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The Credit Line Channel

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The Credit Line Channel

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Abstract

Aggregate U.S. bank lending to firms expanded following the outbreak of COVID-19. Using loan-level supervisory data, we show that this expansion was driven by draws on credit lines by large firms. Banks that experienced larger credit line drawdowns restricted term lending more, crowding out credit to smaller firms, which reacted by reducing investment. A structural model calibrated to match our empirical results shows that while credit lines increase total bank credit in bad times, they redistribute credit from firms with high propensities to invest to firms with low propensities to invest, exacerbating the fall in aggregate investment.

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1 Introduction

What role does firm credit play in the transmission of macroeconomic shocks? This question is at the heart of both the financial accelerator and the credit channel, among the most influential mechanisms in macroeconomics. These theories posit that, due to financial frictions, the investment and output decisions of firms depend on credit availability and pricing. As a result, a shock that increases spreads or tightens credit constraints should create downward pressure on firm borrowing, worsening the drop in real activity.

A central feature of these mechanisms is that they require lenders to be able to control the price and quantity of new borrowing. But importantly, not all forms of credit satisfy these conditions. In particular, credit line facilities allow borrowers to draw credit up to a precommitted amount at a predetermined spread. As a result, firms with unused credit line capacity may be able to sidestep adverse changes in lending conditions, potentially neutralizing these amplification mechanisms central to macrofinancial theory.

This richer look at the structure of corporate credit raises a number of salient questions. First, are undrawn credit line balances available and used in sufficient quantities to be important for macrofinancial dynamics? Second, how are credit lines allocated across firms, and what does this imply for the response of real variables such as investment to macroeconomic disturbances? Third, how do credit line drawdowns affect the banking sector and its ability to intermediate funds in bad times?

In this paper, we seek to answer these questions using detailed U.S. loan-level data to document empirical relationships and a structural model to interpret them. We show that the corporate sector has vast amounts of undrawn credit line commitments available, and uses them heavily following the outbreak of the COVID-19 pandemic. However, credit line capacity is overwhelmingly held by the largest and least financially constrained firms in the economy. When these large firms draw their credit lines, the additional lending lowers bank capitalization, leading banks to cut credit to smaller firms. As a result, our model shows that, despite increasing the total amount of bank credit flowing to the corporate sector, credit lines amplify the drop in aggregate investment in a crisis like the COVID-19 pandemic by reallocating bank credit from small firms that are highly dependent on it to large firms that have access to alternative forms of financing. We refer to this amplification mechanism as the *credit line channel* of macroeconomic transmission.

Our empirical study of the credit line channel centers on the FR Y-14Q data set (Y14), which contains the near-universe of loans to firms by sufficiently large U.S. commercial banks over the period 2012 to 2020, and covers roughly half of U.S. C&I lending. Compared to standard U.S. data sets, which are often restricted to public firms or available at origination only, our data cover more than 200,000 private firms and are updated quarterly. The Y14 data also offer detailed information on loan characteristics unavailable in alternative data sources, distinguishing between term loans and credit lines, and between used and undrawn credit.[1] The data also include detailed financials, including for private firms, which we refine and expand using data from Compustat and Orbis. Equipped with this unique merged data set, we provide a detailed account of bank credit for U.S. firms, and investigate the role of credit lines at both the aggregate and cross-sectional levels.

Our main empirical results are as follows. First, we document that undrawn credit line balances are vast, with a volume nearly 40% larger than the total used balances on bank credit lines and term loans *combined*. The size of undrawn balances is stable over time and is robust to adjusting for effective capacity using typical covenant ratios. At the same time, we find that the distribution of undrawn credit is highly skewed, with more than 70% of undrawn credit (compared to around 40% of used credit), accruing to the top 10% of the firm size distribution. Beyond size, firms with more unused credit line capacity exhibit a number of other characteristics associated with being less financially constrained — including being more profitable, less levered, investment grade, public, and older — confirming earlier findings by Sufi (2009), Acharya et al. (2014), and others on a broader sample of public and private firms.

Turning to macroeconomic shocks, we examine the behavior of credit lines following the COVID-19 outbreak, which caused a steep and unexpected decline in cash flows for many firms. Figure 1.1 shows that bank-firm credit sharply increased over this period, while other major credit categories like consumer and real estate lending showed no such surge. This rise in bank credit is almost completely explained by an increased drawdown of existing credit facilities, rather than new credit issuance (Acharya and Steffen, 2020; Li et al., 2020) — a pattern similar to what was observed during the 2007-09 financial crisis (Ivashina and Scharfstein, 2010). Our data further show that these drawdowns were not evenly distributed across the size distribution but instead flowed overwhelmingly to the largest 10% of firms (see also Chodorow-Reich et al., 2022).

In our final set of empirical results, we investigate the spillover effects of credit line draws through the bank-firm network. Specifically, we study whether the large drawdowns of existing credit lines in 2020:Q1 resulted in crowding out of lending for firms that rely on term loans. Using the fixed effects approach of Khwaja and Mian (2008) on the

[1]While some loan- or firm-level data sets like the Shared National Credit Program ("SNC"), Reuter's Dealscan Database, and Compustat Capital IQ allow for distinctions by loan type and used exposure, they are either available only at an annual frequency and for large syndicated loans (SNC), at origination (Dealscan), or for public firms (Capital IQ). Commonly used bank-level data such as the H.8 releases, Call Reports, or FR Y-9C data do not separate used credit into credit lines and term loans.

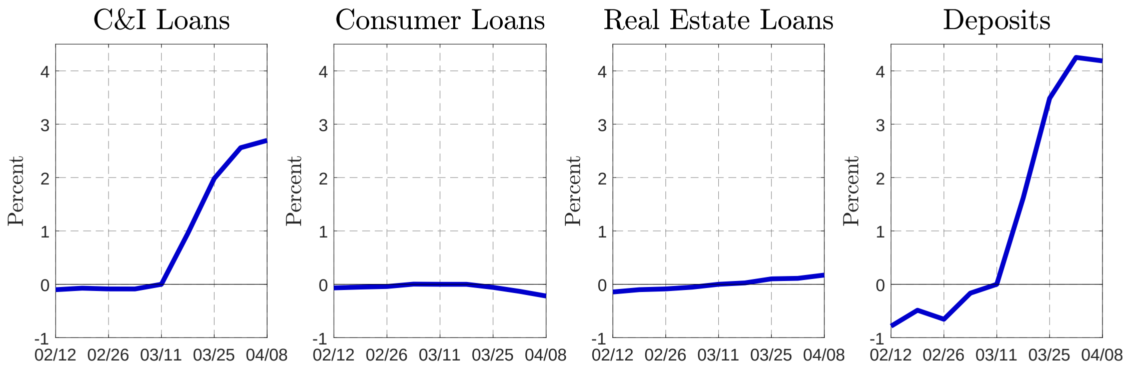

Figure 1.1: U.S. commercial banks' balance sheets around the start of COVID-19.

Notes: The figures show changes in credit relative to total assets on 03/11/2020 around the start of the COVID-19 pandemic in the United States. The series are based on the H.8 releases for U.S. commercial banks from the Board of Governors of the Federal Reserve.

population of firms with term loans from multiple banks, we find that banks experiencing larger credit line drawdowns contract their term lending by more, especially for smaller and non-syndicated loans. Perhaps surprisingly, the negative effect of drawdowns on term lending is not offset at all by the large deposit inflows observed over this period (right panel of Figure 1.1). Instead, our results are more plausibly explained by regulatory limits, as banks with lower pre-crisis capital buffers displayed larger spillovers to term lending. We find that small firms were unable to replace this lost credit, and instead reduced their investment and cash holdings, while total debt at large firms is unaffected by bank-level drawdowns, reinforcing our results on heterogeneity in transmission.

To map our findings into general equilibrium implications, we develop a structural model that highlights the interplay between bank term loans and credit lines. Inspired by our results on firm heterogeneity, our setup features two types of firms: smaller "constrained" firms who borrow using term loans only, and larger "unconstrained" firms who also have access to credit lines and corporate bonds. Each type of firm prefers debt finance due to a tax shield but faces covenant violation risk that increases with firm leverage. Lenders face capital requirements that are tightening with used credit, as well as convex costs of capital financing, so that spreads on new term loans increase as firms obtain more term loans or draw their credit lines.

To mimic the COVID-19 episode, we study the model's response to a set of shocks that decrease output (TFP), increase precautionary firm cash demand, and raise corporate bond spreads. To closely connect the model with our empirical findings, we calibrate the key parameters governing the crowding out effect and the firm's frictions on adjusting dividends and cash holdings to directly match our empirical regression estimates.

We first show that a model in which both types of firms use only term loans fails to match our empirical findings, counterfactually predicting that the relative share of bank credit held by constrained firms increases following an adverse shock. This occurs because unconstrained firms have a more elastic demand for bank credit due to their ability to substitute with corporate bonds, leading to a relative decline in their share of bank credit as spreads rise. Beginning from this baseline, we introduce credit lines, which allow unconstrained firms to borrow at a predetermined, fixed spread. Insulated from rising spreads, unconstrained firms now borrow heavily from banks, crowding out lending to constrained firms, and reproducing the pattern observed in the data.

In aggregate, the presence of credit lines sharply increases total bank credit growth to firms following the negative shock, reproducing the pattern documented in Figure 1.1. But while aggregate bank credit increases, it causes a large flow of credit away from constrained firms, who largely substitute bank credit with investment, and toward unconstrained firms, who primarily substitute bank credit with corporate bond credit. As a result, the decline in aggregate investment is more than 70% larger on impact in an economy with credit lines, despite a larger increase in aggregate bank-firm lending.

Last, we use our model to explore the implications of the Federal Reserve's intervention in corporate bond markets, which is widely credited with bringing down bond spreads following the COVID-19 outbreak. In our model, a similar policy intervention leads to a large issuance of corporate bonds, but little additional investment by the unconstrained firms who issue them, matching the empirical findings of Darmouni and Siani (2020). At the same time, our model reveals important *indirect* effects of this policy not visible in cross-sectional empirical analysis. As these large firms repay their credit lines bank capitalization increases, allowing banks to offer constrained firms lower spreads. Constrained firms respond by borrowing and investing significantly more than they would have absent the policy intervention. These indirect effects allow the policy to stimulate aggregate investment, even though the firms directly affected by the intervention contribute only modestly to this increase, echoing earlier findings on the corporate sector purchase program of the European Central Bank (Grosse-Rueschkamp et al., 2019).

In summary, our results point to a world in which the corporate sector as a whole has access to large amounts of bank credit, even in bad times, but where cross-sectional disparities in access to precommitted credit have powerful implications for the transmission of macroeconomic shocks into corporate debt and investment.

Related Literature. Our paper relates to a large literature on the transmission of macroeconomic shocks through credit markets (e.g., Bernanke et al., 1999, among many others). Our main contribution is the finding that amplification mechanisms are mitigated for a subset of firms — those with credit lines — and, as a result, can be *even stronger* for other firms, amplifying the aggregate effects. In this regard, we contribute to a growing literature that emphasizes the heterogeneous effects of macroeconomic shocks, with several recent contributions focusing on firm responses to changes in monetary policy.[2] Our paper complements this work by demonstrating the centrality of credit lines, which has distinct aggregate and cross-sectional consequences for firm credit and investment.

Turning to the corporate finance literature, we relate to an extensive body of work finding that the pricing and availability of credit lines depend on the risk exposure of both lenders and borrowers.[3] Moreover, several papers have shown that credit lines are an important source of funding for firms in times of distress.[4] Relative to this literature, we take a more macroeconomic perspective that focuses on the aggregate implications of credit lines, made possible by our administrative data and general equilibrium model.

We also connect to a large literature that measures the effects of bank health on the allocation of firm credit (e.g., Khwaja and Mian, 2008) and regional or firm outcomes (e.g., Peek and Rosengren, 2000; Chodorow-Reich, 2014). We present new evidence that precommitted credit lines can drive a quantitatively important shock to bank balance sheets when many firms draw on their existing credit lines simultaneously. In this respect, we join Ivashina and Scharfstein (2010) and Cornett et al. (2011), who provide similar evidence for the 2007-09 financial crisis. Compared to these works, our matched bank-firm data set allows us to: (i) measure the actual drawdowns of credit lines at each bank, rather than using exposure to proxy for this variable; (ii) document which firms and loan types are crowded out; (iii) control for matching between banks and firms using the Khwaja and Mian (2008) borrower fixed effects approach; and (iv) trace out the real effects of crowding out at the firm level. Our cross-sectional estimates further enable us to calibrate a macroeconomic model and derive general equilibrium implications, an approach that we share with Chodorow-Reich (2014), Herreño (2020), and Martín et al. (2020).

A number of contemporaneous papers have also analyzed credit line drawdowns during the COVID-19 episode. While our work focuses on the cross-sectional allocation of unused credit line commitments, arguing that they are plentiful for large firms and scarce for small firms, leading to crowding out, Chodorow-Reich et al. (2022) show that smaller firms also drew less of what unused credit line capacity they had. They attribute this

[2] Examples of recent papers are Ottonello and Winberry (2020), Crouzet and Mehrotra (2020), Jeenas (2019), Cloyne et al. (2019), Bahaj et al. (2020), Darmouni et al. (2020), and Anderson and Cesa-Bianchi (2020), among others, which build on the work by Gertler and Gilchrist (1994).

[3] See, e.g., Campello et al. (2011), Acharya et al. (2013), Acharya et al. (2014), Ippolito et al. (2016), Berg et al. (2017), Acharya et al. (2019), and Acharya et al. (2021a).

[4] See, e.g., Jiménez et al. (2009), Lins et al. (2010), Campello et al. (2010), Berrospide and Meisenzahl (2015), Berg et al. (2016), Nikolov et al. (2019), and Brown et al. (2020).

finding to the shorter maturities typically found on credit lines to SMEs, which increase lenders' discretion and bargaining power — a separate channel impinging smaller firms' credit access over this period that complements the one we describe. Kapan and Minoiu (2021) use syndicated loan data from Dealscan and find evidence of crowding out effects similar to those documented in this paper. Acharya et al. (2021b) show that the liquidity risk posed by credit line drawdowns has explanatory power for bank stock returns during the pandemic, showing that drawdowns not only harmed smaller firms dependent on these banks, but also the banks themselves. Finally, Caglio et al. (2021) use the same Y14 dataset to document several facts about the composition of credit by firm size and investigate the implications for the transmission of monetary policy.

Overview. The rest of the paper proceeds as follows. Section 2 describes the data, while Section 3 establishes several key stylized facts. Section 4 studies the behavior of firm credit in response to the outbreak of COVID-19. Section 5 presents a macroeconomic model with credit lines. Section 6 concludes.

2 Data

This section provides a brief overview of the data we use in our empirical analysis, while complete details including variable descriptions, data sources, and a list of cleaning and data filtering steps can be found in Appendix B. Our primary information on bank-firm relationships comes from the FR Y-14Q H.1 schedule for commercial loans. These data are collected from all bank holding companies (BHCs) sufficiently large to be subject to the Dodd-Frank Act Stress Tests.[5] The Y14 data provide information on the universe of loan facilities with over $1 million in committed amount at these BHCs.[6]

These data provide an unparalleled view into loan contracting arrangements for a broad spectrum of firms. In particular, we observe not only the committed amount of the facility, but also the amount utilized in each quarter, allowing us to precisely measure a

[5]The Federal Reserve requires U.S. BHCs, savings and loan companies, and depository institutions with assets exceeding given thresholds, and also some foreign banking organizations, to comply with the stress test rules. For most of the sample period, the size threshold was set at $50 billion. In 2019, the threshold was increased to $100 billion. The number of BHCs in the Y14 has varied over time, starting with 18 BHCs at inception in 2011:Q3 and peaking at 38 BHCs in 2016:Q4.

[6]A loan facility is a lending program between a bank and a borrower and can include more than one distinct loan, and possibly contain more than one loan type (e.g., credit line or term loan). Banks classify the facility type according to the loan type with the majority of total committed amount. Since term loans are typically fully used immediately after their issuance, the majority of unused term loan borrowing capacity is likely accounted for by unused credit lines. We therefore assume throughout that unused term loans represent unused credit lines, or "unused credit" for short.

Table 3.1: Summary Statistics.

	Total	Credit Lines	Term Loans
Loan Facility Observations	4,496,353	58%	42%
Used Credit	$941B	53%	47%
Committed Credit	$2,231B	78%	22%

Notes: Credit amounts are quarterly averages in billion U.S. Dollars (2015 consumer prices). Sample: 2012:Q3-2019:Q4.

firm's unused borrowing capacity over time. The data include 207,505 distinct Taxpayer Identification Numbers (TINs) over the sample period, of which only 3,222 are public, allowing us to cover a broad set of private firms that are typically challenging to study. In addition, the data include financial information for these firms collected by the BHCs. We replace these data with Compustat data for public firms when available, and supplement the private firm financials with Orbis data. Last, we deflate all nominal variables using the consumer price index for all items.

We restrict the sample to 2012:Q3 - 2020:Q4. This starting point gives a more even distribution of BHCs across quarters and affords a short phase-in period for the structure in which variables are collected to stabilize. We select facilities to firms that are identified as commercial and industrial, "other loans," and loans secured by owner-occupied commercial real estate. We drop all loans to financial firms and firms in the real estate sector. Our analysis therefore focuses on bank credit to nonfinancial firms and does not cover nonbank credit, bank credit extended by non-Y14 banks, or unobserved firms.

3 Descriptive Evidence

In this section, we establish several stylized facts describing the aggregate and cross-sectional patterns of bank credit and credit lines. We focus on the portion of the sample before the start of the outbreak of COVID-19 in the United States (2012:Q3-2019:Q4), and therefore more representative of an economy in "normal times." For this period, the data cover around 4.5 million loan facility observations.

Summary statistics, presented in Table 3.1, show that credit lines are a central form of bank-firm credit, comprising 58% of facilities and 53% of total used credit. But beyond these used balances, credit lines also contain enormous quantities of credit committed by lenders but not yet drawn. The "Total" column shows that committed balances are 2.37 times larger than used balances. This means that committed but undrawn balances

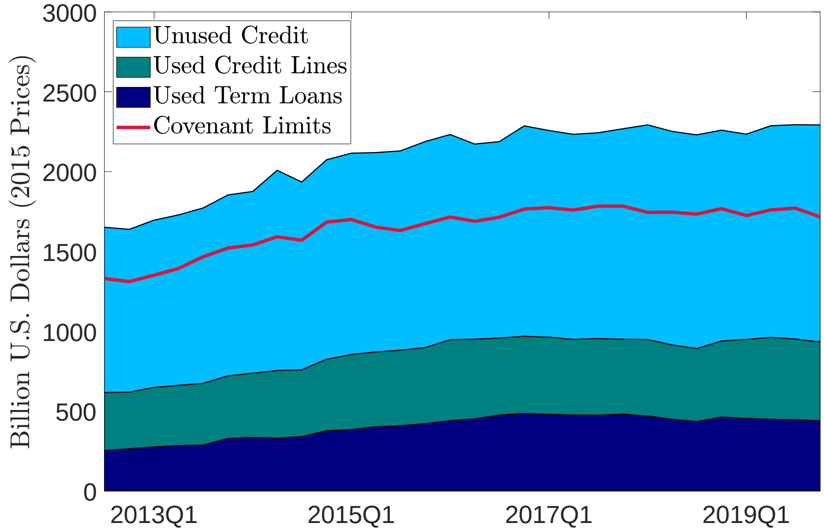

Figure 3.1: Aggregate term loans and credit lines.

Notes: The figure shows the total amount of term loans and credit lines across all banks in billion U.S. dollars. Unused credit is the difference between committed and used credit of credit lines and term loans. The red line indicates covenant-adjusted undrawn borrowing capacity (see text and Appendix B.3 for details). Sample: 2012:Q3 - 2019:Q4.

are nearly 40% larger than total used credit on credit lines and term loans *combined*, representing a vast source of potential financing. Summing over used and unused credit, credit lines account for a large majority of credit committed by banks (78%).

Figure 3.1 shows that these patterns are stable over time, and that unused borrowing capacity substantially exceeds actual used credit throughout the sample. At the same time, not all of this capacity may be freely drawn in practice, since banks frequently add loan covenants to their lending facilities that can restrict drawdowns if a firm's financial ratios deteriorate (Sufi, 2009). While our data lack information on loan covenants, we can address this by assuming typical ratios on the most common financial covenants found in Dealscan: interest-coverage and debt-to-earnings covenants. For each firm, we compute the amount that could be drawn on credit lines without violating these typical limits (see Appendix B.3 for details). We aggregate this covenant-adjusted undrawn borrowing capacity and plot it as the red line in Figure 3.1. While covenant restrictions are nontrivial, roughly two-thirds of unused credit could be drawn without violating typical covenants, resulting in an aggregate borrowing capacity on the order of total used credit.

These data show that the corporate sector in aggregate is far from credit constrained, with more than $1 trillion in committed but undrawn credit available to firms at prenegotiated spreads over our sample period. However, this undrawn credit capacity is not equally held across firms, but instead is dominated by the largest, most profitable firms

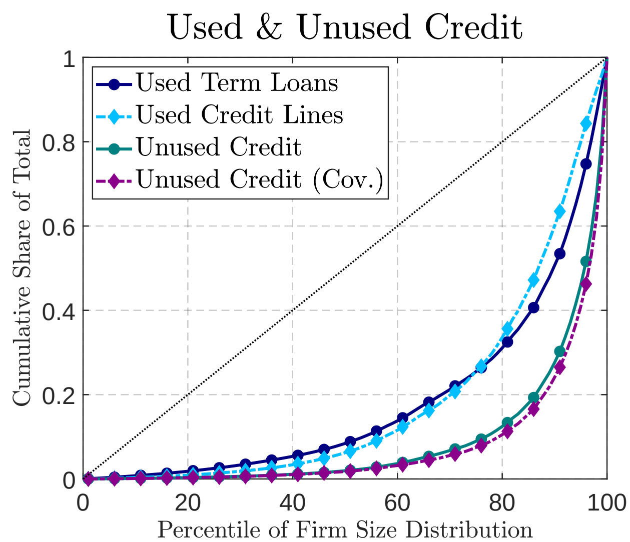

Figure 3.2: Cumulative Shares across Firm Size Distribution.

Notes: The figure shows the cumulative shares of used term loans, used credit lines, unused credit, and unused credit adjusted for generic covenant rules ("Cov.") across the firm size distribution. Unused credit is the difference between all committed and used credit, which is additionally adjusted by applying generic covenant rules (see Appendix B.3 for details). The firm size distribution is obtained for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4.

in the economy. To show this, Figure 3.2 plots Lorenz curves for used and unused credit across the firm size distribution.[7] The figure shows that larger firms unsurprisingly have more used bank credit, with the top 10% of firms holding 39% and 48% of used credit lines and used term loans, respectively. At the same time, we can observe that the distribution of *undrawn* credit is far more unequally distributed (more bowed outward), with the top 10% of firms holding 71% of the total.

Figure 3.3 decomposes this result to show that this relationship between undrawn balances and firm size stems from two forces. First, small firms have lower committed credit line balances. Panel (a) shows that while virtually all of the largest firms have a credit line facility, that share drops to around 60% for the smallest firms.[8] Similarly, Panel (b) shows that the share of committed bank credit in the form of a credit line is also strongly increasing in size. Since firms have incentives to draw credit lines in distress, these patterns may reflect banks' preference for allocating credit line facilities and balances to larger, more profitable firms that are further from the distress boundary (Sufi, 2009).

[7]For context, firms in the 10th, 50th, and 90th percentiles of our size distribution have \$3.6 million, \$21.5 million, and \$582 million in total assets, respectively, in 2016:Q4.

[8]Since we observe only borrowing at a subset of banks, a potential concern is that smaller firms may obtain credit lines from banks that fall outside our data. Because the Y14 data also report a firm's total debt from all sources, we are able to verify that bank debt from our Y14 BHCs represents the majority of total debt for smaller firms in our sample (see Appendix Figure E.2).

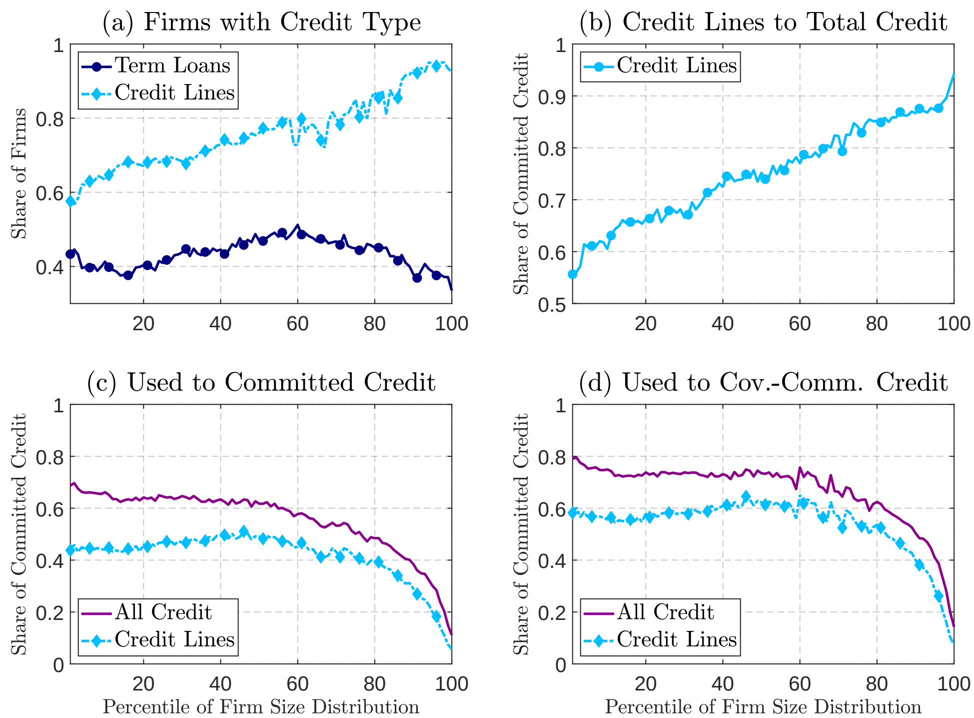

Figure 3.3: Credit Characteristics across Firm Size Distribution.

