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 m at the intra-period costly liquidity. The working-capital constraint is

$$\omega k \leq a + m \tag{5}$$

intra-period debt needs to be repaid at the end of the period, and is subject to an exogenous

[10]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.

and increasing interest rate schedule. The total net cost of borrowing m is given by

$$\mathcal{A}^M(m) = r\exp(s_m m)m \tag{6}$$

where s_m 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 the funds 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 intra-period debt induce firms to hold liquid assets in 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 chose capital k', liquid assets a', and debt b' repays its debt. The price schedule is then given by

$$q(k', a', b') = (1+\chi)\frac{\mathcal{P}(k', a', b')}{1+r} \tag{7}$$

where parameter $\chi > 0$ 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 be firm dividends:

$$div = \pi(z,k) + (1-\delta)k - k' - \mathcal{A}^K(k',k) - b + q(k',a',b')b' + a - q_a a' - \mathcal{A}^M(m) \tag{8}$$

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

$$\mathcal{A}^D(div) = \frac{\rho}{2}\max\{-div, 0\}^2 \tag{9}$$

where $\rho > 0$.

Default. At the beginning of each period, the firm receives i.i.d. extreme-value preference shocks which 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

$$V(k,a,b,\omega,\varepsilon^P,\varepsilon^D) = \max\left\{V^P(k,a,b,\omega)+\varepsilon^P, V^D(k,a,b,\omega)+\varepsilon^D\right\} \tag{10}$$

where V^P is the value of repayment given states (k,a,b,ω) and V^D is value when defaulting. For simplicity we assume that the value of default is equal to zero. 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 becomes

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

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

$$\mathcal{P}(k,a,b) = p_\omega \mathcal{P}(k,a,b,\bar{\omega}) + (1-p_\omega)\mathcal{P}(k,a,b,0) \tag{11}$$

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

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

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

$$\mathcal{V}(k,a,b) \equiv p_\omega \mathcal{V}(k,a,b,\bar{\omega}) + (1-p_\omega)\mathcal{V}(k,a,b,0)$$

Firm's Problem. The full specification of the firm's problem is then

$$\begin{aligned} V^P(k,a,b,\omega) = \max_{k',a',b',m} \quad & div - \mathcal{A}^D(div) + \beta\mathcal{V}(k',a',b') \\ \text{s.t.} \quad & div = \pi(z,k) + (1-\delta)k - k' - b + q(k',b',a')b' + a - q_a a' - \mathcal{A}^K(k',k) - \mathcal{A}^m(m) \\ & \omega k \leq a + m \\ & a',b',k',m \geq 0 \end{aligned} \tag{12}$$

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

4 Calibration

The calibration is annual and targets moments associated with publicly traded US firms. The model calibration combines externally and internally calibrated parameters. We take the external parameters from the literature and are the same for all types of firms. The internal parameters vary across firm types and are chosen to match cross-sectional data 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 firms in this state.

4.1 Externally Calibrated Parameters

Table 4: 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 SS
p_ω	0.5000	Probability of liquidity shock
Prices		
β	0.9500	Discount factor
r	0.0526	Interest rate
q^a	1.0000	Price of liquid assets
s_m	25.0000	Slope of intra-period borrowing cost

Table 4 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.[11] We set the probability of the firm receiving the liquidity shock, p_ω, equal to 0.5, in the absence of moment target that is

[11] 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. For numerical tractability, we allow firms to potentially issue equity, but make it very costly to do so.

informative about this parameter, but we conduct robustness checks in Appendix B.3.

The discount rate, which is the same for lenders and firms, implies an annual discount of 5%, i.e., $\beta = 0.95$ and $r = 1/\beta - 1$. We set the interest rate on liquid assets to zero, thus $q_a = 1$. The slope of the intra-period borrowing cost function is set to 25. This value ensures that the spread on intra-period debt behaves in line with certain moments in the data, as we show in the next sections. We also conduct robustness with respect to this parameter in Appendix B.3. Finally, we normalize the wage and TFP to 1.

4.2 Internally Calibrated Parameters and Firm Types

We consider four different types of firms, $N = 4$. We allow parameters $(\chi_i, \bar{\omega}_i, \kappa_i)$ to vary for each firm type. We then choose the parameters to match their levels of leverage, share of liquid assets, and credit spreads. We define the four groups of firms accordingly to firms having 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 2. We split the panel into four groups, according to which their leverage and liquid asset holdings are below or above the median value in 2007Q2 and 2019Q4, and target average values of leverage/liquidity for each group across the two dates.[12] Since we do not use credit spreads as a criterion for the definition of these groups, we target the same level of credit spreads for all these firms, which corresponds to the sample median for 2007Q2 (166 bps). Finally, we use the number of firms in each subgroup as a percentage of the total number of firms to construct the weights λ_i. These moments are reported in Table 5.

Table 5: Calibration Targets from merged Compustat-FISD/TRACE dataset.

	Aggregate	Type 1	Type 2	Type 3	Type 4
Leverage, %	31.10	45.00	45.00	20.00	20.00
Liquidity, %	4.45	11.00	1.50	11.00	1.50
Credit Spreads, bps	166.00	166.00	166.00	166.00	166.00
Measure of firms	1.00	0.20	0.30	0.30	0.20

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

Table 6 lists the endogenously calibrated values by type and the value of the target moments from the model. Model moments match very closely the moments we target from 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, the liquidity cost parameter $\bar{\omega}$ is larger for firms with more

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

liquid assets. Credit spreads are increasing in κ, with this parameter being chosen to match the target level of 166 bps given liquidity and leverage for a given firm.[13]

Table 6: Targeted moments and internally calibrated parameters.