Notes: The figures show various credit characteristics for percentiles across the firm size distribution. Panel (a) portrays the share of firms that have some committed credit line or term loan. Panel (b) shows the share of committed credit lines relative to all committed credit. Panel (c) displays the share of used relative to committed credit for credit lines and combined credit lines and term loans. Panel (d) shows similar ratios, but additionally adjusts a firm's committed credit for covenant limits, following the computations described in Appendix B.3. The firm size distribution is computed for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4.

Second, small firms have lower *undrawn* credit balances because they utilize more of their committed credit. Panel (c) of Figure 3.3 shows that while firms below the 80th size percentile use between 40% and 50% of their committed credit line balances, the very largest firms use close to none of their committed balances, a disparity that is even stronger adjusting for typical covenants in Panel (d). This pattern may reflect that smaller firms view credit lines as close substitutes for other types of credit like term loans, while larger firms view credit lines almost exclusively as insurance instruments. As a result, even when small firms have access to credit line facilities, their utilization policy may prevent them from drawing additional balances following negative shocks.

To study characteristics beyond size, we regress unused borrowing capacity of firm i at time t on firm characteristics $\boldsymbol{X_{i,t}}$, time fixed effects α_t, and industry fixed effects τ_k:

$$\frac{\text{Unused Credit}_{i,t}}{\text{Committed Credit}_{i,t}} = \alpha_t + \tau_k + \boldsymbol{\beta X_{i,t-4}} + u_{i,t}. \tag{3.1}$$

Table 3.2: Credit Line Borrowing Capacity.

	Size	Age	Public	EBITDA	Leverage	Tangible Assets	Inv. Grade
Coeff.	0.02***	0.02***	0.13***	0.28***	-0.58***	0.18***	0.12***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R-squared	0.27						

Notes: Estimation results for regression (3.1), where the dependent variable is a firm's unused borrowing capacity. Standard errors in parentheses are clustered by firm. Sample: 2012:Q3 - 2019:Q4. Observations: 156,010. Number of firms: 31,209. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

We present the estimation results in Table 3.2, with full details available in Appendix C. We find that firms with a higher fraction of undrawn capacity are larger, older, more likely to be public, more profitable, less levered, have more tangible assets to pledge, and are more likely to be investment grade — all of which are associated with being less financially constrained and having better access to non-bank financing such as corporate bonds. These results are consistent with theoretical models that stress the interplay between firm demand for liquidity insurance with lender concerns about moral hazard and other agency problems (e.g., Holmström and Tirole, 1998; Acharya et al., 2014).

Appendix Figures E.1-E.3 further show that larger firms receive lower interest rates, are rated more creditworthy according to the banks' internal ratings, are less likely to post collateral, and if they do, post fewer collateral relative to the size of the loan. Smaller firms obtain more fixed-rate and nonsyndicated loans, show higher probabilities of default, often use real estate as a form of collateral, and take on longer-maturity term loans but shorter-maturity credit lines (see also Chodorow-Reich et al., 2022; Caglio et al., 2021).

We also investigate credit line pricing. The majority of credit line facilities in the Y14 data are variable-rate with fixed spreads. While spreads can in principle be renegotiated, we find that spreads on more than 90% of credit lines remain unchanged throughout their history, implying it is safe to consider these spreads as constant over time.

Last, Appendix D investigates how credit usage adjusts to changes in firm cash flows. We find that firms increase credit by 33 cents over the first year following a $1 drop in cash flows, primarily driven by a higher use of existing credit lines. The response of term loans is both economically and statistically insignificant, pointing to credit lines as the key margin of adjustment in response to firm cash flow shocks (Brown et al., 2020).

Taken together, these data offer a detailed view into the composition of bank credit for a much larger set of U.S. firms than is typically studied. We show that credit lines account for the majority of used and committed firm credit held by large banks, and have undrawn capacity that exceeds all used bank-firm credit. Cross-sectionally, unused borrowing capacity is overwhelmingly concentrated among the largest, most creditworthy firms, to a degree substantially beyond that of used credit.

4 Behavior of Firm Credit around the COVID-19 Outbreak

In this section, we study the role of credit lines in shaping the response of firm borrowing to the outbreak of COVID-19. We show that credit lines are the main driver of the increase in overall credit and that banks that experienced larger drawdowns on credit lines reduced their term lending supply more, leading to a reallocation of credit.

Since the outbreak of the COVID-19 pandemic entailed a sharp and largely unanticipated fall in cash flows for most firms in the United States, it represents a unique setting for studying changes in firm credit. As the crisis stage of the pandemic in the U.S. began in mid-March 2020, we compare credit measures from the end of 2019:Q4 to the end of 2020:Q1 to study the immediate changes in credit due to this shock.

Figure 4.1 plots differences in used and committed credit between 2019:Q4 and 2020:Q1 for all firms (blue bars) and separately for firms within the top 10% and the bottom 90% of the firm size distribution (orange and yellow bars), with a cutoff between the two groups of around \$1.2 billion in total assets. Specifically, we compute

$$\frac{\left(L^{k,g}_{2020:Q1} - L^{k,g}_{2019:Q4}\right)}{\text{Total Used Credit}_{2019:Q4}}$$

where $L^{k,g}_{t}$ denotes the amount of credit of type k at time t of group g (all firms, top 10%, bottom 90%).[9] Changes are scaled by total used bank-firm credit in 2019:Q4 to allow for an additive decomposition, and differ from Figure 1.1 as a result.

Panel (a) of Figure 4.1 shows that the overwhelming majority of the change in credit during this period, around 90%, stems from existing credit lines. In contrast, issuance of new term loans or new credit lines played little role. Breaking down these effects by firm size, we find that 96% of the additional credit issued over this period flowed to the top 10% of the size distribution, even though these firms hold less than half of all used bank-firm credit in normal times (see Figure 3.2). Existing credit lines of large firms alone explain 77% of the increase in total credit. In contrast, the bottom 90% of firms saw only a modest increase in credit, both from existing lines and overall.

[9] The firm size distribution for both quarters is computed according to firms' total assets in 2019:Q4, meaning that firms remain within the same group across the two quarters. Credit of type k for observations with missing total assets in 2019:Q4 is allocated to the top 10% or the bottom 90% according to the share of each group of total credit of type k across nonmissing observations.

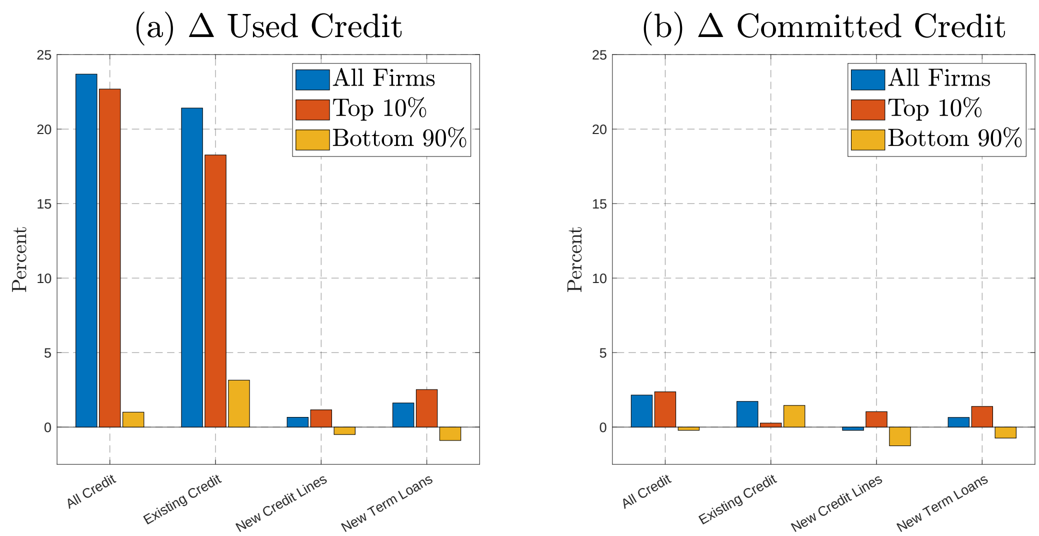

Figure 4.1: Changes in Used and Committed Credit for 2019:Q4 - 2020:Q1.

Notes: The blue bars show aggregate changes in used and committed credit across all banks between 2019:Q4 and 2020:Q1, relative to total used credit in 2019:Q4. The orange and yellow bars display equivalent changes for the 10% and the bottom 90% of the firm size distribution, also relative to total used credit in 2019:Q4. The changes are further separated into differences in existing credit, new credit line issuances, and new term loans (all in percent relative to all used credit in 2019:Q4). The firm size distribution is computed according to firms' total assets in 2019:Q4.

Panel (b) of Figure 4.1 shows changes in committed, rather than used, credit. In aggregate, committed credit barely moved over this period, both in aggregate and for any of the subcategories we consider, showing that credit growth was almost completely accounted for by increased utilization of existing credit line commitments.

Appendix Figure F.1 repeats these calculations for changes from 2019:Q4 to either 2020:Q2 or 2020:Q3, instead of 2020:Q1. This figure shows that growth in used credit through 2020:Q1 is cut in half by 2020:Q2, and effectively reverts to zero in 2020:Q3. However, our result that the growth we observe is dominated by increased credit line utilization by large firms continues to hold. In fact, because bank credit to the bottom 90% turns negative in 2020:Q2, we find that the change in existing credit line balances by large firms explain more than 100% of the rise in credit through 2020:Q2.

4.1 Credit Supply during the COVID-19 Pandemic

While these patterns indicate that access to credit varied among firms, they do not distinguish between credit demand and supply, or account for possible spillovers across firms. In particular, the large withdrawal of existing credit lines may have put pressure on bank balance sheets. In turn, banks may have reduced their supply of term loans, an important source of credit to SMEs. We test for such crowding out effects by employing a fixed effect regression similar to Khwaja and Mian (2008). This methodology for estimating the effects of shifts in credit supply focuses on firms borrowing from multiple banks, where banks differ in their exposure to the outbreak of COVID-19. As a measure of exposure, we use variation in drawdowns on existing credit lines.

The approach relies on two key identifying assumptions. First, the shock must be exogenous, an assumption that we believe is satisfied as the outbreak was largely unanticipated at the end of 2019. Second, a firm's demand for term loans should not depend on its bank's differential exposure to the shock, holding the terms of the loan fixed. This second assumption could be violated if, for example, firms substitute away from term loans and toward credit lines and such substitutions occur more at banks with higher credit line commitments. To ensure that the second identifying assumption is satisfied, we restrict the sample to term loan facilities only, and exclude cases where firms have both term loans and credit lines at the same bank, so that our results are not driven by a substitution between the two. For this restricted data set, we estimate regressions

$$\frac{L^{j,k}_{i,t+h} - L^{j,k}_{i,t-1}}{0.5\left(L^{j,k}_{i,t+h} + L^{j,k}_{i,t-1}\right)} = \alpha^h_{i,k} + \beta^h \frac{\Delta Credit\ Line\ Usage^j_t}{Assets^j_{t-1}} + \gamma^h X^j_{t-1} + u^{j,k}_{i,h} \tag{4.1}$$

for $h = 0, 1, ...,$ where $t-1$ denotes 2019:Q4 and $t+h$ is given by one of the following quarters. To approximate a percentage change, we use the symmetric growth rate for the dependent variable, which is bounded in $[-2, 2]$ and allows for possible zero observations at $t-1$, removing the typical challenge of extreme outliers and the need to winsorize. $L^{j,k}_{i,t}$ is the aggregated term lending between bank j and firm i of credit type k at time t. We consider variable- and fixed-rate loans as separate types k to account for possible differences in the demand for such loans due to changes in short-term interest rates between $t-1$ and $t+h$ that may be correlated with the drawdowns at the bank level.

Our coefficients of interest β^h measure the effect of the change in used balances on existing credit lines at bank j between $t-1$ and t, scaled by total bank j assets at $t-1$, on the growth of term loans of type k to firm i from bank j. Because the firm-specific fixed effect $\alpha^h_{i,k}$ absorbs a firm's common demand for credit type k across lenders, the estimated β^h should capture credit *supply* effects as banks vary their supply of term loans due to their differential intensities of credit line withdrawals.[10] Last, the term X^j_{t-1} represents a

[10] Drawdowns on precommitted credit lines cannot generally be refused by banks, unless the borrower has violated its debt covenants or "material adverse change clauses" (Demiroglu and James, 2011). However, banks may use informal bargaining power to pressure firms not to draw their credit lines (Chodorow-Reich et al., 2022) or react to covenant violations on other credit lines more strongly when they experience

Table 4.1: COVID-19 − Credit Supply.

	(i) 2020:Q1	(ii) 2020:Q1	(iii) 2020:Q1	(iv) 2020:Q2	(v) 2020:Q3	(vi) 2020:Q4	(vii) 2020:Q1
Δ Credit Line Usage	-1.96**	-2.28***	-2.74***	-3.03**	-3.63**	-1.92	-1.83***
	(0.72)	(0.65)	(0.93)	(1.14)	(1.62)	(3.41)	(0.63)
Δ Deposits							0.18
							(0.21)
Fixed Effects							
Firm × Rate	✓			✓	✓	✓	✓
Firm × Rate × Maturity		✓					
Firm × Rate × Purpose			✓				
Bank Controls			✓				✓
R-squared	0.51	0.51	0.55	0.51	0.53	0.55	0.51
Observations	1,678	1,596	1,019	1,519	1,390	1,019	1,678
Number of Firms	749	712	464	682	624	460	749
Number of Banks	28	28	28	28	28	28	28

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit from 2019:Q4 to 2020:Q1 in columns (i)-(iii) and (vii), to 2020:Q2 in column (iv), to 2020:Q3 in column (v), and to 2020:Q4 in column (vi). The regressors "Δ Credit Line Usage" and "Δ Deposits" denote the change of a bank's used existing credit lines or deposits from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. All regressions include firm-specific fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and the remaining maturity (column ii) or the loan purpose (column iii). Maturity fixed effects take the form of three bins according to their remaining maturity in 2019:Q4: (i) less than one quarter, (ii) less than one year, and (iii) more than one year. Columns (iii) and (vii) include various bank controls for 2019:Q4: bank size (natural log of total assets), return on assets (net income/assets), leverage (liabilities/assets), deposit share (deposits/assets), and banks' income gap (see Appendix Table B.1 for details on the data). Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

vector of controls, which are omitted in the baseline specification but added subsequently for robustness. Summary statistics for all regressors can be found in Appendix Table F.1.

The estimation results are shown in Table 4.1. Column (i) shows the results for used term loans between 2019:Q4 and 2020:Q1 ($h = 0$). The negative sign of the coefficient β^0 implies that a bank experiencing a larger drawdown of credit lines restricts its supply of term loans by more, with the effect statistically different from zero at the 5% level. In column (ii), we extend the fixed effect to allow credit type k to also vary with remaining maturity. This extension checks the robustness to the possibility that the amount of credit line drawdowns and the maturity profile of a bank's term loan portfolio are correlated, with firm credit demand depending on this remaining maturity (see also Khwaja and Mian, 2008). If anything, the results become stronger using this extended fixed effect.

large drawdowns (Chodorow-Reich and Falato, 2021). If banks discourage drawdowns more when their own balance sheets are impaired, then the estimated effects in Table 4.1 can be seen as a lower bound on the strength of the crowding out effect.

Another potential identification concern may be that banks specialize in certain types of lending and the associated credit demand for such borrowing is correlated with the credit line drawdowns across banks (Paravisini et al., 2020), for example if banks with larger credit line drawdowns specialize in providing types of term loans that are less connected to firms' short-run liquidity needs. To address this concern, in regression (4.1) we allow the firm-by-credit-type fixed effect to additionally vary with the loan purpose that firms report.[11] To account for other pre-crisis differences across banks, we also include various bank-specific controls that are collected in the vector X^j_{t-1} in regression (4.1). Among these, bank size could account for the possibility that firms may prefer to borrow from smaller relationship banks that offer fewer credit lines during a crisis. Column (iii) in Table 4.1 shows that the results actually intensify with the extended fixed effect and the additional control variables.

In Appendix F, we show that these findings are robust to various modifications of the regression specification. We first test whether our results hold in the absence of the firm fixed effect $\alpha^h_{i,k}$. Table F.2 presents these results for the multi-lender subsample, showing that the resulting coefficients are close to those in Table 4.1. Table F.3 removes the restriction that firms borrow from multiple lenders, estimating coefficients that are slightly attenuated but highly statistically significant for this extended sample of nearly 30,000 firms. Table F.3 further shows strong spillovers for firms with a single lender, a subsample that includes many of the smallest firms that we observe. These results illustrate that firm credit demand and bank credit supply shocks are relatively uncorrelated for that sample of firms, and that the firm fixed effect is not critical to our results.

The crowding out effects that we uncover are potentially a smaller concern if they are short-lived. To test for the persistence of the results, we rerun regression (4.1) at horizons $h = 1, 2, 3$, corresponding to credit growth from 2019:Q4 through 2020:Q2, 2020:Q3, and 2020:Q4, respectively. The results, displayed in columns (iv) - (vi) of Table 4.1 show that the effects found in column (i) not only remain but actually intensify through 2020:Q3. Tables F.4 and F.5 compare alternative fixed effect and control specifications for 2020:Q2/Q3, showing that the results are robust across these quarters as well.

This temporal pattern may seem counterintuitive, since credit line drawdowns peaked in 2020:Q1, and were mostly paid down by the end of 2020:Q3. However, the results largely reflect the practice of measuring credit stocks at the end of each quarter. Much of the term lending in 2020:Q1 was already locked in prior to the intensification in the pandemic, leading us to measure only a partial response within 2020:Q1. In contrast, we

[11] We distinguish between the purposes "Working Capital," "Capital Expenditures" (including real estate), "M&A Financing," and "All Other Purposes" (see also Appendix Table B.2).

observe stronger effects in 2020:Q2 and 2020:Q3, as a larger set of new or rolling-over loans were able to be affected by the initial drawdowns. Last, the effects abate and lose statistical significance in 2020:Q4 as shown in column (vi) of Table 4.1, the first quarter after credit lines were largely paid down.

To measure economic significance, we combine our results using a back-of-the-envelope calculation. Given the average ratio of term lending to bank assets that we observe, these estimates imply a term lending cut of around 10-30 cents during the crisis period for each \$1 drawdown of credit lines.[12] While these spillover effects are already substantial, we consider them a lower bound on total crowding out, which likely extends to other forms of credit outside of our sample such as small business, consumer, and real estate credit.

Last, we test how these spillover effects vary with loan characteristics. Appendix Table F.6 shows that our results are largely explained by a supply contraction of smaller, fixed-rate, and non-syndicated loans. All of these characteristics are more prevalent among SMEs, implying that these smaller firms faced a sharper lending cut due to drawdowns.

Liquidity and Bank Constraints. These results are perhaps surprising given the favorable liquidity environment over this period. Figure 1.1 shows that aggregate bank deposits increased by more than C&I lending over this period. Moreover, as shown by Gatev and Strahan (2006), banks try to match the cyclicality of their deposit flows and credit line draws, potentially providing insurance against these draws. To understand the role of liquidity provision from the deposit market in driving these results, we additionally control for each bank's deposit inflow in the first quarter of 2020, $\Delta Deposits_t^j / Assets_{t-1}^j$, in regression (4.1), beyond our set of bank characteristics previously collected in X_{t-1}^j.[13]

Column (vii) in Table 4.1 shows the estimation results. If bank lending was primarily constrained by liquidity, we should expect that one dollar flowing out due to a credit line drawdown should be offset by one dollar flowing in from deposits, implying that that the coefficients on these variables should have equal magnitudes but opposite signs. Instead, column (vii) shows that our estimate for β^0 remains nearly unchanged compared with the baseline in column (i), while the coefficient on deposit flows is close to zero, allowing us to easily reject that the two coefficients sum to zero. In other words, our estimates

[12]This is computed by multiplying the typical ratio of term lending to bank assets across the Y14 banks ($\sim$5%) with the range of estimates for β^h in Tables 4.1, F.4, and F.5, which lie between -2 and -6.

[13]The regressors of interest in equation (4.1) show substantial variation across banks. The drawdown on existing credit lines relative to lagged assets ranges from -0.2 to around 2.8% with a standard deviation of around 0.8%. The change in deposits relative to lagged assets ranges from 0.9% to around 31% with a standard deviation of around 6.5%. The two variables are negatively correlated with a correlation coefficient of -0.18, suggesting that a mechanism by which credit line drawdowns are immediately re-deposited at the same bank was not a dominant driver of deposit flows.

imply that drawing down a credit line and depositing the drawn balance is not neutral, but instead causes a decrease in that bank's supply of term loans.

These findings indicate that the crowding out effects we observe were not directly driven by liquidity effects. Instead, we hypothesize that our results are explained by bank capital requirements.[14] Undrawn balances on credit lines typically have regulatory risk weights that are at most half those of drawn balances.[15] When credit lines are drawn, risk weighted assets increase, reducing bank capitalization. This decreased capitalization cannot be offset by deposit inflows, but requires that banks either raise capital — likely a costly option during this crisis period — or reduce lending and retain earnings. As a result, in the presence of capital requirements, draws on credit lines can crowd out other forms of lending even in the presence of plentiful liquidity.

To test whether regulatory constraints can explain our results, we consider alternative specifications of regression (4.1) that allow for interactions between the credit line drawdowns and bank capital buffers in 2019:Q4, with results reported in Table 4.2. Consistent with our hypothesis, we find that banks with lower pre-crisis capital buffers restricted their term lending supply to a greater degree in response to drawdowns on their credit lines. To account for the possibility that bank capital is correlated with other bank characteristics, we include additional bank controls as well as interactions of those controls with the credit line drawdowns in columns (ii) and (iii) of Table 4.2, and find that the magnitudes of our estimates increase in the presence of these additional interactions.

A potential concern may be that our results are confounded with losses on legacy loan portfolios. In particular, declining lender health could both lead to lower term lending and a "run" on that lender's credit lines, as firms attempt to draw them while they will still be honored. To address this, we follow two approaches. First, we instrument variation in bank credit line drawdowns in regression (4.1) using banks' ratio of unused credit commitments relative to assets in 2019:Q4, with the identifying assumption that banks with different ratios have otherwise similar loan portfolios.[16] This ensures that our identifying variation is determined prior to the crisis and does not stem from differences in

[14] He et al. (2022) show that in response to muted liquidity provision in March 2020 in the Treasury market, regulators removed Treasuries and reserves from the Supplementary Leverage Ratio, providing supporting evidence that bank balance sheet constraints were relevant at that time.

[15] Under the Basel framework's standardized approach to calculating risk-based capital requirements, off-balance-sheet commitments are assigned credit conversion factors (CCFs) depending on maturity. Exposures with original maturity under one year receive a CCF of 20%, while exposures with maturities over one year receive a 50% CCF. If the commitment can be unconditionally canceled at any time, the exposure receives zero CCF, or a zero-risk weighting.

[16] Bank credit line drawdowns in 2020:Q1 and their unused commitments before the outbreak of the pandemic are strongly positively correlated with a correlation coefficient of 0.67, showing that much of banks' differential exposure in regressions (4.1) originates from differences in prior commitments.

Table 4.2: COVID-19 Credit Supply − Bank Capital.

	(i)	(ii)	(iii)
Δ Credit Line Usage	-3.05***	-3.10***	-4.62**
	(1.05)	(0.82)	(1.74)
Δ Credit Line Usage × Cap-Buffer	1.25***	2.15***	3.34**
	(0.36)	(0.69)	(1.50)
Cap-Buffer	-0.01***	-0.02***	-0.04**
	(0.00)	(0.01)	(0.02)
Fixed Effects: Firm × Rate	✓	✓	✓
Bank Controls		✓	✓
Bank Controls × Δ Credit Line Usage			✓
R-squared	0.51	0.51	0.51
Observations	1,678	1,678	1,678
Number of Firms	749	749	749
Number of Banks	28	28	28

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit between 2019:Q4 and an average across non-missing observations for 2020:Q1-Q3. The regressor "Δ Credit Line Usage" denotes the change of a bank's used existing credit lines from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. "Cap-Buffer" denotes banks' voluntary capital buffers in 2019:Q4, which are defined as the difference between total capital ratios and (8.0 + SCB + GSIB) where SCB is the stress capital buffer and GSIB is the additional buffer for global systemically important banks. "Δ Credit Line Usage × Cap-Buffer" denotes the interaction between the two variables. Columns (ii) and (iii) include various bank controls for 2019:Q4: bank size (natural log of total assets), return on assets (net income/total assets), leverage (total liabilities/total assets), deposit share (total deposits/total assets), and banks' income gap. Column (iii) includes the interactions between each of these controls and "Δ Credit Line Usage." "Cap-Buffer" and all bank controls are normalized by the median sample observation. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

ex-post rates at which commitments are drawn, as would be the case in the run scenario just described. Second, we directly control for the change in the quality of a bank's existing term loan portfolio using banks' reported probabilities of default and provisions for loan losses from banks' income statements. Both sets of results are reported in Appendix Table F.7 and are close to our baseline estimates.