Firm type	**Model Parameter**			**Model Moment**		
	debt preference (χ)	liquidity needs ($\bar{\omega}$)	idiosyncratic risk (κ)	Leverage	Liquid assets	Credit
High lev & high liq	0.0146	0.1880	0.3480	0.4504	0.1101	166
Low lev & high liq	0.0049	0.1892	0.3249	0.2004	0.1101	166
High lev & low liq	0.0139	0.0721	0.3645	0.4501	0.0150	166
Low lev & low liq	0.0045	0.0723	0.3415	0.2003	0.0151	166

4.3 Untargeted Moments

Table 7 presents a first test of model and calibration validity, by comparing untargeted data moments from the data (at the two calibration target dates) to corresponding moments in the model. We focus on four moments: the marginal financing cost for short-term debt, a measure of operating income to assets, debt to income, and the default rate. For the data on the marginal financing cost, we take the spread between the average bank rate on short-term loans to businesses (FRED: DPRIME) and the federal funds rate. For the measure of profitability, we take the median ratio of operating income to lagged assets for the firms in our matched firm-bond panel. We take the median of the ratio of total firm debt to operating income over the same sample. 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 2.47% which is a bit lower than the default rate of speculative-grade firms of 3% (Moody's investors service, 2015).

Table 7: Untargeted moments: model vs. data

Moment	Data		Model
	2007Q2	2019Q4	
Mg Financing Cost, percent	3.00	3.25	3.77
Income to Assets, percent	13.40	11.10	14.82
Debt to Income	2.21	3.24	2.25
Default rate	3.00	3.00	2.47

[13] In Appendix B.2 we illustrate how each of these moments helps identify each parameter.

5 Macro-Financial Crises

We now use the model as a quantitative laboratory to study different crises and policy experiments. These help us to rationalize the differences in the behavior of credit spreads, debt, and liquid assets in the last two crises. Furthermore, these allow us to study the costs and benefits of different policy interventions akin those deployed in the recent crises.

5.1 Modeling Crises

We want to understand how firms reacted during the Great Recession and the COVID-19 pandemic. Neither of these events are traditional business cycle fluctuations, but rather large and unexpected aggregate shocks. Hence, we explore the response of firms to unexpected and transitory shocks. Let Φ denote the set of parameters whose values may change with shocks, such us the TFP z, the financial frictions in debt markets χ_i, and the size of liquidity shocks $\bar{\omega}_i$:

$$\Phi = \{z, \chi_i, \bar{\omega}_i\} \tag{13}$$

Let Φ_1 be the initial set, at the calibrated steady state. At period t a shock occurs so the set becomes Φ_2. For example, productivity z and/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 stay there from then on, while with the remaining probability $1 - \zeta$ it will remain at Φ_2. Hence the expected duration of the shock is $1/\zeta$.

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

$$V^P(k, b, a, \omega|\Phi_2) = \max_{k', a', b', m} \quad div - \mathcal{A}^D(div) + \zeta\beta\mathcal{V}(k', b', a'|\Phi_1) + (1-\zeta)\beta\mathcal{V}(k', b', a'|\Phi_2) \tag{14}$$

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 firms' 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.[14] While χ_i is firm-specific, we assume that the shock corresponds to a situation where χ_i falls to χ^c for all firms. That is, we assume that while different firms experience different levels of distortion of their borrowing decision in 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, $\omega = 0$.

5.2 Aggregate Responses

Our benchmark experiment consists of hitting the economy with the real, financial, and liquidity shocks at the same time. The size of each shock is chosen so the model generates a large financial and economic crisis. The size of the real shock z^c is chosen to target a fall in GDP of 5%, the size of the financial shock χ^c is chosen to match a rise in spreads of around 300 bps, similar to the rise of spreads on impact in each of the crisis that we study, and the size of the liquidity shock ω^c is chosen to match a rise in liquid asset holdings of 25%, similar to what was observed at the beginning of the COVID-19 crisis. The probability of returning to the steady state set of parameters is set at $\zeta = 0.75$, hence the crisis has an expected duration of approximately 1.33 years. 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 shock.

The aggregate results of our benchmark crisis experiment are shown in column (1) of Table 8. The first three rows, underlined, correspond to the explicitly targeted moments. The benchmark crisis, by construction, results in a 300 bps rise in credit spreads, a 5% drop in GDP, and a 25%

[14] 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).

increase 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 inter-period debt issued b' and intra-period debt $(1 + \mathcal{A}^m(m'))m'$. The experiment reproduces the co-movements 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 intra-period borrowings. These borrowings 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 5.77 percentage points drop in the investment rate. Due to the increase in borrowings 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.

Table 8: Quantitative Results

Variation wrt SS	(1) Benchmark	(2) No Liquidity	(3) No Financial	(4) No Real
Spreads, bps	<u>300.01</u>	282.33	21.15	294.78
GDP, percent	<u>-5.00</u>	-5.00	-5.00	0.00
Liquid Assets, percent	<u>25.02</u>	-27.87	59.23	26.71
Debt owed, percent	18.51	-65.21	67.14	16.42
Investment Rate, pp	-5.77	-3.97	-1.40	-5.30
Profit, percent	-112.08	-106.52	-52.40	-111.21
Prob. Default, pp	0.23	0.06	0.20	0.18
Elasticity of spreads wrt leverage	437.67	413.67	25.73	430.71
Elasticity of spreads wrt liquidity	-205.74	64.85	-252.88	-200.16
Elasticity of inv. rate wrt leverage	-0.03	-0.03	0.00	-0.03
Elasticity of inv. rate wrt liquidity	0.08	0.00	0.05	0.07

Notes: Model results from each of the shock experiments: the "benchmark" experiment includes all three shocks. <u>Underlined values</u> are the shock targets. Each successive column omits each one of the shocks. More details in the text.