To supplement our results on the quantity of credit, we repeat (4.1) to measure price responses, with the results reported in Appendix Table F.8. While the estimates are less precise than the quantity results, and more sensitive to the treatment of outliers and controls, we find that credit line drawdowns increase the interest rates charged on term loans by that bank, providing additional support for our crowding out mechanism.[17]

[17] We note that although this evidence supports a rise in interest rates, it is not strictly necessary since our mechanism ultimately works through quantities, as constrained firms adjust other margins such as investment to offset credit lost due to crowding out. While crowding out occurs via credit spread increases

Crowding Out Effects on Total Debt and Investment. Our results so far reflect the responses of term lending by banks in the Y14 sample. However, it is possible that the affected firms are actively substituting term loans from these banks for credit lines or term loans from banks outside of our sample, from non-bank lenders, or from capital markets, leading the effect of drawdowns on total firm debt to differ from our estimates above. Fortunately, the Y14 data also include a measure of total debt at a firm from all sources combined. Using these data, we estimate firm level regressions of the form

$$\frac{D_{i,t+1} - D_{i,t-1}}{0.5\,(D_{i,t+1} + D_{i,t-1})} = \alpha_m + \beta\, CL\ Exposure_{i,t} + \gamma\, X_{i,t-1} + u_{i,t+1} \tag{4.2}$$

where $D_{i,t}$ denotes total debt of firm i at time t, and the left hand side represents a symmetric growth rate from 2019:Q4 to 2020:Q2. The coefficient of interest β relates debt growth to the weighted sum of a firm's exposure to each bank's drawdowns in our data

$$CL\ Exposure_{i,t} = \sum_{j=1}^{J} \omega^{j}_{i,t-1} \left(\frac{\Delta Credit\ Line\ Usage^{j}_{t}}{Assets^{j}_{t-1}} \right) \tag{4.3}$$

where the weights $\omega^{j}_{i,t} = (Term\ Loan^{j}_{i,t})/D_{i,t}$ reflect the share of a firm's total debt in the form of term loans from bank j. The vector $X_{i,t}$ collects various firm controls, including the share of all observed term loans to total debt. Because our regression estimates the response of total debt at the firm level, rather than looking at lending across banks for the same firm, we can no longer use a firm fixed effect as in (4.1). Instead, we include an industry fixed effect α_m and firm-level controls $X_{i,t-1}$, and rely on our results in Table F.2 showing that our findings are not dependent on the inclusion of a firm fixed effect.

Table 4.3 reports the results for regression (4.2). Column (i) finds that the effect of credit line drawdowns is only slightly smaller than our across-bank estimates using the same timing (-3.03, from column (iv) of Table 4.1), showing that firms affected by drawdowns at their lenders were largely unable to substitute into alternative financing and experienced a contraction in their total debt. Column (ii) in Table 4.3 interacts firm term borrowing exposure with measures of firm size, showing that the estimated effects are strongly negative for small firms, while the effect at large firms cannot be distinguished from zero, potentially reflecting their additional outside borrowing opportunities.

To study the impact of crowding out on real investment and cash holdings, we next

in our model, it could also occur via credit rationing as in e.g., Stiglitz and Weiss (1981), with a smaller increase or no increase in spreads, due to information frictions not present in our model.

Table 4.3: COVID-19 — Firm Outcomes.

	Δ Total Debt		Capital Expenditures			Δ Cash Holdings		
	All	Small/Large	All	Small	Large	All	Small	Large
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
CL Exposure	-2.63***							
	(0.69)							
CL Exposure × Small		-2.61***						
		(0.68)						
CL Exposure × Large		0.97						
		(5.72)						
Δ Total Debt			0.03**	0.03***	-0.02	0.07***	0.07***	-0.87
			(0.01)	(0.01)	(0.14)	(0.01)	(0.01)	(0.78)
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Estimator	OLS	OLS	IV	IV	IV	IV	IV	IV
First Stage F-Stat.			248	183	10.6	233	167	10.9
R-squared	0.08	0.08	0.03	0.05	0.03	0.02	0.18	0.02
Observations	3,164	3,164	2,717	1,166	1,550	3,163	1,572	1,590
Number of Firms	3,164	3,164	2,717	1,166	1,550	3,163	1,572	1,590
Number of Banks	28	28	28	24	28	28	24	28

Notes: Columns (i) and (ii) report estimation results for regression (4.2). "Δ Credit Line Usage" denotes results for β. Column (ii) additionally distinguishes the effect by firm size, where a large firm is defined as one with total assets within the top 20% of the firm size distribution in 2019 and the indicator variable is included in the set of firm controls. Columns (iii)-(viii) report estimation results for the instrumental variable regression (4.4) with instruments $CL\ Exposure_{i,t}$ and $\sum_j \omega^j_{i,t-1}$. The "Δ Total Debt" row denotes results for $\tilde{\beta}$. $X_{i,t-1}$ includes firm variables measured in 2019:Q2: net income, cash, tangible assets, total liabilities (all relative to total assets), firm size (natural log of total assets), and a binary variable that indicates whether a firm is publicly traded, as well as $\sum_j \omega^j_{i,t-1}$ in columns (i) and (ii). Columns (iv), (v), (vii), and (viii) restrict the sample by firm size following the definition in column (ii). All specifications include industry fixed effects (two-digit NAICS code). Standard errors in parentheses are clustered by the bank with the largest term loan to firm i. Sample: 2019:Q2 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

use (4.2) as the first stage of the instrumental variable regression

$$y_{i,t+1} = \tilde{\alpha}_m + \tilde{\beta}\frac{D_{i,t+1} - D_{i,t-1}}{0.5\,(D_{i,t+1} + D_{i,t-1})} + \tilde{\gamma} X_{i,t-1} + \tilde{u}_{i,t+1} \tag{4.4}$$

where $y_{i,t+1}$ is either given by $CAPEX_{i,t+1}/Assets_{i,t-3}$ or $(Cash_{t+1} - Cash_{t-3})/Assets_{i,t-3}$. $CAPEX_{i,t+1}$ denotes total capital expenditures which is defined as the 4-quarter trailing sum in our data and we therefore scale both dependent variables by firm total assets at $t-3$ for consistency. As instruments, we use $CL\ Exposure_{i,t}$ and $\sum_j \omega^j_{i,t-1}$, where the latter reflects that firms with more debt in the form of term loans should be more affected by drawdowns. These regressions thus capture the marginal change in investment or cash holdings due to changes in debt driven by credit line drawdowns.

Columns (iii) - (viii) in Table 4.3 report the results for all firms, small firms, and large firms, respectively. The positive coefficients in columns (iii) and (vi) show that reductions in total debt resulted in lower capital expenditures and cash holdings. These relations are again driven by smaller firms (columns (iv) and (vii)), while the estimated coefficients are not statistically different from zero for large firms (columns (v) and (viii)), in part because of the weak link between credit line exposure and total debt in the first stage. These results show that firms were unwilling or unable to absorb the lending cuts using financial adjustments alone, leading to a fall in firm investment.

The effects are economically significant, with the estimated coefficients in columns (iv) and (vii) implying a reduction in capital expenditures and cash holdings of around 12 and 24 cents, respectively, for every $1 decline in firm debt, given the typical debt-to-asset ratio of 0.28 in the data. Since the COVID shock arrived relatively late in 2020:Q1, one can interpret these numbers as contemporaneous quarterly marginal propensities to invest and to adjust cash out of a change in debt. Taken together, our results show that the credit line drawdowns of large firms following the outbreak of COVID-19 crowded out term lending to SMEs, which in turn resulted in a decline of their total debt and investment.

5 Model

In this section we build a structural model to study the general equilibrium implications of the credit line channel. We briefly summarize the key ingredients of the model, present the detailed structure, calibrate the model, and describe our findings.

5.1 Model Overview

Our model is designed to capture the main empirical patterns we document in Sections 3 and 4. To account for heterogeneity in credit line access in a tractable way, we allow for two types of firms: bank-dependent "constrained" firms that borrow using term loans only, and larger "unconstrained" firms that have access to both credit lines and corporate bonds. Importantly, constrained firms are limited in their access to financial instruments, but are not literally *credit* constrained, as both types can obtain additional debt at the margin. Instead, all firms find an interior solution for debt that balances its benefits against the increased covenant violation risk that comes with higher leverage.

To introduce credit lines in a parsimonious manner, we make the simple assumption that credit lines always have a fixed, predetermined spread over the risk-free interest rate, while term loans are priced at the market-clearing rate.[18] Lenders are subject to capital requirements and convex costs of holding bank capital. As a result, borrowing by one type of firm (i.e., unconstrained firms drawing on credit lines) tightens binding capital requirements, increasing the marginal cost of providing credit, and crowding out credit supply for the other firms in the economy.

We embed this structure into a general equilibrium framework. Following an adverse shock designed to mimic the COVID-19 outbreak, firms must adjust along three costly margins: reducing dividends, which impairs smoothing; reducing investment, which incurs adjustment costs; or increasing debt, which increases covenant violation risk. To discipline the frictions firms and banks face along these margins, we provide model equivalents of our regression coefficients from Table 4.3, and directly calibrate our key adjustment cost parameters to align these coefficients in model and data.

5.2 Model Structure

Demographics and Preferences. Households exist in three types: constrained entrepreneurs (denoted C), unconstrained entrepreneurs (denoted U), and savers (denoted S). Each agent trades a complete set of contracts with other households of the same type, but not across types, allowing aggregation and a representative agent for each type.

We assume two types of entrepreneurs, corresponding to the two types of firms we model below, so that each representative firm has an incentive to smooth its own dividends (the consumption of its entrepreneurs), rather than aggregate dividends. An entrepreneur of type j has exponential utility (constant absolute risk aversion) preferences over nondurable consumption $C_{j,t}$ given by

$$U_{j,t} = E_t \sum_{k=0}^{\infty} \beta_j^k \frac{\left(1 - \exp(-\zeta_D C_{j,t})\right)}{\zeta_D}. \tag{5.1}$$

Since entrepreneurs consume dividends, exponential utility provides incentives for firms to smooth dividends but, unlike power utility preferences, can accommodate zero or negative dividends (equity issuance). Throughout the paper, we denote the key model parameters governing frictions on the firm's core margins of adjustment (dividends, debt, capital, and cash) using the letter ζ and a subscript indicating the corresponding margin that is affected. For example, since the risk aversion parameter in (5.1) determines the

[18] In this sense, we take the existence and pricing of credit lines as exogenous. We believe this is appropriate to study how existing credit lines amplify macroeconomic shocks, such as the arrival of COVID-19, and leave the interesting task of microfounding the existence of credit lines to future work.

frictions for firms to adjust their dividend margins, we denote this parameter as ζ_D.

The saver type has risk-neutral preferences over non-durable consumption $C_{S,t}$:

$$U_{S,t} = E_t \sum_{k=0}^{\infty} \beta_S^k C_{S,t}. \tag{5.2}$$

These preferences simplify our analysis, implying exogenous risk-free rates and removing wealth effects on labor supply. Savers inelastically supply $\bar{N}$ units of labor each period.

Productive Technology and Labor Demand. Firm type j produces final goods using

$$Y_{j,t} = Z_t K_{j,t-1}^{\alpha} \bar{N}_j^{1-\alpha}$$

where Z_t is exogenous aggregate productivity, $K_{j,t-1}$ is capital, and $\bar{N}_j$ is labor, which firms use in a fixed quantity at a fixed wage w. The assumptions of fixed labor demand and a fixed wage capture frictions in adjusting labor at the short time horizons we consider, and allows the model to match the decline in corporate profits observed following the COVID-19 outbreak. The assumption of a fixed factor (labor) also allows us to determine the scale of each type of firm by varying $\bar{N}_j$, without taking a stand on the technology that aggregates across the goods produced by these types.

Firm Types. We consider two types of firms: constrained firms (denoted C) and unconstrained firms (denoted U), each of which is owned by entrepreneurs of the corresponding type. The key difference between the two types of firms is their access to financial instruments. In our benchmark model, unconstrained firms have access to both corporate bonds and credit lines, while constrained firms borrow exclusively in term loans.

Debt Contracts. All forms of debt in the model (corporate bonds, credit lines, and term loans) are multiperiod, with a constant fraction ν of debt maturing each period, nesting single-period debt for $\nu = 1$. All debt is floating rate, so that payments equal the risk-free rate times the principal balance along with an additional credit spread that is fixed at origination. Under these assumptions, we can track the dynamics of total debt at a firm of type j across all debt instruments with two state variables: the total principal balance in dollars (denoted $B_{j,t}$), and the spread payments in dollars (denoted $S_{j,t}$) that a firm has promised to pay in the following period.[19] These variables have the laws of motion

$$B_{j,t} = \underbrace{B^*_{j,t}}_{\text{new debt}} + \underbrace{(1-\nu)\bar{\pi}^{-1}B_{j,t-1}}_{\text{existing debt}}$$

$$S_{j,t} = \underbrace{s_{j,t}B^*_{j,t}}_{\text{new spread payments}} + \underbrace{(1-\nu)\bar{\pi}^{-1}S_{j,t-1}}_{\text{existing spread payments}}$$

where $B^*_{j,t}$ is newly issued debt, $s_{j,t}$ is the average spread per dollar of debt issued, and inflation $(\bar{\pi})$ translates the debt balance from nominal to real terms.

The average spread faced by each type of firm $s_{j,t}$ depends on its funding structure. Corporate bonds have spread s^{bond}_t, while bank loans have an endogenously determined spread $s^{loan}_{j,t}$ that depends on the state of the banking sector at equilibrium and the type of the firm (i.e., whether the firm uses credit lines or term loans). Constrained firms can only borrow in bank loans, so $s_{C,t} = s^{loan}_{C,t}$. However, unconstrained firms can endogenously choose between bank loans and corporate bonds. In the absence of frictions, unconstrained firms would finance themselves completely with the cheaper form of credit, at odds with the data where large firms simultaneously borrow in bonds and bank debt. To address this, we assume that for each unit of new bond debt an unconstrained firm draws a transaction cost $q \sim N(\mu_q, \sigma^2_q)$ that must be paid each period until maturity.

The problem for an unconstrained firm of choosing the optimal allocation between loans and bonds can be summarized by the choice of the threshold cost $q^*_{U,t}$ such that the firm will choose to issue bonds for all debt with $q \leq q^*_{U,t}$ and will choose to issue loans for all debt with $q > q^*_{U,t}$. Since transactions costs paid each period are equivalent to spreads, we can absorb this decision into the law of motion for spreads by setting

$$s_{U,t} = \int^{q^*_{U,t}} (s^{bond}_t + q)\, d\Gamma_q(q) + \int_{q^*_{U,t}} s^{loan}_{U,t}\, d\Gamma_q(q) - s^{rebate}_t.$$

The term s^{rebate}_t is treated as fixed by each firm but at equilibrium returns these transaction costs evenly to unconstrained firms, so that they have no resource effects beyond influencing the firm's decision to use bond or bank financing. The optimality condition is $q^*_{U,t} = s^{loan}_{U,t} - s^{bond}_{U,t}$, which implies that firms choose a higher threshold cost — and a relatively larger share of bonds — when the spread on loans grows relative to the spread on bonds, with the strength of this effect modulated by the dispersion of the q distribution.

[19] The reason why we are able to aggregate across both types of debt using the same state variables is that the cost of an additional dollar of principal balance or promised spread *payment* is identical across products, even though the spread measured in basis points (determining the amount of spread payments per dollar of principal balance) may vary across products.

Under this policy, the fractions of newly issued debt that each unconstrained firm allocates to bonds and loans are given by

$$F^{bond}_{U,t} = \Gamma_q(q^*_{U,t}), \qquad\qquad F^{loan}_{U,t} = 1 - \Gamma_q(q^*_{U,t}).$$

The laws of motion for bond and loan balances are

$$B^{bond}_{U,t} = F^{bond}_{U,t} B^*_{U,t} + (1-\nu)\bar{\pi}^{-1} B^{bond}_{U,t-1}, \qquad B^{loan}_{U,t} = F^{loan}_{U,t} B^*_{U,t} + (1-\nu)\bar{\pi}^{-1} B^{loan}_{U,t-1}$$

and the average spread on new debt to unconstrained firms can be rewritten as

$$s_{U,t} = F^{bond}_{U,t} s^{bond}_t + F^{loan}_{U,t} s^{loan}_{U,t}.$$

Credit Lines. A credit line in the model is committed credit promised at a fixed spread $\bar{s}^{line}$. Inspired by our evidence in Section 3, we assume that unconstrained firms, but not constrained firms, can borrow in the form of credit lines. Since spreads rise in our main COVID-19 experiment, making credit lines favorable relative to term loans, unconstrained firms will choose to borrow from banks exclusively using credit lines during this periodmatching the evidence from Figure 4.1, so that $s^{loan}_{U,t} = \bar{s}^{line}$.

Debt Covenants. We impose debt-to-EBITDA covenants — the most relevant financial covenants over our sample — so that firms pay a penalty if their total debt exceeds a multiple of smoothed EBITDA.[20] We define smoothed EBITDA $X_{j,t}$ as

$$X_{j,t} = (1-\rho_X)\underbrace{(Y_{j,t} - w\bar{N}_j)}_{\text{current EBITDA}} + \rho_X \bar{\pi}^{-1} X_{j,t-1} \tag{5.3}$$

where EBITDA is defined as output net of the wage bill, and where inflation $\bar{\pi}$ adjusts for the convention of computing the smoothed average in nominal terms.

We assume that a firm violates its covenant if

$$\bar{\pi}^{-1} B_{j,t-1} > \omega_{i,t} \theta X_{j,t} \tag{5.4}$$

where $\omega_{i,t}$ is drawn i.i.d. from a distribution with mean unity and c.d.f. $\Gamma_{\omega,j}$. The shock

[20]Greenwald (2019) shows that the most common form of covenant is an interest coverage covenant, which limits the ratio of interest payments to EBITDA, followed closely by the debt-to-EBITDA covenant described above. However, the very low interest rates observed entering and following the COVID-19 pandemic imply that interest coverage ratios were largely slack over this period, motivating our choice to focus on the debt-to-EBITDA covenants.

$\omega_{i,t}$ stands in for idiosyncratic risks to a firm's EBITDA that can unexpectedly send it into violation. These shocks motivate firms to keep a precautionary buffer away from the violation threshold. As a result, firms in the model are not literally constrained by their covenants, but instead trade off additional debt against the higher probability of violation due to a smaller buffer. Although we model the ω shocks as affecting only the probability of violation, and not the firms' actual cash flows, we note that the scale of the individual firms is indeterminate, as each firm's problem is linear in its capital stock. As a result, similar implications would be found in a model featuring the capital quality shocks used in Bernanke et al. (1999) and much of the subsequent literature.[21]

Rearranging (5.4), a firm of type j violates its covenant if and only if $\omega_{i,t} < \bar{\omega}_{j,t}$, for

$$\bar{\omega}_{j,t} = \frac{\bar{\pi}^{-1} B_{j,t-1}}{\theta X_{j,t}} \tag{5.5}$$

so that the probability of violation is equal to $\Gamma_{\omega,j}(\bar{\omega}_{j,t})$. As a result, the firm's probability of violation is smoothly increasing with its expected ratio of debt to EBITDA. For the violation penalty, we assume that violating firms pay a cost equal to fraction κ_j of their start-of-period principal balance $\bar{\pi}^{-1} B_{j,t-1}$.

Firm's Problem. The representative firm owned by entrepreneurs of type j chooses dividends $D_{j,t}$, cash holdings $A_{j,t}$, new debt issuance $B^*_{j,t}$, and new capital $K_{j,t}$ to maximize

$$V_{j,t} = D_{j,t} + \exp(\tilde{a}_t)\eta_{A,j} \frac{A_{j,t}^{1-\zeta_A}}{1-\zeta_A} + E_t\left[\Lambda_{j,t+1} V_{j,t+1}\right] \tag{5.6}$$

where $\Lambda_{j,t+1}$ is the stochastic discount factor of the type j entrepreneur

$$\Lambda_{j,t+1} = \beta_j \exp\Big(-\zeta_D (C_{j,t+1} - C_{j,t})\Big) \tag{5.7}$$

which reflects the concave utility of entrepreneurs and provides incentives for firms to smooth dividends at equilibrium. Our assumption that cash provides utility stands in for precautionary motives for firms to hold cash that would otherwise be absent in this deterministic setting. We allow the utility weight $\eta_{A,j}$ to vary by firm type j to match that large and small firms hold different amounts of cash at equilibrium. Cash utility for

[21] For covenants written on non-smoothed EBITDA ($\rho_X = 0$), this model with capital quality shocks would be isomorphic to our baseline model, offering a simple microfoundation. When EBITDA is smoothed, a model with richer shocks would face the serious complications of tracking the history of past $\omega_{i,t}$ shocks for each firm. We therefore consider (5.4) as a parsimonious approximation to this richer model.

both firms depends on an exogenous preference shifter $\tilde{a}_t$ that we vary in our COVID-19 experiment to capture time-varying demand for cash during this period.

The budget constraint for a firm of type j is

$$\begin{aligned} D_{j,t} = & \underbrace{(1-\tau)\left(Y_{j,t} - wN_j\right)}_{\text{after-tax profit}} + \underbrace{\Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t}K_{j,t-1}}_{\text{old capital}} + \underbrace{\bar{\pi}^{-1}A_{j,t-1}}_{\text{old cash}} \\ & - \underbrace{\bar{\pi}^{-1}\left[\Big(\big((1-\tau)r_{t-1} + \nu + \kappa_j\Gamma_{\omega,j}(\bar{\omega}_{j,t})\Big)B_{j,t-1} + (1-\tau)S_{j,t-1}\right]}_{\text{payments on existing debt}} \\ & - \underbrace{Q_{j,t}K_{j,t}}_{\text{new capital}} - \underbrace{A_{j,t}}_{\text{new cash}} + \underbrace{B^*_{j,t}}_{\text{new debt}} \end{aligned} \tag{5.8}$$

where $D_{j,t}$ is dividends paid to the type j entrepreneur, $Q_{j,t}$ is the price of new capital, $\bar{Q}_{j,t}$ is the resale price of old capital, $B^*_{j,t}$ is new debt issued by firm j, r_{t-1} is the risk-free interest rate, τ is the corporate tax rate, and δ is the depreciation rate. This constraint also captures that both depreciation and interest payments on debt are tax-deductible by the firm. Unpacking the "payments on existing debt" term, we see that it consists of base risk-free rate payments net of the tax shield $(1-\tau)r_{t-1}$, principal payments ν, and average violation costs $\kappa_j\Gamma_{\omega,j}(\bar{\omega}_{j,t})$, all per unit of principal balance, in addition to spread payments net of the tax shield $(1-\tau)S_{j,t-1}$.

Government Sector. The monetary authority achieves a constant inflation rate $\bar{\pi}$, while the fiscal authority spends corporate tax revenues with no effect on household utility.

Entrepeneurs' Problems. The unconstrained and constrained entrepreneurs choose consumption $C_{j,t}$ to maximize (5.1) subject to the budget constraint $C_{j,t} \leq D_{j,t}$.

Bank's Problem. The representative bank provides loans to constrained and unconstrained firms. In the baseline model, unconstrained firms borrow in the form of credit lines, which have commitments previously pledged by the bank in amount $\bar{L}$.

Each bank is required to hold χ^B dollars of capital for each dollar of used credit, and χ^L dollars of capital for each dollar of committed but undrawn credit on credit lines. Assuming that unconstrained firms borrow in the form of credit lines, while constrained firms borrow in the form of term loans, this constraint can be represented as

$$k_t \geq \chi^B \underbrace{\left(B^{loan}_{C,t} + B^{loan}_{U,t}\right)}_{\text{used credit}} + \chi^L \underbrace{\left(\bar{L} - B^{loan}_{U,t}\right)}_{\text{undrawn lines}}. \tag{5.9}$$

The representative bank chooses dividends d_t, bank capital k_t, and new debt to constrained firms $B^*_{C,t}$ (but not drawdowns $B^*_{U,t}$, which the bank cannot control) to maximize

$$v_t = \underbrace{d_t}_{\text{dividends}} - \underbrace{\left(\frac{\eta_k}{\bar{k}^{\zeta_L}}\right)\frac{k_t^{1+\zeta_L}}{1+\zeta_L}}_{\text{capital holding costs}} + E_t\left[\Lambda_{S,t+1} v_{t+1}\right]. \tag{5.10}$$

We include capital holding costs in bank utility to capture the financial costs or frictions that lead banks to prefer to hold as little capital as possible, implying that capital requirements are binding at equilibrium and that variation in risk-weighted assets influences bank behavior. This cost has curvature ζ_L, and a level parameter η_k that we scale by $\bar{k}^{\zeta_L}$ (where $\bar{k}$ is steady-state bank capital) to ensure numerical stability of the marginal holding cost when ζ_L is large. The bank maximizes (5.10) subject to (5.9) and the budget constraint

$$d_t \leq \sum_{j \in \{C,U\}} \left\{ \underbrace{\bar{\pi}^{-1}\left[\left(r_{t-1} + \nu\right) B^{loan}_{j,t-1} + S^{loan}_{j,t-1}\right]}_{\text{payments on existing loans}} - \underbrace{F^{loan}_{j,t} B^*_{j,t}}_{\text{new loans}} \right\}. \tag{5.11}$$

which states that bank dividends equal total loan income net of newly issued debt.

Saver's Problem. The saver chooses consumption $C_{S,t}$, new corporate bond issuance $B^{bond,*}_t$, and new government bonds B^G_t to maximize (5.2) subject to the budget constraint

$$\begin{aligned} C_{S,t} \leq & \underbrace{wN}_{\text{labor income}} + \underbrace{d_t}_{\text{bank dividends}} + \underbrace{\bar{\pi}^{-1}\left[\left(r_{t-1} + \nu\right) B^{bond}_{t-1} + S^{bond}_{t-1}\right]}_{\text{existing corp. bonds}} - \underbrace{B^{bond,*}_t}_{\text{new corp. bonds}} \\ & + \underbrace{(1 + r_{t-1})\bar{\pi}^{-1} B^G_{t-1} - B^G_t}_{\text{government bonds}} + \underbrace{T_{S,t}}_{\text{rebate}} \end{aligned}$$

where at equilibrium we must have $B^G_t = 0$ (zero net supply) and $B^{bond,*}_t = F^{bond}_{U,t} B^*_{U,t}$. Corporate bond principal balance and spread payments evolve according to

$$B^{bond}_t = B^{bond,*}_t + (1-\nu)\bar{\pi}^{-1} B^{bond}_t \tag{5.12}$$

$$S^{bond}_t = (s^{bond}_t - q^{bond}_t) B^{bond,*}_t + (1-\nu)\bar{\pi}^{-1} S^{bond}_t \tag{5.13}$$

where q_t^{bond} is an exogenous bond holding cost that drives variation in bond spreads. In Appendix A.1, we show that at equilibrium $s_t^{bond} = q_t^{bond}$, allowing us to consider corporate bond spreads s_t^{bond} as exogenous. Last, $T_{S,t}$ is a lump sum rebate that returns the cost associated with q_t^{bond} to the saver, so that these have no effect on total resources.

Capital Producers. Capital is created for firm type j using technology

$$K_{j,t} = \Phi(i_{j,t})K_{j,t-1} + (1-\delta)K_{j,t-1}$$

where $i_{j,t} = I_{j,t}/K_{j,t-1}$ is the share of investment expenditures to existing capital in sector j. Competitive capital producers buy existing capital at price $\bar{Q}_{j,t}$ and sell new capital at price $Q_{j,t}$, choosing the investment rate $i_{j,t}$ to maximize the static objective

$$Q_{j,t}\Big[\Phi(i_{j,t})K_{j,t-1} + (1-\delta)K_{j,t-1}\Big] - i_{j,t}K_{j,t-1} - \bar{Q}_{j,t}(1-\delta)K_{j,t-1}.$$

5.3 Equilibrium

Competitive equilibrium is the allocation that solves the optimization problems of the firms, entrepreneurs, saver, bank, and capital producer, and that clears the markets for output, capital goods, bank loans, corporate bonds, and government bonds. For the complete set of equilibrium conditions characterizing the model solution, see Appendix A.1.

5.4 Replicating Our Empirical Regressions

To calibrate our model to match the empirical estimates in Table 4.3, we need to compute the coefficients from equivalent regressions in the model. Specifically, we target the first-stage coefficient of credit line usage on debt for small firms of -2.61 (column (ii)), the second-stage coefficient of debt on capital expenditures for small firms (column (iv)), and the second-stage coefficient of debt on the change in cash for small firms (column (vii)). Drawing on Section 3, we map small firms in the data to constrained firms in the model.

We first define the bank's drawdown exposure (Δ Credit Line Usage) as the change in credit line balances from state state scaled by lagged assets:

$$\Delta \text{ Credit Line Usage}_t = \frac{B_{U,t}^{loan} - \bar{B}_U^{loan}}{\bar{B}^{loan}/0.093}$$

where $\bar{B}^{loan}$ is total bank credit. The numerator is simply the change in unconstrained firm bank credit, since credit lines are used only by unconstrained firms, who do not use term loans during this period. For the denominator (bank assets) we need an adjustment to capture that C&I loans are only a fraction of total bank assets (9.3% in our sample). We correspondingly map total bank assets in the data to $\bar{B}_t^{loan}/0.093$ in the model.

We define the other variables to match our definitions in Table 4.3 as follows:

$$\Delta \text{ Total Debt}_{C,t} = \frac{B_{C,t}^{loan} - \bar{B}_C^{loan}}{0.5(B_{C,t}^{loan} + \bar{B}_C^{loan})}$$

$$\text{Capital Expenditures}_{C,t} = \frac{I_{C,t} + I_{C,t-1} + I_{C,t-2} + I_{C,t-3}}{\bar{K}_C}$$

$$\Delta \text{ Cash}_{C,t} = \frac{A_{C,t} - A_{C,t-3}}{\bar{K}_C}$$

where variables without type subscripts represent sums over firm types (i.e., $B_t^{loan} = B_{U,t}^{loan} + B_{C,t}^{loan}$) and where variables with bars represent steady state values (e.g., $\bar{B}^{loan}$).

To compute regression coefficients we need variation within firms of how much drawdown exposure they face. To do this, we create new types of constrained firms and banks, which can be thought of as hypothetical or as actually existing in the economy with infinitesimal size. In particular, we assume that firms of type $C(-)$ borrow from banks of type $(-)$ who have a slightly lower exposure to drawdowns, while firms of type $C(+)$ borrow from banks of type $(+)$ who have a slightly higher exposure to drawdowns:

$$\begin{aligned} B_{U,t}^{loan}(-) &= B_{U,t}^{loan} - \epsilon \times \left(B_{U,t}^{loan} - \bar{B}_U^{loan}\right) \\ B_{U,t}^{loan}(+) &= B_{U,t}^{loan} + \epsilon \times \left(B_{U,t}^{loan} - \bar{B}_U^{loan}\right) \end{aligned}$$

where we use $\epsilon = 10^{-4}$ in our calculations. This leads to different equilibrium spreads $s_t^{loan}(-)$ and $s_t^{loan}(+)$ at these banks, which are faced by the type $C(-)$ and $C(+)$ firms, influencing their behavior. We can then compute the regression coefficients as

$$\beta_{debt} = \frac{\Delta \text{ Total Debt}_{C,t}(+) - \Delta \text{ Total Debt}_{C,t}(-)}{\Delta \text{ Credit Line Usage}_t(+) - \Delta \text{ Credit Line Usage}_t(-)}$$

$$\beta_{capex} = \frac{\text{Capital Expenditures}_{C,t}(+) - \text{Capital Expenditures}_{C,t}(-)}{\Delta \text{ Total Debt}_{C,t}(+) - \Delta \text{ Total Debt}_{C,t}(-)}$$

$$\beta_{cash} = \frac{\Delta \text{ Cash}_{C,t}(+) - \Delta \text{ Cash}_{C,t}(-)}{\Delta \text{ Total Debt}_{C,t}(+) - \Delta \text{ Total Debt}_{C,t}(-)}$$

which correspond to the coefficients in columns (ii), (iv), and (vii) of Table 4.3.[22]

5.5 Calibration

Our quarterly calibration is displayed in Table 5.1. To stay parallel to our empirical findings, we match unconstrained firms to data on firms in the top 10% of the size distribution and constrained firms to data on firms in the bottom 90% of the size distribution.

Adjustment Frictions. The core parameters of our model, denoted ζ with various subscripts, govern the frictions on bank and firm adjustment. We calibrate these so that the coefficients from our empirical regressions in Table 4.3 exactly match their model equivalents computed as in Section 5.4. These parameters, and their corresponding calibration procedure, are essential to our main results in the sense that changing other parameters or model features typically has little influence as long as we recalibrate these ζ parameters to recover our estimated regression coefficients.

On the bank side, the curvature of the capital holding cost (ζ_B) determines how much a change in credit line drawdowns will pass through into spreads, thereby inducing crowding out. We set the capital holding cost curvature parameter $\zeta_B = 15.649$ so that β_{debt} in our model is exactly equal to our estimate in column (ii) of Table 4.3.

On the firm side, the relative frictions on adjusting dividends, cash, and investment determine how heavily these three margins are used following a negative shock. We note that a firm's choice of how much to use its various margins generally depends on the *relative* frictions among them, rather than the absolute degree of frictions. As a result, we have one free adjustment cost parameter governing the absolute level of frictions, after which we can pin down the remaining frictions to match our regressions. We choose this free parameter to be the investment adjustment cost ζ_K, as it is commonly calibrated in the literature, and set $\zeta_K = 0.25$ following Bernanke et al. (1999), but explore robustness to this parameter in Section 5.8. For ζ_D and ζ_A, which govern the frictions on dividends and cash, respectively, we set their values so that our model regression coefficients β_{capex} and β_{cash} exactly match their corresponding values in columns (iv) and (vii) of Table 4.3.

Stochastic Processes We study the response of the economy to a set of shocks at $t = 1$ designed to mimic the COVID-19 outbreak. This episode was characterized by a large and temporary drop in output, a large and relatively persistent increase in cash holdings by

[22] To verify that these formulas indeed solve the relevant OLS or IV regressions, it is straightforward to check that the residuals are zero for this two-observation regression.

Table 5.1: Parameter Values: Baseline Calibration (Quarterly)

Parameter	Name	Value	Internal	Target/Source
Adjustment Frictions				
Cash Utility (Curvature)	ζ_A	16.291	N	β_{cash}
Bank Capital Cost (Curvature)	ζ_B	15.649	Y	β_{debt}
Entrepreneur ARA	ζ_D	0.249	Y	β_{capex}
Capital Adjustment (Curvature)	ζ_K	0.250	N	Standard
Preferences				
Saver Discount Factor	β_S	0.995	N	Standard
Entrepreneur Discount Factor (U)	β_U	0.990	N	Standard
Entrepreneur Discount Factor (C)	β_C	0.990	N	Standard
Debt Contracts				
Frac. Debt Maturing	ν	1.000	N	1Q Maturity
Credit Line Spread	$\bar{s}^{line}$	0.625%	N	250bp Spread (Ann.)
Bond Spread	$\bar{s}^{bond}$	0.625%	N	250bp Spread (Ann.)
Debt-to-EBITDA Limit	θ	15.000	N	Dealscan
Covenant Smoothing	ρ_X	0.750	N	4Q smoothing
Covenant Violation Fee (U)	κ_U	0.00362	N	Leverage, violation rate
Covenant Violation Fee (C)	κ_C	0.00396	N	Leverage, violation rate
Idio. EBITDA Vol. (U)	$\sigma_{\omega,U}$	0.715	N	Leverage, violation rate
Idio. EBITDA Vol. (C)	$\sigma_{\omega,C}$	0.794	N	Leverage, violation rate
Financial				
Cash Utility (Level, C)	$\eta_{A,C}$	0.00097	Y	$\bar{A}/\bar{K} = 7.4\%$
Cash Utility (Level, U)	$\eta_{A,U}$	0.00001	Y	$\bar{A}/\bar{K} = 9.6\%$
Bond Transaction Cost (Mean)	μ_q	-0.00648	Y	Bank debt shares
Bond Transaction Cost (Disp.)	σ_q	0.00494	Y	Bank credit growth
Bank Capital Cost (Level)	η_B	0.00619	Y	250bp Spread (Ann.)
Credit Line Commitments	$\bar{L}$	0.791	Y	Committed-to-used credit
Loan Risk Weight	χ^B	0.080	N	Basel risk weight
Loan Risk Weight	χ^B	0.040	N	Basel risk weight
Technology and Government				
Capital Share	α	0.330	N	Standard
Unconstrained Labor Demand	N_U	0.860	N	Asset shares
Productivity	$\log \bar{Z}$	-0.719	Y	$Y = 1$
Corporate Tax Rate	τ	0.210	N	Standard
Inflation Rate	$\bar{\pi}$	1.005	N	2% inflation

firms, and a moderate and temporary increase in corporate bond spreads. We reproduce these patterns, respectively, using three shocks: (i) a negative shock to TFP, (ii) a positive shock to firms' preference for cash, and (iii) a positive shock to corporate bond spreads.

To implement this experiment in the model, we parameterize our three stochastic processes for TFP ($\log Z_t$), cash demand ($\tilde{a}_t$), and bond spreads (s_t^{bond}) as AR(1) processes:[23]

$$\begin{aligned}
\log Z_t &= (1-\rho_Z)\log \bar{Z} + \rho_Z \log Z_{t-1} + \varepsilon_{Z,t} \\
\tilde{a}_t &= \rho_a \tilde{a}_{t-1} + \varepsilon_{a,t} \\
s_t^{bond} &= (1-\rho_s)\bar{s}^{bond} + \rho_s s_{t-1}^{bond} + \varepsilon_{s,t}.
\end{aligned}$$

We jointly calibrate the shock sizes and persistence parameters so that our model-implied responses to the COVID-19 pandemic (see Section 5.6, below) match the actual responses on several dimensions, while the means $\log \bar{Z}$ and $\bar{s}^{bond}$ are calibrated separately below.

For shock sizes, we set the TFP shock size to $\varepsilon_{Z,1} = -0.1059$ to reproduce the drop in output at $t = 1$, set the cash shock size to $\varepsilon_{a,1} = 0.3227$ to reproduce the rise in cash at $t = 1$, and the bond spread shock size to $\varepsilon_{s,1} = 0.1408\%$ to match the increase in the AAA - BAA spread at $t = 1$. For the persistence of TFP and bond spreads, which have a highly transitory response during the COVID-19 episode, we set $\rho_Z = 0.238$ and $\rho_s = 0.343$ to exactly match output and bond spreads in the quarter following the COVID-19 shock ($t = 2$). Since the rise in cash holdings is more persistent in this episode, we obtain a better fit by setting $\rho_a = 0.869$ to match cash holdings 3Q after the shock (at $t = 4$).

Preferences. For the saver, we set β_S to 0.995 to target a steady state real annualized interest rate of 2%. For the entrepreneurs, we choose a standard value of $\beta_C = \beta_U = 0.990$, which delivers a reasonable value for the capital-output ratio of 2.2, and show in Section 5.8 that our results are not sensitive to this choice.

Debt Contracts. For our baseline results, we consider short-term debt, corresponding to $\nu = 1$, and discuss robustness to this assumption in Section 5.8. We set the fixed spread on credit lines to $\bar{s}^{line} = 0.625\%$ and the steady state spread on corporate bonds to $\bar{s}^{bond} = 0.625\%$, so that all debt has the same spread in steady state.

For the debt covenants, we choose a debt-to-EBITDA limit of 3.75 for annualized EBITDA (15 for quarterly EBITDA), in line with the evidence in Greenwald (2019). We set the smoothing parameter ρ_L to 0.750, consistent with covenants averaging EBITDA

[23] For simplicity, we directly parameterize s_t^{bond} in a slight abuse of notation. This stands in for an identical parameterization of q_t^{bond} combined with the equilibrium relation $s_t^{bond} = q_t^{bond}$.

over four quarters. We parameterize the $\omega_{i,t}$ distribution as lognormal, so that

$$\log \omega_{j,t} \sim N\left(-\frac{1}{2}\sigma^2_{\omega,j}, \sigma^2_{\omega,j}\right).$$

We calibrate the violation costs κ_U, κ_C, and the idiosyncratic volatilities $\sigma_{\omega,U}, \sigma_{\omega,C}$ to match four targets: the ratio of debt to capital (leverage) for $j \in \{C, U\}$, equal to 28% and 32% respectively, and the rate at which firms exceed the model debt-to-EBITDA threshold for $j \in \{C, U\}$, equal to 32% and 34%, respectively. These violation rates are similar to covenant violation rates found in Chodorow-Reich and Falato (2021). Experimenting with alternative values for these parameters had little influence on the results provided they yielded reasonable values for firm leverage.

Financial. For the scale of cash utility at each firm, we set $\eta_{A,C}$ and $\eta_{A,U}$ to target a cash-to-assets ratio of 9.6% for constrained firms and 7.4% for unconstrained firms, matching the corresponding ratios in the Y14 data for small and large firms.

For the distribution of q, the transaction costs that determine unconstrained firms' split between bank loans and corporate bonds, we assume a normal distribution $N(\mu_q, \sigma_q^2)$. We calibrate the mean $\mu_q = -0.00648$ to ensure that 40% of bank debt is held by the unconstrained sector in steady state, consistent with the share held by the 10% largest firms in Figure 3.2. For the dispersion parameter σ_q, which determines the sensitivity of the unconstrained bond/loan split to spreads, we set $\sigma_q = 0.00494$ to match the rise in bank loans at $t = 1$ in our COVID-19 experiment described in Section 5.6 below.

For the bank capital constraint, we set the risk weight on used credit to $\chi^B = 0.080$ and the risk weight on committed but unused credit to $\chi^L = 0.040$, to match typical risk weights under the Basel regulatory framework.[24] We set the capital holding cost scale to $\eta_k = 0.00619$ to ensure a steady state annual term loan spread of 250bp, matching corporate bonds and credit lines. Last, we set the quantity of committed credit lines to $\bar{L} = 0.791$ to match a steady state ratio of committed to used credit of 1.371, as in Table 3.1. This limit never binds, but influences the steady state capital holdings of banks.

[24] Undrawn credit on revokable or very short maturity credit lines have even lower risk weights. Since spillovers are larger when risk weights rise by more as lines are drawn, this is a conservative calibration.

Technology and Government. We set the capital share to a standard value of $\alpha = 0.330$, and $\log \bar{Z} = -0.719$ to target $\bar{Y} = 1$. We parameterize the investment adjustment cost as

$$\Phi(i_{j,t}) = \phi_0 + \phi_1 \frac{i_{j,t}^{1-\zeta_K}}{1-\zeta_K}.$$

We set ζ_K as discussed above, and set ϕ_0 and ϕ_1 to ensure that $\Phi(i) = i$ and $\Phi'(i) = 1$ in steady state. For the labor allocations, we normalize $\bar{N} = 1$, then set $\bar{N}_U = 0.860$ and $\bar{N}_C = \bar{N} - \bar{N}_U$ so that the share of capital held by unconstrained firms in steady state is 0.860, equal to the share of assets held by the top 10% of firms by size in the Y14 data. For the government sector we set τ to 0.210, matching the US corporate tax rate, and the inflation rate to 1.005, implying an annual inflation rate of 2%.

5.6 Results: COVID-19 Experiment

We assume that the model begins in steady state at $t = 0$ (2020:Q1), apply our unanticipated shocks at $t = 1$ (2020:Q2), and then trace the nonlinear transition back to steady state. We choose this timing because, while the pandemic arrived and caused a large financial response during 2020:Q1, this occurred at the very end of the quarter (see Figure 1.1). As such, most real aggregates like output and investment did not react strongly until 2020:Q2. While financial variables like bank loans and cash reach high levels in 2020:Q1, this is largely due to the timing practice of measuring these series at the end of the quarter, whereas their average values over the quarter would be much smaller. As a result, we believe that mapping $t = 0$ to 2020:Q1 delivers the closest fit of the actual events.

To shed light on the specific contributions of credit lines, we compare our benchmark model described above (denoted "Credit Lines" in our figures) against a counterfactual "Term Loans" economy in which unconstrained firms do not have access to credit lines, and instead endogenously allocate their borrowing between corporate bonds and bank term loans. In this counterfactual, unconstrained firms face the same bank loan cost as constrained firms $s_{U,t}^{loan} = s_{C,t}^{loan}$, in place of $s_{U,t}^{loan} = \bar{s}^{line}$ in our benchmark model.

We begin with Figure 5.1, which shows the responses for each type of firm in our benchmark economy and in the counterfactual economy without credit lines. Firms in both versions of our model face pressure following the COVID-19 outbreak to acquire resources to smooth their payouts and increase their precautionary cash holdings. To do so, they have access to four key margins of adjustment: debt, investment, dividends, and cash holdings themselves.

To build intuition, we begin with the simpler Term Loans economy in which all firms

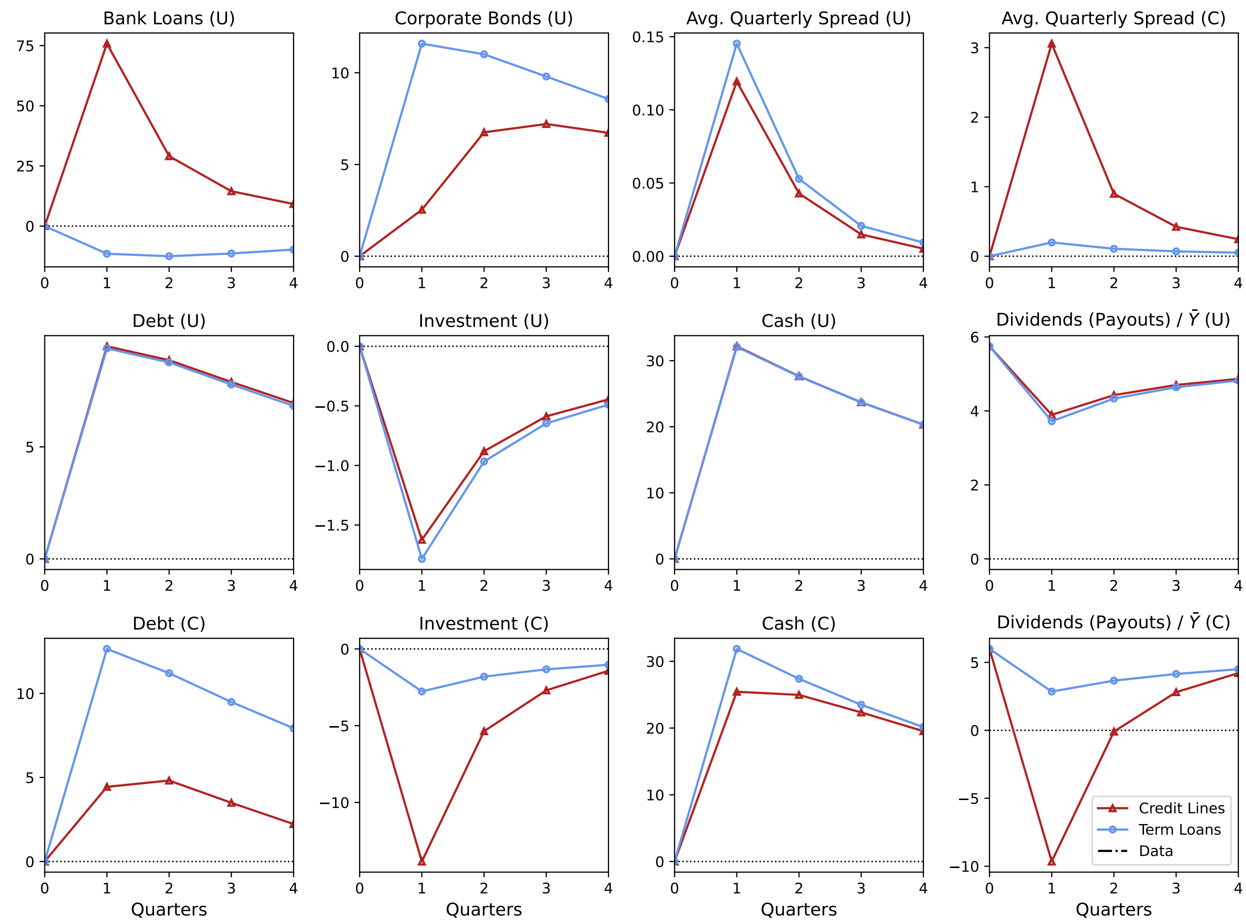

Figure 5.1: Responses by Type, Credit Line vs. Term Loan Economies

Notes: This figure plots the economy's response to the COVID-19 pandemic experiment. Variable definitions are as follows: Bank Loans ($B^{loan}_{j,t}$), Corporate Bonds ($B^{bond}_{j,t}$), Avg. Quarterly Spread ($s_{j,t}$), Debt ($B_{j,t}$), Investment" ($I_{j,t}$), Cash ($A_{j,t}$), Dividends / $\bar{Y}$ ($D_{j,t}/\bar{Y}_j$). Variables followed by (U) refer to the unconstrained firm, while variables followed by (C) refer to the constrained firm. All variables are displayed in percent changes from steady state with the exceptions of Avg. Quarterly Spread, which is displayed percentage point changes from steady state, and Dividends / $\bar{Y}$, which is displayed in percent.

have the same borrowing technology. Here, we observe that constrained and unconstrained firms largely adjust these margins in a similar way. Constrained and unconstrained types at $t = 1$ increase debt substantially (12.6% vs. 9.4%), decrease investment slightly (-2.8% vs. -1.8%), increase cash holdings massively (31.9% vs. 32.1%), and decrease the ratio of dividends to output (6.0pp $\rightarrow$ 2.9pp vs. 6.0pp $\rightarrow$ 3.7pp). These responses are similar across firm types because credit conditions are analogous for constrained and unconstrained firms, with average spreads on new debt increasing by 0.8pp vs. 0.6pp, respectively, leading them to use their debt margins in parallel. Conditional on the debt decision, the optimization problem faced by each type of firm over the remaining margins is largely symmetric, leading to similar responses.

Credit conditions are in turn similar across firm types due to a shift in the composition of unconstrained firm credit. In isolation, an increase in constrained firm bank borrowing would put pressure on bank capital requirements, increasing bank loan spreads. However, because our calibration implies that unconstrained firms are relatively flexible in shifting between bank loans and bonds, rising spreads on bank loans lead unconstrained firms to substitute toward corporate bonds, reducing their bank loans by 11.5% and increasing their corporate bonds by 11.6%. This relieves pressure on bank capital requirements, so that bank loan spreads rise only slightly more than corporate bond spreads, and do not substantially distort constrained firm decisions compared to those of unconstrained firms. Thus, in the term loans economy, market prices are able to direct both types of firms to obtain credit at a relatively low cost.