5.3 Cross-Sectional Responses

The last four rows of table 8 correspond to cross-sectional elasticities implied by the model that are comparable to those estimated from the data in section 2.4. 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: 437.67 in the model vs. 539.74 in the data for leverage, and -205.74 in the model vs. -387.54 in the data for liquid assets. While the coefficients are not exactly the same, they have the correct signs and order 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 -0.03 in the model vs. -0.018 in the data, while the elasticity with respect to liquid assets is 0.08 in the model vs. 0.022 in the data. The main conclusion being that firms that were more leveraged and held less liquid assets experienced relatively larger drops in their investment rates in the model, consistent with the evidence for the COVID-19 crisis.

5.4 Crisis Decomposition

Columns (2)-(4) of table 8 analyze the role of each shock, by turning off one shock at a time.

No Liquidity Shock Column (2) corresponds to an experiment where we feed financial and real shocks of the same sizes as in the benchmark experiment, but no liquidity shock. 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 slightly 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 rising. This is due to two complementing forces. 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 inter-period debt this period, and hence to maintain positive profits for pre-determined 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. 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 slightly less, as the liquidity shock induces an extra incentive to disinvest by amplifying the precautionary motive to hold liquid assets. Similarly, profits fall by slightly less, as firms no longer need to increase their investments in liquid assets. The probability of default increases by less than in the benchmark case, as firms significantly cut their borrowings and therefore endogenously offset the increase in risk.

Regarding the cross-sectional effects, 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 drops in investment. Liquidity, however, loses most of its previous importance: it has basically no effect in 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 that we present in section 2.4: 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. This seems to be consistent with the wide evidence on supply chain and payment network disruptions that was brought about by the COVID-19 crisis (Boissay et al., 2020).

No Financial Shock Column (3) repeats the exercise, but without the financial shock. In this case, there is a rise in the spreads that is 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: this is due to the fact that since spreads do not rise by nearly as much, it is now much cheaper to borrow in inter-period debt, and hence accumulate all the liquidity that is required to cover the constraint without resorting to expensive intra-period borrowings. This is also reflected in the large increase in total borrowings. 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 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. Profits fall by half, and the probability of default rises by 20 basis points, which is a consequence of the large increase in borrowings. 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 optimal scale. As investment and capital drop, so do liquid assets as the liquidity constraint is relaxed. Finally, firms also reduce their borrowings and leverage so as to maintain their interperiod borrowing costs roughly constant.

6 Credit and Liquidity Policies

We now analyze the effects of different credit and liquidity policies in the context of the benchmark shock experiment. 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.

6.1 Credit Policies

Corporate Credit Facilities. Corporate credit facilities (CCF) stand for indirect or direct purchases of corporate debt by the Federal Reserve, on secondary and primary markets, respectively. During the GFC, the Fed 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, as the Fed set up the Secondary and Primary Market Corporate Credit Facilities (SMCCF and PMCCF), which involved the outright purchases of corporate bonds by eligible US companies during 2020.

For simplicity, we assume that there is a one-to-one mapping between quantities purchases 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 7 becomes

$$q^{CCF}(k', a', b') = (1 + \chi + \chi^{CCF})\frac{\mathcal{P}(k', a', b')}{1 + r} \tag{15}$$

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,

$$\mathcal{C}_t^{CCF} = \chi_t^{CCF} \sum_{i=1}^{N} \lambda_i \frac{\mathcal{P}(k_{i,t+1}, a_{i,t+1}, b_{i,t+1})}{1+r} \times b_{i,t+1} \tag{16}$$

Credit Guarantees While neither the US Treasury nor the Fed 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.[15] 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 (7) then becomes

$$q^{CG}(k', a', b') = (1+\chi)\frac{\mathcal{P}(k', a', b')}{1+r} + \phi^{CG}\frac{[1-\mathcal{P}(k', a', b')]}{1+r} \tag{17}$$

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

$$\mathcal{C}_t^{CG} = \phi_t^{CG} \sum_{i=1}^{N} \lambda_i \frac{[1-\mathcal{P}(k_{i,t+1}, a_{i,t+1}, b_{i,t+1})]}{1+r} \times b_{i,t+1} \tag{18}$$

6.2 Liquidity Policies

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 8. The effect of a transfer of size T_t on the liquidity constraint is then:

$$\omega k \leq a + m + T \tag{19}$$

And the total cost of this policy is simply

$$\mathcal{C}_t^{T} = T_t \sum_{i=1}^{N} \lambda_i = T_t \tag{20}$$

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

Subsidized Direct Loans. We also consider the possibility of loans made by the government directly to corporations. During the GFC, the US Department of Treasury directly lent $80.7 billion in corporate debt and preferred equity to major automakers General Motors and Chrysler as part of TARP. During the COVID-19 crisis, a very important component of the fiscal-monetary policy response consisted of programs such as the Paycheck Protection Program, the Economic Stabilization Fund, and the expansion of the 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.

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 5 now becomes

$$\omega k \leq a + m + L \tag{21}$$

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 8. 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 is to be repaid in the following period, and that is added to any other borrowings. This means that total debt owed at the end of the period are equal to $b' + (1+r)L$, and this is taken into account by lenders when pricing loans originated in the current period, i.e. 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 take 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:

$$\mathcal{C}_t^L = \sum_{i=1}^{N} \lambda_i \left[L_t - \frac{(1+r)L_t \mathcal{P}_{it}}{1+r} \right] = L_t \sum_{i=1}^{N} \lambda_i \left[1 - \mathcal{P}_{it} \right] \tag{22}$$

6.3 Credit and Liquidity Policies in Macro-Financial Crises

We consider "blanket" untargeted policies, where the intervention is offered equally to all firms. Table 9 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. The sizes of the policies are chosen so as to reduce drop in the investment rate by 1pp (so that it falls by 4.77 pp as opposed to 5.77 given the baseline shocks). Column (1) refers to the benchmark no policy case that was described in the previous section.