Turning to the Credit Lines economy, we observe several patterns that are strikingly different. Starting in the top row, we see that the unconstrained firms now tilt their borrowing heavily toward bank loans and away from corporate bonds. While unconstrained firms still have very elastic demand for bank loans, the fixed spreads of credit line facilities keep them favorably priced compared to corporate bonds. As a result, unconstrained firm bank loans increase at $t = 1$ by an enormous 75.8% rather than decreasing as in the Term Loans economy. This increase comes at the expense of corporate bonds, which now grow by only 2.5% at $t = 1$ compared to 11.6% in the Term Loans economy.

Moving to the second row, we see that the existence of credit lines makes very little difference for the other allocations of unconstrained firms. These firms use credit lines because their spreads are slightly lower (0.14pp quarterly) than those of corporate bonds. At the same time, these marginal spreads are similar enough that the existence of credit lines has little impact on total unconstrained firm borrowing, and instead simply causes a shift from one form of credit to another. With the cost and quantity of credit essentially unchanged, unconstrained firm adjustment on the investment, cash, and dividend margins are also virtually identical between the Credit Lines and Term Loans economies.

In contrast, allocations for the constrained firms are radically different in the presence of credit lines. Because of larger bank borrowing by unconstrained firms, banks raise quarterly loan spreads by 3.1pp at $t = 1$, compared to just 0.2pp in the Term Loans economy.[25] Facing higher spreads, constrained firms increase debt by only 4.4%, compared to 12.6% in the Term Loans economy. To compensate, constrained firms use their other

[25]While these spreads appear large, they likely stand in for both actual borrowing costs as well as shadow costs to discourage borrowing in the case where banks ration firms from obtaining credit altogether (e.g., Stiglitz and Weiss, 1981).

available margins of adjustment more heavily, with a much larger reduction in investment growth (-13.8% vs. -2.8% in the Term Loans economy), lower cash growth (25.4% vs. 31.9%), and a lower ratio of dividends to output (-9.7pp vs. 2.9pp). In summary, as constrained firm debt is crowded out by credit line draws by unconstrained firms, their allocations change sharply, including a large decline in real investment.

We can now combine across firm types to obtain aggregate responses, which are displayed in Figure 5.2. This figure also displays the actual aggregate data series, mapping 2020:Q1 to $t = 0$ as described above. Because some of the data series have already increased in 2020:Q1, we plot differences in the data compared to 2019:Q4, the last "normal" quarter. We observe that the benchmark Credit Lines model provides an excellent fit for most series, aside from the end-of-quarter timing issue mentioned above, which likely also explains why corporate bonds rise one quarter faster in the data than the model. The two main exceptions are investment, where our model has no way to account for the huge rise in uncertainty over this period that led firms to halt investment projects, and dividends which fall too much in the model relative to the data.[26]

Comparing the Credit Lines and Term Loans economy reveals that credit lines have a major effect on the macroeconomic response to the COVID-19 pandemic. To begin, the Credit Lines economy exhibits a vastly larger increase in bank borrowing compared to the Term Loans economy (33.0% vs. 3.0% at $t = 1$). However, aggregate corporate debt is actually *lower* in the Credit Lines economy compared to the Term Loans economy, as the existence of credit lines leads unconstrained firms to substitute bank loans in place of bonds (which now grow by much less), but not to increase overall borrowing, while constrained firms decrease borrowing due to crowding out.

Figure 5.2 shows that these events in debt markets have strong effects on firms' other allocations. As with debt, these responses largely reflect that unconstrained firm behavior is virtually unchanged between the two economies, while constrained firms exhibit much lower investment, cash accumulation, and dividends. As a result, we see the total decline in investment at $t = 1$ is 74% larger in the Credit Lines economy vs. the Term Loans economy (-3.3% vs. -1.9%), with additional decreases in cash accumulation (31.0% vs. 32.0%) and the ratio of dividends to output (2.0pp vs. 3.6pp). Last, because capital is the only adjustable input in our model, the effects on output occur only through capital accumulation, making them small (although quite persistent). We note that our mechanism could potentially produce larger short-term output effects in a richer model of production such

[26]Increasing the dividend smoothing frictions to match this smaller drop would lead firms to adjust more on the investment margin, amplifying our main results on investment. In this sense, this discrepancy implies that our results can be seen as conservative.

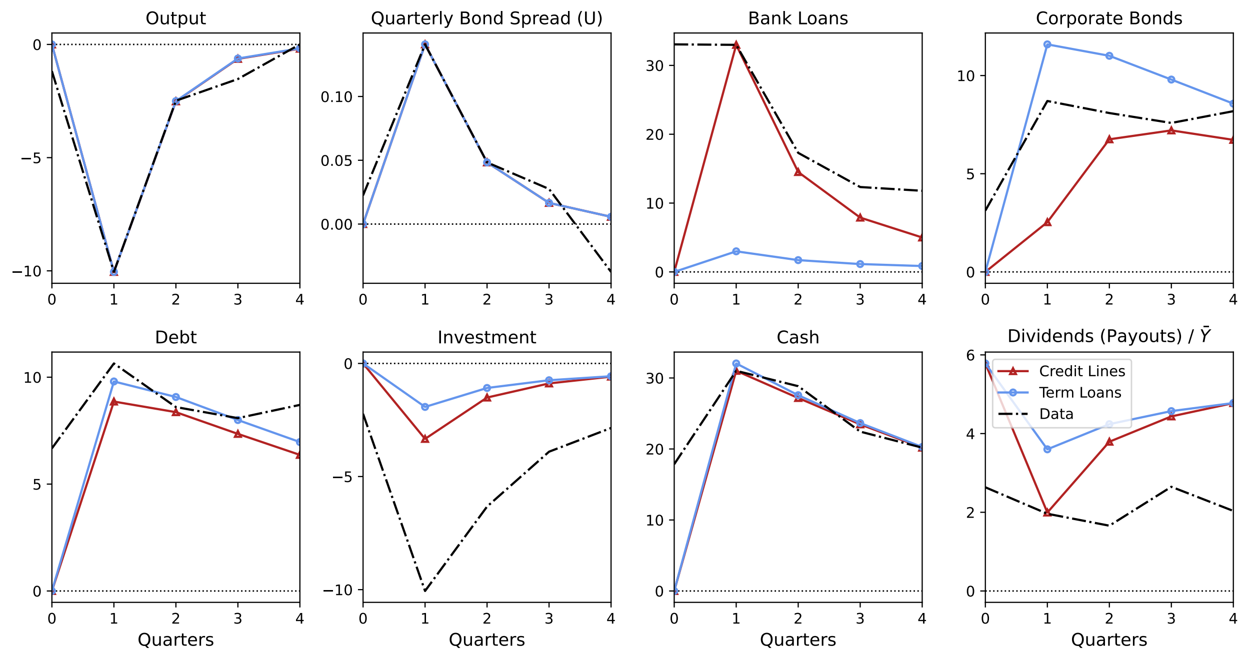

Figure 5.2: Aggregate Responses, Credit Line vs. Term Loan Economies

Notes: This figure plots the economy's response to the COVID-19 pandemic experiment. Variable definitions are as follows: Output (Y_t), Bond Spread (s_t^{bond}), Bank Loans (B_t^{loan}), Corporate Bonds (B_t^{bond}), Debt (B_t), Investment (I_t), Cash (A_t), Dividends / $\bar{Y}$ ($D_t/\bar{Y}$). Aggregate variables are computed as sums over constrained and unconstrained firms. All variables are displayed in percent changes from steady state with the exceptions of Bond Spread, which displays percentage point changes from steady state, and Dividends / $\bar{Y}$, which displays levels in percent. See Appendix B.1.1 for data sources.

Jermann and Quadrini (2012), in which firms must finance working capital to produce.

Overall, the model indicates that although the existence of credit lines facilitates the very large increase in bank credit to firms observed in the COVID-19 crisis, it directly substitutes for corporate bond issuance at large firms, and crowds out bank lending to small firms. As a result, credit lines end up contributing to a larger decline in investment, amplifying the resulting recession despite increasing bank-firm lending.

5.7 Policy Experiment

Beyond providing insight about the mechanisms underlying the response to the COVID-19 pandemic, we argue that the credit line channel also has important implications for the unprecedented corporate bond purchases by the Federal Reserve during this crisis, which are credited with a substantial decline in corporate bond spreads (Haddad et al., 2021). To provide a simple numerical analysis of the effects of such a policy, we compare our baseline economy to a counterfactual economy in which the initial shock to bond spreads $\varepsilon_{s,1}$ was twice as large as in our baseline experiment due to a lack of intervention.

The resulting responses are displayed in Appendix Figure A.1. Taking the difference between our baseline results (solid lines) and this counterfactual economy (dashed lines) to be the effect of the policy, we observe that it is successful at inducing unconstrained firms to issue many more corporate bonds. At the same time, unconstrained firms use little of the raised funds for investment, which is only slightly higher under the policy. Instead, these funds are mostly used by unconstrained firms to rapidly pay down their bank loans. Since these are exactly the empirical patterns documented by Darmouni and Siani (2020), the model thus accurately captures the effects of this policy on large firms, and confirms that the direct effect on investment at these firms was modest.

At the same time, the model shows that this policy had large spillover effects that would be difficult to measure using cross-sectional empirical analysis. Appendix Figure A.1 shows that large (unconstrained) firms substitute bond issuance for credit line draws under the policy intervention, which would otherwise have been even larger. This eases pressure on banks, reducing crowding out of term loans for small firms, whose debt grows by 4.4% in the baseline economy compared to -6.3% in the No Bond Policy counterfactual. Higher debt in turn allows constrained firm investment to fall less than half as much in our baseline (-13.8%) compared to the no policy counterfactual (-28.2%). Aggregating, we find that the Credit Lines economy in our no policy counterfactual sees investment fall at $t = 1$ by 3.2pp more than in our baseline economy. In contrast, the same difference without vs. with the policy in the Term Loans economy is only 0.6pp — more than five times smaller than in a world with credit lines. These results show that bond market interventions can effectively stimulate investment, but that this depends crucially on indirect effects via spillovers from credit line drawdowns.

5.8 Robustness and Extensions

Having established the importance of credit lines to macroeconomic responses and financial policy in our baseline results, we now demonstrate that our findings are robust to several extensions and alternative calibrations. Key to this robustness is our calibration approach, as while some of these changes might influence our results in isolation, recalibrating the model to recover the estimated regression coefficients tightly pins down the strength of our model mechanisms.

Long-Term Debt. In the baseline model we set $\nu = 1$, so that all debt matures after one period. We now relax this assumption to consider $\nu = 0.25$, which corresponds to debt with an average maturity of 4Q. The results, displayed in Figure A.5, show that our main results are all robust to varying debt maturity once we recalibrate the remaining model parameters. In fact, the figure shows that moving to longer-term debt actually increases the resulting decline in investment. We prefer the one-period debt calibration for our baseline due to its simplicity and the slightly better fit to the observed path of loans and bonds, but note that moving to longer term debt would only strengthen our results.

Financial Assumptions. In the model, small (constrained) firms cannot use corporate bonds and credit lines at all, whereas in reality, these firms have at least some access to these instruments. To address these concerns, Figures A.6 and A.7 consider economies in which firms borrow in a fixed mixture of 75% term loans and 25% of either corporate bonds or credit lines, respectively. Similarly, as it is possible that unconstrained firms would hold more cash in the absence of credit lines, Figure A.8 considers a version of the Term Loans economy in which unconstrained firms hold as much cash relative to assets as constrained firms. In both cases we find that our main results are at most minimally affected after recalibrating the model.

Sensitivity to "Free" Parameters. While most of our model's parameters are tightly calibrated, there remain two "free" parameters: the investment friction ζ_K and the entrepreneur discount factor β_E. Figures A.2 and A.3 compare the results of our baseline calibration to alternatives setting $\zeta_K = 0.5$ and $\zeta_K = 0.1$. Results show that while ζ_K is (unsurprisingly) influential for the total decline in investment, the difference in investment between the Credit Lines and Term Loans economy, corresponding to the amplification effect of credit lines during this crisis period, is large and similar across the calibrations. Similarly, Figure A.4 shows results using a lower entrepreneur discount factor (a substantially higher discount factor is not relevant as entrepreneurs would refuse to borrow in steady state) and finds a minimal impact on our results. In summary, we consider our main findings robust to the calibration of these free parameters.

6 Conclusion

In this paper, we have argued that credit lines are central to the transmission of macroeconomic shocks to firm credit, at both the aggregate and cross-sectional levels. Using a highly granular data set, we are able to open the black box of U.S. bank balance sheets to show that unused credit line capacity is vast, but overwhelmingly concentrated among the largest, least financially constrained firms. As a result, while credit lines allowed for a large expansion of aggregate bank-firm credit following the COVID-19 pandemic, they also crowded out credit to constrained firms in favor of unconstrained firms. Our theoretical results show that the predetermined pricing of credit lines is key to this relative flow of bank credit, which would otherwise favor constrained firms. This cross-sectional pattern has important aggregate implications, worsening the drop in investment following negative shocks despite increasing the aggregate flow of bank credit.

To close, we provide two caveats to our findings. First, while we highlight a particular mechanism that may have amplified the impact of the COVID-19 pandemic, this should not be interpreted as showing that credit lines are welfare reducing overall, as they provide an important and flexible source of liquidity to firms. Second, our results are measured in a particular and in many ways extreme economic environment around the COVID-19 outbreak. We leave to future work the task of determining how the strength of our mechanism varies with macroeconomic and banking sector conditions.

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Internet Appendix

A Model Appendix

A.1 Model Optimality Conditions

This section derives the optimality conditions that must hold at equilibrium.

Firms. Define expected violation costs per dollar of debt to be

$$\xi_{j,t} = \kappa_j \Gamma_{\omega,j}(\bar{\omega}_{j,t})$$

which is equal to the product of the cost and probability of violation. The optimality condition for capital for a firm of type j is

$$Q_{j,t} = E_t\left\{\Lambda_{j,t+1}\left[(1-\tau)\underbrace{\frac{\partial Y_{j,t+1}}{\partial K_{j,t}}}_{\text{MPK}} + \underbrace{\Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t+1}}_{\text{remaining capital}} + \underbrace{\Psi_{j,t}\frac{\partial X^*_{j,t+1}}{\partial K_{j,t}}}_{\text{violation costs}}\right]\right\}$$

which equates the cost of a new unit of capital to the discounted value of the marginal income it will provide next period, the marginal sale value of the remaining capital next period, and the effect of that capital on expected violation costs. To this end, the term $\Psi_{j,t}$ represents the marginal benefit of reducing the firm's violation costs by increasing smoothed EBITDA, both today and in the future, and is equal to

$$\Psi_{j,t} = -\bar{\pi}^{-1}\frac{\partial \xi_{j,t}}{\partial X_{j,t}} B_{j,t-1} + E_t\left\{\Lambda_{j,t+1}\Psi_{j,t+1}\frac{\partial X^*_{j,t+1}}{\partial X_{j,t}}\right\}.$$

The optimality condition for debt is

$$1 = \Omega^B_{j,t} + \Omega^S_{j,t} s_{j,t}$$

which sets the benefit of debt (\$1 today) against the marginal cost of carrying an additional \$1 of debt into the next period and promising an additional $s_{j,t}$ in spread payments. The marginal continuation costs of principal balances $\Omega^B_{j,t}$ and spread payments $\Omega^S_{j,t}$ are

$$\Omega^B_{j,t} = E_t\left\{\Lambda_{j,t+1}\bar{\pi}^{-1}\left[\Big((1-\tau)r_t + \nu + \xi_{j,t+1}\Big) + \frac{\partial \xi_{j,t+1}}{\partial B_t} + (1-\nu)\Omega^B_{j,t+1}\right]\right\}$$

$$\Omega^S_{j,t} = E_t\left\{\Lambda_{j,t+1}\bar{\pi}^{-1}\left[(1-\tau) + (1-\nu)\Omega^S_{j,t+1}\right]\right\}$$

The optimality condition for cash is

$$1 = \exp(\tilde{a}_t)\eta_{A,j}A_{j,t}^{-\zeta_A} + \bar{\pi}^{-1}E_t\Big[\Lambda_{j,t+1}\Big]$$

which sets the cost of acquiring \$1 of cash equal to the utility benefit to the firm from the liquidity services as well as the continuation value of \$1 of cash next period, net of discounting and inflation. Last, the derivative terms used above can be evaluated as

$$\frac{\partial Y_{j,t+1}}{\partial K_{j,t}} = \alpha\frac{Y_{j,t+1}}{K_{j,t}} \qquad \frac{\partial X^*_{j,t+1}}{\partial K_{j,t}} = (1-\rho_X)\frac{\partial Y_{j,t+1}}{\partial K_{j,t}} \qquad \frac{\partial X^*_{j,t+1}}{\partial X_{j,t}} = \rho_X\bar{\pi}^{-1}$$

$$\frac{\partial \xi_{j,t}}{\partial X_{j,t}} = -\kappa_j f_{\omega,j}(\bar{\omega}_{j,t})\frac{\bar{\omega}_{j,t}}{X_{j,t}} \qquad \frac{\partial \xi_{j,t+1}}{\partial B_{j,t}} = \kappa_j f_{\omega,j}(\bar{\omega}_{j,t+1})\frac{\bar{\omega}_{j,t+1}}{B_{j,t}}.$$

Saver. The saver's optimality condition for risk-free government debt is

$$1 = (1+r_t)\bar{\pi}^{-1}E_t\Big[\Lambda_{S,t+1}\Big].$$

Under the baseline assumption that the saver is risk-neutral we have $\Lambda_{S,t+1} = \beta$ and so

$$1 + r_t = \bar{\pi}\beta_S^{-1}.$$

The saver's optimality condition for corporate bonds is

$$1 = \Omega^B_{S,t} + \Omega^S_{S,t}(s^{bond}_t - q^{bond}_t) \tag{A.1}$$

which sets the cost of buying \$1 of corporate bonds today equal to the marginal benefit of \$1 of corporate bond balances and the marginal benefit of an extra s^{bond}_t of corporate bond spread payments going forward, net of the holding cost q^{bond}_t. These marginal continuation values are equal to

$$\Omega^B_{S,t} = E_t\left\{\Lambda_{S,t+1}\bar{\pi}^{-1}\Big[r_t + \nu + (1-\nu)\Omega^B_{S,t+1}\Big]\right\} \tag{A.2}$$

$$\Omega^S_{S,t} = E_t\left\{\Lambda_{S,t+1}\bar{\pi}^{-1}\Big[1 + (1-\nu)\Omega^S_{S,t+1}\Big]\right\}. \tag{A.3}$$

Under our benchmark assumption that savers have risk-neutral preferences, so that $\Lambda_{S,t+1} = \beta_S$ and $1 + r_t = \bar{\pi}\beta_S^{-1}$, we can guess and verify that these quantities are both equal to constants:

$$\Omega^B_{S,t} = 1 \qquad \Omega^S_{S,t} = \frac{1}{r+\nu}.$$

Substituting into the optimality condition, we obtain

$$s_t^{bond} = q_t^{bond}$$

so that the corporate bond spread is effectively exogenous.

Bank. The optimality conditions for the representative bank with respect to capital is

$$\mu_t = \eta_k k_t^{\zeta_B} \tag{A.4}$$

where μ_t is the multiplier on the capital requirement. The optimality condition for constrained debt issuance $B^*_{C,t}$ is

$$0 = -1 - \Xi_t + \Omega_{B,t} + s_{C,t}^{loan}\Omega_{S,t}$$

where $\Omega_{B,t}$ and $\Omega_{S,t}$ are defined as in (A.2) and (A.3), and Ξ_t represents the present and future cost of tightening the capital requirement. Intuitively, the $\Omega_{B,t}$ and $\Omega_{S,t}$ expressions are re-used because the saver's marginal value of an additional dollar of principal balance or additional dollar of promised spread payments is the same across both products, although the amount of spread payments promised per dollar of bank loan and corporate bond may differ.

The marginal holding cost term Ξ, after applying (A.4) above, is equal to

$$\Xi_t = \chi^B \eta_k k_t^{\zeta_B} + E_t\left[\Lambda_{S,t+1}\bar{\pi}^{-1}(1-\nu)\Xi_{t+1}\right].$$

Substituting for this term and applying (A.2) and (A.3) now yields

$$s_{C,t}^{loan} = \Omega_{S,t}^{-1}\left(1 + \Xi_t - \Omega_{B,t}\right) = (r+\nu)\Xi_t.$$

In the case $\nu = 1$ (short-term debt), this becomes

$$s_{C,t}^{loan} = (1+r)\chi^B \eta_k k_t^{\zeta_B}.$$

Capital Producer. The optimality condition for a capital producer of type j is

$$\begin{aligned} Q_{j,t} &= \Phi'(i_{j,t})^{-1} \\ \bar{Q}_{j,t} &= Q_{j,t} + \frac{Q_{j,t}\Phi(i_{j,t}) - i_{j,t}}{1-\delta} \end{aligned}$$

where $i_{j,t} \equiv I_{j,t}/K_{j,t-1}$. The difference between $Q_{j,t}$ and $\bar{Q}_{j,t}$ is second order and would disappear in a linearized solution.

A.2 Model Robustness and Extensions

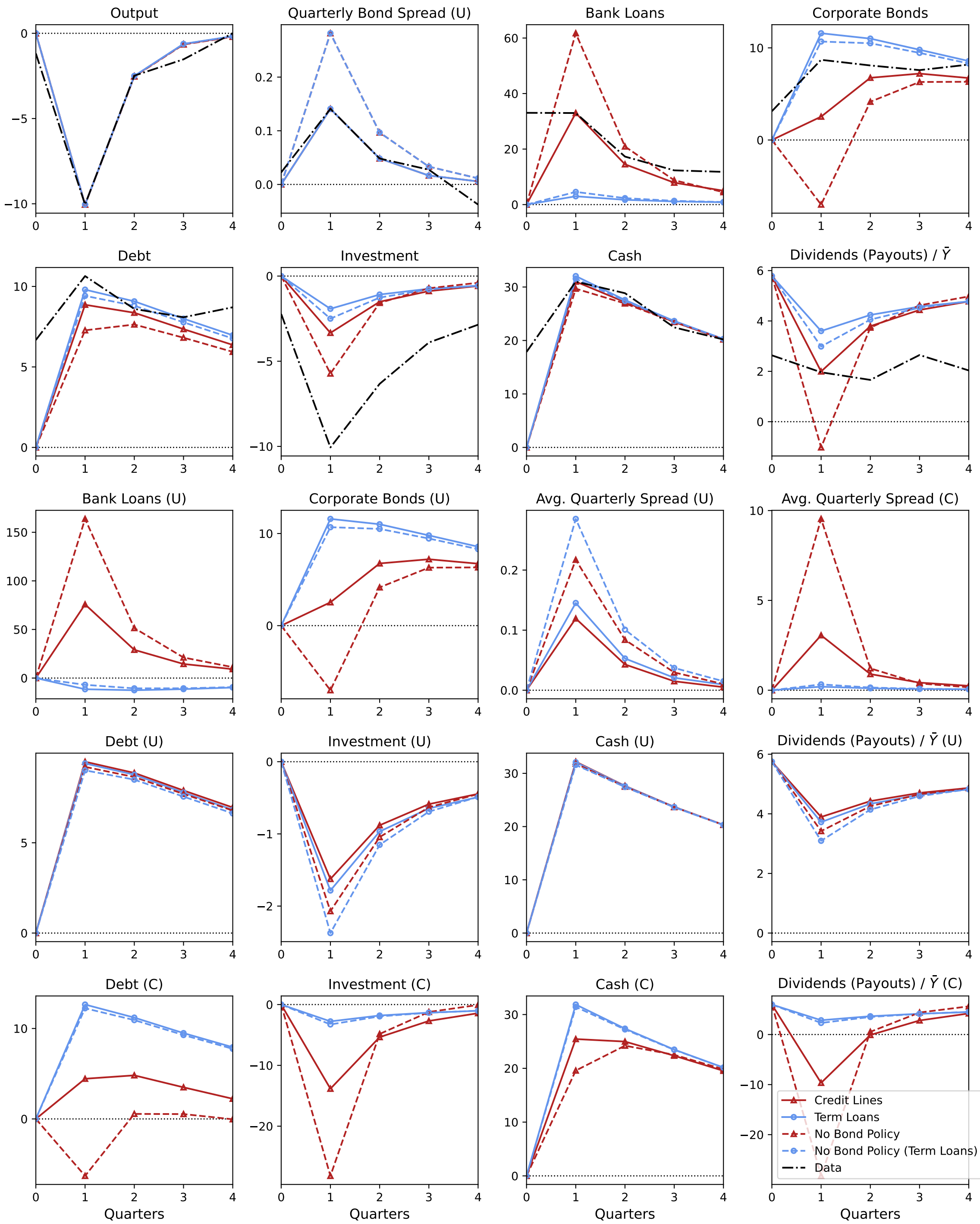

Figure A.1: Response of Baseline vs. No Bond Intervention

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines economy is defined as in these figures. The No Bond Policy economy is defined as an alternative version of the Credit Lines economy in which the shock to bond spreads is twice as large as in our baseline experiment.