Table 9: Policy Interventions

Variation wrt SS	(1) No Policy	(2) CCF	(3) Credit Guarantee	(4) Transfer	(5) Loan
Spreads, bps	300.01	233.52	222.08	276.13	289.42
GDP, percent	-5	-5	-5	-5	-5
Liquid assets, percent	25.02	32.86	33.14	3.96	-3.03
Debt owed, percent	18.51	24.79	25.25	-20.62	-13.86
Investment rate, pp	-5.77	-4.76	-4.77	-4.77	-4.76
Profit, percent	-112.08	-108.65	-107.71	-105.41	-102.7
Prob. Default, pp	0.23	0.22	0.22	0	0.13
Cost of policy over GDP, pp	0	0.18	0.21	6.27	0.18
Elasticity of spreads wrt leverage	437.67	432.67	313.06	405.22	422.05
Elasticity of spreads wrt liquidity	-205.74	-201.99	-146.1	-93.9	-70.83
Elasticity of inv. rate wrt leverage	-2.77	-2.34	-2.01	-3.12	-3.5
Elasticity of inv. rate wrt liquidity	7.59	6.72	6.71	5.38	5.96

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 each of the policies activated 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 offsets the effects of the financial shock and allows firms to borrow more to counter the effects of the liquidity shock: this 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-a-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.

Column (3) shows the effects of the credit guarantee. 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 different between CCF and guarantees is that the CCF is a relatively larger subsidy to safer firms, while guarantees consist of a relatively larger subsidy to riskier firms. To see this, recall the effects on debt prices of these two policies:

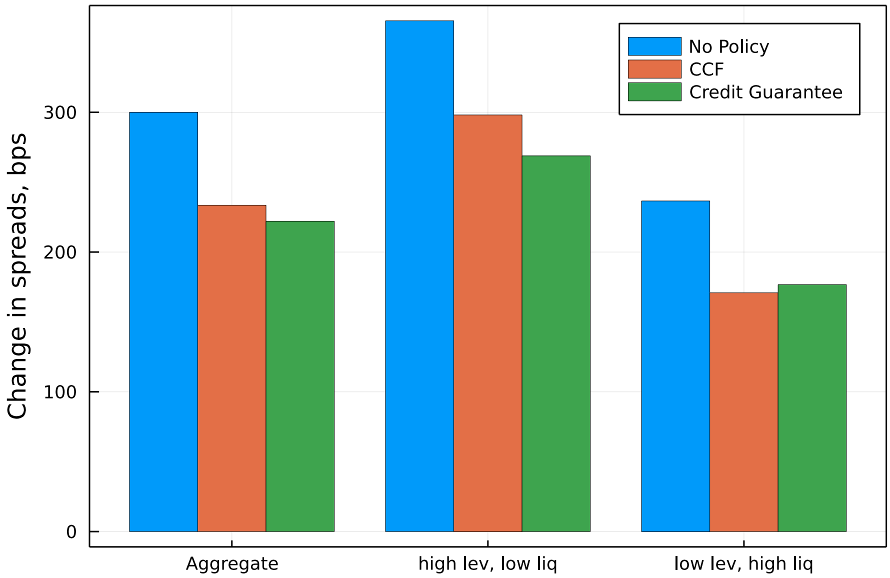
$$q^{CCF}(k',a',b') = (1+\chi+\chi^{CCF})\frac{\mathcal{P}(k',a',b')}{1+r}$$
$$q^{CG}(k',a',b') = (1+\chi)\frac{\mathcal{P}(k',a',b')}{1+r} + \phi^{CG}\frac{[1-\mathcal{P}(k',a',b')]}{1+r}$$

From here, we can see that 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 to understand why guarantees seem to have a much larger effect on elasticities of spreads and investment rates with respect to leverage and liquidity than CCF, 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 by more during the crisis. By helping these firms relatively more, guarantees contribute to muting the response of spreads and investment to differences in leverage and liquidity.

Figure 3 illustrates this by plotting the differential response of credit spreads from different policies on two types of firms: high leverage and low liquidity firms, which are presumably more impacted both by financial and liquidity shocks, and low leverage and high liquidity, which are less impacted. The figure shows that the credit guarantee generates a relatively larger drop in credit spreads for the high leverage/low liquidity firm in relation to the CCF (i.e., the orange bar is taller than the green bar), while the opposite is true for the low leverage/high liquidity firm (orange bar shorter than green bar). Hence, riskier firms benefit more from credit guarantees while safer firms benefit more from CCF.

Liquidity Policies Column (4) corresponds to the transfer that, as described, helps firms satisfy the liquidity constraint. This offsets the liquidity shock, and allows firms to increase their holdings of liquid assets by much less, as well as decrease their borrowings. 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 incentive is weakened, and this 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 the firm's 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

Figure 3: Cross-Sectional Effects of Credit Policies



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

default, it is also significantly more expensive than other policies, costing over 6% of steady state GDP (compared to 0.18% of GDP for CCF, for example).[16] Finally, the transfer policy weakens the elasticity of spreads and investment with respect to liquidity, which suggests that this is a relatively effective policy at offsetting the liquidity shock.

Column (5) shows the effects of the subsidized loan program. The results are overall relatively 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, debt not falling by as much, 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 this 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 as reducing probabilities of default as the transfer, it is much cheaper than the transfer, with a cost that is similar to that of the CCF.

[16]Table 9 in Appendix B.4 repeats the exercise but where we choose the size of each policy so as to reduce the increase in credit spreads by 100 bps. The basic qualitative results remain unchanged.

Also note that the loan policy along with the transfer reduce the magnitude of the elasticity of spreads and investment rates with respect to liquidity, which suggests that they are particularly effective policies at offsetting liquidity shocks and reducing the importance of firm liquidity overall during crises.

7 Policy Cross-Sectional and Aggregate State Dependence

We now investigate how different policies interact with different shocks. We aim to understand why different policies are most effective against different types of shocks and/or different objectives (i.e., stimulate investment or avoid bankruptcies). To this end, we run a series of experiments, in which we hit the economy with one shock and one policy at a time. The shock and policy sizes are the same that we considered in the previous section. We focus on the effects on impact for two variables: the probability of default and the investment rate. The effects for other real outcomes, such as output or employment, are qualitatively similar to those on the investment rate.

Table 10 shows the response to different shocks and policies. For each shock (each of the four panels), we consider different policies. As a benchmark for comparing the effectiveness of different policies, the first row of each panel corresponds to the no policy case. First, we start with the no shock case, in which we consider impulses at the steady state after a policy intervention. We observe that all policies can reduce the probability of default. Transfers, in particular, has a much larger effect on default as they raise the value of the firm in a more direct way. While CCF and Transfers raise the investment rate, both credit guarantees and loans lower it. Loans reduce the investment rate by burdening firms with a liability to be repaid in the following period when firms are relatively unconstrained. Credit guarantees, as we showed in the previous section, induce riskier firms to borrow more. By lowering the credit spreads at which they can borrow, credit guarantees also induce disinvestment. Without policy, the riskier firms understand that they can improve their borrowing terms by maintaining a relatively high stock of capital (as this affects their price of debt positively). With the credit guarantee, however, these riskier firms can afford to reduce their stock of capital and still be able to borrow at relatively low spreads. Hence, credit guarantees induce disinvestment in the absence of shocks.

Credit Policies The CCF seems to be relatively effective at stimulating investment in face of all of the shocks, but not particularly effective at changing the probability of default vis-a-vis the no policy baseline. The positive effects on the investment rate arise from the fact that the CCF is effectively a larger subsidy for firms that have a lower expected probability of default. This induces firms to disinvest less, as this lowers their probability of default. Since they also borrow more, in order to effectively take advantage of the subsidy, this results in more investment but a relatively unchanged probability of default.

The effects of Credit Guarantees on default probabilities are similar to those of the CCF, but this policy tends to worse in terms of stimulating investment, for the reasons explained before. In particular, credit guarantees reduce the investment rate below the laissez-faire level for all shocks except for the financial shock, against which they are moderately effective at curbing the drop in the investment rate (but still do worse than any other policy). Thus credit guarantees can be effective against financial shocks, but are a counterproductive policy in effectively any other situation.

Liquidity Policies Transfers are always extremely effective at reducing default probabilities, and also relatively effective at curbing drops in investment. The reduction in the default probability is more important when the economy is hit by a liquidity shock, as this is the kind of shock that triggers the largest increase. This means that transfers are an attractive tool for a policymaker whose objective is to reduce bankruptcies, rather than maximize the effects of policy on investment or GDP, for example. The main drawback of transfers is that they tend to be expensive, as we have shown in the previous section. Loans are overall a weaker version of transfers: less effective and reducing default probabilities and investment drops in the case of liquidity and financial shocks (and actually counterproductive when the economy experiences no shocks or TFP shocks). The main advantage of loans is that they are much cheaper than transfers, and so may be an attractive policy option if the government is subject to fiscal constraints.

In summary, we show that different policies can be more or less effective vs. different shocks, depending on the objectives of the policymaker. In terms of credit policies, CCF is always effective in terms of reducing the fall in investment, but has little to no effect on default probabilities. Credit guarantees are always counterproductive except against financial shocks, where they produce effects that are similar to those of the CCF. Regarding liquidity policies, transfers are always effective in reducing default, but are more expensive and have a more muted effect on investment. They are particularly effective against liquidity shocks, as this type of shock raises default probabilities substantially. Loans are a weaker version of transfers, but counterproductive vs. TFP shocks.

Table 10: Effects of shocks and policies on the probability of default and investment rate.

Shock	Policy	Δ Prob. Default (pp)	Δ Inv. Rate (pp)
No shock	*None*	*0.00*	*0.00*
	CCF	-0.01	0.56
	Credit Guarantee	-0.02	-0.10
	Transfer	-0.20	0.13
	Loan	-0.01	-0.36
Liquidity	*None*	*0.15*	*-0.97*
	CCF	0.15	-0.52
	Credit Guarantee	0.14	-1.05
	Transfer	-0.06	-0.65
	Loan	0.07	-0.91
Financial	*None*	*0.02*	*-3.49*
	CCF	0.01	-2.66
	Credit Guarantee	0.01	-2.71
	Transfer	-0.12	-2.63
	Loan	0.01	-2.69
Real	*None*	*0.04*	*-0.41*
	CCF	0.04	0.01
	Credit Guarantee	0.03	-0.48
	Transfer	-0.09	-0.39
	Loan	0.04	-0.73

Notes: Impact responses of different combinations of shocks and policies on the probability of default and investment rate. Shock and policy sizes chosen to be the same as in the previous section.

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 level, 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, i.e. 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 liquid 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. Policies such as corporate credit facilities are effective at simulating investment, but not necessarily at preventing bankruptcies. Other policies such as credit guarantees can be counterproductive depending on the type of the shock. Finally, policies such as transfers and loans to firms are useful against liquidity and financial shocks, if the policymaker's objective is to reduce bankruptcies.

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).

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., Sanchez, J. M., Sapriza, H., and Yurdagul, E. (2021). Sovereign debt restructurings. *American Economic Journal: Macroeconomics*.

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.

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. (2018). Financial heterogeneity and the investment channel of monetary policy. Technical report, National Bureau of Economic Research.