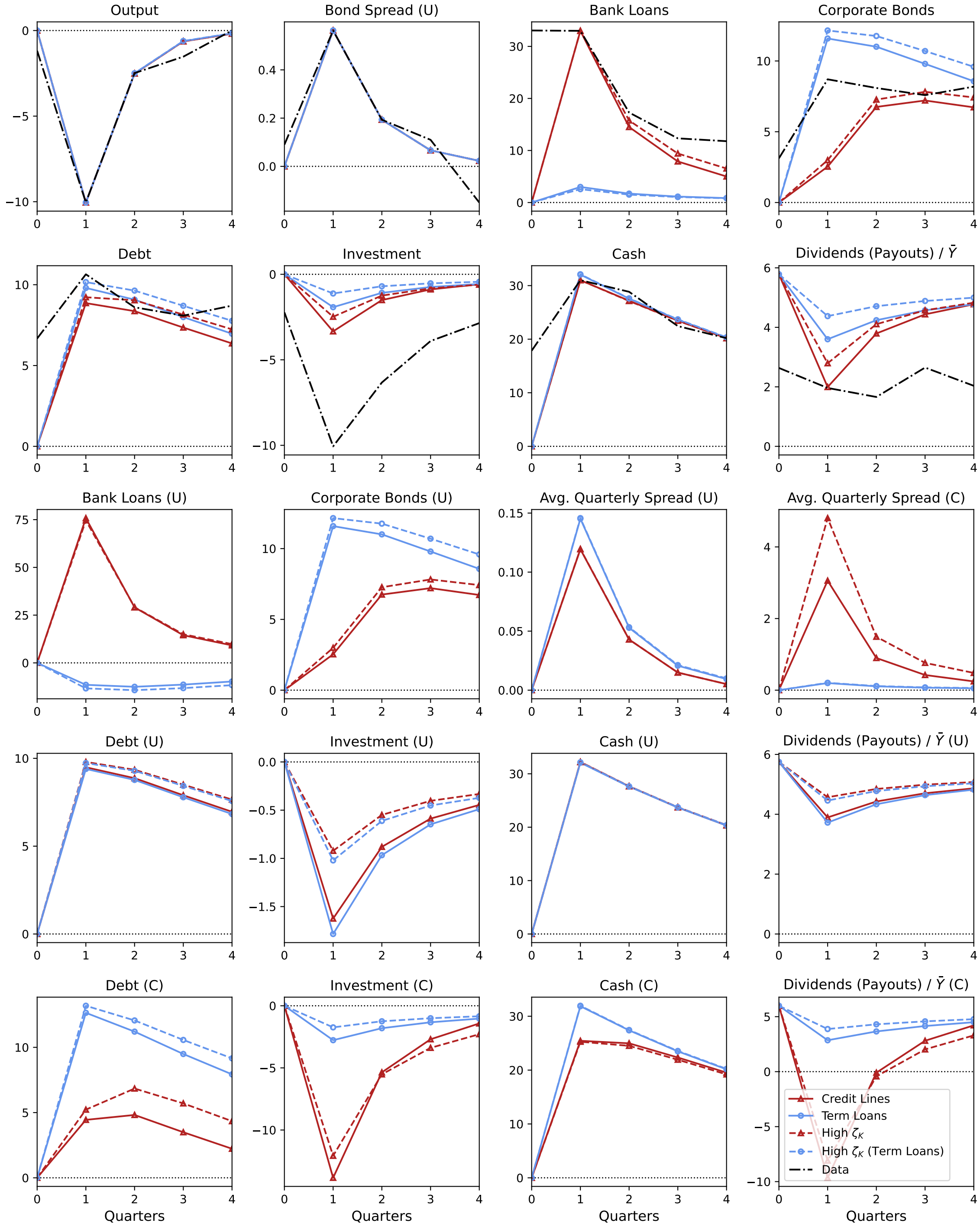

Figure A.2: Response of Baseline vs. High ζ_K

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The High ζ_K and High ζ_K (Term Loans) lines display the responses in versions of the Credit Lines and Term Loans economies in which $\zeta_K = 0.5$, compared to our baseline calibration of $\zeta_K = 0.250$.

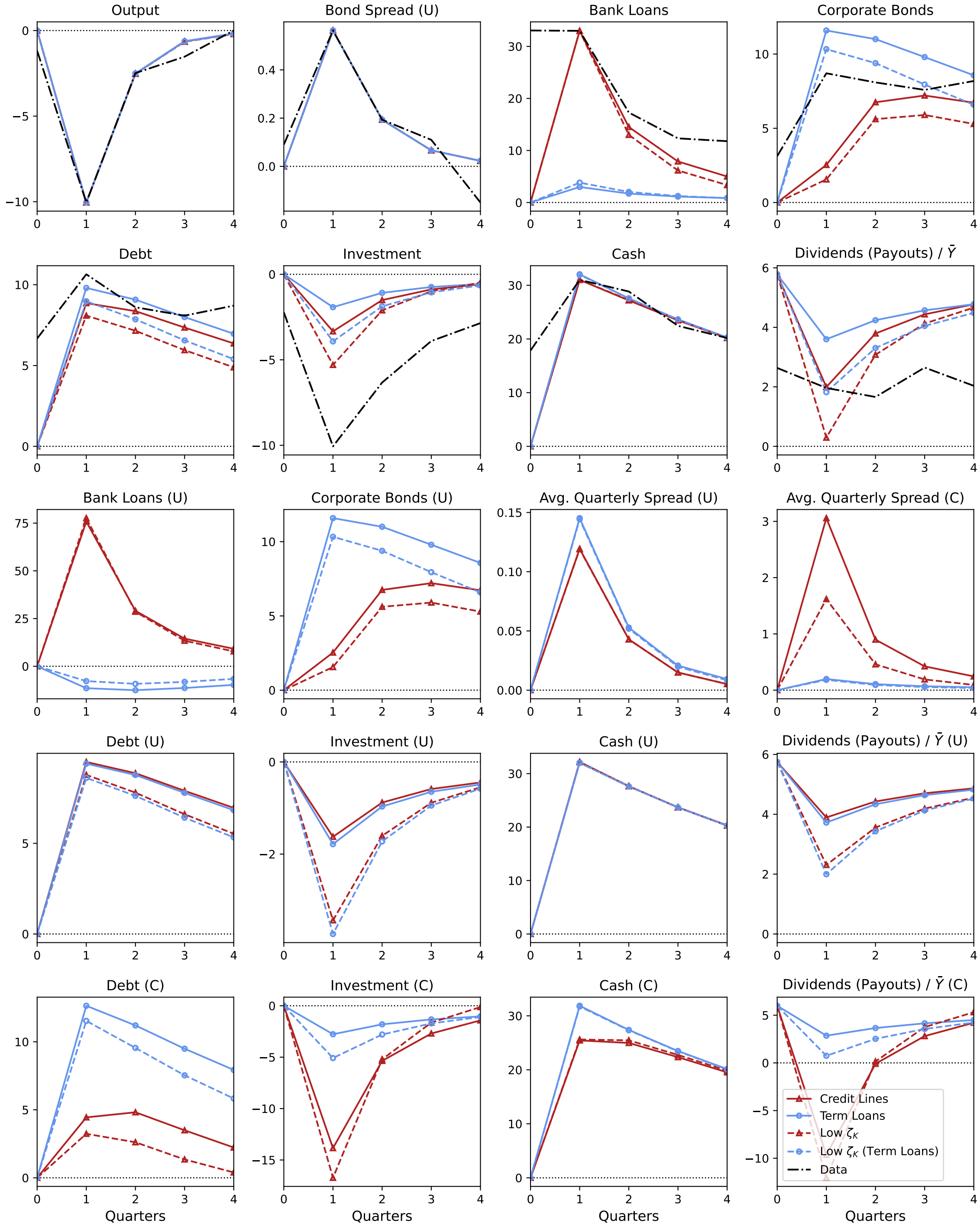

Figure A.3: Response of Baseline vs. Low ζ_K

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The Low ζ_K and Low ζ_K (Term Loans) lines display the responses in versions of the Credit Lines and Term Loans economies in which $\zeta_K = 0.1$, compared to our baseline calibration of $\zeta_K = 0.250$.

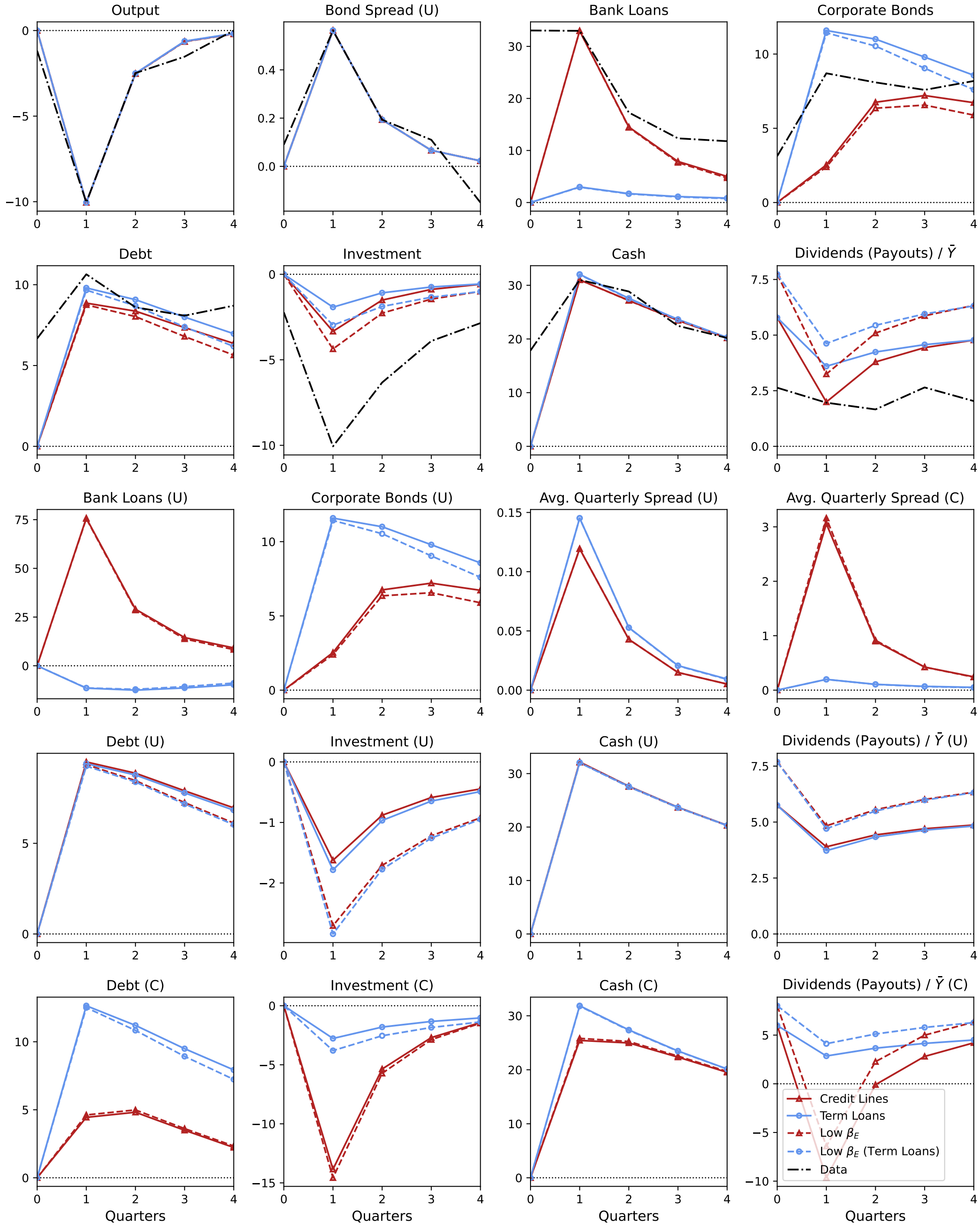

Figure A.4: Responses by Entrepreneur Discount Factor β_E

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The Low β_E and Low β_E (Term Loans) lines display the responses in versions of the Credit Lines and Term Loans economies in which $\beta_E = 0.985$, compared to our baseline calibration of $\beta_E = 0.990$.

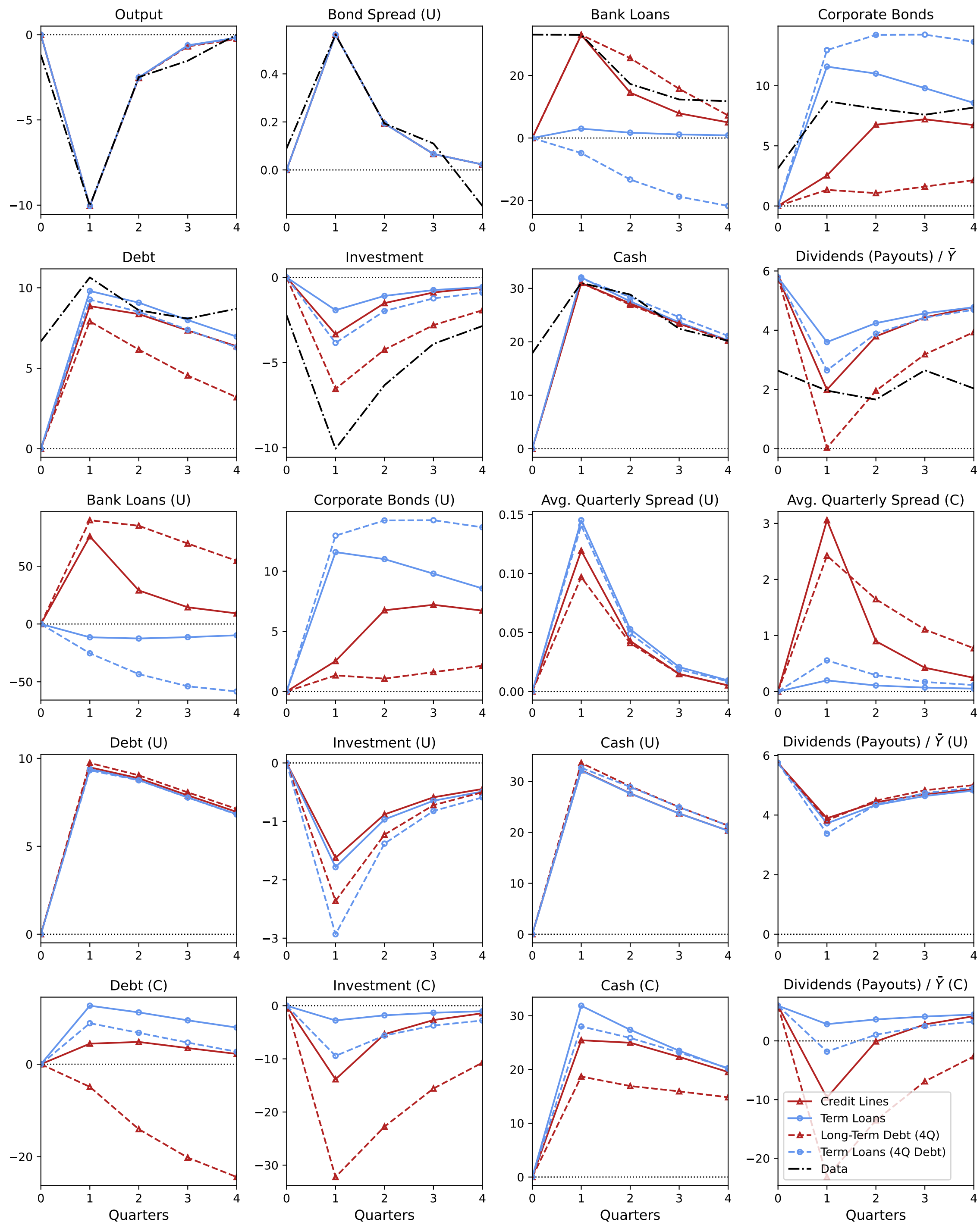

Figure A.5: Responses by Debt Maturity

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The Long Term Debt (4Q) and Term Loans (4Q Debt) lines display the responses in versions of the Credit Lines and Term Loans economies in which all debt has average maturity 4Q ($\nu = 0.25$).

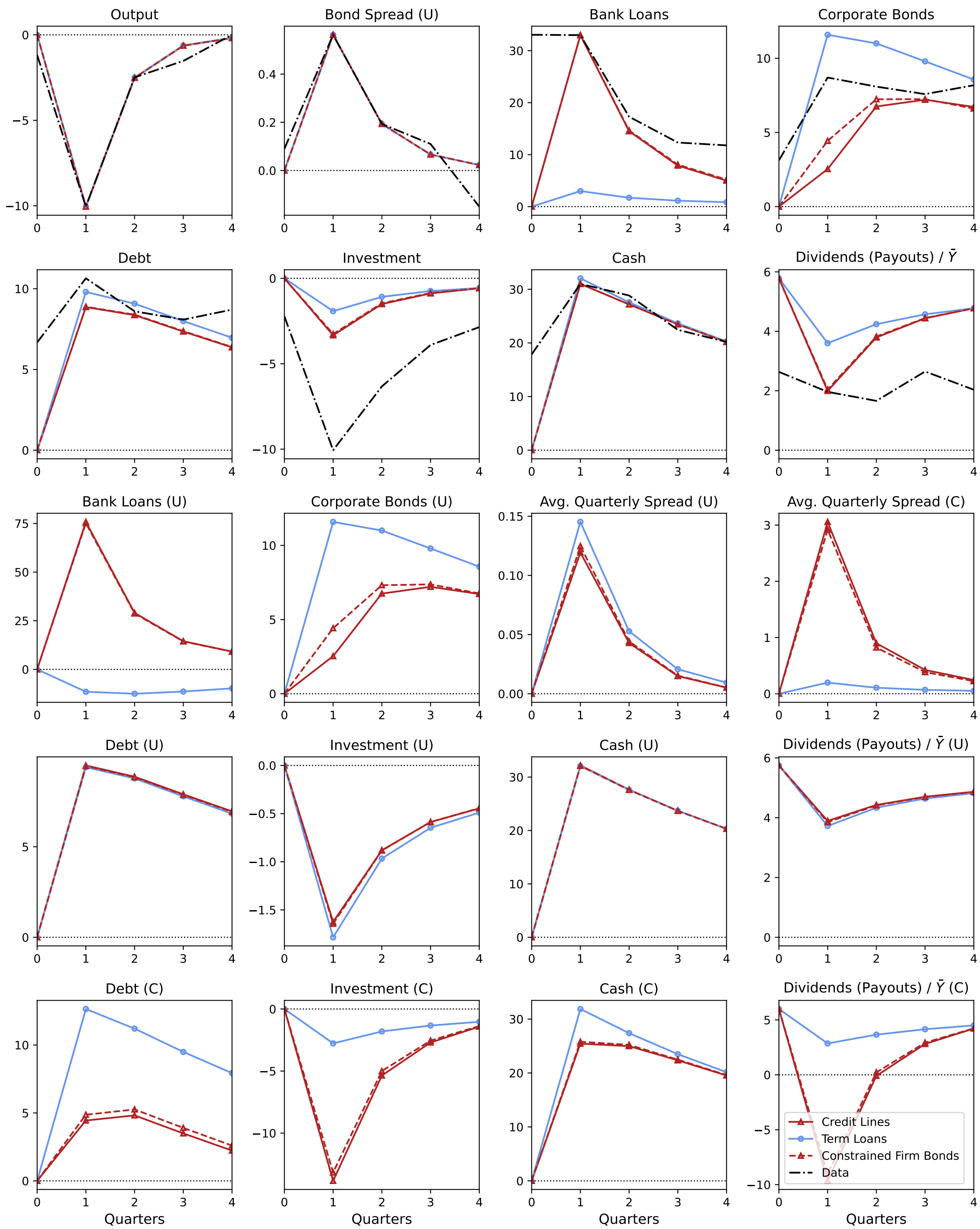

Figure A.6: Response of Baseline vs. Constrained Firm Bonds

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The Constrained Firm Bonds series display the responses in versions of the Credit Lines and Term Loans economies in which constrained firms borrow using a mixture of 75% term loans and 25% corporate bonds, compared to our baseline model where constrained firms borrow 100% in term loans.

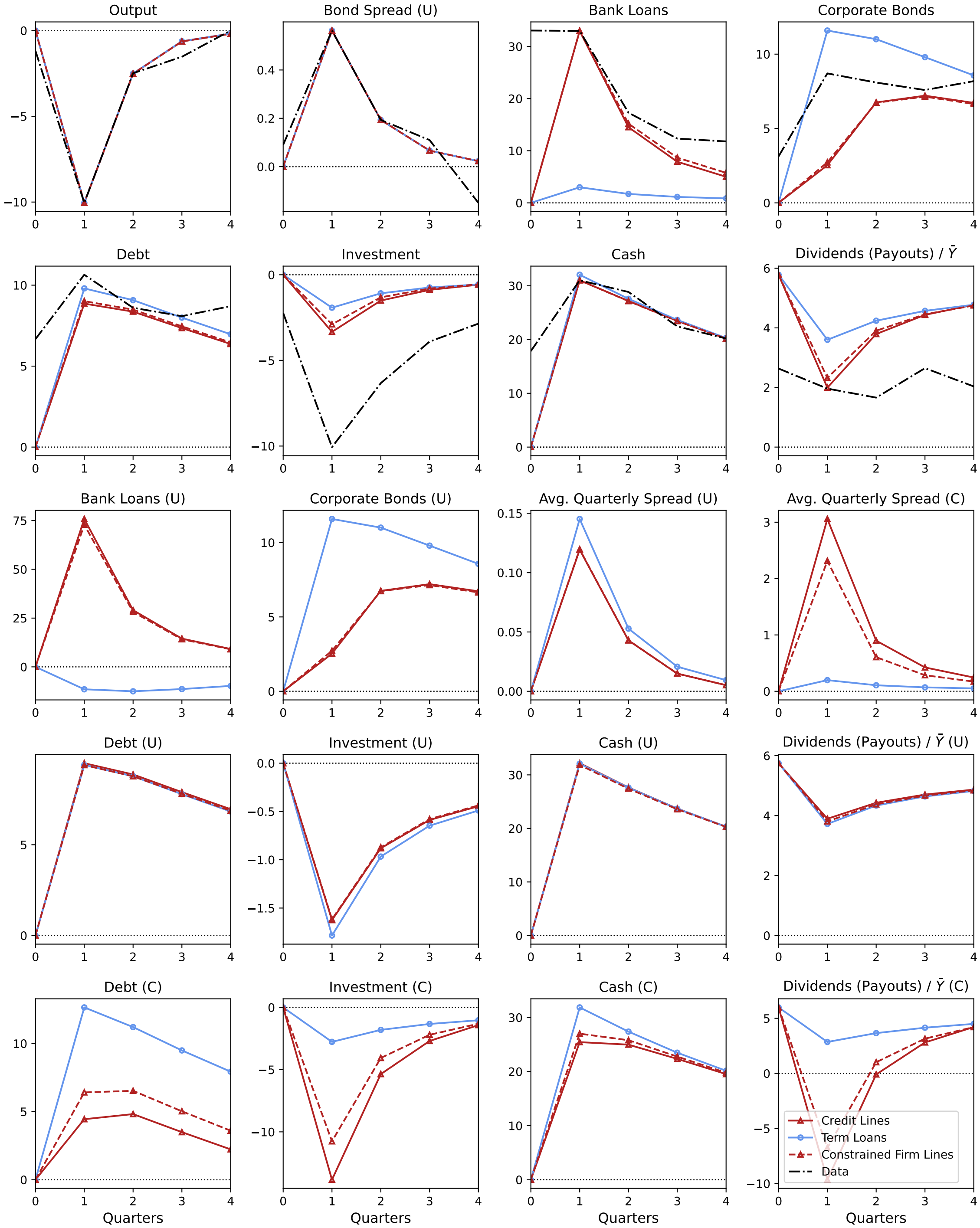

Figure A.7: Response of Baseline vs. Constrained Firm Credit Lines

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The Constrained Firm Lines series display the responses in versions of the Credit Lines and Term Loans economies in which constrained firms borrow using a mixture of 75% term loans and 25% credit lines, compared to our baseline model where constrained firms borrow 100% in term loans.