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

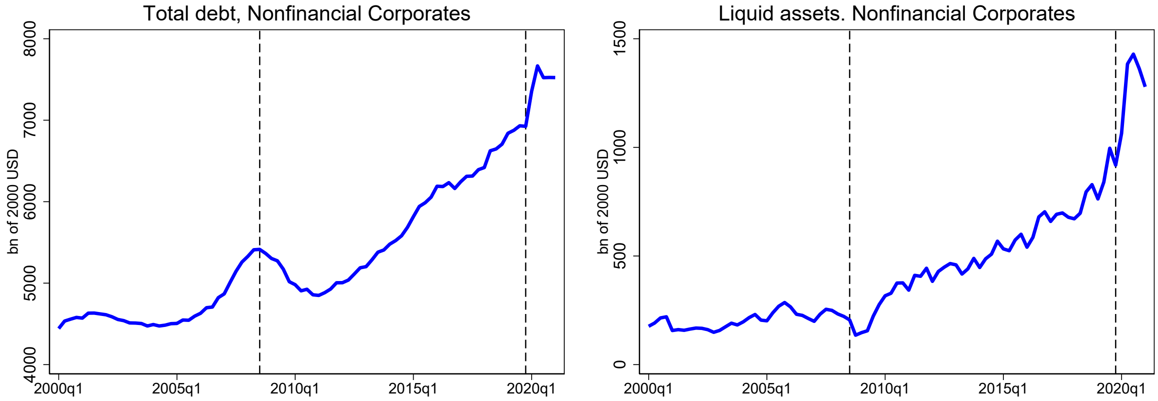
Reinhart, C. M. and Rogoff, K. S. (2009). *This time is different: Eight centuries of financial folly*. princeton university press.

Appendix

A Data Appendix

A.1 Flow of Funds Data

Figure A1: Debt and Liquid Assets



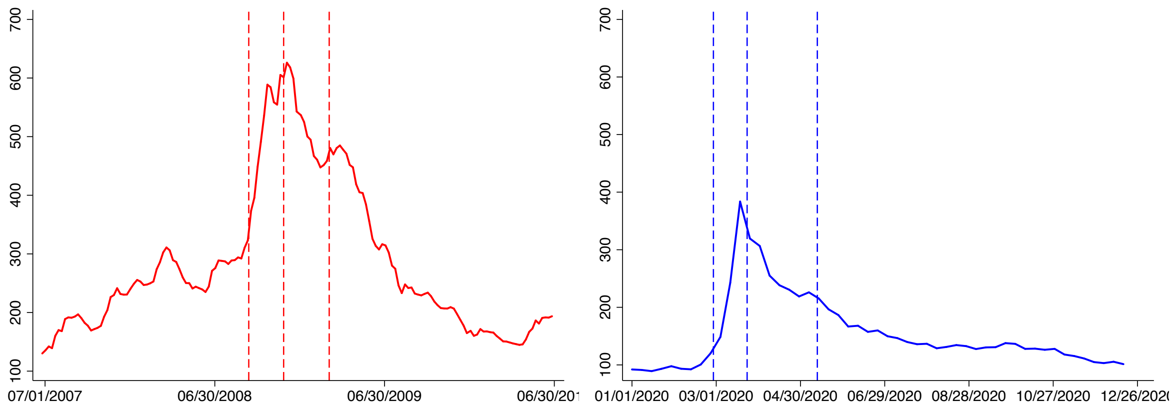
Notes: Real total debt for US nonfinancial corporates (left panel) and real liquid asset holdings for US nonfinancial corporates (right panel). Data sources: Financial Accounts of the United States (FRB) and FRED (St. Louis Fed). Vertical dashed lines correspond to 2008Q3 and 2019Q4.

A.2 Median Credit Spreads

Panel (a) of Figure A2 plots the median spread starting on July 2007, when financial markets start displaying signs of potential stress. Median spreads hover around 120 bps in early Summer of 2007, when they start rising. There is a local peak of 300 bps in the first quarter of 2008, around the time of the failure (and rescue) of the investment bank Bear Stearns. The first dashed line corresponds to September 15, 2008, the date of the failure of the investment bank Lehman Brothers, which triggers a large jump in the median spread to about 600 bps. The second dashed line corresponds to the announcement of the first round of unconventional monetary policy measures by the Federal Reserve (including the first round of quantitative easing and the Term Asset-Backed Securities Loan Facility, TALF). The final dashed line corresponds to March 3, 2009, when TALF is implemented, and after which the median spread falls consistently, stabilizing at around 200 bps for the following year. The Lehman and TALF implementation dates are therefore natural dates to "bound" the crisis in the corporate bond market around the Great Recession.

Panel (b) of Figure A2 plots the median spread since the beginning of the year 2020. Starting from a stable level of around 100 bps, credit spreads start rising at the end of February 2020, as it starts becoming evident that COVID-19 would directly affect advanced economies. The first dashed line corresponds to February 28, 2020, the date of the largest single-week stock market decline since 2008. The median spread rises during March, reaching 500 bps, until the 23rd day of that month, when the Federal Reserve announces a series of interventions aimed at stabilizing financial markets. From then on, the median spread started falling, and by July 2020 it was already below 200 bps. Interestingly, and unlike in the Great Recession, most of the decrease seems to have been triggered by the announcement, and not necessarily the implementation, of most policy programs: the third dashed line corresponds to May 12, 2020, when the Secondary Market Corporate Credit Facility was implemented.

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



Notes: The first and second panel shows the evolution of credit spreads during the Great Recession and COVID-19, respectively. Vertical lines correspond to the beginning of each crisis and to major Federal Reserve interventions in credit markets. See text for more details.

A.3 Table 2 Details

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

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

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 at 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. In addition, we define $inv^k_{f,t}$ as capital expenditures divided by $k_{f,t-1}$.

For Table 2 we drop observations where leverage is less than 0 or greater than 10. In addition, we keep observations where leverage, liquidity, and investment rate are between the 1st and 99th percentiles of their respective samples.

Subsequently we merge the firm-panel to our bond panel, which as mentioned in the main text limits our sample of firms to: (1) Non-financial US Firms, (2) Fixed- and zero-coupon bonds issuers, (3) Bond credit spread between 5 and 3500 basis points, (4) Bond issuance amount greater than \$1 million, and (5) Maturity at issuance between 1 and 30 years.

A.4 Alternative Lag Lengths

Table A1: Panel Regressions: Different Lags

	(1)	(2)	(3)	(4)
	Credit Spreads		Investment Rate	
	$r = 2$	$r = 6$	$r = 2$	$r = 6$
Leverage				
Normal	436.091***	198.075***	-0.017***	-0.012***
	(35.957)	(24.809)	(0.002)	(0.002)
GFC	1091.190***	851.340***	-0.016***	-0.011***
	(127.931)	(104.695)	(0.004)	(0.003)
COVID	663.921***	455.649***	-0.020***	-0.012***
	(67.796)	(49.795)	(0.001)	(0.002)
Liquidity				
Normal	-193.898***	-106.837***	0.011***	0.006**
	(27.708)	(29.588)	(0.002)	(0.002)
GFC	61.114	290.417***	0.007*	0.005
	(71.910)	(91.447)	(0.004)	(0.005)
COVID	-410.930***	-254.870***	0.026***	0.015***
	(47.668)	(25.585)	(0.005)	(0.003)
N	42068	36022	40072	34413
R2	0.69	0.69	0.35	0.34

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

Table A1 presents results of equation (2) at alternative lag lengths r. Columns (1) and (2) present results of the credit spread regressions with identical fixed-effects, clustering and controls with 2-quarter and 6-quarter lag lengths, respectively. Similarly, columns (3) and (4) provide the analog results for $inv_{f,t}$. Overall, the coefficients are quantitatively very similar. The independent variables in equation (2) are lagged so as to provide us during the event of a crisis an understanding of how pre-crisis financial conditions such as solvency and liquidity affect investment and credit spreads. Results in Table A1 provide evidence that the results in Table 2 are not sensitive to what is defined as the pre-crisis period.

A.5 Alternative Event Definition

Table A2: Alternative Dating of Crises

	(1) Credit Spreads	(2) Investment Rate
Leverage		
Normal	309.693***	-0.015***
	(27.799)	(0.002)
GFC	629.814***	-0.015***
	(143.631)	(0.003)
COVID	508.435***	-0.020***
	(71.388)	(0.002)
Liquidity		
Normal	-167.660***	0.008***
	(29.228)	(0.002)
GFC	-0.971	0.011***
	(70.382)	(0.003)
COVID	-361.784***	0.017***
	(60.762)	(0.005)
N	39211	37352
R2	0.69	0.36

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

Table A2 presents results of equation (2) with alternative definition of the occurrence of the Great Financial Crises. We consider 2007:Q3 to 2009:Q2 to be the period identified as the GFC, adding two quarters, and 2020:Q1 to 2020:Q2 to be the period identified as the COVID-19 crisis, restricting the crises to trough. Overall, qualitatively our conclusions in Section 2.4 hold. We find that leverage is important in all periods but much more significant in the GFC and during the pandemic relative to normal times. With respect to liquidity, we find again that a better liquidity position predicts lower credit spreads during normal times and and during the pandemic. In addition, the pandemic response is statistically different from the response of credit spreads to liquidity during normal times up to the 95-percent confidence level.

A.6 Alternative Investment Rate Definitions

Table A3: Alternative Investment Measures

	(1) $\widetilde{inv}_{f,t}$	(2) $inv^c_{f,t}$	(3) $inv^k_{f,t}$	(4) $\Delta log(k_{f,t})$
Leverage				
Normal	-0.015***	-0.011***	-0.024***	-0.036***
	(0.002)	(0.001)	(0.002)	(0.004)
GFC	-0.015***	-0.010***	-0.023***	-0.040***
	(0.003)	(0.001)	(0.003)	(0.008)
COVID	-0.018***	-0.010***	-0.030***	-0.041***
	(0.002)	(0.001)	(0.001)	(0.005)
Liquidity				
Normal	0.013***	0.005***	0.030***	0.036***
	(0.002)	(0.001)	(0.003)	(0.006)
GFC	0.013***	0.008***	0.034***	0.045***
	(0.005)	(0.002)	(0.005)	(0.008)
COVID	0.025***	0.013***	0.029**	0.050***
	(0.006)	(0.002)	(0.011)	(0.017)
N	38250	37939	37929	38486
R2	0.26	0.71	0.57	0.20

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

Table A3 presents results of equation (2) with alternative investment definitions. The four columns correspond, in order, to the following definitions: (1) gross investment rate ($\widetilde{inv}_{f,t}$), (2) $inv^c_{f,t}$, (3) $inv^k_{f,t}$, and (4) the percentage change in capital stock $\Delta log(k_{f,t})$. Overall, conclusions from column (2) of Table 2 apply to columns (1) and (2) of Table A3. Response of investment to leverage is negative, positive to liquidity, and are mostly similar in magnitude during the three time periods. Only the response of investment to liquidity is greater during COVID-19 than in normal times. Using the quarterly rate of change as the definition of the investment rate, column (4), yields responses response to leverage which are negative and responses to liquidity which are positive. However, we observe a qualitatively similar response in investment to liquidity and leverage during the Great Recession, COVID-19, and in normal times.