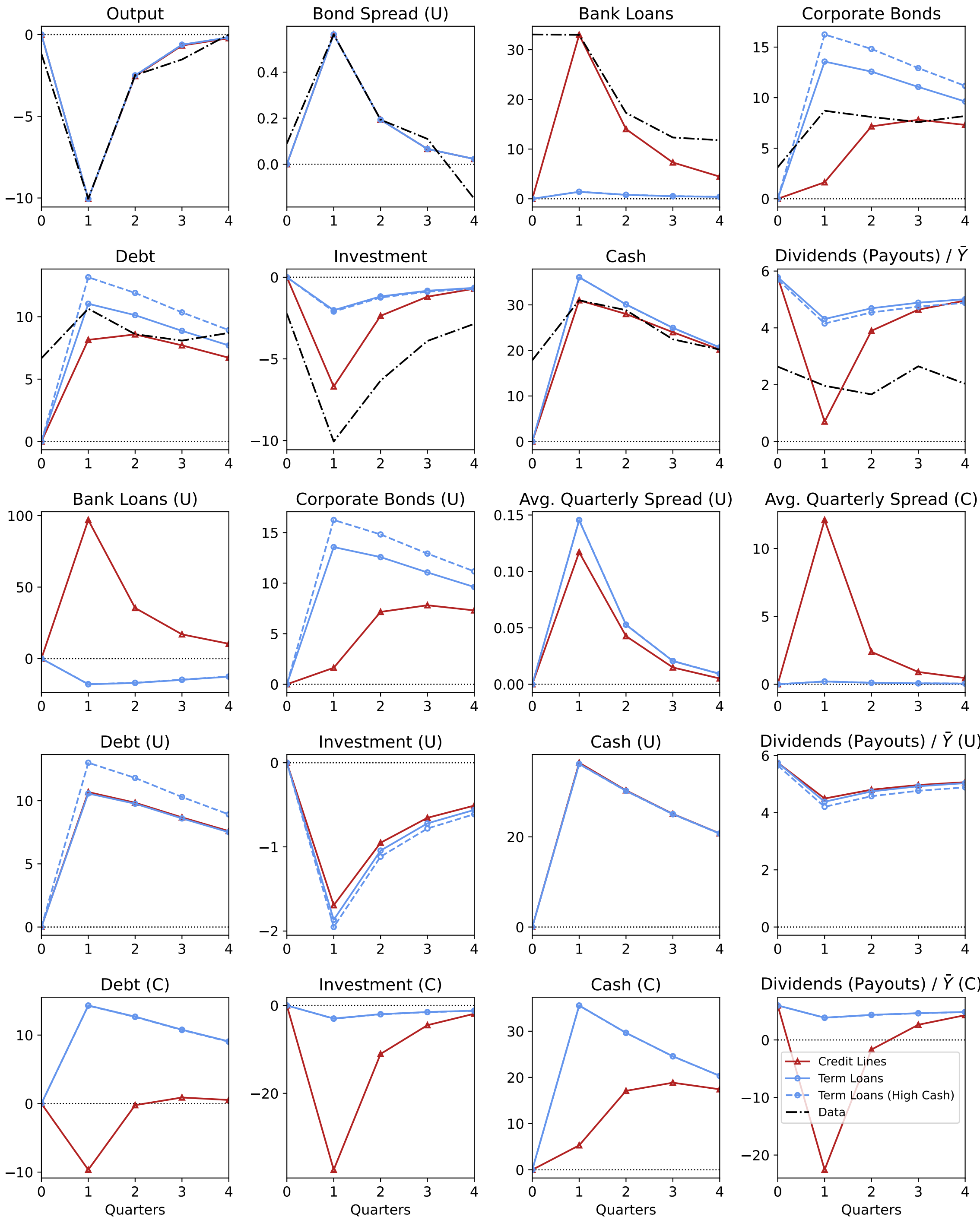

Figure A.8: Response of Baseline vs. High Cash

Notes: See notes for Figures 5.1 and 5.2. The Credit Lines and Term Loans responses are as in these figures. The Term Loans (High Cash) series displays a version of the Term Loans economy in which unconstrained firms hold the same ratio of cash to assets as constrained firms.

B Data

B.1 Variable Definitions and Data Sources

In Tables B.1-B.4, we provide names, definitions, and sources for all variables that are used in the empirical analysis. The variables from the FR Y-9C Filings are described in Table B.1. Table B.2 collects all variables that are used from the FR Y-14Q H.1 data, Table B.3 the ones from Compustat, and Table B.4 reports the ones from Orbis. These variables are employed in Sections 3-4 and the Appendix. Last, we describe the aggregate series used in the model figures in Section B.1.1.

Table B.1: Variables from Y-9C filings.

Variable Code	Variable Label
BHCK 2170	Total Assets
BHCK 2948	Total Liabilities
BHCK 4340	Net Income
BHCK 3197	Earning assets that reprice or mature within one year
BHCK 3296	Interest-bearing deposit liabilities that reprice or mature within one year
BHCK 3298	Long-term debt that reprices within one year
BHCK 3408	Variable-rate preferred stock
BHCK 3409	Long-term debt that matures within one year
BHDM 6631	Domestic offices: noninterest-bearing deposits
BHDM 6636	Domestic offices: interest-bearing deposits
BHFN 6631	Foreign offices: noninterest-bearing deposits
BHFN 6636	Foreign offices: interest-bearing deposits
BHCK JJ33	Provision for loan and lease losses
BHCA 7205	Total Capital Ratio

Notes: The table lists variables that are collected from the Consolidated Financial Statements or FR Y-9C filings for Bank-Holding Companies from the Board of Governors' National Information Center database. The one-year income gap is defined as $(\text{BHCK}\,3197 - (\text{BHCK}\,3296 + \text{BHCK}\,3298 + \text{BHCK}\,3408 + \text{BHCK}\,3409))\,/\text{BHCK}\,2170$. Total deposits are given by $(\text{BHDM}\,6631 + \text{BHDM}\,6636 + \text{BHFN}\,6631 + \text{BHFN}\,6636)$. Nominal series are converted into real series using the consumer price index. The FR Y-9C form for March 2020 can be found at: https://www.federalreserve.gov/reportforms/forms/FR_Y-9C20200401_f.pdf.

Table B.2: FR Y-14 Variable Definitions.

Variable Name	Description / Use	Field No.
Zip code	Zip code of headquarters	7
Industry	Derived 2-Digit NAICS Code	8
Internal risk rating	Internal risk rating mapped to S&P scale	10
TIN	Taxpayer Identification Number	11
Internal Credit Facility ID	Used together with BHC and previous facility ID to construct loan histories	15
Previous Internal Credit Facility ID	Used together with BHC and facility ID to construct loan histories	16
Origination Date	Used to distinguish new and existing loans	18
Maturity Date	Used to determine remaining maturity	19
Term Loan	Loan facility type reported as Term Loan, includes Term Loan A-C, Bridge Loans, Asset-Based, and Debtor in Possession.	20
Credit Line	Loan facility type reported as revolving or non-revolving line of credit, standby letter of credit, fronting exposure, or commitment to commit.	20
Purpose	Credit facility purpose	22
Committed Credit	Committed credit exposure	24
Used Credit	Utilized credit exposure	25
Line Reported on Y-9C	Line number reported in HC-C schedule of FR Y-9C	26
Secured Credit	Security type of credit	36
Variable Rate	Interest rate variability reported as "Floating" or "Mixed"	37
Interest Rate	Current interest rate	38
Date Financials	Financial statement date used to match firm financials to Y-14 date	52
EBITDA	Derived from operating income plus depreciation and amortization	56, 57
Interest Expense	Used in calculating implied covenants	58
Net Income	Current and prior year net income for trailing 12-months used to construct cash flow changes	59, 60
Cash and Securities	Cash and marketable securities	61
Tangible Assets	Tangible assets	68
Total Assets	Total assets, current year and prior year	70
Short Term Debt	Used in calculating implied covenants & total debt	74
Long Term Debt	Used in calculating implied covenants & total debt	78
Total Liabilities	Total liabilities	80
Capital Expenditures	12-month trailing CAPEX	82
Probability of Default	Probability of default for firms	88
Collateral Value	Collateral market value	93
Syndicated Loan	Syndicated loan flag	100

Notes: All nominal series are converted into real series using the consumer price index. The corresponding "Field No." can be found in the data dictionary (Schedule H.1, pp. 162-217): https://www.federalreserve.gov/reportforms/forms/FR_Y-14Q20200331_i.pdf

Table B.3: Compustat Variable Definitions.

Variable Name	Description	Compustat Name
Total Assets	Total firm assets	atq
Cash and Short-Term Investments	Cash and short-term investments	cheq
Tangible Assets	Constructed from cash, fixed assets, receivables, and inventories	cheq + invtq + ppentq + rectq
EBITDA	Earnings before interest, taxes, and depreciation and amortization, annual series (only matched to Y14 for Q4-observations)	ebitda
Employer Identification Number	Used to match to TIN in Y14, successful merges are basis for publicly traded designation	ein
Total Liabilities	Total firm liabilities	ltq
Net Income	Firm net income (converted to 12-month trailing series)	niq
Total Debt	Debt in current liabilities + long-term debt	dlcq + dlttq
Capital Expenditures	CAPEX (converted to 12-month trailing series)	capxy

Notes: All data are obtained from the Wharton Research Data Services. Nominal series are converted into real series using the consumer price index.

Table B.4: Orbis - Bureau van Dijk Variable Definitions.

Variable Name	Description	BvD Name
Employer Identification Number	Used to match to TIN in Y14	EIN
Cash	Cash and cash equivalent assets	CASH
Incorporation date	Date of firm incorporation	DATEINC, DATEINC_YEAR
EBITDA	Earnings before interest, taxes, and depreciation and amortization	EBTA
Total Liabilities	Non-current liabilities + current liabilities	NCLI + CULI
Net Income	Firm net income	ONET
Total Assets	Total firm assets	TOAS

Notes: All data are obtained from Orbis - Bureau van Dijk. Nominal series are converted into real series using the consumer price index.

B.1.1 Aggregate Series for Model Figures

Our aggregate data series used for comparison with the model in Figure 5.2 and others are defined as follows.

1. Output is gross domestic product from the BEA (via FRED, code GDP).
2. Bond Spread (U) is the BAA - AAA spread from Moody's (via FRED, codes BAA, AAA).
3. Bank Loans is depository institution loans from Table B.103 of the Flow of Funds (code FL103168005).
4. Corporate Bonds is debt securities (liability) from Table B.103 of the Flow of Funds (code FL104122005).
5. Debt is the sum of Bank Loans and Corporate Bonds as just defined.
6. Investment is private nonresidential fixed investment from the BEA (via FRED, code PNFI).
7. Cash is obtained from Table B.103 of the Flow of Funds as the sum of foreign deposits (FL103091003), checkable deposits (FL103020000), time savings deposits (FL103030003), MMF shares (FL103034000), repos (FL102051003), and debt securities (asset) (LM104022005).
8. Dividends (Payouts) / $\bar{Y}$ is obtained from Table F.103 of the Flow of Funds as net dividends (FA106121075) minus the flow of corporate equities (FA103164103).

All series with the exception of Bond Spread (U) are deflated by the GDP deflator (source: BEA, FRED code: GDPDEF).

B.2 Data Construction, Cleaning, and Sample Restrictions

The firm financial statement variables are combined from three sources: Compustat, the Y14, and Orbis. We use financial statement data from the quarterly Compustat files whenever possible because publicly traded firms have accurate and uninterrupted quarterly data for the key variables of interest. For all other firms we default to the Y14 financials data, which is typically recorded annually. Since firm financial data are reported at the facility level in the Y14 data, we measure financial variables for a given firm as the medians of those variables over all facilities held by that firm. In addition, if a variable is also observed for a private firm in Orbis, we average the variables from the two sources as a way of further reducing measurement error. If the Y14 and Orbis data do not differ by more than 5% for a particular firm-date observation, then we average the variables from the two sources but exclude the observation otherwise. The Orbis data also provides us with a measure of firm age for a wide range of private and public firms, defined as the number of years between the data observation date and the firm incorporation date. For additional information on firm age, we use the Field-Ritter data set of company founding dates for public firms (Field and Karpoff, 2002; Loughran and Ritter, 2004), using the Field-Ritter date whenever the value in the Orbis data is missing or the Field-Ritter founding date is older than the one according to Orbis.

We apply the following set of sample restrictions to the Y14 data:

1. We restrict the sample to begin in 2012:Q3. The Y14 collection began in 2011:Q3, but there was a significant expansion in the number of BHCs required to submit Y14 commercial loan data until 2012:Q3. Moreover, the starting date in 2012:Q3 also affords a short phase-in period for the structure of the collection and variables to stabilize.

2. We constrain the sample to loan facilities with line reported on the HC-C schedule in the FR Y9-C filings as commercial and industrial loans, "other" loans, "other" leases, and owner-occupied commercial real estate (corresponding to Field No. 26 in the H.1 schedule of the Y14 to be equal to 4, 8, 9, or 10; see Table B.2). In addition, we drop all observations with NAICS codes 52 and 53 (loans to financial firms and real estate firms).

3. When we use information about the facility type (credit line or term loan) or interest rate variability type (i.e., fixed or floating), we exclude observations for which this information is missing or changing over the facility history.

4. Drop all facility records with origination dates before 1990 and maturities greater than 30 years, to minimize the potential influence of data entry errors.

5. Observations with negative or zero values for committed exposure, negative values for utilized exposure, and with committed exposure less than utilized exposure are excluded.

6. When aggregating loans at the firm-level, we exclude observations for which the firm identifier "TIN" is missing. To preserve some of these missing values, we fill in missing TINs from a history where the non-missing TIN observations are all the same over a unique facility ID.

7. When using information on firms' financials in the analysis, we apply a set of filters to ensure that the reported information is sensible. We exclude observations (i) if total assets, total liabilities, short-term debt, long-term debt, cash assets, tangible assets, or interest expenses are negative, (ii) if tangible assets, cash assets, or total liabilities are greater than total assets, and (iii) if total debt (short term + long term) is greater than total liabilities.

8. In parts of the empirical analysis, we differentiate between new and existing loans. In some instances, the reporting banks change the IDs for the same facility over time, which would lead to an incorrect classification of such loans as newly issued. To address this issue, we use information on whether a credit facility previously had a different ID, which banks have to report in the Y14 (see Table B.2). If we can find a record for the prior ID, we append the history of the new ID onto the history of the prior ID.

9. While a loan facility may include both credit lines and term loans, we observe a binary facility type designation, corresponding to which loan type constitutes the majority share. As a result, we observe facilities designed as term loan facilities, but that nonetheless contain committed but unused credit, strongly implying that the facility contains a credit line. To address this, we assume that all unused credit (i.e., committed exposure net of utilized exposure) represents unused capacity on the firm's credit lines. In other words, we count unused credit on facilities that designed as term loans as part of that firm's unused credit line balances.

10. When using the interest rate on loans in our calculations, we exclude observations with interest rates below 0.5 or above 50% to minimize the potential influence of data entry errors.

B.3 Covenants

Bank credit facilities often come with debt covenants that can effectively limit firm borrowing, even on precommitted credit lines. To account for these, we adjust firms' unused borrowing capacity to account for possible covenant limits that are unobserved in our data sources. As shown by Greenwald (2019), the two most frequently applied covenants are the "Interest-Coverage" (IC) and "Debt-to-Earnings" (DE) covenants (see, e.g., Figure 1 therein). The IC covenant demands that

$$\frac{EBITDA}{Interest\ Expenses} \geq \kappa\ ,$$

whereas the DE covenant requires that

$$\frac{Debt}{EBITDA} \leq \tau.$$

Based on data from Dealscan, Greenwald (2019) shows that κ and τ are relatively stable over time (see, e.g., Figure 2 therein). In particular, weighting loans by the deal-amount, κ is around 2.75

and τ is approximately 3.75. We use these two covenant rules and the calibrations for κ and τ to adjust firms' borrowing capacity. To this end, we apply the following steps. Based on firms' EBITDA, stock of debt (short-term debt + long-term debt), and interest expenses, we compute the "debt room" that a firm has until either of the two constraints binds. For the IC covenant, we calculate the debt room based on the average interest rate on a firm's outstanding debt. If a firm's debt room is smaller than its unused capacity, then we assume that a firm's actual unused capacity is equal to the debt room.[27] Based on this procedure, we find that around 37% of firms violate one of the two constraints in normal times (2012:Q3-2019:Q4). Chodorow-Reich and Falato (2021) find a slightly lower share of violations across loans (around 25%). Hence, while in the same range, our procedure can be viewed as conservative, since firms with looser limits or without the type of covenants that we assume could in fact be non-violaters.

C Which firms have credit line borrowing capacity?

We explore specifications related to those in Sufi (2009) and Campello et al. (2011) to understand which type of firms possess credit line borrowing capacity. To this end, we aggregate all credit indicators at the firm level and estimate (3.1) where the dependent variable is the firm's level of unused borrowing capacity on credit lines (1-used credit/committed credit). All specifications include time (α_t) and industry (τ_k) fixed effects. The vector $X_{i,t-4}$ collects several controls that are lagged by four quarters. Firm size is defined as the natural log of a firm's noncash assets. EBITDA and tangible assets are scaled by a firm's noncash assets, while leverage is defined as total liabilities over total assets.[28] Investment Grade and Public are dummy variables denoting whether a firm has an internal rating of BBB or better, and is publicly traded, respectively. For the estimation, we also adjust firms' unused and committed balances for covenants as described above in Section 3.

The results in Table 3.2 show that a higher unused borrowing capacity is more commonly observed among large, old, public, and profitable firms with low leverage that possess more tangible assets and are well rated. These are all well-known proxies for firm credit constraints (see, e.g., Cloyne et al., 2019). These results are consistent with theoretical models that stress the interplay between firm demand for liquidity insurance with lender concerns about moral hazard and other agency problems (e.g., Holmström and Tirole, 1998; Acharya et al., 2014).

[27] To account for covenant limits in Figure 3.1, we adjust the total amount of unused credit based on the ratio of debt room to unused credit for firms for which we observe all balance sheet and income information within a period.

[28] To eliminate outliers and data entry errors, we exclude observations within the 1% tails of the distributions for EBITDA, tangible assets (both relative to noncash assets), and leverage.

D Credit Responses to Cash Flow Changes

In this section, we investigate how firms use various bank credit instruments to smooth through shocks to their cash flows. We estimate credit responses using the local projections

$$\frac{L_{i,t+h-3} - L_{i,t-4}}{0.5\left(L_{i,t+h-3} + L_{i,t-4}\right)} = \alpha_i^h + \tau_{t,k}^h + \beta^h \frac{\Delta^4 CF_{i,t}}{Assets_{i,t-4}} + \gamma^{\boldsymbol{h}} \boldsymbol{X_{i,t-4}} + u_{i,t-3}^h \tag{D.1}$$

where $h = 0, 1, 2, ..., 8$ and $L_{i,t}$ denotes credit of firm i at time t. In this regression setup, we use the symmetric growth rate of firm i's credit as the dependent variable. We measure growth between $t-4$ and $t+h-3$ due to a timing feature of our data. Specifically, our main cash flow variable records total net income over the preceding 12 months. As a result, the 4Q change in this variable at time t reflects changes in the period from $t-3$ to t relative to the period from $t-7$ to $t-4$. Since the change in cash flows could thus have occurred as early as $t-3$, we begin our impulse response at that time ($h = 0$). At the same time, $\Delta^4 CF_{i,t}$ reflects changes in cash flows as late as time t, we should expect the estimated effects to build between $h = 0$ (time $t-3$) and $h = 3$ (time t) as additional shocks arrive.

Our coefficient of interest is β^h, associated with a firm's change in cash flow $\Delta^4 CF_{i,t}$ scaled by total assets. In addition, all specifications include a firm-horizon fixed effect (α_i^h) and an industry-time-horizon fixed effect ($\tau_{t,k}^h$). The vector $X_{i,t-4}$ contains several firm controls: log of total assets, (cash and marketable securities)/total assets, tangible assets/total assets, and leverage. All firm financial variables are lagged by four quarters. In addition, $X_{i,t-4}$ includes two lagged values of the change in the cash flow variable and two lags of the four-quarter change in the dependent variable to account for possible serial correlation. Moreover, to address outliers and measurement error in $\Delta^4 CF_{i,t}/Assets_{i,t-4}$, as well as to focus on typical cash flow changes, we exclude absolute annual changes of $\Delta^4 CF_{i,t}/Assets_{i,t-4}$ that are larger than 5 percentage points.[29]

The various control variables are intended to absorb non-cash flow drivers of firm credit, so that β^h captures the remaining variation due to cash flow changes. Even so, interpreting β^h as a causal estimate would face identification challenges. Instead, our results focus on the differences in β^h across credit categories to decompose the roles of credit lines and term loans in driving the observed correlations of cash flow changes and credit growth at various horizons.

Figure D.1 shows the negative of the estimated coefficients β^h to facilitate the interpretation. After a fall in net income, firms increase their total use of credit immediately (Panel (a)). The rise in credit to a negative cash flow change reaches a peak after three quarters, and actually becomes negative after around six quarters, indicating that firms' creditworthiness deteriorates in the medium run. Panels (b) and (c) show that the rise in total credit is completely accounted for by

[29] This assumption approximately corresponds to excluding observations below the 15th and above the 85th percentiles of the sample distribution. In addition, the sample is also constrained to a balanced panel and loan histories with time gaps are excluded. Our results are robust to considering absolute annual changes in net income relative to assets that are smaller than 10 p.p.

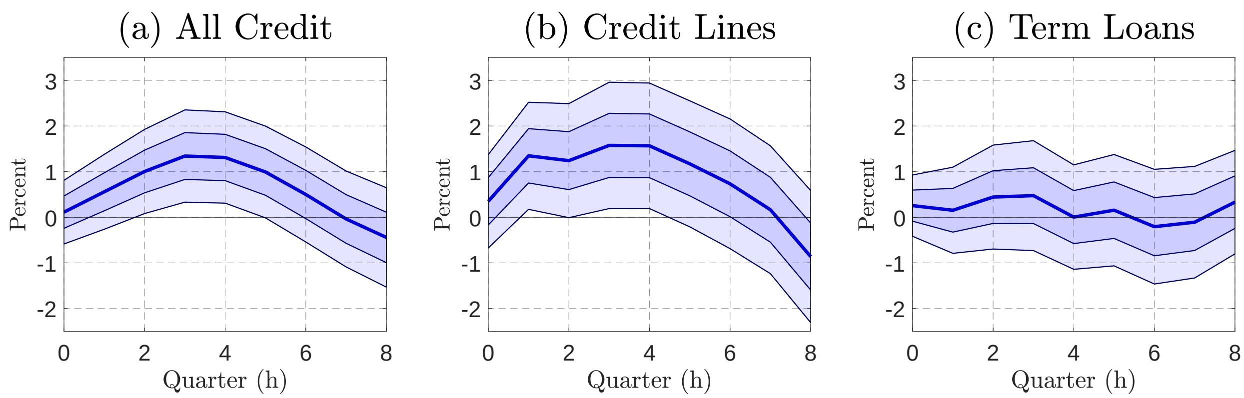

Figure D.1: Credit Responses to a Cash-Flow Change.

Notes: Responses of firms' total used credit, credit lines, and term loans to a one-unit decrease in net income relative to assets, based on the local projection approach in (D.1). Plots display estimates $-\beta^h$, corresponding to a decline in cash flows. Observations with absolute annual changes in net income relative to assets larger than 5% are excluded. The estimations are based on a balanced panel for each credit type and include 9448 (Panel (a)), 6751 (Panel (b)), and 3913 (Panel (c)) observations for each impulse response horizon. 95% and 68% confidence bands are shown using standard errors that are clustered by firm. Sample: 2012:Q3 - 2019:Q4.

the adjustment in credit lines. By contrast, there is no statistically significant adjustment in term loan usage, with point estimates close to zero at all horizons.

To understand the quantitative importance of these effects, we re-estimate regression (D.1) using the one-year change in total firm debt relative to assets as a dependent variable. We find that a $1 drop in net income is associated with an increase in total debt of around 33 cents, which is statistically different from zero at the 5% level. This estimate is very close to the one by Brown et al. (2020) who use weather events to instrument for cash-flow shocks and find a total debt increase of 35 cents for a $1 drop in net income. Most important for our analysis, we find that more than half of this change can be accounted for by credit lines drawn in our data, a lower bound given that we observe only a subset of banks.

E Additional Descriptive Evidence

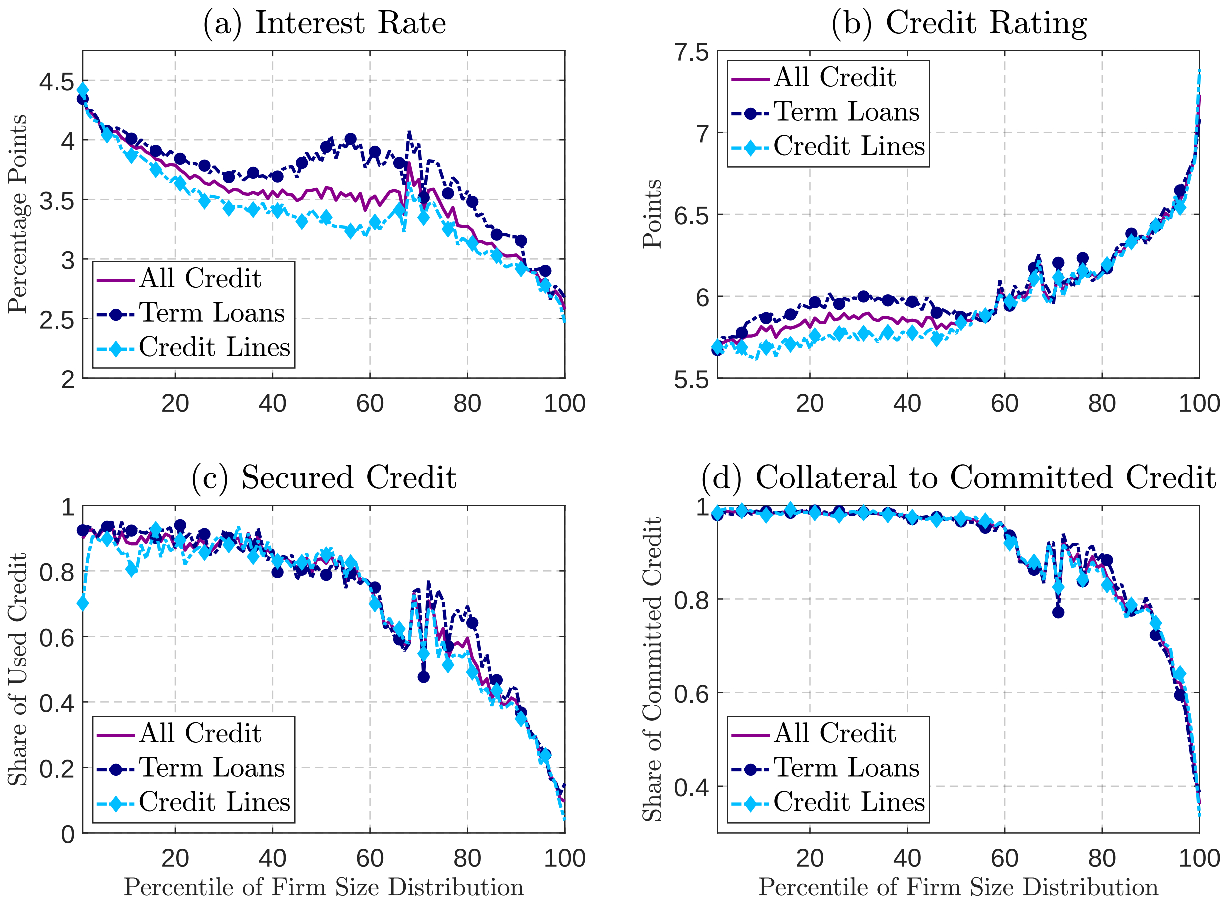

Figure E.1: Credit Characteristics across Firm Size Distribution.