B Model Appendix

B.1 Calibration Leverage and Liquidity Tables

Our goal is to understand the role that leverage and liquidity play in the differential responses of firms in each group to shocks and policy. Hence, to compute elasticities we need to consider two firms that vary only in one dimension. However, High-Leverage/High-Liquidity and High-Leverage/Low-Liquidity firms, for example, also slightly differ with respect to their leverage (44.2% vs 42.6%). This small difference in leverage may contaminate the pure differential response to shocks that is attributable to liquidity. Since these differences are relatively small, we fix each characteristic for all groups at a level that is either high or low. Thus we target a leverage of 45% for the two firms with high leverage. We do the same for the other variables. Specifically, we target a low leverage of 20%, a high liquidity of 10.5%, and a low liquidity of 1.5%. Regarding credit spreads, we target a value of 166 bps for all firms, the median level in the sample. This calibration ensures that comparisons between the responses of firms in different groups to the same shock or policy are consistent.

Table B4: Calibration Moments 2007Q2

	Sample	H-Lev,H-Liq	H-Lev,L-Liq	L-Lev,H-Liq	L-Lev,L-Liq
Leverage (%)	31.1	44.2	42.6	20.1	22.6
Liquidity (%)	4.45	10.4	1.3	12.3	1.8
Credit Spreads (bp)	166	221	197	133	118
# of Firms	859	149	211	218	142

Notes: Calibration Targets from 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 B5: Calibration Moments 2019Q4

	Sample	H-Lev,H-Liq	H-Lev,L-Liq	L-Lev,H-Liq	L-Lev,L-Liq
Leverage (%)	37.8	48.7	50.8	26.5	30.4
Liquidity (%)	4.75	11.2	1.7	11.8	1.8
Credit Spreads (bp)	151	183	233	117	127
# of Firms	743	124	185	183	126

Notes: Calibration Targets from 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.

B.2 Identification

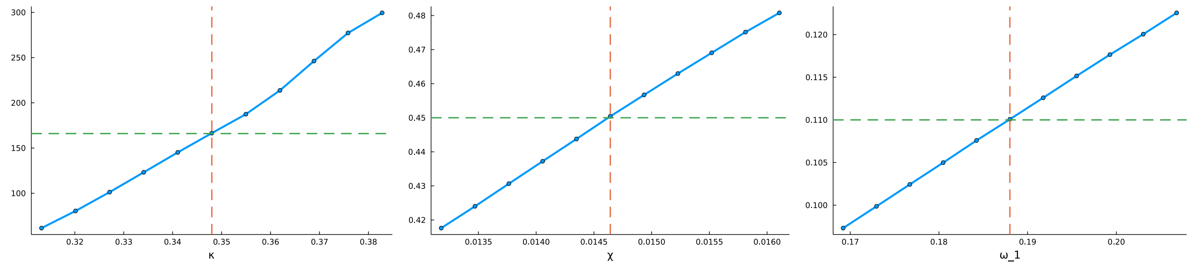
Figure B3 shows how credit spreads help us identify the parameter κ, leverage help us with χ, and liquid assets help us with ω_1.

B.3 Calibration: Robustness

Table B6 shows that our main results do not depend on the calibration of s_m nor on the value of p_ω.

Figure B3: Parameters Identification

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



Notes: The figures show how credit spreads, leverage, and liquid assets change when we move κ, χ, and ω_1, respectively. For illustration we consider the firm with high leverage and high liquidity. The vertical line corresponds to the value of the calibrated parameter and the horizontal line corresponds to the value of the target moment.

Table B6: Robustness

	Benchmark	Higher s_m	Higher p_ω
Spreads, bps	300.30	300.15	299.21
GDP, percent	-5.00	-5.00	-5.00
Liquid assets, percent	24.87	25.13	24.39
Debt owed, percent	19.06	18.90	10.36
Investment rate, pp	-5.78	-5.92	-5.96
Profits, percent	-112.02	-112.17	-112.07
Prob. Default, pp	0.23	0.25	0.23
Elasticity of spreads wrt leverage	439.02	440.71	449.17
Elasticity of spreads wrt liquidity	-205.92	-312.41	-248.52
Elasticity of inv. wrt leverage	-11.19	-10.46	-10.85
Elasticity of inv. wrt liquidity	30.37	33.44	34.02

Notes:The second column recalibrates the model when $s_m = 30$ and the third column recalibrates the model for $p_\omega = 0.6$.

B.4 Policy Experiments, targeting spreads

Table B7: Policy Experiments, targeting spreads

Variation wrt SS	(1) No Policy	(2) CCF	(3) Transfer	(4) Loan	(5) Credit Guarantee
Spreads, bps	300.01	200.10	199.99	200.60	207.26
GDP, percent	-5.00	-5.00	-5.00	-5.00	-5.00
Liquid assets, percent	25.02	36.67	-26.81	35.13	98.86
Debt owed, percent	18.51	27.95	-99.93	27.10	506.19
Investment rate, pp	-5.77	-4.24	-1.14	-4.49	44.13
Profit, percent	-112.08	-106.88	-20.99	-106.43	668.18
Prob. Default, pp	0.23	0.22	-0.71	0.22	-0.64
Cost of policy over GDP, pp	0.00	0.28	40.28	0.27	6.18
Elasticity of spreads wrt leverage	437.67	430.10	298.99	279.19	352.46
Elasticity of spreads wrt liquidity	-205.74	-200.07	10.11	-130.04	278.09
Elasticity of inv. rate wrt leverage	-2.77	-2.15	-1.87	-1.79	-14.34
Elasticity of inv. rate wrt liquidity	7.59	6.30	1.24	6.50	-54.87

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 each of the policies activated at a time. Size of policy interventions chosen to target a reduction of 100 bps in credit spreads.