Notes: The figures show various credit characteristics for percentiles across the firm size distribution. Weighted by used credit, Panel (a) portrays firms' interest rate and Panel (b) shows banks' internal credit rating (we assign a number to each rating ranging from 10 (AAA) to 1 (D)). Panel (c) displays the share of credit that is secured by collateral (value of collateral is set to loan commitment amount if it exceeds this amount). Panel (d) shows the value of collateral relative to committed credit. The firm size distribution is computed for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4.

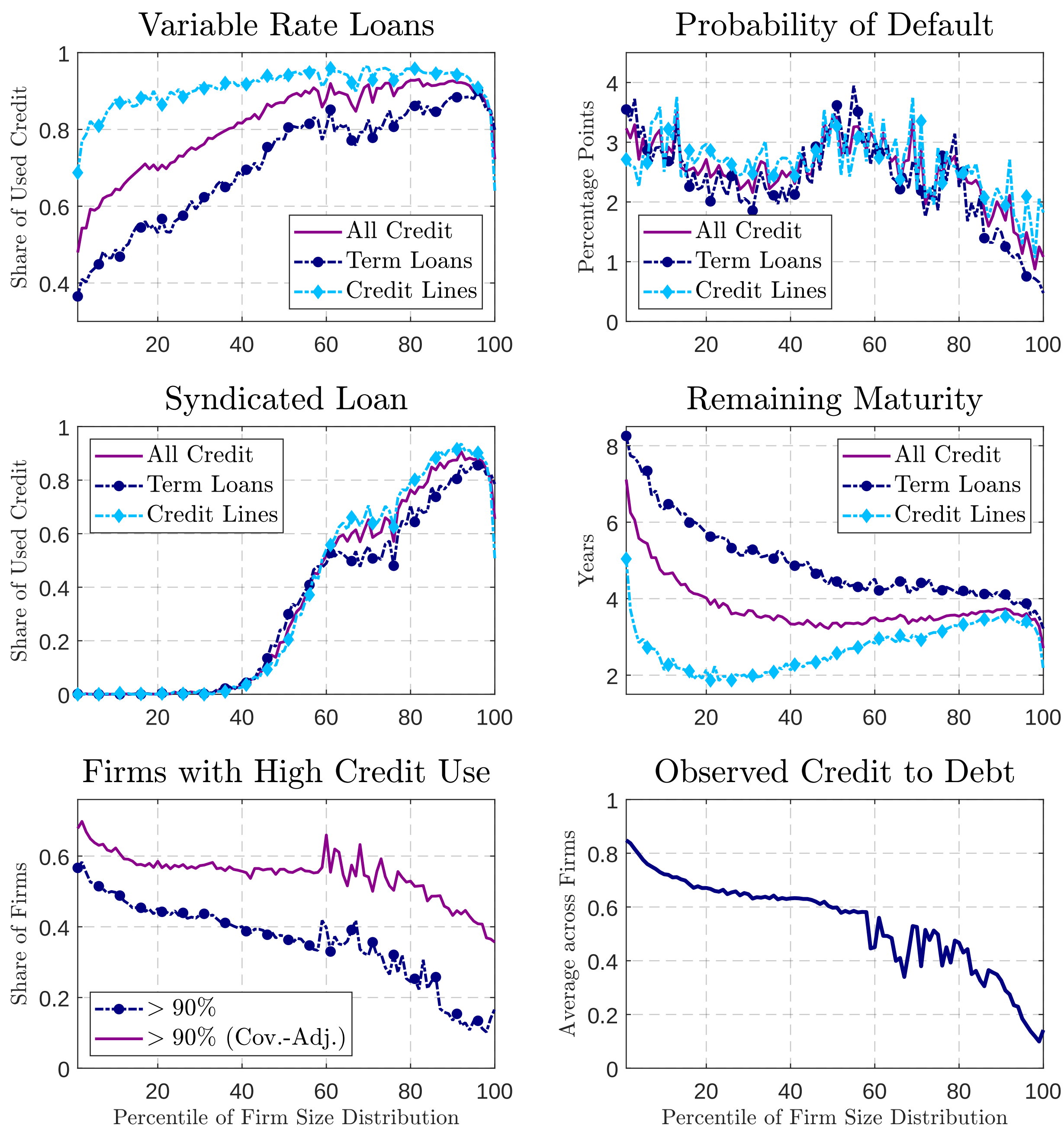

Figure E.2: Credit Characteristics across Firm Size Distribution.

Notes: The figures show various credit characteristics for percentiles across the firm size distribution. The top left gives the share of loans that carry a variable rate. The top right shows banks' assessed probability of default. The middle left gives the share of used credit that is syndicated and the middle right shows remaining maturity weighted by all used credit. The bottom left gives the share of firms that use at least 90% of their committed credit, which is additionally adjusted for covenants (see Appendix B.3). The bottom right graph shows the average share of observed credit in our data relative to total debt. The firm size distribution is computed for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4.

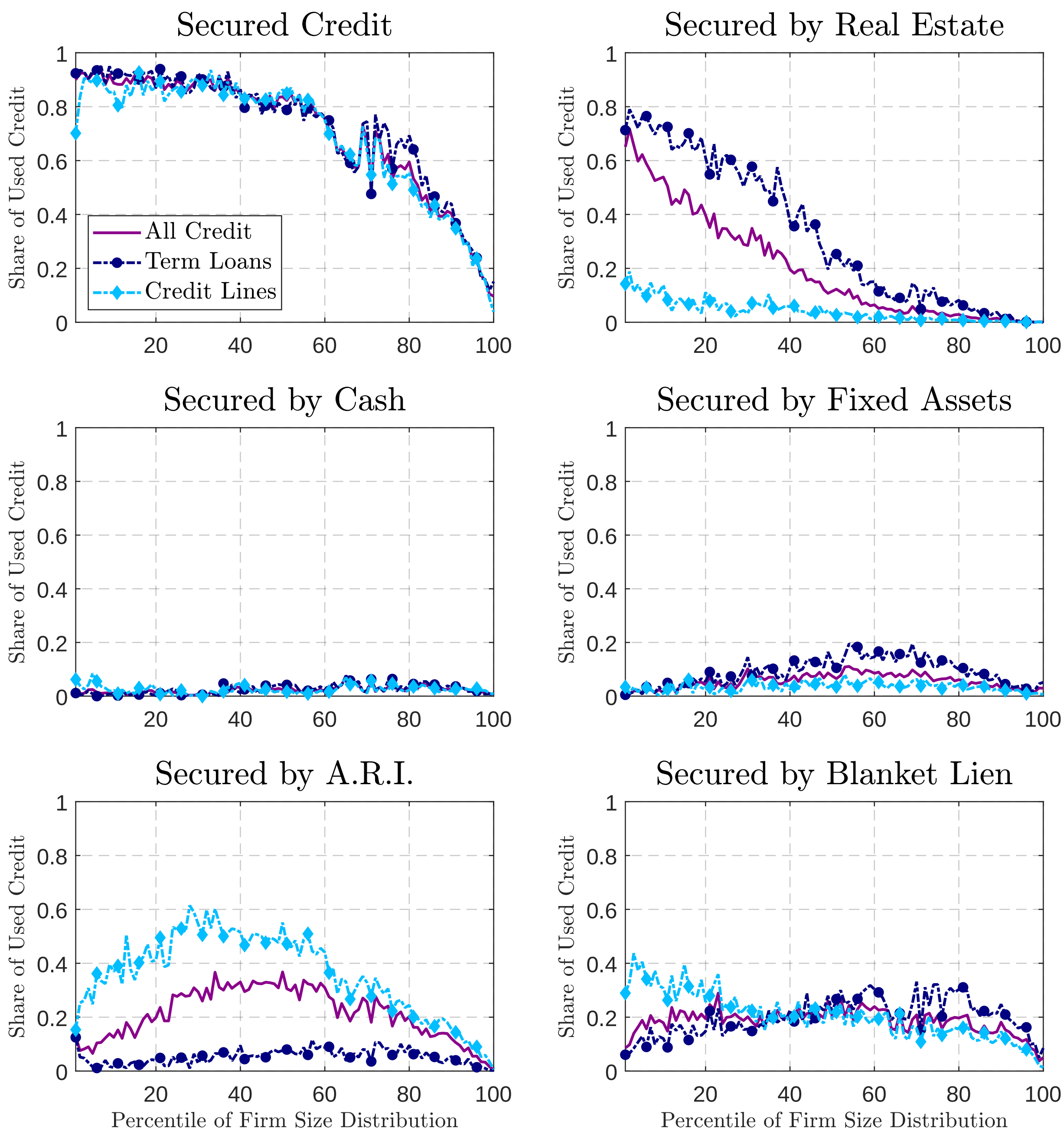

Figure E.3: Credit Characteristics across Firm Size Distribution.

Notes: The figures show the share of used credit that is secured by collateral for percentiles across the firm size distribution. The top left gives the share of loans that is secured by some type of collateral. The remaining graphs show the share of used credit secured by real estate (top right), cash and marketable securities (middle left), fixed assets excluding real estate (middle right), accounts receivables and inventory (A.R.I., bottom left), or by a blanket lien (bottom right). The firm size distribution is computed for each date according to firms' total assets. Sample: 2012:Q3 - 2019:Q4.

F Behavior of Firm Credit during COVID-19 crisis

Table F.1: Summary Statistics.

Variable	Obs.	Mean	Std.	P10	Median	P90
Main Regressors						
Δ Credit Line Usage/Assets	28	.010	.008	.001	.001	.026
Δ Deposits/Assets	28	.061	.065	.012	.043	.164
Total Capital Buffer	28	4.094	2.007	2.134	3.473	7.482
Unused Credit Lines/Assets	28	.096	.053	.021	.092	.173
Bank Controls						
ROA	28	.009	.005	.002	.010	.014
Income Gap	28	.334	.110	.177	.345	.451
Leverage	28	.885	.022	.853	.891	.914
Ln(Total Assets)	28	19.486	1.019	18.518	19.081	21.308
Deposit Share	28	.629	.164	.383	.683	.791
Δ Provision Losses/Assets	28	-.000	.002	-.002	0	.001
Δ Probability Default	28	.013	.015	0	.007	.036

Notes: Summary statistics for the main regressors in regression (4.1). All variables are at the bank level for 2019:Q4, while changes are between 2019:Q4 and 2020:Q1.

Table F.2: COVID-19 Credit Supply − Firm Fixed Effect.

	(i) 2020:Q1	(ii) 2020:Q1	(iii) 2020:Q1	(iv) 2020:Q2	(v) 2020:Q3	(vi) 2020:Q4	(vii) 2020:Q1
Δ Credit Line Usage	-1.81***	-1.81***	-2.70***	-3.19***	-3.72**	-1.99	-1.62***
	(0.55)	(0.51)	(0.82)	(0.73)	(1.36)	(3.02)	(0.57)
Δ Deposits							0.23
							(0.19)
Fixed Effects							
Maturity		✓					
Purpose			✓				
Bank Controls			✓				✓
R-squared	0.01	0.01	0.02	0.01	0.01	0	0.01
Observations	1,678	1,596	1,022	1,519	1,390	1,019	1,678
Number of Firms	749	712	464	682	624	460	749
Number of Banks	28	28	28	28	28	28	28

Notes: Estimation results for regressions (4.1) that omit the firm fixed effect. The dependent variable is given by changes in credit between 2019:Q4 and 2020:Q1 in columns (i)-(iii) and (vii), from 2019:Q4 to 2020:Q2 in column (iv), from 2019:Q4 and 2020:Q3 in column (v), and from 2019:Q4 and 2020:Q3 in column (vi). The regressors "Δ Credit Line Usage" and "Δ Deposits" denote the change of a bank's used existing credit lines or deposits from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. Column (ii) includes a fixed effect that varies by the remaining maturity and column (iii) includes a fixed effect that varies by the loan purpose. Maturity fixed effects take the form of three bins according to their remaining maturity in 2019:Q4: (i) less than one quarter, (ii) less than one year, and (iii) more than one year. Columns (iii) and (vi) include various bank controls for 2019:Q4: bank size (natural log of total assets), return on assets (net income/total assets), leverage (total liabilities/total assets), deposit share (total deposits/total assets), and banks' income gap (see Appendix Table B.1 for details on the data). Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.3: COVID-19 Credit Supply − Alternative Fixed Effects.

	(i)	(ii)	(iii)	(iv)
Δ Credit Line Usage	-0.86***	-0.87***	-0.97**	-1.63***
	(0.30)	(0.26)	(0.36)	(0.56)
Fixed Effects				
Rate	✓	✓		
Rate × Industry × Location			✓	
Rate × Industry × Location × Size				✓
Single Lender		✓		
R-squared	0	0	0.44	0.49
Observations	31,246	23,444	11,399	5,266
Number of Firms	28,569	23,444	9,569	3,538
Number of Banks	29	29	29	29

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit between 2019:Q4 and an average across non-missing observations for 2020:Q1-Q3. The regressor "Δ Credit Line Usage" denotes the change of a bank's used existing credit lines from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. All regressions omit firm-specific fixed effects and include single bank-firm relations. Columns (i) and (ii) include fixed effects that vary by rate type (adjustable- or fixed-rate). Columns (iii) and (iv) additionally allow the fixed effects to vary by industry (two-digit NAICS code), location (zip code of a firm's headquarter), and ten equally sized groups of the distribution of total observed credit to proxy for firm size. Column (ii) considers only firms with a single lender within our data. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.4: COVID-19 − Credit Supply in 2020:Q2.

	(i)	(ii)	(iii)	(iv)
Δ Credit Line Usage	-3.03**	-3.40***	-4.51***	-2.88***
	(1.14)	(1.05)	(1.31)	(1.03)
Δ Deposits				0.23
				(0.28)
Fixed Effects				
Firm × Rate	✓			✓
Firm × Rate × Maturity		✓		
Firm × Rate × Purpose			✓	
Bank Controls			✓	✓
R-squared	0.51	0.52	0.54	0.51
Observations	1,519	1,472	925	1,519
Number of Firms	682	661	421	682
Number of Banks	28	28	28	28

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit between 2019:Q4 and 2020:Q2. The regressors "Δ Credit Line Usage" and "Δ Deposits" denote the change of a bank's used existing credit lines or deposits from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. All regressions include firm-specific fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and the remaining maturity (column (ii)) or the loan purpose (column (iii)). Maturity fixed effects take the form of three bins according to their remaining maturity in 2019:Q4: (i) less than one quarter, (ii) less than one year, and (iii) more than one year. Columns (iii) and (iv) include various bank controls for 2019:Q4: bank size (natural log of total assets), return on assets (net income/total assets), leverage (total liabilities/total assets), deposit share (total deposits/total assets), and banks' income gap (see Appendix Table B.1 for details on the data). All specifications are estimated using OLS. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q2. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.5: COVID-19 − Credit Supply in 2020:Q3.

	(i)	(ii)	(iii)	(iv)
Δ Credit Line Usage	-3.63**	-3.72**	-6.37***	-3.47**
	(1.62)	(1.66)	(1.33)	(1.61)
Δ Deposits				0.23
				(0.33)
Fixed Effects				
Firm × Rate	✓			✓
Firm × Rate × Maturity		✓		
Firm × Rate × Purpose			✓	
Bank Controls			✓	✓
R-squared	0.53	0.53	0.54	0.53
Observations	1,390	1,358	856	1,390
Number of Firms	624	610	390	624
Number of Banks	28	28	28	28

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit between 2019:Q4 and 2020:Q3. The regressors "Δ Credit Line Usage" and "Δ Deposits" denote the change of a bank's used existing credit lines or deposits from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. All regressions include firm-specific fixed effects that additionally vary by rate type (adjustable- or fixed-rate) and the remaining maturity (column (ii)) or the loan purpose (column (iii)). Maturity fixed effects take the form of three bins according to their remaining maturity in 2019:Q4: (i) less than one quarter, (ii) less than one year, and (iii) more than one year. Columns (iii) and (iv) include various bank controls for 2019:Q4: bank size (natural log of total assets), return on assets (net income/total assets), leverage (total liabilities/total assets), deposit share (total deposits/total assets), and banks' income gap (see Appendix Table B.1 for details on the data). All specifications are estimated using OLS. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.6: COVID-19 Credit Supply − Sample Splits.

	(i) Fixed-Rate	(ii) Adj.-Rate	(iii) Small Loans	(iv) Large Loans	(v) Non-Synd.	(vi) Synd.
Δ Credit Line Usage	-3.53**	0.14	-3.19***	0.03	-3.11**	-0.29
	(1.29)	(0.97)	(1.11)	(1.67)	(1.18)	(1.98)
Fixed Effects						
Firm	✓	✓				
Firm × Rate			✓	✓	✓	✓
R-squared	0.5	0.55	0.49	0.68	0.48	0.67
Observations	1,312	366	1,270	165	1,378	186
Number of Firms	587	166	573	77	618	82
Number of Banks	22	26	26	22	23	21

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit between 2019:Q4 and an average across non-missing observations for 2020:Q1-Q3. The regressor "Δ Credit Line Usage" denotes the change of a bank's used existing credit lines from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. All regressions include firm-specific fixed effects that additionally vary by rate type (adjustable- or fixed-rate) in columns (iii) - (vi). Columns (i) and (ii) split the sample into fixed-rate and adjustable-rate loans. Columns (iii) and (iv) divide the sample into small and large loans according to the threshold between the bottom 90% and the top 10% of the unconditional loan size distribution in 2019:Q4. Columns (v) and (vi) split the sample into non-syndicated and syndicated loans. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.7: COVID-19 Credit Supply − IV-Estimation & Portfolio Losses.

	Baseline (i)	IV-Estimation (ii)	Portfolio Losses (iii)
Δ Credit Line Usage	-2.63**	-2.93*	-2.57***
	(1.04)	(1.69)	(0.85)
Δ Probability Default			-0.17
			(0.79)
Δ Provision Losses			3.55
			(9.44)
Fixed Effects: Firm × Rate	✓	✓	✓
Bank Controls	✓	✓	✓
Estimator	OLS	IV	OLS
First Stage F-Stat.		31	
R-squared	0.51	0.51	0.51
Observations	1,678	1,678	1,678
Number of Firms	749	749	749
Number of Banks	28	28	28

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in credit between 2019:Q4 and an average across non-missing observations for 2020:Q1-Q3. Column (i) reports the baseline specification corresponding to column (i) in Table 4.1. The regressor "Δ Credit Line Usage" denotes the change of a bank's used existing credit lines from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4, and is instrumented with a bank's ratio of unused credit commitments relative to assets in 2019:Q4 in column (ii). The regressor "Δ Probability Default" denotes the reported change in the probability of default of a bank's existing term loan portfolio between 2019:Q4 and 2020:Q1, relative to total assets in 2019:Q4 and excluding the loan related to the dependent variable. The regressor "Δ Provision Losses" denotes the change in the provision for loan and lease losses reported in banks' income statement between 2019:Q4 and 2020:Q1, relative to total assets in 2019:Q4. All specifications include various bank controls for 2019:Q4: bank size (natural log of total assets), return on assets (net income/total assets), leverage (total liabilities/total assets), deposit share (total deposits/total assets), and banks' income gap (see Appendix Table B.1 for details on the data). Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table F.8: COVID-19 Credit Supply − Interest Rates.

	Δ Interest Rate			Δ Interest Rate (Trimmed)		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	2020:Q1	2020:Q2	2020:Q3	2020:Q1	2020:Q2	2020:Q3
Δ Credit Line Usage	-0.51	1.68**	2.22**	0.85	0.94	1.41
	(1.02)	(0.75)	(0.98)	(0.63)	(0.66)	(0.84)
Fixed Effects						
Firm $\times$ Rate	✓	✓	✓	✓	✓	✓
R-squared	0.76	0.9	0.92	0.83	0.94	0.94
Observations	1,644	1,487	1,359	1,598	1,444	1,319
Number of Firms	733	667	609	714	648	591
Number of Banks	28	28	28	28	28	28

Notes: Estimation results for regressions (4.1), where the dependent variable is given by changes in interest rates ($r^{j,k}_{i,t+h} - r^{j,k}_{i,t-1}$) between 2019:Q4 and 2020:Q1 in columns (i) and (iv), from 2019:Q4 to 2020:Q2 in columns (ii) and (v), and between 2019:Q4 and 2020:Q3 in columns (iii) and (vi). Columns (iv)-(vi) exclude observations within the 1% tails of the distribution of the dependent variable. The regressor "Δ Credit Line Usage" denotes the change of a bank's used existing credit lines from 2019:Q4 to 2020:Q1, relative to total assets in 2019:Q4. Standard errors in parentheses are clustered by bank. Sample: 2019:Q4 - 2020:Q3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

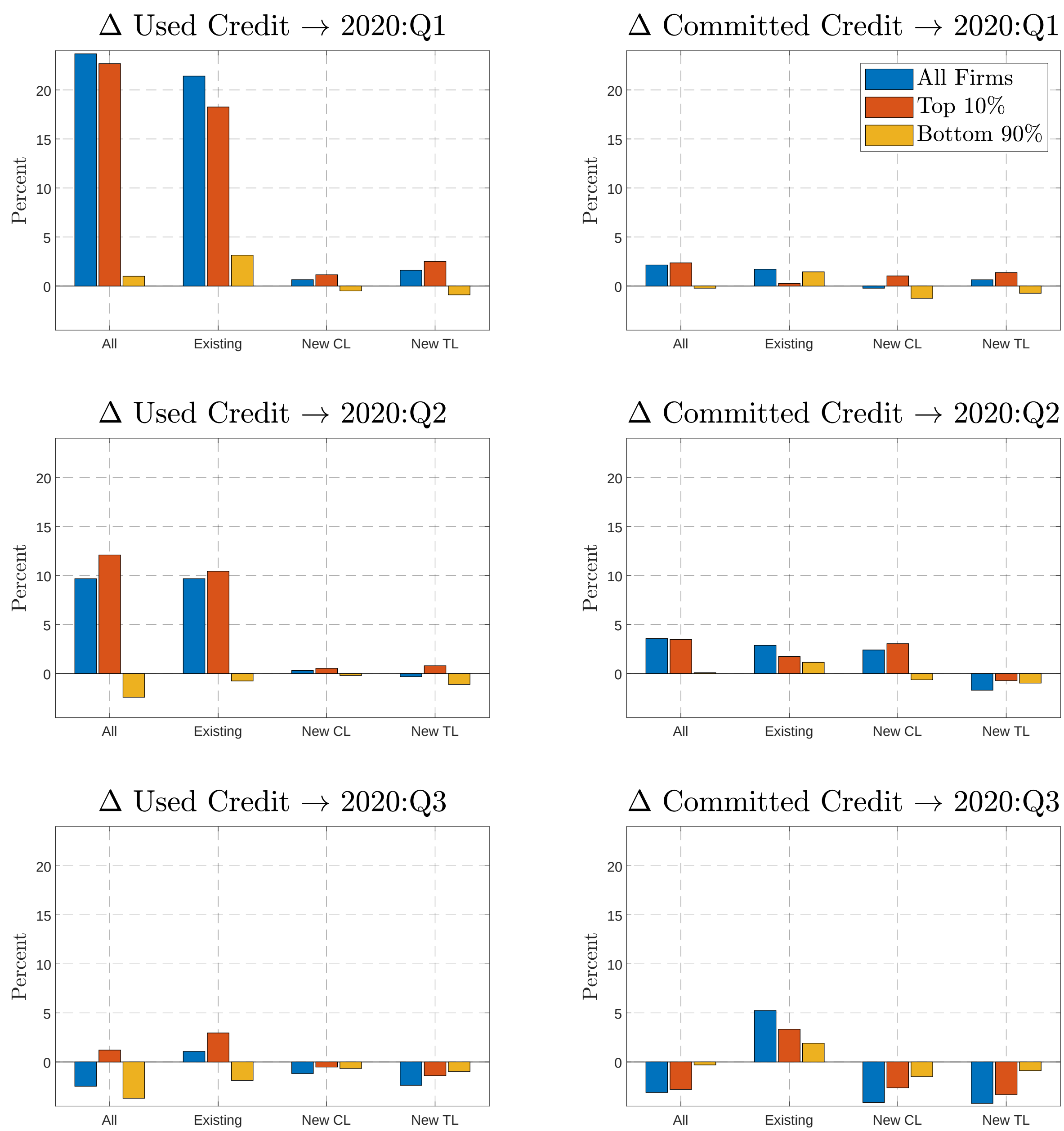

Figure F.1: Changes in Used and Committed Credit for 2019:Q4 - 2020:Q3.

Notes: The blue bars show aggregate changes in used and committed credit across all banks and firms from 2019:Q4 to 2020:Q1 (top), 2020:Q2 (middle), or 2020:Q3 (bottom), all relative to total used credit in 2019:Q4. The orange and yellow bars display equivalent changes for the top 10% and the bottom 90% of the firm size distribution, also relative to total used credit in 2019:Q4. The changes are further separated into differences in existing credit ("Existing"), new credit line issuances ("New CL"), and new term loans ("New TL"), all in percent relative to all used credit in 2019:Q4. The firm size distribution is computed according to firms' total assets in 2019:Q4 for each quarter.